COVID-19 pandemic and stock performance: evidence from Sub-Saharan African stock markets

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Declaration

I, **Mbongiseni Ncube (student number 220101144)**, declares that this thesis titled **“COVID-19 pandemic and stock performance: evidence from sub-Saharan African stock markets”** and the material enclosed in this PhD thesis are an outcome of my original empirical research work. I hereby proclaim that:

- This research project was conducted when I was a PhD (Finance) candidate at the University of KwaZulu-Natal;

- The research work has not been previously submitted in its totality, or in part, at any other institution for the award of any degree;

- I have acknowledged all sources through referencing and citations; and

- I authorise the University of KwaZulu-Natal to replicate for research purposes either the whole or any section of this thesis in any way possible.

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Full Name

16/07/2024

Date

Publications associated with this research

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Dedication

I dedicate this research to my two daughters, Nomabusiso and Nasya.

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Abstract

This study examined the impact of the COVID-19 pandemic on stock performance in sub-Saharan Africa utilising data from the two largest exchanges and two smaller exchanges in the region. While previous studies have primarily analysed the impact of the pandemic on overall stock market performance, this study investigated its prolonged effects from 2020 to the end of 2022, focusing on both sector- and firm-level effects. An event study methodology was applied to assess the impact of the pandemic outbreak and related events on stock returns, and Explainable Artificial Intelligence was employed to analyse the impact on stock volatility. The study also explored the role of firm-specific factors on stock performance during the pandemic and further investigated the possibility of constructing a factor portfolio that could enhance investor returns during crisis periods. The findings revealed that larger stock markets experienced more pronounced declines and higher volatility than smaller ones following the outbreak of the COVID-19 pandemic and related events. Although the pandemic disrupted markets, rising infections and deaths had no significant direct impact on stock performance in sub-Saharan Africa. Instead, government-imposed restrictions negatively impacted stock performance, while introduction of vaccination programmes helped to stabilise the markets. Although the sectoral impact of the pandemic varied, in larger exchanges, sectors that struggled were those impacted by supply shocks, whereas in smaller exchanges, sectors that faced demand shocks were most affected. The healthcare sector proved to be the most resilient, maintaining stability, even under strict government measures. Additionally, economic stability played a more crucial role, as inflation and exchange rate fluctuations significantly influenced stock returns, particularly in countries with high inflation. Firm-specific factors also shaped stock performance, with momentum stocks and stocks for financially robust companies demonstrating resilience while weaker firms struggled. The study's findings also revealed that factor portfolios were more robust than traditional market cap-weighted portfolios, offering better protection to investors during crises. The study emphasised the importance of sector and stock diversification as a risk management strategy during crises periods. Governments are also encouraged to balance public health policies with economic stability to support stock market resilience in sub-Saharan Africa.

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List of acronyms

ARs	Abnormal returns
ASEA	African Securities Exchanges Association
CARs	Cumulative Abnormal returns
CFO	Cash flow from Operations
COVID-19	Coronavirus Disease 2019.
EPS	Earnings per Share
ETFs	Exchange Traded Funds
FCF	Free Cash flow
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
GICS	Global Industry Classification Standards
IMF	International Monetary Fund
JSE	Johannesburg Stock Exchange
LuSE	Lusaka Stock Exchange
NGX	Nigerian Stock Exchange Group
NI	Net Income
ROA	Return on Assets
ROE	Return on Equity
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus.
SHAP	SHapley Additive Explanations.
SSA	sub-Saharan Africa
WHO	World Health Organisation
XAI	Explainable Artificial Intelligence
XGboost	Extreme Gradient Boosting
ZSE	Zimbabwe Stock Exchange

Chapter 1. Introduction

1.1 Introduction

The COVID-19 pandemic is an ongoing global health crisis attributable to the SARS-CoV-2 virus, first detected in late 2019. This infectious disease has profoundly impacted worldwide public health, economies, and financial markets. On 11 March 2020, the World Health Organization (WHO) categorised COVID-19 as a global pandemic citing its swift worldwide spread and considerable impact on public health (World Health Organization, 2020). This pandemic is particularly noteworthy in the context of the previous global health crises. For instance, by September 2021, the number of viral deaths in the US had surpassed the 675 446 total deaths from the 1918 Spanish flu, which was previously regarded as the worst US pandemic-related death toll on record. Additionally, the COVID-19 pandemic has resulted in an estimated 7 million deaths worldwide, surpassing the number of deaths from the H1N1 "swine flu" pandemic of 2009-2010, which had an estimated 200,000 to 500,000 deaths globally (Dawood, Iuliano, Reed, Meltzer, Shay, Cheng, Bandaranayake, Breiman, Brooks, & Buchy, 2012; Worldometer, 2024). Furthermore, the COVID-19 pandemic stands out because of its unprecedented speed of global spread. Within a few months, it affected over 100 countries and prompted governments to implement widespread lockdowns and travel restrictions (World Health Organization, 2021).

The COVID-19 pandemic has had far-reaching consequences beyond its immediate health impact. This crisis has been further marked by disruptions to global trade and supply chains, soaring government debts and fiscal deficits, high unemployment rates, and widespread business closures and bankruptcies, as noted by the International Monetary Fund (International Monetary Fund, 2020c). Additionally, financial markets have been severely affected, with major indices, such as the S&P 500, experiencing sharp declines. For instance, the S&P 500 fell by more than 30% between its peak in February 2020 and its trough in March 2020 (Reuters, 2020). The CBOE Volatility Index (VIX), a measure of market uncertainty, also reached levels not seen since the 2008 financial crisis (Apergis, Mustafa, & Malik, 2023).

Stock markets serve as economic barometers, reflecting investor sentiment, financial health, and market stability, particularly during crises such as the COVID-19 pandemic (Abberger, Graff, Campelo, Lemos Gouveia, Müller, & Sturm, 2020; Jagannarayan & Jayachitra, 2021). The significant declines observed in global stock indices highlight heightened investor uncertainty and anticipated economic downturns, exacerbated by disruptions to supply chains, reduced consumer spending, and business closures prompted by COVID-19 containment measures (Cevik, Kirci Altinkeski, Cevik, & Dibooglu, 2022). Despite the initial decline in stock market indices at the onset of the pandemic, it was found that stock markets quickly rebounded, with indices such as the S&P 500 reaching a record high by August 2020 (Reuters, 2020). Although the recovery of stock market indices may suggest a positive trend, it does not necessarily translate into positive investment performance across all sectors and stocks. Some sectors may have rebounded quickly, while others may have continued to struggle. An in-depth analysis of industry- and firm-level performance is crucial to understanding the actual dynamics of the stock market during the COVID-19 pandemic and the impact on investments.

General index levels or stock prices do not solely measure stock performance. Key metrics such as returns and volatility are essential for assessing investment yield, market risk and investor confidence. Returns represent the gain or loss of an investment over a specific period, whereas volatility indicates the degree of price fluctuations, reflecting market uncertainty and risk. Moreover, portfolio investment performance should be evaluated rather than individual stocks. Portfolio performance provides a more comprehensive view of investment outcomes by considering diversification and risk-management strategies. This approach is critical during periods of market turbulence, such as the COVID-19 pandemic, when different sectors and stocks are more likely to experience varying levels of impact and recovery.

Generally, stock market performance varies considerably among countries and regions, often correlating with the level of economic development (Chikwira & Mohammed, 2023; Yartey, 2008; Yartey & Adjasi, 2007). While there is no consensus on which stock markets are the best performing, it is generally observed that stock markets in developed economies tend to be more liquid and exhibit higher trading activities. In contrast, while often more volatile, stock markets in emerging economies offer substantial growth opportunities (Akhtar, 2021; Yartey, 2008). Developed markets, such as those in the United States and Europe, benefit from robust financial infrastructure, regulatory frameworks and investor confidence, contributing to their liquidity and stability. Conversely, emerging markets, including those in sub-Saharan Africa (SSA), Asia, and Latin America, are characterised by higher levels of risk and volatility but also have significant potential for growth due to expanding economies and increasing capital inflows (Claessens, Dell'Ariccia, Igan, & Laeven, 2010; Lane & Milesi-Ferretti, 2017).

The emergence of the COVID-19 pandemic added another layer of complexity to stock market performance owing to its novelty and unprecedented global impact on economies and financial systems. This situation has necessitated a thorough investigation into the performance of stock markets during the pandemic. This study, therefore, investigates stock performance during the COVID-19 pandemic, with a specific focus on sub-Saharan African stock markets. This study systematically examines sector-level, individual, and portfolio performance to understand how the pandemic outbreak and its events affected investment performance in SSA stock markets. Understanding these dynamics is crucial for assessing the pandemic's lasting impact on investment performance in SSA and informing future crisis management strategies.

This chapter introduces the study by discussing the background and context, followed by the research aim, problem statement, objectives, and questions. Next, it highlights the study's significance and contribution. The chapter also outlines the delimitations and concludes with the assumptions underlying the research.

1.2 Background and Motivations

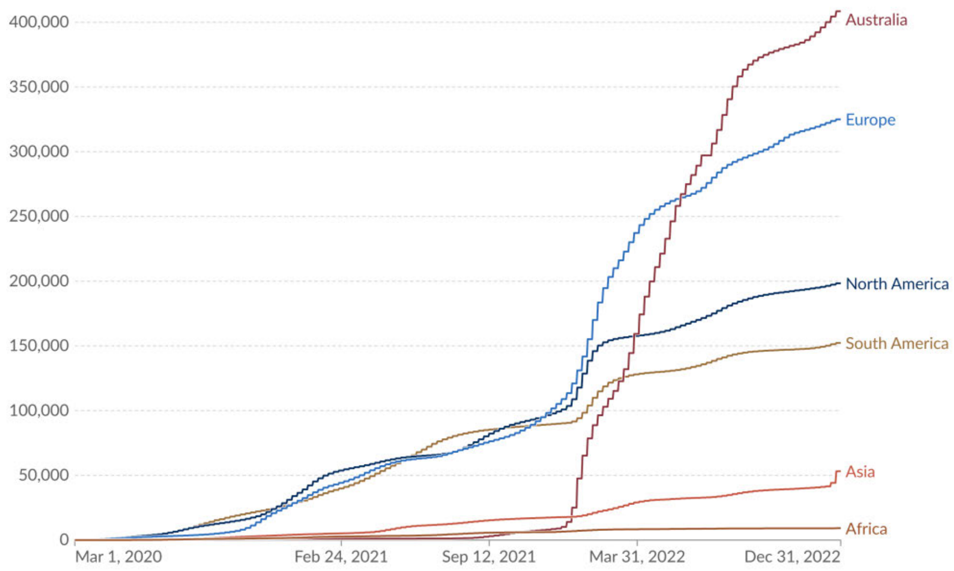
The COVID-19 epidemic has had a far-reaching impact on economies and financial markets across the globe, precipitating the most severe global recession since the Great Depression of 1930 (Gopinath, 2020). The pandemic has exposed vulnerabilities in global supply chains, labour markets, and financial systems, leading to a sharp contraction in economic activity and a significant increase in uncertainty (Pak, Adegboye, Adekunle, Rahman, McBryde, & Eisen, 2020). The global economic ramifications of the COVID-19 pandemic have been substantial, far surpassing those of the global financial crisis (Gopinath, 2020). Countries worldwide experienced supply chain disruptions, increased unemployment rates, and reduced consumer demand (Pak *et al.*, 2020). Governments around the globe responded by implementing diverse strategies to mitigate the spread of the virus. These measures include cancellations of public events, limitations on social gatherings, constraints on internal movement, controls on cross-border travel, school and workplace closures, and stay-at-home requirements (Hale, Angrist, Goldszmidt, Kira, Petherick, Phillips, Webster, Cameron-Blake, Hallas, &

Majumdar, 2021; International Monetary Fund, 2020a; World Health Organization, 2021). On the other hand, the pandemic prompted governments and central banks to implement unprecedented stimulus measures to support economies. These measures have included fiscal stimulus packages, monetary policy interventions, and liquidity injections to stabilise the economy and prevent widespread economic collapse (Hale *et al.*, 2021).

Although the COVID-19 pandemic emerged as a health catastrophe that was exogenous to the economy, its impact has been severe to the extent that it suddenly affected the global economies within a short time. As put forth by Baldwin and Di Mauro (2020) and Strauss-Kahn (2020), the COVID-19 pandemic is distinct from prior crises, such as the 2007–2009 global financial crisis, in that it has had an immediate and severe impact on the real economy, causing a complete shutdown of supply and demand. In contrast, the 2008 financial crisis began with disruptions in the United States of America's real estate and financial markets, and its effects on the rest of the world were somewhat delayed (Strauss-Kahn, 2020). Additionally, studies show that financial crises usually result from adverse shocks in demand (Benguria & Taylor, 2020; Zaman, 2013). However, the financial crisis caused by the COVID-19 pandemic resulted from both demand and supply shocks, primarily due to the imposition of economic lockdowns and other government stringencies, resulting in an unprecedented impact on the global financial markets (Baldwin & Di Mauro, 2020; Benguria & Taylor, 2020). Le and Chang (2015) highlight financial markets respond differently to external shocks such as war, oil price shocks, pandemics, and economic crises; therefore, the nature of the shock is essential in determining how the financial market reacts.

The COVID-19 pandemic, first reported in late 2019 in China, rapidly disseminated to other nations across the world, affecting nearly all countries within three months (Baldwin & Di Mauro, 2020). By the 11th of March, more than 100,000 cases of COVID-19 had been reported, prompting the World Health Organization (WHO) to declare it a global pandemic (Baldwin & Di Mauro, 2020; World Health Organization, 2021). As shown in Figure 1.1, the European and North American regions had the highest cumulative record of COVID-19 infections, with Australia joining the top group after experiencing a surge in cases at the beginning of 2022. On the other hand, Africa has recorded the lowest number of COVID-19 infections compared to other regions. By the end of 2022, the cumulative record of COVID-19 infections in the African region was approximately

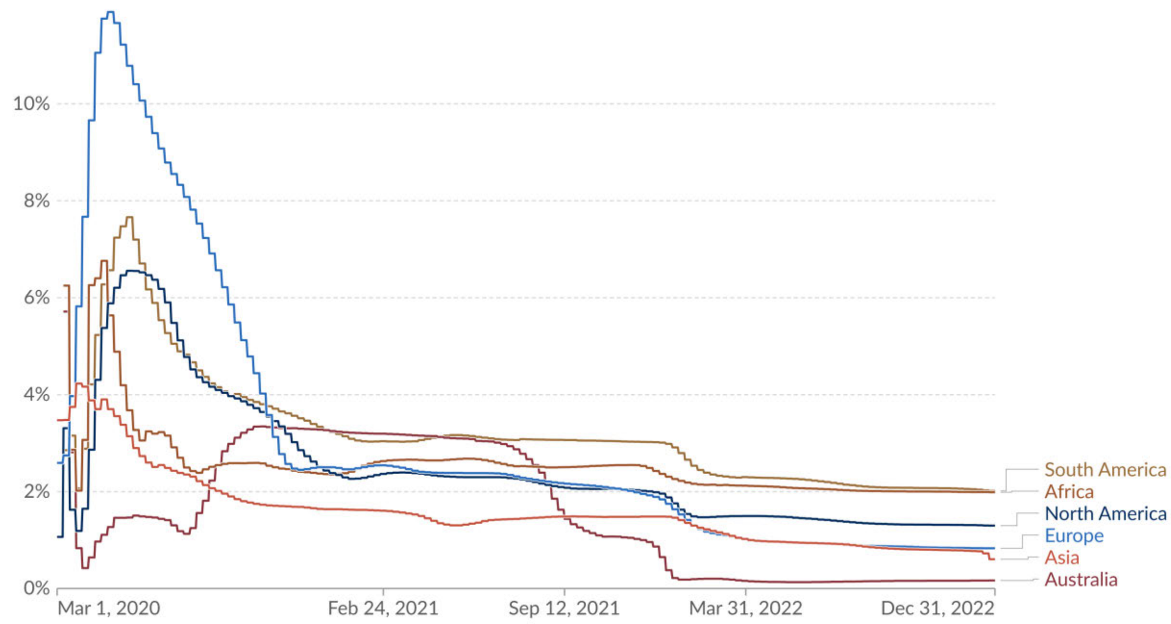
9000 per 1 million people, significantly lower than those in regions such as Europe and Australia, which topped the world with approximately 325000 and 400000 cases per 1 million people, respectively. However, despite the fewer cases, Africa had a high case fatality rate, with an average daily fatality rate of 2% in 2022, second only to South America, which had an average daily fatality rate slightly above 2% (see Figure 1.2).



Source: Our World in Data

Figure 1.1: Cumulative COVID-19 cases per million people

Thus, despite low COVID-19 infections and deaths recorded in SSA, the region had one of the highest case fatality rates. The high fatality rate in SSA can be attributed to the region's poor health infrastructure and low vaccination ratio (Hakobyan, Rawlings, & Yao, 2022; Nkengasong & Mankoula, 2020). As of mid-August 2022, the vaccination rate in SSA was around 19.5 per cent, substantially lower than 61 per cent in other emerging markets and developing economies and 75 per cent in advanced economies (Hakobyan *et al.*, 2022). This disparity in vaccination rates has been attributed to various factors, including limited access to vaccines, inadequate healthcare infrastructure, and logistical challenges in distributing vaccines to remote areas (International Monetary Fund, 2022b).



Source: Our World in Data

Figure 1.2: Case fatality rate of COVID-19.

Despite low infection rates, the economic impact of the COVID-19 pandemic was severe in SSA (International Monetary Fund, 2022a). Sub-Saharan Africa experienced a contraction in economic growth of -1.7% in 2020, which was significantly more severe than that of other emerging and developing economies in Asia, which stood at -0.9% and equivalent to that of emerging and developing Europe. This contraction was, however, less severe than that of advanced economies and the Middle East region, which recorded declines of 4.5% and 3.2%, respectively (International Monetary Fund, 2022a). Although the decline in economic growth in SSA was lower than expected, it is estimated to be the worst on record (International Monetary Fund, 2021a).

The negative economic growth in SSA is attributed to factors such as less fiscal space and high debt levels, with some countries already in debt distress in the pre-pandemic period, making it difficult to contain the pandemic and support economic recovery. The region is also characterised by high inflation (around 11% in 2020 when the pandemic hit the region), high food and commodity prices and very volatile exchange rates (International Monetary Fund, 2021a), making it difficult for central banks in some countries to implement monetary policies that could help the economy to recover. Furthermore, economic lockdowns and restrictions on movement significantly disrupted economic activity, causing widespread job losses, especially for women

(Aslam, Fuje, & Rawlings, 2021). Despite the decline at the onset of the pandemic, in 2021, the GDP for SSA rebounded to 4%, albeit lower than that of the Middle East and North Africa, emerging and developing Asia, emerging and developing Europe and advanced economies that stood at 4.1%, 7.2%, 6.5% and 4% respectively (International Monetary Fund, 2022a).

The outbreak of the COVID-19 epidemic has not only adversely impacted economic growth but has also precipitated instability in the financial markets across the globe.(Baker, Bloom, Davis, Kost, Sammon, & Viratyosin, 2020; Khan, Zhao, Zhang, Yang, Shah, & Jahanger, 2020; Kusumahadi & Permana, 2021; Li, Zhuang, Wang, & Dong, 2021; Zhang, Hu, & Ji, 2020; Zhao, Rasoulinezhad, Sarker, & Taghizadeh-Hesary, 2023). Following the pandemic outbreak, most stock markets experienced a decline in returns and an increase in volatility. For example, in the early stages of the pandemic, the S&P 500 experienced its fastest decline in history, with the index falling by over 30% in just a few weeks (Reuters, 2020). The COVID-19 epidemic has also led to an increase in uncertainty, with investors being uncertain about the duration and impact of the virus on the global economy and financial markets. This uncertainty has led to a significant increase in volatility, with many markets experiencing significant swings in both directions (see Efimova & Rozhnova, 2021). However, the global stock markets have shown a quicker rebound from the COVID-19 pandemic than other health-related crises, although the recovery has been uneven across different sectors and regions (International Monetary Fund, 2020a). Various factors, including policy interventions and the rapid development of vaccines, have contributed to the market's resilience. These interventions have helped restore investor confidence and stabilise the markets (International Monetary Fund, 2020a; Nguyen., Anh, & Gan, 2021).

In the bond market, government bond yields in developed markets declined as investors sought safe assets, leading to lower borrowing costs (International Monetary Fund, 2020a). However, in emerging markets, government bond yields witnessed a substantial rise in government bond yields due to credit downgrades and aversion to emerging markets (International Monetary Fund, 2020a). There was also an increase in credit spread and some liquidity strain in fixed-income securities (International Monetary Fund, 2020a). The job losses also resulted in declining borrowers' repayment capacity in both emerging and developed economies (International Monetary Fund, 2020b), increasing default risk in the bond market. In the foreign exchange

(FX) market, emerging market currencies weakened against the United States of America Dollar (USD), while developed market currencies appreciated relative to the USD during the pandemic period (Efimova & Rozhnova, 2021). However, the stress in FX markets was lower than during the 2007–09 global financial crisis, with less noticeable demand for dollar liquidity (International Monetary Fund, 2020b).

Extant literature has indicated interconnectedness between stock markets and economic growth (Pradhan, Arvin, Hall, & Bahmani, 2014; Yartey & Adjasi, 2007). Stock markets are commonly perceived as barometers of national economic growth. They provide a conducive environment for acquiring additional financial resources for investment projects and risk-sharing, albeit at times being identified as a hindrance to economic development because of their vulnerability to market failures (Fosback, 2016; Łon, 2020). The advancement of stock markets enables investors to access financial resources and promotes the efficient allocation of resources, thereby enhancing both domestic and foreign investments (Pradhan *et al.*, 2014). According to Carp (2012), stock markets play a crucial role in the global economy, and their impact on economic growth can permeate the real economy. They can influence economic growth by providing liquidity and attracting investments from domestic and international sources, stimulating economic activity (Carp, 2012). In addition, they enable investors to diversify their investments across various securities and sectors, thus mitigating risk.

Although the COVID-19 pandemic affected stock markets across the globe, findings show that the impact of the pandemic differed across capital markets for developed and developing economies (Kusumahadi & Permana, 2021; Ridhwan, Juhro, Ismail, Nijkamp, & Hidayat, 2024; Zhao *et al.*, 2023). Studies indicate that the pandemic had a more pronounced adverse impact on developed countries' stock markets than developing markets (Núñez-Mora, Santillán-Salgado, & Contreras-Valdez, 2022; Shah, Raza, & Mustafa Hashmi, 2022). Developed economies experienced increased market volatility, but they also experienced a positive risk premium as returns exceeded pre-pandemic levels, supported by factors such as government stimulus, monetary policy changes, and technological advancements (Shah *et al.*, 2022). This aligns with the research findings of Seven and Yılmaz (2021) and indicates that developed country stock markets rebounded quickly after government stimulus support, outperforming emerging markets. Hui and Chan (2022) further highlight that countries that quickly implemented quarantine measures experienced a lower impact of the pandemic on their stock markets.

Despite their resilience during crises, developed nations' stock markets were more susceptible to pandemic-related shocks than emerging nations (Belcaid, El Aoufi, & Al-Faryan, 2023; Gunay & Can, 2022). For instance, although the COVID-19 pandemic began in China, the United States of America (USA) experienced the most significant impact on global equity markets (see for example, Belcaid *et al.*, 2023). Muzindutsi, Sheodin and Dube (2022) on the other hand argue that emerging markets experienced more pronounced contagion effects than developed ones due to their inherent instability. However, Zhao *et al.* (2023) elucidate that the pandemic predominantly influenced stock markets in developed countries through economic shocks, such as supply and demand reduction and instability. Conversely, developing nations were affected through social factors, including changes in confidence, consumption patterns, and herding behaviour. Farooq, Nasir and Bashir (2022) further highlight that stock markets in developed countries experienced greater negative returns at the outset of the pandemic. In contrast, developing countries experienced substantially negative abnormal returns during the second wave.

A significant number of studies have been done that considered the influence of the COVID-19 epidemic on developed and other emerging economies; however, less focus has been placed on the stock markets in SSA. Stock markets in SSA form a significant part of capital markets, predominantly featuring stocks issued by large corporations. However, these stock markets are relatively small and illiquid compared to those in developed and other emerging markets (Hartland-Peel, 2022; Soumaré, Kanga, Tyson, & Raga, 2021). Stock markets in this region are also highly volatile, with trading heavily concentrated in a limited number of stocks representing a substantial portion of the total market capitalisation (European Investment Bank, 2022a; Soumaré *et al.*, 2021). For example, in 2020, the average market capitalisation of listed companies in Africa was 63.6% of GDP, compared to almost 100% in East Asia and the Pacific (see report by European Investment Bank, 2022a).

Furthermore, stock exchanges in SSA are still in their early stages of development, with a limited number of trading instruments that primarily focus on stocks and bonds and a relatively small number of listed companies (Soumaré *et al.*, 2021). The 2022 European Investment Bank report revealed that in 2020, Africa had 1,251 companies listed on its stock exchanges, almost half the number on the London Stock Exchange and 40% of Nasdaq listings. Of these, almost 397 traded in North African exchanges alone, while the remaining 854 traded in SSA. Some exchanges, such as Bourse des Valeurs Mobilières de l'Afrique Centrale, which serves the Economic and Monetary Community of Central Africa (EMCCA), had only four listed companies across all six member countries (European Investment Bank, 2022a). This lack of diversity in listed stocks poses a significant challenge to African stock market growth.

Furthermore, stock market investments in SSA are heavily concentrated in a few countries. (African Securities Exchanges Association, 2022). In a region with 46 countries, there are approximately 29 stock exchanges spread across 38 countries and a combined market capitalisation of around $1.6 trillion in 2022. The Johannesburg Stock Exchange (JSE) remains the largest in the region in terms of market capitalisation and the number of securities listed on the exchange (African Securities Exchanges Association, 2022). For the total market capitalisation of $1.6 trillion for the sub-Saharan African stock exchanges as of mid-year 2022, the JSE's market capitalisation was estimated at $1 trillion, representing more than 60% share, and Nigeria, the second-largest stock exchange in the sub-Saharan African region, had a market capitalisation of $68.9 (ASEA, 2022). Of the 1250 securities listed on the exchange, if we exclude those listed on the JSE, the number of firms on sub-Saharan African exchanges decreases to 523 (EIB, 2022).

Despite their smaller size and lower level of development, stock markets in SSA have shown some resilience and growth in recent years, which presents opportunities for value preservation and risk diversification for both local and international investors (Hartland-Peel, 2022; Soumaré *et al.*, 2021). Experience from previous pandemics, such as Ebola, SARS, and other respiratory diseases, and the 2007–2009 global financial crisis, shows that stock markets in sub-Saharan Africa have been more resilient to the shocks of these health and financial crises than developed markets (Emenike, 2018; Ichev & Marinč, 2018; Sugimoto, Matsuki, & Yoshida, 2014). For example, the Ebola outbreak harmed stock markets geographically closer to the birthplace of Ebola and US stocks than on other stock markets in sub-Saharan Africa (Ichev & Marinč, 2018). Although the global financial crisis led to a decline in security returns and increased risk levels in sub-Saharan stock markets, it mainly impacted the US and other developed country stock markets (Emenike, 2018), and the increase in some African stock exchanges was mainly a result of spillovers from developed country stock markets (Emenike, 2018; Sugimoto *et al.*, 2014).

Given the investment opportunities in SSA, why is the stock market investment still low? According to a report from the Economic Commission for Africa (2020), the limited diversity of financial instruments and the limited number of listed stocks are significant hindrances to potential investors in sub-Saharan African stock markets, as they restrict the ability of investors to diversify their portfolios effectively. More related findings were previously echoed by Moss, Ramachandran and Standley (2007), who found that lack of security diversity, small numbers of traded securities, and low levels of liquidity were major deterrents for foreign institutional investors in sub-Saharan African stock exchanges.

The sub-Saharan African region primarily offers two main avenues for investing in African stocks: direct purchase of individual stocks and investment through funds, including exchange-traded funds (ETFs) and mutual funds (African Securities Exchanges Association, 2022). Most ETFs in sub-Saharan Africa are passive investment and sector- and market-cap-based index funds (African Securities Exchanges Association, 2022). This contrasts with stock markets in developed and other emerging countries, which have a variety of investment vehicles, such as smart beta factor-based index funds. Smart beta index funds are innovative investment options that can deliver more different returns than traditional passive investments (Morgan Stanley, 2023). Studies show that smart beta investment strategies diversified across various factors during crisis periods tend to offer better returns than purely passive market-cap-weighted index funds (Meng, Shen, & Xiong, 2023; Morgan Stanley, 2023; Zaher, 2019). Thus, sub-Saharan African stock exchanges need to create a range of investment securities, such as ETFs that track the performance of securities that have demonstrated resilience to the pandemic or multi-factor-based portfolios that have the potential to diversify risk and deliver better returns during crises periods, such as the COVID-19 pandemic. To achieve this, it is necessary to conduct comprehensive research to evaluate the performance of various stocks during the pandemic and to identify the traits of stocks that have demonstrated resilience during this period. Portfolio managers can then utilise this information to construct investment portfolios.

Although some studies have focused on the influence of the COVID-19 pandemic on equity market performance in SSA, most have focused on equity market performance at the initial stage of the pandemic. For example, Takyi and Bentum-Ennin (2021) found that the COVID-19 pandemic negatively affected stock market performance in SSA. However, their investigation focused on the performance of African stock exchanges between October 2019 and June 2020. Conversely, studies by Jamilu and Rafindadi (2022); Kumeka, Ajayi and Adeniyi (2022) suggest that sub-Saharan African stock markets have shown resilience to the COVID-19 outbreak, although their analyses were confined to the initial stages of the pandemic outbreak. Furthermore, researchers have indicated that the rise in COVID-19 cases and fatalities did not significantly affect equity market returns in the African region. Instead, the short-term impact primarily stems from external factors such as elevated inflation, currency exchange rate fluctuations, and unstable commodity prices (Jamilu & Rafindadi, 2022; Kumeka *et al.*, 2022). Considering the circumstances surrounding COVID-19's emergence, its rapid spread across the world, and the unprecedented events that followed, it is essential to examine how the ensuing events affected stock performance in SSA. These events include the implementation and relaxation of lockdown measures, the rollout of vaccination programs, the introduction of economic stimulus packages, and the occurrence of new COVID-19 variants. A comprehensive study is necessary to analyse the effects of these factors on the region's stock markets.

Furthermore, research on the consequences of the pandemic on equity market performance in SSA has mainly concentrated on overall stock market performance at the index level without evaluating the impacts on specific sectors and companies (Bayero, Safiyanu, & Bakabe, 2021; Kumeka, Ajayi, & Adeniyi, 2021; Tetteh, Amoah, Ofori-Boateng, & Hughes, 2022). Studies from developed stock markets that considered the impact of the pandemic at the sector level revealed variations in sector responses. For example, Mazur, Dang and Vega (2021) found that in US equity markets, stocks in the food, software, healthcare and natural gas sectors generated significantly higher returns. In contrast, stocks in the real estate, hospitality, petroleum and entertainment sectors experienced stark declines. Similarly, Alam, Wei and Wahid (2021) found that on the Australian stock exchange, sectors such as food, telecommunications, pharmaceuticals, and healthcare recorded good performance, whereas the transportation industry performed poorly during the pandemic's outbreak. Thus, although the overall stock market quickly recovered from the pandemic's effects, not all sectors rebounded. This necessitates further investigation in SSA to assess how different sectors and stocks were impacted by the emergence of the pandemic. For investment performance analysis, there is a need to understand how various stocks performed during the pandemic to identify those sectors and stocks that are candidates for selection in constructing portfolios that can perform well even in crisis periods.

This study aims to bridge the existing gaps in theoretical understanding and empirical evidence in scholarly discourse. It expands the knowledge base by focusing on the effects of the COVID-19 epidemic on stock performance at sector and firm levels, as previous studies in SSA have primarily examined overall market performance at the index level (Bayero *et al.*, 2021; Kumeka *et al.*, 2021; Tetteh *et al.*, 2022). This approach provides more granular insights into the impact of COVID-19 on equity markets in SSA, and helps to reveal the sector- and firm-level exposure of stocks to the COVID-19 epidemic. The study also considers the impact of events that followed the initial outbreak of the pandemic, such as the imposition of lockdowns, the introduction of vaccinations, stimulus packages, and the occurrence of new COVID-19 variants, as previous research has primarily concentrated on the pandemic's early stages (Jamilu & Rafindadi, 2022; Kumeka *et al.*, 2022). By investigating the effects of these subsequent events, this study provides an extensive understanding of the pandemic's prolonged impact on stock markets in SSA.

Another critical contribution of this study is its assessment of the influence of firm-specific factors on stock market performance. By identifying the characteristics of firms that demonstrated resilience during the pandemic, this study provides valuable insights for investors and portfolio managers in picking stocks for companies that are more robust to extreme market events such as COVID-19. This can guide the construction of multi-factor portfolios or smart beta portfolios resilient to market crises. This is particularly important given the region's limited diversity of financial instruments traded on the exchanges and the predominance of passive investment funds (ETFs) that are sector-based and market-cap-based.

1.3 Aim

The overarching aim of this study is to comprehensively analyse the effect of the COVID-19 pandemic on stock performance in SSA. Specifically, this research investigates how the COVID-19 outbreak and its associated events, including government stringency measures, economic support measures, vaccinations, and the emergence of other COVID-19 variants, have affected stock performance in SSA. Furthermore, this study analyses the significance of firm-specific factors on stock performance in SSA to identify the factors that characterised stocks that demonstrated resilience to the adverse impact of the COVID-19 epidemic.

1.4 Problem statement

The COVID-19 pandemic has had profound implications for global financial markets, and sub-Saharan African financial markets are no exception. While existing studies have investigated the effects of the COVID-19 epidemic on equity market performance in SSA, the analyses have been limited to broad market indices, overlooking the critical nuances at the sector and firm levels (Bayero *et al.*, 2021; Kumeka *et al.*, 2021; Tetteh *et al.*, 2022). Some findings from developed stock exchanges show that the rebound in stock markets a few months after the pandemic was driven by factors such as the sectoral composition of the stock market. For instance, US stock market performance was boosted by a large share of tech firms in the S&P 500 index, as the introduction of lockdowns led to an increase in spending on new technologies, thus boosting the performance of stocks in the Information Technology (IT) sector (International Monetary Fund, 2020a). The stock exchange might appear to have survived during the pandemic, but not all sectors or firms would have fared well. Despite the above findings from developed markets, in emerging markets, particularly SSA, there is a lack of in-depth investigation of how the pandemic has affected stock performance at the sector and firm levels. This deficiency in empirical evidence may lead to suboptimal investment decisions, increased exposure to sector-specific vulnerabilities, and limited capacity to capitalise on emerging trends and opportunities within specific industries. Understanding the impact of the pandemic on stock market performance at the sector and firm level offers insights into how different sectors and individual companies responded to the pandemic, enabling more conversant investment decisions and risk management strategies in the future.

Additionally, studies conducted so far on the impact of pandemic on stock performance in SSA have been limited to the earlier stages of the pandemic, with analysis mainly focused on how the stock market returns responded to the occurrence of the COVID-19 epidemic (Kumeka *et al.*, 2022; Takyi & Bentum-Ennin, 2021). The COVID-19 epidemic emerged as a global phenomenon distinct from other epidemics and financial crises, characterised by a complex interplay of factors including the implementation of economic lockdowns, social distancing measures, travel restrictions, the development of vaccination programmes, and the emergence of various viral mutations subsequent to its initial outbreak. Therefore, it is crucial to examine how these pandemic-associated events influenced not only the returns but also the volatility of stocks in sub-Saharan African exchanges. Jana, Ghosh and Goyal (2022) highlight that the stock market's response to black swan events varies according to the nature of that event and cannot be generalised from the findings from past events. Therefore, investors need to fully understand how the events that accompanied the COVID-19 pandemic affected the stock performance before they make an investment decision.

Furthermore, investment management involves asset allocation decisions and portfolio management. Studies in other economies and experiences from past financial crises show that asset allocation and portfolio management strategies that work in typical economic environments tend to fail during market turmoil (Wenjian, 2020; Zaher, 2019). Therefore, portfolio managers need to frequently rebalance their portfolios, especially in times of market crisis. Efficient asset allocation decisions require that the portfolio manager first understands the risk and return inherent in the security being considered and the characteristics of securities that perform well in a given economic environment before they can be included in a portfolio. To the reserchers best knowledge, no study has considered the impact of firm specific factors on stock performance in SSA during the pandemic or assessed how stock portfolios have been affected by the outbreak of the COVID-19 pandemic. Understanding the influence of firm-specific variables on stock performance is crucial. It enables portfolio managers to utilise the most significant variables to select securities that can perform more effectively during periods of market crisis, such as the recent COVID-19 pandemic, and construct more robust portfolios that are resilient to market crises. Therefore, the responsiveness of stocks in sub-Saharan African stock markets to the emergence of the COVID-19 pandemic and its associated events and the resulting impact on portfolio performance is a problem that needs to be investigated.

1.5 Objectives of the study

This thesis seeks to achieve the following objectives in the context of the COVID-19 epidemic and stock performance:

i. To investigate the impact of the COVID-19 outbreak and its associated events on stock returns in sub-Saharan Africa.
ii. To investigate the impact of the COVID-19 outbreak and its associated events on stock volatility in sub-Saharan Africa.
iii. To analyse the influence of firm-specific factors on stock performance during the COVID-19 pandemic in sub-Saharan stock markets.
iv. To develop a factor-based portfolio strategy for extreme market events like the COVID-19 pandemic and assess its performance compared to a passive market-capitalisation-weighted portfolio.

1.6 Research Questions

i. How did the outbreak of the COVID-19 epidemic and its associated events impact stock returns in sub-Saharan African stock markets?

ii. How did the COVID-19 outbreak and its associated events affect stock volatility in sub-Saharan African stock markets?

iii. What firm-specific factors were the key drivers of stock performance in the sub-Saharan African stock markets during the COVID-19 epidemic?

iv. How does the performance of the factor-based portfolio compare to the market-capitalisation-weighted portfolio during the COVID-19 period?

1.7 Significance of the study

This research project greatly interests investors, portfolio managers, government, policymakers, regulators and academics.

1.7.1 Investors and portfolio managers:

The sector-level analysis offers valuable insights into the diverse effects of the pandemic across industries, enabling investors and portfolio managers to identify the sectors in which they can invest their funds and the stocks they can offload from their portfolios. Examining firm-specific factors driving stock performance during the COVID-19 pandemic would aid portfolio managers in identifying the factors influencing stock performance and equipping them to construct more robust portfolios resilient to market turbulence. The development of a portfolio that demonstrates resilience during periods of economic volatility, such as the COVID-19 pandemic, would be of significant interest to investors and portfolio managers seeking to optimise the performance of their portfolios and mitigate the risks associated with extreme market events

1.7.2 Policymakers and Regulators:

The findings regarding the impact of governmental policies and measures on the performance of equities in SSA would provide valuable insights to policymakers, enabling them to formulate more effective measures to support financial markets during crisis periods. Insights into the sector-level and firm-specific factors driving stock performance would help policymakers identify the industries and companies that require targeted support to mitigate the economic consequences of black-swan events. The study's analysis of the pandemic's impact on stock market volatility and the development of resilient portfolio strategies would inform the design of regulatory frameworks and risk management policies to enhance the stability and resilience of the financial system.

1.7.3 Academics and Researchers:

This study enhances the existing literature by offering a more extensive comprehension of the pandemic's effects on stock exchanges in SSA. It addresses the current gaps in research on the impact of pandemics on sector performance and firm-specific analyses, and the impact of government policies and interventions on stock market performance during crises. Developing a factor-based portfolio strategy that can outperform the market portfolio during turbulent times would interest researchers exploring the application of alternative investment approaches in emerging and frontier markets.

1.8 Contributions of the study

This study extends the limited research on the influence of the COVID-19 epidemic on equity market performance in SSA by providing a comprehensive analysis at the sector and individual firm levels and addressing the gap in the current literature on the effect of the COVID-19 epidemic on stock market performance, which has primarily focused on index-level performance. Furthermore, this study is among the pioneering studies that empirically examine the effects of government policies, restrictions, eco-economic support measures, and vaccination efforts on stock performance in SSA, addressing a critical gap in the existing literature. Second, this study explores firm-specific factors that have driven stock performance during the pandemic, offering new insights into the characteristics of stocks that have been resilient to the adverse impact of the pandemic. Such information is needed by portfolio managers in their asset allocation decisions, especially in times of financial crises, as they need to know which stocks to offload and which ones to include in their portfolios. Third, in this study, we created a factor-based portfolio strategy that can outperform the traditional market-cap-weighted portfolio even during the pandemic. Therefore, this study adds a more diverse method for constructing portfolios in SSA that can be utilised by active investors seeking to earn a positive alpha from their investments beyond what they could earn by using passive investment strategies.

Finally, this study adds a novel method for modelling the relationship between COVID-19 events and stock performance. Most studies apply traditional regression models to analyse the relationships between these variables. However, these methods are effective when the data meet the underlying assumptions and are applicable when there are many observations. This research utilises explainable artificial intelligence (XAI) techniques, particularly Sharply Additive Explanations (SHAP), to address the issue of low data frequency in many sub-Saharan African stock exchanges. The SHAP method is advantageous as it can be applied effectively even in scenarios with limited observations (Bhattacharya, 2022). The SHAP method is also considered model-agnostic, implying that no assumptions need to be made regarding the distribution of the underlying data (Bhattacharya, 2022).

1.9 Delimitations of the study

The study focuses solely on sub-Saharan African stock markets, concentrating on the effect of the pandemic on individual sectors rather than on overall market indices. Only four stock exchanges were included, two large and two small exchanges in SSA. By including two large and two small exchanges, this study aims to capture a representative sample of the stock market landscape in SSA and to ensure that the findings are generalisable to both large and small exchanges. Focusing on a limited number of exchanges further ensures the feasibility of the study, given the potential challenges in obtaining reliable and consistent data from a more significant number of exchanges. By concentrating on four exchanges, the study can ensure that the data collection and analysis processes are manageable and that the findings are based on a robust dataset.

Additionally, stocks in each exchange are grouped into sectors using the Global Industry Classification Standards (GICS) approach, which groups stocks into 11 sectors. This allows for a more feasible analysis of all stocks trading in each exchange and, at the same time, ensures that stocks in all sectors are well represented compared to simply choosing a sample of stocks in the universe of stocks in a given exchange. To analyse individual stock performance, stocks with infrequent trading or missing values for the factor variables are excluded to ensure the results' reliability and validity. Including stocks with missing data for the variables can skew the results and lead to incorrect conclusions regarding the drivers of stock performance during the pandemic. This delimitation is consistent with the recommendations in the literature on addressing potential issues arising from thin trading, such as adjusting for non-trading days, filtering out illiquid stocks, or using alternative trading measures.

This study focused on the 2020 to 2022 study period, which covered the entirety of the COVID-19 pandemic. The year 2023 was excluded as most countries in SSA recorded few to nil COVID-19 cases and deaths (Worldometer, 2024). Furthermore, the World Health Organization (WHO) announced in May 2023 that the COVID-19 pandemic was no longer considered a Public Health Emergency of International Concern (PHEIC) due to the substantial decrease in global COVID-19-related fatalities and hospitalisations (World Health Organization, 2024). Although the 2019 dataset was not incorporated into the primary analysis, it was utilised as a proxy for the pre-crisis period to compare stock performance in the periods before and during COVID-19.

1.10 **Assumptions of the study**

It is assumed that the findings from the study can be reasonably generalised to other countries in the region and to different periods during the pandemic. The study aims to provide insights specific to the analysed markets and periods and broadly applicable across the sub-Saharan African region and various pandemic stages. The study also assumes that the data used for analysis, including stock prices, COVID-19 statistics, government policy announcements, and firm-specific variables, is accurate, complete, and free from significant manipulations. It is assumed that COVID-19 events and government policies are exogenous to stock market performance, implying that stock returns do not influence them. This allows for establishing a causal relationship between these factors and stock performance.

1.11 **Limitations of the study**

This study only covers the COVID-19 pandemic period. Due to the limited historical stock data on sub-Saharan African stock exchanges and time constraints, this study did not cover other extreme market events in sub-Saharan Africa, such as the Ebola outbreak, political unrest in Africa, and other economic crises. Despite this limitation, the researchers believe that the conclusions drawn from this COVID-19 period could be used to prepare for future extreme market events in the sub-Saharan region. However, findings from other researchers concerning the influence of black swan events on equity market performance in emerging and developing markets have been used to support the findings of this study.

Another limitation of this study is that it covers only four stock exchanges in the region, which might make it difficult for the findings to be generalised to some economies in the sub-Saharan African region. Since the analysis was conducted at the sector and firm level, it was not feasible, given the time and resource constraints, to gather and analyse the data for all or even 50% of stock exchanges traded in the region. Africa had approximately 28 regional stock exchanges as of mid-year 2022, when the study was initially conducted. However, to counter this, a careful sample selection was performed to ensure a complete representation of regional stock exchanges. The sample consisted of the two largest stock exchanges in the sub-Saharan African region, located in countries with high COVID-19 infections, and two smaller stock exchanges in countries with low COVID-19 infections. Additionally, the sample consisted of countries with varying economic stability levels.

1.12 Thesis outline

This thesis comprises five chapters. The first chapter serves as an introduction, delivering a broad overview of the COVID-19 pandemic in SSA and its repercussions on the global economy and financial markets. This chapter also addresses general concerns related to stock markets in SSA, including their size, liquidity, and performance. Moreover, it presents the study's objectives, research questions, significance, contributions, limitations, and assumptions. The second chapter investigates the impact of the COVID-19 pandemic on sector returns in SSA. This chapter was published in the Journal of Economies of the Multidisciplinary Digital Publishing Institute (MDPI). An event study methodology was applied to investigate whether the pandemic and its associated events led to abnormal returns in the region's stock markets. It further evaluates the influence of COVID-19 and macroeconomic factors on stock returns. The third chapter examines the influence of the pandemic on sector volatility in SSA. This work has also been published in the Journal of Economies of the MDPI. The research employs XAI analysis to investigate how COVID-19 and macroeconomic factors have affected sector volatility in the region's stock markets.

Chapter 4 analyses stock-specific factors affecting stock performance during the pandemic in SSA. The analysis aims to identify the characteristics of stocks that have been resilient to the pandemic and those that have been adversely affected. This information is helpful in factor investing, where investors select stocks for inclusion in their portfolios based on their exposure to specific factors known to be drivers of asset returns. This work is currently under review by the Cogent Economics and Finance Journal of Tailor and Francis. Chapter 5 concludes the study and provides policy recommendations. This chapter ties together the findings from the previous three chapters and highlights how the COVID-19 pandemic and the events that followed its outbreak affected stock performance in SSA. The chapter also presents the implications of the findings in the previous three chapters and then makes theoretical and practical recommendations and recommendations for further studies.

1.13 Summary

This chapter served as an introduction. We presented the introduction, background, motivations, aim of the study, statement of the problem, study objectives, research questions, significance of the study, limitations and assumptions, and an outline of the thesis. The significance of stock markets in economic development and the limited research on the effect of the COVID-19 epidemic on stock performance in SSA highlights the need for a study to unpack the responsiveness of stocks to the outbreak of the COVID-19 pandemic. The background and problem statement highlighted the shortcomings of prior studies in emerging stock markets and in Africa in that they focused on the effects of the pandemic on stock market performance at its initial stage and did not consider the influence of the events that followed the outbreak of the pandemic. Additionally, it highlighted the dearth of research focusing on factor investing in SSA and the opportunity this modern investment management approach can bring to stock market investors. Furthermore, this chapter reveals that stock market investment in sub-Saharan exchanges is low despite the growth opportunities presented by the markets. The lack of diversity regarding the securities available for investment has been highlighted as a significant hindrance. Therefore, this study aimed to address the identified research gaps.

The subsequent chapters are structured to address the specific objectives of this study. Chapter 2 addresses objective number one, which examines the ramifications of the COVID-19 crisis and related events on stock returns in SSA. The third chapter tackles the second objective, which analyses how the pandemic and its associated occurrences influenced stock volatility in sub-Saharan stock exchanges. Chapter 4 encompasses the third and fourth objectives, initially exploring firm-specific factors that influenced stock performance in sub-Saharan markets during the COVID-19 pandemic, followed by constructing a factor portfolio designed to maximise risk-adjusted returns of stocks in this period. The study concludes with Chapter 5, which synthesises the findings of the preceding three chapters.

Chapter 2. COVID-19 Pandemic and Stock Performance: Evidence from the Sub-Saharan African Stock Markets

(*This chapter has been published in MDPI Journal of Economies (see* Appendix 1*)*

2.1 Introduction

The novel coronavirus disease, which began in late 2019 in Wuhan, China and was later dubbed the COVID-19 pandemic, has had a substantial influence on global economies and financial markets worldwide. It has been found that the COVID-19 pandemic has plunged most economies around the world into a recession and triggered one of the largest global economic crises in more than a century (Alam *et al.*, 2021; World Bank, 2020). Similarly, stock markets around the world suffered a heavy blow as stock prices plummeted at the end of the first quarter of 2020 when the pandemic hit almost all countries worldwide (Shehzad, Zaman, Liu, Górecki, & Pugnetti, 2021; Zhao, Rasoulinezhad, Sarker, & Taghizadeh-Hesary, 2022). Several studies, for example Shehzad *et al.* (2021);Chaudhary, Bakhshi and Gupta (2020); Shaikh (2021);Izzeldin, Muradoğlu, Pappas and Sivaprasad (2021);Awan, Khan, Haq and Kazmi (2021), found that the COVID-19 epidemic has negatively impacted most stock markets around the globe, whether in developing or developed markets. As a result of limited resources to deal with the repercussions of the pandemic, equity markets in developing countries are expected to have suffered the most. However, some studies (Phan & Narayan, 2020; Singh & Shaik, 2021) revealed that the impact of the COVID-19 epidemic has been more severe in developed than in developing nations. Zhao *et al.* (2022) further indicate that the influence of the COVID-19 pandemic in developed nations was driven by supply and demand reduction, and economic instability, while in developing economies, it was mostly related to changes in consumption patterns and other social issues, such as expectations and confidence.

Despite the above studies on the COVID-19 pandemic and performance of equity markets in emerging markets, most have been limited to aggregate stock market performance—that is, the performance of the stock market index—rather than performance at the sector or firm level. That being the case, it can be argued that such an analysis was made assuming that the COVID-19 epidemic had a uniform impact across all sectors and industries.

The aim of this study is to investigate the impact of the pandemic on sector performance among the sub-Saharan stock markets, as previous studies focus on the stock market as a whole and pay less attention to the sector and firm-level performance. As seen in Figure 1 below, several stock markets in sub-Saharan Africa (SSA) experienced a decline in returns when the COVID-19 epidemic hit the region in March 2020, but the markets seem to have quickly recovered within a space of few months.

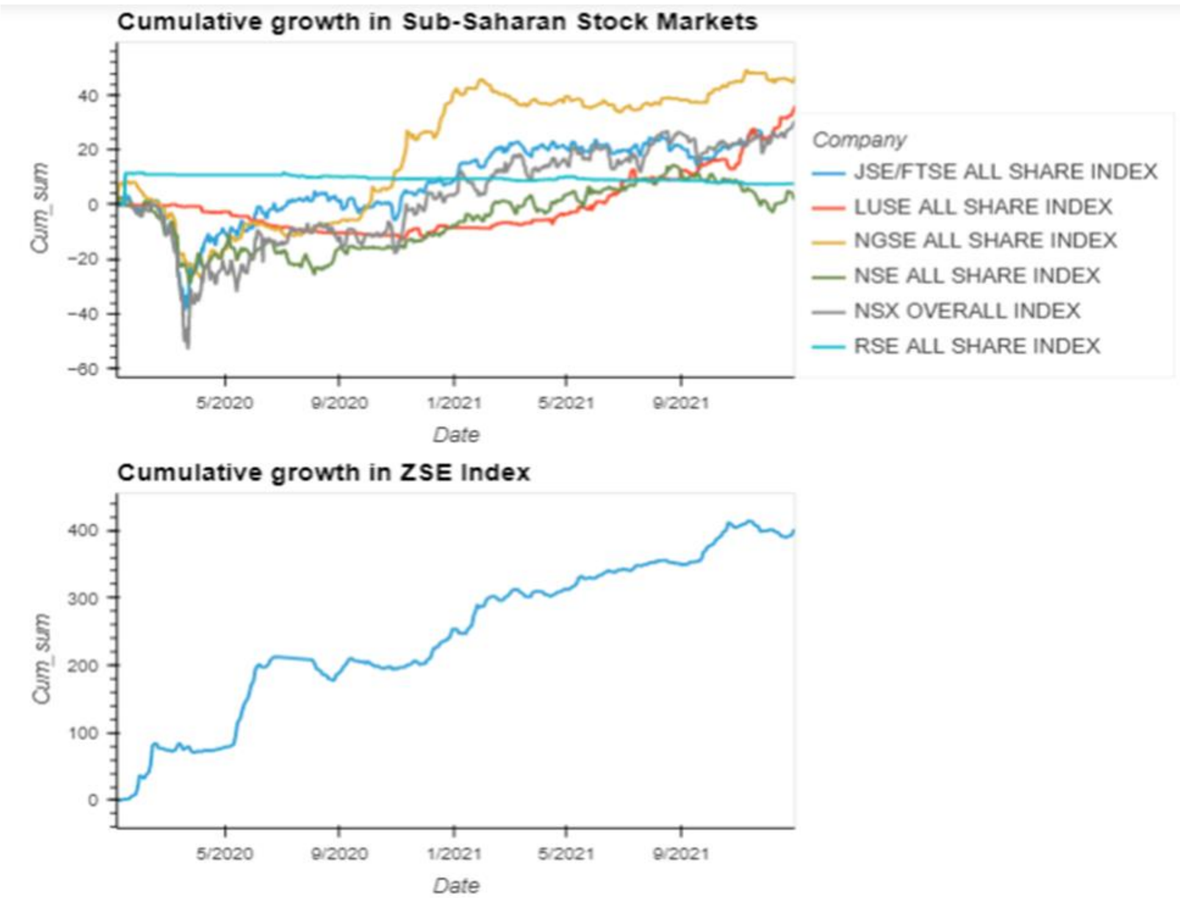


Figure 2.1: Cumulative return growth for sub-Saharan African stock markets during the pandemic.

However, some stock exchanges appear to be unaffected by the emergence of the COVID-19 pandemic, such as the Rwandan Stock Exchange (RSE), the Lusaka Stock Exchange (LUSE), and the Zimbabwean Stock Exchange. The Zimbabwean Stock Exchange emerged as the fastest-growing stock exchange during the pandemic, recording a cumulative growth rate of approximately 200% in 2020.

Despite some evidence of an adverse impact on stock market returns at the onset of the pandemic, there is a need for an investigation into how various sectors and industries in the sub-Saharan African region reacted to the COVID-19 pandemic. Research from other regions, mostly from developed markets, which explored the impact of the epidemic on various sector performance, revealed that the coronavirus had varying degrees of impact on industries and sectors (Alam *et al.*, 2021; Izzeldin *et al.*, 2021; Mazur *et al.*, 2021), even though it had an overall negative impact on stock exchanges around the globe. The pandemic was determined to have had a negative impact on real estate, transportation, energy, leisure, entertainment, and materials, whereas companies in technology, consumer staples, and healthcare performed well.

Given the difference in the economies of developed and developing nations, and the differences in measures that the government of these nations took to try and combat the pandemic, the findings from the developed economies cannot be generalized to these developing economies. Accordingly, this study investigates the impact of the pandemic on performance of various stock market sectors in SSA. To the best of our knowledge, no studies have examined the influence of the pandemic and the subsequent events that followed its outbreak on stock performance at the sector or firm level in SSA. Studies completed so far, for instance, Kumeka *et al.* (2021); Tetteh *et al.* (2022); Bayero *et al.* (2021), investigated the effects of the pandemic on overall stock market performance but did not consider how individual firms and sectors were impacted by the pandemic.

Severe pandemic diseases have become more recurrent and are posing to be a threat not only to human life but to financial markets and the entire global economy as well. Therefore, identifying the impact of the pandemic and its accompanying events on sector performance in SSA is of paramount importance, particularly for investors and portfolio managers. This analysis will facilitate the identification of sectors and stocks that offer protection to investments during periods of extreme market events such as the recent COVID-19 pandemic. Furthermore, it elucidates the effects of government policies and measures implemented to combat the spread of the pandemic on stock performance in SSA.

This paper's unique feature is that it explores how daily changes in COVID-19 cases and deaths, as well as government actions such as lockdowns and economic stimulus packages, were received by various stock market sectors in the sub-Saharan African region.

2.2 Literature Review

2.2.1 Stock Market Development in Sub-Saharan Africa

The development of stock exchanges in Africa has experienced rapid progress in the past two decades. Although many of these exchanges still have relatively low market capitalization, accounting for only 2% of the global total, the number of countries with active exchanges has increased from eight in 2002 to thirty-eight as of mid-2022 (African Securities Exchanges Association, 2022). Additionally, the combined market capitalization of African exchanges has shown substantial growth, rising from $260 billion in 2000 to $738 billion in 2011, and reaching $1.6 trillion by the end of 2021. Despite these advancements, the majority of African stock exchanges continue to face structural challenges that impede their growth. With the exception of the Johannesburg Stock Exchange (JSE) in South Africa and to a lesser extent, the prominent exchanges in Nigeria and Kenya, most African exchanges struggle with issues such as limited liquidity, sparse listings, and minimal engagement from retail investors. Consequently, these challenges have hindered the full potential of African stock markets to contribute to economic development and provide opportunities for local retail and institutional investors (Raubenheimer, 2019).

The turnover ratio, which represents the percentage of shares traded compared to total market capitalization, typically remains below 5% for the majority of sub-Saharan African stock markets (see African Securities Exchanges Association, 2022). In contrast, the Johannesburg and Namibian stock exchanges reported turnovers exceeding 30% by the end of 2021. As of mid-2022, the JSE's market capitalization was estimated at $1.16 trillion, further highlighting its significant presence in the region. Nigeria, the second-largest stock exchange in SSA, with a market cap of $68.9 billion as of mid-2022, continues to grapple with a low turnover of approximately 5% (African Securities Exchanges Association, 2022). Despite efforts to enhance capital markets trading activity across African exchanges, high trading costs have emerged as a significant obstacle.

Although exchanges such as NGX and JSE dominated African IPOs by value from 2014 to 2019, with JSE listings accounting for over 65% of the capital raised on the continent, recent years have witnessed a decline in the pipeline of IPOs and offerings across all African exchanges, including the influential South African market. Other countries such as Zimbabwe and Zambia did not recognize any IPO for the past 4 years prior to the COVID-19 outbreak. This trend, which pre-dates the Covid-19 epidemic, has accelerated during the pandemic period (European Investment Bank, 2022b). Furthermore, the amount of capital raised through initial public offerings and rights issues in South Africa is relatively low when compared to countries such as South Korea, Singapore, and Malaysia (Githinji Njenga, Josephat Machagua, & Samwel Gachanja, 2022b). In addition, sub-Saharan African countries rely heavily on external debt financing, which often comes with high-interest rates and the risk of default (Njenga *et al.*, 2022b). Financial markets in SSA have recently realised a notable increase in investment in the bond market. By the end of 2021, the JSE's bond market capitalisation reached 254 billion, representing 20% of the equity market capitalisation, valued at 1.3 trillion while the ETF market capitalisation stood at 7.6 billion. Conversely, for NGX, bond market capitalisation totalled 45 billion, while equity market capitalisation amounted to 68.9 billion (African Securities Exchanges Association, 2022).

2.2.2 **Theoretical Literature review**

2.2.2.1 **Efficient Market Hypothesis (EMH)**

The efficient market hypothesis developed by Fama (1970) postulates that all the available market information is captured in stock prices, implying that it is impossible to consistently outperform the market on a risk-adjusted level. Fama (1970) identified three types of market efficiency, which are weak-form, semi-strong and strong form of market efficiency. Each type of market efficiency has distinct implications for trading strategies and the potential to achieve abnormal returns. The weak form EMH claims that security prices reflect all the information implying that traders cannot use past price and volume information to predict future movement of security prices. Thus, technical analysis cannot generate positive adjusted returns. Semi-Strong Form Efficiency extends the weak form by asserting that all public information is already incorporated into security prices, thereby negating the effectiveness of fundamental analysis in achieving above-average returns. Strong-form efficiency goes further, asserting that all information, both public and private, is reflected in security prices, implying that even insider information cannot provide an advantage.

The emergence of the COVID-19 epidemic has resulted in an influx of information related to reports on COVID-19 infections and deaths, introduction of lockdowns and other government stringency measures, development of vaccines, and announcement of new COVID-19 variants. These elements have potential implications for EMH, specifically the semi-strong and strong forms, which assert that security prices reflect all publicly available information and that even insider information cannot lead to consistent excess returns. The question arises as to whether such information was absorbed and reflected in stock prices and whether stock markets were able to discriminate between positive and negative news. Moreover, investors' behavioural aspects may have influenced stock market movements during the COVID-19 period. Investor sentiment was predominantly characterised by fear and uncertainty, potentially leading to irrational decision-making that could contradict the principles of the efficient market hypothesis. Herd behaviour, exacerbated by wide media coverage, may have distorted market reactions, resulting in overreactions to negative news or underestimations of positive developments.

2.2.2.2 **Behavioural Finance Theories**

Behavioural finance theorists posit that investors' cognitive and emotional biases significantly influence asset price variations and should therefore be considered when investing in securities (Ferreruela & Mallor, 2021). Behavioural finance challenges the proposition by EMH that it is impossible to outperform the market, highlighting instances observed during asset bubbles where stocks traded above their fair values, and during crashes and financial crises, where their values fell below the fair market values. Consequently, the prevalent market anomalies undermine the validity of traditional finance theories. Some of the most frequently cited behavioural finance theories that attempt to elucidate investor behaviour during crisis periods include the Anchoring Bias, Loss Aversion Bias, and Herding. According to Anchoring Bias, individuals tend to anchor in their decision-making process, placing excessive emphasis on an initial piece of information that may or may not be relevant as a reference point when making a decision (Muradoğlu & Harvey, 2012). This argument is corroborated by Choi and Munro (2022); Kuruppu and De Zoysa (2020), who assert that during market declines, investors make choices based on their prior financial crisis experience. Conversely, loss-aversion bias postulates that investors tend to prefer avoiding losses to achieving gains (Tversky & Kahneman, 1991). Loss-averse investors experience greater discomfort from losses than satisfaction from gains. Consequently, the individual is more inclined to take risks in the hope of avoiding losses but is not prepared to assume the same level of risk for a potential gain. Herding behaviour is one of the most prominent behavioural biases employed to explain investors' behaviour during times of crisis. In financial markets, herding occurs when investors prefer to follow market consensus or those they perceive it to be better informed, rather than their own information and beliefs (Ferreruela & Mallor, 2021). According to some scholars (see Baker *et al.*, 2020; Choi & Munro, 2022; Ferreruela & Mallor, 2021), investors' propensity to imitate others increases during periods of severe market volatility, primarily because of loss aversion. The abrupt market downturn and subsequent swift recovery during the COVID-19 crisis could potentially be attributed to investors' behavioural biases. In the early phases of the COVID-19 pandemic, uncertainty regarding its future trajectory and concerns about potential investment losses may have driven individuals to hastily sell their assets, exacerbating the decline in asset values.

