UNIVERSITY OF CAPE COAST

DOWNSIDE RISK ESTIMATIONS OF BANKS LISTED ON THE GHANA STOCK EXCHANGE

BY

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DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature ………………………………. Date…………………..

Name: Zynobia Barson

Supervisors' Declaration

I hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

Supervisor's Signature …………………………… Date…………….......

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ABSTRACT

In the financial system, banks are exposed to market risk which has to be assessed in line with regulatory risk measurement standards of Value-at-Risk and Expected Shortfall. The study adopts a quantitative approach and a descriptive design using weekly stock returns of banks listed on the Ghana Stock Exchange from January 2017 to December 2021. Using GARCH-based Value-at-Risk and Expected Shortfall, this study assessed the downside risks of the listed banks. Also, the study examined the tails of the returns distributions and nominally ranked the banks based on the level of risk. The mean returns showed that investors get little compensation for investing in the listed banks as against the high volatility associated with these investments. The findings of the study showed that the distributions of the returns of the listed banks are leptokurtic and positively skewed, reflecting fat, asymmetric tails; an indication of high-risk tendencies in the banks. Also, the study showed that the Value-at-Risk and Expected Shortfall can predict the downside risks in listed banks in Ghana, and help investors understand the potential losses and tail events associated with their investments. The nominal ranking of the banks based on the downside risk measures showed that Agricultural Development Bank Plc. is least risky in the market and Societe General Ghana limited has the highest risk. With the risk levels in the respective banks, it is recommended that investors should be careful in the market in an attempt to diversify against downside risk by spreading across the banks. The Governor, Bank of Ghana should enforce that financial institutions measure their downside risk using the Basel regulatory risk framework for a stable and confident financial system. The banks should also take strategic measures that protect them against extreme risk.

KEY WORDS

Expected Shortfall

GARCH

Ghana

GSE

Value-at-Risk

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DEDICATION

To Daddy, Mama, Prince Jefferson and Valeria

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LIST OF ACRONYMS

AIC	Akaike Information Criterion
AQR	Asset Quality Review
BCBS	Basel Committee of Banking Supervision
BIC	Bayesian Information Criterion
BoG	Bank of Ghana
EGARCH	Exponential Generalised Autoregressive Conditional Heteroscedasticity
ES	Expected Shortfall
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GFC	Global Financial Crisis
GJR-GARCH	Glosten-Jagannathan-Runkle Generalised Autoregressive Conditional Heteroscedasticity
GSE	Ghana Stock Exchange
IFRS	International Financial Reporting Standards
MAE	Mean Absolute Error
-norm	Gaussian distribution
RMSE	Root Mean Squared Error
sMAPE	symmetric Mean Absolute Percentage Error
-std	Student-*t* distribution
-sstd	Skewed Student-*t* distribution
VaR	Value-at-Risk

CHAPTER ONE

INTRODUCTION

The banking industry contributes immensely to domestic and international economies. Banking and the risks that come with it are expected (Odonkor et al., 2011). The globalisation of the financial environment exposes the industry to market risks that are inherent in all other risk profiles that the industry expects as a system. The extant literature shows that banks have implemented measures to mitigate such risks. However, the 2007-08 financial crisis showed that the industry's strategies were not sufficient to provide a safety net. In Ghana, the recent Asset Quality Review report (AQR) showed that the banking industry was in crisis and that clean-up was necessary (Aboagye, 2020). Consequent to the clean-up are several requirements that the Governor, Bank of Ghana (BoG) expects of the banks to ensure stability in the industry. The market risk of the Ghanaian banking industry must however be assessed to ensure that the financial viability of the industry is sustained and to promote banking confidence. Yet, in the AQR, the level of risk in the industry was not quantified. Therefore, this study seeks to use regulatory framework for modelling risk in line with the Basel III requirements for market risk assessment.

Background to the Study

Banking institutions act as financial intermediaries between deficit and surplus units to promote economic activity globally. Banks do not only provide investment and savings opportunities but also provide loans and insurance covers to customers. The banking system is a large part of the financial sector, and economic growth is heavily dependent on the industry's role in guaranteeing a financial system that promotes socio-economic development (Swamy, 2014; Beck & Levine, 2018; Asteriou & Spanos, 2019; Ntarmah, 2019; Duho et al., 2020; Obuobi, 2020).

The banking industry is considered one of the most innovative sectors globally (Ameme & Wireko, 2016; Obeng-Osei, 2019; Zaleska & Kondraciuk, 2019). It has contributed immensely to growth, improved service provision and increased banking awareness in Ghana (Abor, 2005; Dohemer et al., 2014; Ameme & Wireko, 2016; Obeng-Osei, 2019). Nevertheless, these sectoral innovations and developments have led to the adoption of some practices that have put the industry at risk due to increasing competition and restrictions internally and from external sources, such as the stock markets and foreign banks (Ameme & Wireko, 2016; Yuzvovich et al., 2016; Polizzi & Scannella, 2020). Moreover, the impact of globalisation on banking innovations, changes in customer needs, as well as competition, influences the risk level of their operations (Yuzvovich et al., 2016; Okafor & Fadul, 2019).

Risk in banking is inescapable and there are a myriad of risks that weigh heavily on other sectors. Categorically, banks face systematic and unsystematic risks that could cripple the entire system if not mitigated (Tsuji, 2019; Roman, 2021). Systematic risk is inherent in the entire market and can affect a large number of assets. This risk cannot be completely avoided, but could theoretically be mitigated if a bank has a strong capital base (Hirtle, 2003; Taylor, 2019; Rabie, 2020; van Greuning & Bratanovic, 2020). However, unsystematic risk (credit, liquidity, operational risk, etc.) can be diversified to avoid sectoral crises arising from any domino effects (Roman, 2021).

Increasingly, the literature shows that banks are highly exposed to credit, operational, liquidity and market risks which are relatively changing due to the need to diversify in an attempt to reduce total risk (Penza & Bansal, 2001; Rabie, 2020). These risk profiles determine the level of bank profitability and performance (Odonkor et al., 2011; Boahene et al., 2012; Lartey et al., 2013; Duho et al., 2020). However, because banks operate in an interrelated market, these risk profiles could generate into financial crises if they are not controlled at the firm level. A bank's market risk defines its position. A bank's inability to predict changes in credit spreads, foreign exchange, equity prices, interest rates and commodity prices in the market contribute to its market risk (Dowd, 2007; Rabie, 2020). Banks' risk profiles are subjectively interdependent; however, market risk is more prominent and inherent to other risk profiles, as it could cause reputational loss to the banking industry leading to an overall increased risk level (Penza & Bansal, 2001; Greuning & Bratanovic, 2009; Rabie, 2020).

More often than not, research shows that the different risk profiles that banks experience have a primary relationship with performance and profitability indicating the risky nature of banking (Greuning & Bratanovic, 2009; Doku, 2021). Through the assessment of risk, financial institutions put measures in place toward mitigating these systematically unavoidable risks and ensuring a stable system (Lönnbark, 2016). Risk assessment ultimately provides information on potential risks and threats that reflect financial viability and weakness, which informs the financial condition and feasibility of prospects, ensuring transparency (Greuning & Bratanovic, 2009). Thus, banks must conduct a regulatory assessment to promptly and accurately identify the expected risks arising from their activities. This regulatory assessment would help financial institutions identify, quantify, and develop appropriate risk mitigation strategies to avoid or reduce the impact of systematic breakdowns and loss of confidence in the financial system leading to a crisis.

Globally, commercial and universal banks experienced a financial crisis in 2007-08 which led to a loss of confidence in the financial system (Moosa, 2010; Ntarmah, 2019; Zhang & Broadstock, 2020). The crisis was a result of the lessened regulation in the banking system leading to the subprime mortgage crisis. The similarity and interrelatedness in the operations of banks led to instability and insolvency that implicitly hit the markets (Greuning & Bratanovic, 2009). Banks were compelled to reassess their risk levels and devise effective risk management strategies to mitigate their risks to enhance performance and profitability (Adelopo et al., 2018; Alexakis et al., 2019). The Basel Committee in an attempt to manage these banking sector risks restructured the regulatory and supervisory framework for banks with the promulgation of the Basel III Accord to capture uncertainties (Moosa, 2010; Clifton et al., 2017; Roulet, 2018; Nolan, 2019; Anginer et al., 2021).