2.2.2.3 **Adaptive Market Hypothesis (AMH)**

The adaptive market hypothesis combines the efficient market hypothesis and behavioural finance. The AMH agrees that people are rational; however, they tend to overreact during periods of high market volatility(Lo, 2005). The AMH posits that investors are usually rational but not perfectly rational. They satisfice and not optimise in their decision-makings. Accordingly, investors develop heuristics for investment decision-making based on the economic environment to which they are exposed. Therefore, investors are likely to act rationally, similar to EMH, in situations where these heuristics apply. However, when there are major changes in the economic environment, adaptive heuristics are likely to be maladaptive, leading to investors' irrational behavior (Lo, 2005; Urquhart & McGroarty, 2016). The pandemic created unprecedented market volatility, leading to a re-evaluation of the established heuristics and investment strategies that investors had relied upon in more stable times. For instance, investors may have relied on trends and historical data to inform their decisions, but the pandemic introduced a range of new uncertainties, including public health concerns, government interventions, and shifts in consumer behaviour. The AMH also posits that heuristics can become maladaptive during periods of significant change (Willett, 2022). As the pandemic progressed, some investors might have remained clung to outdated strategies that were no longer applicable, resulting in suboptimal investment decisions.

2.2.2.4 Contagion Theory and Financial Market Linkages

According to Hansen (2021), in financial markets, the term 'contagion' refers to the spread of shocks among participants, institutions, and markets. Widespread interconnectedness and heightened correlation between markets, actors, and investment strategies are frequently cited as the primary drivers of the proliferation of this phenomenon. Contagion theory suggests that financial distress in one market can propagate quickly to others, especially during crises (Hansen, 2021). The COVID-19 pandemic has simultaneously affected global economies, leading to synchronised declines across various stock markets as investor sentiments adjusted to a more pessimistic economic outlook. Additionally, as international investors sought to mitigate risks, they may have withdrawn funds from smaller, less stable markets, amplifying declines in these areas and contributing to a broader global downturn. This phenomenon could have been further exacerbated by the interconnectedness of global financial systems, in which capital flows and investment decisions are influenced by events occurring in distant markets. As major economies implemented lockdowns and travel restrictions, ripple effects were felt across supply chains, leading to production halts and decreased global consumer demand. The interconnectedness of financial markets meant that even stock markets that were initially less affected by the pandemic were vulnerable to fallout from more significantly impacted regions.

2.2.3 Black Swan Events and Stock Market Performance

A black swan is an extremely unusual occurrence that is unanticipated and can have disastrous repercussions (Taleb, 2007) . A black swan event can take many forms, including a natural disaster, a war, a financial crisis, or a virus outbreak. According to Taleb (2007), a black swan has the following three main characteristics; First, it is an unpredictable event that occurs outside of usual expectations; second, it has a significant and far-reaching impact on the economy, society, and or the entire planet. Lastly, once it occurs, it is less random and more predictable than before. According to Teitler-Regev and Tavor (2019), black swan events such as natural disasters, terrorism attacks, and man-made disasters usually have an adverse impact on the stock market and the economy as a whole. However, it has been discovered that the impact on stock markets is typically short-term, with stock markets quickly returning to normal levels a few days after the event. As noted by Seetharam (2017), the stock market’s reaction to black swan events is determined by the company's level of exposure to those events. For example, firms such as those in tourism, travel, and leisure, are associated with lower returns than the non-exposed when an environmental disaster strikes.

Black swan events frequently lead to black swan investing, in which investors seek out stocks and other safe haven assets that will hold their value if the market falls due to a catastrophic event (Kuruppu & De Zoysa, 2020; Lybeck, 2017). Other researchers have shown that black swan events are associated with behavioural biases such as fear, loss aversion, and hindsight bias (Bekiros, Boubaker, Nguyen, & Uddin, 2017; Nafday, 2009; Yarovaya, Matkovskyy, & Jalan, 2021). Another significant revelation is made by Tastsidis Olsson and Löfberg (2014), who point out that black swan events lead to herding behaviour because investors tend to take sides taken by the masses, such as buying when others are also buying, or selling when others are selling, and this often leads to inefficient markets.

The COVID-19 epidemic is widely viewed as a Black Swan event due to its unforeseen emergence, its massive and immediate global disruption and retrospective analysis that suggests its inevitability. The consequences of COVID-19 were unprecedented, disrupting economies, public health systems, and daily life across the globe (WHO, 2020b). According to Johns Hopkins University (2021) database, by January 2021, over 88 million people had been infected, and more than 1.9 million had died due to COVID-19. The sheer scale of these disruptions reflects the severity of the pandemic, a key feature of Black Swan events. The severe consequences of the COVID-19 epidemic were also seen through its adverse impact on the global economy and financial markets. The COVID-19 pandemic led to sharp contractions in economic activity, with global GDP shrinking by 3.5% in 2020 , the vilest economic recession since the Great Depression of the 1930s (International Monetary Fund, 2021b; Kurowski, Evans, Tandon, Eozenou, Schmidt, Irwin, Cain, Pambudi, & Postolovska, 2021). .The major stock indices in developed economies such as United States , European Union and Japan fell by approxmately 30% due to the pandemic outbreak which was the largest drop since the 1987 stock market crash (Gormsen & Koijen, 2020)

2.2.4 **Respiratory Diseases and Stock Market Performance**

Although the COVID-19 epidemic is regarded as a black swan event, the world did experience other related pandemics, such as Severe Acute Respiratory Syndrome (SARS), EBOLA, Middle East Respiratory Syndrome (MERS), which were found to have affected stock markets around the globe (David, Inácio Jr, & Machado, 2021). Chen et al. (2018) examined the impact of SARS on Asian security markets and found that the epidemic weakened the stock market integration in the region. Nippani and Washer (2004), on the other hand, examined the influence of the SARS pandemic on stock market returns for all the affected countries, and the results indicated no significant negative impact except for the equity markets of China and Vietnam. However, a sector analysis by Chen, Jang and Kim (2007), using an event study methodology, indicated that stocks in the hotel industry faced a decline in returns during the outbreak of the SARS. Other sectors, such as retail, manufacturing and banking, were not significantly affected.

Choe, Wang and Song (2021) explored the impact of the MERS on the Korean tourism industry and found that the occurrence of the pandemic negatively affected the performance of this sector and also depressed the Korean economy. The negative performance was mainly due to a reduction in the number of tourists visiting the country, which led to a loss of about 3.1 billion USD between the period of June 2015 to September 2015. Further analysis by Joo, Maskery, Berro, Rotz, Lee and Brown (2019) shows that the MERS had a detrimental effect on other tourism-related industries, such as food and beverages, transportation, and accommodation. Studies on the effects of Ebola on stock markets performance show that the news on the outbreak of the pandemic led to an increase in selloffs in affected stock markets, which negatively impacted the stock prices (Funck & Gutierrez, 2018; Ichev & Marinč, 2018). The effect was more pronounced in vulnerable and small industries such as the airline, food and beverage, and leisure industries. Ichev and Marinč (2018) further reveal that the impact of Ebola was more significant in the US, European, and West African regions and that fear and anxiety rather than real economic factors influenced the inventors' decisions.

Despite the world having experienced previous health crisis, none of those crisis have had a severe adverse impact on the global economy and financial markets like the COVID-19epidemicm (World Health

Organization, 2020) . One of the most distinctive features of the COVID-19 pandemic was the use of widespread economic lockdowns to contain the virus. Entire sectors of the global economy, particularly those reliant on face-to-face interaction like tourism, hospitality, and retail, were forced to shut down (Philips, Akinseye, & Oduyemi, 2022; Platto, Wang, Zhou, & Carafoli, 2021; World Health Organization, 2020). Travel bans, quarantines, and social distancing measures resulted in a drastic reduction in global demand for goods and services. According to the World Trade Organization (WTO), world merchandise trade volume fell by 5.3% in 2020 (World Trade Organization, 2020). Such a prolonged and widespread halt in economic activity is unprecedented in modern history, making the economic impact of COVID-19 far more severe than that of earlier pandemics. Another factor that worsened the effect of the COVID-19 pandemic was the emergence of new variants of the virus. As countries began to implement measures to contain the initial outbreak, more infectious mutations, such as the Delta and Omicron variants, emerged, leading to renewed waves of infections and prolonging the crisis (World Health Organization, 2021). These mutations exacerbated the economic fallout, as many countries were forced to reinstate restrictions or delay reopening their economies. This prolonged nature of the pandemic, driven by successive waves of infections, distinguishes COVID-19 from past pandemics, which were typically one-off events with a clearer trajectory towards resolution.

2.2.5 **COVID-19 Pandemic and Stock Market Performance**

Several studies have been done that assessed the effect of the COVID-19 epidemic on stock market performance. Researchers such as Xu (2021); Alam *et al.* (2021);Yousfi, Zaied, Cheikh, Lahouel and Bouzgarrou (2021); Baker *et al.* (2020) and Cetenak (2022) considered the effect of the pandemic on equity markets of developed economies and found that the outbreak of the pandemic led to a decline in equity market returns. These studies revealed that the surge in COVID-19 infections and deaths adversely impacted the stock market performance, while the imposition of measures to revive the economy, such as economic stimulus packages, helped the stock markets to recover. Yousfi *et al.* (2021) further highlight that the government restrictions such as economic lockdowns and restriction to gatherings gave the COVID-19 pandemic a more adverse influence on stock markets compared to previous pandemics.

Studies from emerging markets also had similar findings to those from developed economies (see for instance Kharbanda & Jain, 2021; Sachdeva & Sivakumar, 2020; Topcu & Gulal, 2020). Kharbanda and Jain (2021) used a GARCH model to assess the impact of COVID-19 infections and deaths on stock market performance of BRIC countries while Sachdeva and Sivakumar (2020) performed an event study on the same BRIC stock exchanges , and they both confirm that an increase in COVID-19 infections and deaths had an adverse impact on equity market returns. Stock markets were found to be more sensitive to the pandemic during the first wave, but later on, they seemed to be less responsive. In a more related study, Topcu and Gulal (2020) investigated the effect of the COVID-19 pandemic focusing on equity markets of emerging European and Asian countries. Their study highlighted that COVID-19 initially had a sharp adverse impact on stock markets at the onset of the pandemic; however, the impact decreased over time, with signs of recovery by mid-April 2020. The study further reveals that the impact of the COVID-19 epidemic on the equity markets of emerging economies was smaller in countries where the government responded swiftly to put measures in place to curb the pandemic and where there was more government support in the form of economic stimulus packages. This is further supported by Singh and Shaik (2021), who found that, as in developed markets, stock markets of emerging markets also quickly recovered when the government put measures to revive the economy.

Research conducted by Ledwani, Chakraborty and Shenoy (2021); Uddin, Chowdhury, Anderson and Chaudhuri (2021) examined the influence of the COVID-19 epidemic on stock markets in both emerging and developed economies. Their findings revealed that while stock markets in both economies experienced negative effects, developed markets showed greater volatility in response to news on COVID-19 infections and deaths. Despite this increased sensitivity, developed economies proved more adept at managing stock market fluctuations than their emerging counterparts. Uddin *et al.* (2021) further highlighted that in developed markets, governance issues, economic freedom, productivity were the key factors in controlling stock market volatility during the pandemic. In contrast, in emerging markets, economic support measures and the quality of health services were the most significant factors in mitigating stock market instability.

Ashraf (2020a) examined the influence of the pandemic on 77 stock markets around the globe by applying a panel regression on daily stock market returns. Their findings reveal that COVID-19 restrictions that have an adverse effect on economic activity, such as social distancing and lockdowns, negatively affect stock market returns, but over the long term they have a positive effect due reduction in COVID-19 cases. On the other hand, government support programs, such as economic stimulus packages, testing, and quarantining, were found to be having a direct positive effect on stock market returns. More related findings were echoed by Phan and Narayan (2020), who conducted a study of stock markets in 25 countries most affected by the pandemic. Through an event study analysis, the researchers found that 24 of the 25 stock markets recorded negative returns on the day the World Health Organisation (WHO) declared COVID-19 a global pandemic on the 11th of March 2020. Furthermore, it was found that 12 of the 25 countries, mostly European countries, recorded positive returns when the travel ban was imposed by the governments of those nations, while only 8 reacted positively to the imposition of the lockdown measures. Similar to Ashraf (2020a), the researchers established that the introduction of the stimulus package had positive returns in most stock markets, although the effects were more significant in those countries that had already introduced the lockdown measures.

2.2.6 **COVID-19 Pandemic and Sector Performance**

Most studies on COVID-19 and stock market performance have focused on aggregate stock market performance as measured by changes in the value of an index. However, there are a few studies in developed markets that went a step further and considered the impact of the pandemic on sector performance. For example, Elhini and Hammam (2021); Olczyk and Kuc-Czarnecka (2021) found that the pandemic had a negative impact on sectors such as consumer discretionary, communications, consumer staples, health, technology, and materials in the first three months after the occurrence of the pandemic. Other sectors, such as finance, information technology, industrials, and utilities, demonstrated a significant positive relationship with the pandemic from the start of the pandemic, whereas the energy and real estate sectors appeared unaffected. In an event study analysis of sectors for the Australian stock exchange, Alam *et al.* (2021) show that the sensitivity of the sectors to the announcement of the pandemic differed among the sectors. On the day of the announcement, the retail, pharmaceutical, and healthcare sectors exhibited strong positive returns. Later on, telecommunications exhibited strong positive returns together with healthcare and pharmaceuticals, while the transportation industry continued to perform poorly.

Studies performed prior to the COVID-19 pandemic also confirm that stock market sectors react to the market crisis in different ways. For instance, a study by Ranjeeni (2014), which focused on New York Stock Exchange sectors, discovered that the global financial crisis had a positive influence on utilities, consumer staples, consumer discretionary, and health care while negatively impacting energy, information technology, and financial services. However, the materials and industrial sectors were more resilient to the crisis. On the other hand, Bekaert, Ehrmann, Fratzscher and Mehl (2014) analyzed 415 country-sector equity portfolios across 55 countries and found that the only sectors negatively impacted by the global financial crisis were materials, consumer cyclical, and financials.

2.2.7 **Summary of literature and implications**

Most studies on COVID-19's impact on stock markets have been heavily skewed towards developed economies or, to a lesser extent, emerging markets in Asia and Latin America (see Alam *et al.*, 2021; Baker *et al.*, 2020; Xu, 2021; Yousfi *et al.*, 2021) . However, research on sub-Saharan African stock markets remains sparse, particularly in assessing how pandemics like COVID-19 have affected these smaller, less liquid, and structurally challenged markets. While some studies have analyzed the impacts of previous pandemics such as Ebola, SARS, MERS on other regions (Chen, Lee, Lin, & Chen, 2018; David *et al.*, 2021; Funck & Gutierrez, 2018; Ichev & Marinč, 2018), there is a distinct lack of empirical evidence on how the sub-Saharan African stock markets responded to the novel COVID-19 pandemic. Furthermore, while global stock market literature has started considering the heterogeneity of the COVID-19 impact (see for instance Elhini & Hammam, 2021; Olczyk & Kuc-Czarnecka, 2021), it often fails to account for the structural vulnerabilities and macroeconomic fragility of African economies. African economies especially sub-Saharan economies were already facing significant macroeconomic instability characterized by high inflation, volatile exchange rates and low fiscal space before the pandemic, and COVID-19 exacerbated these pre-existing vulnerabilities (Africa Development Bank Group, 2021; International Monetary Fund, 2022a). Given these unique economic challenges faced by African economies, there is a need for a dedicated study on how these factors interact with the pandemic's economic shocks to influence the stock market performance.

Studies that have analyzed sector-specific performance, such as by Alam *et al.* (2021); Olczyk and Kuc-Czarnecka (2021), have also been mainly conducted in developed economies. While these studies provide valuable insights, they do not fully account for the sectoral differences within SSA. There is limited research on how industries such as tourism, agriculture, or energy, critical to many African economies, responded to the COVID-19 pandemic. The disruptions in global supply chains may have different implications for resource-dependent economies versus economies focused on financial services or healthcare, making a sectoral breakdown essential for nuanced analysis.

Additionally, current literature focuses heavily on the immediate effects of the COVID-19 epidemic on stock market performance (Uddin *et al.*, 2021; Xu, 2021), with less attention paid on how events that followed the outbreak of the COVID-19 pandemic, such as imposition of lock-economic lockdowns, introduction of vaccines and various COVID-19 waves, impacted the stock market performance in SSA. For SSA, the economic and market recovery trajectory may differ significantly from that of other regions due to distinct macroeconomic factors and political instability.

This research therefore provides a deeper understanding of how African markets, which are structurally distinct, have responded to the pandemic. The sector specific analysis was also explored to identify industries that have been more resilient and those which have been hardest hit by the COVID-19 pandemic. The study will also focus on how the events that followed the outbreak of the COVID-19 pandemic such as imposition of lockdowns, vaccinations, and various COVID-19 waves impacted stock performance in SSA.

2.3 Materials and Methods

In this section, the samples, variables, data sources, and methodology adopted to investigate the influence of the COVID-19 epidemic on stock performance in SSA are explained.

2.3.1 Samples and Variables

This study examined a sample of four stock markets, including two large stock exchanges, the Johannesburg Stock Exchange (JSE) and the Nigerian Stock Exchange (NGX), as well as the two small stock exchanges, the Zimbabwe Stock Exchange (ZSE) and the Lusaka Stock Exchange (LSE). The study period spans from

February 2020 to July 2022. The selection of this timeframe was based on the accessibility of COVID-19 data for SSA. This chosen period encompassed all coronavirus events and variants that impacted the region, thus enabling a thorough and comprehensive examination. Table 2.1 summarizes the COVID-19 period in each sampled country.

Table 2.1: COVID-19 pandemic periods for selected sub-Saharan African stock markets.

Country	First COVID Case	COVID-19 Period
South Africa	05 March 2020	05 March 2020 to 31 July 2022
Nigeria	27 February 2020	27 February 2020 to 31 July 2022
Zimbabwe	20 March 2020	20 March 2020 to 31 July 2022
Zambia	18 March 2020	18 March 2020 to 31 July 2022

Source: Author compilation.

Table 2.2: COVID-19 and macro-economic variables

Variable	Description	Source
COVID-19 deaths	This variable measures the daily deaths from the COVID-19 pandemic. It is gathered per country.	Our World in Data website. https://ourworldindata.org/explorers/coronavirus-data-explorer. Accesed on 24 September 2022
COVID-19 Cases	This variable measures the daily reported COVID-19 infections. It is gathered per country.	
Δ_Cases	Change in new COVID-19 cases from day t − 1 to day t	
Δ_Deaths	Change in new COVID-19 deaths from day t − 1 to day t	
Hosp_rate	Total number of hospitalized patients on day t divided by cumulative number of confirmed cases on day t	
str_index	The change in the government stringency index between day t and day t − 1. The stringency index is a composite measure that incorporates 9 response indicators, such as economic lockdowns, restrictions on gatherings, travel bans, school and workplace closures, and it is scaled from 0 to 100.	
CF_rate	The case fatality rate represents the number of deaths on day t divided by the cumulative number of confirmed cases on day t	
+ve rate	The share of COVID-19 tests that are positive, given as a rolling 7-day average	
Stock Returns	This variable is used as a perfomance measure. The variable is c2alculated daily from the stock prices as the log of current stock price divided by previous day stock price. $R_t = ln\left(\frac{P_t}{P_{t-1}}\right)$ The returns for the stocks are then averaged per sector to obtain sector returns. The data is gathered per2 share for each stock market sampled.	Investing.com website. accesed on 23 September 2022
Dollar trading volume	This variable measures daily dollar trading volume per stock. It is calculated as the product of the total number of shares traded per stock and closing stock price. Trading volume data were gathered for each share of each sampled stock market. To obtain the daily dollar trading volume per sector, we averaged the daily trading volumes across all shares in each sector	Investing.com website. accesed on 27 September 2022
Ln_Volm	Natural log of total dollar trading volume per sector on day t	
FX_rate	Exchange rate given as number of USD per unit of a country’s currency	
Inflation	Inflation rate	Accessed from the websites of the central banks for the respective countries.

To assess the influence of the COVID-19 epidemic on sectorial performance, an event study analysis was conducted followed by a regression analysis to check for the relationship between COVID-19 metrics such as cases and deaths, stringency measures, vaccinations, and hospitalisation as well as macro-economic factors on stock returns. The variables of interest and their sources are shown in Table 2.2.

2.3.2 **Event Study Methodology**

As highlighted by Woon (2004), an event analysis is conducted in order to investigate the effect of an event on a dependent variable. This involves first defining an estimation window that represents a normal economic environment and an event window that represents the period when the event occurred. After that, statistical methods can be used to test the hypothesis on whether the performance of a dependent variable has changed due to the occurrence of an event. This research aimed investigating the hypothesis that the emergence of the COVID-19 pandemic has had a significant influence on stock returns in sub-Saharan stock markets.

For ease of analysis, the stocks were first grouped into sectors following the Global Industry Classification Standards (GICS). The Abnormal returns (AR) and cumulative abnormal returns (CAR) were calculated from the stock returns for each sector across the event window, and were further tested for the significance of the AR and CAR results. The analysis is based mainly on the CAR as it gives a comprehensive measure of stock performance during a given event. Panel data regression was then applied to assess the impact of COVID-19 variables as well as macro-economic variables on the CAR. The research is quantitative in nature since the analysis is based solely on quantitative secondary data.

2.3.2.1 **Estimation Window**

In this research a shorter estimation window of 40 days prior to the event was chosen due to multiple events that followed the outbreak of the COVID-19 pandemic. Events, such as the introduction of lockdowns, economic policies, vaccine introduction, and the various COVID-19 variants that emerged, are likely to have exerted differing impacts on stock returns, thus necessitating a more granular approach to analysing the consequences of the COVID-19 events on stock performance. As highlighted by Krivin, Patton, Rose and Tabak (2003), a longer estimation window of 60 days to one year is considered to be appropriate in situations where the stock market did not undergo any major structural changes. However, as noted by Dang Ngoc, Vu Thi Thuy and Le Van (2021), an estimation window period must be sufficiently long to weather-out the effects of short-term fluctuations in the data. An estimation window of 40 days, which is equivalent to two months of trading days, was considered long enough to smooth out the effects of short-term fluctuations in the time-series data. The mean-adjusted model (MAD) was used to estimate the expected return in the estimation window.

2.3.2.1.1 Mean-Adjusted Model

The mean-adjusted model calculates the mean return, $\overline{R_i}$, for the estimation window as the average of the daily stock returns observed in the 40-day window period. The mean model is used instead of the market model in order to avoid the challenges of finding the proxy for the market portfolio when estimating the market model. The mean model is also less data intensive and therefore it becomes a more practical choice in situations where there is limited or there are missing values like in the sub-Saharan African stock exchanges which have less frequent trading. The mean adjusted model although simple, often yields results more similar to those of more sophisticated model such as the market models and factor models (Brown & Warner, 1985; Campbell, Lo, MacKinlay, & Whitelaw, 1998)

2.3.2.2 Event Window

The event analysis was conducted for each sector in the four stock markets being analysed. We have multiple event windows which are determined by major COVID-19 events such as the introduction of economic lockdowns, the announcement of economic stimulus packages, the easing of lockdowns, the introduction of vaccines and the emergence of new COVID-19 variants. The event window dates differ among the stock exchanges depending on the dates on which the event occurred in each country. However in all the stock exchanges our event window starts 10 days prior to the event date , in order to assess the reaction of the market prior to the occurrence of the event, and it runs for 20 days post the event date giving a length of 31 days for the event window after including the event date. Daily abnormal returns were then calculated in each of the event windows for each sector in the sampled stock markets. The choice of a longer event window is supported by Brown and Warner (1985) who posit that event study test statistics tend to be well specified when the event period becomes longer.

2.3.2.2.1 Abnormal Returns (AR)

The abnormal returns were calculated for each sector as the difference between the sector returns in the event window and the average return computed in the estimation window.

$$AR_{it} = R_{it} - \overline{R_i} \qquad \textbf{2.1}$$

Where:

$\overline{R_i}$ is the mean return for sector *i* over the estimation window period, and

R_{it} is the daily return for sector *i* over the event window period.

2.3.2.2.2 Cumulative Abnormal Returns (CAR)

The CAR is calculated for sector *i* over a window period w_0 to w_1 in order to explore the accumulated impacts of a certain event during a specified time frame. The CAR is computed as the summation of the ARs over the window period as shown in equation 2.2. The meaning of the parameters is as explained in Equation 2.1

$$CAR_{it} = \sum_{t=w_0}^{w_1} AR_{it} \qquad 2.2$$

2.3.2.2.3 Test Statistic

The t-statistic is calculated in order to test for the significance of the AR and CAR results. This helps to check if the abnormal returns during the event period are significantly different from zero. If it is significant, then it implies that the COVID-19 event has a substantial effect on sector returns. The t-statistic is computed by dividing the ARs by the aggregate standard deviation of the daily returns in the estimation window, as shown below.

$$AR_t t_{stat} = \frac{AAR_t}{\sigma_{Ae}} \tag{2.3}$$

Where σ_{Ae} is the aggregate estimation period standard deviation calculated as follows:

$$\sigma_{Ae} = \sqrt{\frac{\sum_{i=1}^{N} \sigma_{i,e}^2}{N^2}} \tag{2.4}$$

Additionally, $\sigma_{i,e}$, which is the estimation period standard deviation is calculated as follows:

$$\sigma_{i,e} = \sqrt{\frac{\sum_{t=1}^{T} (AR_{i,t} - E(AAR_e))^2}{T}} \tag{2.5}$$

where AAR_e is the average abnormal return of stock *i* for the estimation period.

To calculate the significance of the coefficient for a certain event window $(w_1 - w_2)$ CAR is used and the *t* statistic is computed as follows:

$$CAR_t \;\; t_{stat} = \frac{CAR_t}{\sigma_{Ae}\sqrt{T_{t+1}}} \tag{2.6}$$

2.3.2.3 **Advantages of an event study methodology**

The event study methodology proved to be more suitable for this research than conventional analytical approaches, such as regression, in analysing the influence of the COVID-19 epidemic on equity market performance in SSA. One of the primary advantages of the event study methodology is its ability to isolate the effects of specific events on stock prices by measuring abnormal returns. Abnormal returns are computed as the deviation of actual returns from the expected returns during a defined event window. This allows researchers to assess the direct impact of the event without the confounding influences of other factors that may affect stock prices over time (see Corrado, 2011). Furthermore, the event study methodology allows the examination of a wide range of events, including both exogenous and endogenous events. Given that the occurrence of the

COVID-19 pandemic was accompanied by a plethora of issues, such as the imposition of lockdowns, introduction of vaccination programs, and other COVID-19 variants that occurred, this renders the event study methodology most suitable for this analysis. By contrast, regression analysis often requires the inclusion of multiple variables to control for other influences, which can complicate the interpretation of results and obscure the direct impact of the event in question (Bremer, Buchanan, & English, 2011). Moreover, the event study methodology is particularly effective in situations in which the timing of the event is critical. For instance, during the COVID-19 epidemic, equity market reactions were often abrupt and erratic in response to new information such as lockdown announcements or vaccine approvals. The event study methodology can effectively capture these rapid changes in stock returns following the occurrence of these events, and hence provide a clearer picture of how specific events influence stock returns (Corrado, 2011). Regression analysis, however, may not adequately account for the temporal dynamics of such events, leading to potential biases in the estimation of their effects. Most traditional methods of analysis, such as regression analysis, often make several assumptions about the relationships between variables, potentially leading to misinterpretation if the model is misspecified. However, the event study methodology is a straightforward application that does not require assumptions on the relationship between dependent and independent variables to be met but simply identifies abnormal returns following the occurrence of an event.

2.3.3 **Panel Data Regression**

As previously stated, panel data regression was employed to determine whether COVID-19 events, which include reports on COVID-19 cases and deaths, government stringency measures, and reports on hospitalisation and vaccinations, had a significant impact on sector abnormal returns. We also include some control variables and these include the macro-economic variables as control variables, which are inflation and exchange rates and the trading volumes as proxy for stock market liquidity. This work serves as a robustness check for the event analysis results. Though event analysis can tell whether an event has had an impact on stock returns, it is difficult to determine which COVID-19 events have resulted in abnormal returns, necessitating a regression analysis. While time-series analysis could be employed to examine how COVID-19 and economic factors influence stock returns, the potential for high multicollinearity among COVID-19 variables (such as case numbers, fatalities, and hospital admission rates) presents a challenge. To address the issue of multicollinearity that may occur when modelling time series individually, panel data regression was utilised.

2.3.3.1 **Analytical Model**

The following panel data regression model is used to analyse the effects of COVID-19 variables and macro-economic variables on cumulative abnormal returns (CAR). We include the volume variable to evaluate if abnormal returns are associated with market selloffs.

$$CAR_{it} = \alpha + \beta x_{i,t} + \varepsilon_{i,t} \qquad \textbf{2.7}$$

CAR_{it} denotes the cumulative abnormal returns for sector i at time t, $x_{i,t}$ is a vector of 1x k observations on the explanatory variables and β is a k× 1 vector of parameters to be computed from the explanatory variables. $,t = 1, \dots T$; $i = 1 \dots N$, with T representing the total number of all time series observations while N represents the total number of sectors for a given exchange. α is the intercept term and ε is the error term.

For example, if we consider the following explanatory variables used for panel regression at the JSE, we can express our panel data regression model as;

$$\begin{aligned} CAR_{it} = \alpha + \beta_1 Cases\_pm_t + \beta_2 Deaths\_pm_t + \beta_3 \mathrm{str\_index_t} + \beta_4 \ln(Vacc_t) + \beta_5 Infl_t \qquad \textbf{2.8} \\ + \beta_6 FX\_rate_t + \beta_7 \ln(Volm_{it}) + \varepsilon_{it} \end{aligned}$$

Where;

- $Cases\_pm_t$ denotes the number of daily COVID-19 infections per million people at time t,
- $Deaths\_pm_t$ represents the number of daily COVID-19 deaths per million people at time t,
- $\mathrm{str\_index_t}$ is the stringency index, capturing the intensity of government measures implemented to control the COVID-19 pandemic at time t ,
- $\ln(Vacc_t)$ is the natural logarithm of the daily number of vaccines administered at time t ,
- $Infl_t$represents the inflation rate at time t ,

- FX_rate_t denotes the exchange rate between the USD and the currency of the country corresponding to sector i at time t.
- $\ln(Volm_{it}$ is the natural logarithm of the daily dollar trading volume for sector i at time t,
- ε_{it} represents the error term

Further information concerning the computation of these variables is detailed in Table 2.2.

It is important to note that, with the exception of trading volume, the COVID-19 variables and macro-economic variables, while varying over time, remain constant across sectors within the same stock exchange. To address this, a suitable panel data model must be employed. Initially, analyses using both fixed effects and random effects models were conducted, which are the two most commonly utilized methods in panel data analysis. Subsequently, the Hausman test was employed to compare the fixed effects and random effects models and determine the superior approach for further investigation. This panel data regression framework enables one to examine the impact of various factors, including COVID-19 cases, deaths, government severity measures, vaccination rates, inflation, exchange rates, and trading volumes, on the abnormal returns of different sectors over time, while accounting for individual sector characteristics through the use of fixed or random effects.

2.3.3.2 **Hausman Test**

The Hausman test is a panel data analysis tool that is used to decide between the random effects and fixed effects models, which are the two most commonly employed approaches in panel data regression. In contrast to the fixed effects model, which incorporates individual-specific intercepts to account for unobserved heterogeneity, the random effects model presumes that individual-specific effects are not correlated with the independent variables. The Hausman test is commonly employed to compare the estimates from both models. Under the null hypothesis, the random effects model is deemed consistent and efficient, whilst the alternative hypothesis suggests it is inconsistent. If the null hypothesis is not rejected, it indicates no correlation between the error term and independent variables in the panel data model, thus favouring the random effects model. Conversely, rejecting the null hypothesis implies a correlation exists between the error term and independent variables, necessitating the use of the fixed effects model.

2.3.4 **Analytical Software**

The Python programming language was used as the primary analysis tool. Python's libraries provide numerous benefits, ranging from data cleansing to statistical analysis. The Pandas library allowed the researchers to cleanse their data and remove outliers that could cause erroneous results. Furthermore, with the help of the Pandas library, COVID-19 data that is recorded every day was easily mapped to stock price data that is only recorded on trading days. The *eventpy* Python library was used for event analysis in order to compute the abnormal and cumulative abnormal returns. The Python programming language was also used in the regression analysis and visual display of results. Moreover, Python's ability to handle large datasets and its scalability were crucial in this research, as it allowed the researchers to process and analyse the vast amounts of COVID-19 and stock price data.

2.4 **Results**

2.4.1 **Descriptive Statistics**

Table 2.2 presents the descriptive statistics for the abnormal returns and trading volume for the sectors for all selected stock exchanges. On the Johannesburg Stock Exchange (JSE), the ICT and healthcare sectors had the highest average daily abnormal returns of 0.21% and 0.15%, respectively, whereas energy had the lowest abnormal returns of -0.32%. The energy, real estate consumer discretionary, and materials sectors, which dealt with non-essential goods and services, had negative average abnormal returns over the study period, while all other sectors recorded positive abnormal returns. More than 50% of the time, the energy sector and real estate had negative abnormal returns. The energy sector also had the highest standard deviation of abnormal returns of 3.14% compared to the materials sector, which was the second largest at 1.88 %, and the consumer staples, which had the lowest standard deviation among all the sectors, at 1.14%. The high volatility in the abnormal returns for the energy sector was also shown by having recorded a minimum abnormal return of -11% and a maximum abnormal return of 9.6%, the highest range among all sectors, while the consumer staples was the most stable sector with the narrowest range, with a minimum abnormal return of -3.6% and a maximum of 3.4%.

The energy and consumer discretionary sectors boast the highest average daily trading volumes at 33 billion and 26 billion ZAR, respectively. We also note that the energy sector achieved a record-high daily trading volume of 124 billion ZAR during the study period. Trading activity is lower in industrial, materials, and real estate, with their daily trading volume below 10 billion ZAR. However, on average, the trading activity at the JSE appeared to be higher in all sectors compared to other exchanges, and was concentrated towards the mean.

On the Nigerian Stock Exchange (NGX), the healthcare and consumer staples sectors had the highest average daily abnormal returns of 0.1%, while the consumer discretionary sector was the worst performer with average abnormal returns of -0.13%. Additionally, the energy, financial, consumer discretionary, and industrial sectors had negative average abnormal returns over the study period. These sectors still recorded negative abnormal returns for more than 50% of the time, whereas all other sectors recorded positive abnormal returns. The highest standard deviation of the daily abnormal returns was recorded in the energy sector at 1.11%. The financial sector had the highest average daily dollar trading volume at 68 million naira, followed by the ICT sector at 32 million naira. However, the energy sector had the highest standard deviation of trading volumes, and it had a record of one of the largest daily trading volumes of 1 billion naira. It is noteworthy that, in all sectors, the distribution of trading volumes was positively skewed, as shown by a mean value greater than the median (50th percentile), indicating that there were some days with significantly higher trading volumes than normal.

On the Zimbabwean Stock Exchange (ZSE), the ICT sector was found to be the only sector with negative average daily abnormal returns. The financial and consumer staples sectors have the highest average daily abnormal returns of 0.87% and 0.69%, respectively. Significant variability in the abnormal returns of the ICT, material, and real estate sectors were observed, which had reached a daily minimum abnormal return of -7% and below as well as a high positive abnormal return of 9% or higher. Nonetheless, the majority of sectors at the ZSE exhibited positive abnormal returns throughout the study period, as evidenced by the fact that in over half of the time, most sectors recorded positive abnormal returns. The consumer staples sector boasted the highest average daily trading volume, which was approximately 10 million, double the volume of the second-highest sector, the consumer discretionary sector. Moreover, this sector recorded the largest daily trading volume of approximately 1.2 billion during the study period. In all sectors, we saw that trading volumes were positively skewed, indicating that trading activity is lower at the ZSE, but increases drastically during certain periods.

Table 2.3: Descriptive statistics

	Abnormal Returns					Dollar Volume of trade					Abnormal Returns					Dollar Volume of trade				
	Johannesburg Stock Exchange										Nigerian Stock Exchange									
	mean	std	50%	Min	max	mean	50%	Std	Min	max	Mean	std	50%	min	max	mean	std	50%	min	max
Sector																				
CD	-0.03863	1.726398	0.087	-7.436	3.583	2.58E+10	2.31E+10	1.17E+10	1E+10	9.18E+10	-0.12543	0.718116	-0.119	-3.357	1.842	1377707	1767710	691993.4	8940.418	13047958
CS	0.067428	1.136561	0.121	-3.598	3.399	1.09E+10	9.78E+09	4.36E+09	4.18E+09	3.08E+10	0.100016	0.978163	0.021	-2.586	5.118	29992791	35169591	19757796	3846670	3.2E+08
EN	-0.31879	3.14251	-0.395	-11.265	9.626	3.31E+10	2.91E+10	1.84E+10	1.16E+10	1.24E+11	-0.02317	1.114692	-0.042	-3.287	4.76	17029847	75236173	6043519	583740	1.01E+09
FIN	0.085841	1.329718	0.027	-4.373	4.201	1.13E+10	1.01E+10	5.1E+09	4.83E+09	3.97E+10	-0.06092	1.060842	-0.005	-3.504	3.545	68405943	54580972	54038865	9123738	4.5E+08
HC	0.152219	1.787331	0.11	-5.232	4.908	1.03E+10	9.01E+09	6.03E+09	3.44E+09	6.82E+10	0.107005	1.014542	0.037	-1.997	3.905	1730805	4396900	748528.2	59586.37	40517813
ICT	0.214214	1.763101	0.11	-4.385	5.35	1.02E+10	8.81E+09	5.79E+09	2.72E+09	4.52E+10	0.079813	0.831911	0.056	-2.802	2.015	32228648	49861206	16717079	1300654	3.65E+08
IND	0.008458	1.321098	0.122	-5.44	3.034	7.25E+08	6.49E+08	3.56E+08	1.78E+08	2.48E+09	-0.04687	0.677217	-0.032	-1.86	3.584	26043924	41183607	13625864	1395587	4.4E+08
MAT	-0.07345	1.883041	0.066	-7.804	5.604	6.07E+09	5.2E+09	4.38E+09	2.68E+09	5.31E+10	0.053861	0.353556	0.012	-0.937	1.328	5874815	26089233	1310525	4335.786	2.76E+08
RE	-0.19238	1.658807	-0.225	-5.563	5.216	4.78E+09	3.99E+09	2.51E+09	1.4E+09	1.87E+10										
	Zimbabwe Stock Exchange										Lusaka Stock Exchange									
	mean	std	50%	Min	max	mean	50%	Std	Min	max	Mean	std	50%	min	max	mean	std	50%	min	max
Sector																				
CD	0.495562	2.385012	0.2115	-4.798	10.08	540980.9	267703	1101532	0	11111266	0.008294	0.117581	0	0	1.667	136.49	1274.414	0	0	17250
CS	0.691007	2.375804	0.3935	-5.035	8.787	10972449	1522304	1.02E+08	1959.448	1.23E+09	0.01496	0.026004	0.018	-0.246	0.083	40158.99	231445.3	0	0	2025709
EN											-0.02136	0.321388	-0.017	-3.142	3.209	18420.02	230973.4	0	0	3273380
FIN	0.87041	1.952462	0.5725	-3.67	10.162	3374777	316084.4	18411594	159.5455	1.74E+08	-0.02575	0.143514	-0.025	-1.811	0.616	63301.15	378910.2	151.0714	0	3776311
ICT	-0.22214	3.102545	-0.5485	-8.905	11.678	3233644	1774300	5167258	25393.29	37642985	-0.00168	0.014077	-0.003	-0.003	0.178	4028.23	43809.97	0	0	589800
IND	0.533611	1.765609	-0.06	-3.596	9.221	367314.8	38887.38	1183325	0	11881312	-0.10539	0.822239	-0.121	-7.813	4.567	4461793	63068094	0	0	8.94E+08
MAT	0.472146	2.356767	0.29	-6.604	9.416	2511942	36033.59	28566190	12.675	3.43E+08	-0.00553	0.057616	-0.004	-0.614	0.512	8821.802	44175.89	0	0	530000
RE	0.527278	2.930905	0.008	-7.642	12.894	596663.6	8943.028	3875637	0	45053434										
UTL											-0.17939	1.841866	-0.297	-8.192	10.048	233425.5	2333091	1960	0	32938060

On the Lusaka Stock Exchange (LUSE) it was found that all sectors recorded negative average daily abnormal returns, with the exception of consumer staples and consumer discretionary, which had positive abnormal returns. However, the consumer discretionary sector appears to be dormant with rare trading activity. The Utilities and industrial sectors were the most negatively affected, with average daily abnormal returns of approximately -0.18% and 0.11%, respectively, and minimum daily abnormal returns of -8%. Although all other sectors had, on average, negative abnormal returns, they were close to zero, indicating that there was little change in stock returns in these sectors. Low trading activity on the LUSE was evident when considering the descriptive statistics for trading volumes. The highest daily trading volume was in the utilities sector, with approximately 233000 Zambian Kwacha worth of shares traded on average every day, and the lowest was in the consumer discretionary sector, with an average of 136 worth of shares traded daily. In all sectors, except utilities and financial, 50% of the time there was no trading, indicating that most of the days had no trading on the LuSE.

2.4.2 **Event Analysis Results**

In this section, the outcomes of the event analysis are presented. The results are presented separately for each stock exchange to initially evaluate the impact of COVID-19 events on sector performance across all stock exchanges. As part of the analysis, a graphical plot of our cumulative abnormal returns (CARs) is first presented for each sector in order to showcase how each sector performed during a specific event window. Following this, the results that display the significant CARs in each event window are presented, making it possible to determine whether the given COVID-19 event had any significant influence on CAR for a particular sector.

2.4.2.1 **Johannesburg Stock Exchange**

According to the cumulative abnormal return plots for the Johannesburg Stock Exchange (JSE) in Figure 2.2, all sectors displayed significant negative abnormal returns following the outbreak of the COVID-19epidemic and the implementation of a full lockdown in South Africa. Despite the government's economic recovery package, the negative abnormal returns persisted until the end of

April. However, the Stimulus package event window showed that the CARs recovered from a negative trajectory, indicating positive abnormal returns, except for the energy sector, which continued to decline. The healthcare sector was quickest to recover among all sectors. As lockdowns were eased, most sectors demonstrated signs of having adapted to the pandemic, with less fluctuation in the ARs. The healthcare and ICT sectors continued to outperform, recording positive cumulative abnormal returns during the period after the easing of lockdowns. The outbreak of the beta variant did not seem to have a significant impact on JSE stocks, as most sectors recorded close to zero abnormal returns, except for the energy sector, which experienced a sharp decline in CARs.

The introduction of vaccines at the beginning of 2021 was accompanied by a positive response from most sectors, which recorded positive CARs during this period, except for the real estate sector, which continued to underperform. The energy sector outperformed all stock sectors during the vaccination event window, and there was a significant recovery in the industrial sector. The impact of the Beta and Omicron variants on most stocks at the JSE was minimal, with the majority of sectors maintaining positive CARs, except for the energy sector, which experienced a decline in CAR during these two event periods. Although the Delta variant led to tighter lockdown measures in June 2021, most sectors showed stability with minimal abnormal returns. The healthcare sector, in particular, recorded significant positive cumulative abnormal returns. On the other hand, the materials, energy, and real estate sectors experienced a decline in cumulative abnormal returns during the same lockdown event window.

Table 2.4 displays the results for the days with significant cumulative abnormal returns for the four sampled stock exchanges. The data in Table 2.4 shows that almost all sectors recorded significant negative abnormal returns at the onset of the pandemic, except for the healthcare sector, which did not record any significant negative CAR. The consumer discretionary, industrial, energy, and real estate sectors continued to display negative cumulative abnormal returns even after the injection of the economic stimulus into the economy. Among these sectors, the energy sector was the most severely impacted, recording 22 days of significant negative abnormal returns. However, in subsequent event windows, there were no significant negative cumulative abnormal returns recorded in most sectors, except for the real estate sector, which had 10 days of significant negative returns after the easing of lockdowns, and the energy sector, which had 2 days of significant negative abnormal returns during the Beta variant event window.

On the other hand, we observe from Table 2.4 that certain sectors of the Johannesburg Stock Exchange (JSE) exhibited significant positive cumulative abnormal returns (CARs) during the study period. For instance, shortly after the government implemented the economic stimulus package, the healthcare and ICT sectors displayed significantly positive CARs. Similarly, during the beta variant window, the consumer staples sector recorded six days of significantly positive CARs. Furthermore, despite the outbreaks of the delta and omicron variants, several notable positive CARs were recorded in the industrial sector in 2021, particularly after the introduction of vaccines in South Africa. However, not all sectors experienced positive CARs; sectors such as energy, financial, materials, and real estate did not record any significant positive CARs throughout the study period. Overall, the analysis reveals that sectors listed on the JSE encountered negative abnormal returns more frequently than positive ones during the COVID-19 pandemic.

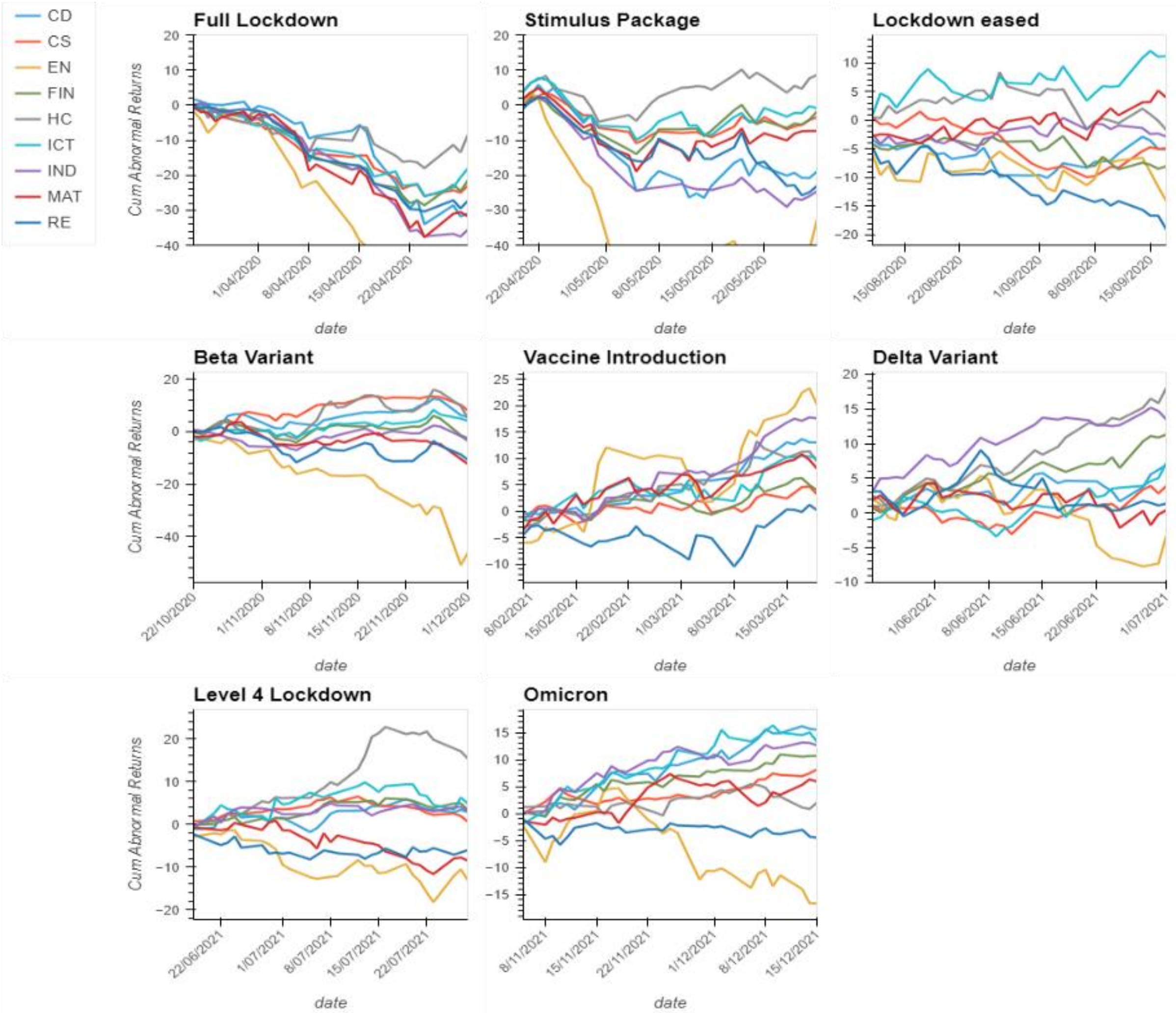


Figure 2.2: Johannesburg Stock Exchange (JSE) cumulat8ive abnormal returns.

Table 2.4: Number of days with significant cumulative abnormal returns.

	Johannesburg Stock Exchange		Nigerian Stock Exchange	
Sector	***Significant Positive CAR***	***Significant Negative CAR***	***Significant Positive CAR***	***Significant Negative CAR***
CD	Stimulus: 1 Omicron: 1	Full Lockd: 9, Stimulus: 19	Lockd eased: 2, Vaccine: 1, Delta: 3	COVID outbreak: 3, Full lockd + Stimulus: 3, Lockd relaxed: 13
CS	Beta: 6	Full Lockd: 16, Stimulus: 2	COVID outbreak: 2, Lockd relaxed: 8, Beta: 25, Vaccine: 6	Full lockd + Stimulus: 15, Lockd eased: 11
EN		Full Lockd: 16, Stimulus: 22, Beta: 2	Beta: 23	Full lockd+ Stimulus: 5, Lockd eased: 3, Vaccine: 13
FIN		Full Lockd: 16, Stimulus: 6	COVID outbreak: 4, Beta: 17, Vaccine: 2	Full lockd + Stimulus: 14, Lockd eased: 9, Vaccine: 2
HC	Stimulus: 4, Level 4 Lockd: 7		Lockd eased: 13, Beta: 10, Vaccine : 3	COVID outbreak: 1
ICT	Stimulus: 4, Omicron: 1	Full Lockd: 15	Beta: 6, Vaccine: 1,Omicron: 22	
IND	Vaccine: 6, Delta: 15, Omicron: 7	Full Lockd: 15, Stimulus: 23	COVID outbreak: 9, Beta: 6	Full lockd + Stimulus: 13, Lockd eased: 7
MAT		Full Lockd: 14, Stimulus: 5	Full lockd + Stimulus: 2, Lockd eased: 12, Vaccine: 6	Beta: 1
RE		Full Lockd: 16, Stimulus: 19, Lockd eased: 10, Beta: 1, Vaccine :1		

	Zimbabwe Stock Exchange		Lusaka Stock Exchange	
Sector	***Significant Positive CAR***	***Significant Negative CAR***	***Significant Positive CAR***	***Significant Negative CAR***
CD	COVID outbreak + lockd: 24, Lockd: intf 19, Lockd relaxed: 14, Beta : 3 ,Vaccine : 18, Omicron: 6	Stimulus: 13	Stimulus: 13, Delta: 19	
CS	COVID outbreak + lockdown: 25, Lockd int: 19, Beta: 6 ,Vaccine: 18, Omicron: 27	Lockd relaxed: 4		
EN	N/A	N/A		Strict Health measures: 28
FIN	COVID outbreak + lockd: 24, Lockd intf: 19, Lockd relaxed: 10, Beta: 1,Vaccine: 23, Delta + local lockd: 9			Vaccine: 21
ICT	COVID outbreak + lockd: 14, Lockd intf: 18, Vaccine: 14, Omicron: 10	Lockd relaxed: 18		Beta: 1, Vaccine: 6
IND	COVID outbreak + lockd: 18 Stimulus: 1, Lockd intf: 18, Lockd relaxed: 6, Beta: 10, Vaccine: 25		Lockd relaxed: 3	Strict Health measures: 8, Omicron: 15
MAT	COVID outbreak + lockd: 15, Lockd intf: 19; Lockd relaxed: 2, Vaccine : 6	Stimulus: 13		
RE	COVID outbreak + lockd: 23, Stimulus: 1, Lockd intf: 19, Vaccine: 17, Delta + local lockd: 5			
Utilities	N/A		Strict Health measures: 2	Stimulus : 2, Vaccine : 2, Omicron: 23

2.4.2.2 Zimbabwe Stock Exchange

The cumulative abnormal return plots for the Zimbabwe Stock Exchange (ZSE) are shown in Figure 2.3. From the plots, it can be seen that the outbreak of the pandemic and the imposition of lockdown did not have a significant impact on stock performance on the Zimbabwean stock exchange, as all sectors displayed positive cumulative abnormal returns. This suggests that stocks continued to outperform after the pandemic outbreak and during the lockdown period. Additionally, the intensification of lockdown measures in August 2020 was associated with positive cumulative abnormal returns in all sectors of the ZSE.

However, during the economic stimulus event window, although sectors were expected to outperform, most sectors recorded negative cumulative abnormal returns. Furthermore, the sectors continued on a downward trajectory soon after the lockdown were eased, although they later recovered. The outbreak of the beta variant in Zimbabwe at the end of 2020 was associated with negative abnormal returns in most sectors, but an upward turn in all sectors occurred after the introduction of vaccines in Zimbabwe at the beginning of 2021, with all sectors recording positive cumulative abnormal returns. The behaviour of stocks on the ZSE was contrary to what might be expected during a pandemic, which could suggest that factors other than COVID-19 events might have been driving stock returns on the Zimbabwean stock exchange. Moreover, the outbreak of the delta and omicron variants did not have a negative impact on most sectors at the ZSE as they continued to record positive CARs.

According to the results in Table 2.4, no sector experienced a significant negative abnormal return during the initial outbreak and lockdown period and in most other events. Only the consumer discretionary and materials sectors recorded significant negative returns in the event period after the economic stimulus package was introduced, while the consumer staples and ICT sectors did so after the lockdown measures were relaxed. All sectors generally recorded significantly positive CARs most of the time, with the most positive CARs being recorded during the initial outbreak and lockdown window and the second lockdown phase in August 2020, when lockdowns were intensified with most sectors recording more than 15 days of significant positive CARs.

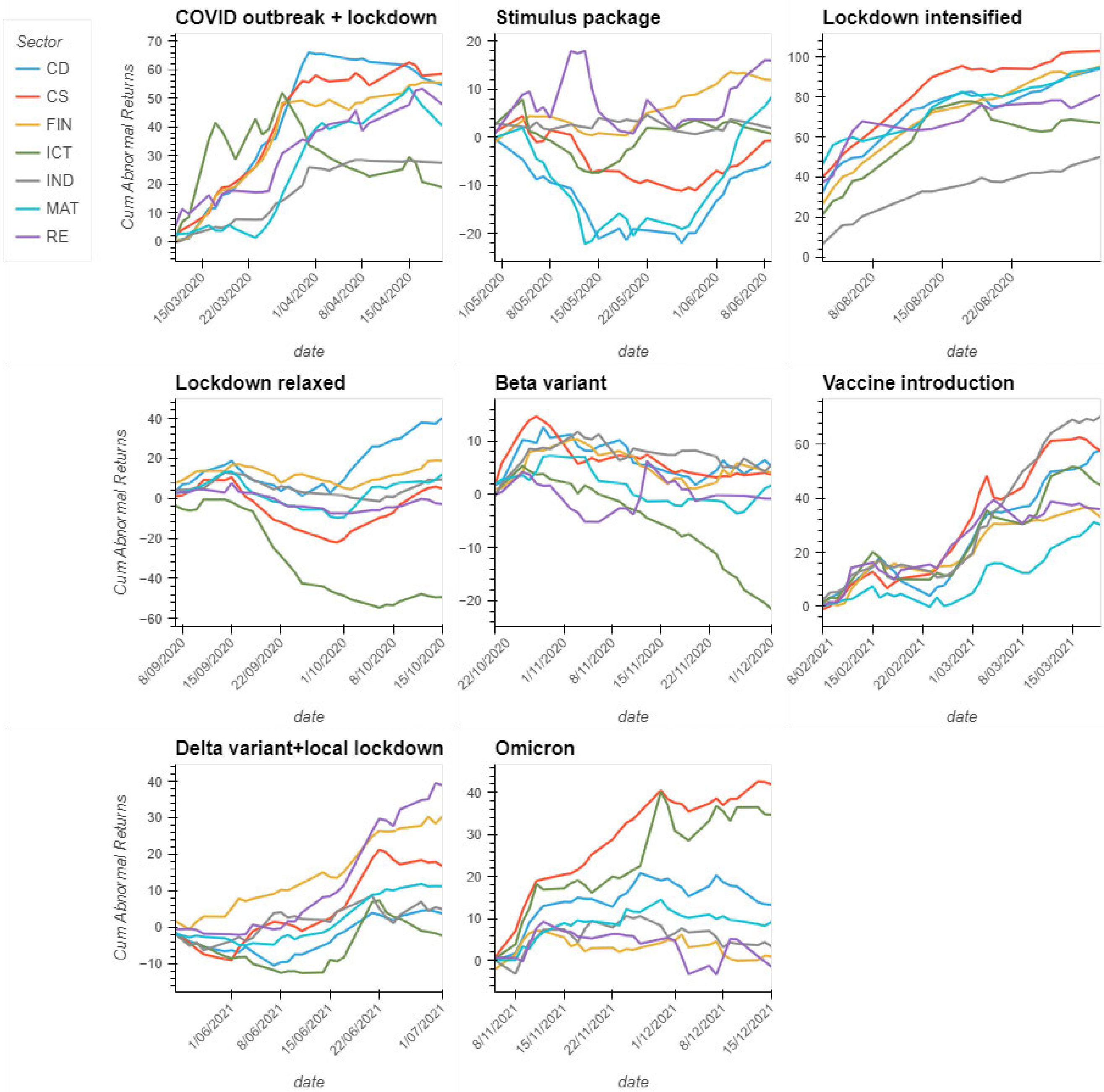


Figure 2.3: Zimbabwe Stock Exchange (ZSE) cumulative abnormal returns.

The introduction of vaccines was met with significant positive CARS across all sectors, with the industrial, financial, consumer staples, and consumer discretionary sectors recording more than 15 days of positive CARs. Additionally, the consumer staples and ICT sectors experienced several days of significant positive CARs towards the end of the year, following the Omicron outbreak.

2.4.2.3 **Nigerian Stock Exchange**

Figure 2.4 depicts the results of cumulative abnormal returns (CARs) for the Nigerian Stock Exchange. Except for the material sector, most sectors recorded a decline in cumulative abnormal returns in the period following the outbreak of the pandemic, which persisted even during the lock-down period until they recovered towards the end of April 2020, after the government injected some economic recovery stimulus funds. Following the easing of lock-downs in Nigeria, most sectors recorded close to zero abnormal returns, as shown by stable CARs, except for the healthcare sector, which saw a surge in cumulative abnormal returns from below zero to about 15% within less than one month. However, following the relaxation of lockdown measures in October 2020, it is noticeable that the consumer staples and ICT sectors accumulated positive abnormal returns, while the consumer discretionary continued to show a downward trend. Additionally, it can be seen that sectors continued to record positive CARs, even during the beta-variant event window. The introduction of vaccines surprisingly seemed associated with a decline in cumulative CARs in energy, financials, and consumer discretionary, showing that these sectors recorded negative abnormal returns (ARs). The outbreak of delta and omicron variants were not associated with any negative impact on sector returns. Rather, the surge in CARs signified that most of these sectors had positive ARs.

From Table 2.4, the outbreak of the COVID-19 pandemic, though it led to negative ARs at the NGX, had no significant impact, as only the consumer discretionary had some days with significant negative CARs. However, the introduction of lockdowns severely affected the consumer staples, industry, financial, and energy sectors, as these sectors had several days of significantly negative abnormal returns during the lockdown event window.