The Basel Committee on Banking Supervision (BCBS) has proposed that Value-at-Risk (VaR) and Expected Shortfall (ES) be used in banking institutions to assess market risk globally. This stems from the vulnerability in the financial system that was exposed in the global financial crisis and the BCBS's attempt to ensuring a stable and sound global banking system. Following the global financial crisis of 2007-08, banks' attention was drawn to the consequences that could arise if measures to mitigate market risk are not put in place. While VaR provides a summary assessment of market risk under normal market conditions, ES enhances the market risk by accounting for tail risk and potential losses during extreme events. In theory, the tails of a financial asset's distribution show infrequent and severe market moves or significant price variations that might lead to market crashes and financial crises. VaR and ES implicitly seek to handle tail risks by predicting possible losses over a given threshold while taking into account the frequency and severity of extreme occurrences.

Ultimately, for enhanced market risk management, VaR and ES are used to capture a bank's market risk exposure, rationalise the financial markets; allowing a more resilient banking system. Also, the ability to assess market risk would inform a bank's market capital needs (Trenca et al., 2015). Hendricks and Hirtle (1997), Hirtle (2003), and Penza and Bansal (2001) show that banks theoretically hold capital against market risk. Also, there is a statistical relationship between regulatory capital holding requirements and the risks the banks can absorb in market downturns. This shows the relevance for banks to comply with using VaR and ES to assess market risk to avoid a financial downturn. Financial institutions do not only protect their own viability but also contribute to the broader stability of the financial system by successfully managing risk. A strong and robust financial system is required for supporting long-term economic growth and development.

The Ghanaian banking sector like that in most developing countries was introduced during the colonial era to meet the financial needs of the administration and enterprises in the 1920s (Obuobi et al., 2020). Since then, steps have been taken to rebrand the industry stemming from the names, ownership structures, laws and regulatory and supervisory frameworks that were necessary for the industry (Obuobi et al., 2020). Currently, there are 23 universal banks as well as several rural banks, with only eight banks listed on the Ghana Stock Exchange (GSE) (BoG, 2020).

Banks in Ghana have been subject to several sectoral reforms to assess the industry’s performance and to further strengthen the sector (Antwi-Asare & Addison, 2000; Owusu-Antwi, 2009; Biekpe, 2011; Akoena et al., 2013; Bokpin, 2016). Recently, the banking industry, led by the BoG assessed the viability and financial standing of the industry through an Asset Quality Review (AQR) in 2016 and documented that the industry was in crisis (Aboagye, 2020; Amenu-Tekaa, 2021). Following this, a sectoral clean-up led to mergers, takeovers and liquidation of some banks (Aboagye, 2020; Affum, 2020). Also, there was the promulgation of laws – Banks and Specialised Deposit-Taking Institutions Act 930 and the Deposit Protection Act 931, all of 2016 – and regulatory frameworks in an attempt to fundamentally ensure a stable financial environment (Elsinger et al., 2006; Affum, 2020; Carsamer et al., 2021). These sectorial clean-ups and reforms have undoubtedly contributed to the improvement of the banking industry through technological advancements and development, outreach and diversity in banking operations in Ghana (Alhassan & Ohene-Asare, 2016; Bokpin, 2016; PricewaterCoopers (PwC) Survey Ghana Banking, 2019; BoG, 2020; Doku, 2021).

Although the Governor’s report on the AQR painted a picture of a banking system that was on the verge of collapsing, the report did not capture market risk that is empirically considered an inherent risk to banking. If the banking industry reflects the financial viability of the economy, then the industry must assess its inherent risk to show investors the confidence they can put into the industry. The capital market is unsteady and complex making market risk unpredictable (Trenca et al., 2015). Investors in these capital markets also contribute to an increase in banks' exposure to market risks because of their need to diversify against systemic risk (van Greuning & Bratanovic, 2020). However, to reduce the total risk of banks in Ghana and that of their customers, market risk must be assessed. Information from assessing market risk using VaR and ES can be useful to investors in hedging against this risk and banks can also keep enough capital on hand to serve as a buffer against potential market losses to avoid financial crises. It is for this reason that this study seeks to assess the market risk of listed banks in Ghana.