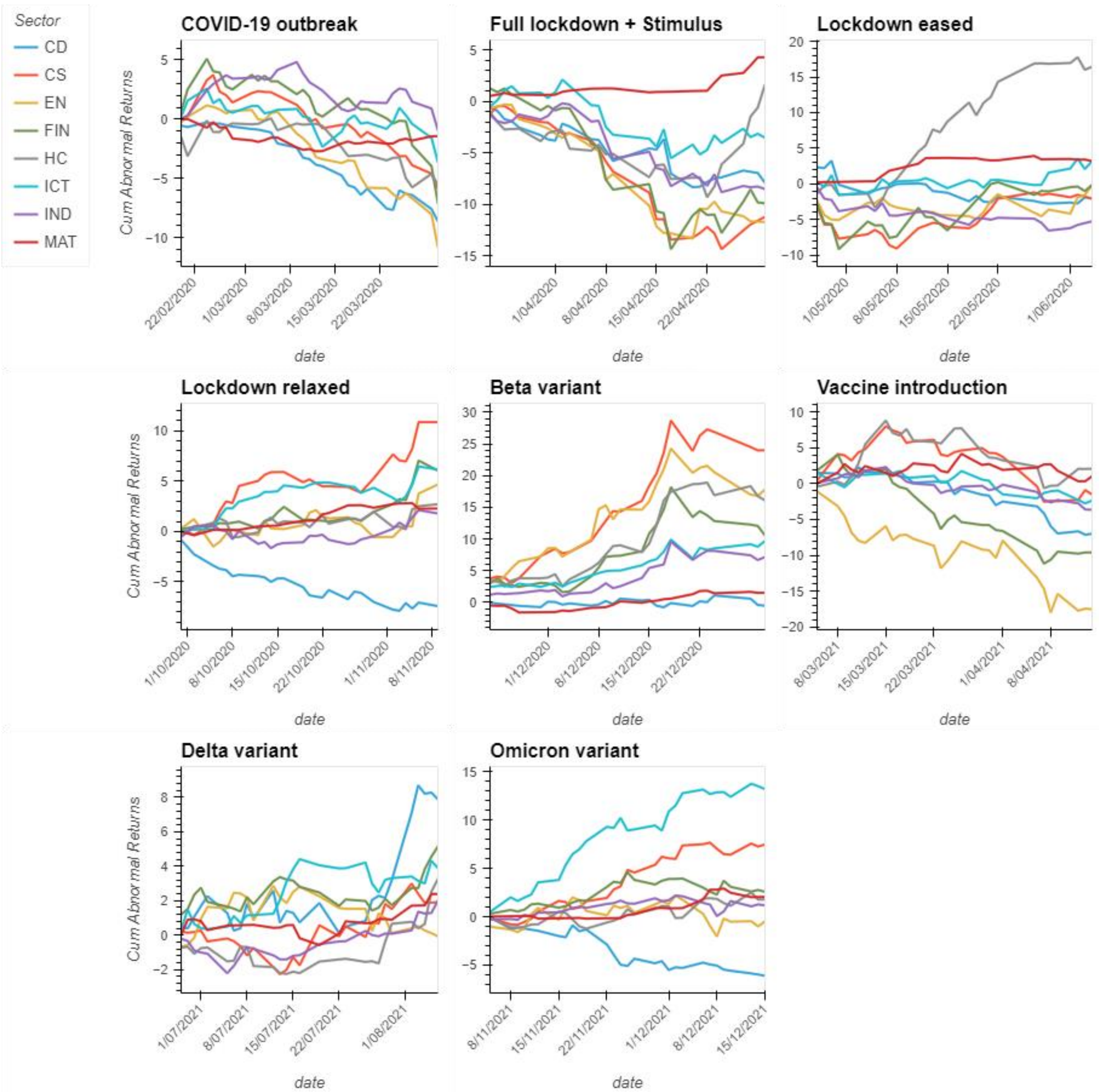


Figure 2.4: Nigeria Stock Exchange (NGX) cumulative abnormal returns.

Another event window with most sectors experiencing significant negative CARs was the period after the relaxation of the lockdown measures. Several sectors recorded significant negative CARs during that period, with the consumer discretionary, consumer staple financial, and industrial sectors recording seven days and more significant negative CARs. As shown in Table 2.2, most sectors recorded significant positive cumulative abnormal returns after vaccine introduction, except for the energy sector, which recorded significant negative CARs for a total of 13 days. Furthermore, most sectors recorded significantly positive CARs during the beta variant event window, except for the consumer discretionary and materials sectors.

2.4.2.4 **Lusaka Stock Exchange**

Figure 2.5 displays the plots for the cumulative abnormal returns for LuSE. From the plots, only the utilities sector showed a decline in cumulative abnormal returns, whereas the other sectors remained constant and recorded close to zero abnormal returns. The results indicate that the pandemic did not bring much change to sector returns on the LuSE. However, from the results in Table 2.4, we find that the Energy and Industrial sectors recorded several days of significant negative cumulative abnormal returns following the introduction of strict health care measures by the Zambian government. The Financial, ICT, and Utilities sectors also recorded some negative CARs during the period of vaccine introduction in Zambia. The Utilities and Industrial sectors further recorded significantly negative CARs during the Omicron outbreak.

Most sectors did not record significantly positive abnormal returns during the study period. The Consumer Discretionary sector had significant positive abnormal returns during the stimulus package and delta variant periods. The Utilities sector had a few days of significant positive abnormal returns during the period when the government introduced strict healthcare measures, while the industrial sector had three days of positive CARs when the government relaxed lockdown measures.

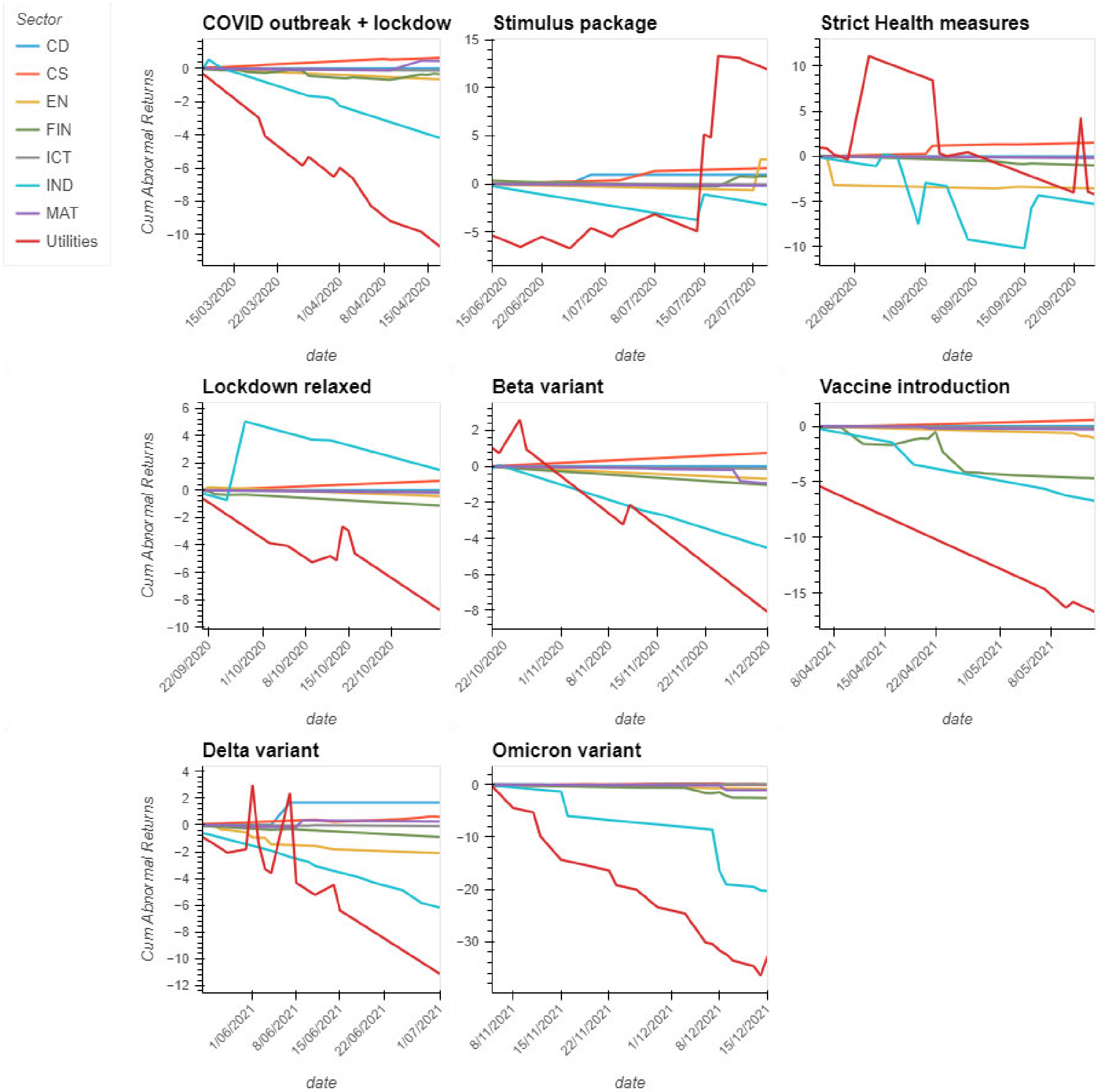


Figure 2.5: Lusaka Stock Exchange (LSE) cumulative abnormal returns.

2.4.3 Panel Data Regression Results

In this section, we present the panel data regression results for the four stock exchanges to examine the influence of the COVID-19 variables and macroeconomic factors on the sector's abnormal returns observed during the pandemic. To achieve this, panel data regression analysis was utilised. The specific purpose of this section is to analyse the influence of the pandemic on the sector's returns, considering both macroeconomic and COVID-19 variables. The results of the regression analysis offer insights into how these variables affected sector performance during the pandemic and also serve as a robustness check on the event analysis results presented in section 2.4.2.

2.4.3.1 **Johannesburg Stock Exchange**

Table 2.5 show the panel data regression results for the Johannesburg Stock Exchange (JSE). The p-value for the Hausman test is very high, close to one, as shown in Table 2.5. Therefore, the null hypothesis, which states that the random-effects model is the most appropriate, was not rejected. Consequently, the random effects model was applied in favour of the fixed effects model to assess the impact of the pandemic on sector performance on the Johannesburg Stock Exchange (JSE). The findings revealed that the stringency index and vaccination variables were the most significant factors. The negative relationship between the stringency index variable and cumulative abnormal returns (CARs) indicates that the JSE sectors performed poorly as the government intensified its stringency measures, such as economic lockdowns, travel bans, school closures, and quarantine measures. On the other hand, the positive and significant log of the Vaccine variable demonstrates that the introduction of vaccines was associated with the accumulation of positive abnormal returns, and stock performance improved as more vaccines were administered. The number of daily COVID-19 cases, inflation, and exchange rate variables show no significant influence on stock performance. If anything, the stocks appear to have been performing better when inflation was higher.

The trading volume coefficient is positive and statistically significant, indicating that an increase in trading is associated with positive abnormal returns. This relationship suggests that high trading in stocks was associated with an increase in stock prices, deducing from the relationship between COVID-19 events and stock performance, that traders were buying into stock due to improved confidence as the pandemic waned. The number of deaths per million was found to be positive and statistically significant, but this does not necessarily imply that an increase in deaths resulted in better stock performance. Rather, it could be an indication that the stock market had adapted to the pandemic, even during periods of high death rates, particularly in light of the emergence of new COVID-19 variants.

Table 2.6 displays the sector-level regression results for all the stock exchanges in the sample. The findings reveal that the stringency index remained negatively and significantly associated with all sectors at the JSE, which aligned with the previous event analysis results, demonstrating that stock performance declined as the government intensified its stringency measures. The sectors most affected appear to be consumer discretionary, consumer staples, and energy. Conversely, the log of the vaccine variable was found to be positively and significantly associated with most sectors, except for consumer discretionary, consumer staples, and real estate, confirming the previous finding that the introduction of vaccines was linked to an improvement in JSE stock performance.

Whilst Table 2.5 indicated that inflation had a negligible effect on abnormal returns, further analysis presented in Table 2.6 reveal a more nuanced picture. The results reveal that inflation has a positive and significant influence on abnormal returns in the consumer discretionary, industrial, and real estate sectors, and a negative influence on arbormal returns in the healthcare sector. Moreover, holding macroeconomic and COVID-19 factors constant, the consumer staples sector emerged as the best performer, as evidenced by its significant and positive constant on average. Although the variable for the number of deaths per million appeared significant in the panel regression results, it revealed a positive and significant association only with the energy, industrial, and real estate sectors at the sector level and was insignificant in all other sectors. These findings suggest that an increase in COVID-19 deaths did not significantly affect stock performance in South African markets.

Table 2.5: JSE panel regression results.

RandomEffects Estimation Summary			
Dep. Variable:	CARet	R-squared:	0.3740
Estimator:	RandomEffects	R-squared (Between):	-0.4505
No. Observations:	1809	R-squared (Within):	0.3743
Date:	Tue, Apr 30 2024	R-squared (Overall):	0.2268
Time:	12:00:41	Log-likelihood	-6456.8
Cov. Estimator:	Clustered		
		F-statistic:	153.69
Entities:	9	P-value	0.0000
Avg Obs:	201.00	Distribution:2	F(7,1801)
Min Obs:	201.00		
Max Obs:	201.00	F-statistic (robust):	115.04
		P-value	0.0000
Time periods:	176	Distribution:	F(7,1801)
Avg Obs:	10.278		
Min Obs:	9.0000		
Max Obs:	18.000		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-51.206	31.978	-1.6013	0.1095	-113.92	11.512
Cases_pm	-0.0002	0.0082	-0.0284	0.9773	-0.0163	0.0158
Deaths_pm	0.8596	0.2685	3.2014	0.0014	0.3330	1.3863
str_index	-0.2309	0.0343	-6.7392	0.0000	-0.2981	-0.1637
FX_rate	26.384	66.598	0.3962	0.6920	-104.23	157.00
Inflation	1.0476	0.7003	1.4959	0.1349	-0.3259	2.4211
Ln_Vaccin	0.2488	0.0749	3.3212	0.0009	0.1019	0.3958
Ln_Volm	2.3822	1.2167	1.9580	0.0504	-0.0040	4.7684

'Hausman Test p-Value:0.9999999999990635

Table 2.6: Sector regression results

Variables	Cases_pm	Deaths_pm	FX_rate	Inflation	Ln_Vaccin	Ln_Volm	const	str_index
Sector			*Johannesburg Stock Exchange*					
Consumer Discretionary	0.017*	0.359	60.33	2.066**	0.062	0.368	-3.327	-0.322***
Consumer Staples	0.029***	-0.009	-131.147	-0.486	-0.169	-1.278	59.406**	-0.345***
Energy	-0.072***	5.117***	665.29	3.206	0.812**	-0.782	-41.13	-0.249**
Financials	0.027***	0.286	102.134	-0.469	0.331***	-0.085	2.87	-0.169***
Health Care	0.035***	0.218	141.163	-3.915***	0.283***	-0.449	22.041	-0.109***
ICT	0.025***	0.774*	-84.309	-1.2671*	0.336**	1.138	-8.125	-0.154***
Industrials	0.005	2.042***	282.878	2.57**	0.459***	1.502	-53.532*	-0.191***
Materials	0.001	0.823*	248.316	-1.098	0.413***	1.8	-49.31	-0.139***
Real Estate	-0.009	1.136***	219.81	3.817***	-0.037	0.302	-35.386	-0.114***
			Nigerian Stock Exchange					
Consumer Discretionary	0.334	43.919**	1887.833	0.628	0.02	0.411**	-21.066*	0.004
Consumer Staples	2.625***	-11.634	18540.0***	5.507***	-1.022***	0.698*	-108.99***	-0.165***
Energy	2.785***	-38.779	517.473	2.815***	-0.74***	0.239	-31.638	-0.094***
Financials	1.591***	-1.942	235.032	2.611***	-0.623***	-0.647	-8.832	-0.148***
Health Care	2.128***	111.518***	14780.0***	0.931	-0.121	1.588***	-69.618***	-0.028
ICT	1.116***	-27.304*	1009.155	2.038***	-0.234***	0.305	-25.928**	-0.041***
Industrials	0.87***	-10.916	3046.251	1.197***	-0.258***	0.102	-16.503**	-0.12***
Materials	0.055	22.225***	1290.696	0.479***	-0.027	0.043	-11.166***	0.045***
				Zimbabwe Stock Exchange				
Consumer Discretionary	0.004	21.92***	-583.67***	0.087***	1.417*	-3.623***	58.084**	-0.49**
Consumer Staples	0.035	29.568***	-451.794**	0.106***	3.209***	-3.499	33.118	-0.334
Financials	-0.02	27.602***	-305.297**	0.096***	2.219***	-1.627**	-0.754	-0.187
ICT	0.036	26.303***	-28.233	0.094***	3.162***	0.752	-48.394	-0.241
Industrials	-0.04*	6.625	-246.90***	0.029***	1.109***	-0.771**	8.354	-0.022
Materials	0.01	26.78***	-497.78***	0.102***	2.179***	-0.858	-21.231	-0.163
Real Estate	-0.043	33.113***	-166.119	0.104***	3.216***	-1.537***	-30.925**	-0.068
			Lusaka Stock Exchange					
Consumer Staples	11.626	0	0.156*	-14.319**	-0.065***	0.001	2.31***	
Energy	32.258	-0.011**	-0.122	18.925	0.099***	-0.023	-3.384***	
Financials	-21.966	0.01***	0.102	16.895	-0.205***	-0.003	1.93**	
ICT	0.188	0	-0.005	2.38***	0.002*	0	-0.21***	
Industrials	81.264	0.01	-0.446	-126.07**	-0.394***	-0.126*	11.099***	
Utilities	391.166	0.041	-0.533	-296.4***	-1.044***	-0.48***	30.525***	

2.4.3.2 Zimbabwe Stock Exchange

The results of the panel regression analysis for the Zimbabwe Stock Exchange (ZSE) are displayed in Table 2.7. Similar to the findings for the Johannesburg Stock Exchange (JSE), the Hausman test also favours the random effects model for analysing the impact of the pandemic on sector performance on the Zimbabwe Stock Exchange. The random-effects model regression results show that the variable for COVID-19 cases is insignificant, while the death variable is positive and significant. The stringency index variable is negative and significant, indicating that stricter measures imposed by the Zimbabwean government have a negative impact on stock performance in Zimbabwe. The sector-level regression results, as shown in Table 2.6, reveal that the stringency index variable is significant only for the consumer discretionary sector. Results in Table 2.7, also show that the vaccination variable is positive and significant, suggesting that the introduction of vaccines is associated with positive CARs, thus aligning with the event analysis results. The sector-level analysis results show that the vaccination variable is positive and significant for all sectors, except the consumer discretionary sector, indicating that stocks at the ZSE outperformed after the introduction of vaccines. The inflation variable is positive and significant, while the exchange rate variable is negative and significant. This suggests that an increase in the inflation rate and depreciation of the Zimbabwean currency were both associated with an increase in stock performance on the Zimbabwean stock exchange. The sector-level regression results in Table 2.6 also indicate that in all sectors, cumulative abnormal returns increase with an increase in the inflation rate and depreciation of the Zimbabwean currency, and the exchange rate variable is insignificant for the ICT and real estate sectors. No significant relationship was found between trade volume and cumulative abnormal returns at the ZSE.

Table 2.7: ZSE panel regression results.

RandomEffects Estimation Summary						
Dep. Variable:	CARet		R-squared:	0.2172		
Estimator:	RandomEffects		R-squared (Between):	-0.0743		
No. Observations:	1008		R-squared (Within):	0.2263		
Date:	Tue, Apr 30 2024		R-squared (Overall):	0.2172		
Time:	11:28:34		Log-likelihood	-4643.2		
Cov. Estimator:	Clustered2					
2			F-statistic:	39.638		
Entities:	7		P-value	0.0000		
Avg Obs:	144.00		Distribution:	F(7,1000)		
Min Obs:	144.00					
Max Obs:	144.00		F-statistic (robust):	-1.194e+13		
			P-value	1.0000		
Time periods:	144		Distribution:	F(7,1000)		
Avg Obs:	7.0000					
Min Obs:	7.0000					
Max Obs:	7.0000					
Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
Const	-13.531	6.6451	-2.03638	0.0420	-26.571	-0.4914
Cases_pm	-0.0007	0.0109	-0.0686	0.9453	-0.0221	0.0206
Deaths_pm	23.910	3.0391	7.8673	0.0000	17.946	29.873
str_index	-0.1990	0.0465	-4.2830	0.0000	-0.2902	-0.1078
FX_rate	-300.60	51.582	-5.8277	0.0000	-401.82	-199.38
Inflation	0.0873	0.0092	9.4820	0.0000	0.0692	0.1053
Ln_Vaccin	2.2308	0.3306	6.7471	0.0000	1.5820	2.8796
Ln_Volm	-0.5488	0.4294	-1.2780	0.2015	-1.3915	0.2938
Hausman Test p-Value:1.0						

2.4.3.3 Nigerian Stock Exchange

The outcomes of the panel data regression for the Nigerian Stock Exchange (NGX) are depicted in Table 2.8. The investigation is centered on the Random effects model since the Hausman test endorses this type of panel data regression technique. The stringency index coefficient is negative and significant, suggesting that the stricter measures implemented by the Nigerian government led to a drop in the performance of stocks on the NGX. The sector analysis results in Table 2.6 indicate that most sectors, excluding consumer discretionary and healthcare, were adversely impacted by the government's stringency measures. The introduction of vaccines, however, appears to be associated with a decline in stock performance at the NGX. This unusual situation suggests that other factors may be driving stock performance beyond the pandemic factors. The positive and significant inflation variables suggest that an increase in the inflation rate is associated with positive abnormal returns, indicating improvements in stock performance as inflation rises.

From Table 2.6, it can be observed that sectors that exhibit significant positive inflation factors also display significant negative vaccination factors. For instance, the consumer staples, energy, and financials sectors, which are most positively affected by inflation, are also the sectors most negatively associated with the vaccination factor. This suggests that the decline in CARs as the number of vaccines administered increases may be due to stocks reacting to inflation rather than to vaccination. Additionally, in Table 2.8, we see that the coefficient for the foreign exchange rate factor is statistically significant and positive. This suggests that stocks tend to perform well when the Nigerian Naira appreciates, while its depreciation appears to lead to a decline in performance. The coefficient for the COVID-19 cases variable is positive and significant, whereas the coefficient for the COVID-19 deaths variable is insignificant. The positive association between the daily COVID-19 cases and stock performance does not imply that the surge in COVID-19 cases directly leads to an increase in stock performance. Rather, the link may be due to the inflation factor. As shown in Table 2.6, sectors with higher sensitivity to the inflation rate factor also have higher sensitivity to the COVID-19 cases factor.

Table 2.8: NGX panel regression results.

Random Effects Estimation Summary						
Dep. Variable:	CARet		R-squared:		0.3258	
Estimator:	RandomEffects		R-squared (Between):		2.22e-16	
No. Observations:	1496		R-squared (Within):		0.3260	
Date:	Tue, Apr 30 2024		R-squared (Overall):		0.3000	
Time:	11:35:58		Log-likelihood		-4330.0	
Cov. Estimator:	Clustered					
			F-statistic:		119.95	
Entities:	8		P-value		0.0000	
Avg Obs:	187.00		Distribution:		F(6,1489)	
Min Obs:	187.00					
Max Obs:	187.00		F-statistic (robust):		10.864	
			P-value		0.0000	
Time periods:	177		Distribution:		F(6,1489)	
Avg Obs:	8.4520					
Min Obs:	8.0000					
Max Obs:	16.000					
Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-32.33	9.4271	-3.4295	0.0006	-50.822	-13.838
Cases_pm	1.4466	0.3310	4.3710	0.0000	0.7974	2.0958
Deaths_pm	12.804	16.934	0.7561	0.4497	-20.413	46.021
str_index	-0.0673	0.0249	-2.7068	0.0069	-0.1160	-0.0185
FX_rate	4896.9	2331.4	2.1004	0.0359	323.78	9470.1
Inflation	2.1230	0.5297	4.0076	0.0001	1.0839	3.1622
Ln_Vaccin	-0.3942	0.1204	-3.2734	0.0011	-0.6304	-0.1580
Hausman Test p-Value:1.0						

2.4.3.4 **Lusaka Stock Exchange**

The outcomes of the panel data regression analysis for the Lusaka Stock Exchange (LuSE) are depicted in Table 2.9 below. Similar to other exchanges, the Hausman test indicates a preference for the Random effects model, as the null hypothesis that Random effects is the appropriate model is not rejected. As shown in Table 2.9, the majority of the variables are insignificant, with only the inflation and trading volume variables demonstrating significance at the 10% level. High levels of inflation corresponds with a decline in stock performance on the LuSE. The sector analysis results in Table 2.6 reveal that inflation had a adverse impact on the consumer staples, industrial, and utilities sectors. The trading volume coefficient is negative and significant, suggesting that heightened trading activity typically occurs during selloffs, leading to a decline in stock returns. However, at the sector level, as shown in Table 2.4, the trading volume coefficient is significant only for the utilities sector. Furthermore, the introduction of vaccines is associated with a decline in abnormal sector returns in most sectors, implying that factors other than vaccine introduction affect stock performance. There is no significant relationship between CARs and COVID-19 deaths and cases at the LuSE.

Table 2.9: LuSE panel regression results.

RandomEffects Estimation Summary						
Dep. Variable:	CARet		R-squared:	0.1286		
Estimator:	RandomEffects		R-squared (Between):	0.3148		
No. Observations:	1206		2R-squared (Within):	0.0695		
Date:	Tue, Apr 30 2024		R-squared (Overall):	0.1286		
Time:	11:46:09		Log-likelihood	-3431.2		
Cov. Estimator:	Clustered					
			F-statistic:	29.486		
Entities:	6		P-value	0.0000		
Avg Obs:	201.00		Distribution:	F(6,1199)		
Min Obs:	201.00					
Max Obs:	201.00		F-statistic (robust):	1.221e+13		
			P-value	0.0000		
Time periods:	189		Distribution:	F(6,1199)		
Avg Obs:	6.3810					
Min Obs:	6.0000					
Max Obs:	12.000					
Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
Const	5.8369	4.0615	1.4371	0.1509	-2.1315	13.805
Cases_pm	0.0105	0.0077	1.3647	0.1726	-0.0046	0.0255
Deaths_pm	-0.1065	0.1039	-1.025	0.3057	-0.3104	0.0974
FX_rate	-48.876	39.327	-1.2428	0.2142	-126.03	28.282
Inflation	-0.2262	0.1337	-1.692	0.0908	-0.4884	0.0360
CF_rate	87.432	59.337	1.4735	0.1409	-28.984	203.85
Ln_Volm	-0.3177	0.1743	-1.8227	0.0686	-0.6596	0.0243
Hausman Test p-Value:1.0						

2.5 Discussion of results

This study investigates the influence of the COVID-19 epidemic on sector performance among the sub-Saharan African equity markets. To achieve this, abnormal sector returns were calculated for different event windows and subsequently analysed for statistical significance to determine whether the outbreak of the pandemic and its associated events had a significant impact on sector performance. Additionally, regression methods were used to assess the influence of COVID-19 factors, such as the number of daily infections and deaths, government stringency, and vaccines administered on sector performance as measured by abnormal returns.

The findings show that most sectors in the Johannesburg Stock Exchange (JSE) and Nigerian Stock Exchange (NGX) experienced a significant drop in returns at the onset of the pandemic and during the lockdown period, and the impact has been more severe on the JSE. In contrast, sectors listed on the Zimbabwe Stock Exchange (ZSE) continued to record positive abnormal returns despite the pandemic outbreak and implementation of lockdown measures, while those on the Lusaka Stock Exchange (LuSE) remained unchanged. Thus, the findings highlight that the outbreak of the pandemic had a more pronounced impact on larger exchanges with high trading activity than on smaller ones with less trading activity.

The findings further reveal that the healthcare sector demonstrated resilience to the COVID-19 pandemic as it did not experience a significant decline in cumulative abnormal returns following the outbreak of the pandemic and the introduction of economic lockdowns in the respective countries. Additionally, other sectors that recorded more significant positive cumulative abnormal returns than negative ones include ICT and consumer staples. The shift to remote working and implementation of quarantine measures likely contributed to the increased demand for ICT equipment, thereby boosting the performance of ICT stocks. Furthermore, as the pandemic spread and demand for medical equipment and drugs surged, healthcare stocks also experienced improved returns. Given that many sub-Saharan countries have low incomes and a high proportion of employment in the informal sector, lockdown measures led consumers to shift their purchases toward staples, while reducing spending on non-staple items. These findings align with previous studies such as those of Alam *et al.* (2021); Elhini and Hammam (2021) , who demonstrated that industries focused on essential services fared better during the pandemic. However, these studies were conducted in developed countries outside of Africa.

Conversely, the Energy sector emerged as the worst-performing sector following the pandemic outbreak and implementation of lockdown measures. Energy stocks are commonly affected by international news related to oil prices and the COVID-19 pandemic in other countries, particularly oil-producing nations, was no different. As a result, the sector's performance may be more heavily influenced by international news on COVID-19 events other than domestic news, which can explain why the performance of this sector tended to differ from that of other sectors. Companies in the industrial, materials, and real estate sectors were also severely affected by lockdown measures, especially in larger capital markets. As people were working from home, the demand for office space was low, which could explain the poor performance of the real estate sector.

The results align with those of Alam *et al.* (2021) and He, Sun, Zhang and Li (2021) which indicated that the pandemic had a favourable impact on the food, healthcare, and communication technology industries, while having an adverse effect on the real estate, transportation, and energy sectors. However, their research was limited to the initial stage of the COVID-19 epidemic and did not take into account subsequent COVID-19 events and variants. This research therefore contributes to the existing body of literature by presenting evidence from the stock markets in sub-Saharan Africa and their performance during various COVID-19 variants, not only the early stages.

Although easing lockdowns helped stocks to recover, it was observed that stocks in both larger and smaller stock exchanges recorded significant positive cumulative abnormal returns following the introduction of vaccination programs in the respective countries. Thus, the introduction of vaccines helped improve sector performance in sub-Saharan African stock exchanges. The emergence of other variants of the COVID-19 pandemic, such as Beta, Delta and Omicron, did not have a significant impact on sector performance in SSA, which appeared to have adapted to the pandemic and remained resilient to the new COVID-19 variants that emerged.

Regarding the factors affecting sector performance during the pandemic, we found that stringency measures adopted by the governments of different nations to combat the spread of the virus led to a decline in sector performance in both large and small stock exchanges in SSA, as evidenced by a significant negative stringency index variable in the panel data regression model. In large capital markets, sectors with large trading activities such as energy, consumer discretionary, consumer staples and financial services were the most negatively affected by these stringency measures, while in smaller capital markets, sectors that suffered the most were those dealing with non-essential services, such as consumer discretionary.

The implementation of economic recovery stimulus packages did not prove to be effective in aiding the markets to recover, as the sectors continued to decline. This could be attributed to the severity of the lockdown measures and the size of the stimulus package that countries in SSA had in comparison to other developed countries, which failed to provide sustainability for businesses during lockdowns. As noted by Topcu and Gulal (2020) ,countries with larger stimulus packages were less impacted by the outbreak than those with smaller packages.

The number of vaccines administered is positively related to sector performance. Stocks appeared to have fared well as more vaccine doses were administered. However, the introduction of vaccines had a more positive impact on the JSE and ZSE sectors, with the energy, industrial, and materials sector being the most impacted at the JSE, while at the ZSE, it was the consumer staples, financial, and real estate sectors. This signifies the differential impact of pandemic events even across stock exchanges. The negative response of sector returns to the introduction of vaccines at the Nigerian stock exchange indicates that the sectors responded to factors other than the introduction of vaccination programs. This research uncovered that the sector performance observed was affected by the stocks' reaction to macroeconomic factors such as inflation, rather than the rollout of vaccinations. This aligns with the conclusions drawn by Uddin *et al.* (2021), who pointed out that stock markets in countries with weaker economic foundations exhibited a greater sensitivity to changes in macroeconomic factors than to the consequences of the pandemic itself.

Additionally, the economic stability of a nation and the quality of its financial institutions play a significant role in lessening the adverse effects of the pandemic. The government intervention in the market to curb the adverse impact of the pandemic was felt more in countries with stable economies and more fiscal space. This underscores the significance of economic resilience in managing market fluctuations (Uddin *et al.*, 2021) . The growth in COVID-19 infections and deaths does not seem to pose a significant threat to sector performance in all stock exchanges. Most of the time, in all stock exchanges, sectors performed well with the increase in COVID-19 deaths, while COVID-19 cases were not significantly related to stock performance. These findings align with those of Del Lo, Basséne and Séne (2022), who discovered that increases in COVID- in death rates had an insignificant influence on the stability of African stock markets. Kumeka *et al.* (2022) further show that African stock markets appeared more stable against the pandemic outbreak but were more sensitive to exogenous shocks such as volatility in exchange rates and commodity prices.

This analysis also included macroeconomic factors as control variables, and the findings indicate that inflation had a more significant impact on sector performance on NGX, ZSE, and LuSE, while it had no significant impact on JSE. Inflation had a more significant impact on stock exchanges, where inflation was higher during the COVID-19 pandemic. At the ZSE and NGX, higher cumulative abnormal returns were associated with higher rates of inflation, which can be attributed to buying stocks as the rate of inflation surged. This aligns with the Fisher hypothesis, which suggests that investors buy stocks when inflation rises because stocks can offer protection against the erosion of purchasing power caused by inflation. In contrast, the LuSE experienced a negative correlation, whereby stocks performed poorly as inflation increased. This negative correlation indicates that investors divested in stocks as inflation rose and invested in other assets. The consumer staple sector was the most positively impacted in both the NGX and ZSE sectors, followed by the energy, financial, ICT, and real estate sectors. Conversely, the consumer staples, industrial, and utilities sectors on the LuSE and healthcare sector on the JSE were negatively affected.

The exchange rate also had a significant impact on sector performance on the ZSE and NGX. However, a divergence in the relationship between exchange rates and stock returns in these two exchanges was observed. On the ZSE, sectors recorded an increase in cumulative abnormal returns as the Zimbabwean dollar depreciated, while on the NGX, sectors recorded an increase in abnormal returns as the Nigerian Naira appreciated. However, sector-level analysis indicates that the impact on NGX was only felt in the healthcare and consumer staple sectors. The Zimbabwean dollar has experienced a severe loss of value since its reintroduction in 2019, following the country's decision to de-dollarize. This decline has contributed to inflation in the country, causing investors and the public to favor stocks over Zimbabwean dollar holdings. Consequently, stock prices have risen in tandem with inflation.

The link between exchange rates and stock performance can be attributed to investors' expectations of future inflation. Investors in Zimbabwe purchase stocks when the currency depreciates, as they anticipate higher inflation. Owing to the limited availability of asset classes that act as hedges against inflation, such as real estate at affordable prices, investors prefer to offload their Zimbabwean dollar-denominated holdings and invest in stocks instead. In the Nigerian stock market, investors may have sold their stocks in anticipation of currency depreciation and instead invested in assets, such as gold and real estate that act as hedges against inflation. Consequently, declining prices may occur because of currency depreciation. In addition, the COVID-19 pandemic has been accompanied by various government interventions through monetary and fiscal policies to maintain economic stability. These interventions may have caused the association between the stock market and macroeconomic factors to diverge from norms.

The volume of trade variable is notably insignificant for the JSE, with a positive and significant impact on the consumer discretionary and healthcare sectors. This suggests that investors were buying stocks in these sectors, which led to an increase in returns as more volume was traded. On the other hand, at the ZSE, there is a negative association between trading volume and sector performance in non-essential service sectors such as consumer discretionary, financials, industrials, and real estate during the pandemic. On the LuSE, the negatively impacted sector is the utilities sector, implying significant selloffs during the pandemic or times of macroeconomic instability. Overall, the volume of trade had little to no influence on sector performance in the sub-Saharan

African stock markets. These findings align with those of Harjoto, Rossi, Lee and Sergi (2021), who found that the COVID-19 epidemic had a smaller impact on trading volumes in emerging markets than in developed markets. The insignificant influence of trading volumes on stock performance may be attributed to the low liquidity of emerging stock markets, as suggested by Mikhaylov, Dinçer and Yüksel (2023). If market participation is low, extreme negative events may not trigger strong reactions in the form of massive selloffs, and excessive stock purchases will not occur in response to positive news.

2.6 Conclusion

This paper used an event study to investigate the effects of COVID-19 events on performance of stocks in SSA. Most previous studies in the region focused on the impact of COVID-19 deaths and cases on aggregate stock market performance, ignoring sector-level performance as well as the influence of government policies, introduction of vaccination programs and the emergency of new COVID-19 variants on stock performance. According to the study's findings, the outbreak of the pandemic in SSA had a more severe impact on larger capital markets with high trading activity than on smaller ones with low trading activity. However, the negative impact was more severe at the onset of the pandemic during the period when government introduced lockdown to try and curb the spread of the virus but later on the markets recovered especially after easing of lockdowns.

The study further reveal that government stringency measures had a more significant negative impact on stock performance in SSA than the growth in COVID-19 infections and deaths. The impact of the government stringency was more severe in larger capital markets such as the JSE, while on smaller exchanges with weak macro-economic fundamentals, stock market seemed to react more to macro-economic factors than COVID-19 events. On the other hand, the introduction of vaccines helped to boost performance of stocks and the positive response was higher in stock market in countries with stable macro-economic environment while in those markets with less stable economic environment, the responsiveness was less and sometime negative if it coincided with periods of macro-economic instability such as high inflation. Thus, we can conclude that the effect of the

COVID-19 pandemic on equity markets in SSA was brought about by the economic impact it had and not the outbreak itself. We also note that the emergence of COVID-19 variants such as beta, delta and omicron later on, as well as the strengthening of lockdown measures. did not have a adverse impact on stock performance, as markets continued in their usual trend. This was an indication that the markets had adapted to the shocks of the pandemic.

Concerning the impact of the COVID-19 epidemic on sector performance, it can be concluded that the outbreak of the pandemic had almost similar impact on sectors within an exchange as the sectors went up or down together, although the impact varied on similar sectors across stock exchanged in SSA. In large stock exchanges in countries with stable economic environment sectors performed poorly when the government introduced stricter measures to curb the spread of the pandemic and performed well after the easing of lockdowns and introduction of vaccination programs. In countries with weaker economic fundamentals such as high inflation rates and unstable currencies, sectors reacted positively to an increase in inflation and the sensitivity has been high in essential service sectors such as the consumer staples, ICT and Financials. Furthermore, in countries with weaker financials, non-essential service sectors experienced huge selloffs. Thus the conclusion that can be drawn from this is that traders sold non-essential service sectors and bought into essential service sector stocks so as to hedge against inflation.

Overall in larger exchanges, the energy and real estate sector emerged as the worst performing sectors while the health care and ICT were the best performing sectors during the COVID-19 pandemic. In smaller exchanges, the materials and the real estate sectors are the worst performing sectors during the COVID-19 pandemic. The consumer discretionary although it is the worst performing sector during times when the government introduced high stringency measures, tended to quickly recover when the government relaxes its stringency measures. The consumer staples sector appeared to be the most stable sector with less variability of returns in all the stock exchanges both large and small. It had a record of more positive return than negative ones.

The research findings suggest that the pandemic's effects on sectoral performance in sub-Saharan Africa were not uniformly observable, as the impact appeared to vary on a country-by-country basis. Stock performance appeared to be dependent on the economic stability of the country and actions of investors and not the nature of the sector itself. We also see that were more responsive to government measures put forth to curb the spread of the pandemic than the actual outbreak of pandemic and the increases in COVID-19 cases and deaths. The sentiment of investors concerning COVID-19 measures and the expectation on macro-economic conditions also influenced their action on the stock exchanges thus impacting stock market performance.

The study’s findings can be of benefit to equity investors and traders in identifying securities that offer better returns during times of crisis. Investors seeking more stable income over time can consider investing in the consumer staples sector, which have maintained more stable performance while those who expect the pandemic to continue and seek to profit from the stock that outperforms during the pandemic can invest in the health care and ICT sectors even during times of crisis. International diversification across stock markets in SSA is also possible, as sector performance varied across stock exchanges during the pandemic. It is recommended that the government strike the balance between containing the virus and economic stability. They should consider implementing policies that ensure that business continue to operate at the same time making sure that they reduce the spreads of the pandemic. Further research is recommended to assess the effects of the COVID-19 epidemic on stock volatility in SSA. Additionally, there is a need to consider the influence of investor sentiment and firm-specific factors on stock performance in SSA during the pandemic.

Chapter 3. Investigating the Effects of the COVID-19 Pandemic on Stock Volatility in Sub-Saharan Africa: Analysis Using Explainable Artificial Intelligence

(*This chapter has been published in MDPI Journal of Economies (see* Appendix 2*)*

3.1 Introduction

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, emerged in late 2019 and quickly spread worldwide, leading to widespread health, social, and economic disruptions. The COVID-19 epidemic has emerged as a unique and unprecedented crisis affecting the global economy in distinct ways. Unlike past epidemics, such as the Spanish flu and SARS outbreaks, the COVID-19 epidemic rapidly spread across borders, resulting not only in widespread infections and healthcare disruptions, but also economic disruptions (Foley, Kwan, Philip, & Odegaard, 2022; Kusumahadi & Permana, 2021; Priscilla, Hatane, & Tarigan, 2022). In reaction to the COVID-19 epidemic, governments worldwide implemented various measures to control the virus's spread. These measures included the imposition of economic lockdowns, introduction of fiscal stimulus packages, and introduction of vaccination programs.

Recent studies show that the policies and measures implemented in response to the pandemic were diverse and had varying effects on different countries' economies and financial markets (Bakry, Kavalmthara, Saverimuttu, Liu, & Cyril, 2022; Mishra, Rath, & Dash, 2020; Phan & Narayan, 2020). For instance, developing economies typically have less advanced healthcare infrastructure and fiscal and monetary policies, making it challenging to deal with the adverse impacts of the pandemic on their economies. However, a study by Kumeka *et al.* (2022) show that equity markets in developing nations were more resilient to the effects of the pandemic than developed countries. On the other hand, researchers such as Harjoto and Rossi (2021); Takyi and Bentum-Ennin (2021) have found that the negative impacts of the pandemic were short-lived in developed country stock markets, as stocks quickly rebounded. The divergence in their findings can be attributed to the methodological approach adopted by Takyi and Bentum-Ennin (2021), who concentrated on examining aggregate stock market indices. This approach fails to capture sector-specific stock performance and the differential impacts of the pandemic across various industries. As a result, a more comprehensive analysis is necessary to elucidate the specific impacts of the pandemic outbreak on various stock market sectors.

This study investigates the impact of the COVID-19 epidemic on sector volatility in sub-Saharan African equity markets. Volatility in financial markets refers to the degree of variation in security prices over time. It is a measure of the dispersion of the returns of a security or market index from its mean level, reflecting the level of uncertainty or risk in the market. High stock volatility indicates larger price fluctuations and, hence, a high risk inherent in that stock, whereas low volatility suggests more stable and predictable price movements. Similar to other regions, the sub-Saharan African region suffered greatly from the pandemic, resulting in a 3.4% contraction in the continent's GDP, which is the largest decline in almost three decades (Toure, 2020; UN, 2021).

Given the region's weak macroeconomic fundamentals, including low commodity prices, high public debt, and the dominance of the informal sector, the economies in the region were more vulnerable to the pandemic's shocks (Djankov & Panizza, 2020; Elkhishin & Mohieldin, 2021; UN, 2021). The sub-Saharan African region's stock markets are relatively small, accounting for approximately 1.3% of the total global market capitalization as of 2020 (ASEA, 2020; Githinji Njenga, Josphat Machagua, & Samwel Gachanja, 2022a). Owing to their modest size, these markets tend to experience heightened volatility and low liquidity, rendering traditional analyses focused on aggregate indices insufficient to fully comprehend the intricate dynamics driving market movements.

Research on the consequences of the COVID-19 epidemic on stock volatility in sub-Saharan African equity markets has been scant. Although Ncube, Sibanda and Matenda (2023) assessed the impact of the pandemic on sector performance, their study was limited to the return measure. Relying solely on absolute returns as a measure of stock performance may be a significant oversight, as stock markets could appear to have recovered from the pandemic, but still experience excessive volatility, in turn resulting in substantial losses for investors (Będowska-Sójka & Kliber, 2019; Choi & Munro, 2022). Examining the influence of the pandemic on sector volatility is crucial to gaining a comprehensive understanding of the risks associated with investing in equity markets in sub-Saharan Africa (SSA) during crises periods. Additionally, the few studies that examined the impact of the COVID-19 pandemic on stock market volatility in some African nations primarily focused on the overall market performance rather than sector-level volatility (Del Lo *et al.*, 2022; Zaremba, Kizys, Aharon, & Demir, 2020). Given that the pandemic has not affected all sectors of the economy equally, a study that investigates only the overall stock market may not accurately capture the sector-specific effects of the pandemic and the potential for risk diversification by investing in sectors that are more robust to the pandemic.

This study therefore adds to the scant body of literature on the COVID-19 pandemic and sector volatility in SSA. Understanding volatility is crucial for investors and policymakers because it influences investment decisions, risk management strategies, and market stability. First, we employ the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models to estimate the sector volatility in each of the selected stock exchanges. Subsequently, we utilize Explainable Artificial Intelligence (XAI) techniques to comprehend how COVID-19 events, such as infections and deaths, and government actions, including the implementation of economic lockdowns, vaccinations, and economic indicators, influenced sector-specific volatility. By harnessing XAI methods, such as decision trees and Shapley Additive Explanations (SHAP), this study seeks to unveil the key drivers of volatility and pinpoint the specific time frames when certain COVID-related factors exert significant influence on stock market volatility. This comprehensive analysis offers valuable insights for policymakers, putting measures to curb the negative effects of the pandemic, and also assists stakeholders interested in investing in industries that are more resilient to the pandemic's negative effects.

The rest of the paper is organized as follows: Section two describes the theoretical and empirical literature related to this study. Section three discusses the data sources and methodology followed to assess the influence of the pandemic on sector volatility. Section four presents and discusses the results, and section five concludes the study.

3.2 Literature Review

3.2.1 Theories Related to the Impact of the Pandemic on Volatility

This section examines the theoretical foundations that connect pandemics with financial market volatility. Pandemics are typically viewed as health crises; however, their occurrence has also been demonstrated to have a noteworthy impact on financial markets. Comprehending these theoretical viewpoints is essential for analysing how such an external shock can influence market volatility.

3.2.1.1 Black Swan Theory

The black swan, as defined by Taleb (2007) refers to rare and unpredictable events that have a significant impact on the global economy and financial markets. These events are characterized by their extreme rarity, high impact, and often unforeseeable nature. However, once they occur, they tend to be less random and more predictable. The COVID-19 pandemic has been dubbed a “black swan” event because of its unexpected nature and extreme impact (Ahmad, Kutan, & Gupta, 2021), which resulted in millions of deaths and significant economic and social upheaval, with lockdowns, travel restrictions, and social distancing measures causing massive economic instability. Studies have shown that the pandemic has led to increased volatility in stock markets globally, with different regions experiencing varying degrees of impact (Kusumahadi & Permana, 2021; Machado, 2023). Black swan events, such as the COVID-19 pandemic, can trigger sell-offs, causing a decline in stock liquidity in certain sectors, leading to heightened market volatility. According to Ahmad *et al.* (2021), the COVID-19 pandemic manifested itself as a black swan event in the US and European stock markets in March 2020, when most stock markets experienced a severe decline in returns, leading to limited investment opportunities in most sectors.

3.2.1.2 Herding Behaviour Theory

The herding behavior hypothesis is a significant theoretical concept that can shed light on the dynamics of stock market volatility, especially during crises such as the COVID-19 pandemic. Herding behavior refers to the tendency of individuals to follow the actions of a larger group rather than making independent decisions based on private information. The roots of the herding behavior hypothesis can be traced back to Keynes, who highlighted the motivations behind imitating and following group behaviors in uncertain environments. Keynes viewed herding as a response to uncertainty and individuals' perceptions of their own ignorance, whereby people may follow the crowd, assuming that others possess superior information (Keynes, 1937, 1964). In the context of financial markets, herding behavior can lead to exaggerated price movements and increased volatility as investors react to the actions of others rather than fundamental market factors. During times of uncertainty, such as the COVID-19 pandemic, investors may exhibit herd behavior because of factors such as regret aversion, lack of information, and trust in others' decisions. This collective behavior can amplify market volatility and impact stock prices in ways that may not align with fundamental market conditions.

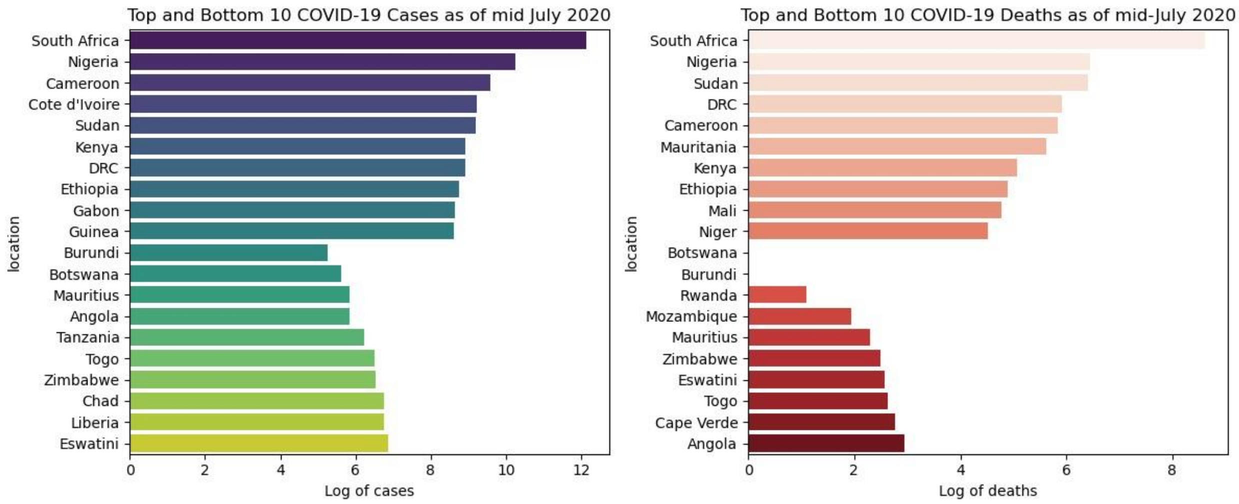
3.2.1.3 Lucas Critique

The Lucas Critique, proposed by Lucas (1976), is a critique of econometric models that aim to predict the effects of policy changes based solely on historical data. According to the Lucas Critique, such models may be inadequate because they do not account for the fact that people may change their behavior in response to policy changes, which can lead to unintended consequences. In the context of stock markets, the Lucas Critique suggests that government actions to temper the economy can affect stock market volatility by changing investors' expectations and behavior. Governments around the globe have enacted various policies with the expectation that they will help reduce the spread of the pandemic and foster economic growth. However, if investors anticipate that a government policy will lead to lower economic growth, they may become more pessimistic and sell off stocks, leading to higher volatility. Therefore, the Lucas Critique highlights the importance of considering how people's expectations and behavior may change in response to policy changes when trying to predict the effects of those policies on stock market volatility.

3.2.2 **Outbreak of COVID-19 Pandemic in Sub-Saharan Africa**

The first COVID-19 case in Africa was recorded on February 14, in Egypt, which marked the onset of the pandemic on the continent. Subsequently, COVID-19 cases emerged in various countries across Africa (Chitungo, Dzobo, Hlongwa, & Dzinamarira, 2020). Despite this spread, the absolute numbers of COVID-19 cases and deaths in SSA have remained notably lower compared to higher-income countries and some low-middle-income countries (WHO, 2020a). In 2020, Africa accounted for only 4% of all confirmed cases and 3% of all deaths globally. The peak of daily COVID-19 cases and deaths in Africa during 2020 occurred in mid-July, with approximately 117,000 new daily cases reported across the region (WHO, 2023). Among the top countries in terms of COVID-19 cases were South Africa, Nigeria, Cameroon, Cote d'Ivoire, Sudan, Kenya, and the Democratic Republic of Congo. South Africa reported the highest number of cumulative cases, reaching approximate.,ly 264,184 by mid-July, followed by Nigeria with 32,987 cases. In contrast, countries such as Zimbabwe, Botswana, Mauritius, Angola, Tanzania, Togo, and Burundi had lower COVID-19 case numbers, below 1000, in SSA during this period (see Figure 3.1Figure 3.1: Total COVID-19 cases and deaths for the selected sub-Saharan countries as of July 2020.**Error! Reference source not found.**). Figure 3.1**Error! Reference source not found.** illustrates the total COVID-19 cases and deaths for the top ten and bottom ten countries in SSA as of mid-July 2020. The figures are presented as the natural logarithm of the total number of COVID-19 infections and deaths in each country as of mid-July 2020.

The emergence of COVID-19 variants has further impacted the sub-Saharan African region. Notably, four main variants that affected sub-Saharan African countries were detected. The Beta variant (B.1.351) was first detected in South Africa in October 2020 and led to a surge in cases, reaching a peak in January 2021. This was followed by the gamma variant (P.1) from Brazil and the Delta variant (B.1.617.2) from India (Makulo, Wumba, Mandina, Mbala, Aziza, Nlandu, Kabwe, Mangala, Bepouka, & Odio, 2023). The Delta variant caused another surge in mid-July 2021, with a significant increase in daily infections and deaths. The Omicron variant (B.1.1.529), discovered in South Africa and Botswana in November 2021, exhibited higher transmissibility than previous variants but was less deadly than Delta. Its emergence led to a spike in daily COVID-19 cases across Africa, with a record high of approximately 290, 000 by the end of December 2021. Subsequently, after mid-year 2022, daily COVID-19 cases in Africa decreased significantly, with some countries reporting no new cases or deaths (Makulo *et al.*, 2023; Murewanhema & Dzinamarira, 2022). This decline marked a potential end to the pandemic in the region. In response to these challenges posed by variants, sub-Saharan African countries began rolling out vaccines at the beginning of January 2021 to combat the spread of the virus. However, vaccination rates remained low across the region, falling short of the targets set by international organizations, such as the IMF, to fully vaccinate a 40% portion of the population by the end of 2021.



Source: Author compilation.

Figure 3.1: Total COVID-19 cases and deaths for the selected sub-Saharan countries as of July 2020.

3.2.3 Stock Market Development and Challenges in Sub-Saharan Africa

Stock market capitalization is generally lower in sub-Saharan African markets than in other developing economies, except for the Johannesburg Stock Exchange (JSE). According to the European Investment Bank (EIB) report by Colin, Claudio, Nina and Ricardo (2022), as of 2021, the JSE had the highest market capitalization at $1 trillion, representing 313.5% of its GDP. The Nigerian Stock Exchange (NGX) followed, with a market capitalization of $56 billion, equivalent to 12% of its GDP. The Nairobi Stock Exchange (NSE) had a market capitalization of $21.4 billion, while that of Ghana's stock exchange was $9.2.6 billion. Bourse régionale des valeurs mobilières, which spans eight countries in the West African Economic and Monetary Union, had a market capitalization of 7.3 billion USD, accounting for a significant portion of its GDP. Additionally, the stock exchanges in Lusaka, Zimbabwe, Malawi, Uganda, and Namibia were among the smallest in SSA, with market capitalizations below 6 billion USD as of early 2021 (Kossi, 2021).

Despite their small size, stock exchanges in these countries have shown resilience and the potential for growth. For example, the Zimbabwe Stock Exchange experienced a substantial increase in market capitalization from USD 318 billion at the beginning of 2021 to USD 1300 billion by the end of the year, marking a growth of about 300% before adjusting for annual inflation at 61% (Sengere, 2022). This growth positions the stock exchange as one of the fastest-growing exchanges during the pandemic (Sengere, 2022).

While stock exchanges in SSA have existed for some time, many still lag behind in terms of development due to limited tradable instruments and a small number of listed stocks, which present significant constraints on stock market development in Africa (Colin *et al.*, 2022). The number of listed firms on African stock exchanges remains relatively low; in 2020, there were only 1251 listed companies on African stock exchanges, compared to 2347 on the London Stock Exchange and 2933 on Nasdaq. Of these, 397 were listed on North African stock exchanges and 854 on exchanges in SSA (Colin *et al.*, 2022). After excluding firms listed on the Johannesburg Stock Exchange, the number of listed firms on sub-Saharan African stock exchanges was reduced to 523. Furthermore, stock exchanges in SSA exhibit low turnover ratios relative to other emerging economies' stock exchanges. The turnover ratio reflects the ease or difficulty in selling shares of a particular stock in the market. The combination of a small number of companies and low stock turnover contributes to low liquidity and increased volatility in these markets.

3.2.4 **COVID-19 Pandemic and Stock Market Performance**

Studies have explored the effects of the COVID-19 epidemic on stock market volatility using diverse methodologies across different regions. Papadamou, Fassas, Kenourgios and Dimitriou (2020) utilized panel data analysis to demonstrate how COVID-19 news heightened investor anxiety, leading to increased volatility in equity markets in Europe, the USA, Australia, and Asia. Similarly, Baek, Mohanty and Glambosky (2020) employed the Markov-switching AR model to identify shifts in volatility levels, revealing that negative COVID-19 news had more lasting impact on volatility than positive news. Expanding the research scope to global markets, Kusumahadi and Permana (2021) applied the TGARCH modeling, and their findings indicated a moderate rise in volatility during the pandemic, driven by multifaceted factors beyond the direct influence of COVID-19. Ibrahim, Kamaludin and Sundarasen (2020) highlighted the role of government interventions in mitigating equity market volatility in both advanced and emerging markets in the Asia-Pacific region, with stricter measures, such as lockdowns, correlating with increased volatility. Conversely, Bakry *et al.* (2022) observed that higher COVID-19 death rates amplified volatility in emerging countries, but effective government interventions helped to reduce stock market volatility.

Furthermore, comparative studies by Topcu and Gulal (2020), Ashraf (2020a), and Uddin *et al.* (2021) underscore the negative impact of the pandemic on global stock markets. Notably, they found that news related to COVID-19 cases and fatalities spurred higher volatility in advanced markets than in developing markets. However, Ledwani *et al.* (2021) underscored the importance of economic development and government support in reducing the adverse effects of the COVID-19 epidemic on stock markets. Their study shows that equity markets in developed G7 countries were negatively impacted, but quickly recovered, while emerging stock markets exhibited a diverse response, with some taking longer to recover and others seemingly unaffected.

Analyzing African stock markets during the pandemic, Kumeka *et al.* (2022) attributed market fluctuations to external shocks, such as oil price and exchange rate variations, rather than to COVID-19 cases or deaths. Other studies explored the effect of government interventions in the form of economic lockdown policies, travel restrictions, school closures, and quarantines on stock market volatility. For example, Zaremba, Aharon, Demir, Kizys and Zawadka (2021) analyzed the impact of government interventions on volatility in equity markets and discovered that non-pharmaceutical interventions led to increased volatility in most stock markets worldwide. Furthermore, government intervention significantly increases volatility in global stock markets prior to the introduction of the vaccination program; after the introduction of vaccines, government stringency policies had less effect on stock volatility (Abdullah, Wali Ullah, & Chowdhury, 2022; Yu & Xiao, 2023). Abdullah *et al.* (2022) show that the effect of government intervention varies among stock markets in different countries. In high-income countries, government interventions led to a decline in stock volatility, while in lower- and middle-income countries, it led to an increase in volatility.

Most studies on the effects of the COVID-19 epidemic on stock performance have focused on returns rather than volatility. Xu (2021) conducted an in-depth investigation on the effect of COVID-19 cases and the ensuing uncertainty on equity markets in developed countries, such as the US and Canada, revealing a negative correlation between increasing COVID-19 cases and declining stock returns. Similarly, Harjoto *et al.* (2021) demonstrated a decline in equity returns in developed countries in response to rising COVID-19 cases, employing a robust regression method to analyze the impact of the pandemic on both developed and emerging markets. In contrast, Yousfi *et al.* (2021) used a regression analysis to show that COVID-19 cases and fatalities led to diminished stock market returns during the initial wave of the pandemic. However, swift market recoveries were observed, particularly in nations where government interventions such as economic recovery stimulus programs were implemented.

Further comparative analyses by Kharbanda and Jain (2021), Sachdeva and Sivakumar (2020), and Topcu and Gulal (2020) underscored the heightened vulnerability of emerging markets to the adverse effects of the pandemic, resulting in decreased stock market returns as COVID-19 cases surged. Alam *et al.* (2021) and Ncube *et al.* (2023) employed event study analyses to explore the influence of the pandemic on equity market returns across various sectors. Alam *et al.* (2021) who considered stock markets in developed countries, highlighted positive returns in sectors such as food, pharmaceuticals, and healthcare following the pandemic announcement in contrast to the poor performance observed in the transportation sector. Ncube *et al.* (2023) focused on sub-Saharan stock markets, revealing sector-specific variations in performance across exchanges after pandemic outbreak, with consumer staples emerging as resilient to the pandemic's adverse effects. Takyi and Bentum-Ennin (2021) focus on the effects of the COVID-19 outbreak on stock market performance in African countries using a Bayesian structural time series approach. They find that while most nations experienced notable declines in stock market performance during and after the pandemic, some countries were relatively unaffected. These researchers suggest that there is no chance that the COVID-19 pandemic could positively affect stock market performance in Africa. However, their study was based on stock market performance at the index level and was limited to the short-term pandemic period up to June 2020.

3.2.5 **Summary of Literature review**

A review of the existing studies on the impact of the COVID-19 epidemic on stock market volatility reveals a significant gap. Most studies have approached this issue from a broad perspective, analysing the pandemic's impact on the overall stock market without delving into sector-specific effects. This generalised approach fails to capture nuanced differences on how various sectors responded to crisis-induced volatility. Consequently, our understanding of how distinct industries, such as healthcare, technology, energy, and consumer goods, are uniquely positioned to weather the economic turmoil, adapt to swift changes, and recover from the initial shock is limited. For example, while technology firms may have experienced increased profits due to accelerated digitalisation and remote work trends, sectors such as travel and hospitality face unprecedented downturns, highlighting stark contrasts in their resilience and recovery patterns. Given that a company's operational performance directly influences stock returns and volatility, it is crucial to investigate how stocks within specific sectors react to the COVID-19 epidemic.

Additionally, the literature review shows that most of the studies were conducted in developed and emerging markets, leaving more work to be done in SSA. Sub-Saharan African stock markets possess distinctive structural and economic characteristics that distinguish them from their larger, more liquid counterparts. Sub-Saharan African markets typically feature reduced liquidity, elevated transaction costs, a limited number of securities traded, and concentrated trading. Such conditions are likely to intensify the impact of external shocks, such as a pandemic, with the region's economic fragility and constrained fiscal responses potentially amplifying volatility to a greater extent than in robust diversified economies. A further crucial observation is that existing studies primarily scrutinise short-term volatility that occurred a few months following the pandemic outbreak without considering the long-term ramifications of sustained policy interventions. For example, recurrent lockdowns, shifting policies, and uneven vaccine distribution could have impacted volatility in SSA in a way that is different from other emerging and developed economies. This underscores the necessity of investigating how ongoing pandemic waves and policy measures have contributed to stock volatility in SSA.

Therefore, this study extends the previous work by Ncube *et al.* (2023) and considers how the outbreak of the COVID-19 pandemic and its associated events, such as imposition of lockdowns, introduction of vaccines, and the emergence of various COVID-19 waves, affected stock market volatility in SSA. Previous work by Ncube *et al.* (2023) focused on the impact of the COVID-19 pandemic on stock returns only. This study will help inform strategies that portfolio managers can use to manage stock market risk in SSA, and guide policymakers in formulating responses that can better stabilise such markets during global crises.

3.3 Materials and Methods

3.3.1 Data and Sources

This study examined the effects of the COVID-19 pandemic on market volatility in the sub-Saharan African stock markets. This study focused on four exchanges that comprised the Johannesburg Stock Exchange (JSE) and the Nigeria Stock Exchange (NGX), which are the two largest exchanges in sub-Saharan Africa by market capitalization, and the Zimbabwe Stock Exchange (ZSE) and Lusaka Stock Exchange (LUSE), which represent relatively smaller exchanges in the region. Three sets of data were collected in this study. First, stock-specific data, comprising daily stock prices and trading volumes from each sampled exchange, were gathered from the Market Watch website at; https://www.marketwatch.com/investing/stock/{ticker}/download-data?countrycode (accessed on 27 December 2023). COVID-19 data, which include COVID-19 metrics such as cases, deaths, vaccinations, hospitalizations, and government policies, were obtained from the Our World in Data website at: https://github.com/owid/covid-19-data/tree/master/public/data (accessed on 15 January 2024).

Lastly, macroeconomic data was collected for the inflation and exchange rate variables corresponding to each selected country's stock exchange sourced from the respective country's Central Bank websites. The selection of inflation and exchange rates as macroeconomic variables was based on their availability in more frequent periods, which aligns with the daily recording frequency of COVID-19 and stock data. While the inflation data were originally recorded on a monthly basis, they were further interpolated to daily data using the spline interpolation method to maintain consistency. The study period spans from January 2019 to July 2022. This period was selected based on the availability of data concerning COVID-19 events in SSA, and this time frame adequately covered all COVID-19 variants that affected the region, ensuring a comprehensive analysis. While 2019 is utilized as a benchmark for comparison, it is excluded from the assessment of how COVID-19 events influenced stock market volatility, because data on COVID-19 are not available for that period. Table 3.1 summarizes the COVID-19 period in each sampled country.

Table 3.1: COVID-19 pandemic periods for selected sub-Saharan African stock markets.

Country	First COVID Case	COVID-19 Period
South Africa	05 March2020	05 March 2020 to 31 July/2022
Nigeria	27 February2020	27 February2020 to 31 July 2022
Zimbabwe	20 March2020	20 March2020 to 31 July2022
Zambia	18 March2020	18 March2020 to 31 July2022

Source: Author compilation.

Furthermore, the study focuses on the sector-specific effects of the COVID-19 pandemic. Thus, we further segmented the stock exchanges into various sectors using Global Industry Classification Standards (GICS). GICS classifies stocks into 11 sectors: consumer discretionary, consumer staples, energy, financial, healthcare, information technology, communication, industry, materials, real estate, and utilities. However, since sub-Saharan African stock markets have fewer stocks traded and some stocks have missing information, not all 11 sectors were included. Additionally, we combined the information technology and communication sectors to create the ICT sector because of fewer stocks in these sectors. Table 3.2 summarizes information on the sectors covered by each exchange and the number of stocks included in each sector.

Table 3.2: Number of sampled stocks by sector on the selected stock exchanges.

Sector	JSE	NGX	ZSE	LUSE
Consumer Discretionary	32	13	6	2
Consumer Staples	24	22	12	6
Energy	4	11	--	1
Financials	73	54	11	7
Health Care	11	8	--	--
ICT	24	12	2	1
Industrials	43	22	7	2
Materials	37	13	7	4
Real Estate	22	1	3	--
Utilities	--	1	--	1
Total	270	157	48	24

Note: The blank cells in the table indicate that there were no stocks available for sampling from that particular sector in the respective stock exchange during the study period.

Source: Author compilation.

3.3.2 **Methodology and Justification of Variables**

This study analyses the impact of the COVID-19 epidemic on stock volatility using a two-stage approach. First, the conditional volatility for each sector was estimated using the generalized auto-regressive conditional heteroskedasticity (GARCH) models and then used the Akaike Information criterion (AIC) to select the best model. The model with the lowest AIC was applied to analyze the impact of the pandemic on stock volatility. The second stage involved assessing the effect of the pandemic on stock volatility. First the GARCH model results were analysed to check for the relationship between conditional volatility and exogenous variables to determine the impact of COVID-19 factors, as well as other control variables, on stock volatility in each sector. Following the GARCH analysis, Explainable Artificial Intelligence (XAI) was applied in the form of SHapley Additive exPlanations (SHAP) to identify the most significant factors driving stock volatility during the COVID-19 pandemic and how these factors are related to stock volatility. SHAP serves as a method of addressing the weakness found in traditional regression models in that it is model-agnostic, and thus there is no need to make assumptions regarding the distribution of the data for the variables used. It also clarifies how the results of the analysis were arrived at.

3.3.2.1 **Volatility Estimation**

To estimate daily stock volatility, GARCH models were employed. GARCH models are widely used in financial econometrics to estimate volatility as they effectively capture the clustering and persistence of volatility typically observed in financial time-series data (Bollerslev, 1986). Specifically, we employed Asymmetric GARCH models, including GJR-GARCH and Exponential GARCH (EGARCH), which are more effective in modeling financial time series data that often exhibit a fat-tailed distribution and volatility clustering observed during crisis (Alberg, Shalit, & Yosef, 2008; Gökbulut & Pekkaya, 2014; Miron & Tudor, 2010). Additionally, these models capture the leverage effect. The leverage effect is the observation that negative shocks to security returns tend to cause more volatility than positive shocks (Brooks, 2019).

We estimated the daily stock volatility from stock returns. We calculated the stock returns from the daily stock prices as the natural logarithm of the current stock price divided by the previous day's stock price, as shown in Equation 3.1.

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

Following the computation of stock returns, we grouped them by sector and then computed average sector returns. Grouping returns rather than prices allows for a more accurate comparison of performance across different sectors within and across different stock exchanges as it normalizes the data and eliminates the impact of varying stock prices. Although some stock exchanges may have market capitalization-weighted sector indices, the sector classification may not be consistent with the GICS classification.

3.3.2.1.1 GJR-GARCH Model

This model was suggested by Glosten, Jagannathan and Runkle (1993) as an extension of the GARCH model to capture asymmetries in terms of negative and positive shocks. To this end, the model adds a dummy variable to the variance to determine whether there is a statistically significant difference when the shocks are negative.

The GJR-GARCH model can be represented using the following formula:

$$h_t = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i D_{t-i})\varepsilon_{t-i}^2 \; + \sum_{k=1}^{p} \beta_k (h_{t-k}) + \sum_{u=1}^{v} \pi_u X_t \qquad \textbf{3.2}$$

The GJR-GARCH model parameters include, the constant term ω, ARCH coefficient α, GARCH coefficient β, and GJR-GARCH coefficient γ. The constant term represents the unconditional variance of the series, whereas the ARCH coefficients capture the impact of the past squared errors on the current conditional variance. The GARCH coefficient captures the impact of past conditional variances on current conditional variance, and the GJR-GARCH coefficient captures the impact of negative shocks on volatility. The dummy variable D_t takes the value of 1 for $\varepsilon_t < 0$ and 0 otherwise. If γ_i is significant and positive, it means negative shocks have a larger effect on h_t than do positive shocks. The non-negativity conditions $\omega > 0$, $\alpha > 0$, $\beta > 0$, and $\alpha + \gamma \geq 0$ are artificially imposed to ensure that the coefficients are positive. $\mathrm{X_t}$ is a vector of exogenous variable values indexed by time *t*. In this case, X_t represents the COVID-19 metrics as well as macroeconomic variables while π_u represents the coefficient of the exogenous variable X.

3.3.2.1.2 Exponential GARCH (EGARCH)

The EGARCH model was coined by Nelson (1991) and, like the GJR-GJR model, it is an extension of the simple GARCH model that accounts for the asymmetry in volatility estimation. However, in the EGARCH model, volatility is modelled as the log of variance, and this property makes it superior to other GARCH models as there is no need to artificially impose non-negativity constrictions on the parameters of the model. The EGARCH model with exogenous variables can be expressed with the following equation:

$$log(h_t) = \omega + \sum_{i=1}^{q} \alpha \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{i=1}^{q} \gamma \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^{p} \beta lo\, g(h_{t-k}) \ + \sum_{u=1}^{v} \pi_u X_t \qquad \textbf{3.3}$$

The parameters ω, α, β, and π are interpreted as in the GJR-GARCH model. Gamma (γ) represents asymmetry in the volatility response to positive and negative shocks. A positive gamma value indicates that the impact of a negative shock on volatility is greater than that of a positive shock of the same magnitude. Because we are modelling the log of variance, $log(h_t)$, even if the parameters are negative, h_t will be positive. The exogenous variable X is interpreted in the same way as in the GARCH models. Table 3.3 provides a description of the exogenous variables used in this study.

Table 3.3: Description of Analytical Variables.

Variable	Description
Δ_Cases	Change in new COVID-19 cases from day t − 1 to day t
Δ_Deaths	Change in new COVID-19 deaths from day t − 1 to day t
Vaccin_ratio	Vaccin_ratio—represents the total number of vaccinations on day t divided by the cumulative number of confirmed infections on day t
CF_rate	The case fatality rate represents the number of deaths on day t divided by the cumulative number of confirmed cases on day t
str_index	The change in the government stringency index between day t and day t − 1. The stringency index is a composite measure that considers 9 response indicators including economic lockdowns , workplace closures, school closures and travel bans, rescaled to a value from 0 to 100
Hosp_rate	Total number of hospitalized patients on day t divided by cumulative number of confirmed cases on day t
+ve rate	The share of COVID-19 tests that are positive, given as a rolling 7-day average
Ln_Volm	Natural log of total dollar volume of shares traded per sector on day t
Inflation	Inflation rate
FX_rate	Exchange rate given as number of USD per unit of a country's currency

A multifaceted approach to modeling the impact of the pandemic on stock volatility was used to comprehensively capture both the healthcare and economic impacts of the COVID-19 pandemic in various contexts. Variables such as cases, deaths, hospitalizations, and vaccination rates directly reflect the severity of a health crisis and influence investor sentiment and market dynamics. The stringency index captures the regulatory environment and restrictions imposed, impacting business operations, and consequently, stock market volatility. Additionally, economic indicators such as inflation, exchange rates, and the volume of shares traded are considered control variables to account for broader macroeconomic trends that can shape investor behavior.

3.3.3 Explainable Artificial Intelligence.

Explainable Artificial Intelligence (XAI) is a machine learning approach that can produce human-understandable explanations of AI-based information systems (Ahmed, Jeon, & Piccialli, 2022). It overcomes the weaknesses of primitive machine learning models, such as logistic regression and linear regression, which assume a linear dataset. XAI can handle nonlinear data, which is common in real-world data (Ali, Abuhmed, El-Sappagh, Muhammad, Alonso-Moral, Confalonieri, Guidotti, Del Ser, Díaz-Rodríguez, & Herrera, 2023). Moreover, other ML techniques, such as deep neural networks, need to be trained on large datasets; however, given the constraints on access to data in developing markets, AI models, such as XAI, are preferable as they can be trained on smaller datasets and still produce more accurate results by increasing the number of filters an AI uses (Molnar, 2020).

To apply XAI, Random Forest, Support Vector Machine, and XGboost types of machine learning algorithms were trained on a dataset of COVID-19 events. The input variables include COVID-19-related data and macroeconomic variables. Each ML algorithm was trained on historical data to understand the relationships between input variables and stock market volatility. The model with high explanatory power was then selected for further analysis using a method in XAI known as SHapley Additive exPlanations (SHAP).

SHAP is a mathematical method based on game theory that aims to explain machine learning model predictions by calculating the contribution of each feature to the prediction. It provides insights into how individual features influence model predictions and enhance transparency and interpretability. The SHAP values are determined using coalitional game theory, which optimizes feature selection by considering interactions and dependencies.

The SHAP value is calculated as the marginal contribution of a feature value to the prediction across all possible coalitions, ensuring a fair distribution of rewards among the features based on their contributions. This approach allows for efficient computation of feature importance, even in high-dimensional datasets. It addresses redundancy by evaluating the correlations among features and computing feature importance scores. The SHAP methodology is model-agnostic, which means that it does not make any assumptions about the algorithm used in black-box models; therefore, it can be used to interpret any machine learning model, regardless of its type or structure (Bhattacharya, 2022).

For a dataset of N features, the marginal contribution of feature i can be calculated using the formula of the SHapley values shown in Equation (4), as proposed by Bhattacharya (2022).

$$\varphi(i) = \sum_{S \subseteq N/i} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!}(v(S \cup \{i\} - v(S)) \qquad \textbf{3.4}$$

In this research we define $\varphi(i)$ as the contribution of exogenous variable i to stock volatility, S as the coalition subset of exogenous variables, and (S) as the total value of S.

SHAP values can be positive or negative, where a high positive value indicates a high positive contribution to the explained variable, and a high negative value shows a more significant negative contribution. Compared to other XAI techniques like the LIME framework, SHAP provides a more robust explanation, as stated by (Bhattacharya, 2022). Furthermore, SHAP is model-agnostic, which means that it does not make any assumptions about the algorithm used in black-box models.

Given the inherent complexity of SHapley values, their interpretation requires intuitive visualizations. For deeper understanding, we employed SHAP summary plots, a powerful tool for visualizing global model explainability. It highlights the important features and the impacts of each feature on the explained variable. These plots display feature instances along the horizontal axis, color-coded (blue for lower values, red for higher values), and positioned, based on their contribution to the model output (positive on the right, negative on the left).

3.3.4 **Analytical Software**

Our main analytical tool was Python 3.11.7, which enabled us to work with large datasets of stock market data and COVID-19 cases and deaths. Python 3.11.7, through its Pandas library, helped us organise our stocks into sectors with ease. With a few lines of coding, we were able to map stocks with their respective sectors. The Pandas library also enabled researchers to handle stocks with missing data. Despite the large dataset of stock prices and trading volumes, we were able to quickly search for stocks with missing values and drop them. Furthermore, using functions built on the *Pandas* and *Numpy* libraries, we computed our variables of interest, such as stock returns and dollar trading volumes. The scikit-learn library was used for data scaling, normalization, and in handling outliers. The *statsmod* library was used in econometric modeling, such as in the estimation of our GARCH models. This library also has built-in functions for selecting the mean model and testing for ARCH effects. Finally, Python was used to run the machine learning algorithms. This includes training the machine learning models, such as Random Forest, XGBoost and Support Vector Machines (SVM) on our dataset, as well as in feature analysis using SHAP.

3.4 **Results**

In this section, we delve into our research findings concerning the impact of the COVID-19 pandemic and its related occurrences on stock volatility within the sub-Saharan African region. The initial subsection presents descriptive statistics. Subsequently, we showcase our results from the GARCH estimation and the outcomes of the analysis using explainable Artificial Intelligence (XAI). Following the presentation of the results, we consolidate our findings in the Discussion section by comparing the effects of the COVID-19 pandemic across different sectors and stock markets and establishing connections with other researchers to enhance our findings.

3.4.1 **Descriptive Statistics**

Table 3.4 displays the descriptive statistics for the COVID-19 factors and macroeconomic variables in each country in which the selected stock exchange is located. South Africa exhibited the highest mean daily COVID-19 deaths and cases at 4121 and 121, respectively, significantly surpassing those of Zimbabwe, Nigeria, and Zambia. Despite Nigeria experiencing high case and death rates in the early stages of the 2020 pandemic (refer to Figure 1), the mean daily COVID-19 cases and deaths over a three-year period were 293 and 3, respectively, lower than those of Zimbabwe and Zambia. This finding suggests that Nigeria may have effectively managed the spread of the COVID-19 pandemic and reduced case fatalities. While South Africa reports the highest mean daily COVID-19 vaccination records, Nigeria led in the daily COVID-19 vaccine rollout, achieving a peak daily record of 797,209 compared to South Africa's 414,065. This highlights Nigeria's dedication to curbing the spread of this virus. Regarding the positivity rate from COVID-19 tests, South Africa's mean was 11%, followed by Zimbabwe at 6%, and Nigeria at 5%. No records were available for Zambia. However, Zimbabwe once recorded the highest positive rate at 44%, surpassing South Africa and Nigeria, which had highest records of approximately 30%. Data on hospitalizations were only available for South Africa, with no records for Zimbabwe, Nigeria, or Zambia. Zimbabwe exhibited the highest average stringency index at 62%, indicating stricter government measures, such as business lockdowns, school closures, and travel restrictions, compared to Nigeria and South Africa, which hovered around 50%.

In terms of macroeconomic variables, Zimbabwe faced the highest inflation with an average of 290% annually, alongside an ever-depreciating currency that reached a peak of 628 Zimbabwean dollars (ZWL) per USD from a low of 25 ZWL per USD over the study period. South Africa maintained an average inflation rate of approximately 4.6% during the study period, while Nigeria and Zambia recorded mean inflation rates of 13% and 17%, respectively. Currency stability was observed for South Africa, Nigeria, and Zambia throughout the study period, in contrast to the high standard deviation in Zimbabwean inflation and currencies, which had significant volatility in these economic indicators.

Table 3.4: Descriptive statistics for the variables, for all the four stock exchanges.

	count	mean	std	min	25%	50%	75%	Max	count	mean	std	min	25%	50%	75%	max
Variable	(A) Descriptive statistics for the variables used to model volatility at the Johannesburg stock exchange								(B) Descriptive statistics for the variables used to model volatility at the Nigerian stock exchange							
new_cases	5301	4121.48	5149.19	0	581	1866	5771	26,389	4732	292.82	449.11	0	26	138	416	6158
new_deaths	5301	121.12	153.64	0	15	67	160	844	4732	3.19	5.07	0	0	1	5	31
icu_patients	5301	732.34	712.21	0	194	532	998	2694	4732	0	0	0	0	0	0	0
hosp_patients	5301	5350.78	4619.42	0	2003	4274	7700	18,034	4732	0	0	0	0	0	0	0
positive_rate	5301	0.11	0.09	0	0.04	0.08	0.18	0.33	4732	0.05	0.06	0	0	0.02	0.08	0.3
new_vaccinations	5301	26,276.13	56,754.24	0	0	0	16,390	414,065	4732	4555.02	44,753.75	0	0	0	0	797,209
stringency_index	5301	48.21	21.99	2.78	36.19	48.15	63.89	87.96	4732	50.71	15.27	0	39.49	47.22	58.33	85.65
FX_rate	5301	15.79	1.24	13.43	14.8	15.46	16.75	19.11	4732	399.98	18.6	360.5	381.2	410.3	415.12	444.97
Inflation	5301	4.64	1.58	1.99	3.17	4.67	5.77	7.8	4732	12.84	2.11	9.4	10.96	13.17	13.93	17.67
Dollar_Volm	5301	1.32×10^{10}	1.57×10^{10}	80,905,585	4.77×10^{9}	9.01×10^{9}	1.59×10^{10}	4.53×10^{11}	4732	4.63×10^{9}	5.75×10^{9}	1331	1.97×10^{9}	3.34×10^{9}	5.56×10^{9}	2.2×10^{11}
	(C) Descriptive statistics for the variables used to model volatility at the Zimbabwean stock exchange								(D) Descriptive statistics for the variables used to model volatility at the Lusaka stock exchange							
new_cases	4326	322.55	807.48	0	16	57.5	227	9027	4504	383.7	773.47	0	17	85	322	5555
new_deaths	4326	6.86	14.92	0	0	1	5	107	4504	4.2	10.26	0	0	0	3	72
icu_patients	4326	0	0	0	0	0	0	0	4504	0	0	0	0	0	0	0
hosp_patients	4326	0	0	0	0	0	0	0	4504	0	0	0	0	0	0	0
positive_rate	4326	0.06	0.07	0	0.01	0.03	0.08	0.44	4504	0	0	0	0	0	0	0
new_vaccinations	4326	13,178.34	24,821.17	0	0	1597.5	16,349	175,915	4504	0	0	0	0	0	0	0
stringency_index	4326	61.7	15.68	0	51.05	57.41	71.3	87.96	4504	0	0	0	0	0	0	0
FX_rate	4326	149.62	149.73	24.75	82.42	85.6	130.12	628.21	4504	18.69	2.25	13.94	16.97	18.13	21	22.68
Inflation	4326	289.09	249.02	49.37	66.55	213.54	394.13	839.08	4504	17.07	4.74	9.7	13.9	16.09	21.83	24.8
Dollar_Volm	4326	5,400,966	30,335,077	0	43,116.32	359,761.1	2,499,130	1.23×10^{9}	4504	278,375.2	13,394,094	0	0	0	1480.98	8.94×10^{8}

Note: The descriptive statistics for each stock exchange were calculated from the data for the country where the stock exchange is domiciled. The meaning of the variables is as explained in Table 3.

3.4.2 **Diagnostics Checks**

3.4.2.1 **Testing for ARCH Effects**

One of the requirements of GARCH modelling is to test for the existence of ARCH effects, and the Lagrange Multiplier (LM) test was employed to do so. The test compares the null hypothesis that there are no ARCH effects against the alternative hypothesis that ARCH effects are present. If the null hypothesis is not rejected, it indicates that the variance in the errors is constant over time, and therefore ARCH effects are not present. If the null hypothesis is rejected in favour of the alternative hypothesis, this implies that past error terms predict future variance, thereby indicating time-varying volatility and confirming the existence of ARCH effects in the data. The results of the LM test for all sectors in each of the four stock exchanges are presented in Table 3.5.

Table 3.5: LM test for ARCH effects

Sector	JSE_Pvalue	NGX_Pvalue	ZSE_Pvalue	LUSE_Pvalue
Consumer Discretionary	0.000	0.0328	0.0010	0.000
Consumer Staples	0.000	0.0000	0.0000	0.050
Energy	0.000	0.0045	--	1.000
Financials	0.000	0.0001	0.0029	0.000
Health Care	0.000	0.0009	--	--
ICT	0.000	0.0011	0.0000	0.0000
Industrials	0.000	0.9929	0.9045	0.0000
Materials	0.000	0.0252	0.0087	0.2503
Real Estate	0.000	--	0.0685	--
Utilities	--	--	--	0.34069

According to the results inTable 3.5., the p-value of the test is less than 0.05 for the majority of sectors on the JSE, NGX, and ZSE. This indicates that the null hypothesis should be rejected in favour of the alternative hypothesis, which posits that the time series exhibits ARCH effects. Thus, it is appropriate to apply GARCH models to estimate volatility. GARCH models can be applied to the five sectors of LUSE, with p-values below 5%. However, caution must be exercised when fitting GARCH models to the energy, materials, and utilities sectors, as these sectors do not appear to demonstrate ARCH effects. The absence of ARCH effects in these LuSE sectors is expected because of the low trading frequency in most sectors on this exchange. The selection of the mean model for use in estimating residuals was automatically done in the *pdarima* python library. The mean model chosen by the *pdarima* library reflects the underlying data structure and is pivotal for capturing the trends and seasonality inherent in the dataset.

3.4.2.2 **Selecting the GARCH model**

Following the identification of the ARCH effects, the next step involved specifying the appropriate GARCH model to capture the dynamic nature of volatility. Since numerous GARCH models have been proposed for modelling volatility on time series data, we used the Akaike Information Criterion (AIC) to select the GARCH model that best fits the data. The results for the two models we used EGARCH and GJRGARCH, are presented in Table 3.6.

Table 3.6: Results for the Akaike Information Criterion(AIC)

Sector	Model	Consumer Discretionary	Consumer Staples	Energy	Finan-cials	Health Care	ICT	Industrials	Materials	Real Estate	Utilities
JSE	eAIC	1725.469	1661.437	2420.98	1704.36	2064.458	1937.377	1655.613	1939.607	1701.776	NaN
	gjrAIC	1730.582	1662.863	2464.19	1704.59	2073.971	1964.258	1655.052	1944.255	1735.027	NaN
NGX	eAIC	710.7879	1048.577	1352.45	950.713	1351.182	1136.287	766.4913	326.1999	NaN	NaN
	gjrAIC	713.7033	1053.576	1355.34	953.931	1349.391	1135.77	765.8781	407.7333	NaN	NaN
ZSE	eAIC	-895.488	-1964.05	NaN	-1690.71	NaN	-1692.2	-844.777	-1046.09	-401.715	NaN
	gjrAIC	-900.006	-1966.37	NaN	-1691.41	NaN	-1698.58	-823.326	-1045.61	-403.161	NaN
LUSE	eAIC	-914.666	409.1708	292.184	815.921	NaN	991.413	1228.9	411.1505	NaN	2355.52
	gjrAIC	-366.258	657.8494	1076.85	972.598	NaN	990.8844	1499.16	754.4266	NaN	2368.21

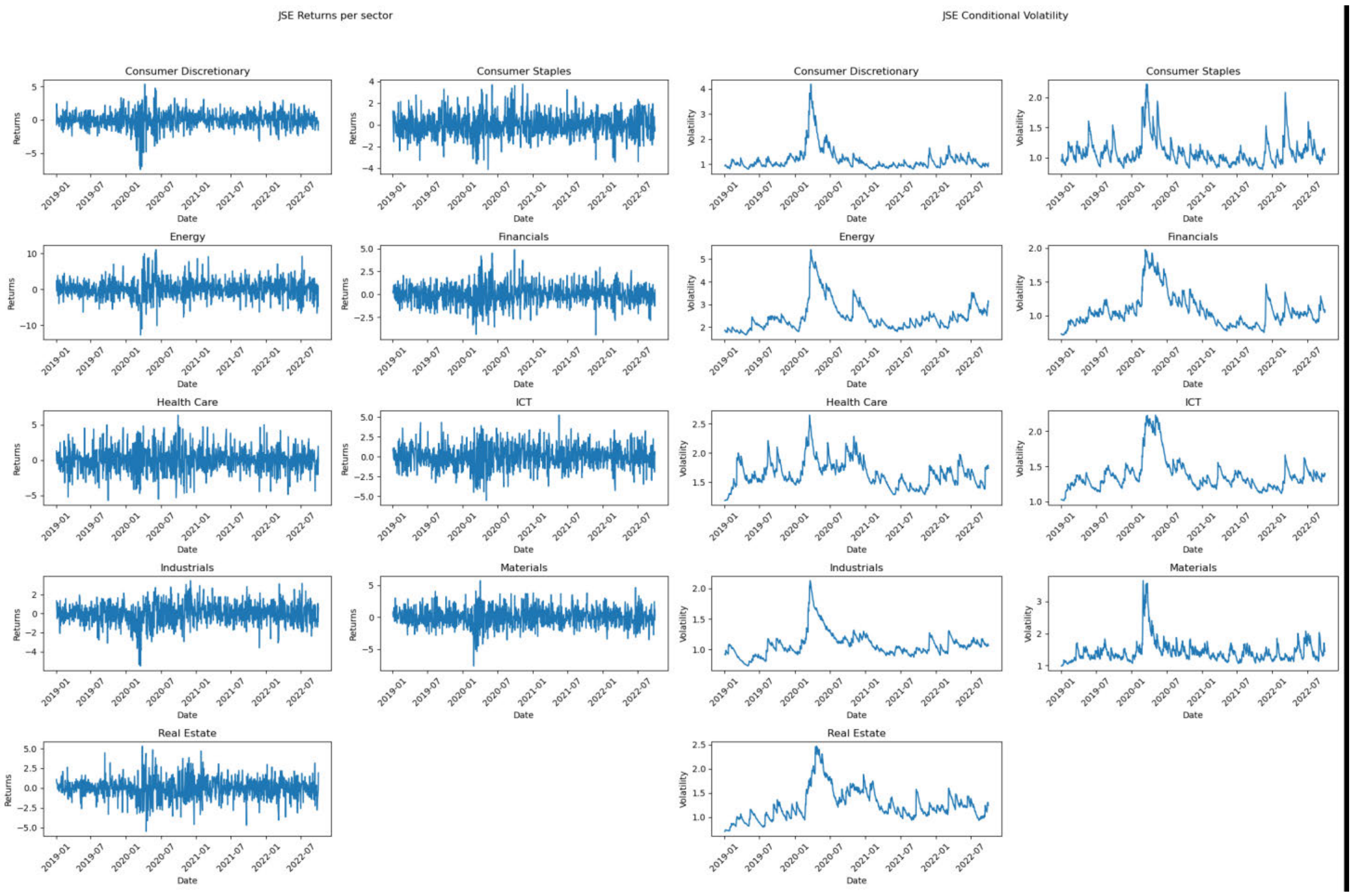
The model with the lowest AIC value is the preferred model. For the JSE, the EGARCH model is the best for most sectors; thus, our analysis is primarily based on this model. For NGX, the results are tilted towards the E-GARCH model; thus, our analysis is based on the E-GARCH model estimates. For the ZSE, almost all sectors favour the GJR model, whereas for the LUSE, the EGARCH model is the best.

3.4.1 GARCH Results

3.4.1.1 Trend Analysis

In this section, a trend analysis of stock returns and volatility is provided for each sector of the sampled stock exchanges. This analysis allowed us to verify the accuracy of the estimated conditional volatility by comparing it with the observed volatility in stock returns. Furthermore, we compared the volatility levels in the pre-pandemic period and during the pandemic to understand the changes in equity market stability due to the outbreak of the pandemic. Figure 3.2 illustrates the results for the returns and volatilities of the Johannesburg Stock Exchange (JSE) sectors. The results show that for all sectors, there was a spike in volatility following the outbreak of the pandemic in March 2020, as seen in the returns plots and confirmed by higher volatility values in the conditional volatility plots. This confirms the reliability of our volatility estimation using the GARCH models.

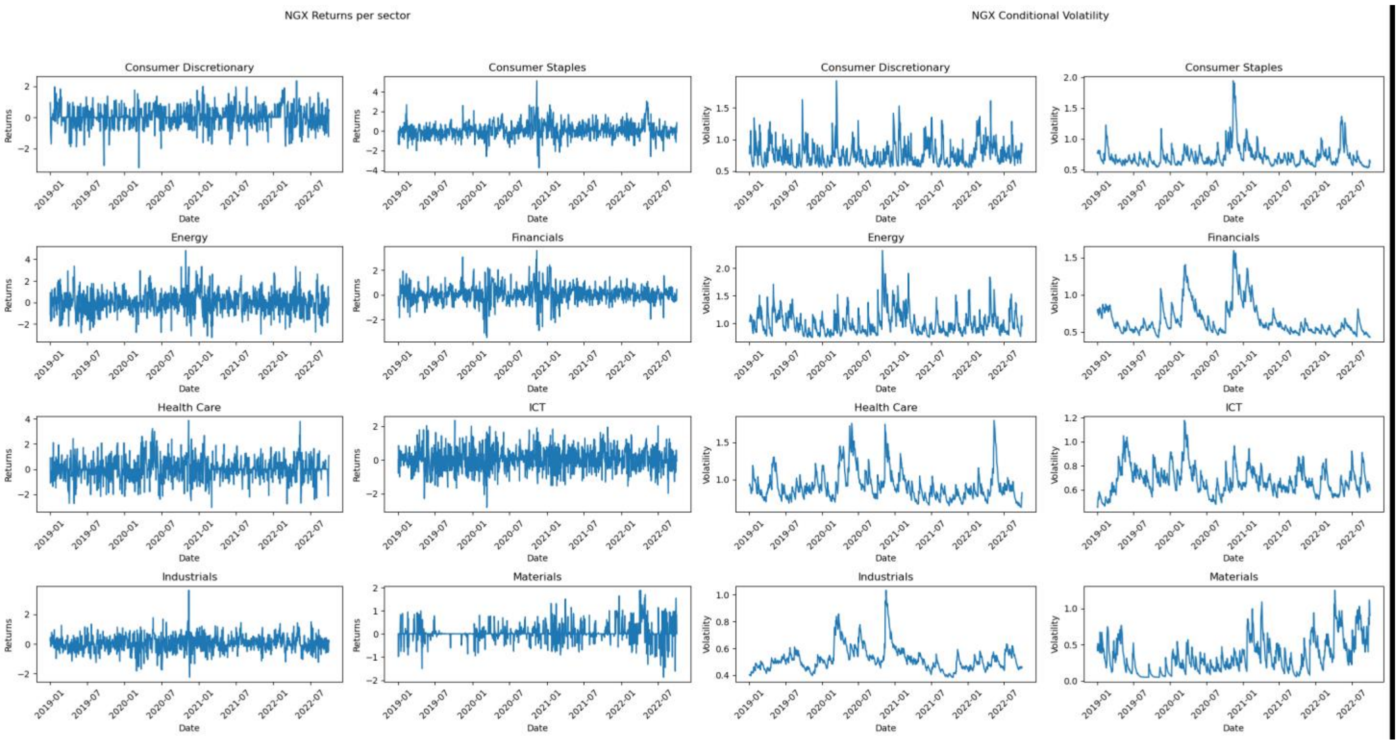
Some volatility persistence was observed in the energy, ICT, financial, industrial, and real estate sectors, where the volatility in these sectors took time to return to pre-pandemic levels. However, in sectors such as consumer discretionary, consumer staples, and materials, the spike in volatility quickly dropped to pre-pandemic levels within a few months. The plots in Figure 3.2 also show some leverage effects, with higher volatility occurring in most sectors during times of negative returns rather than positive returns.



Note: The plot illustrates the daily returns and conditional volatility in percentage terms for each sector during the COVID-19 period.

Figure 3.2: Plot of daily returns and volatility for each sector on the JSE.

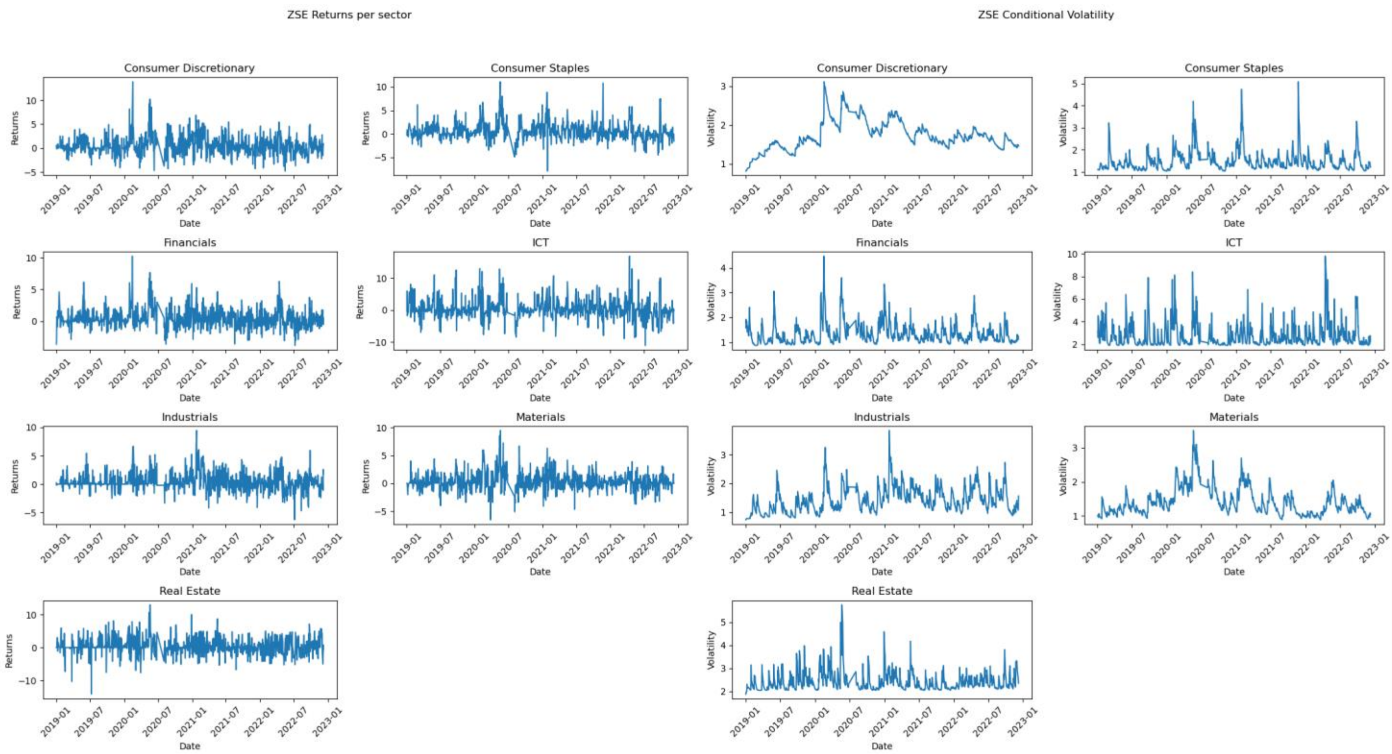
Figure 3.3 presents the results for the Nigerian Stock Exchange (NGX). Following the outbreak of the pandemic in March 2020, an increase in volatility was observed in the ICT, financial, healthcare, and industrial sectors. Both the returns and volatility plots confirm these results. In contrast, sectors such as consumer staples, energy, and materials experienced higher volatility towards the end of 2020, joined by sectors such as financials, healthcare, and industrials. This period coincided with the second wave of the COVID-19 pandemic in SSA, due to the outbreak of the beta variant. Volatility clustering can be observed in the ICT, healthcare, industrial, and materials sectors, where periods of higher volatility seemed to persist for longer. The leverage effect can be seen in sectors such as healthcare and ICT, where periods of higher volatility are mostly associated with negative returns in the returns plot.



The plot illustrates the daily returns and conditional volatility in percentage terms for each sector during the COVID-19 period.

Figure 3.3: Plot of daily returns and volatility for each sector on the NGX

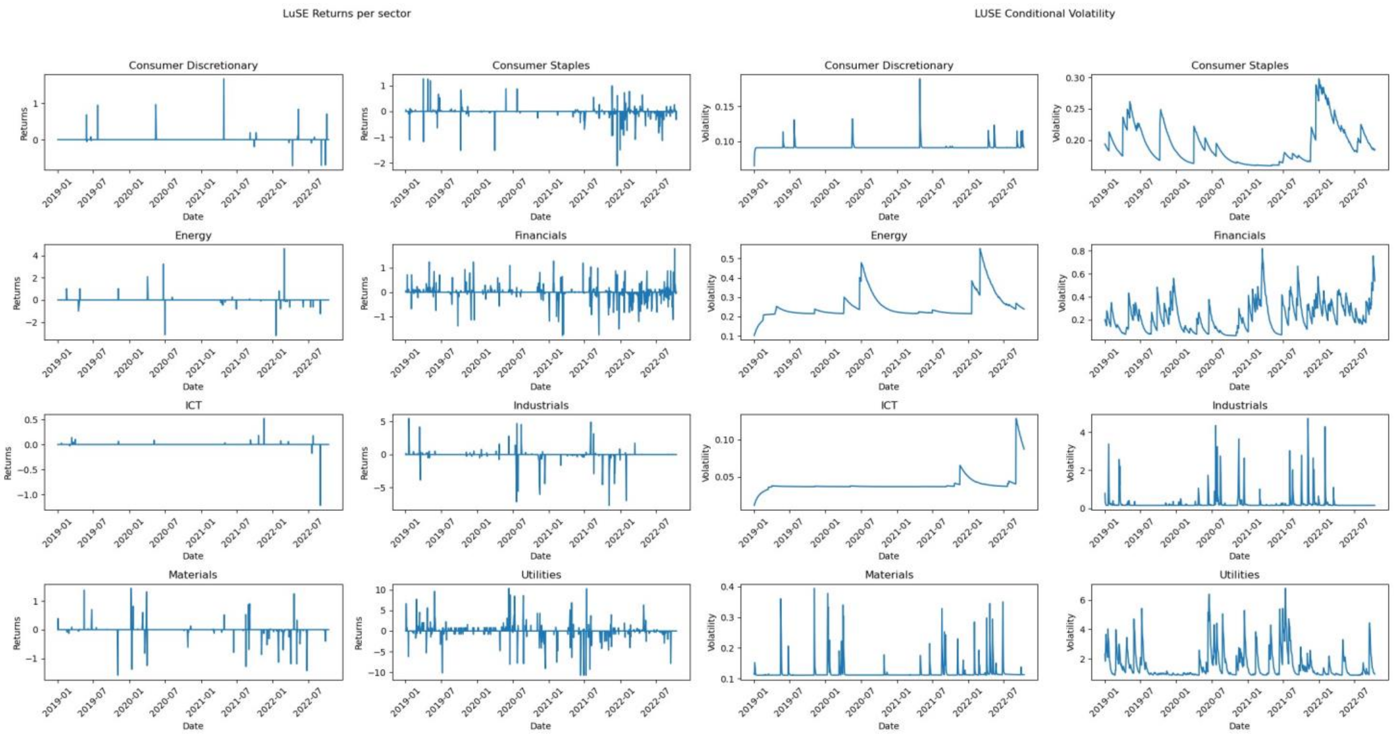
Figure 3.4 depicts the returns and conditional volatility for the Zimbabwean Stock Exchange (ZSE). An increase in volatility in the consumer discretionary, industrial, materials, and real estate sectors was observed at the onset of the pandemic. However, the volatility in the real estate sector is transient. The ICT and financial sectors experienced heightened volatility, even before the pandemic. The volatility in the consumer staples sector remained low, with a few instances of increased volatility at the beginning and end of 2021, coinciding with the emergence of the beta and omicron COVID-19 variants. It appears that there is minimal volatility persistence in most sectors of the ZSE, except for the materials and consumer discretionary sectors, where higher volatility seems to endure longer. The spikes in returns in the returns plot, align well with the increase in volatility observed in the conditional volatility plot, validating the reliability of the GARCH estimation. Moreover, an increase in volatility in most sectors on the ZSE is more closely linked to positive spikes in stock returns than to negative ones.



Note: The plot illustrates the daily returns and conditional volatility in percentage terms for each sector during the COVID-19 period.

Figure 3.4: Plot of daily returns and volatility for each sector on the ZSE.

Regarding the Lusaka Stock Exchange (LuSE), Figure 3.5 displays the returns and volatility plots. Although the exchange experienced infrequent trading, there was consistency in volatility and return plots. Periods with spikes in returns are associated with an increase in volatility, confirming the reliability of our volatility estimates using GARCH models. Interestingly, there was no increase in volatility at the onset of the pandemic in any sector except for the utility sector. In the financial sector, volatility increased at the beginning of 2021, coinciding with the period during the beta variant in sub-Saharan Africa. Although volatility remained, low on the LuSE, the industrial and utilities sectors had the highest volatility, with certain days recording an average daily volatility of more than 4%, notably in mid-year 2020 and mid-year 2021.



Note: The plot illustrates the daily returns and conditional volatility in percentage terms for each sector during the COVID-19 period.

Figure 3.5: Plot of daily returns and volatility for each sector on the LuSE

3.4.1.2 GARCH parametric results

In this section, we present the results of GARCH modeling. We used two GARCH models, GJR-GARCH and EGARCH, and selected the model with the lowest AIC for further analysis. We included COVID-19 events and macroeconomic variables as exogenous variables to examine their impact on volatility. Table 3.7 presents the results for the E-GARCH model for the sectors on the JSE. Significant positive alpha coefficients for the consumer discretionary, energy, and industrial sectors indicate that past news shocks led to increased stock volatility in these sectors. A significantly negative alpha value for the ICT sector suggests that news shocks actually resulted in a decline in volatility in this sector. Higher and significant beta values for most sectors indicate high volatility persistence on the JSE during the COVID-19 pandemic. The significantly negative gamma coefficient for most sectors, except for industrials and materials, confirms the presence of the leverage effect in these sectors, where volatility is higher when prices fall than when they rise, as shown in the trend analysis section.

The results in Table 3.7 indicate that the change in COVID-19 cases and deaths (represented by variables Δ_Cases and Δ_Deaths) as well as the rate of positive COVID-19 tests had no significant influence on stock volatility in all sectors. However, the stringency of government policies such as travel bans, social distancing measures, intensification of economic lockdowns, and business closures had a significant and positive impact on stock volatility in most sectors, except for the healthcare sector, where volatility decreased as government measures became more stringent. A positive and significant hospitalization ratio in most sectors indicates that an increase in hospitalizations led to an increase in volatility in most sectors, except for the healthcare, consumer discretionary, and materials sectors, where the coefficient is negative and significant, suggesting that volatility actually decreased as hospitalizations increased. The negative and significant vaccination ratio variable for all sectors indicates that an increase in vaccines administered led to a decrease in stock volatility in all sectors except for the real estate sector, which was unaffected.

The exchange rate variable, which is negative and significant, suggests that the depreciation of the South African Rand against the USD led to an increase in stock volatility across all the sectors. The coefficient of the inflation variable is positive and significant in most sectors, except for consumer staples, consumer discretionary, ICT, and real estate, where it is negative, and the financial sector, where it is insignificant. Therefore, an increase in inflation is associated with increased volatility in the healthcare, industrial, energy, and materials sectors. In most sectors, the volume of trade variable is positive and significant, suggesting that increased trading activity on the stock exchange exacerbates stock volatility.

Table 3.7: Results of the Exponential GARCH model for the JSE Sectors.

Variable	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	ICT	Industrials	Materials	Real Estate
omega	0.01	0.013	0.018 *	0.003	0.024	0.005 ***	0.003	0.045	0.007
alpha [1]	0.107 **	0.123	0.075 ***	0.043 *	0.059	−0.042 ***	0.087 **	0.15	0.078
gamma [1]	−0.08 ***	−0.098 **	−0.061 ***	−0.043 ***	−0.051 **	−0.041 ***	−0.029 *	−0.078 *	−0.049 ***
beta [1]	0.977 ***	0.94 ***	0.992 ***	0.989 ***	0.979 ***	0.992 ***	0.986 ***	0.936 ***	0.991 ***
+ve Cases	−1.285 ***	−0.168	−2.094 ***	−0.385 ***	0.191	−0.54 ***	−0.326 ***	−0.544 ***	−0.642 ***
Δ_Cases	0.008	−0.009	−0.007	−0.008	0.001	0.003	−0.001	0.003	−0.011
Δ_Deaths	0.012	0.007	0.011	0.004	0.01	0.003	0.003	0.004	0.008
str_index	0.009 ***	0.002 ***	0.012 ***	0.002 ***	−0.005 ***	−0.001 *	0.002 ***	0.002 *	0.004 ***
FX_rate	−41.375 ***	−13.044 ***	−78.308 ***	−35.809 ***	−36.609 ***	−35.377 ***	−18.839 ***	−26.257 ***	−30.715 ***
Inflation	−0.125 ***	−0.061 ***	0.146 ***	0.014	0.058 ***	−0.071 ***	0.01	0.133 ***	−0.068 ***
Ln_Volm	0.093 ***	0.1 ***	−0.081 *	0.076 ***	0.057 ***	0.029 *	0.004	−0.011	0.044 **
Vaccin_ratio	−0.048 ***	−0.02 ***	−0.072 ***	−0.031 ***	−0.02 ***	−0.069 ***	−0.014 ***	−0.061 ***	−0.012 ***

Key: *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 3.8 presents the results of the E-GARCH analysis for the Nigerian stock exchange (NGX). A positive alpha coefficient in most sectors indicates that past news shocks led to an increase in stock volatility in these sectors. The financials, healthcare, and ICT sectors were the most affected, as shown by their higher alpha coefficients. The beta values for all sectors were high and significant, indicating persistent volatility in these sectors during the COVID-19 pandemic, although persistence was lower in the consumer discretionary and energy sectors. The insignificant constant omega in all the sectors suggests that volatility tends to stem from news shocks and that unconditional volatility is low.

The coefficients for the daily changes in COVID-19 cases and deaths are insignificant in all sectors, indicating that the growth in COVID-19 cases and deaths did not affect volatility in various sectors on the NGX. The variable for the rate of positive COVID-19 cases is also insignificant, except for the consumer staples, financial, and energy sectors, where a higher rate of positive COVID-19 tests is associated with an increase in stock volatility. For the consumer discretionary, consumer staples, energy, and real estate sectors, the stringency index variable is positive and significantly even at 1% level, suggesting that the government's stringent measures exacerbated volatility in these sectors. However, these measures do not seem to affect the industrial and financial sectors much, while the healthcare and ICT sectors saw a decline in volatility as government restrictions increased. The vaccination variable exhibits a positive and statistically significant relationship across all sectors, suggesting that heightened vaccination rates correspond to heightened stock volatility in each sector. Conversely, the inflation and exchange rate variables demonstrate negative and significant coefficients, signifying that rising inflation levels are linked to decreased volatility in most sectors, while the devaluation of the Nigerian naira against the USD is associated with amplified stock volatility. Notably, the volume of trade variable is positive and statistically significant across all sectors, underscoring that high trading activity is associated with increased volatility within the NGX exchange.

Table 3.8: Results of the Exponential GARCH (E-GARCH) model for the NGX Sectors.

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	ICT	Industrials	Materials
Variable								
omega	−0.046	−0.048	0.009	−0.01	0.003	−0.037	−0.036	0.353
alpha [1]	0.38	0.212 *	0.229	0.15 ***	0.169 ***	0.147 **	0.114 *	0.652 *
gamma [1]	0.038	0.056 **	0.036	0.04 **	0.059 *	0.01	0.003	0.509 *
beta [1]	0.804 ***	0.923 ***	0.889 ***	0.98 ***	0.942 ***	0.948 ***	0.969 ***	1.0 ***
Δ_Cases	0	0	0	0	0	0	0	0
Δ_Deaths	0.004	−0.002	0.007	0.002	0.006	0.001	−0.002	−0.002
+ve Cases	0.005	−0.43 **	0.861 ***	0.301 *	0.164	−0.14	−0.022	0.607 ***
Vaccin_ratio	0.001 ***	0.0 *	0.001 ***	0.001 **	0.002 ***	0.0 ***	0.001 ***	0.001 ***
str_index	0.003 ***	0.002 **	0.004 ***	0.002 **	−0.004 ***	−0.002 ***	0.001 **	0.003 ***
Inflation	−0.05 ***	−0.029 ***	−0.011	−0.035 ***	−0.078 ***	−0.011 **	−0.051 ***	0.016
FX_rate	0	−0.002 ***	−0.004 ***	−0.004 ***	−0.001	−0.002 ***	−0.001 ***	−0.001
Ln_Volm	0.04 ***	0.054 ***	0.04 ***	0.099 ***	0.068 ***	0.001	0.009 **	0.014 **

Key: *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

In Table 3.9, the results of the GJR-GARCH model for the Zimbabwean Stock Exchange (ZSE) are presented. The GJR-GARCH model was selected because of its superior performance over the E-GARCH model. The alpha coefficients for the consumer staples, financial, ICT, and materials sectors are positive and significant, indicating that news shocks during the pandemic increased stock volatility in these sectors. Moreover, a positive and significant omega value for the financial and ICT sectors suggests high unconditional volatility in these sectors. Although the beta values are significant, they are generally low, indicating that volatility tends to dissipate quickly. Furthermore, our analysis found no evidence of a leverage effect on the ZSE. The negative and significant gamma coefficient in the ICT sector suggests that positive shocks have a greater influence on volatility than negative shocks.

The coefficients of the change in COVID-19 cases and deaths indicate that their impact on stock volatility is insignificant in all sectors. Similarly, the variable for the rate of positive COVID-19 tests is positive and significant only for the consumer discretionary and consumer staples sectors. This indicates that the increase in COVID-19 infections and deaths did not have a significant influence on stock volatility in most of the Zimbabwean sectors. The consumer discretionary real estate and materials sectors, which mostly provide non-essential services, have positive and significant stringency index variables. This means that the government's stringency measures led to high volatility in these sectors. A negative and significant vaccination ratio for the consumer discretionary sector indicates that the introduction of vaccinations led to a decrease in volatility only in this sector.

Table 3.9: Results of the Exponential GARCH (E-GARCH) model for the ZSE Sectors.

	Consumer Discretionary	Consumer Staples	Financials	ICT	Industrials	Materials	Real Estate
Variable							
Omega	0.283	0.354	0.245 ***	1.735 **	0.298	0.05	0.678
alpha [1]	0.083	0.272 **	0.162 ***	0.801 **	0.161 **	0.156 **	0.241
gamma [1]	0.024	−0.053	−0.085	−0.567 *	−0.035	−0.04	−0.115
beta [1]	0.83 *	0.648 ***	0.757 ***	0.482 ***	0.751 ***	0.855 ***	0.74 ***
Δ_Cases	−0.001	0.013	0.003	−0.004	−0.002	−0.024 *	−0.015
Δ_Deaths	−0.008	0.002	0.018	−0.072	−0.006	0.011	0.01
+ve_Cases	1.092 ***	1.506 *	0.088	−0.502	0.779	0.587	−1.312
str_index	0.003 **	0.01 *	0.004	0.007	−0.001	0.008 ***	0.013 **
FX_rate	4.811 ***	8.084 **	4.555 *	11.38	0.307	13.448 ***	11.992 **
Ln_Infl	0.123 ***	0.258 ***	0.114 **	0.318 *	0.165 ***	0.329 ***	0.22 *
Ln_Volm	0.024 ***	0.052	0.058 ***	0.127 **	0.046 ***	0.044 ***	0.085 ***
Vaccin_ratio	−0.005 ***	0.014 ***	0.003	0.028 ***	0.007 **	0.007 ***	0.009

Key: *** significant at 1 % level, ** significant at 5 % level, * significant at 10% level.

The inflation and exchange rate variables are positive and significant in most sectors. Inflation appears to have significantly contributed to an increase in volatility in all sectors, with the largest impact in the consumer staples, industrials, and materials sectors. The appreciation of the Zimbabwean dollar led to an increase in volatility in almost all sectors except the financial, ICT, and industrial sectors. The Volume of trade variable is positive and significant in most sectors, indicating that high trading volume is associated with increased stock volatility on the ZSE.

Table 3.10 displays the volatility results for the Lusaka Stock Exchange (LuSE). The GJR_GARCH was chosen for the analysis. The utilities sector exhibits a high and positive omega value, which is significantly different from zero, indicating a higher level of unconditional volatility, while a high positive and significant alpha value suggests that news shocks have increased this sector's volatility. A high and significant beta value for the consumer staples, energy, and ICT sectors indicates volatility persistence in these sectors, while a significant negative gamma for the utilities sector signifies that volatility responds more to positive shocks than to negative ones.

Table 3.10: Results of the GJR model for the LuSE Sectors.

	Consumer Discretionary	Consumer Staples	Energy	Financials	ICT	Industrials	Materials	Utilities
Variable								
omega	0.001 ***	0.001 ***	0.001 ***	0	0.0 ***	0.001	0.005	0.131 **
alpha [1]	0.01 ***	0.01 *	0.01 ***	0.984	0.01 ***	0.725 *	0.424	0.323 ***
gamma [1]	0.01	0.01	0.01	−0.828	0.01 **	−0.336	0.003	−0.235 ***
beta [1]	0.869 ***	0.965 ***	0.965 ***	0.415	0.965 ***	0.186	0.404	0.794 ***
Δ_Cases	0	0	0	−0.003	0	0	−0.001	−0.01
Δ_Deaths	0	0.001	−0.001	−0.003	0.001	−0.024	−0.003	−0.006
str_index	0	0	0	−0.0 **	0	0	−0.0 ***	0
+ve_cases	0.0 ***	−0.0 ***	−0.0 ***	−0.0 **	0	0	0.0 ***	0
FX_rate	0	−0.004 ***	0.001	−0.012 ***	−0.001 ***	0.037 ***	−0.001	−0.014
Inflation	0	−0.002 ***	−0.007 ***	0.006 ***	−0.001 ***	−0.003	0	0.091 ***
Ln_Volm	−0.0 ***	0.001 ***	0.002 ***	0.008 ***	0	0.028 ***	0.005 ***	−0.018 ***
CF_rate	−0.001	−0.439	2.982 *	−6.879 **	−0.553	3.814	10.141 ***	15.009

Key: *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

The variables representing changes in COVID-19 cases and fatalities as well as the rate of positive COVID-19 tests demonstrate no statistically significant influence on stock market volatility across the majority of sectors on the LuSE. The case fatality rate is also insignificant in most sectors, suggesting that reports on COVID-19 cases and deaths do not have a substantial impact on stock market volatility in most sectors on the LuSE. Additionally, the stringency index variable is not significantly different from zero in all sectors, suggesting no effect of government stringency on volatility. Macroeconomic variables and trading volumes are the variables that seem to have a significant influence on stock market volatility on the LuSE. A high level of inflation is associated with a decrease in volatility in the consumer staples, energy, and ICT sectors and is associated with increased volatility in the financial and utilities sectors. Similarly, the depreciation of the Zambian Kwacha corresponds with increased volatility in the consumer staples, energy, and ICT sectors. The dollar volume of shares traded is positive and significant in the consumer staples, energy, financials, industrials, and materials sectors. This indicates that volatility increases with trading volume in these sectors, while it decreases with trading volume in the utilities sector.

3.4.2 **Robustness Check**

GARCH models make an assumption about the distribution characteristics of standardised residuals. If the model is doing a good job in explaining the data, the standardised residuals should not exhibit data clustering or autocorrelations. The Ljung-Box test was used to test the reliability of the GARCH models used in volatility estimation. The null hypothesis is that there is no autocorrelation remaining in the residuals after fitting the GARCH model. If the p-value is larger than the specified significance level, the null hypothesis cannot be rejected, implying that the model adequately captures the conditional heteroskedasticity in the data and that no significant autocorrelation remains in the squared residuals. From the Ljung-Box test results in Table 3.11, we see that the p-value for all sectors in the four stock markets is greater than 0.05, except for consumer discretionary at the JSE. This implies that the results of the GARCH estimates can be relied on in analysing volatility in sub-Saharan African stock markets.

Table 3.11: Ljung-Box test for reliability of GARCH models

Sector	JSE_pvalue	NGX_pvalue	ZSE_pvalue	LUSE_pvalue
Consumer Discretionary	NaN	0.977607	0.527436	0.943504
Consumer Staples	0.5593	0.822323	0.713751	0.998984
Energy	0.944583	0.914129	NaN	0.934473
Health Care	0.115519	0.873414	NaN	NaN
Financials	0.955398	0.929504	0.785936	0.818639
ICT	0.807173	0.608014	0.948448	0.943504
Industrials	0.997991	0.73492	0.704195	0.528687
Materials	0.987698	0.75114	0.762892	0.904571
Real Estate	0.561877	NaN	0.412107	NaN
Utilities	NaN	NaN	NaN	0.978927

3.4.3 **Explainable Artificial Intelligence (XAI) Results**

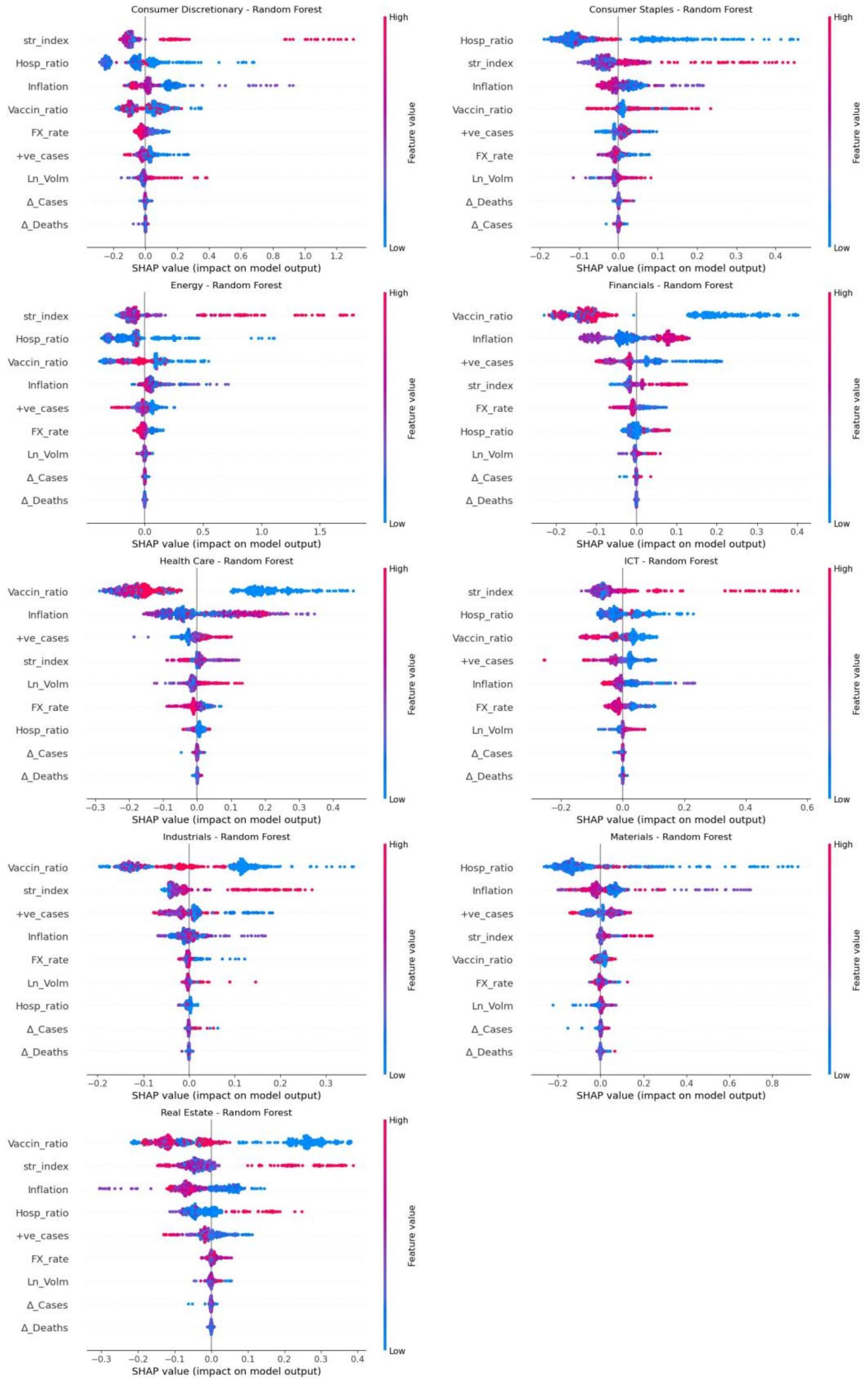
In this sub-section, the results of the analysis using Explainable Artificial Intelligence (XAI), particularly the SHAP method, are presented. XAI is applied to assess the influence of COVID-19 factors on stock volatility in sub-Saharan stock markets. The XAI method was selected not only to address discrepancies identified in our analysis using the GARCH model, but also to provide a visual illustration of the decision-making process made by the model, which further improves the accuracy of our results. First the R-squared results are presented to showcase the performance of various machine learning training models, including Random Forest, XGBoost, and Support Vector Machines (SVM), as shown in Table 3.12, and the best model for further analysis using SHAP is chosen. Upon analyzing the results in Table 3.12, it is evident that the Random Forest model outperforms the other models, demonstrating the highest R-squared values across all sectors among the stock exchanges studied.

Table 3.12 : R-squared results for the data set training.

	JSE			NGX			ZSE			LuSE		
Sector	Random Forest	XGBoost	SVM	Random Forest	XGBoost	SVM	Random Forest	XGBoost	SVM	Random Forest	XGBoos t	SVM
Consumer Discretionary	0.8732	0.5009	0.867	0.3596	0.0423	0.2992	0.9683	0.3101	0.8329	−0.310	−0.014	−0.368
Consumer Staples	0.8574	0.2938	0.7115	0.8012	0.0974	0.4106	0.6505	0.0922	0.2823	0.8117	−0.001	−1.561
Energy	0.9523	0.5384	0.8487	0.1333	0.0241	0.1586				0.7441	−0.032	0.2261
Financials	0.967308	0.4004	0.8930	0.8843	0.2851	0.6382	0.5727	0.0866	0.1607	0.536	−0.011	0.2285
Health Care	0.8887	0.2741	0.8344	0.7847	0.1886	0.3015						
ICT	0.9547	0.4457	0.9029	0.8309	−0.000	0.5130	0.3720	0.0591	0.0402	0.5411	−0.002	−6.801
Industrials	0.9583	0.3780	0.8551	0.8009	0.0408	0.4922	0.5457	0.0718	0.2493	0.0275	−0.015	−0.002
Materials	0.7185	0.3343	0.6384	0.7891	0.2161	0.590	0.8076	0.3081	0.6534	0.0712	−0.004	−0.424
Real Estate	0.9261	0.4530	0.8477				0.3583	0.1431	0.1214			
Utilities										0.7955	0.4243	0.4196

Note: The table shows the explanatory power (R-squared) for the three machine learning models used in training explanatory variables on the target variable (sector returns). The results are shown for each sector in the stock exchange involved.

The results on the impact of COVID-19 features and macro-economic variables on stock volatility are presented using SHAP summary plots below. A SHAP summary plot provides insight into the dominant factors affecting volatility in each of the sectors for a given stock exchange. In addition, a time-series plot was created to illustrate the impact of these features on volatility over time. In Figure 3.6, the SHAP summary plots for the JSE are presented, which reveal that the stringency index is a significant factor affecting volatility in the consumer discretionary, consumer staples, energy, ICT, industrial, and real estate sectors. Across all sectors, high levels of stringency such as economic lockdowns, school closures, and travel restrictions are associated with increased stock volatility.



Note: The features are arranged by their order of importance on volatility, with the most significant features being at the top. The feature values are color-coded, with red representing high feature values and blue representing low feature values.

Figure 3.6: SHAP summary plots for the feature impact on sector volatility on the JSE

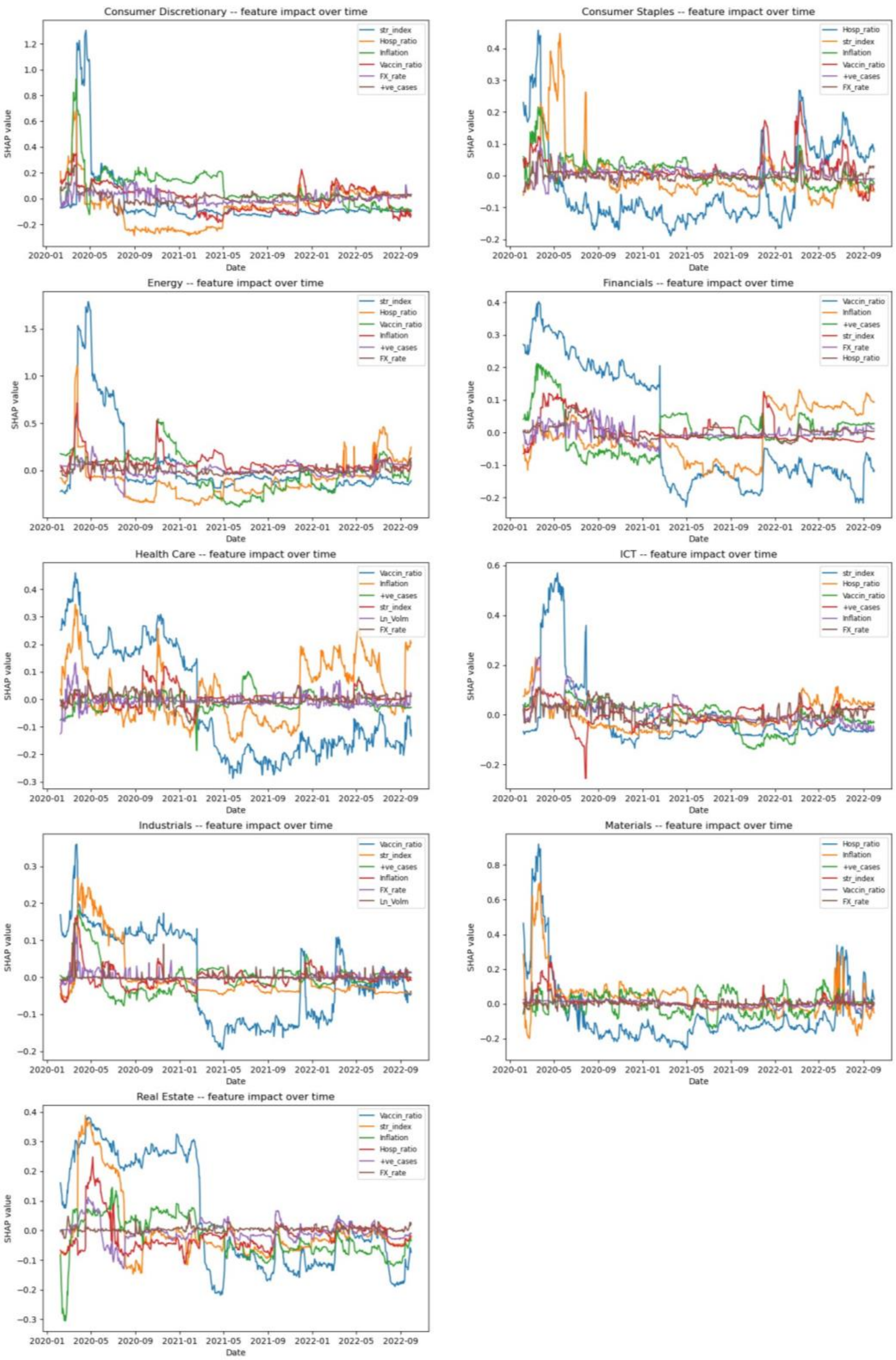


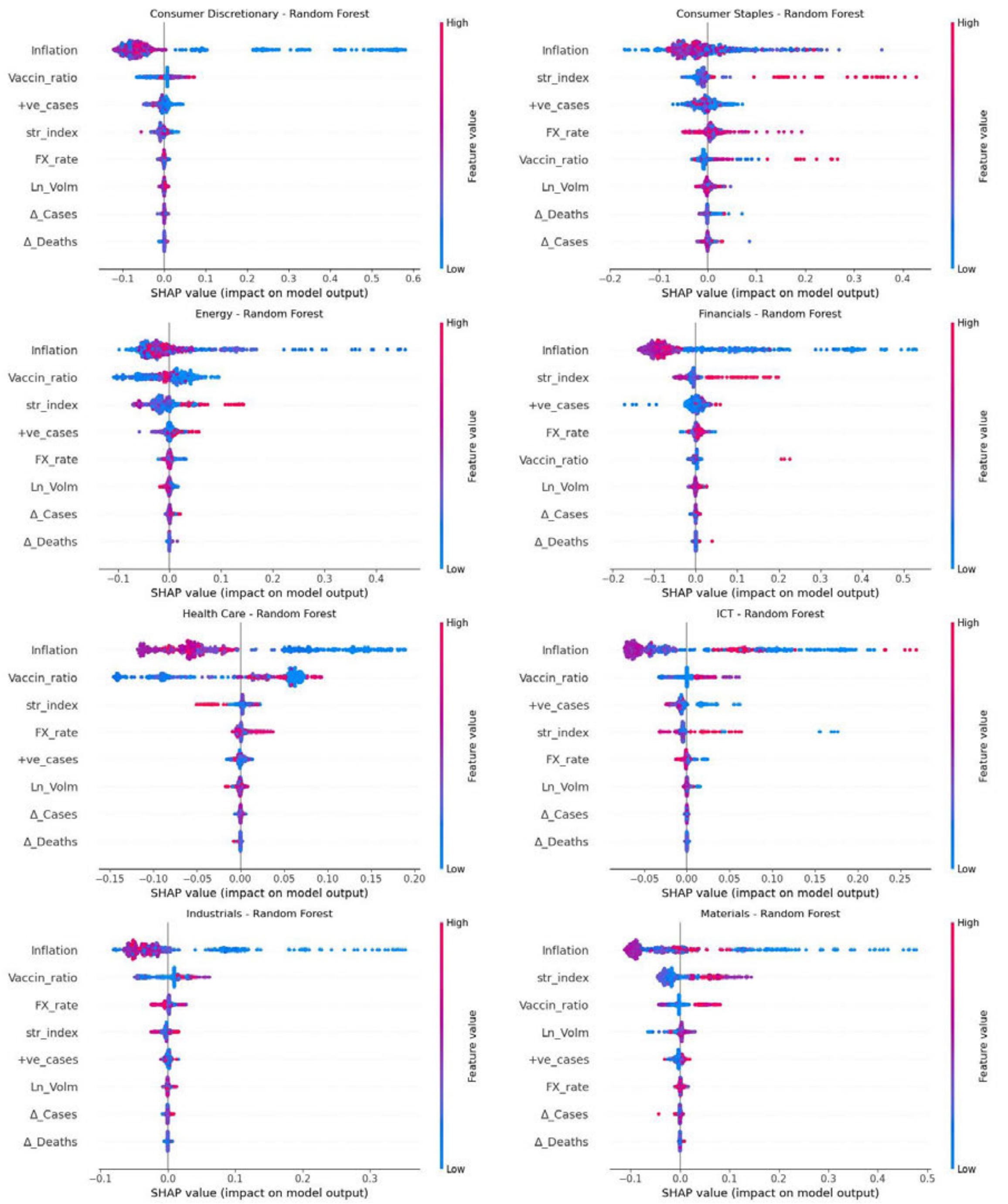
Figure 3.7: Time series plot of Shapley Additive (SHAP) values for the JSE sectors.

Another critical factor is the vaccination ratio, which exhibits a strong correlation with low volatility in the healthcare, energy, financial, real estate, and industrial sectors. As shown in Figure 3.7 which depicts the feature impact on stock volatility over time in the JSE, the introduction of vaccines in South Africa in early

2021 led to a significant reduction in volatility in the aforementioned sectors. Although an increase in hospitalization appears to be associated with a decline in volatility in the consumer staples, energy, and materials sectors, Figure 3.7 clarifies this matter. It shows that low values of hospitalization at the onset of the pandemic coincided with higher values of volatility as the stock market reacted to the outbreak of the pandemic and imposition of government stringency measures. In other words, it was not low hospitalization rates that led to increased volatility, but rather the market's response to the pandemic and associated restrictions.

Similar to the results obtained from GARCH models, the increase in COVID-19 infections and deaths did not have a substantial impact on stock volatility across all sectors. Furthermore, an increase in the rate of positive COVID-19 tests did not lead to increased stock volatility except in the healthcare sector, where a positive association between the rate of positive COVID-19 tests and stock volatility appears to exist. Low inflation rates are associated with higher volatility in most sectors except for the healthcare and financial sectors where higher inflation rates are linked to increased volatility. However, it can be seen that for the sectors where we have negative relationships, the higher values of inflation are clustered around SHAP values of zero, indicating no significant influence of higher inflation on volatility. Conversely, currency rate fluctuations and trading volumes do not seem to have a significant impact on stock volatility across all sectors in the JSE.

Figure 3.8 displays the SHAP summary plots, while Figure 3.9 **Error! Reference source not found.**illustrates the feature's impact over time on stock volatility among the NGX sectors. Inflation is the most prominent factor that influences stock volatility. Low inflation is associated with increased stock volatility in all sectors. As previously discussed, the results align with those of the GARCH model. The plot in Figure 3.9 demonstrates that the high stock volatility associated with low inflation in Nigeria occurred at the onset of the pandemic in 2020, whereas the low volatility associated with higher inflation occurred later, in 2021 and beyond. However, we observe that higher values of volatility are clustered close to SHAP values of zero, indicating that high inflation had no significant influence on stock volatility. High stringency measures are associated with increased volatility in the consumer staples, financials, and materials sectors. Figure 3.9 shows that the most significant impact was felt primarily during the first half of 2020, at the start of the pandemic. High vaccination rates appear to be associated with increased stock volatility in most NGX sectors. However, the time series feature impact plots in Figure 3.9 reveal that the healthcare and energy sectors experienced a decline in volatility following the introduction of the vaccination program in Nigeria at the beginning of 2021. It can also be seen that the growth in COVID-19 cases and deaths did not have any significant impact on stock volatility for all sectors. Additionally, an increase in the rate of positive COVID-19 test results did not lead to increased stock volatility in most sectors. The changes in the value of the Nigerian naira and trading volumes also did not have a significant influence on stock volatility for the NGX sector.



Note: The features are arranged by their order of importance on volatility, with the most significant features being at the top. The feature values are color-coded, with red representing high feature values and blue representing low feature values.

Figure 3.8: SHAP summary plots for the feature impact on sector volatility on the NGX

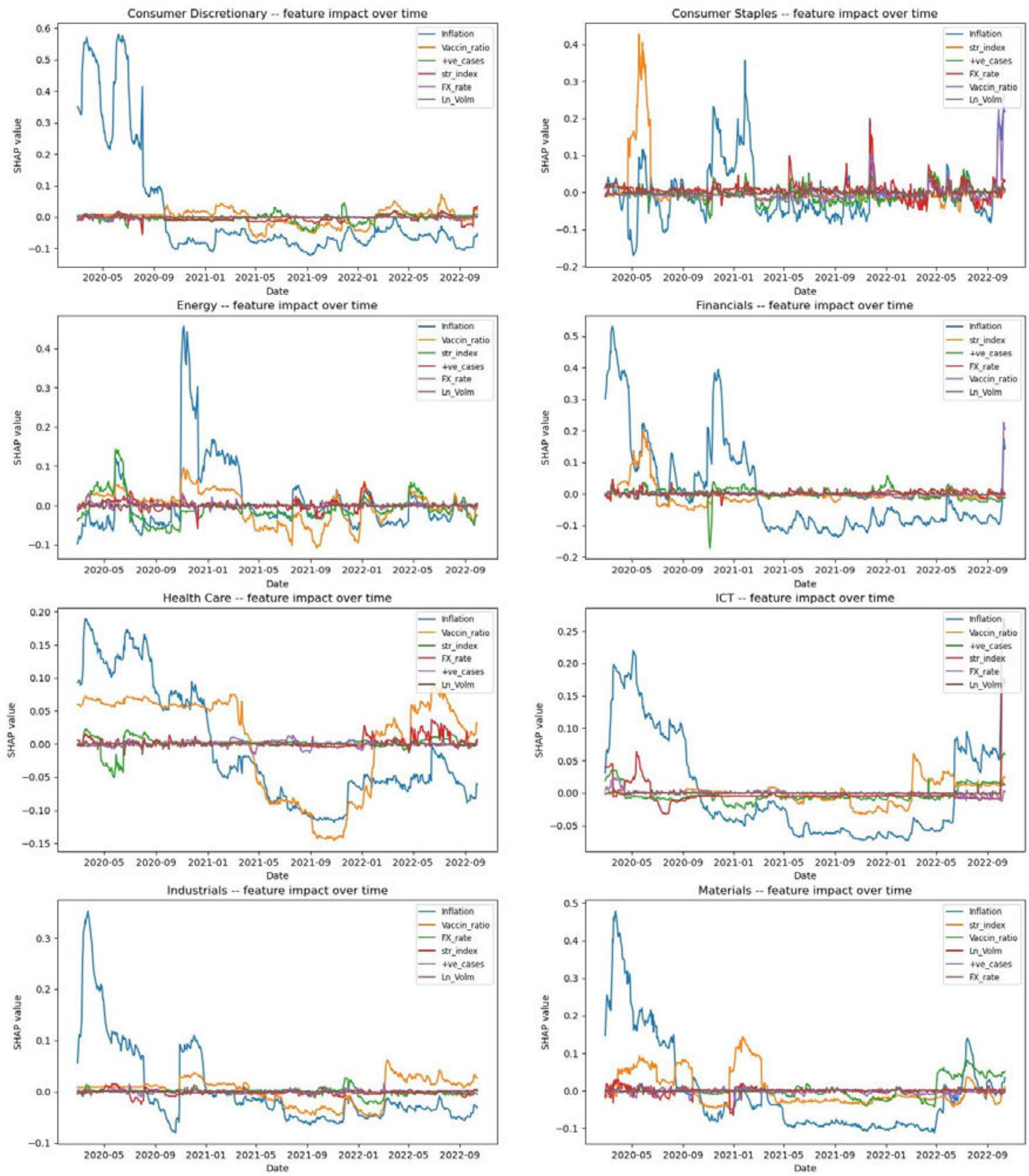
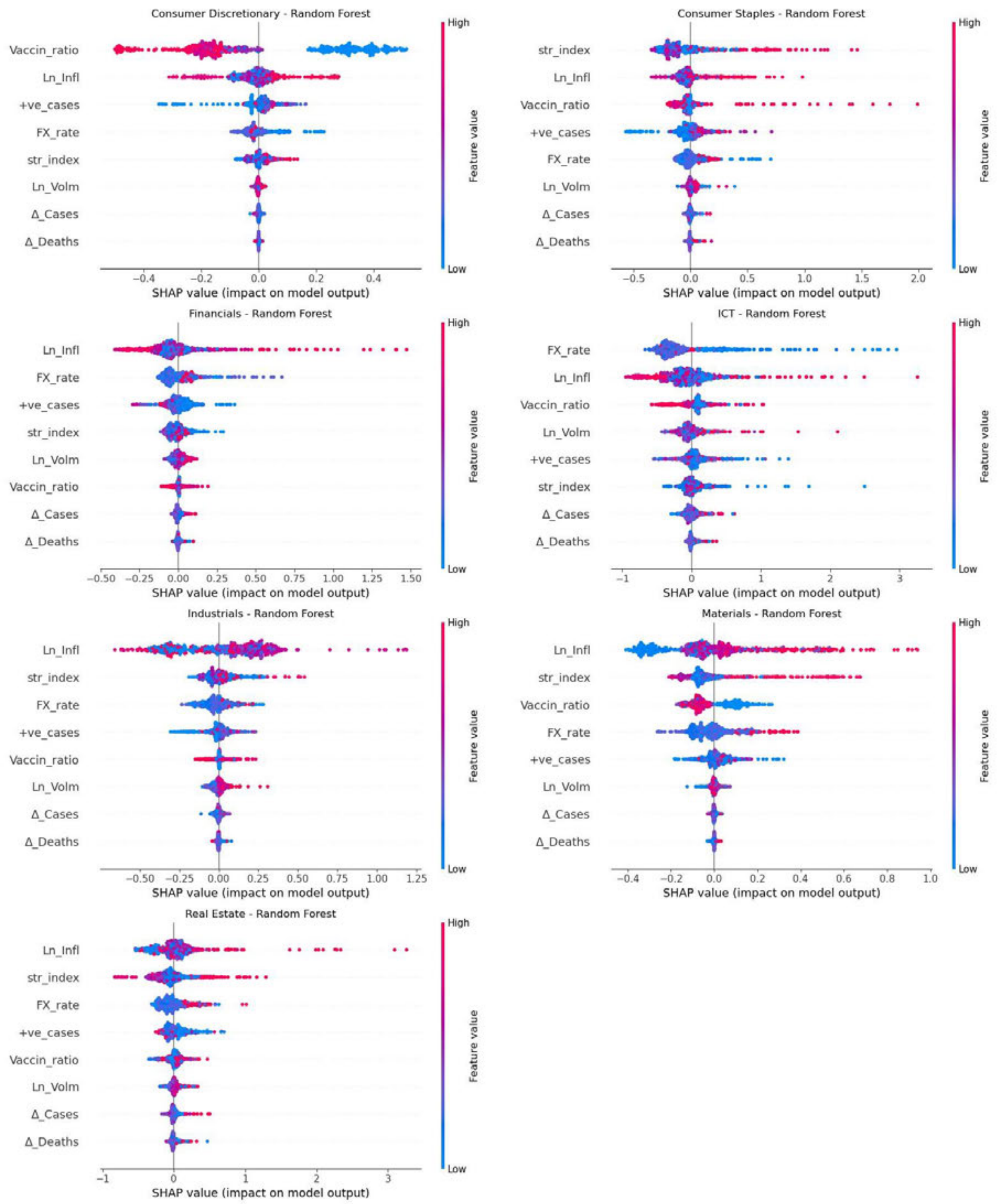


Figure 3.9: Time series plot of Shapley Additive (SHAP) values for the NGX sectors.

In Figure 3.10, the SHAP summary plot for the Zimbabwean Stock Exchange (ZSE) reveals inflation as a significant driver of stock volatility across all the sectors. High-inflation periods (highlighted in red) display varying volatility levels, while low-inflation periods (highlighted in blue) cluster at SHAP values of zero, indicating minimal impact.



Note: The features are arranged by their order of importance on volatility, with the most significant features being at the top. The feature values are colour-coded, with red representing high feature values and blue representing low feature values.

Figure 3.10: SHAP summary plots for the feature impact on sector volatility on the ZSE.

As illustrated in Figure 3.11, which shows the time series feature impact for ZSE sectors, inflation had a positive effect on volatility across several sectors from the beginning of the pandemic until August 2020. These sectors included consumer discretionary, financial, ICT, and consumer staples. Subsequently, high inflation was linked to reduced volatility until the end of 2020, with no notable influence post-2020. Notably, instances of exceptionally high stock volatility in these sectors align with increased inflation levels, affirming the significantly positive coefficient of the inflation variable in the GARCH model. For the material and real estate sectors, the results clearly show that higher volatility is associated with higher inflation.

The stringency index is another variable that has a significant influence on stock volatility, particularly in sectors such as consumer discretionary, consumer staples, industrials, materials, and real estate. Figure 3.11 illustrates that increased volatility due to high stringency occurred mainly at the onset of the pandemic and at the beginning of 2021, coinciding with intensified lockdowns in response to the beta variant. However, this volatility surge due to government stringency is short-lived. By contrast, the financial sector and ICT are less susceptible to these stringent measures. The advantages of SHAP analysis over traditional regression methods are evident when we consider the impact of the stringency variable on stock market volatility. While GARCH results may indicate the insignificance of the stringency variable across most sectors due to its reliance on average values, the SHAP analysis precisely identifies the specific points where the stringency index has the most significant influence.

The vaccination ratio variable, which is generally insignificant across sectors, notably impacts the consumer discretionary sector. Here, the introduction of vaccines coincides with a marked decrease in volatility, reflecting the positive influence of vaccination on businesses in the hotel and tourism industry. The exchange rate is another significant factor. While the GARCH results suggest a positive correlation between currency appreciation and average volatility, from the summary plot in Figure 3.10, it can be seen that this results from instances of currency depreciation being concentrated on both positive and negative SHAP values while instances of currency appreciation are clustered close to SHAP values of zero. However, it can also be seen that periods of extreme volatility are associated with depreciation of the Zimbabwean dollar in most sectors. Although trading volume is not significant in most sectors, higher trading volumes are associated with increased volatility. Similar to the GARCH results, the increase in the number of COVID-19 cases, deaths, and rate of positive cases does not significantly affect stock volatility across all sectors.

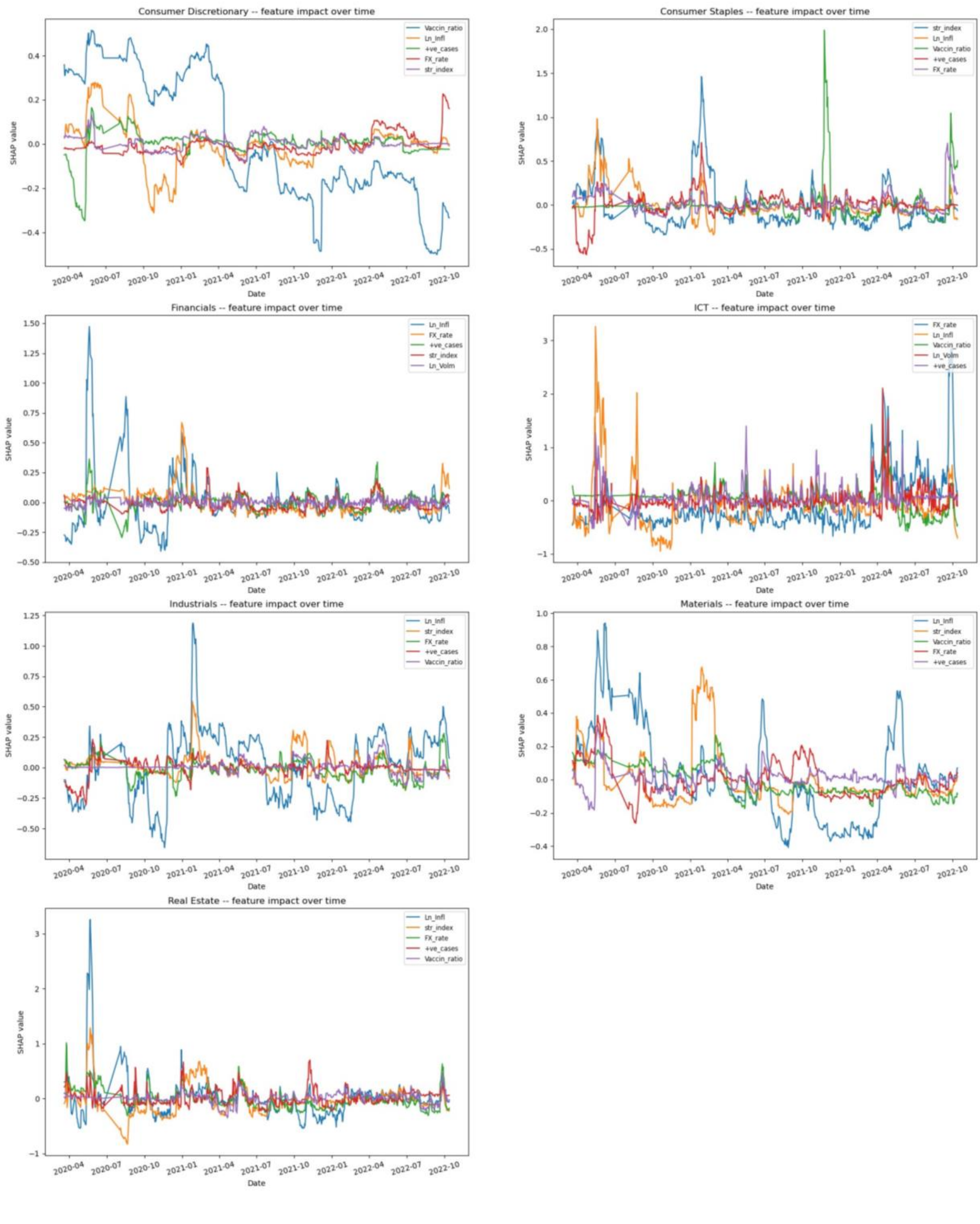
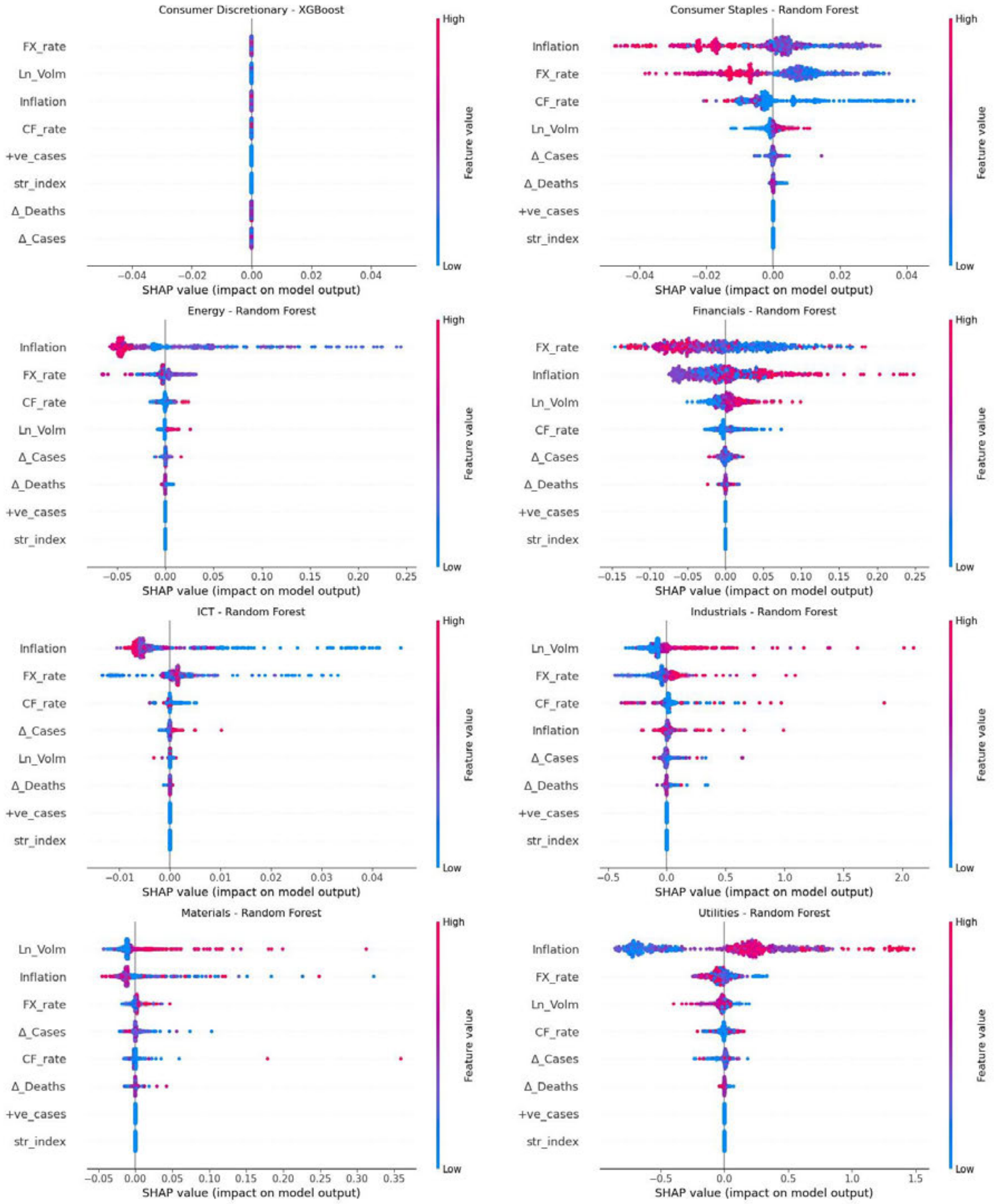


Figure 3.11: Time series plot of Shapley Additive (SHAP) values for the ZSE sectors.

The SHAP analysis results for the Lusaka Stock Exchange (LuSE) are presented in Figure 3.12 and Figure 3.13.



Note: The features are arranged by their order of importance on volatility, with the most significant features being at the top. The feature values are color-coded, with red representing high feature values and blue representing low feature values.

Figure 3.12: SHAP summary plots for the feature impact on sector volatility on the LuSE

Figure 3.12 shows the summary plots and Figure 3.13 depicts the feature impact on stock volatility over time. Notably, the SHAP values for the consumer discretionary sector are consistently zero across all features due to limited volatility data resulting from infrequent trading in this sector.

Figure 3.13: Time series plot of SHapley Additive (SHAP) values for the LuSE sectors.

Macroeconomic factors and trading volumes primarily influence volatility in most sectors, with COVID-19 playing a minor role. The plots show that low inflation periods coincide with increased stock volatility, whereas high inflation periods are associated with a decrease in volatility, particularly in the ICT, energy, and consumer staples sectors. Conversely, the financial and utility sectors exhibit opposite trends. Most sectors experience higher stock volatility because of the devaluation of the Zambian kwacha, with the exception of the industrial and materials sectors, where kwacha appreciation leads to an increase in volatility. Higher trading volumes are associated with increased stock volatility in sectors such as industrials, materials, and financials, energy, and consumer staples, with notable impacts on these sectors. Interestingly, the utility sector shows lower volatility during high trading activity. The case fatality rate significantly affects the industrial sector, with higher fatality rates correlating with increased volatility, particularly at the start of the pandemic.

3.5 Discussion of Results

The influence of the COVID-19 pandemic on equity market volatility in SSA was observed in various sectors across different stock exchanges. For instance, in the Johannesburg Stock Exchange (JSE), the spread of the pandemic in March 2020 caused a surge in volatility across various sectors, with some maintaining heightened volatility even after the initial shock. Similarly, the Nigerian Stock Exchange (NGX) experienced increased volatility in sectors such as the ICT, financial, energy, healthcare, and industrial sectors following the pandemic and during the latter part of 2020 due to the second wave of the beta variant. By contrast, the Zimbabwean Stock Exchange (ZSE) witnessed an increase in volatility in sectors such as consumer discretionary, industrials, materials, and real estate at the onset of the pandemic, with the real estate sector showing transient volatility. However, the Lusaka Stock Exchange (LuSE) did not experience an increase in volatility across all sectors except for the utility sector. The analysis reveals an asymmetric response to news shocks on the JSE and NGX, with bad news having a greater influence on volatility than good news in all sectors at the JSE and in the ICT, healthcare, and consumer staples sectors on the NGX.

Further analysis using SHAP revealed that the government's stringency measures, such as lockdowns, social distancing, and business closures, led to an increase in stock volatility in most sectors across exchanges in SSA, except for the healthcare sector in the JSE and the financial sector in the NGX, where volatility decreased as government measures became more stringent. In smaller stock exchanges, such as the ZSE, the most affected sectors were those dealing with non-essentials, such as consumer discretionary, materials, and real estate. Notably, it was found that sectors that responded more to negative news were those that were significantly affected by the government's stringency measures. The increase in volatility as the government imposed more stringent measures suggests that these measures, which were put in place to curb the spread of the pandemic, were perceived negatively by investors in those affected stocks. These findings align with those of Abdullah *et al.* (2022); Yu and Xiao (2023), who discovered that highly stringent COVID-19 government interventions had a negative impact on stock markets in lower and middle-income countries. The Lucas critique (Lucas 1976) also suggests that the impact of a policy change cannot be determined by past experiences alone but rather depends on how individuals respond to the new policy.

On the other hand, the introduction of vaccines led to a decrease in volatility in all sectors at the JSE, while at the NGX, only the energy and healthcare sectors experienced a decline in volatility. At the ZSE, it is the consumer discretionary sector that experienced a decline in volatility after the introduction of vaccines. The findings also indicate that following the introduction of vaccines in South Africa, the impact of government stringency on stock volatility at the JSE was less severe than before the introduction. This is consistent with the findings of (Yu & Xiao, 2023), who noted that the impact of government stringency measures became less effective on stock market volatility in several developed economies after the introduction of vaccination programs. In contrast, factors such as the increase in COVID-19 cases and deaths, the rate of positive COVID-19 tests, and hospitalization were not found to have a significant influence on stock volatility in most sectors across the sub-Saharan stock markets. This aligns with the findings of Kumeka *et al.* (2022), who showed that COVID-19 cases and deaths had no significant effect on return fluctuations in African stock markets, but rather that the fluctuations were linked to macroeconomic factors such as exchange rate volatility and changes in oil prices. While other studies, such as those by Topcu and Gulal (2020) and Ashraf (2020a) show that the pandemic had a significant impact on stock performance at the onset, this study shows that over the long term, the increase in COVID-19 cases and deaths had no significant impact on stock volatility.

Inflation is another key factor influencing stock market volatility in SSA during the pandemic. However, the impact varies across sectors and stock exchanges. In the Zimbabwean stock exchange (ZSE), most sectors experienced high volatility during periods of heightened inflation. The results in this study show that high inflation at the onset of the pandemic led to increased stock volatility, mostly in sectors such as materials, real estate, and consumer discretionary. Contrary to the theory that suggests a positive relationship between inflation and stock volatility, low inflation is associated with high stock volatility in most sectors in the NGX. The observed relationship between low inflation and high stock volatility in the NGX could be due to policy responses from the Central Bank of Nigeria, such as cutting interest rates from 9% to 5% as noted by Olawoye and Erediauwa (2023), which reduced inflation during this period. The clustering of high inflation values close to the SHAP values of zero in Figure 3.8 is another cause for concern, indicating that high inflation had no significant impact stock volatility in NGX.

For the JSE, it was found that while low inflation was associated with increased stock volatility in most sectors, it was not the primary factor. Similar to the NGX findings, it was observed that, in the JSE, high inflation values clustered at zero SHAP values, suggesting that inflation had a negligible effect on stock volatility, except in the financial services sector, where high inflation values were associated with increased stock volatility. The increase in inflation in South Africa from 2021 to 2022 does not have a significant impact on stock volatility. We expect the financial sector to experience the impact of inflation because of its sensitivity to changes in inflation, which can impact interest rates and securities prices, thereby escalating volatility. Similarly, in the Lusaka Stock Exchange (LuSE), it was found that an increase in inflation leads to an increase in volatility in both the financial services and utilities sectors.

Across all stock markets, the depreciation of a country's currency against the USD leads to an increase in stock volatility across all sectors. However, in larger stock exchanges such as the JSE and NGX, the exchange rate does not appear to be a significant factor. In contrast, during the pandemic, high volatility in the ZSE was associated with depreciation of the Zimbabwean currency. As shown in Figure 3.10, instances of high inflation align well with low values of the Zimbabwean dollar for extreme positive SHAP values. This aligns with findings from other researchers that high inflation in Zimbabwe has been linked to depreciation of the Zimbabwean currency (IMF, 2024; Nyamunda, 2023). The inflation hedging hypothesis posits that equity serves as a hedge against inflation as it represents claims against real assets (Bodie, 1976; Cooper & Kaplanis, 1994). Therefore, when investors anticipate an increase in inflation in Zimbabwe, they prefer to sell their Zimbabwean dollar holdings in exchange for stocks to preserve the value of their investment. This leads to fluctuations in stock prices, and hence, high volatility. Therefore, the high stock volatility in the Zimbabwean sectors is attributed mainly to inflation and currency issues and less to the pandemic outbreak. Moreover, the depreciation of the Zambian kwacha resulted in increased volatility in the consumer staples, financial, and ICT sectors in the LuSE.

An increase in trading volume on all stock exchanges is associated with high stock volatility. However, trading volume is not the most significant factor influencing stock volatility on most stock exchanges, except for LuSE, where high trading volume is one of the most significant factors fueling stock volatility, especially in the materials, industrials, and financial sectors.

3.6 Conclusions and Policy Implications

In conclusion, the COVID-19 epidemic has significantly impacted stock volatility in SSA, with varying effects across sectors and stock exchanges. In larger stock exchanges such as the JSE and NGX, government stringency measures, including economic lockdowns, social distancing, school closures, and travel restrictions, were the primary drivers of increased volatility. However, the introduction of vaccination programs has helped to reduce volatility. It was also found an asymmetric response to news shocks, with bad news leading to higher volatility than good news. For smaller exchanges such as the ZSE and LuSE, weaker macroeconomic fundamentals had a more significant impact on stock volatility than the pandemic itself. The healthcare sector was found to be the most resilient, while sectors dealing in non-essentials were more exposed to the negative effects of the pandemic, mainly on smaller stock exchanges. In larger stock exchanges, exposure is more concentrated in sectors with high trading activity. Volatility in the financial sector is more exposed to high inflation and currency depreciation than pandemic-related factors in all stock exchanges.

The findings reveal that stock markets in SSA reacted more to governmental actions to control the spread of the pandemic than to the outbreak itself. Additionally, this investigation of sector-specific effects reveals that the extent of the impact of black swan events on sector performance depends on the susceptibility of each sector to a specific event. For instance, non-essential sectors were more prone to the adverse effects of stringency measures, while the healthcare sector displayed a more defensive stance, and the financial sector was more sensitive to macroeconomic factors.

Several policy recommendations have been proposed to address the challenges raised in this study. First, it is recommended that governments balance public health concerns with economic stability to reduce the impact of stringency measures on stock market volatility. This can be achieved, for example, by maintaining economic lockdowns at levels that will not hurt the performance of businesses, while simultaneously reducing the spread of the pandemic. Governments should also provide more support in the form of economic recovery packages for businesses affected by stringency measures. Moreover, governments should implement sound fiscal and monetary policies to control inflation and promote exchange rate stability because high levels of inflation and a weakening currency result in high investment risks in the stock market. For investors in smaller stock exchanges, diversifying portfolios across sectors is recommended to reduce investment risk. For larger stock exchanges, diversifying across asset classes is recommended, rather than keeping investments only in the form of equity holdings.

The varying responses of sectors across exchanges also present an opportunity for international portfolio diversification by investing in stock exchanges in other countries. Investors should focus on government policies and macroeconomic factors when making investment decisions. Given the variation in the impact of the pandemic on sector performance, for future research, a study is recommended that considers firm-specific factors that drive stock returns during pandemics. By implementing these recommendations, governments and investors can better navigate the challenges brought about by pandemics and ensure the long-term stability of stock markets in SSA.

Chapter 4. Factor investing during crises: Analysing the influence of firm-specific factors on stock performance in sub-Saharan Africa amid COVID-19 pandemic.

(*This chapter has been published in Tailor and Francis journal of cogent Economics and Finance (see* Appendix 3*)*

4.1 Introduction

The economic consequences of the COVID-19 epidemic have presented investors with a plethora of issues, which include, among them a decline in asset returns and increased market volatility (European Investment Bank, 2022a; Kusumahadi & Permana, 2021; Rakshit & Neog, 2022). These challenges have increased the demand for new investing techniques, with factor-based approaches gaining attention for their potential to effectively manage risk and yield superior returns for investors (Rao, 2022; Zaher, 2019). While stock markets globally appear to have been adversely affected by the pandemic at its inception, empirical literature indicates that various sectors and individual companies have exhibited varying degrees of resilience and recovery during this crisis (Harjoto *et al.*, 2021; Ncube, Sibanda, & Matenda, 2024). Some companies have managed to thrive, adapt, or gain a competitive advantage, whereas others have struggled or faced severe setbacks.

Studies in both developed and developing countries confirmed that stock markets worldwide reacted negatively to the pandemic outbreak, as evidenced by a decline in stock returns and an upsurge in volatility (Ashraf, 2020b; Baig, Butt, Haroon, & Rizvi, 2021; Daglis, Melissaropoulos, Konstantakis, & Michaelides, 2022; Danisman, Demir, & Zaremba, 2021). Further investigation, however, reveals that the severity of the pandemic's impact on most developed stock markets was felt when the World Health Organisation (WHO) pronounced COVID-19 a global pandemic (Yunus Kasim, Muslimin, & Dwijaya, 2022) while in developing countries when the governments initiated lock-down measures (Ncube *et al.*, 2023). Additionally, research indicates that stock market liquidity has diminished in both advanced and developing economies (Baig *et al.*, 2021; Haroon & Rizvi, 2020). Conversely, other investigations demonstrate that the reduction in share prices coincided with a rise in liquidity (Zhang, Gao, & Li, 2021). This phenomenon was attributed to pessimistic investors who, at the pandemic's outset, capitalised on high stock liquidity and reduced trading expenses to sell-off their shareholdings.

While numerous studies have documented the widespread impacts of the pandemic on stock returns and volatility, the underlying factors driving these outcomes remain complex and multifaceted. Previous research has established the importance of firm characteristics, such as size, liquidity, volatility, and profitability, in determining stock performance during market downturns (Gold, Wang, Cao, & Huang, 2017; Gupta & Subramanian, 2014; Zaher, 2019). Moreover, traditional factor models, such as the three-factor model of Fama and French (1993) and its subsequent iterations (Fama & French, 2015, 2020), have highlighted the role of firm characteristics in explaining stock performance. Despite these advancements, the literature on the impact of firm-specific factors on stock performance during the COVID-19 pandemic in sub-Saharan Africa (SSA) remains scant.

Studies that compared the performance of stock markets in different economies show that stock markets in sub-Saharan Africa managed to fare surprisingly well compared with others in emerging and developed economies (Barua, 2021; Fernandes, 2020; Kumeka *et al.*, 2022). Sector-specific studies also reveal that despite the pandemic negatively impacting overall stock market performance, the response varied across different sectors (Curto & Serrasqueiro, 2022; Ncube *et al.*, 2023; Nguyen, 2022). In developed markets, essential service sectors such as healthcare, communication services, and information technology were initially expected to fare better because of their crucial role. However, Curto and Serrasqueiro (2022) show that these sectors also experienced negative returns and increased volatility in the early stages of the COVID-19 epidemic. Unsurprisingly, transportation and tourism, directly impacted by lock-down measures, became the worst-performing sectors (Shen, Fu, Pan, Yu, & Chen, 2020). Other researchers show that the sectors that managed to weather the effects of the pandemic are those that received support from the government, especially in the form of economic recovery stimulus packages (Huynh, Nguyen, & Dao, 2021; Narayan, Phan, & Liu, 2021).

Considering the unique socio-economic conditions in SSA characterized by weak macroeconomic fundamentals and heterogeneous market structures (Ashraf, 2020a; European Investment Bank, 2022a; IMF, 2020), it becomes imperative to understand whether firm-specific factors can explain the variance in stock returns observed in this region during the pandemic. Indeed, several studies have suggested that stocks in economies with weak economic fundamentals suffered the most from the effects of the pandemic (Barua, 2021; Fernandes, 2020). However, this was not the case in the sub-Saharan African stock exchange, as it was observed that some stock markets were on an upward trend despite the outbreak of the pandemic, with some sectors remaining resilient during the COVID-19 pandemic. Therefore, answering the question of whether firm-specific characteristics can explain the variation in stock returns observed in sub-Saharan African stock markets during the pandemic is crucial for understanding the investment opportunities that sub-Saharan African markets offer despite its weak economic infrastructure, and the potential for building more robust investment portfolios capable of navigating future crises.

To address this knowledge gap, this study utilizes Explainable Artificial Intelligence (XAI) and machine learning techniques to analyse the impact of firm-specific factors on stock performance during the COVID-19 pandemic in SSA. There is growing interest in leveraging novel analytical tools, such as XAI, to model more complex relations between input features and its target variables, such as the intricate relationships between firm-specific factors and stock performance (Gao, 2020; Tjoa & Guan, 2020; Xu, Uszkoreit, Du, Fan, Zhao, & Zhu, 2019). Traditional statistical methods have been applied in most factor models. However, these models often struggle to capture nonlinear interactions and complex patterns inherent in real-world datasets (Hastie, Tibshirani, Friedman, & Friedman, 2009). On the contrary, XAI algorithms excel in handling high dimensionality, nonlinearity, and interdependencies that are inherent in financial data (Ali *et al.*, 2023; Goodell, Kumar, Lim, & Pattnaik, 2021), thus making them suitable for exploring the relationships between firm-specific factors and stock performance during the pandemic.

This study is structured as follows: Section 2 reviews the literature. Section 3 outlines the methodology employed in this study, including the data sources and the analysis method. Section 4 presents and discusses the results, and Section 5 concludes the study.

4.2 **Literature review**

4.2.1 **Morden Portfolio Theory**

Markowitz (1952) proposed a framework for constructing security portfolios that quantitatively considers each investment in the context of the portfolio rather than in isolation, which is now known as the modern portfolio theory (MPT). The MPT fundamentally altered the investors' approaches to portfolio construction. This theory emphasises the importance of diversification, positing that an investor can construct a portfolio that optimises the expected return for a given level of risk. This is achieved through careful selection of a mix of assets that are not perfectly correlated, thus reducing the overall risk of the portfolio without necessarily sacrificing returns (Markowitz, 1952; Markowitz, 2010).

Market capitalisation (market cap) weighted portfolios are a common method of constructing portfolios that align with the MPT principles. In a market cap-weighted portfolio, the weight of each asset in the portfolio is proportional to its market capitalisation. This implies that larger companies exert a greater influence on portfolio performance than smaller companies do. By including a range of companies across different sectors and sizes, market-cap-weighted portfolios inherently provide diversification. As market conditions change, the weights of assets in a market cap-weighted portfolio naturally adjust. For instance, if a company's stock price rises significantly, its portfolio weight increases, reflecting its greater market value. Market cap-weighted portfolios can also face challenges, particularly in the context of factor investment. While MPT and market cap weighting focus on overall portfolio risk and return, factor investing seeks to exploit market inefficiencies by investing in assets that exhibit certain characteristics. Market cap-weighted portfolios can become overly concentrated in a few large companies, especially during times of market volatility. This concentration can lead to an increased risk if companies underperform. During a market rally, market cap weighting may inadvertently lead to exposure to certain factors. For example, large-cap stocks may outperform, which could skew the portfolio's risk-return profile.

Some researchers have questioned the validity of the MPT in times of heightened market volatility as increases in asset correlation may negatively impact portfolio diversification (Holton, 2009; Patev, Kanaryan, & Lyroudi, 2006). As market conditions deteriorate, assets that hedge against one another may begin to move in tandem, diminishing the effectiveness of diversification strategies. This phenomenon has led to a re- evaluation (Ang, 2014) of the Modern Portfolio Theory (MPT) framework, prompting researchers to explore alternative models that account for the changing correlations and nonlinear dynamics of financial markets

4.2.2 **Factor Investing**

Factor investing has emerged as a prominent investment strategy, capturing the attention of both academics and practitioners. Its core principle lies in identifying and targeting specific drivers of returns across asset classes to enhance portfolio performance. Factors serve as building blocks of returns in capital markets. They represent the quantifiable characteristics of securities that explain variations in their risk and return behaviour. According to Blitz and Vidojevic (2019), these factors show why certain groups of securities move together and why some exhibit higher expected returns than others. By incorporating these elements in portfolio construction, investors seek to capture the elusive risk premium associated with each factor. While many factors can influence security prices, some have established themselves as the cornerstones of factor investment. Size, value, quality, low volatility, dividend yield, and liquidity factors stand out in their pervasiveness and academic backing.

The quality factor embodies companies with robust business models and enduring competitive advantages. Gupta and Subramanian (2014) highlight that these firms historically outperformed during market downturns, earning them the moniker "defensive" factor. Their resilience stems from their strong profitability, stable earnings, and conservative financial structures. Rao (2022) further strengthens this claim, showing that high-quality firms across diverse market segments consistently outperformed their lower-quality counterparts over the past two decades. Notably, their performance remained robust even during periods of heightened market stress, as evidenced by their outperformance during events like the 2008 financial crisis.

Value investing is also among the most established factor investing strategies. As Zaher (2019) put it, it revolves around buying undervalued stock trading below their intrinsic worth. Traditional metrics such as price-to-book ratio, price-to-earnings ratio, and enterprise value-to-EBITDA ratio serve as guideposts in this pursuit. Low ratios in these metrics indicate companies whose market value underestimates their book value, earnings power, or cash-generating ability. Such discrepancies suggest potentially undervalued stocks that may be attractive bargains for investors. These investors anticipate that the price of these companies will increase to their actual value in the future, thereby securing a return on their investment.

Low-volatility investing has become increasingly recognized, particularly after the 2008 and Eurozone debt crises. These events highlight the importance of capital preservation and diversification, leading to a surge in the demand for low-volatility strategies among institutional and retail investors (Zaher, 2019). Extensive research demonstrates that stocks exhibiting lower volatility than the market consistently deliver superior risk-adjusted returns, attracting conservative investors seeking growth and stability (Bender, Briand, Melas, & Subramanian, 2013; Chong & Phillips, 2012; Hsu & Li, 2013). The appeal of low-volatility stocks can be attributed to several factors. First, investors often overprice risky stocks in pursuit of high returns, neglecting the potential for significant losses (Blitz & Vidojevic, 2019). This leaves low-volatility stocks systematically undervalued, allowing investors to seek stable returns. Additionally, Tversky and Kahneman (1991) concept of loss aversion suggests that investors are more sensitive to potential losses than gains, making them naturally drawn to less volatile options during periods of uncertainty. Since less volatile stocks experience smaller declines during downturns, this makes them particularly appealing during market turbulence.

Momentum investing is also a prominent investment style institutional and individual investors employ. It capitalizes on the tendency of securities to exhibit persistence of past returns, particularly within the short-term horizon. This principle postulates that stocks showing substantial price increases (winners) are likely to continue outperforming, while those experiencing significant price declines (losers) are prone to further underperformance. The reasons behind this phenomenon are debated, and psychological and rational explanations are offered. Psychologically, herding and representativeness biases can lead investors to follow the crowd and project recent trends into the future, amplifying price movements (Papaioannou, Park, Pihlman, & Van der Hoorn, 2013).

Additionally, confirmation bias can cause investors to seek information confirming their beliefs and further fueling momentum. On the rational side, momentum can be attributed to investors reacting efficiently to unpredictable news and gradually incorporating it into prices over time. Information cascade theory proposes that early investors with valuable information attract subsequent investors, leading to price momentum.

Momentum strategies typically fall into cross-sectional and time-series momentum (Zaher, 2019). The cross-sectional approach compares the best and worst-performing stocks within an index over a look-back period. Stocks with high past returns are considered winners and are expected to continue outperforming, whereas those with low past returns are considered losers and expected to underperform. The time-series approach focuses on individual stocks, selecting winners (for long positions) and losers (for short positions) based on their absolute historical returns over a look-back period.

The size of a company, reflected in the "size factor" of small-cap, mid-cap, and large-cap stocks, significantly affects its investment characteristics. While small- and mid-cap stocks exhibit higher growth potential and potentially higher returns, this comes at the cost of increased volatility, limited liquidity, and greater sensitivity to economic fluctuations. Small-cap stocks often suffer from liquidity risk, characterized by lower trading volumes and wider bid/ask spreads, making it harder to buy and sell quickly without impacting prices. This, coupled with their inherent higher volatility and less-established financials, justifies the expectation of higher returns. Furthermore, the growth potential plays a key role. Smaller companies often possess a more potent internal growth engine, allowing them to capitalize on new opportunities and achieve rapid expansion, potentially translating to higher returns. Investor familiarity bias has been proposed as a potential explanation for this size premium. This bias leads investors to favour popular, well-known stocks, often large caps, owing to their frequent media coverage and compelling narratives. The limited news coverage of smaller companies can lead to undervaluation, presenting a lucrative opportunity for savvy investors, who can exploit these inefficiencies and achieve significant outperformance.

The dividend yield factor captures excess returns to stocks with higher average dividend yields, making it a compelling strategy for income-seekers and long-term growth investors (Pappas & Dickson, 2015). Asness, Porter and Stevens (2000) observed that high-yield portfolios in the US delivered an average annual excess return of 4.6% over low-yield alternatives. Notably, this outperformance persisted, even after controlling for other risk factors, highlighting the independent contribution of the dividend yield factor. Some theories have been proposed to elucidate the mechanisms driving dividend yield premiums. Lintner (1956) Cash Flow signalling hypothesis suggests that consistent dividend pay-outs reflect solid fundamentals and future growth potential. Another research by Dreman (2008) posits that high-yield stocks represent undervalued contrarian bets that momentum-driven investors often shun. The market eventually corrects such mispricing, which leads to positive long-term returns for high-yield stocks. Additionally, dividend-paying companies, particularly in mature sectors, may exhibit lower volatility and offer defensive shields during market downturns (Black & Scholes, 1974).

Factor portfolios are typically constructed by grouping securities based on their factor characteristics, prioritizing those with favourable scores, and potentially shorting those with unfavourable scores. However, navigating the intricacies of factor investment requires strategic approaches. Blitz and Vidojevic (2019) advocated for a multi-factor approach, highlighting the limitations of "smart beta" strategies focused solely on maximizing exposure to a single factor. Such narrow approaches potentially neglect the impact of other relevant factors on stock returns, leading to a return drag and underperformance. Therefore, a diversified multifactor approach, grounded in solid theoretical foundations and periodic rebalancing, offers a more robust and sustainable solution. The cyclical nature of the factor returns presents another layer of complexity. Although sensitive to macroeconomic and market forces, different factors exhibit varying degrees of correlation. Although factor underperformance periods can occur because of economic shifts, diversification across multiple factors can mitigate such temporary setbacks. Bender, Sun, Thomas and Zdorovtsov (2018) caution against "factor timing," as its success hinges on a long investment horizon and a deep understanding of market dynamics. They emphasize the merits of a parsimonious multifactor portfolio with sound theoretical grounding and consistent rebalancing.

4.2.3 **Theoretical Factor Models**

Although factor investing has grown in popularity as an investment technique in recent years, its origins can be traced back to the work of Sharpe (1964), who introduced the capital asset pricing model (CAPM) and identified the market portfolio as a single factor driving stock returns. Exposure to this factor, measured by asset beta, leads to a reward in the form of a risk premium. Stocks with higher exposure to the market portfolio are expected to have a higher rate of return to compensate investors for bearing systematic risk. However, several studies have been published that criticized the applicability of CAPM, which has led to the loss of its credibility (Carhart, 1997; Fama & French, 1993, 2004; Grinold, 1993; Jensen, Black, & Scholes, 1972). Jensen et al. (1972) found that stocks with low beta values had higher returns than those predicted by CAPM. The results were contrary to what the CAPM claimed: that low-beta stocks, or less volatile stocks, must have lower returns than higher-beta stocks.

Furthermore, Fama and French (1993) found that a multi-factor model explains the variations in security returns better than the CAPM single-factor model. They discovered that systematic exposure to small-cap stocks tends to produce higher returns than exposure to large-cap stocks and that cheap stocks, companies with low price multiples, have higher returns than expensive ones. This led to the development of a three-factor model that included the CAPM market factor, the size factor measured by market capitalisation, and the style factor measured by the book value to market value ratio. While the CAPM could explain about two-thirds of the difference between two well-diversified portfolio returns, Fama and French (1993) found that the three-factor portfolio could explain the above 90 per cent difference in returns between two well-diversified portfolios.

Carhart (1997) extends the Fama-French three-factor model to include a momentum factor, which captures the difference in the performance of stocks whose prices have been rising against those whose prices have been falling. The researcher found that stocks whose prices have been rising in the past few months continue to perform well, whereas those whose prices have been falling tend to continue experiencing a decline in returns. The researcher further shows that the four-factor model performs better than the CAPM and FFM three-factor models as it reduces the average pricing errors relative to those models. Pastor and Stambaugh (2003) add a liquidity factor to the Fama-French three-factor model in order to capture the return premium for relatively illiquid stocks. They showcase that stocks with higher sensitivity to aggregate liquidity shocks tend to offer higher expected returns. In a later study, Fama and French (2015) expanded on the traditional three-factor model by adding two more factors to account for profitability and investment patterns in equity returns. They found that the five-factor model better modelled the security returns that three-factor model, although adding those two factors made the value factor redundant. Additionally, Horstmeyer, Liu, and Wilkins (2022) show that investing in the quality factor of the Fama-French five-factor model by going long on profitable firms and shorting low-quality or unprofitable counterparts has continued to deliver excess returns to investors, although other factors have not.

Despite the prominence of these traditional factor models, their applicability to developing economies has been questioned. Researchers have argued that these models were primarily developed and tested on stocks traded on the stock exchanges of developed economies, particularly the US equity markets, and may not be suitable for use in developing stock markets. Extensive research beyond standard traditional factor models has been conducted, and the findings from most researchers indicate that the inclusion of more factors tends to explain the cross-sectional variation in equity returns better (Chordia, Goyal, & Shanken, 2017; Feng, Giglio, & Xiu, 2017; Hou, Karolyi, & Kho, 2011; Maio & Philip, 2015). Hou *et al.* (2011) reported using models with a few factors, such as Fama-French and CAPM, to estimate individual stock returns in favour of models with significantly more factors. Researchers recommend starting with hundreds of factors and then using factor analysis (FA) to reduce them to fewer factors that capture more significant variations in asset returns. Chordia *et al.* (2017)In their cross-sectional analysis of stocks traded on the US stock exchange, Chordia et al. (2017) found that the explanatory power of their model was higher when firm characteristics were included in the regression model than when they were not.

Proponents of behavioural finance theories, such as Taleb (2007), highlight that most traditional finance models do not account for the probability of extreme market events in their risk modelling because of the assumption of a normal distribution of stock returns, where the occurrence of substantial return deviations is nearly impossible. Another fundamental assumption of the models is that investors are rational, risk-averse beings who consistently aim to optimize their utility. However, this assumption has been questioned during market crises, as emotions often influence investor behaviour more than the need to maximize utility. Lo (2004), in his theory, the Adaptive Market Hypothesis (AMH), argues that investors are motivated by self-interest when making decisions, making mistakes, and adapting and learning from them. Although the AMH agrees that investors are rational, in line with the efficient market hypothesis (EMH), they sometimes overreact, especially during times of heightened market volatility when their heuristics become maladaptive.

Furthermore, Lin and Tsai (2019) and Fama and French (2020) point out that the primary flaw of most factor models is that they are that they assume the risk factors used in asset return modelling are static rather than dynamic, which makes these traditional factor models unreliable for forecasting future returns. To address this issue, they proposed a time-varying regression-based model that considers the likelihood of each factor's contribution to asset return fluctuating over time.

4.2.4 **Factor performance in crisis periods.**

As Ang (2014) put it, “each factor defines a different set of bad times." This suggests that factor performance is time-varying, implying that factor diversification can be a helpful strategy for hedging against bad times. Pastor and Stambaugh (2003) found that stock returns are positively correlated with changes in volume; however, the correlation reverses when there is a notable decrease in liquidity, particularly during times of crisis, which may signify a flight to quality. Wang, Meric, Liu and Meric (2009), in their analysis of stock market crashes from 1962 to the 2007 global financial crisis, found that large-cap stocks, more liquid stocks, and stocks with high volatility prior to the crash had significantly lower returns during stock market crashes. Moreover, stocks of firms with high leverage, lower profitability, and lower cash flow per share record lower returns during stock market crashes. Although value investing, which involves buying high-book-to-market stocks and shorting low-book-to-market stocks, has, on average, done well, it experienced some drawbacks during the tech boom of the late 1990s and the 2008 financial crisis (Ang, 2014). This is further supported by Horstmeyer, Liu and Wilkins (2022), who demonstrate that value stocks outperformed low book-to-market stocks from 1926 until the onset of the Great Recession 2007. However, following the recession, growth stocks surpassed value stocks in performance.

Coqueret and Guida (2023) discovered that stocks with high volatility, high enterprise value (EV), and those classified as losers exhibited lower vulnerability to the 2008 global financial crisis. EV is widely regarded as an accurate indicator of a company's true worth. The strong performance of companies with higher enterprise value during crises highlights this quality factor's significance. In their study, Barroso and Santa-Clara (2015) assessed the performance of a momentum strategy from the 1930s to 2009, covering the two largest recessions, using data on stock trading in US stock markets. Their findings revealed that momentum-based investment strategies crashed during the 1930s Great Depression and the 2009 global recession. The underperformance of past winners indicates a momentum crash that typically occurs during market crises. Consistent with the research conducted by Barroso and Santa-Clara (2015), Ghayur, Heaney and Platt (2019) demonstrate that momentum strategies tend to deliver strong performance in bullish market conditions but perform poorly in bearish market conditions. After the global financial crisis of 2007–2008, portfolios relying on momentum performed poorly in both the US and emerging markets. The researchers also highlight flight-to-quality as the primary factor behind the superior performance of quality-based portfolios during the global financial crisis. This is because investors tend to be risk-averse during such periods and, therefore, invest their funds in high-quality securities.

Wang *et al.* (2009) examined the significance of the size factor in eight instances of stock market crashes that occurred in the United States from 1962 to 2007. Their research showed that large-cap stocks were more vulnerable to stock market crashes, underperforming small-cap stocks during the crash but outperforming them during the post-crash recovery phase. Further relevant findings can be found in Fauzi and Wahyudi (2016), who examined Indonesian companies from 1983 to 2014, spanning four stock market crashes, including the 2008 global financial crisis and the burst of the dot-com bubble in 2000. The researchers found that during crash events, stocks with larger market capitalisation, greater volatility in the year leading up to the crash, higher leverage for firms, lower liquidity, and lower profitability experienced greater losses in value. In their study of Chinese companies, Meng *et al.* (2023) discovered that stocks with higher profitability and operating efficiency had fewer price crashes, highlighting the significance of the quality factor during market crises.

Factor-based strategies, particularly those favouring defensive assets such as profitability and quality, often underperform during crises, such as recessions, due to a confluence of factors. According to Zaher (2019), investors seeking higher compensation for risk during these times shift towards safer assets, driving down the prices of defensive portfolios associated with low-growth, stable companies. Additionally, as noted by Gupta and Subramanian (2014), the historical outperformance of these factors attracts heavy investment in bull markets, creating a performance drag with higher valuations and potential mean reversion after the crisis. Given that emerging markets and Africa present unique challenges and opportunities during pandemic times understanding the reasons behind the variations in performance among stock markets is crucial to the ever-evolving landscape of post-pandemic investing. By considering both firm-level and sector-specific dynamics, investors can develop informed strategies that capitalize on opportunities and mitigate the risks of this unprecedented global event.

Attempts have been made to assess the factors that influence stock performance during the COVID-19 pandemic, although in regions outside the sub-Saharan region. Nieto and Rubio (2022)and Louraoui (2023) analysed the performance of traditional equity factors, such as momentum, quality, and value, following the COVID-19 outbreak. Specifically, Louraoui (2023) investigated the volatility dynamics of US equity factors using GARCH modelling and found significant market stress during the early months of the COVID-19 pandemic. Although factors displayed varying responses to the pandemic, some recovering faster than others, the volatility factor was resilient as it exhibited lower fluctuations. In contrast, value and momentum were the most negatively affected as they experienced heightened volatility during the pandemic.

On the other hand, Nieto and Rubio (2022) examined how momentum, quality, value, and size factors behaved during two crises: the COVID-19 pandemic and the Great Recession. Using daily data across international countries from Europe, Asia, Oceania, and North America, they found that momentum and quality factors performed well during both crises, whereas value and size factors exhibited weaker performance, particularly during the pandemic. In contrast to Louraoui (2023) U.S.-focused study, Nieto and Rubio (2022)offer an international perspective, highlighting differences in factor behaviour across crises and geographic regions. Their results underscore the robustness of quality and momentum factors during the COVID-19 pandemic.

Another study by Hamad, Qader, Gardi, Abdalla, Hamza and Anwar (2021) focused on individual investors in Iraq, providing a different perspective on factor investing during the pandemic by examining the macroeconomic indicators that drive investment decisions. The findings reveal that economic growth, employment patterns, and demographic trends significantly influenced financial markets during the pandemic. Similarly, Diaz, Ibrushi and Zhao (2021) introduce ESG as a critical investment factor during the COVID-19 pandemic, expanding the literature by showing that ESG considerations have become indispensable in explaining stock market returns during crises.

Regarding the studies conducted so far, to the researcher's best knowledge, a notable gap remains in the context of factor investing in SSA, particularly during the COVID-19 pandemic. While studies like Nieto and Rubio (2022)and Louraoui (2023) offer insights into U.S. and international markets, the impact of crises like the COVID-19 pandemic on factor performance in SSA has yet to be comprehensively studied. Our study aims to fill this gap by analysing factor investing during crises in sub-Saharan African stock markets, applying explainable artificial intelligence (XAI) techniques to enhance the understanding of factor performance in these under-researched markets.

4.2.5 **Summary of Literature and implications**

. The concept of factor investing has roots in classical financial theory such as the CAPM model. Over time, it has evolved through models such as the Fama-French three-factor model, the Carhart four-factor model, and more recent developments, such as the Fama-French five-factor model. These models explain stock returns by considering factors such as size, value, momentum, and profitability. However, these traditional models often fall short in crisis periods, as shown by Ang (2014); Pastor and Stambaugh (2003); Wang *et al.* (2009), among others, who highlight that factors behave differently in times of market stress. The limitations of these traditional models are amplified during crises, with research showing the importance of dynamic rather than static factor exposures (Lin & Tsai, 2019).

Several studies have advocated for expanding factor models, especially in emerging markets, to capture stock return variations better (Carrieri, Errunza, & Hogan, 2007; Dekker, Houweling, & Muskens, 2021; Rahman, Sadique, & Chowdhury, 2012). Still, these models have been mainly tested in developed markets like the US, with limited attention to sub-Saharan African stock markets, especially during extreme events like the COVID-19 pandemic. Sub-Saharan African markets present unique dynamics, such as market liquidity constraints and higher exposure to firm-specific factors, often neglected in mainstream research. Despite the global rise in factor investing, its application in these markets remains underexplored, especially in the context of pandemic-induced market shocks (see Fama & French, 2020). Furthermore, traditional factor models often assume static risk factors and ignore the impact of rapidly changing macroeconomic environments, such as those caused by the pandemic. This under-researched area has led to sub-optimal investments, particularly during crisis periods, contributing to investor losses (Fama & French, 2020). This study will consider factors that have significantly driven stock returns in SSA during the COVID-19 pandemic and compare the performance of factor-weighted portfolios during the pre-pandemic and pandemic periods.

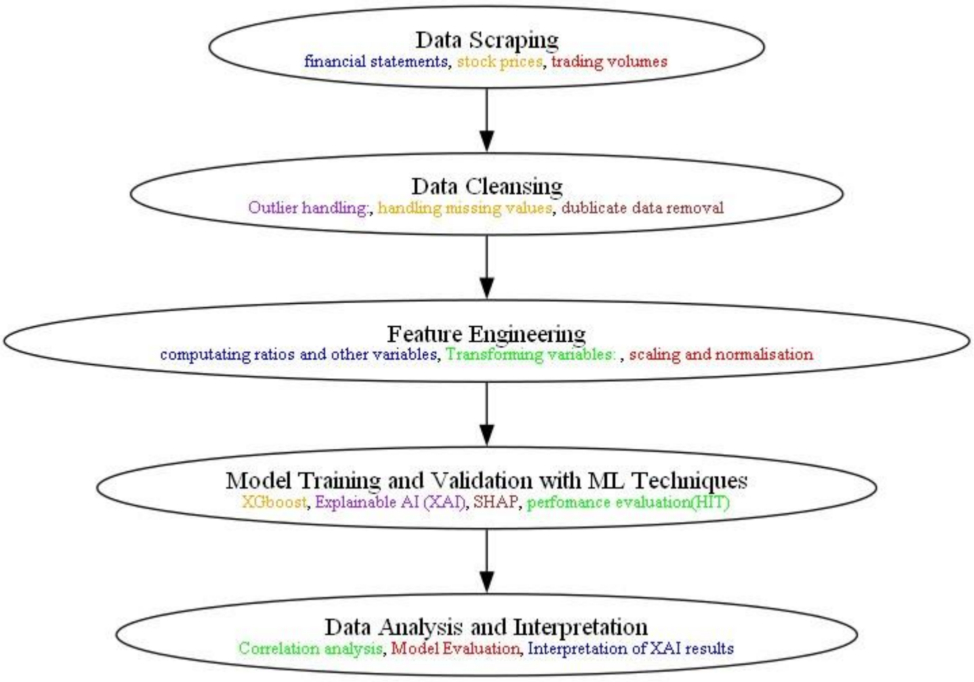
While previous studies have explored factor performance during crises like the global financial crisis, they do not fully capture the complexity of the COVID-19 pandemic (Fauzi & Wahyudi, 2016; Meng *et al.*, 2023) Studies that considered factor investing during the COVID-19 pandemic were concentrated in developed stock markets of US and European countries. This study uniquely focuses on the COVID-19 pandemic, characterised by health and economic shocks and explores the pandemic's impact on sub-Saharan African stock markets. Additionally, most traditional factor models assume a linear relationship between the asset returns and factors that drive returns and are often modelled using linear regression models. This study employs Explainable AI techniques to try to model the complex relationships between stock returns and firm-specific factors and make the modelling factors driving stock returns more interpretable.

4.3 Methodology

4.3.1 Data Sources

In this study, we analysed the significance of firm-specific factors on stock performance by investigating a sample of four stock exchanges in SSA. Specifically, we focused on the Johannesburg Stock Exchange (JSE) and the Nigeria Stock Exchange (NGX), the two largest exchanges in market capitalisation and located in nations with the highest COVID-19 infection rates. In contrast, the Zimbabwe Stock Exchange (ZSE) and the Lusaka Stock Exchange (LUSE) were selected to represent smaller exchanges in countries with fewer

COVID-19 cases. This approach allows us to explore the potential effects of firm-specific factors across different market sizes and pandemic exposure levels. To conduct our analysis, we first extracted data to compute our variables from the financial statements of the firms listed on each of the four exchanges. The financial statements data was extracted from the MarketWatch website (www.marketwatch.com/investing/stock/financials?countrycode) utilising a web-scraping technique known as BeautifulSoup which is implemented in Python programming language. The methodological approach, from data collection to analysis, is illustrated in Figure 4.1.



Source: Author compilation

Figure 4.1: Methodology flow chart.

Our study period is from 2020 to 2022, encompassing the COVID-19 pandemic, and we gathered annual financial data for each stock listed on each exchange. Additionally, we obtained 2019 data to compare performance in the pre-pandemic period. The total number of companies per exchange for which complete financial statements were successfully retrieved is presented in Table 4.1. Not all companies listed on each exchange were included in the final dataset. This exclusion was due to some companies' absence of publicly available financial information.

Table 4.1: Number of sampled stocks per each stock exchange

	Stock Markets.			
	JSE	NGX	ZSE	LUSE
Number of stocks scrapped	255	116	33	15
Approximate Number of stocks at the Exchange in the year 2020	330	160	60	25

The second stage involved data cleansing. This encompasses identifying and handling missing values in the dataset. Stocks with missing financial information were excluded from the dataset. However, in cases where the stock had few missing values, meaning that the information was available to compute most ratios but not for a few, we filled the missing values using the industry average for the year concerned. Additionally, we utilised a more related performance measure if information on a certain ratio was missing in most stocks. For example, if there was no full information among the stocks to compute the debt-to-equity ratio, we used another leverage ratio, such as the debt-to-asset ratio. Data cleansing also included outlier detection. We could detect outliers using the Interquartile range (IQR) technique with the assistance of box plot techniques. We then used looping techniques in Python to loop through the data frame and find stocks with values above or below the range. If the stock had many outliers, it was removed. We also checked for duplicate records and removed them if any were present. This was easily achieved using the Python 'match' function that searches for similarities in the dataset.

4.3.2 **Variables**

4.3.2.1 **Stock Factors**

After data cleansing, we moved to the next feature engineering stage, where relevant financial ratios and other variables were computed. The relevant financial ratios for each selected stock were computed for each year from 2019 to 2022. The complete set of financial ratios and their computations are listed in Table 4.2. Since our sample consists of financial and non-financial institutions, we used the ratios common to both financial and non-financial institutions in each class of financial ratios. Among the variables presented in Table 4.2, stock returns, momentum, volatility, and dollar trading volumes are not directly extracted from financial statements. Instead, their computations involve specific methodologies tailored to each metric.

Momentum, a key factor in stock analysis, captures the tendency of winning stocks to sustain their performance over time. In this study, we classify it as a binary variable that assigns a value of one to stocks classified as winners and zero to those classified as losers. To develop this metric, we first defined our stock universe within each exchange and set a uniform look-back period of six months before March for each year under consideration. We chose March because it aligns with the month of the pandemic outbreak in SSA for 2020, and we maintained the same month for all other years. Expected returns for the study period were calculated and used to rank stocks, with winners identified as stocks in the top 50th percentile and losers in the lower 50th percentile.

Table 4.2: Variables and their computations.

Variable	**Ratio computation**	**Factor Type**
Price to Book Value (P/B)	$\text{Market price per share} / \text{Book Value per share}$	Style factors
Price-Earnings ratio (P/E)	$\text{Market price per share} / \text{Earnings per share}$	
Market capitalisation (Size)	common shares outstanding x share price	Size factor
Return on Assets (ROA)	$Net\ Income / Total\ shareholder's\ equity$	Quality Factors
Return on Equity (ROE)	$Net\ Income / Total\ shareholder's\ equity$	
Debt to Total Assets (DTA)	$\text{Total Liabilities} / \text{Total Assets}$	
Debt to Equity	$\text{Total Liabilities} / Total\ shareholder's\ equity$	
Cashflow from Operations to Free Cashflow (CFO/FC)	$Cashflow\ from\ Operations / \text{Free Cashflow}$	
Net Profit Margin	$Net\ income / Revenue$	
Earnings Per Share (EPS)	$Net\ income / \text{average number of common shares outstanding}$	
Free Cashflow to the Firm (FCF)	$Ln(FCF)$	
EBIT to Enterprise Value (EBIT/EV)	$EBIT / \text{Enterprise Value}$	
Retention Rate (RetnR)	$Reteined\ Earnings / \text{Net Income}$	
Net Income growth(NIg)	$Net\ Income_t / \text{Net Income}_{t-1}$ -1	
Current Ratio	$\text{Current Assets} / \text{Current liabilities}$	
Dividend pay out ratio	$\text{Dividends paid} / \text{Net Income}$	Dividend Yield
Dividend yield	$\text{Dividends paid}_t / \text{stock price}_t$	
Dollar volume of trade	$Number\ of\ shares\ traded\ x\ share\ price$	Liquidity Factor
Momentum	Winners =1 , Losers = 0	Momentum factor
Volatility/ Standard deviation.	Standard deviation of returns $\sqrt{\frac{\sum_{i=1}^{N}(Return_i - Expected\ Return)^2}{N}}$	Volatility factor
Stock returns (Ret)	$Ln\left[Stock\ price\_t / Stock\ price_{t-1}\right]$	Target variable
Risk-adjusted return (Risk_ret)	$\left[Stock\ return / Standard\ deviation\right]$	Target variable

Volatility, a key measure represented by the standard deviation of stock returns, is calculated following a specific formula outlined in Table 4.2. The process involves computing daily variance as the sum of squared deviations from the expected return divided by the total observations. The daily standard deviation is then derived by taking the square root of this variance. In this study, we utilized Python's 'std' function within the NumPy library for precise and efficient standard deviation calculations. The annualised standard deviation is then derived by multiplying the daily standard deviation by the square root of trading days within the relevant period. The dollar trading volume, serving as a liquidity measure, was computed as the product of the number of traded shares and closing price.

4.3.2.2 **Target Variable**

Our performance measure, the target variable in this analysis, is the risk-adjusted return of stocks. We first compute stock returns, derived from daily prices, by calculating the logarithm of the current price divided by the previous day's price, as shown in Table 4.2. The risk-adjusted return is computed as the return of a stock divided by its standard deviation, thereby capturing the risk-adjusted performance of a given stock. We use the risk-adjusted return over pure stock returns because it considers the risk associated with investing in the stock, which is a crucial aspect of evaluating investment performance.

Stage four involved model training and validation utilising machine-learning techniques (ML), while the final stage focused on interpreting the results, which are comprehensively discussed in the subsequent sections.

4.3.3 **Method of Analysis**

4.3.3.1 **Explainable Artificial Intelligence.**

We used a specialised version of machine learning known as explainable artificial intelligence (XAI) to identify the most significant factors driving stock returns. XAI is a set of processes and methods capable of producing human-understandable explanations of artificial intelligence (AI)-based information systems (Ahmed *et al.*, 2022). Although machine learning algorithms can often provide highly accurate predictions, they are often seen as "black boxes," making it difficult for users to understand how the algorithm arrived at its results (Ryo, 2022).

Our initial step involved training a machine-learning model on our datasets. These datasets include firm characteristics as independent variables and stock returns as the target variable. We opted for the eXtreme Gradient Boosting (XGBoost) algorithm, given its established reputation for accuracy and robustness in diverse research domains (Chen & Guestrin, 2016; Midtfjord, De Bin, & Huseby, 2022; Oh, Park, Cho, & Kim, 2021). XGBoost has several crucial advantages for our analysis. First, its inherent regularisation and cross-validation parameters minimize bias and variance issues, ensuring model stability. Second, it incorporates a built-in feature importance function, perfectly aligning with our objective of identifying the key drivers of stock return variations during the pandemic. Furthermore, XGBoost displays resilience to multicollinearity among explanatory variables, which is an essential attribute considering the potentially high correlation between stock factors extracted from financial statements. Additionally, XGBoost exhibits exceptional compatibility with diverse data types, effectively handles missing values, and demonstrates robustness to outliers (Hastie *et al.*, 2009). This characteristic is invaluable when analysing financial data from various stocks, often including outlying instances.

4.3.4 **SHapley Additive Explanations (SHAP)**

We employed SHapley Additive explanations (SHAP), an Explainable Artificial Intelligence (XAI) technique, to identify the most influential factors driving stock return variations. SHAP leverages the notion of SHapley values, which represent the average marginal contribution of each feature value across all possible combinations within the feature space (Cohen, Dror, & Ruppin, 2007). Rooted in coalitional game theory, SHapley values provide interpretable insights into model predictions by decomposing them into contributions from individual features represented as binary variables (the presence/absence of a covariate). This is achieved by iteratively retraining the model on all possible feature subsets and attributing the prediction changes to the inclusion or exclusion of each variable.

Mathematically, if we assume that there are N features, where S is the coalition subset of features and $v(S)$ is the total value of S features, then by the formula of SHapley values, as proposed by Ali *et al.* (2023), the marginal contribution of feature i is given as follows:

$$\boldsymbol{\varphi(i) = \sum_{S \subseteq N/i} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} (v(S \cup \{i\} - v(S))} \qquad \textbf{4.1}$$

We define $\boldsymbol{\varphi(i)}$ as the contribution of firm-specific factors to stock returns, SHAP values can be positive or negative, where a high positive value indicates a high positive contribution to the explained variable and a high negative value indicates a more significant negative contribution. Compared with other XAI techniques, such as the LIME framework, SHAP provides a more robust explanation (Bhattacharya, 2022).

4.3.5 **Visualisation in SHAP**

Given the inherent complexity of Shapley values, there is a need for a more intuitive visualisation method that can explicitly demonstrate the relationship between the features and the explained variable. This study employed SHAP summary plots to evaluate the impact of firm-specific factors on stocks' risk-adjusted returns in sub-Saharan African markets during the COVID-19 pandemic. These plots present feature instances along the horizontal axis, colour-coded (blue for lower values, red for higher values), and positioned according to their contribution to the model's output (positive impact on the right and negative impact on the left). Each feature instance corresponds to a specific factor value for a stock. Clustering around the zero line indicates minimal influence of the factor on a stock's risk-adjusted returns, whereas clustering at extreme ends on either side suggests that the factors have a more substantial impact. Notably, the concentration of red (blue) instances on the positive (negative) side indicates that higher (lower) values of that factor positively (negatively) influence the stock risk-adjusted returns.

4.3.6 **Advantages of the Methodological approach**

A key benefit of Explainable Artificial Intelligence (XAI) is its ability to overcome the limitations inherent in primitive machine learning models, such as logistic regression and linear regression. These models often struggle with nonlinear data, a common characteristic of real-world datasets (Ali et al., 2023). Additionally, although deep neural networks offer powerful capabilities, they typically require substantial training data volumes. The XAI models have become particularly attractive given the data access constraints in sub-Saharan African markets. Their ability to function effectively on smaller datasets and their potential to increase accuracy through filter expansion (Molnar, 2020) makes them a strong choice for our analysis.

XAI techniques are white-box models, which makes modelling more interpretable. As put forth by Christoph (2020, pp. 18-19), in predictive modelling, it is not enough to understand the predictive performance of a model on a dataset; there is also a need to explain how a model arrived at that prediction. This can help the model learn more about a problem and why that model might fail. XAI models are interpretable, meaning they show not only the important factors driving asset returns but also why those factors are important. Linear regression models may identify significant factors that drive asset returns but do not explain why those factors are important. For example, a size factor may positively affect asset returns because a few large-cap companies have higher returns, whereas the rest have returns close to zero. However, with XAI, we can visually see that only a few large companies had a positive impact, while the rest had close to zero, and hence, we can probe further to find out why those few companies exhibited such behaviour.

4.3.6.1 **Random Regression Trees**

In this study, random regression trees were utilised to determine the most significant factors for developing a multifactor portfolio in stock markets across sub-Saharan Africa. While the SHAP summary plots highlight key factors affecting risk-adjusted returns, they fail to reveal a combination of factors that maximise risk-adjusted returns. Thus, there was a need to utilise decision trees, such as the Random Regression Tree (RRT), to identify the factors that combine to maximise the risk-adjusted returns. Random regression trees are a non-parametric approach to regression that do not assume a specific functional form for the relationship between input features and the target variable. Unlike traditional linear models, which rely on predefined equations, random regression trees partition the data into different regions based on feature values, allowing complex, nonlinear relationships to be captured without requiring assumptions about data distribution or linearity. This flexibility makes random regression trees particularly effective for handling large high-dimensional datasets with intricate patterns or interactions among variables.

The objective function of the RRT is to select splits that minimise the Mean Squared Error (MSE) within the nodes. The model chooses a feature and a split point that minimises the MSE. Thus, for a given node, if we split the data at point on the feature, the MSE for that split can be computed as shown in the equation below:

$$MSE_{split} = \frac{n_{left}}{n}.MSE_{left} + \frac{n_{right}}{n}.MSE_{right} \qquad \mathbf{4.2}$$

Where: n_{left} and n_{right} are number of samples in the left and right nodes after the split, MSE_{left} and MSE_{right} are the MSEs of the left and right nodes respectively.
Thus, the algorithm searches for feature X_j and splits that minimise MSE_{split} across all possible splits.

The process of finding the best split repeats recursively for each child node until one of the stopping criteria is met, such as reaching the specified maximum depth or minimum samples per leaf. To avoid overfitting, cost-complexity pruning prunes nodes that do not significantly improve the model's performance. The pruned tree minimizes the following cost-complexity function $\mathrm{R}_\alpha(T)$;

$$\mathrm{R}_\alpha(T) = R(T) + \alpha.|T| \qquad \mathbf{4.3}$$

$R(T)$ is the sum of MSEs for all terminal nodes in the tree T, α is the complexity parameter that balances the trade-off between tree size and fit, $|T|$is the number of terminal nodes in tree T.

Once the tree is built, predictions for the value of the explained variable within a given node is made by averaging the values of the predicted variable within the terminal node as shown in equation 4.4.

$$\hat{y} = \frac{1}{n_t}\sum_{i=1}^{n_t} y_i \qquad \mathbf{4.4}$$

Where $n_t$the number of samples is in the terminal node, y_i are the observed risk adjusted returns in that node**.**

We chose decision trees for this analysis because of their advantages in that they have high interpretability, can handle complex, non-linear relationships, and are adaptable to various types of data without extensive pre-processing. This choice is particularly important given the nature of data in sub-Saharan stock exchanges, which consists of missing values and the complex relationship inherent in financial data. Furthermore, this research aimed to identify the crucial factors influencing stock performance and pinpoint company-specific elements that collectively optimise risk-adjusted returns. The decision-tree framework provides valuable insights into the significance of various features and their interactions. Additionally, unlike parametric models, such as linear regressions, random regression trees impose no assumptions about data distribution, allowing for flexibility in uncovering hidden patterns within diverse economic conditions and financial variables.

The model training process was conducted in Python using the DecisionTreeRegressor class in the scikit-learn library. We selected DecisionTreeRegressor because of its support for customisable split criteria, depth control, and pruning, which collectively mitigates overfitting and ensures meaningful insights. Owing to the capability of decision trees to efficiently process numerical data, only minimal data preparation was necessary. For instance, imputation techniques were employed to handle missing values. A train-test split was performed with the training set used to fit the tree, and the test set was reserved for performance evaluation. To limit the complexity of the tree and prevent overfitting, we initially used a maximum depth of 3, with adjustments made based on performance. We also controlled for the minimum number of samples per split to ensure that each node split was informed by a sufficient sample size, preventing the formation of overly specific decision rules and reducing sensitivity to noise. Additionally, we set the minimum number of samples per leaf to avoid overfitting and ensure more generalised predictions

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4.3.7 Factor portfolio construction

4.3.7.1 Factor Rank score and portfolio construction

Following the feature identification process using XAI, we selected a parsimonious subset of significant factors to construct a factor-weighted portfolio. These factors significantly influenced risk-adjusted stock returns during the COVID-19 pandemic. We then assigned weights to the selected factors based on their feature importance, measured by their absolute SHAP values. Thus, the weight for factor j is given as follows:

$$WF_j = \frac{|SvF_j|}{\sum_{j=1}^{N} |SvF_j|} \tag{4.5}$$

The numerator in Equation 4.5 is the mean absolute SHAP value for factor j, representing the average marginal contribution of the factor to the explained variable (risk-adjusted returns), and the denominator is the sum of the absolute SHAP values for all the selected factors.

After identifying the factor weights, the next step is the scoring process, in which stocks are assigned scores based on their factor values. Before implementing the scoring process, the factor values were normalised owing to their varying ranges, with some being expressed as ratios, while other factors, such as the market cap, took large values in billions of dollars. Some factors can have positive and negative values, whereas others are constrained to nonnegative values. Additionally, some values were negatively related to the target values, implying that the factor values must be ranked reversely. Normalisation was performed using a formula that scales the values between zero and one, as shown in Equation 4.6. Equation 4.7 addresses the negative relationship between a given factor and the target variable.

$$\mathrm{X}_{\mathrm{normalised}} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad \mathbf{4.6}$$

$$\mathrm{X}_{\mathrm{normalised}} = 1 - \frac{X - X_{min}}{X_{max} - X_{min}} \qquad \mathbf{4.7}$$

X represents the value of the factor being normalised, X_{min} is the minimum value of factor X within a given stock universe, and X_{max} is the maximum value within that universe. The computations in the above equations were efficiently performed using the min-max scaling function in Python.

After the normalisation of factor values, the score for each stock, $\mathrm{S_i}$, was determined by multiplying the factor value for stock i under factor j, Fv_{ij}, by feature weight WF_j. For instance, assuming that ROA is among the most significant factors, we multiply the ROA value for stock i by its feature weight. The product of the factor values and feature weights was then summed to obtain the overall score for stock i. This procedure is summarised in Equation 4.8.

$$\mathrm{S_i} = \sum_{j=1}^{N} Fv_{ij} * WF_j \qquad \mathbf{4.8}$$

After determining the individual stock scores, we evaluated and ranked the stocks according to their scores, with the highest-scoring stock occupying the top position. Next, we selected a predetermined group of top-performing stocks, which comprised the best 50% in the stock universe in this instance.

Next, we created a factor portfolio. The weights of the stocks in the factor portfolio were determined based on the stocks' overall score, with the top-ranked stock in the top 50% universe having the largest weight. The weight of a stock in the factor portfolio is computed as:

$$\mathrm{WS_i} = \frac{\mathrm{S_i}}{\sum_{i=1}^{N} S_i} \qquad \textbf{4.9}$$

$\mathrm{S_i}$ is computed as shown in Equation 4.8

Having determined the weight of each stock in the factor portfolio, comprising stocks in the top 50th percentile, we compute that portfolio's expected return and standard deviation. The expected return of a portfolio is the weighted average of the stock's returns, as shown in Equation 4.10.

$$Er_p = \sum_{i=1}^{N} \mathrm{WS_i} * R_i \qquad \textbf{4.10}$$

Where $R_i$is the annualised return for stock i and $\mathrm{WS_i}_i$is as explained in Equation 4.9.

The standard deviation of this portfolio is computed as shown in equation 4.11.

$$\sigma_p = \sqrt{\sum_{i=1}^{N} .\,\omega_i^2 \sigma_i^2 + 2 \sum_{i=1}^{N-1} .\, \sum_{j=i+1}^{N} \mathrm{WS_i}.\mathrm{WS_j} \;\; \sigma_i.\sigma_j.\rho_{ij}} \qquad \textbf{4.11}$$

σ_p is the standard deviation of the portfolio, N is the number of assets in the portfolio, $\mathrm{WS_i}$ is the weight of the ith asset in the portfolio, σ_i is the standard deviation of the ith asset, ρ_{ij} is the correlation coefficient between the ith and jth assets. From Equation 4.11, the first part is the weighted mean of the individual asset variances, while the second part represents the computation of the covariance between the pairs of all assets in the portfolio.

In constructing an asset portfolio, it is crucial to consider the correlation between assets, as combining assets with a correlation of less than 1 in a portfolio helps to diversify-away unsystematic risk, leading to a lower risk of an investment. Computing the variance of a portfolio with many assets using equation 4.11 is cumbersome because it means that for a portfolio of N assets, one has to compute $\frac{N(N-1)}{2}$ covariances of a pair of assets on top of N-weighted variances. We employed matrix operations to compute the portfolio variance and simplify the calculation. To achieve this, first, we create an array ω containing the weights of our assets in the factor portfolio. We also develop a covariance matrix Γ, representing the covariance between each pair of stocks. Using this covariance matrix, we compute the portfolio variance as the dot product of the weights and covariances, as shown in Equation 4.12.

$$\sigma_p = \sqrt{\omega^T . \Gamma . \omega} \tag{4.12}$$

σ_p is the portfolio volatility, Γ is the covariance matrix of returns, ω^T. Represents transposed portfolio weights and $\cdot$ is the dot-multiplication operator. This study used the Python '.dot()' method from the NumPy library to perform dot product operations. This method is designed to handle arrays and matrices of various dimensions, making it an efficient tool for our calculations.

4.4 Results

4.4.1 Correlation Analysis

This section presents the correlation results for firm-specific factors across four sampled stock exchanges: the Johannesburg Stock Exchange (JSE), the Nigerian Stock Exchange (NGX), the Zimbabwe Stock Exchange (ZSE), and the Lusaka Stock Exchange (LuSE). Correlations among the factors were computed from the financial ratios for the COVID-19 period, which ranged from the beginning of 2020 to the end of 2022. Figure 4.2 displays the correlation results for the JSE, Figure 4.3 for the NGX, Figure 4.4 for the ZSE, and figure 4.5 for the LuSE. As expected, strong positive correlations among key profitability ratios, such as net income (NI), return on assets (ROA), and earnings per share (EPS) and return on equity (ROE), were observed across all four exchanges. These results validate the reliability of the ratio computations.

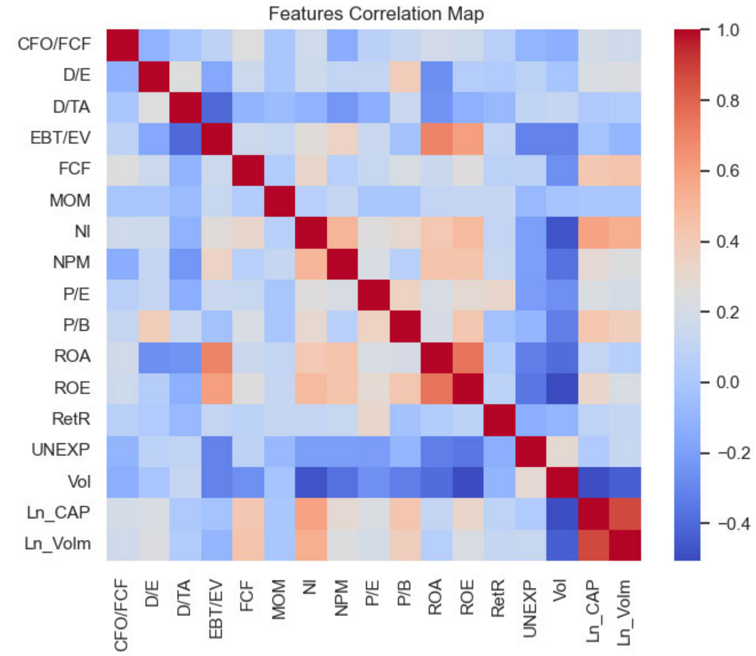

Figure 4.2: JSE correlation map

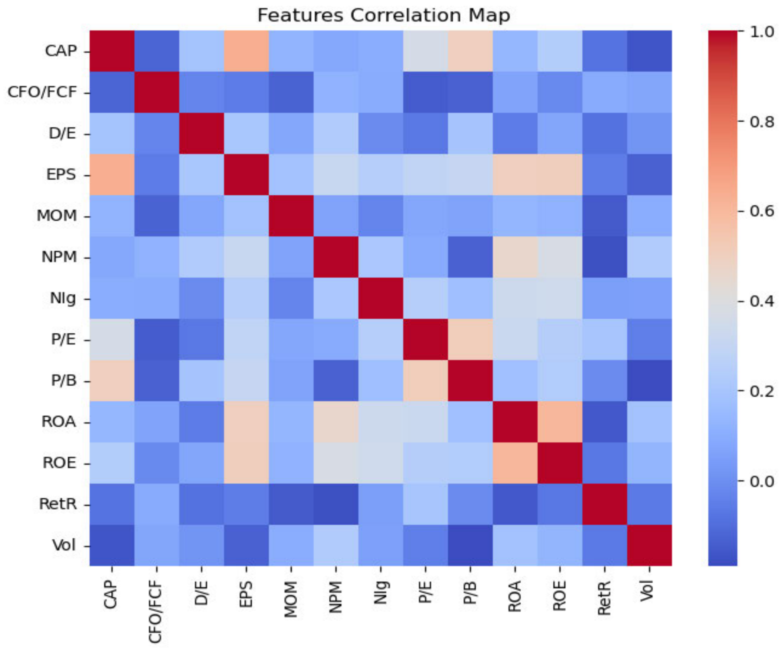

Figure 4.3: NGX correlation map

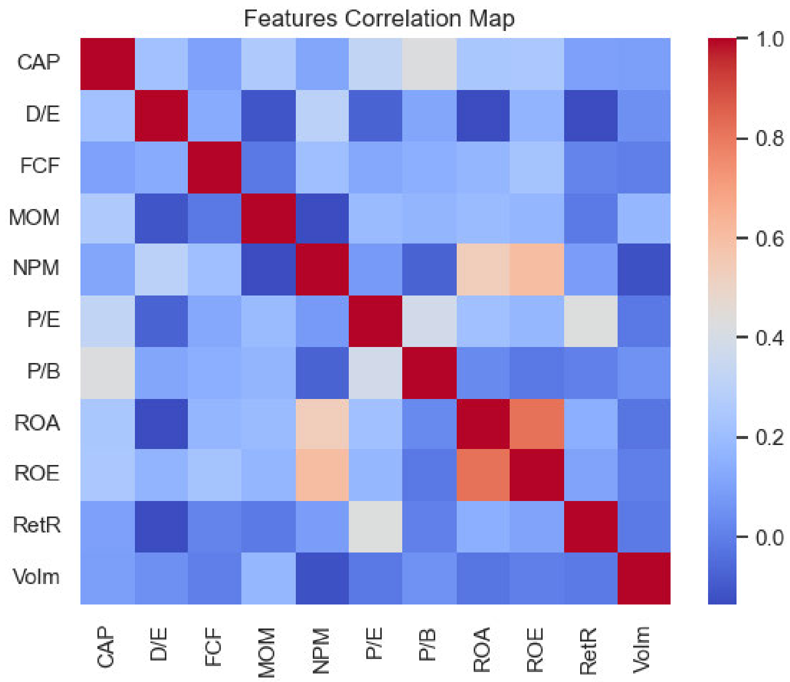

Figure 4.4: ZSE correlation map

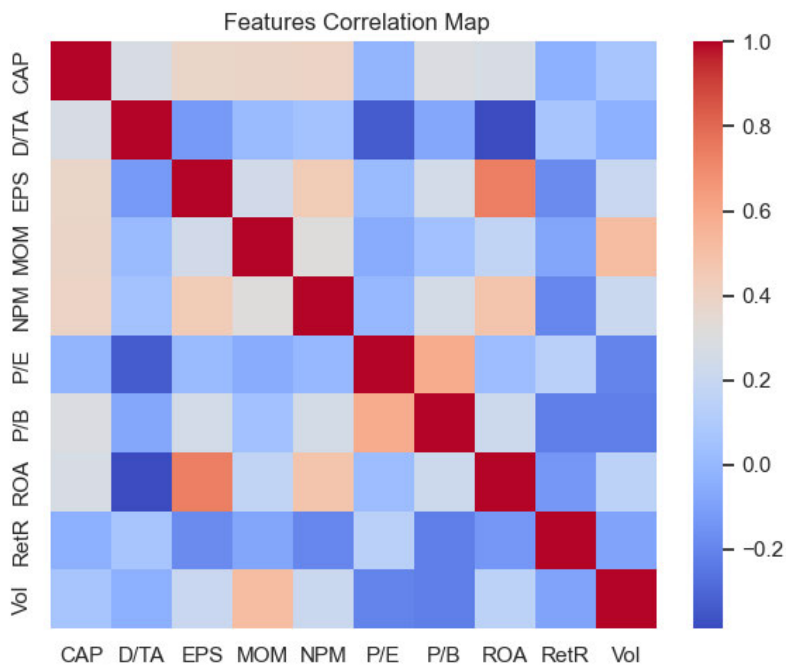

Figure 4.5: LuSE correlation map

Volatility exhibited consistent relationships with other factors across exchanges. In general, volatility negatively correlates with size (market capitalisation) and profitability, suggesting that smaller and less profitable companies tend to be more volatile. However, it is essential to note that the correlation between size and profitability is sometimes weak or even positive. A consistent positive correlation was observed between the trading volume and size across all exchanges. This finding suggests that larger companies trade more actively, attracting greater investor attention and liquidity.

A negative correlation was also observed between leverage ratios, debt-to-asset ratio (D/TA), debt-to-equity (D/E), and profitability ratios, implying that highly leveraged firms face greater financial challenges. For the JSE (Figure 4.2), a strong positive correlation between the size factor (CAP) and trading volume (Volm) was observed, indicating that the most traded stocks during the pandemic were large-cap stocks. At NGX (Figure 4.3), we observe a weak correlation between profitability ratios and valuation metrics (price-to-book and market cap), suggesting a less pronounced differentiation in performance based on growth potential. At the ZSE (Fuigure 4.4), the momentum factor is negatively correlated with the leverage factor, indicating that in most instances, companies with higher leverage are classified as losers. On the LuSE (figure 4.5), the size factor has a low correlation with profitability ratios, highlighting no significant difference in financial performance between small and large stocks. Additionally, the debt-to-asset ratio is negatively correlated with profitability, indicating that less leveraged companies fared better, and the positive correlation between volatility and momentum indicates that winners were more volatile during the crisis.

4.4.2 **Factor analysis**

This section examines the factors driving stock performance during the COVID-19 period. Performance is measured using risk-adjusted returns. Firm-specific factors, consisting mainly of financial ratios for 2020 to 2022, were first trained on the risk-adjusted returns using the XGboost machine learning method. The Sharply Additive Explanations (SHAP) were then used for feature selection to identify the factors influencing stock returns during these periods. The results are presented as bar and summary plots in the figures below. The x-axis of the bar plots shows the aggregated mean absolute SHAP values of the firm-specific factors, and the y-axis presents these factors in their correlation clusters, with the length of the bar representing the relative importance of a factor in determining stock returns. The Summary plot shows the importance of individual input factors by ranking them in descending order on the y-axis, whereas the x-axis shows the feature impact of a particular observation (factor value for a given stock) of an input variable on the model's output. Values to the left of the zero vertical line negatively impact risk-adjusted stock returns, while those on the right exert a positive impact. The Summary plot is also colour-coded, with red representing high feature values and blue representing low feature values.

The results of the JSE SHAP analysis are shown in Figure 4.6, which indicates that profitability factors have the most significant influence on risk-adjusted returns. As shown in the summary plot in Figure 4.6, companies with high net profit margins (NPM) and higher retention rates have high risk-adjusted returns during the pandemic. Additionally we observe that companies with high price-to-earnings ratios (P/E) have high risk-adjusted returns, while those with low P/E ratios tend to experience lower risk-adjusted returns. The findings further reveal that the momentum factor (MOM) contributes positively to risk-adjusted returns, with companies classified as winners having high risk-adjusted returns, while losers experienced depressed risk adjusted returns. Another factor significantly influencing risk-adjusted return is unexpected expenditures (UNEXP), which are unexpected costs that arise unexpectedly and are not budgeted for. Undoubtedly, the outbreak of the COVID-19 pandemic led to an increase in unexpected expenditures, and companies with low unexpected expenditures have higher risk-adjusted returns than those with high unexpected expenditures. On the other hand, leverage ratio as measured by debt to total assets (D/TA), the size factor measured by market capitalisation (CAP), and trading volume have less influence on risk-adjusted returns during the pandemic period.

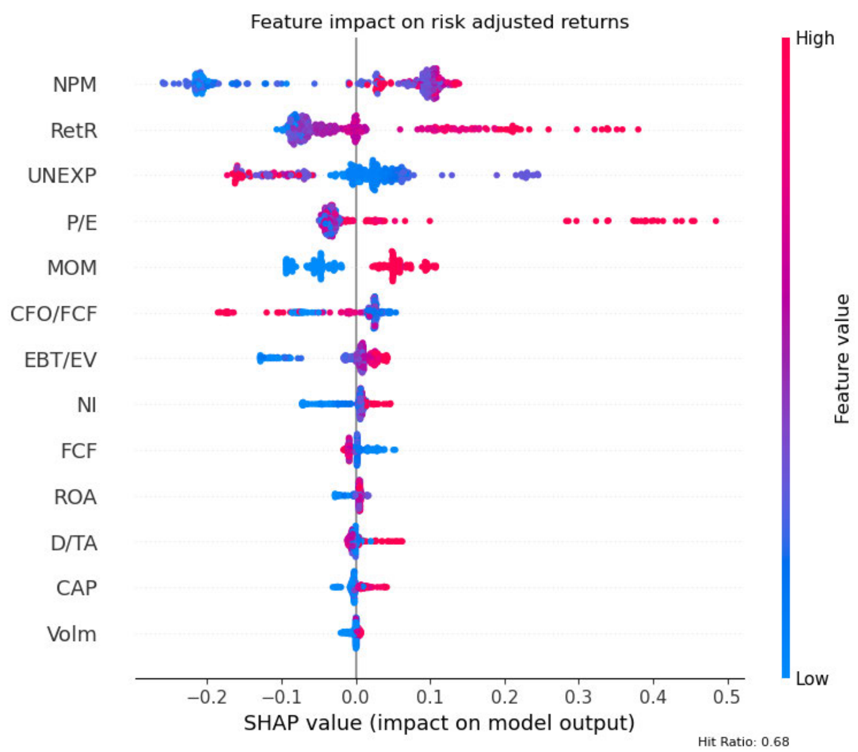

Figure 4.6: JSE summary plot showing feature impact on risk-adjusted returns.

The SHAP analysis results for the Nigerian Stock Exchange (NGX) are shown in Figure 4.7. Some key factors that influence stocks during the COVID-19 period are observed. Notably, measures of profitability, specifically net profit margins and net income growth, appear to be the most significant drivers of risk-adjusted returns, underscoring the significance of solid financial fundamentals for generating positive returns. Nonetheless, the momentum factor emerges as the most influential factor driving the risk-adjusted returns, and from Figure 4.7, it is shown that companies classified as winners outperform those classified as losers in risk-adjusted terms. For profitability ratios, companies with high NPM and NI growth have higher risk-adjusted returns. However, price multiples, such as price-to-book value and market capitilisation, have an insignificant influence on risk-adjusted returns on NGX. Additionally, leverage has no significant influence on risk-adjusted returns. Thus, stock performance at the NGX during the pandemic was driven mainly by internal financial performance, suggesting potential investor behaviour shifts to companies with strong financial performance.

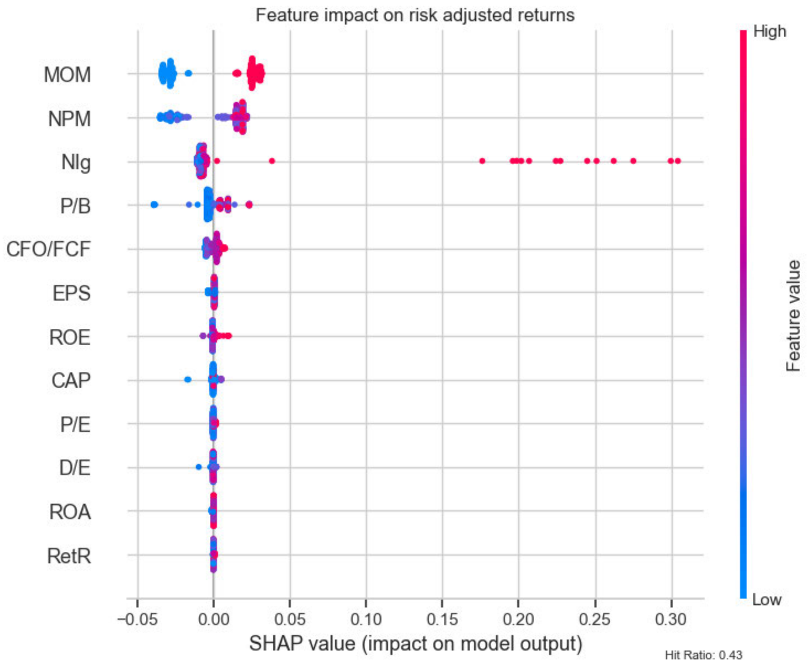

Figure 4.7: NGX Summary plot showing plots feature impact on risk-adjusted returns.

Figure 4.8 presents the SHAP analysis results for the Zimbabwean Stock Exchange. Market capitalisation emerged as the dominant driver of stock performance during COVID-19, with small capitalisation stocks outperforming large capitalisation stocks in risk-adjusted returns. In addition, the P/B and P/E ratios had a significant influence on risk-adjusted returns, and companies with high price multiples had higher risk-adjusted returns than those with low price multiples. Financial performance ratios also significantly influence risk-adjusted returns. However, the most important factors were free cash flows (FCF) and retained earnings (RetR), and companies with higher values in those factors had higher risk-adjusted returns than those with low values on these metrics. This signifies the importance of the cashflow-generating ability of a company on the Zimbabwean Stock Exchange. In contrast, there was no significant difference in performance between companies with high profitability ratios, such as ROE, ROA, and NPM, and those with low profitability ratios. This indicates that investors prefer cash flow strength to accounting profit.

Furthermore, companies with high trading volumes exhibited higher risk-adjusted returns. The positive correlation between these two variables suggests that elevated trading activity is associated with increased stock prices, indicating that investors have been engaging in more buying than selling activities. Notably, the momentum factor did not exert a significant influence on the risk-adjusted returns on the ZSE during the pandemic. This observation implies that winners did not consistently outperform losers on the ZSE during the COVID-19 pandemic. The debt-to-equity (D/E) ratio also appear to be insignificant, signifying that corporate leverage had no discernible impact on stock's risk adjusted returns on the ZSE during the pandemic.

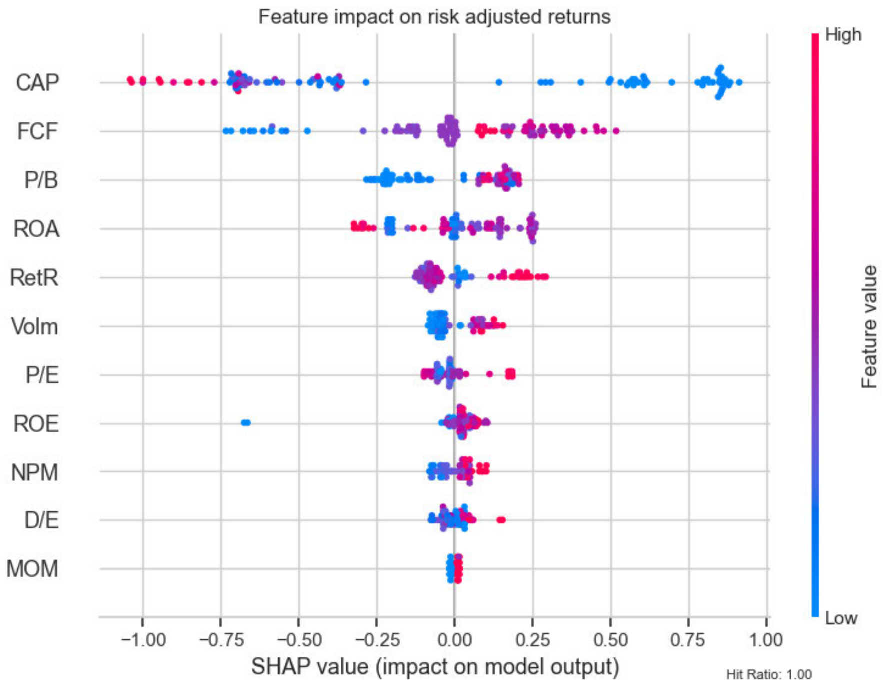

Figure 4.8: ZSE Summary plot showing feature impact on risk-adjusted returns.

The SHAP analysis results for the LuSE are shown in Figure 4.9. The momentum factor emerged as the most significant factor driving stock returns on the LuSE, with companies classified as winners outperforming losers. Our analysis further reveals that low debt-to-total asset (D/TA) values are associated with higher risk-adjusted returns. Thus, companies with low leverage performed better than those with high leverage. This finding suggests that investors preferred companies with lower debt levels, potentially reflecting their desire for reduced financial risk and greater stability in their investment portfolios. The profitability metrics, which include ROA, EPS, and NPM, are also the dominant drivers of returns on the LuSE . This consistent influence underscores the fundamental importance of strong financial performance for investors seeking optimal returns. Although market capitalisation has a lower significance, small-cap stocks have higher risk-adjusted returns than their larger counterparts do. The results underscore the importance of quality factors on the LuSe during the pandemic

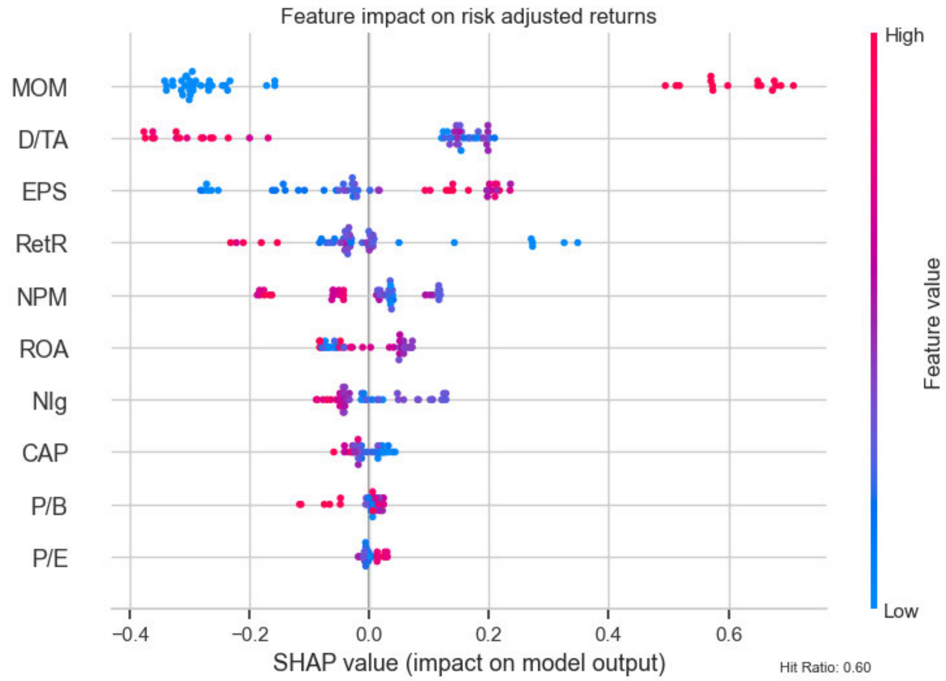

Figure 4.9: LuSE Summary plot showing feature impact on risk-adjusted returns.

4.4.3 Factor identification and portfolio construction.

Following a comprehensive examination of the key factors influencing stock performance, this research proceeded to address the subsequent aim of developing a factor-based investment portfolio. The methodology employed, from establishing factor weightings and calculating individual stock scores to the ultimate construction of the factor portfolio, is detailed in section 4.3.3 of the methodological framework. The results for each stock exchange are presented in this section.

A regression tree was used to identify the factors that combined to result in higher risk-adjusted returns; the results are shown in Figure 4.10. We see from Figure 4.10 that the split start with earnings before interest and tax to enterprise value (EBT/EV) factor. It can be seen that higher values of EV/EBT results in higher risk-adjusted returns. The next split occurs in the RetR factor, and we see that selecting companies with higher retention rates results in improved risk-adjusted returns compared to those with lower retention rates. This leads us to a split based on the market capitalisation (CAP) factor. We observe that selecting companies with larger market capitalisation (higher than 43.7 billion Rands) improves risk-adjusted returns from 0.76% to 1.3%. Although the results of the SHAP summary plots identified the CAP factor as having an insignificant influence on risk-adjusted returns, we observe the power of the regression tree in that it managed to pick the interaction of CAP with the RetR factor and identified its significance in influencing the stock's risk-adjusted returns. SHAP analysis shows feature contribution but does not necessarily indicate which factors maximise or optimise the target, and might also overlook interactions or specific splits that are highly beneficial for the target.

On the right side of our regression tree, we observe another split in the momentum factor and find that selecting companies classified as winners (MOM > 0.5) results in improved risk-adjusted returns. On the other hand, a split using the cashflow from operations to free-cashflow ratio CFO/FCF, we find that companies with lower CFO/FCF ratio have higher risk-adjusted returns. Therefore, it is evident that investing in companies characterised by higher earnings, higher retention rates, large-cap stock companies, and companies classified as winners results in higher risk-adjusted returns.

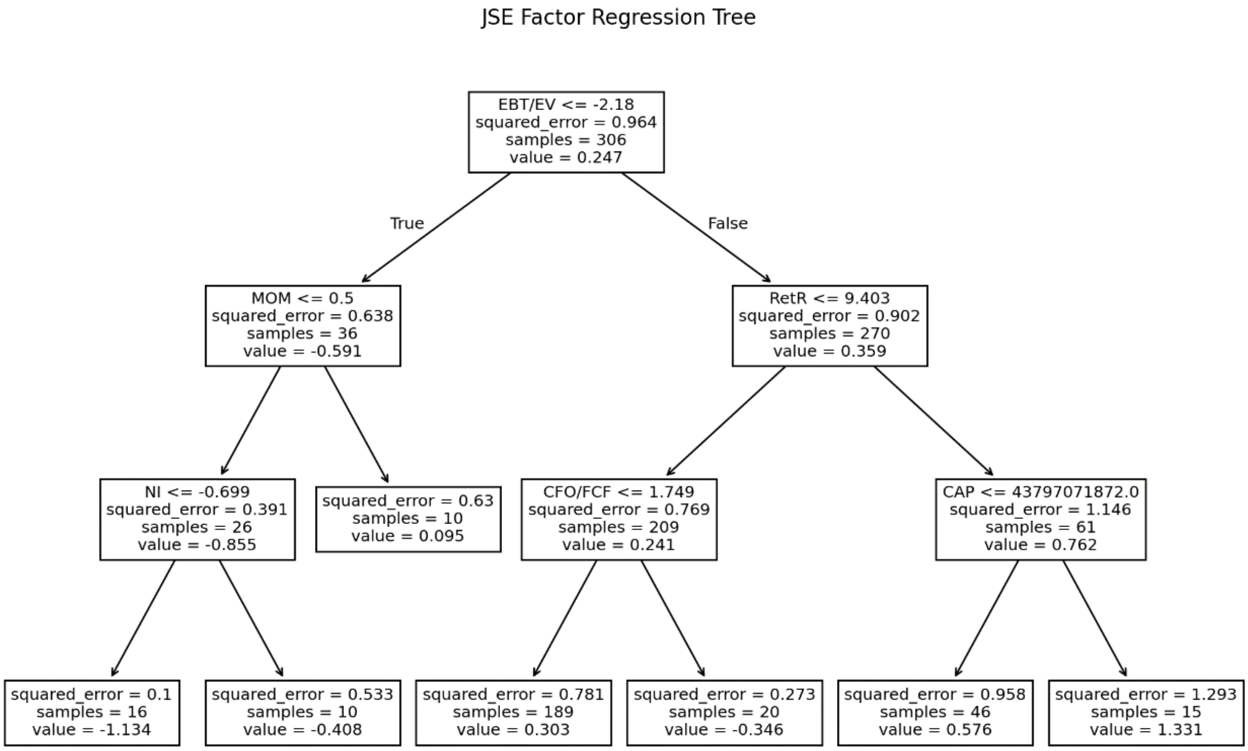

Figure 4.10: JSE Regression tree showing the significant firm-specific factors and their impact on risk-adjusted returns.

Table 4.3 details the weights of these most significant factors, which were calculated based on the factor importance as measured by SHAP values.

Table 4.3: Most significant factors used in determining score for stocks traded on the JSE.

Selected Factors	Feature Weights
EBT/EV	0.380839
RetR	0.27396
MOM	0.185358
CAP	0.130608
CFO/FCF	0.029236

EBT/EV is the factor with the largest weighting among the five selected factors, carrying a weight of 38%. This shows that investing in highly profitable companies in the JSE results in higher risk-adjusted returns. The second most significant factor is the retention rate, with a weight of 27%, followed by the MOM factor, CAP factor, and CFO/FCF. However, for the CFO/FCF ratio, companies with lower ratio values had higher risk-adjusted returns. Using the above identified factor weights, we determined the factor scores for each firm as the weighted average of the product of the factor weights and factor values. After computing the factor scores, we ranked the firms in descending order and selected the top 50% for inclusion in our portfolio. Thus, at the JSE, large cap stocks with high profitability and classified as winners will receive high scores and are highly likely to be selected for inclusion in the factor portfolio.

Figure 4.11 displays the portfolio performance results for a market cap-weighted portfolio and a factor-weighted portfolio for the JSE in both the pandemic and pre-pandemic periods. The market cap weighted portfolio consists of all stocks in the JSE sampled and used for analysis in this study. The stocks are weighted using their market capitalisation and the portfolio returns are compared to those of a factor portfolio. The weights for the stocks in the factor portfolio are based on the factor score for a given stock, with the stock with the highest factor score having the highest weight in the portfolio and the one with the lowest score having the lowest weight. We use the market cap portfolio for comparison because most stock market indices used as benchmarks are market cap weighted. The findings, as depicted in Figure 4.11, indicate that both the factor portfolio and the market capitalisation portfolio exhibited lower risk and significantly higher expected returns than individual stocks both prior to and during the pandemic. The low volatility in these portfolios demonstrates the power of diversification brought about by combining stocks with lower covariance. Additionally, a factor portfolio outperforms a market-cap weighted portfolio in terms of risk-adjusted returns during the pandemic period (year 2020), as it lies northwest of the market cap portfolio. During the 2020 pandemic period, the weighted return for a factor was 12.3%, with a standard deviation of 16.2%, whereas the return for a market cap portfolio was 7.7%, with a standard deviation of 21%. The outperformance of the factor portfolio, even in the pre-pandemic period, enhances the robustness of the factor portfolio in that it outperforms out of the sample. These results indicate that portfolio performance can be enhanced by picking stocks based on the firm's fundamental factors.

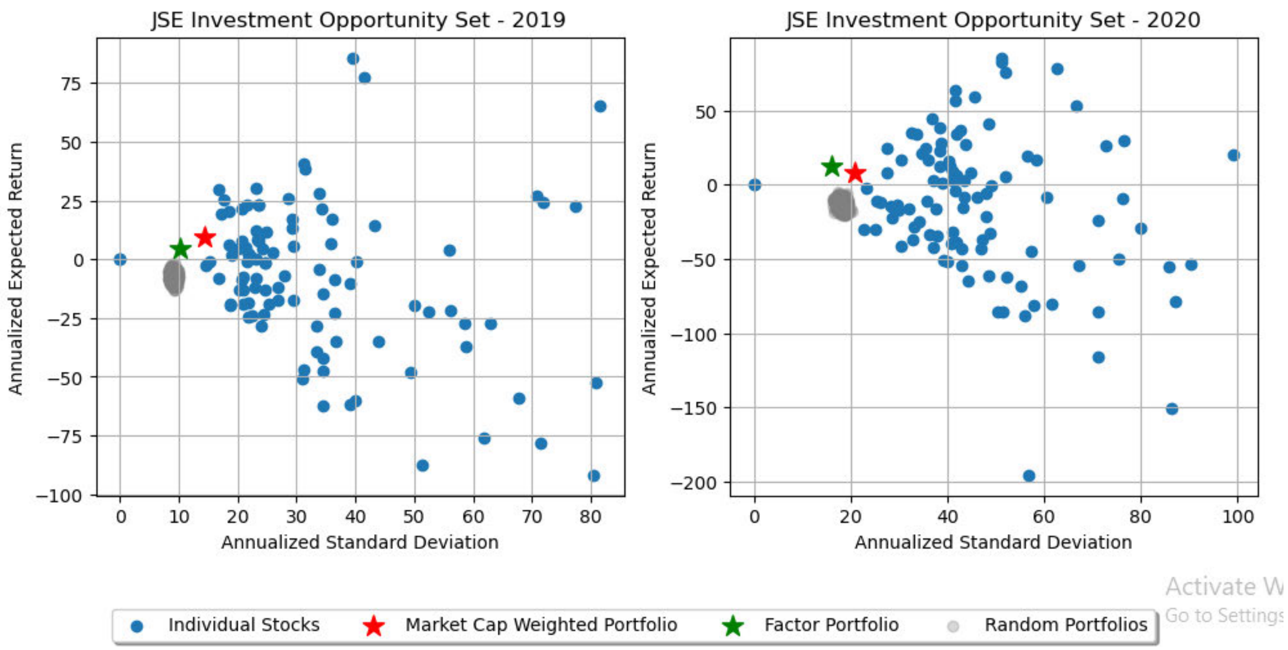

Figure 4.11: Market Cap weighted vs factor weighted portfolio on the JSE.

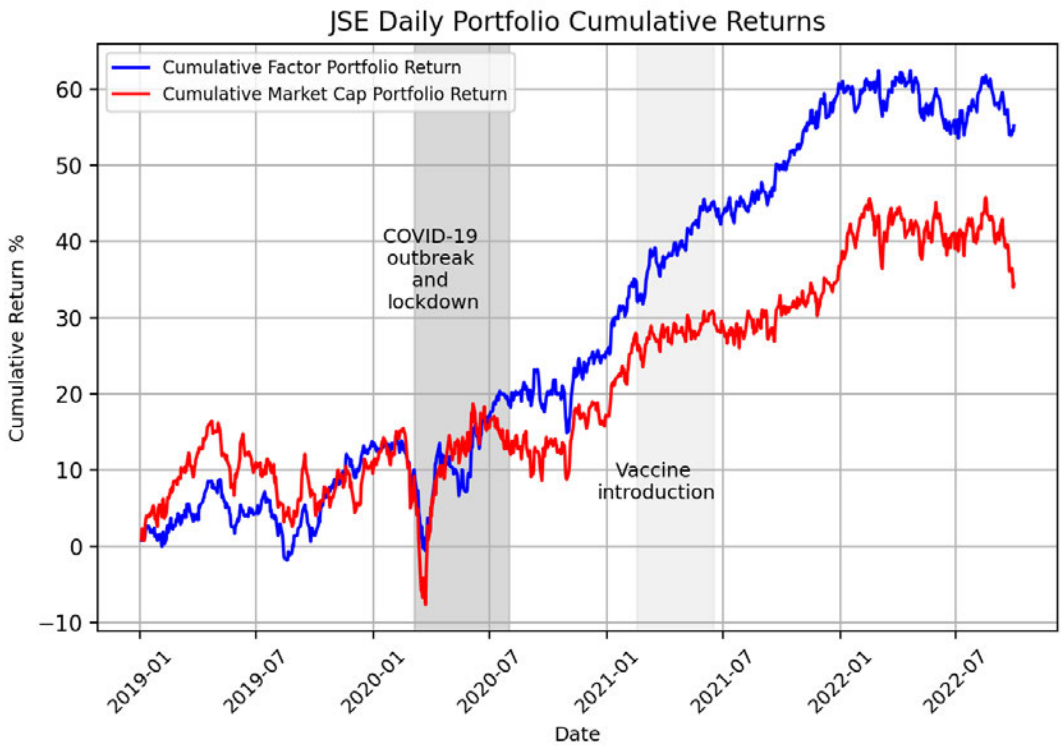

Figure 4.12: JSE daily cumulative return plot for the factor and market-cap weighted portfolios.

To further assess the performance of the factor portfolio in the pre-pandemic period and across the pandemic period, a time-series analysis of our factor portfolio and market cap-weighted portfolio for the JSE was conducted and the results are illustrated in Figure 4.12. Our results show that the factor portfolio outperformed the market cap-weighted portfolio during the pandemic period despite the better performance of the market cap in the pre-pandemic period. Although both portfolios faced a decline in returns as the pandemic struck in the sub-Saharan African region in March 2020, the impact was less severe on the factor portfolio compared to the market factor portfolio. Additionally, we observed that the factor portfolio was quick to recover from the negative effects of the pandemic when compared to the market cap portfolio. This finding affirms the significance of constructing factor portfolios in times of market turbulence.

Figure 4.13 displays the factor regression tree for the Nigerian stock exchange. Net income growth (NIg) forms the root node of the regression tree. Investing in companies with higher earnings growth results in higher risk-adjusted returns. The next split occurs at the price-to-book value (P/B) ratio, and investing in companies with higher price-to-book value, commonly known as value stocks, results in higher risk-adjusted returns. displays the factor regression tree for the Nigerian stock exchange.

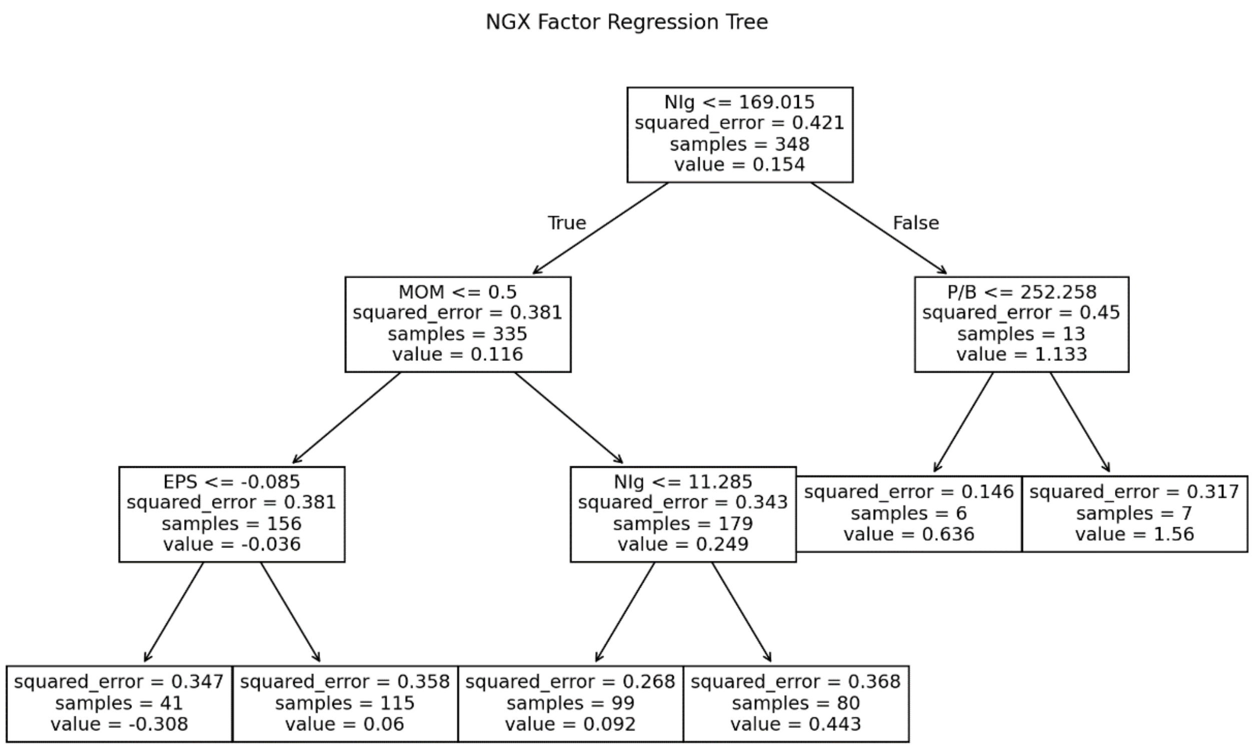

Figure 4.13: NGX Regression tree showing the significant firm--specific factors and their impact on risk-adjusted returns.

Table 4.4 displays the weights for the significant factors utilised in selecting stocks for inclusion in the factor portfolio on the NGX. The significant factors identified in the regression tree were assigned weights based on the importance of these factors, as measured by their SHAP values. As shown in Figure 4.4, the NIg factor has the largest weighting of approximately 55.6%, followed by the MOM factor which has a weight of 32.7%, whereas P/B and EPS have lower weights. The results show that investing in companies with high earnings growth and those classified as winner stocks results in higher risk-adjusted returns.

Table 4.4: Most significant factors used in determining score for stocks traded on the NGX.

Selected Factors	Feature Weights
NIg	0.556865
MOM	0.327415
P/B	0.095061
EPS	0.020659

Figure 4.14 shows a mean-variance plot for the factor portfolio, market cap portfolio, and individual stocks on the Nigerian stock exchange. We observe that a multi-factor-weighted portfolio (factor portfolio) performs better than a market-capitalisation-weighted (market-cap) portfolio in both the pre-pandemic and pandemic periods. The outperformance of a factor-based portfolio is more evident during the pandemic period (see figure 4.14, 2020 plot). The average return for the factor-based portfolio is 7.3% with a standard deviation of about 15%, while a market-cap portfolio has an average return of -7% and a higher standard deviation of about 18%. The results clearly demonstrate the superiority of a factor-based portfolio during the pandemic.

A time series analysis of the performance of the factor and market portfolios from 2019 to 2022 is shown in figure 4.15. The findings of this investigation corroborate the study's assertions, indicating that the factor portfolio demonstrated superior performance compared to the market capitalisation portfolio during both the pre-pandemic and pandemic phases. Although we see some drops in returns when the pandemic struck the region in March 2020, the drop in the factor portfolio does not go below zero, whereas the market cap portfolio drops to below 20% due to the outbreak of the COVID-19 pandemic. Additionally, although there is a significant recovery in returns for both portfolios after the lock-down period, the returns for the market cap-portfolio remain negative up to the end of 2020. The results also show that the factor portfolio would have accumulated 100% return from the time of recovery from the pandemic to the end of year 2022 when the pandemic was declared a variance of no significant concern, while the market cap portfolio would have accumulated only to 40%. This demonstrates the importance of investing in factor portfolios during the pandemic period on the Nigerian Stock Exchange.

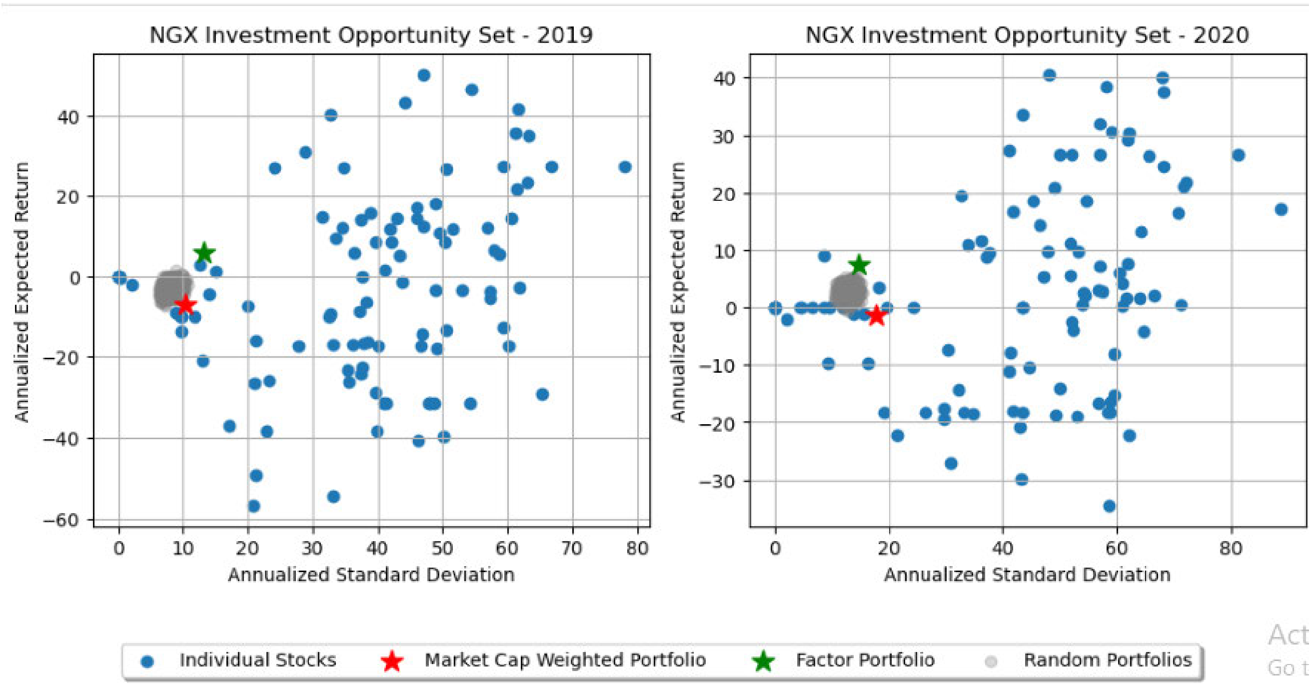

Figure 4.14: Market Cap weighted vs factor weighted portfolio returns on the NGX.

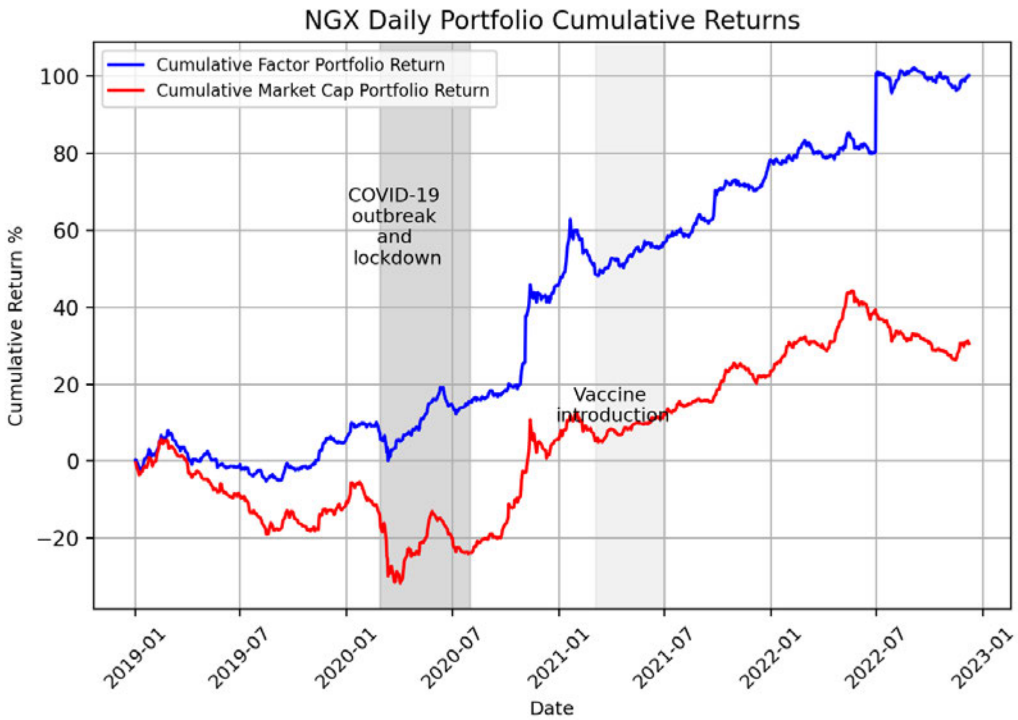

Figure 4.15 NGX daily cumulative return plot for the factor and market-cap weighted portfolios

A Factor regression tree for the Zimbabwean Stock Exchange is shown in Figure 4.16. The root of the tree starts with the size factor measured by the market capitalisation (CAP) factor. From the results in Fig 4.16, we see that investing in low-cap stocks, those with a market capitalisation of less than 1 billion Zimbabwean dollars, results in higher risk-adjusted returns. Another highly significant factor is return on equity (ROE). Companies with a high ROE have higher risk-adjusted returns. Similarly, high P/E companies have higher risk-adjusted returns than low P/E ratio companies. Another significant factor is free cash flow per share (FCF). The results in Figure 4.16 show that investing in companies with high FFC results in higher risk-adjusted returns, thus confirming the superiority of a company's cashflow-generating ability on the ZSE. It can be seen that the highest returns can be generated by investing in low-cap stocks, which have an ROE greater than 7% and positive free cash flows. This results in an average daily risk-adjusted return of approximately 4%.

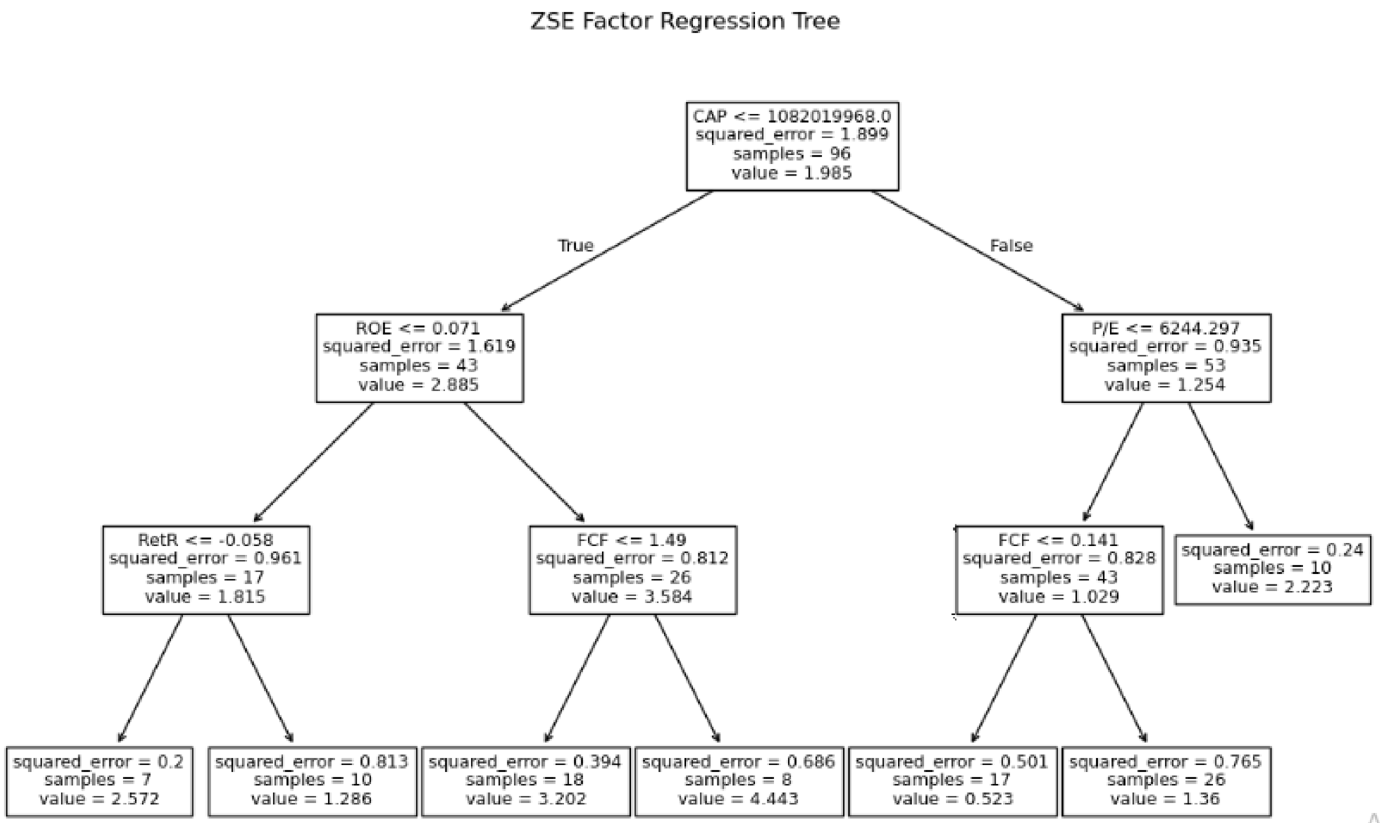

Figure 4.16 ZSE Regression tree showing the significant firm--specific factors and their impact on risk-adjusted returns.

Table 4.5 shows the weights for the dominant factors utilised in the construction of a factor portfolio on the ZSE. The most significant factor is market capitalisation which carries a weight of 66%, followed by return on equity, with a weight of 23%, while the P/E and FCF ratios each contribute approximately 5 %. The significant factors identified in the regression tree were assigned weights based on their importance. Thus, from the results, it is found that investing in small caps with high profitability results in higher risk-adjusted returns.

Table 4.5: Most significant factors used in determining score for stocks traded on the ZSE.

Selected Factors	Feature Weights
CAP	0.662522
ROE	0.232446
P/E	0.057607
FCF	0.047426

Figure 4.17 shows the portfolio returns for the market cap-weighted and factor-based portfolios for the ZSE. The outperformance of a factor-based portfolio over a market-cap weighted portfolio was observed in both the pre-pandemic and pandemic periods. In the pre-pandemic period, the factor portfolio has a lower standard deviation and higher return than the market-cap –weighted portfolio. During the pandemic, the factor-portfolio has almost the same standard deviation as the market-cap portfolio of 45% but the expected return is higher for a factor portfolio at approximately 407% while that of the market cap-weighted portfolio is 342%.

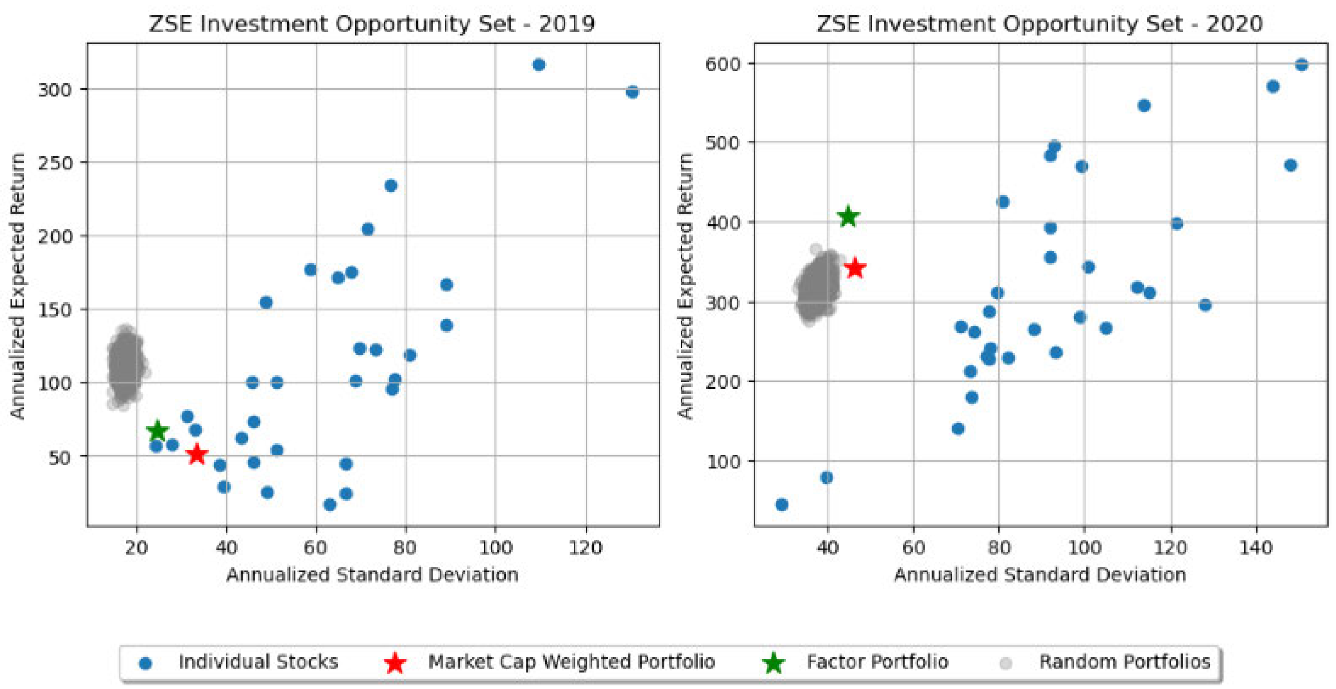

Figure 4.17: Market Cap weighted vs factor weighted portfolio on the ZSE

Figure 4.18 illustrates the portfolio returns for the market cap-weighted and factor-based portfolios for the ZSE. The results of the time-series analysis for the portfolio performance of both the factor and market capitalisation portfolios, as presented in Figure 4.18, demonstrate that stock returns exhibit an upward trajectory on the ZSE even during the COVID-19 period. The outbreak of the COVID-19 pandemic and the implementation of lockdowns did not appear to have had a negative impact on the performance of the Zimbabwean exchange. The accumulation of stock returns on the ZSE is of such magnitude that an investment in the factor portfolio would have accumulated to 800% from 2019 to the end of 2022. From Figure 4.8, it can be observed that the increase in portfolio returns at the onset of the pandemic aligns with the concurrent surge in inflation rates in Zimbabwe. The steepest increase in portfolio returns coincides with the highest inflation rates observed in the country during the study period. It is also noted that as inflation declined after the lockdown period, there was a low accumulation of portfolio returns. Thus, the results indicate that the performance of ZSE portfolios is more closely related to hyperinflation in the country than the outbreak of the pandemic itself. Given this situation in the Zimbabwean stock exchange, the primary concern is not merely to develop a portfolio that hedges against the negative impact of the pandemic, but also protects against the decline in real value caused by inflation.

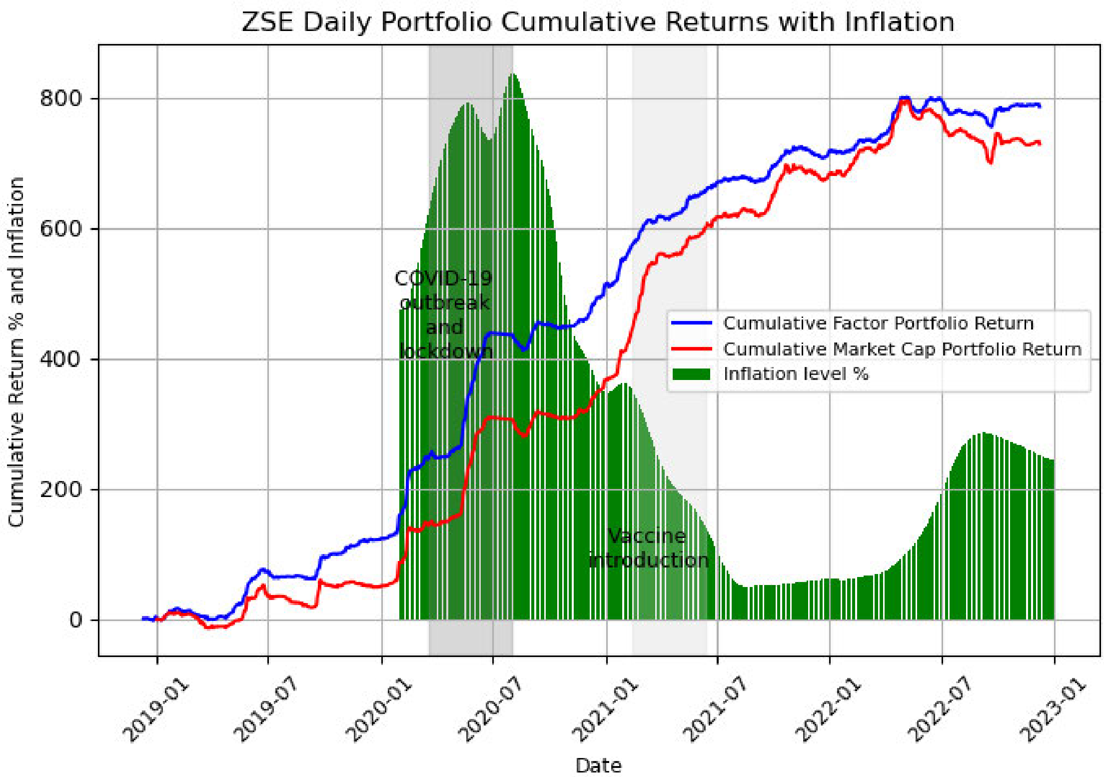

Figure 4.18 ZSE daily cumulative return plot for the factor and market-cap weighted portfolios.

The results of the factor analysis and portfolio construction for LuSE are presented in subsequent sections. The factor regression tree is shown in Fig. 4.19. The momentum factor constitutes the root node of the regression tree, and stocks with a momentum value exceeding 0.5 (classified as winners) exhibit higher risk-adjusted returns than losers. The subsequent split occurs in the price-to-book value ratio, and it is noted that stocks with higher P/B ratios, commonly referred to as value stocks, demonstrate higher risk-adjusted returns. Furthermore, on the right branch, companies with a low D/TA factor, representing a low debt-to-total asset ratio, exhibit higher risk-adjusted values than those with higher debt ratios. The results also indicate the significance of the profitability ratio as measured by the EPS ratio. Investment in companies with high earnings per share yields improved returns. For instance, an investor who allocates capital to companies with EPS exceeding 0.567 Kwacha per share during the pandemic period will observe an improvement in average risk-adjusted returns from 0.127 per unit of risk to approximately 0.7 per unit of risk, whereas those investing in low EPS companies will experience negative returns. The highest risk-adjusted returns are achieved by investing in winning stocks with low P/B ratios. This strategy enhances the risk-adjusted returns from an average of 0.375% per 1% risk level to approximately 2% per 1% risk level.

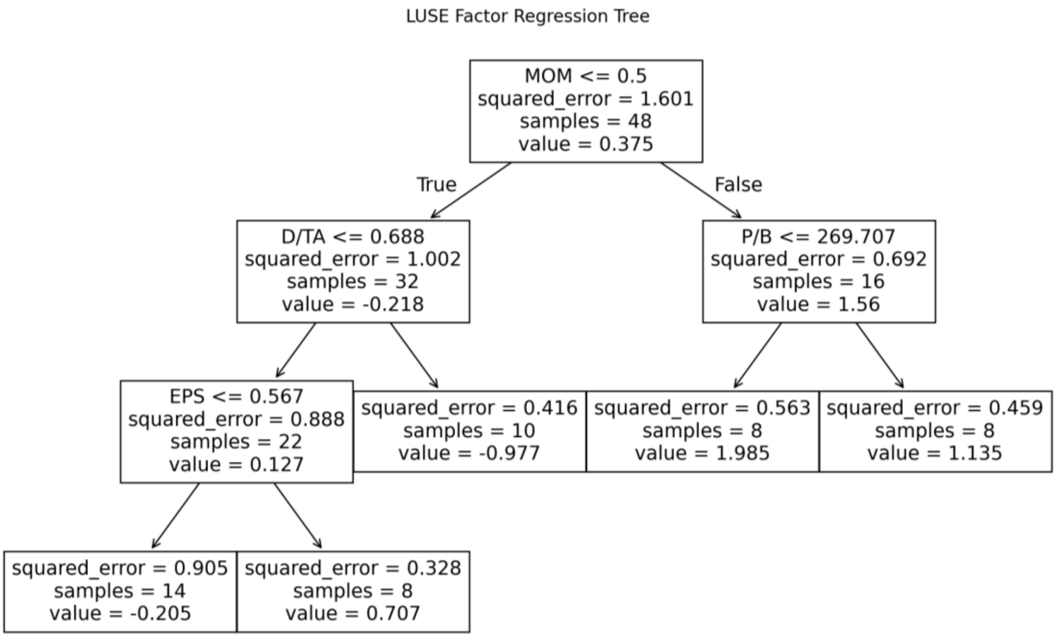

Figure 4.19: LuSE Regression tree showing the significant firm--specific factors and their impact on risk-adjusted re-turns.

The weights for the identified most significant factors used in constructing a factor portfolio on the Lusaka stock exchange are shown in Figure 4.6. The P/B factor exhibits the highest weighting at approximately 52%, followed by the D/TA factor with a weight of 28%. The MOM factor accounts for 18% of the weighting, whereas EPS has the lowest weight of approximately 2%. The results show that investing in value stocks that are classified as winners and have low leverage results in higher risk-adjusted returns.

Table 4.6 Most significant factors used in determining score for stocks traded on the LuSE.

Selected Factors	Feature Weights
P/B	0.520365
D/TA	0.276947
MOM	0.177717
EPS	0.024972

Figure 4.17 compares the performance of the factor portfolio and market cap-portfolio for the pre-pandemic period (2019) and the pandemic period (2020). The results show the outperformance of the factor portfolio over the market portfolio in both the pre-pandemic and pandemic periods. Although both portfolios have negative returns, constructing a factor portfolio helps reduce losses during COVID-19.

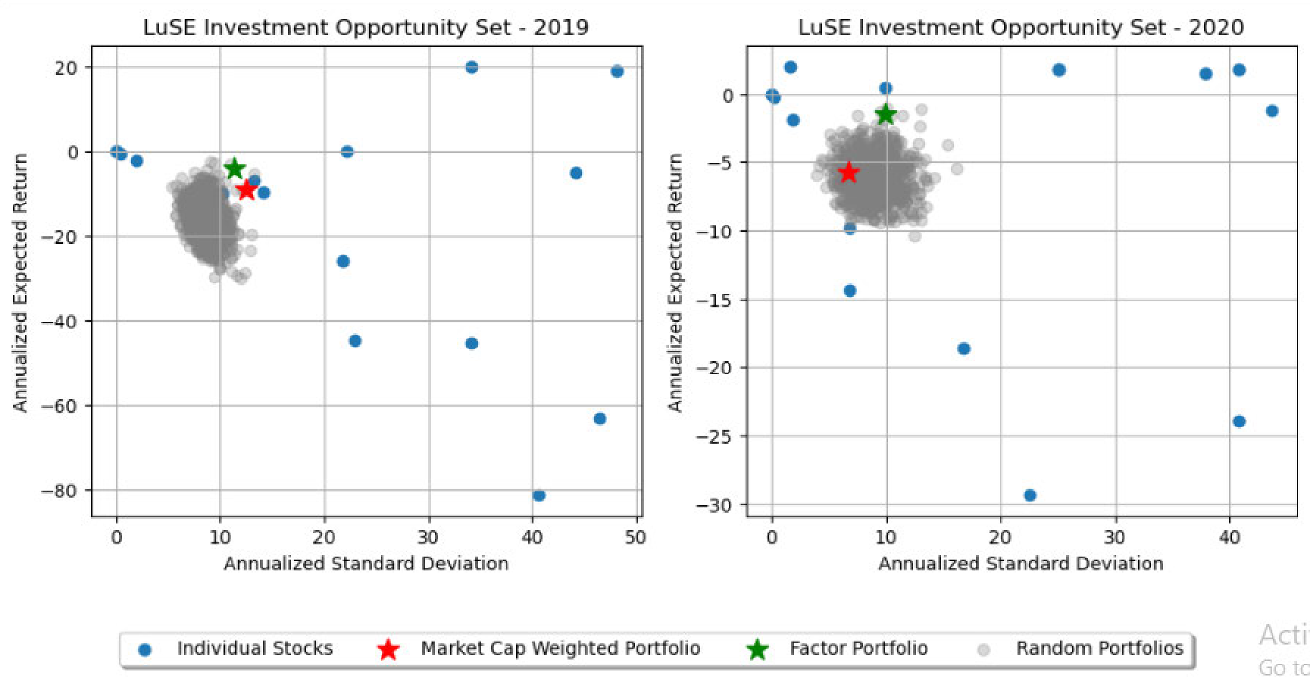

Figure 4.20: Market Cap weighted vs factor weighted portfolio on the LuSE.

A time-series plot illustrating the performance of a market cap-weighted portfolio and a factor portfolio is presented in Figure 4.20. The results indicate that stocks on the LuSE have experienced losses since mid-year 2019, with further losses exacerbated by the COVID-19 outbreak. Both the market cap and factor portfolios have negative portfolio returns during the pandemic and only recover post-lockdown. However, it is observed that a factor would accumulate positive returns significantly earlier, by the start of 2021, while for the market cap portfolio, positive returns accumulate late in mid-year 2021. This observation confirms the superior performance of the factor portfolio over the market cap portfolio.

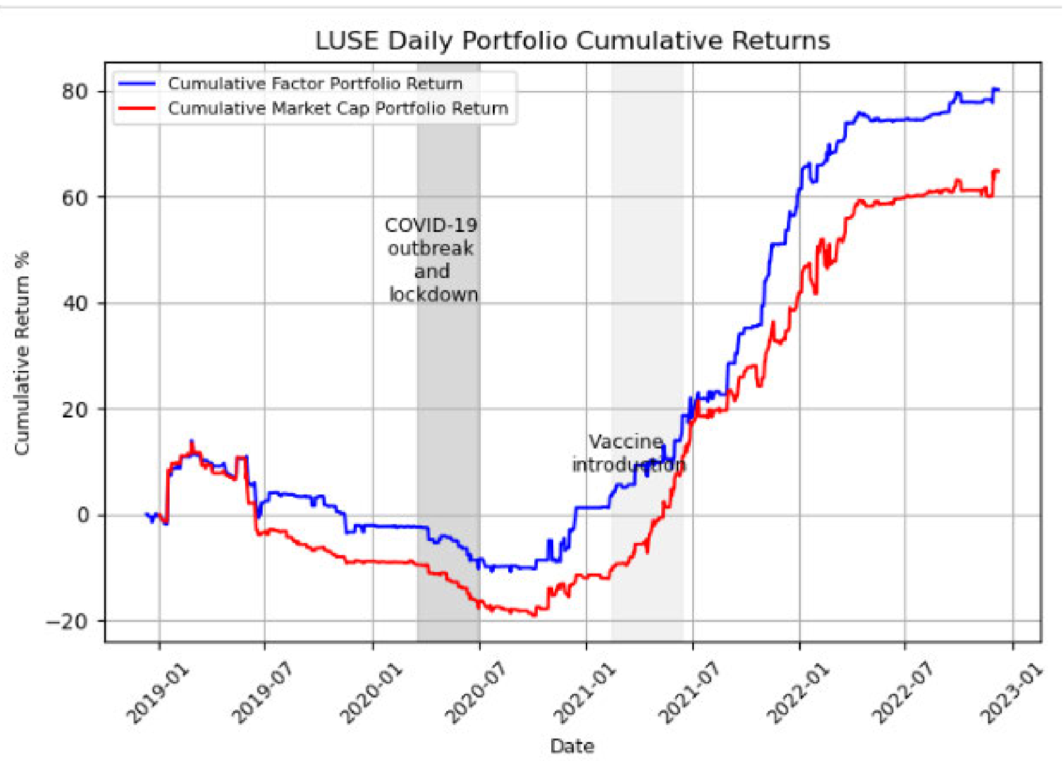

Figure 4.21: LuSE daily cumulative return plot for the factor and market-cap weighted portfolios.

4.4.4 Impact of COVID-19 events and economic factors on Portfolio performance

In this section, we assess the impact of COVID-19 events and macroeconomic factors on portfolio returns presented in the previous section. The SHAP analysis was performed for all four stock exchanges, and the results are displayed in the SHAP heat maps in the figures presented below. For the JSE, we see in Figure 4.22 that the FX rate, new deaths, and inflation are the factors classified as having higher importance, but taking a closer look at the plot, we see that these factors are significant in only a few instances. For example, inflation and exchange rates have a positive influence on portfolio returns in the first few instances, and later, the factors appear insignificant. In the first 40 instances, the f(x) value is slightly positive, and we see that the main factors contributing positively are the exchange rate and inflation. Factors such as new COVID-19 cases, stringency measures, introduction of vaccines, and reports on positive COVID-19 cases appear to have insignificant effects on portfolio returns on the JSE. Additionally, an f(x) line hovering around zero and a very low R-squared of about 1% show that the COVID-19 pandemic and macroeconomic factors have no significant influence on the factor portfolio returns, thus confirming the robustness of our factor portfolio against the adverse impact of the COVID-19 epidemic.

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Mean Squared Error (MSE): 0.7691342296992537
R-squared (R²): 0.013272253586261495
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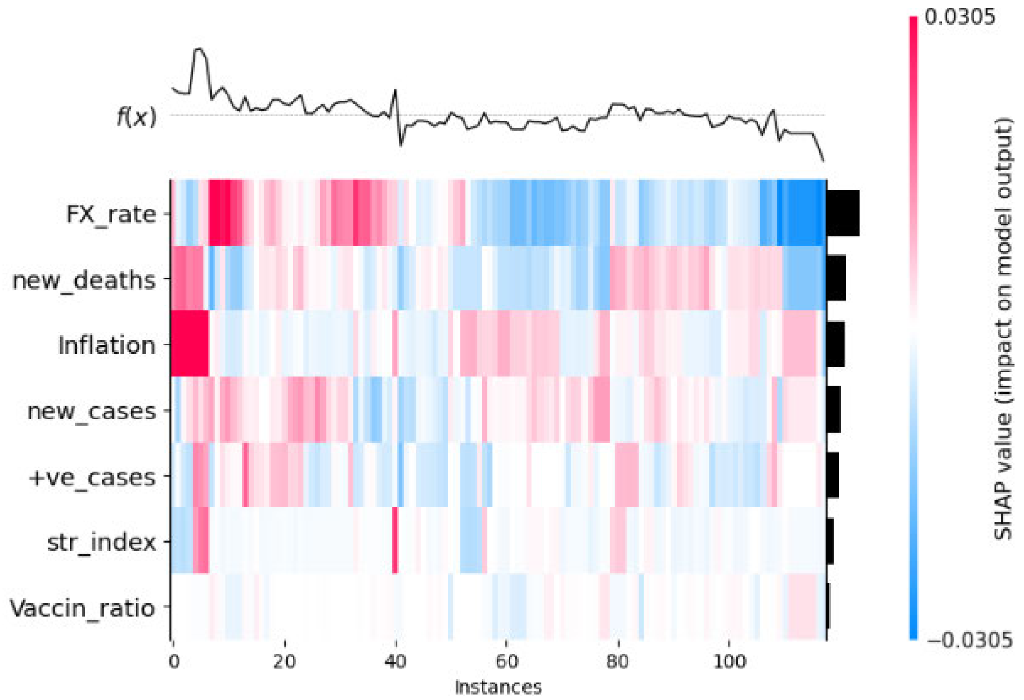

Figure 4.22: SHAP heat-map showing impact of COVID-19 events on portfolio returns on the JSE.

The impact of COVID-19 events on the performance of factor portfolios on the Nigerian Stock Exchange is presented in Figure 4.23.

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Mean Squared Error (MSE): 0.4555652163126969
R-squared (R²): 0.0018447591830548227
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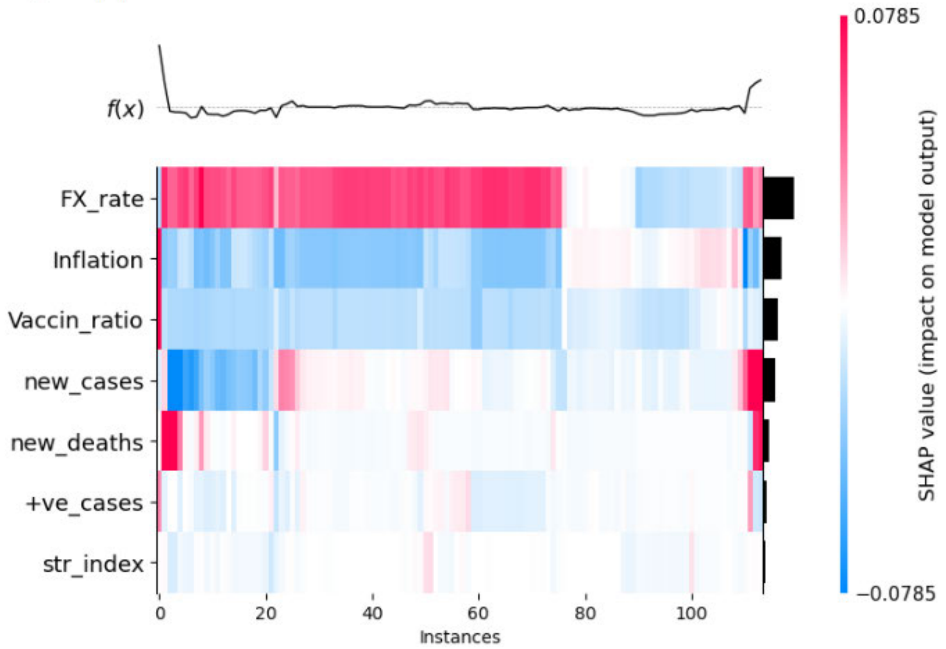

Figure 4.23: SHAP heat-map showing impact of COVID-19 events on portfolio returns on the NGX

We observe from Figure 4.23 the dominance of the exchange rate and inflation as the primary determinants of portfolio returns on NGX. In most instances, the exchange rate appears to exert a positive (colour-coded red) impact on portfolio returns, whereas inflation appears to exert a negative influence. COVID-19 factors demonstrate an insignificant influence on portfolio returns across all instances, as evidenced by the muted colour coding for the COVID-19 features, indicating that these features exert an insignificant influence on the model's output. Furthermore, despite the dominance of inflation and exchange rates over all other features, their influence on portfolio returns appears to be insignificant as the predicted f(x) value lies close to the zero line and the R-squared value is very low. This signifies that factors other than COVID-19 and macroeconomic factors drive portfolio returns, thus proving the robustness of the factor portfolio against extreme COVID-19 and macroeconomic events.

The results for the impact of COVID-19 events and macroeconomic factors on portfolio performance on the Zimbabwean Stock Exchange are shown in Figure 4.24.

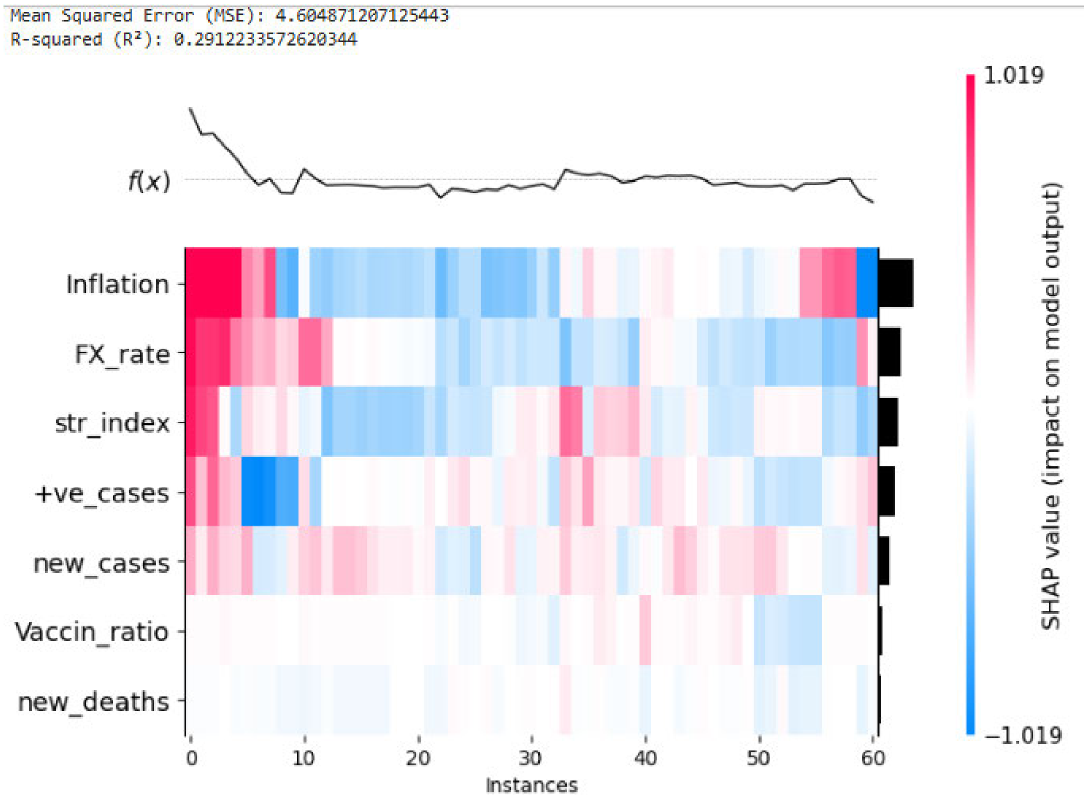

Figure 4.24: SHAP heat-map showing impact of COVID-19 events on portfolio returns on the ZSE.

The results for the ZSE are presented in Figure 4.24. The findings demonstrate the predominance of inflation and, in certain instances, the exchange rate on factor portfolio returns on the ZSE. A high R-squared value of 29% indicates that inflation accounts for a substantial proportion of the variation in the portfolio returns on the ZSE. An examination of the f(x) line reveals that this influence occurs primarily when inflation exerts a positive impact on portfolio returns, which is observed during periods of exceptionally high inflation. COVID-19-related variables, including mortality rates, case numbers, stringency measures, and vaccine introduction, exhibit an insignificant influence on factor portfolio returns. The findings also substantiate the robustness of the factor portfolio, although portfolio returns appear compromised during periods of hyperinflation.

For the LuSE, Figure 4.25 shows that only the inflation rate and new cases are classified as factors of higher importance. However, a very low R-squared value and a stable f(x) line lying on the zero line indicate that, despite their dominance, these factors exert an insignificant influence on portfolio returns. Factors such as new COVID-19 deaths, stringency measures, the introduction of vaccines, and reports on positive COVID-19 cases are also found to have insignificant effects on portfolio returns on the Lusaka Stock Exchange. This confirms the robustness of the factor portfolio against the adverse impact of the COVID-19 epidemic on the LuSE.

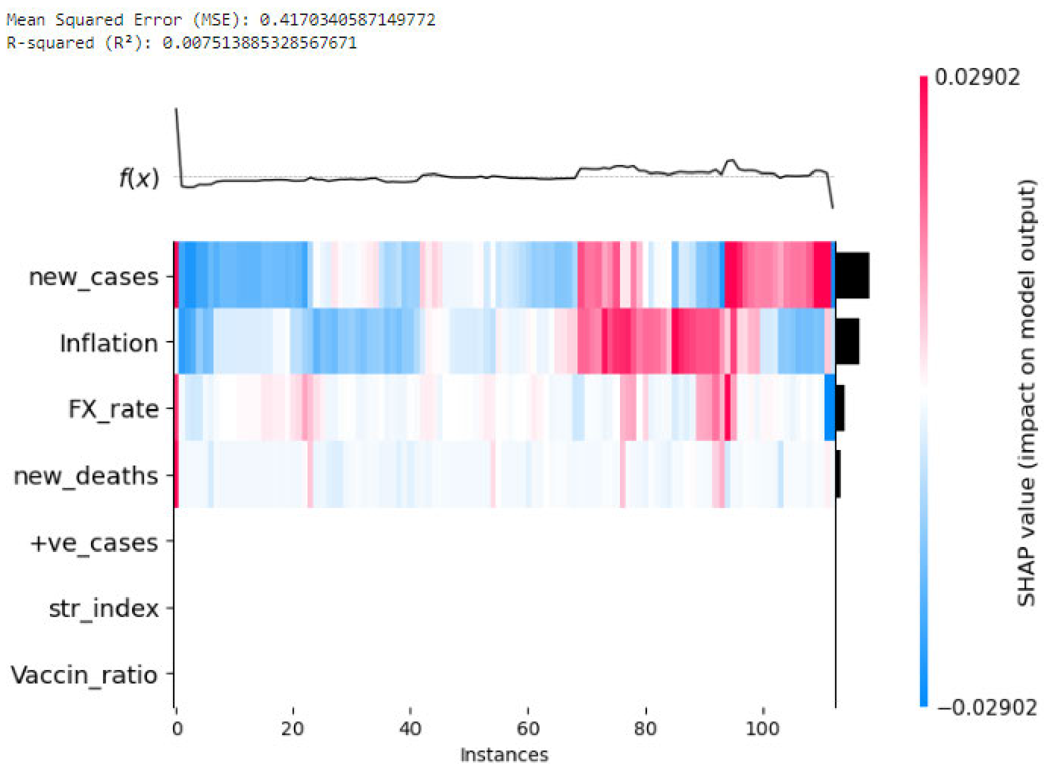

Figure 4.25: SHAP heat-map showing impact of COVID-19 events on portfolio returns on the LuSE.

4.5 **Discussion of Results**

In this section, the study's findings are discussed. The findings demonstrate the dominance of profitability factors, such as EBIT to enterprise value, return on equity, and net income growth in driving risk-adjusted returns in all four stock exchanges. Highly profitable companies recorded higher risk-adjusted returns, outperforming those with low profitability ratios on all four stock exchanges. However, it was further found that in smaller stock exchanges, cash flow factors such as free cash flow mattered the most compared to accounting profits, implying that in these markets during the COVID-19 pandemic, investors placed more importance on the company’s ability to generate and manage its cash flows than just its accounting profits. Smaller stock markets often consist of companies with limited access to external financing compared with those with larger exchanges. During the COVID-19 pandemic, cash flow was essential for these companies to continue operating, cover expenses, and weathering market disruptions. Investors likely prioritised cash flow because it directly affected a company's ability to remain solvent in the face of unexpected disruptions. As noted by Brunnermeier and Pedersen (2009) investors often prioritize cash flow as a determinant of a firm’s resilience in adverse market conditions. Additionally, in smaller stock exchanges, information asymmetry often prevails, in line with the findings of Brent and Addo (2012), and market participants may have less access to a comprehensive financial data . Thus, investors seek clear and concrete evidence of a company's operational efficiency, particularly in the form of available cash after capital expenditure.

The leverage ratio was also a significant driver of risk-adjusted returns on smaller stock exchanges, with companies with low debt-to-equity ratios outperforming those with higher debt-to-equity ratios. Lower leverage generally implies a stronger balance sheet with less financial risk, as these companies are less burdened by debt obligations. This characteristic is desirable for companies in smaller stock exchanges with less liquidity, which find it difficult to raise funding by issuing more shares. Overall, the findings highlight the crucial role of quality factors in a company's financial health, such as high profitability, high cash flow generating ability, and low leverage, particularly during the pandemic. This is in line with the findings of Bender *et al.* (2018), who underscored the outperformance of quality factors during extreme market events such as the 2007-2009 global financial crisis. This also resonates with “defensive” quality stocks, offering stability and resilience in turbulent times. As highlighted by Asness (2000), the allure of such investments lies not only in their potential for steady returns but also in their capacity to provide a buffer against the inherent risks of the market.

The findings also revealed the significance of the momentum factor in explaining stock return variations, particularly on stock exchanges in the sub-Saharan African region. Stocks classified as winners have higher risk-adjusted returns than those classified as losers. This indicates that stocks that recorded positive price trends in the past months outperformed in subsequent periods. For example, for the year 2020, stocks that had been on a positive trend six months prior to the outbreak of the pandemic had higher risk-adjusted returns than those which had been on a downward trend. These findings reveal that investors engaged in momentum investing during the pandemic, buying stocks that have performed well in the past and selling stocks that have performed poorly. This observation aligns with the well-established momentum strategy, emphasising investing in past winners as they tend to continue outperforming past losers (Carhart, 1997; Jagadeesh & Titman, 1993).

However, there is no significant difference in the performance of winners and losers on the Zimbabwean stock exchange. What mattered the most was the cash flow generation ability of the company and the size factor. According to Ncube *et al.* (2023, 2024), stock returns and volatility on the ZSE reacted more to macroeconomic factors such as high inflation rates and volatile exchange rates and less to the pandemic outbreak. Thus, investors might have preferred to invest in small-cap stocks and stocks for companies with high cash flow-generating ability as a way to hedge against inflation rather than basing their investment decisions on the past performance of stocks. Flight to quality, as explained by Coqueret and Guida (2023), could also be the reason for the observed momentum break in the ZSE. During financial crises, investors tend to prioritise stable, high-quality stocks, and this flight to quality can overshadow momentum-driven strategies by pushing down winner prices as investors seek safer havens.

Additionally, it was found that stocks with high-price multiples, commonly referred to as growth stocks recorded higher risk adjusted returns among the sub-Saharan stock exchanges. These stocks are overvalued owing to their growth potential. The findings strengthens the significance of a company's cash flow and earnings growth potential to investors during the pandemic. However, the findings contradict the proposition of Fama and French (2015, 2020) that value stocks tend to outperform growth stocks. This unexpected outcome raises important questions about the assumptions underlying traditional asset pricing models and the applicability of these traditional factors models in emerging sub-Saharan stock markets. On the other hand, the finding is consistent with the results reported by Wang *et al.* (2009) and Asness, Moskowitz and Pedersen (2013), who observed that during times of uncertainty, investors tend to favour the potential growth and perceived stability of growth stocks over the discounted opportunities presented by value stocks.

The influence of the size factor on the risk-adjusted returns of stocks is predominantly observed in small exchanges (ZSE and LuSE), where small-capitalisation (small-cap) stocks outperform large-capitalisation(large-cap) stocks. Conversely, in larger exchanges, large-capitalisation stocks exhibit superior performance compared to small-capitalisation stocks. According to Fama and French (2015), small-cap stocks tend to have higher returns than large-cap stocks because of the risk premium that investors demand for investing in riskier and illiquid small-cap stocks. However, their analysis did not consider macroeconomic factors such as inflation and crisis periods, such as black-swan events. The correlation results revealed that companies with low market caps in smaller exchanges tend to have high profitability ratios, while large-cap stocks have high profitability ratios in larger stock exchanges. Thus, the outperformance of small-cap stocks in small exchanges and large-cap stocks in larger exchanges can be attributed to investors buying shares with high financial strength to safeguard against the pandemic and high inflation rates in smaller exchanges. Another factor significantly influencing risk-adjusted returns is unexpected expenditures (UN-EXP), and their significance was observed in countries with high COVID-19 infections such as in South Africa. Companies with low unexpected expenditures had higher risk-adjusted returns. The pandemic outbreak brought about unexpected expenditures that were not budgeted for, and those companies with high unexpected expenditures might have faced reduced profits, causing investors to shun them because of their poor financial performance.

This study further investigated the performance of a factor-based portfolio both pre-pandemic and during the pandemic. The performance of factor-based portfolios has been superior to that of market-weighted portfolios in sub-Saharan African stock markets during the pandemic. Although the market-cap weighted portfolio could have performed better or similar to the facto-weighted portfolio in the pre-pandemic period, during the pandemic, the factor portfolio far outperformed the market-cap portfolio in all the exchanges. These findings underscore the significance of factor investing in sub-Saharan African equity markets.

The results reveal that a factor portfolio constructed using a multi-factor approach outperforms smart beta strategies based on a single factor, such as the size factor. Weighting the stocks in the portfolio based on factors that maximise the stock returns per unit of risk leads to the creation of low-volatility portfolios that are robust to the negative shocks of the pandemic and simultaneously give investors a substantial amount of returns. The findings provide empirical evidence against relying solely on "smart beta" strategies focusing on exposure to a single factor. This aligns with the recommendation of Blitz and Vidojevic (2019), who show that generic single-factor portfolios, which invest in stocks with high scores on one particular factor, are suboptimal because they ignore the possibility that these stocks may be unattractive when evaluated from the perspective of other factors. Individual factors within the portfolio may experience cyclical fluctuations. However, their interconnectedness and diverse risk profiles likely contribute to overall stability and outperformance during crises periods. Bender et al. (2018) also cautioned that narrow approaches may neglect the interplay of other relevant factors and can lead to return drag and underperformance.

For further analysis and for robustness checks, a time series SHAP analysis was conducted to examine the influence of COVID-19 and the macroeconomic variables on portfolio performance. The findings reveal that COVID-19 factors, such as COVID-19 cases and deaths, government stringency measures, and vaccinations, do not have any significant influence on portfolio returns across all sampled stock exchanges. This confirms the resilience of the multifactor portfolio to the adverse effects of the pandemic. However, the findings demonstrate that macroeconomic factors such as inflation and exchange rates influenced portfolio returns, with the impact being most pronounced in the stock exchanges of countries that experienced hyperinflation during the pandemic, such as Zimbabwe. Periods of hyper-inflation correlated with increased portfolio returns on the ZSE. As noted in a previous study by Ncube *et al.* (2023), the rise in stock prices on the Zimbabwean stock exchange has been associated with an increase in inflation since the introduction of the Zimbabwean dollar in 2019. Therefore investors were buying stocks as a way to hedge against inflation and they offloaded their Zimbabwean dollar holding into the stock market.

However in economies with lower levels inflation and less volatile exchange rates, it was found that macro-economic factors multi-factor portfolios had less influence of portfolio returns. The portfolio returns were mainly influenced by firm specific factors such as momentum, size, leverage and profitability. Thus the results confirm the significance of firm-specific factors in selecting stocks for inclusion in the factor portfolio, except in times of hyperinflation or in countries with weak economic fundamentals, where it is also necessary to incorporate macroeconomic factors, such as inflation and exchange rates.

4.6 **Conclusion**

The COVID-19 pandemic presented a unique and challenging landscape for sub-Saharan African stock markets. Despite their weak macroeconomic fundamentals, these markets exhibit surprising resilience compared with other emerging economies and there was variation in performance of sectors in stock exchanges in the same region. This raises the pivotal question of whether firm-specific characteristics played a statistically significant role in explaining the observed variation in stock returns in sub-Saharan African equity markets during the pandemic. The findings highlight the importance of financial health in selecting stocks for investment in sub-Saharan African stock markets. Companies with strong financial performance, measured by profitability and cash flow generation, outperformed those with weaker financial performance. In smaller stock exchanges, cash flow factors, rather than mere accounting profits, are of great significance as determinants of stock performance, indicating the importance of a company's cash flow-generating ability in less liquid markets. Market capitalisation also emerged as a significant driver of stock performance in sub-Saharan exchanges exchanges. In smaller exchanges, companies with low market capitalisation outperformed large capitalisation stocks while in larger exchanges large capitalisation stocks dominated the small-capitalisation stocks. This relationship however appeared to be related to small-cap stocks being more profitable in smaller exchanges while in larger exchanges it was the large-cap stocks that were more profitable.

The momentum factor also emerged as a crucial factor influencing stock performance in sub-Saharan stock market. Stocks that had recorded positive price trends even prior to the pandemic continued to outperform. The significance of a momentum factor suggests a behavioural bias among investors, demonstrating their irrationality in equity valuation and investment decision-making as noted by Chan, Jegadeesh and Lakonishok

(1996). This indicates that investor sentiment also influenced stock performance in SSA during the pandemic. However, the importance of stock momentum was less evident in high-inflation economies such as Zimbabwe. In countries with weak macroeconomic fundamentals, historical price trends were less relevant; rather, fundamental factors such as a company's financial strength appeared to be more significant as a hedge against inflation risk.

This study further highlights the adverse impact of unexpected expenditures on risk-adjusted returns. Companies that managed to keep expenditures low fared better, particularly in larger exchanges in countries with high COVID-19 infection rates. Price multiples also significantly influenced stock performance on smaller exchanges in SSA. Specifically, low market cap stocks and stocks with high price multiples had higher risk-adjusted returns. These findings reflect the outperformance of small-cap growth stocks in smaller exchanges during the COVID-19 pandemic. Therefore, it can be concluded that the financial strength of a company and investor perception of a stock's expected performance are important determinants of stock performance in SSA, particularly during market crises such as the COVID-19 pandemic. Investors should therefore prioritise the profitability and earnings growth potential of a company, as well as its momentum, when selecting stocks for investment in sub-Saharan stock markets in economically stable countries. Furthermore, when investing in smaller stock exchanges with low liquidity, investors should consider the cash flow-generating capacity of a company as well as the level of debt that a company holds on its balance sheet. This is particularly crucial during periods of market crisis. In addition, investors must consider macroeconomic factors when investing in economically unstable countries.

Furthermore, these research findings demonstrated the superiority of factor-based portfolios over traditional market-weighted portfolios in sub-Saharan African stock markets during the pandemic period. The factor portfolio constructed by picking stocks for companies with high profitability, low leverage, high cash flow-generating ability, and momentum stocks proved more resilient to the negative impact of COVID-19 factors. The findings reveal that multi-factor portfolios have the potential to preserve value for investors as they have lower volatility and higher returns than market cap portfolios, even during the pandemic. Thus, investors should adopt multifactor investment strategies that integrate various fundamental and technical factors when building their portfolios, as this approach offers enhanced risk diversification and resilience during economic crises. The outperformance of fundamental factor-based portfolios over passive market portfolios demonstrated the inefficiency of sub-Saharan African stock exchanges during the COVID-19 pandemic. This allows investors in sub-Saharan African equity markets to reap positive risk-adjusted returns through active investing

Based on the findings of this study, it is recommended that investors prioritise quality, growth, and momentum factors in stock selection decisions in SSA. Investors should also emphasise a company's ability to generate and manage cash flows in smaller, less liquid stock exchanges. It is also recommended that investors adopt multifactor investment strategies that integrate various financial metrics to build their portfolios because this approach offers enhanced risk diversification and resilience during economic crises. While this study sheds light on the influence of firm-specific factors during the pandemic, it acknowledges its limitations and opens doors for further exploration. Future research that delves deeper into the psychological and behavioural aspects influencing investor preferences during a crisis could provide valuable insights into portfolio construction and risk management.

Chapter 5. Summary, Conclusions and Recommendations

5.1 Introduction

This study examined the consequences of the COVID-19 epidemic on performance of stocks in sub-Saharan Africa (SSA). The COVID-19 pandemic was accompanied by a plethora of issues, making it a unique health crisis. The repercussions of the pandemic have extended beyond human lives to affect the economies of numerous countries, necessitating an enquiry into its impact on stock markets, particularly in emerging economies, such as SSA, where limited research has been conducted. The study findings are predicated on the analysis of four stock exchanges, comprising the Johannesburg Stock Exchange and the Nigerian Stock Exchange, the two largest in SSA, along with the smaller Zimbabwe and Lusaka Stock Exchanges. The data used for the analysis were collected for the period between 2020 and 2022, with 2019 used for comparison.

The study was divided into four primary research objectives to evaluate the effect of the COVID-19 epidemic on stock performance in SSA. The first objective investigated the impact of the COVID-19 pandemic and its associated events on stock performance in SSA. Performance was measured using abnormal stock returns, and an event study methodology was employed to assess whether the outbreak of the pandemic and its associated events led to significant change in stock returns in sub-Saharan African equity markets. To facilitate analysis, stocks were categorised into sectors based on the Global Industry Classification Standard, and abnormal returns were calculated for each sector. The study additionally evaluated the influence of various COVID-19-related factors, including infections and fatalities, stringency measures, vaccine administration, and macroeconomic variables, including inflation and exchange rates, on abnormal sector returns. To accomplish this, a panel data regression model was employed.

The second objective of this study investigated the impact of the COVID-19 epidemic on stock volatility in sub-Saharan Africa. To attain this objective, GARCH models were utilized to measure volatility, while SHAP, an XAI method, was implemented to ascertain whether the emergence of the pandemic and associated events had a significant impact on stock volatility in SSA. Similar to the first objective, stocks were first categorised into sectors using GICS and volatility was estimated for each sector. Volatility serves as a risk measure for an investment; stocks may have higher returns during the pandemic period, but if higher returns are accompanied by higher volatility, this indicates that there is a higher risk in the stock market. Thus, this study assessed the influence of the COVID-19 epidemic on stock volatility to evaluate the extent to which the outbreak of the pandemic impacted investment risk levels in sub-Saharan African equity markets.

The third objective of this study assessed the influence of firm-specific factors on stock performance in SSA amid the COVID-19 pandemic. This study aimed to identify the characteristics of stocks that were resilient to the pandemic and those that were adversely affected. A cross-sectional SHAP analysis was conducted to evaluate how these firm-specific factors affected stocks' risk-adjusted returns during the pandemic. Understanding the firm-specific factors that drive stock performance is essential for factor investing, as it helps investors pick stocks that are more robust to extreme market events such as the COVID-19 pandemic.

The final objective of the study was to build a factor portfolio resilient to the negative effects of the pandemic. This portfolio was created by selecting stocks based on the most significant firm-specific factors that maximise stock returns for a given level of volatility. The performance of this factor portfolio was then compared to the benchmark market cap-weighted portfolio. The ultimate goal was to assess whether it is possible to create a low-volatility portfolio with substantially higher returns during extreme market events such as the COVID-19 pandemic. Although the pandemic negatively affected overall stock performance, not all stocks suffered, implying that careful selection of stocks can result in the creation of portfolios with substantially higher risk-adjusted returns during the pandemic period.

5.2 Summary of key findings

The major findings of this study are highlighted in this section.

5.2.1 Impact of COVID-19 pandemic on stock returns in sub-Saharan African stock markets

In this objective, we assessed the impact of the COVID-19 epidemic on stock returns in sub-Saharan African stock exchanges. Sector abnormal returns were computed for different event windows and tested for significance to establish whether the outbreak of the pandemic and its associated events had a significant impact on sector performance. The findings revealed that larger stock markets experienced a significant drop in returns at the onset of the pandemic and during the lockdown period. However, smaller exchanges were not affected by the outbreak of the pandemic, as most sectors continued to record positive abnormal returns at the onset of the pandemic and the subsequent period following the implementation of lockdown measures. Thus, the findings highlight that the outbreak of the pandemic had a more pronounced impact on larger exchanges with high trading activity than on smaller exchanges with less trading activity.

At the sector level, we found that the healthcare sector was more resilient to the COVID-19 pandemic, as it did not experience a significant decline in cumulative abnormal returns following the outbreak of the pandemic or the implementation of economic lockdowns in the respective countries. Additionally, other sectors that performed well during the pandemic were ICT and consumer staples sectors. The shift to remote working and implementation of quarantine measures likely contributed to the increased demand for ICT equipment, thereby boosting stock performance in the ICT sector. Furthermore, as the pandemic spread and the demand for medical equipment and drugs surged, healthcare stocks also experienced improved returns. Given that many sub-Saharan countries have low incomes and a high proportion of employment in the informal sector, lockdown measures undoubtedly led to consumers shifting their purchases toward staples while reducing spending on non-staple items. However, the energy sector emerged as the worst-performing sector following the pandemic outbreak and implementation of lockdown measures. The energy sector's performance was more sensitive to international news of COVID-19 events than to domestic news, which may explain the divergence in performance between this sector and others. Companies in the industrial, materials, and real estate sectors were also severely affected by the lockdown measures, especially in larger capital markets. The poor performance of the real estate sector is likely a result of low demand for office space, as people were working from home following the introduction of lock-downs. The study also revealed that most sectors in both larger and smaller stock exchanges recorded significant positive cumulative abnormal returns following the introduction of vaccination programs in the respective countries. Thus, the introduction of vaccines helped improve stock performance on sub-Saharan African stock exchanges. The findings further indicate that the emergence of other variants of the COVID-19 pandemic, such as beta, delta, and omicron, did not have a significant impact on stock performance in sub-Saharan Africa, indicating that stocks adapted to the COVID-19 pandemic and became resilient to the new COVID-19 variants that emerged.

Regarding the impact of COVID-19 related events on stock performance, stringency measures adopted by the governments of different nations to combat the spread of the virus have led to a decline in sector returns on both large and small stock exchanges in SSA. In large capital markets, sectors with large trading activities such as energy, consumer discretionary, consumer staples, and financial services were the most negatively affected by the stringency measures, while in smaller capital markets, sectors that suffered the most were those dealing with non-essential services, such as consumer discretionary. The implementation of economic recovery stimulus packages was ineffective in aiding market recovery. This could be attributed to the severity of the lockdown measures and the smaller size of the stimulus package that sub-Saharan African countries had compared with developed countries. The introduction of vaccines has had a positive impact on sector returns. Most stocks performed well as more vaccines were administered. However, a significant impact was observed among the JSE sectors, which included the energy, industrial, and material sectors, and the ZSE sectors, which included the consumer staple, financial, and real estate sectors. The growth in COVID-19 cases and deaths did not pose a significant threat to the sector performance on all stock exchanges. In most cases, the sectors recorded positive abnormal returns despite an increase in COVID-19 cases and deaths.

The analysis also included macroeconomic factors as control variables, and inflation was found to have a more significant impact on sector performance in countries with high levels of inflation, such as Zimbabwe and Nigeria. A high inflation rate was associated with increased stock performance, and sectors that had high trading activity, such as consumer staples, energy, financial, and ICT, were the most positively impacted in both NGX and ZSE. This signifies that investors bought stocks in these sectors as inflation increased. In addition, the exchange rate had a significant influence on sector performance in the ZSE and NGX. On the ZSE, the sectors recorded high abnormal returns as the Zimbabwean dollar depreciated, while on the NGX, sectors recorded high abnormal returns as the Nigerian Naira appreciated. However, sector-level analysis indicated that the impact on NGX was only felt in the healthcare and consumer staple sectors. The Zimbabwean dollar has experienced a severe loss of value since its reintroduction in 2019, following the country's decision to de-dollarise. The link between exchange rates and stock performance can be attributed to investors' expectations for future inflation. Investors in Zimbabwe purchase stocks when the currency depreciates, as they anticipate higher inflation. Owing to the limited availability of asset classes that act as hedges against inflation, such as real estate at affordable prices, investors prefer to offload their Zimbabwean dollar-denominated holdings and instead invest in stocks.

Trading volume exhibited an insignificant influence on stock performance across the majority of sectors in SSA. This insignificant influence of trading volume on stock performance may be attributed to the low liquidity characteristic of emerging stock markets. In circumstances where market participation is limited, extreme negative events may not trigger strong reactions in the form of massive selloffs and excessive stock purchases will not occur in response to positive news.

5.2.2 **Influence of COVID-19 pandemic on stock volatility in sub-Saharan African stock markets**

As previously highlighted, the second objective of this study investigated the effects of the COVID-19 pandemic on stock volatility in SSA. GARCH models were used to estimate volatility and SHAP analysis was applied to assess the impact of COVID-19 events on stock volatility. The analysis was conducted at the sectoral level. The findings reveal that the COVID-19 epidemic has had a significant influence on stock volatility in SSA, with the impact most felt in larger exchanges, which is the JSE and NGX. All sectors on the JSE experienced a surge in stock volatility following the outbreak of the COVID-19 pandemic, with some sectors retaining higher volatility even after the initial shockwave. The NGX on the other hand experienced a surge in volatility in sectors that had high trading activity, such as ICT, financials, energy, and healthcare. In contrast, the ZSE experienced high volatility in non-essential service sectors such as consumer discretionary, materials, and real estate at the onset of the pandemic, while on the LuSE, it was only the utility sector that experienced an increase in volatility.

Further analysis showed that the government's stringent measures, such as lockdowns, business closures, social distancing, and stay at home policy, increased stock volatility in most sectors across SSA's exchanges, except in the healthcare sector of the JSE and the financial sector of the NGX, where volatility decreased despite the heightened stringency measures. On the ZSE, non-essential sectors like consumer discretionary, materials, and real estate were the most affected, with stock returns in these sectors reacting negatively to the government's measures, indicating investors' adverse perceptions. However, the introduction of vaccines reduced volatility across all sectors of the JSE and in the energy and healthcare sectors of the NGX. Furthermore, the consumer discretionary sector on the ZSE saw a decline in volatility following the vaccine rollout.

Additionally, the results indicate that subsequent to the implementation of vaccination programmes in South Africa, governmental stringency measures exerted a less pronounced impact on stock volatility on JSE-listed equities compared to the pre-vaccination period. In contrast, variables such as increasing COVID-19 cases and fatalities, positive test rates, and hospitalisations did not demonstrate a statistically significant effect on stock volatility across the four stock exchanges. On the other hand, inflation emerged as a key driver of stock market volatility in countries that experienced a surge in inflation during the pandemic, such as Zimbabwe. We found that most sectors on the ZSE faced high volatility during inflationary periods, particularly non-essential sectors, such as materials, real estate, and consumer discretionary. In other countries, inflation generally did not increase stock volatility, except in the financial sector on the JSE and utilities sector on the LuSE. It is expected that inflation will have a significant influence on returns in the financial sector given the sensitivity of the financial institutions assets to inflation. As inflation rises, the cost of borrowing tends to increase, which can lead to reduced consumer and business spending. In addition, the value of fixed-income assets may decrease, affecting banks’ balance sheets and investment returns.

The depreciation of a country's currency against the U.S. dollar is associated with an increase in stock volatility across all stock exchanges. However, this effect is more pronounced for smaller exchanges than for larger ones. For instance, on the Zimbabwe Stock Exchange (ZSE), high stock volatility across all sectors is associated with the depreciation of the Zimbabwean dollar, which correlates with hyperinflation in the economy. Our results indicate that high stock volatility on the ZSE is primarily due to high inflation and currency depreciation rather than the pandemic outbreak itself. On the other hand, we found that trading volume does not significantly influence stock volatility on either larger or smaller stock exchanges.

5.2.3 **Influence of firm specific factors on stock performance in sub-Saharan Africa during the COVID-19 pandemic.**

The third objective of this study was to analyse the influence of firm-specific factors on stock performance in sub-Saharan African markets during the COVID-19 pandemic and identify the factors that are associated with high risk-adjusted returns. The findings reveal that profitability factors such as EBIT to enterprise value, net profit margin, return on assets/equity, and net income growth had a significant influence on stock performance in all four exchanges during the pandemic. Highly profitable companies outperformed low-profitability ones in risk- adjusted return measures during the pandemic. Furthermore, in smaller stock exchanges, which include LuSE and ZSE, cash flow factors had a more significant influence on risk-adjusted returns than accounting profits alone. Thus, a company's cash flow-generating ability was more important as a determinant of stock performance during the pandemic in smaller, less liquid stock exchanges. The leverage ratio was also found to be a significant driver of risk-adjusted returns on the smaller stock exchanges with stocks of companies with low debt-to-equity ratios having higher risk-adjusted returns. Thus, the financial health of a company mattered the most during the pandemic, and stocks for companies that were financially strong outperformed those for financially weaker companies.

The analysis also reveals the significance of the momentum factor in explaining stock return variations in sub-Saharan African stock markets. Stocks classified as winners (stocks that have experienced a positive trend in their prices in recent history) had higher risk-adjusted returns than those classified as losers (stocks that have experienced a decline in stock prices in recent history). These findings reveal that investors can maximise their returns during the pandemic by utilising momentum investment strategies to buy stocks that have performed well in the recent past and selling those that have performed poorly. However, it is crucial to consider a country's economic stability. In countries with high inflation rates and volatile currencies, such as Zimbabwe, the future performance of a company is bleak, and investing based on the past performance of a stock may not yield higher risk-adjusted returns; rather, the financial strength of a company matters the most.

The results also revealed that size, as measured by market capitalisation, had a significant influence on risk-adjusted returns. In smaller exchanges, small-cap stocks outperformed large-cap stocks, while in larger exchanges large-cap stock performed better than small-cap stocks. However, the outperformance of small capitalisation in small exchanges was due to their financial strength, as these companies had high profitability and cash flow ratios. Price multiples such as P/B and P/E ratios are some of the factors that significantly influenced the performance of stocks on the ZSE and LuSE. Stocks with high P/B and P/E ratios, also called growth stocks have higher risk-adjusted returns. Therefore, these findings reveal the significance of a company's cash flow and earnings growth potential during the pandemic. However in larger exchsnges,value stocks, which are stocks with low P/B and P/E ratios, performed better than growth stock. Another factor with a significant influence on risk-adjusted returns is unexpected expenditures, and the significance of this factor is observed in larger stock exchanges. High-unexpected expenditures were observed mainly in companies for stock exchanges domiciled in countries with high COVID -19 infections such as the JSE. Companies with low unexplained expenditure had higher risk-adjusted returns.

5.2.4 **To develop a factor-based portfolio strategy for extreme market events like the COVID-19 pandemic and assess its performance compared to a passive market-capitalisation-weighted portfolio.**

The final objective of this study aimed to develop a factor-based portfolio using firm-specific factors that maximise the risk-adjusted returns of stocks during the COVID-19 pandemic and to analyse the performance of this portfolio. A benchmark portfolio in the form of a market–cap weighted portfolio was also developed to bench-mark the performance of the factor portfolio. The factor portfolio predominantly comprised stocks of companies that demonstrated robust financial performance, characterised by high EBIT to enterprise value, substantial net income growth, high earnings, and high return on equity. Momentum stocks also constituted a portion of the securities included in the construction of the factor portfolio. Growth stocks, stocks of low-leverage companies, and stocks of firms with high cash flow ratios were also incorporated into the factor portfolio, particularly in smaller stock exchanges.

The results show that multi-factor-weighted portfolios performed better than market cap-weighted portfolios both prior to and throughout the pandemic. Through the allocation of stocks in the portfolio based on factors that maximise the stock's risk-adjusted returns, low-volatility portfolios that demonstrated resilience to the adverse shocks of the pandemic and yielded substantial returns to investors were constructed. Our findings offer empirical evidence against relying solely on "smart beta" strategies that concentrate on maximising exposure to a single factor in favour of multi-factor-based portfolios. Furthermore, the findings revealed that the outperformance of factor-based portfolios over market-cap-weighted portfolios was more pronounced during the pandemic. This demonstrates the robustness of factor-based investment strategies in sub-Saharan African stock markets during the pandemic period.

Although passive indices that mimic the performance of market cap weighted indices could also achieve risk diversification, we found that diversification can be further enhanced by creating factor portfolios, and the diversification benefits were visible even during the COVID-19 pandemic. Factor portfolios also performed well out of sample', mainly in smaller exchanges, further demonstrating the superiority of factor-based portfolios even in non-pandemic periods. The superior performance of factor portfolios compared to passive investment strategies suggests that the stock markets in SSA are inefficient. In an efficient market, investors cannot obtain abnormal positive returns by selecting stocks based on their corporate fundamentals, because stock prices already include this information implying that after costs, active investors will not constantly outperform the market.

5.3 Conclusion

This study evaluated the impact of the COVID-19 epidemic on performance of stocks in SSA. The findings indicate that the pandemic negatively affected stock performance, as shown by decreased returns and increased volatility. Larger capital markets with high trading activity experienced a more significant drop in returns and increased volatility than smaller, less active markets. The adverse effects were most pronounced at the beginning of the pandemic, when governments implemented lockdowns, although markets later recovered as restrictions eased. The impact of COVID-19-related events on stock performance was also evident, as the imposition of government restrictions, such as economic lockdowns, school closures, travel bans, and stay-at-home policies, negatively affected most stock markets in SSA.

However, the consequences differed across sectors. In larger exchanges, all sectors except for the healthcare sector experienced a surge in volatility when the government intensified its stringency measures, and most sectors also experienced a decline in returns as these stringency measures intensified. However, despite recording an increase in volatility, sectors such as consumer staples and ICT recorded higher returns as the government intensified its stringency measures. This indicates that investors bought these stocks to preserve value during the pandemic, leading to a surge in their prices and increased volatility. The healthcare sector experienced low volatility and increased returns despite governments intensifying their stringency measures, signifying the robustness of this sector during the pandemic. In smaller exchanges, the introduction of more stringent measures negatively affected the performance of non-essential service sectors, such as the consumer discretionary, materials, and real estate sectors, as they experienced an increase in stock volatility and a decline in stock returns.

Thus, stock performance in various sectors has been significantly influenced by the demand and supply shocks resulting from the COVID-19 pandemic. The performance of stocks listed on large and more liquid stock exchanges appears to be affected by both positive demand shocks and negative supply shocks, as evidenced by the increased returns on stocks that have benefited from the pandemic, such as Healthcare and IT poor performance in the energy sector, which is heavily reliant on the global supply chain. By contrast, the performance of stocks listed on smaller and less liquid stock exchanges appears to be related to negative demand shocks, as demonstrated by the decline in returns for stocks in sectors that have been heavily impacted by government stringency measures.

The introduction of vaccination programs, on the other hand, helped counter the negative effects of the pandemic on stock performance in SSA. Most sectors in both the larger and smaller stock exchanges recorded increased stock returns and a decline in volatility as more vaccines were rolled out. The positive impact of vaccine introduction was felt in most sectors in larger stock exchanges, while in smaller stock exchanges, it was recognized mainly in those mostly affected by stringency measures such as the consumer discretionary sector. The findings also showed that the intensification of stringency measures and the outbreak of other COVID-19 variants did not have a severe negative impact on stock performance after vaccine introduction. Additionally, the study revealed that the increase in COVID-19 cases and deaths did not adversely influence stock returns and volatility. Macro-economic factors, inflation rates, and exchange rates had an insignificant effect on stock performance in most sectors, except in countries that had high levels of macroeconomic instability. For example, in Zimbabwe, most stocks recorded an increase in returns and a surge in volatility following an increase in inflation and the depreciation of the country's currency. This indicates that investors were buying stocks by disposing of their dollar-denominated holdings to hedge against inflation.

Furthermore, this study sought to assess firm-specific factors influencing stock performance during the COVID-19 pandemic. The ultimate goal was to establish whether the fundamental strength of a firm helped the stock withstand the negative effects of the pandemic, and to identify the factors that mattered the most. The findings established that stocks that were most negatively affected during the COVID-19 pandemic were those with weak financial strength, such as those with low profitability, low earnings growth, low cash flow-generating ability, high unexpected expenditures, and higher leverage. However, stocks of companies with high financial strength had higher risk-adjusted returns during the pandemic. Financial leverage and cash flow-generating ability seem to matter most for stocks in small exchanges that have low liquidity.

Stock momentum also emerged as a major determinant of stock performance. Stocks known to have a history of a positive trend in their prices, often called winners, had higher risk-adjusted returns, whereas those known to face price declines, commonly called losers, had lower risk-adjusted returns. This signifies that investor perceptions also had a significant impact on stock performance in SSA during the pandemic, as investors appeared to have bought stocks known to be winners and neglected those known to be losers. However, the significance of the momentum factor mattered only as far as macroeconomic factors were concerned. In stock exchanges in countries with high inflation levels, investors seem to be concerned with the value preservation of a stock in the form of its financial strength rather than its momentum.

Finally, this study sought to create a factor portfolio as a strategy to enhance investment performance in sub-Saharan Africa during periods of extreme market events in which value preservation matter the most. The variation in stock performance at the firm and sector levels during the COVID-19 pandemic signifies the possibility of creating a portfolio that can reduce the adverse impact of the COVID-19 epidemic on stock performance. A factor portfolio was created by selecting stocks with characteristics that maximise the returns per level of volatility. While the factors differed across stock exchanges, the portfolios were predominantly composed of stocks with strong profitability, robust cash flow generation, potential for high earnings growth, low leverage, and momentum stocks. In each of the stock exchanges, the factor portfolios formed exhibited lower volatility compared to individual stocks, yet delivered significantly higher returns, ensuring investors a positive return even during crisis periods such as the COVID-19 pandemic. Additionally, these factor portfolios surpassed market cap-weighted portfolios in risk-adjusted returns during the COVID-19 pandemic. This indicates that portfolio managers in SSA can enhance the performance of their portfolios beyond the benchmark market-capitalisation-weighted portfolios by creating a factor weighted portfolio.

In conclusion, the influence of the COVID-19 epidemic on stock performance in SSA depends on a plethora of issues, including the economic impact of government policies introduced to curb the spread of the pandemic, macroeconomic stability of a country, financial strength of a company, and investors' perceptions of a given stock's future performance. In larger exchanges with a more stable economic environment, government policies and their economic impacts seem to have had a significant effect on stock performance. On the other hand, in stock markets of countries with high macro-economic instability it was found that factors such as inflation and exchange rate volatility had a significant adverse impact on stock performance. There is also the possibility of enhancing portfolio performance in sub-Saharan African stock exchanges, even during market crisis, through factor investing, where portfolio managers pick stocks for inclusion in their portfolios based on fundamental and technical factors. Most stock indices in SSA are market-cap weighted, which are based on the efficient market hypothesis, thus the outperformance of factor-weighted portfolios over the market portfolios signify that there is possibility of generating above average returns by exploiting inefficiencies in market pricing.

5.4 Contributions and Implications of the study

The study makes several contribution in understanding how the pandemic outbreak affected stock performance in SSA and has some policy implications that are of benefit to investors, portfolio managers and governments in SSA. Initially we observe that the COVID-19 pandemic had the most impact on stock markets in SSA mainly at the onset of the pandemic which aligns with the findings of other studies in developed and emerging economies, for example, Harjoto and Rossi (2021); Ashraf (2020b); Takyi and Bentum-Ennin (2021). However, most of these studies were limited to the onset of the COVID-19 pandemic and did not consider how the events that accompanied the outbreak of the pandemic such as imposition of lockdowns, vaccination programmes and other variants of COVID-19 waves affected stock market performance especially in SSA. Additionally, the studies considered the performance of the stock market as a whole neglecting the sector and firm specific impact of the pandemic. This study contributes to the research gap showing that intensification of government stringency measures had a negative impact on stock market performance in SSA as it led to decline in returns and increased stock volatility while introduction of vaccination program helped to tame the negative impact of the stringency measures. Our findings further show that stringency measures had a higher impact mainly in larger sub-Saharan African stock exchanges that are characterized by high trading activity than on smaller exchanges. This indicate that more liquid market were more sensitive to policy shocks, possibly due to the rapid dissemination of information and greater investor reaction in these stock exchanges.

Sector level analysis performed in this study revealed further insights. The healthcare sector's resilience across large stock exchanges, even in the face of heightened government stringency measures, emphasizes its importance as a defensive sector during crises. Healthcare stocks often act as safe-haven investments during crises periods such as the COVID-19 due to consistent demand for health services, which may remain unaffected or even increase during a health crisis. This suggests that investors should prioritize sectoral allocation toward healthcare in portfolio construction when navigating health crisis periods to mitigate risks and enhance returns. The performance of the ICT and consumer staples sectors, which exhibited increased returns despite heightened volatility, points to sectors that benefit from positive demand shocks in times of crisis. ICT stocks likely surged as the pandemic accelerated the digital transformation across businesses and consumer activities, while consumer staples that remain essential regardless of economic conditions and thus saw increased demand. In smaller, less liquid stock exchanges, the primary factor affecting stock performance appeared to be negative demand shocks as evidenced by the decline in returns in non-essential as more stringency measures were put by the government in respective countries.

On the other hand, the rollout of vaccination programs in SSA appears to have restored investor confidence in both larger and smaller stock exchanges. The increased returns and decreased volatility in most sectors following the vaccine rollout indicate that the market saw vaccines as a positive turning point in managing the pandemic. This suggests that investor sentiment was closely tied to public health developments, and positive health interventions translated into stabilized financial markets. The sector-specific recovery patterns observed in both larger and smaller exchanges highlight that sectors previously impacted by stringency measures were more sensitive to the positive effects of the vaccine introduction. This indicates that sectors directly tied to consumer activity and discretionary spending were heavily influenced by the recovery of economic activity, as people felt more secure resuming normal behaviors post-vaccination.

The sharp shifts in sector performance during lockdowns and post-vaccination provide evidence for strategic sector rotation for investors in sub-Saharan African stock exchanges. Investors in larger and more liquid exchanges should rotate between cyclical sectors that are highly sensitive to negative supply shocks, such as energy sector during downturns and move to more defensive sectors, such as healthcare and consumer staples. In smaller exchanges investors need to consider liquidating their investments in stocks that are sensitive to demand shocks and invest their money in real assets such as real estate gold. This dynamic approach to portfolio management will allow investors to mitigate losses during the demand shocks caused by lockdowns. Conversely, traders looking to capitalize on rapid sectoral rebounds should monitor the introduction of public health measures and immediately target sectors that are likely to benefit from such interventions. This could involve taking short positions in cyclical sectors during the lockdown phase and rotating to long positions when recovery signals, such as vaccine rollouts, emerge.

From a policy standpoint, the response of the stock markets to lock-down measures and introduction of vaccinations suggest that governments can have a direct influence on market recovery through public health measures. The positive market response to vaccine rollouts shows that investor confidence is highly dependent on effective government intervention. Policymakers should therefore consider the financial impact of health policies as part of broader economic recovery plans. Ensuring timely and widespread access to vaccines or other health interventions could accelerate recovery and contribute to financial market stability.

Another novelity brought about by this study is that on top of COVID-19 events, it considers the impact that macro-economic factors had on stock performance in SSA. Although findings from studies in developed economies (see for example Narayan *et al.*, 2021), reveal that government policies such as introduction of economic lockdowns, school closures, travel bans and stimulus packages had a positive impact on stock performance, some related studies show that the pandemic’s influence on security markets was exacerbated by economic uncertainty that it brought (Baker *et al.*, 2020; Xu, 2021). Most countries in SSA are characterised by economic instability and these conditions play a critical role in shaping investor behavior and stock market performance, especially during crises. For example, inflationary pressures in Zimbabwe led investors to shift from holding cash to buying stocks as a hedge against inflation, which in turn resulted in increased returns despite the pandemic. Our study findings suggest that, despite the disruptive nature of the COVID-19 pandemic, investors in sub-Saharan African markets, particularly those in hyperinflationary environments were more concerned with economic stability than the pandemic itself. In contrast, in more economically stable countries, the pandemic's direct effects, such as government stringency measures, introduction of vaccines had a more prominent influence on stock performance. In countries that were economically unstable at the onset of the pandemic, hyperinflation and currency instability led to a rush toward stocks that provided hedge against inflation. However, in more stable environments, the economic shocks induced by the pandemic such as demand and supply chain disruptions had a more pronounced effect on stock performance. Therefore investors and portfolio managers in SSA need to consider macro-economic factors in their strategic asset allocation decisions and include scenarios of worst-case macro-economic events when stress testing their portfolios against extreme market events.

Governments in SSA also need to be tactical when implementing their policies. Pandemics have been shown to be a threat to stock markets whenever their emergence or the policies put forth to control them, cause economic instability. Thus, the government should implement measures that bring about economic stability while fighting pandemics and natural disasters. For example, in the face of a health crisis, lockdowns can be partially implemented with full funding made available to reduce the impact of demand and supply shocks in the economy.

To assist investors and portfolio managers in security selection decisions, this study further considered the influence of the pandemic on individual stock performance. To the researcher's best knowledge, such a study has not been done in SSA. Specifically the study considered the firm specific factors driving stock performance during the COVID-19 pandemic and several insights were derived from the analysis. The study underscores the importance of financial strength as a critical determinant of stock resilience during economic downturns. The findings suggest that strong financial fundamentals enhance stock resilience during crises, indicating that investors should prioritize profitability, earnings growth of a firm when constructing portfolios for better risk-adjusted returns. Furthermore, when investing in smaller stock exchanges with low liquidity, investors should consider the cash flow-generating ability of a company as well as the amount of debt that a company holds in its balance sheet. They must buy stocks for companies with high cash flow growth and a low debt ratio, and offload stocks for companies with negative cash flows and high debt, especially in times of high market turbulence.

Stock momentum also emerged as a major determinant of stock performance. Stocks known to have a history of a positive trend in their prices, often called winners, had higher risk-adjusted returns, whereas those known to face price declines, commonly called losers, had lower risk-adjusted returns. As noted by Chan *et al.* (1996) existence of a momentum factor is an indication of some behavioural bias among the investors as it illustrates the investor's irrationality in valuing equity and making investment decisions. This signifies that investor perceptions also had a significant impact on stock performance in SSA during the pandemic. Investors were likely influenced by herd behavior and past performance, expecting that winners would continue their positive trends. While momentum was a key driver of stock performance, its significance was less pronounced in high-inflation markets, where fundamentals like financial strength became more important. This suggests that in stable economies, investors are more likely to follow momentum, but in unstable environments, investors seem to be concerned with the value preservation of a stock in the form of its financial strength rather than its momentum. Thus, portfolio managers need to incorporate investor sentiments in security pricing and in evaluating portfolio performance rather than relying solely on models that assume rational investor behaviour.

Finally, this study sought to create a factor portfolio as a strategy to enhance investment performance in sub-Saharan Africa during periods of extreme market events in which value preservation matter the most. The variation in stock performance at firm and sector levels during the COVID-19 pandemic signified the possibility of creating a portfolio that can reduce the adverse impact of the pandemic on stock performance. A factor portfolio was created by selecting stocks with characteristics that maximise the returns per level of volatility. While the factors differed across stock exchanges, the portfolios were predominantly composed of stocks with strong profitability, robust cash flow generation, potential for high earnings growth, low leverage, and momentum stocks. In each of the stock exchanges, the factor portfolios formed exhibited lower volatility compared to individual stocks, yet delivered significantly higher returns, ensuring investors a positive return even during crisis periods such as the COVID-19 pandemic. The portfolio was further tested and found to be resilient against COIVID-19 factors such as cases and deaths, lockdowns, and macro-economic factors. Additionally, these factor portfolios surpassed market cap-weighted portfolios in risk-adjusted returns during the COVID-19 pandemic. This signifies that portfolio managers in SSA have the potential to enhance the performance of their portfolios beyond the benchmark market-capitalisation-weighted portfolios by creating a factor weighted portfolio.

As mentioned in much of the literature, many stock exchanges in sub-Saharan Africa lack diversity in the securities traded (Economic Commission for Africa, 2020). Stock indices and ETFs on these exchanges are limited to market capitalisation and sector-based indices. The emergence of the COVID-19 pandemic has exposed the vulnerability of the stock market sectors and individual securities, highlighting the need for more diversified multifactor-based strategies. The study's findings indicate that portfolios constructed from multiple factors offer better risk diversification and enhanced returns than a market cap-weighted portfolio, especially during extreme market events. This implies that security diversity could be improved in sub-Saharan stock exchanges by creating ETFs and investable indices based on more robust factors, instead of relying solely on the direct purchase of securities at the exchange or investing in traditional market-cap weighted indexes and/or ETFs.

In addition to the mentioned contributions, this study added a novel Machine Learning approach for modelling security returns and constructing portfolios during crisis periods such as the COVID-19 pandemic. Decision trees were employed for security selection, whereas SHAP analysis was used to determine security weights for portfolio construction to select securities that maximise risk-adjusted returns. Traditional methodologies, such as Harry Markowitz's Mean-Variance Optimisation (MVO), focus on constructing efficient portfolios that maximise expected returns for a given level of risk. While these methods successfully identify efficient portfolios, they typically rely on historical data and often do not reveal the underlying characteristics of the selected securities. Consequently, the selection of securities within these portfolios is based predominantly on past performance without explicitly considering the factors influencing future returns. This limitation becomes pronounced during extreme market events, such as the COVID-19 pandemic, where historical models may falter because of significant deviations from expected patterns. Machine learning approaches, in contrast to traditional methods, continuously adapt to new data, which allows for real-time adjustments to portfolio composition. This characteristic made machine-learning methods more suitable for this research, which focused on modelling returns and constructing portfolios during crisis periods. Additionally, Decision trees presented a more transparent method of portfolio construction. These trees explicitly delineated the interplay of factors influencing stock returns in sub-Saharan Africa during the pandemic. Model interpretability proved valuable not only for identifying the factors influencing risk-adjusted returns but also for comprehending the nonlinear associations and interplay of factors driving asset returns. Such insights might be overlooked by traditional mean-variance optimisation methods, which typically assume linear relationships of factors driving asset returns. After the initial selection of securities using decision trees, SHAP analysis, a model-agnostic method, was used to determine the weight of each security in the portfolio. Unlike traditional methods, which often assign portfolio weights based on market capitalisation with SHAP, the securities in the portfolio were weighted based on their marginal contribution to risk-adjusted returns, providing a more dynamic approach to portfolio construction.

5.5 Recommendations for further research

This section outlines issues for further research emanating from the research findings. One implication of our findings is that investor sentiment and behavioral elements may have had a substantial influence on stock performance. Therefore, further research should explore the impact of investor sentiment, psychology, and behavioral biases on stock performance in sub-Saharan African markets during pandemics and financial crises. This could offer valuable insights into the underlying causes of stock performance and help with investment decision making and risk management during crisis periods.

Future research could also consider incorporating more extreme market events and analysing their impact on stock performance in sub-Saharan Africa, as this study was limited to the COVID-19 pandemic. This could include analysing stock performance during events such as the Global Financial Crisis, commodity price shocks, and political instability in Africa. By examining multiple crisis episodes, researchers can gain a more comprehensive understanding of the factors driving stock performance in these markets under different economic and market conditions. Another recommendation is a study that considers the impact of policy uncertainty on stock performance in SSA. SSA is characteriseed by continuous policy changes as the region tries to grapple with economic instability (Africa Development Bank, 2021). The findings of this study revealed that stocks in some exchanges, although highly volatile, appeared to be insensitive to COVID-19 events. This indicates that other factors may also be influencing the performance of these stocks.

Dynamic factor modelling is another area of future research. Future studies should consider employing dynamic factor modelling techniques rather than relying on static factor models. This would allow for an examination of how the significance of various factors, such as profitability, leverage, and momentum evolve over time and across different crisis periods. This approach could provide valuable insights into the factors that are significant in both the crisis and pre-crisis periods, help investors, and portfolio managers prepare for unforeseen events that could significantly affect their investments.

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Appendices

Appendix 1: Cover page for the published article (chapter two)

Open Access Article

COVID-19 Pandemic and Stock Performance: Evidence from the Sub-Saharan African Stock Markets

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Abstract

Emerging stock markets provide great opportunities for investment growth and risk diversification. However, they are more vulnerable to extreme market events. This study examines the effects of the COVID-19 pandemic on stock performance in sub-Saharan African stock markets. An event study method was used to determine whether there was any significant difference in sector returns before and during the pandemic, and panel data regression was used to determine the causal relationship between COVID-19 events and the abnormal returns observed. Four stock exchanges were chosen, including the two largest and two fastest-growing markets in sub-Saharan Africa. According to the study's findings, the information technology, consumer staples, and healthcare sectors outperformed during the pandemic, while the industrials, materials, and real estate sectors underperformed. The financial and consumer

Appendix 2: Cover page for the published article (chapter three)

Open Access Article

Investigating the Effects of the COVID-19 Pandemic on Stock Volatility in Sub-Saharan Africa: Analysis Using Explainable Artificial Intelligence

by Mbongiseni Ncube *, Mabutho Sibanda and Frank Ranganai Matenda

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(This article belongs to the Section Macroeconomics, Monetary Economics, and Financial Markets)

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Abstract

This study examines the impact of the COVID-19 pandemic on sector volatility in sub-Saharan Africa by drawing evidence from two large and two small stock exchanges in the region. The analysis included stock-specific data, COVID-19 metrics, and macroeconomic indicators from January 2019 to July 2022. This study employs generalized autoregressive conditional heteroskedasticity (GARCH) models to estimate volatility and Explainable Artificial Intelligence (XAI) in the form of SHapley Additive exPlanations (SHAP) to identify significant factors driving stock volatility during the pandemic. The findings reveal significant volatility increases at the onset of the pandemic, with government stringency measures leading to increased volatility in larger exchanges, while the introduction of

Appendix 3: Cover page for the article under review (chapter four)

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Cogent Economics & Finance

Factor investing during crises: Analysing the influence of firm-specific factors on stock performance in sub-Saharan Africa amid COVID-19 pandemic

Submission ID	242637835
Article Type	Research Article
Keywords	Stock markets, sub-Saharan Africa, COVID-19 pandemic, Explainable Artificial Intelligence, Factor investing
Authors	Mbongiseni Ncube, Mabutho Sibanda, Frank Ranganai Matenda

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Note for Reviewers:

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Appendix 4: Language editing certificate

C Woudberg

Language Practitioner

[redacted] | [redacted]

To whom this may concern:

I hereby confirm that I have completed the language editing of the **COVID-19 Pandemic and Stock Performance research paper: evidence from Sub-Saharan Stock Markets** by Mbongiseni Ncube (Student No: 220101144). My involvement was restricted to language usage, spelling, completeness, and consistency. I did not structurally rewrite the content or influence the academic content in any way.

[redacted]

Kind regards,

Christelle Woudberg

ND Language Practice

Member of the South African Translators 'Institute

Appendix 5: Sample python codes for Event study Analysis (chapter 2)

Import relevant libraries

```python
import pandas as pd
import time
import datetime
import eventstudy as es
from eventstudy import Single, models, Multiple
from matplotlib.gridspec import GridSpec
import matplotlib.gridspec as gridspec
import seaborn as sns
from eventstudy import excelExporter
import glob
import statsmodels.api as sm
import warnings
warnings.filterwarnings("ignore")
```

```python
import hvplot
import holoviews as hv
import numpy as np
import hvplot.pandas
from bokeh.models import DatetimeTickFormatter

from holoviews import opts
import bokeh.sampledata
hv.extension('bokeh')
from IPython.display import clear_output; clear_output
```

```
<function IPython.core.display_functions.clear_output(wait=False)>
```

Event Analysis code

```python
import numpy as np
import pandas as pd

path = r'C:\Users\Ncube\Desktop\python_notebooks\Financial-Machine-Learning-code\JSE_sectors'

tickers = ['Consumer Discretionary', 'Consumer Staples', 'Energy', 'Financials', 'Health Care', 'ICT', 'Industrials', 'Materials', 'Real Estate']

events = {
    'COVID-19 outbreak + Lockdown': np.datetime64('2020-04-15'),
    'Stimulus Package': np.datetime64('2020-04-30'),
    'Lockdown eased':  np.datetime64('2020-08-18'),
    'Beta Variant': np.datetime64('2020-11-01'),
    'Vaccine Introduction': np.datetime64('2021-02-17'),
    'Delta Variant':np.datetime64('2021-06-01'),
    'Level 4 Lockdown': np.datetime64('2021-06-28'),
'Omicron':np.datetime64('2021-11-15')
}

# Load the original dtdc DataFrame
dtdc = jse_event
dtdc['date'] = pd.to_datetime(dtdc['date'])  # Convert 'Event Dates' to datetime64[ns]

combined_df = pd.DataFrame()  # Initialize an empty DataFrame to store combined results

for sector in tickers:
    sector_results = pd.DataFrame()  # Initialize an empty DataFrame to store results for each sector

    for event_name, event_date in events.items():
        dtdc_filtered = dtdc[dtdc['ticker'] == sector].copy()  # Make a copy of the filtered data
        dtdc_filtered['date'] = pd.to_datetime(dtdc_filtered['date'])
        dtdc_filtered = dtdc_filtered[dtdc_filtered['date'] <= event_date]  # Filter data up to the event date

        event = Single(models.constant_mean, model_data=dtdc_filtered, event_window=(-10, 30), estimation_size=60, buffer_size=30, keep_model=True, description=sector, eve
```



```python
        rez = event.results()
        rez['Sector'] = sector
        rez['Event'] = event_name
        rez['Event Date'] = event_date  # Include the event date in the results

        # Add a column for the actual dates corresponding to each day within the event window
        event_dates = [event_date + np.timedelta64(i, 'D') for i in range(-10, 31)]
        rez['Event Dates'] = event_dates

        sector_results = pd.concat([sector_results, rez[['AR', 'CAR', 'Sector', 'Event', 'Event Date', 'Event Dates']]], ignore_index=True)

    # Merge the results with the original dtdc DataFrame for the specific sector and event date
    sector_merged = pd.merge(sector_results, dtdc[dtdc['ticker'] == sector],
                             left_on='Event Dates', right_on='date', how='left')

    combined_df = pd.concat([combined_df, sector_merged], ignore_index=True)

# Save the combined DataFrame to a CSV file
combined_df.to_csv('combined_results_with_dates.csv', index=False)
```

Appendix 6: Sample python codes for Volatility Analysis using GARCH models (chapter 3)

Import relevant data

```
ngx_event = pd.read_csv('ngx_event.csv',index_col = [0])
ngx_event['perc_chng']=  ngx_event['security_returns']*100
ngx_event.drop(index=ngx_event[ngx_event['ticker'] == 'Index'].index, inplace=True)
ngx_event.drop(index=ngx_event[ngx_event['ticker'] == 'Utilities'].index, inplace=True)
ngx_event.drop(index=ngx_event[ngx_event['ticker'] == 'Real Estate'].index, inplace=True)
```

Diagonistics checks and GARCH modelling

```
3]: tickers =  ['Consumer Discretionary','Consumer Staples','Energy','Financials','ICT','Industrials','Materials','Health Care']
garchdfPrCo = []
for ticker in tickers:
    ngx_PrCo= ngx_event.loc[ngx_event["date"].between("2019-01-01", "2023-12-31")]
    dtdc= (ngx_PrCo.loc[(ngx_PrCo['ticker'] == ticker)])
    #fit a GARCH(1,1) model on the residuals of the ARIMA model
    arima_model = pmdarima.auto_arima(dtdc['security_returns'])
    p, d, q = arima_model.order
    arima_residuals = arima_model.arima_res_.resid
    egarch = arch_model(arima_residuals, p=1, o=1, q=1,vol = 'EGARCH',dist= 'skewt')
    Gjrgarch = arch_model(arima_residuals, p=1, q=1, o=1, vol = 'GARCH',dist= 'skewt')
    garch = arch_model(arima_residuals, p=1, q=1, vol = 'GARCH',dist= 'skewt')
    egarch_fitted = egarch.fit(update_freq = 10,disp='off', show_warning=False,)
    Gjrgarch_fitted = Gjrgarch.fit(update_freq = 10,disp='off', show_warning=False,)
    garch_fitted = garch.fit(update_freq = 10,disp='off', show_warning=False,)

    LM_pvalue = het_arch(arima_residuals, ddof = 4)[1]
    LJbox=acorr_ljungbox(Gjrgarch_fitted.resid,lags=[1],return_df= True)
    #print(ticker + 'LM-test-Pvalue:', '{:.4f}'.format(LM_pvalue))
    Lmtest_df = (pd.DataFrame([ticker ,'{:.5f}'.format(LM_pvalue)], index=['Sector', 'LM_test-Pvalue'])).T

    garch_rez = (pd.DataFrame([Gjrgarch_fitted.conditional_volatility ,Gjrgarch_fitted.resid])).T
    garch_rez['Sector'] = ticker
    garch_rez['date'] = ngx_PrCo['date']
    garch_rez.to_csv(fr'C:\\Users\Mr Ncube\Desktop\financial python\garch_ngx\\{ticker}.csv')
    #garch_rez.to_csv('garch_res.csv')

    ngx_param = pd.DataFrame({
```

```
    'egarch_params': egarch_fitted.params,
    'P-value': egarch_fitted.pvalues,
    'gjrgarch_params': Gjrgarch_fitted.params,
    'P-Value': Gjrgarch_fitted.pvalues})
ngx_param['sector']= ticker
ngx_param.reset_index(inplace = True)

ngx_param.to_csv(fr'C:\\Users\Mr Ncube\Desktop\financial python\garchcof_ngx\\{ticker}.csv')
ngx_IC = (pd.DataFrame([egarch_fitted.aic ,Gjrgarch_fitted.aic,garch_fitted.aic,egarch_fitted.bic,Gjrgarch_fitted.bic,garc
ngx_IC['Sector'] = ticker
ngx_IC.to_csv(fr'C:\\Users\Mr Ncube\Desktop\financial python\IC_ngx\\{ticker}.csv')
Lmtest_df.to_csv(fr'C:\\Users\Mr Ncube\Desktop\financial python\ngx_Lmtest\\{ticker}.csv')
LJbox['Sector'] = ticker
LJbox.to_csv(fr'C:\\Users\Mr Ncube\Desktop\financial python\ngx_LJbox\\{ticker}.csv')

fig, ax = plt.subplots(1, 2, figsize = (18,5))
sgt.plot_acf(arima_residuals**2, zero = False, lags = 40, ax=ax[0])
sgt.plot_pacf(arima_residuals**2, zero = False, lags = 40, ax=ax[1])
#plt.show()
plt.savefig('ArchEffects.png')
```

Appendix 7: Sample python code for web-scrapping financial data (chapter 4)

```
In [1]: import requests
        from bs4 import BeautifulSoup # pip install beautifulsoup4
        import pandas as pd # pip install pandas
        import win32com.client as win32
        import pandas as pd

In [2]: stocks = pd.read_csv('zse_stocks_MktW.csv',encoding= 'unicode_escape')

        tickers= []
        for stock in stocks['Name']:
            ticker = stock.split('(')[-1].split(')')[0].lower()
            tickers.append(ticker)
        print(tickers)

        ['artd', 'aris', 'bat', 'cafca', 'cbz', 'cfi', 'dzl', 'dlta', 'ehzl', 'eco', 'edgr', 'fbc', 'fmhl', 'fmp', 'gbh', 'gbzw', 'hip
        o', 'mash', 'mshl', 'meik', 'npkz', 'nts', 'nmb', 'okz', 'prol', 'rtg', 'rioz', 'sacl', 'truw', 'tsl', 'turn', 'unif', 'wild',
        'zbfh', 'zimp', 'zimw', 'zimr']

In [3]: def parse_figure(figure):
            figure = figure.replace('(', '-').replace(')', '')  # Remove brackets and add a negative sign
            if figure.endswith('K'):
                return float(figure[:-1]) * 1000  # Convert K to thousands
            elif figure.endswith('M'):
                return float(figure[:-1]) * 1000000  # Convert M to millions
            elif figure.endswith('B'):
                return float(figure[:-1]) * 1000000000  # Convert B to billions
            elif figure.endswith('%'):
                return figure.replace(',', '')# Convert B to billions

            else:
                try:
                    return float(figure)  # Convert other figures directly to float
                except ValueError:
                    return None  # Return None for non-numeric values

        statements = ['Income Statement', 'Balance Sheet', 'Cash Flow']
        tickers = ['artd', 'aris', 'bat', 'cafca', 'cbz', 'cfi', 'dzl', 'dlta', 'ehzl',
                   'eco', 'edgr', 'fbc', 'fmhl', 'fmp', 'gbh', 'gbzw', 'hipo', 'mash', 'mshl', 'meik', 'npkz', 'nts', 'nmb',
                   'okz', 'prol', 'rtg', 'rioz', 'sacl', 'truw', 'tsl', 'turn', 'unif', 'wild', 'zbfh', 'zimp', 'zimw', 'zimr']
```

```
for ticker in tickers:
    ticker_df = pd.DataFrame()  # Create an empty DataFrame for the ticker

    for statement in statements:
        if statement == 'Income Statement':
            url = f"https://www.marketwatch.com/investing/stock/{ticker}/financials?countrycode=zw"
        else:
            url = f"https://www.marketwatch.com/investing/stock/{ticker}/financials/{statement.lower().replace(' ', '-')}?coun

        response = requests.get(url)
        soup = BeautifulSoup(response.text, "html.parser")

        tables = soup.find_all("div", class_="overflow--table")
        for table in tables:
            header_row = table.find("tr")
            headers = [th.get_text(strip=True) for th in header_row.find_all('th', class_="overflow__heading")]

            data_rows = []
            for row in table.find_all("tr"):
                data = [td.get_text(strip=True) for td in row.find_all('td')]
                if len(data) == len(headers):
                    data_rows.append(data)

            if len(data_rows) > 0:
                df2 = pd.DataFrame(data_rows, columns=headers)
                df2.iloc[:, 1:] = df2.iloc[:, 1:].applymap(parse_figure)  # Apply parse_figure function to convert figures sta
                ticker_df = pd.concat([ticker_df, df2], ignore_index=True)  # Append the data to ticker_df

    ticker_df.to_csv(f'{ticker}_financials.csv', index=False)  # Save the combined DataFrame to a single CSV file
```

Appendix 8: Sample python code for the Factor analysis (chapter 4)

```
import pandas as pd
import numpy as np
import sklearn
from sklearn.preprocessing import MaxAbsScaler
from sklearn.impute import SimpleImputer
import xgboost
import shap
import os

# Assuming xgb_df is already loaded

# Handle NaNs in features
ave_valstd = xgb_df['Std'].mean()
xgb_df['Std'] = xgb_df['Std'].fillna(ave_valstd)
ave_vol = xgb_df['Vol'].mean()
xgb_df['Vol'] = xgb_df['Vol'].fillna(ave_vol)
xgb_df['Risk_ret'] = xgb_df['Returns'] / xgb_df['Std']

# Drop unnecessary columns
X_19 = xgb_df.drop(columns=['Ticker', 'Year', 'Close', 'P/Sals','Risk_ret', 'Returns','Ln_CAP', 'Ln_Volm','Vol','Std', 'D/E', 'P/B','ROE'])

# Replace infinite values with NaN
X_19.replace([np.inf, -np.inf], np.nan, inplace=True)

# Clip very large values
max_float64 = np.finfo(np.float64).max
X_19 = X_19.clip(upper=max_float64)

# Check for NaNs and handle them
print(X_19.isna().sum())
```



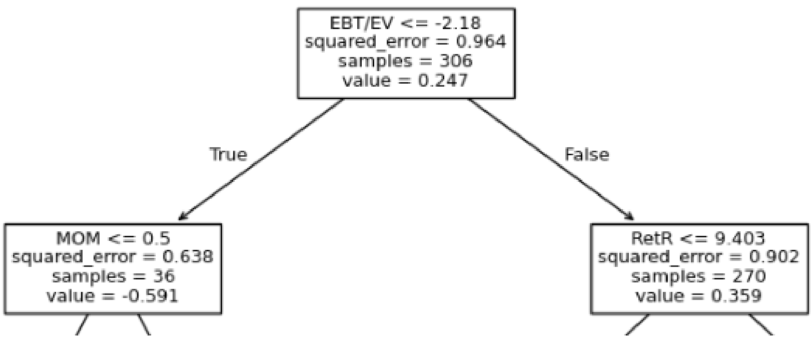
```
# Initialize scaler and imputer
sc = MaxAbsScaler()
imputer = SimpleImputer(strategy='mean')
# Fit and transform scaler
#X_19 = sc.fit_transform(X_19)
# Impute missing values
X_19 = imputer.fit_transform(X_19)
# Convert back to DataFrame
X_19 = pd.DataFrame(X_19, columns=col_nm)
# Handle NaNs, infinite, and large values in target variable
y_19 = xgb_df['Risk_ret']
# Replace infinite values with NaN in target variable
y_19.replace([np.inf, -np.inf], np.nan, inplace=True)
# Fill NaN values with the mean of the column
y_19 = y_19.fillna(y_19.mean())
```

```
# Function to train XGBoost model
def fit_xgboost(X, y):
    """ Train an XGBoost model with early stopping. """
    X_train, X_test, y_train, y_test = sklearn.model_selection.train_test_split(X, y, test_size=0.1, random_state=200)
    dtrain = xgboost.DMatrix(X_train, label=y_train)
    dtest = xgboost.DMatrix(X_test, label=y_test)
    model = xgboost.train(
        {"eta": 0.001, "subsample": 0.8, "max_depth": 2, "objective": "reg:linear"},
        dtrain,
        num_boost_round=200000,
        evals=[(dtest, "test")],
        early_stopping_rounds=20,
        verbose_eval=False
    )
    return model, X_train, X_test, y_train,y_test

# Train the model
model, X_train, X_test ,y_train,y_test= fit_xgboost(X_19, y_19)
# SHAP analysis
explainer = shap.Explainer(model)
shap_values = explainer(X_19)
dtest = xgboost.DMatrix(X_test)
predic = model.predict(dtest)
hitratio = np.mean(predic*y_test>0)
print(f'Hit Ratio: {hitratio}')
# Clustering and plotting SHAP values
clust = shap.utils.hclust(X_19, y_19, linkage="single")
shap.plots.bar(shap_values, clustering=clust, clustering_cutoff=2, max_display=9)
```

Appendix 9: Factor Inentification with Regression Tree (chapter 4)

```
X_19 = pd.DataFrame(X_19, columns=col_nm)
# Handle NaNs, infinite, and large values in target variable
y_19 = xgb_df['Risk_ret']
# Replace infinite values with NaN in target variable
y_19.replace([np.inf, -np.inf], np.nan, inplace=True)
# Fill NaN values with the mean of the column
y_19 = y_19.fillna(y_19.mean())
# Clip very large values
y_19 = y_19.clip(upper=max_float64)
# Ensure there are no inf values
if np.isinf(y_19).values.any():
    print("Warning: There are still inf values in the target variable!")
# Function to train XGBoost model
def fit_xgboost(X, y):
    """ Train an XGBoost model with early stopping. """
    X_train, X_test, y_train, y_test = sklearn.model_selection.train_test_split(X, y, test_size=0.1, random_state=200)
    dtrain = xgboost.DMatrix(X_train, label=y_train)
    dtest = xgboost.DMatrix(X_test, label=y_test)
    model = xgboost.train(
        {"eta": 0.001, "subsample": 0.8, "max_depth": 2, "objective": "reg:linear"},
        dtrain,
        num_boost_round=200000,
        evals=[(dtest, "test")],
        early_stopping_rounds=20,
        verbose_eval=False
    )
    return model, X_train, X_test, y_train,y_test

# Train the model
model, X_train, X_test ,y_train,y_test= fit_xgboost(X_19, y_19)
# SHAP analysis
explainer = shap.Explainer(model)
shap values = explainer(X 19)
```

```
from sklearn import tree # Treemodule
X = X_19 # recallfeatures/pred.fullsample
y = y_19 # recalllabel/Dependentvar.fullsample
fit_tree = tree.DecisionTreeRegressor(# Definingthemodel
min_samples_split=20,# Minnbobsrequiredtocontinuesplitting
max_depth = 3, # Maximumdepth(i.e.treelevels)
ccp_alpha=0.000001, # complexityparameters
min_samples_leaf =10
# Minnbofobsrequiredineachterminalnode(leaf)
)
fit_tree.fit(X, y) # Fittingthemodel
fig, ax = plt.subplots(figsize=(13, 8)) # resizing
tree.plot_tree(fit_tree,feature_names=X.columns.values,ax=ax)
plt.title('JSE Factor Regression Tree', fontsize=12)
plt.savefig('jse_factortree.png', dpi=200)
# Plotthetree
plt.show()
```



Appendix 10: Python code for the portfolio construction (chapter 4)

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Load data (assuming your data loading and preprocessing steps are already done)

# Function to plot the efficient frontier for a given year
def plot_efficient_frontier(ax, std_devs, returns, portfolio_std_dev_mkt_cap, ER_factor_p_mk, portfolio_std_dev_factor, ER_factor_p, year):
    ax.scatter(std_devs, returns, marker='o', label='Individual Stocks')
    ax.scatter(portfolio_std_dev_mkt_cap, ER_factor_p_mk, color='red', label='Market Cap Weighted Portfolio', marker='*', s=150, zorder=5)
    ax.scatter(portfolio_std_dev_factor, ER_factor_p, color='green', label='Factor Portfolio', marker='*', s=150, zorder=5)
    ax.set_xlabel('Annualized Standard Deviation')
    ax.set_ylabel('Annualized Expected Return')
    ax.set_title(f'JSE Investment Opportunity Set - {year}')
    ax.grid(True)


# Function to plot random portfolios
def plot_random_portfolios(ax, cov_matrix, mean_returns, num_portfolios=1000, alpha=0.3):
    results = np.zeros((2, num_portfolios))
    for i in range(num_portfolios):
        weights = np.random.random(len(mean_returns))
        weights /= np.sum(weights)
        std, ret = portfolio_performance(weights, mean_returns, cov_matrix)
        results[0, i] = std
        results[1, i] = ret
    ax.scatter(results[0, :], results[1, :], color='gray', alpha=alpha, label='Random Portfolios')
# Function to calculate portfolio performance
def portfolio_performance(weights, mean_returns, cov_matrix):
    returns = np.dot(weights, mean_returns)
    std = np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))
    return std, returns

# Create a figure with two subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 4.5))

# Plot efficient frontier for 2019
plot_efficient_frontier(
    ax1,
    aligned_ret_data['Std_19'],
    aligned_ret_data['Returns_19'],
    portfolio_std_dev_mkt_cap19,
    ER_factor_p19mk,
    portfolio_std_dev_factor19,
    ER_factor_p19,
    '2019'
)

# Plot efficient frontier for 2020
plot_efficient_frontier(
    ax2,
    aligned_ret_data['Std_20'],
    aligned_ret_data['Returns_20'],
    portfolio_std_dev_mkt_cap20,
    ER_factor_p20mk,
    portfolio_std_dev_factor20,
    ER_factor_p20,
    '2020'

# Plot random portfolios for 2019
plot_random_portfolios(ax1, cov_matrix19mk, ret_std_data19['Returns_19'])

# Plot random portfolios for 2020
plot_random_portfolios(ax2, cov_matrix20mk, ret_std_data20['Returns_20'])

# Move the legend outside the plot
handles, labels = ax1.get_legend_handles_labels()
fig.legend(handles, labels, loc='upper center', bbox_to_anchor=(0.5, -0.05), fancybox=True, shadow=True, ncol=4)

plt.tight_layout()
plt.savefig('efficient_frontier_plot.png', dpi=200)  # Adjust dpi as needed for resolution
plt.show()
```

Appendix 11: Ethical clearance letter

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

23 Aug 2022

Mr Mbongiseni Ncube (220101144)
School Of Acc Economics&Fin
Westville

Dear Mr Mbongiseni Ncube,

Original application number: 00018272
Project title: The effects of the COVID-19 pandemic on stock performance: Evidence from the Sub-Saharan African stock markets.

Exemption from Ethics Review

In response to your application received on 16 Aug 2022 , your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]

Prof Josue Mbonigaba
Academic Leader Research
School Of Acc Economics&Fin

UKZN Research Ethics Office
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
Website: http://research.ukzn.ac.za/Research-Ethics/

Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

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