Statement of the Problem

Since the inception of banking in Ghana, the industry has been subjected to several reforms with the primary intention of ensuring a more sturdy, healthy, and stabilised economy (Antwi-Asare & Addison, 2000; Owusu-Antwi, 2009; Biekpe, 2011; Bokpin, 2016). The Ghanaian banking industry has recently "cleaned up" and revived the industry following the report of the AQR that the banking sector was weak and in crisis (Aboagye, 2020; Affum, 2020; Amenu-Tekaa, 2021). The aftermath of the 2016-17 financial reform confirmed that the sector needs to assess its risk exposure levels frequently to avoid issues of illiquidity and insolvency.

Looking at the annual financial statements of banks in Ghana, there is no disclosure of risk neither is there any evidence that the banks have adopted the proposed risk measures of the Basel III – VaR and Expected Shortfall (ES) – to assess their market risks. Of the eight listed banks on the GSE, Ecobank

Ghana Limited and Standard Chartered Bank Ghana Public Limited Company (PLC) are the only banks that report that they model their respective bank market risks using VaR (and stress-testing). The other banks reserve that the assessment of market risk is solely the responsibility of the Asset-Liability Committee (ALCO) thus, do not explicitly report on what their respective market risk levels are. However, it is mandatory per international standards such as International Financial Reporting Standards 9 (IFRS 9 – Financial Instruments: Disclosure), Basel II (Market Discipline) and Basel III (Disclosure Requirements) that risk is disclosed. Coming down to the banking regulations in Ghana, risk disclosure is regulated by the Security Industry Act (2016), Securities and Exchange Commission (2009) particularly for the listed banks and generally, the BoG Corporate Governance Directive regulates risk disclosure for all banks in Ghana.

This is to say that the banks that are disclosing their market risks are voluntarily complying with these regulations. However, a bank's failure is at the mercy of market risk (Zolkifli et al., 2019). Thus, if banks are not disclosing their market risks, how will investors know the extent of risk they are facing by trading in these banks? A typical investor with experience or one who requires more information on the banks may not be interested in just the total risk (as computed by standard deviation) but rather the downside risk (which provides a more comprehensive and realistic assessment for severe losses or adverse outcomes in assets) of the banks. Downside risk measures factor in the tail risks in financial assets just like the VaR and ES which are in line with Basel III. Hence, it is important that banks use VaR and ES to assess market risk and exclusively disclose the risk so that investors and other stakeholders can be informed about the level of risk the industry is exposed to.

In Ghana, extensive studies have been conducted on risk management, credit risk, liquidity risk, operational risk and market risk on profitability and bank performance, the risk level of listed banks, and the relationship between risk management and bank performance and profitability (Kumah & Sare, 2013; Ofosu-Hene & Amoh, 2016; Gadzo & Asiamah, 2018; Boateng, 2019). The findings from these studies show that there is a thin line between risk and the performance and profitability of banks. Ofosu-Hene and Amoh (2016) sought to model the risk index of listed banks on the Ghana Stock Exchange (GSE) with data spanning from 2007 to 2014. In their study, they used financial ratios to construct an index for risk. Their findings showed that the risk level of the listed banks was increasing and the bank regulator needed to implement solvency measures. Ofosu-Hene and Amoh (2016) further acknowledged the growing interest in using VaR to model risk among other risk estimators in Ghana, they failed to adopt this risk measure to quantify an overall bank risk index for the banks.

Following the 2016-17 AQR, the regulator reported that banks should adopt excerpts from Basel II and III to ensure a viable and solvent financial sector. To model financial risks, the Basel III Accord was proposed as a supervisory and regulatory framework for banks and is expected to be fully adopted in 2027 (Owusu Junior & Alagidede, 2020). Because of the interrelatedness of banks' operations arising from the nature of their operations and competitiveness (Biekpe, 2011) and their exposure to market risk, their risk levels must be assessed in a regulatory setting to avoid the collapse of the economy (Polizzi & Scannella, 2020). Irrespective of banks' initiative to try and mitigate banking risk in Ghana, no research has emphatically assessed the market risk of listed banks in line with the Basel III regulatory framework neither is there any literature that has sort to rank the banks using their market risk levels. Thus, this study bridges this gap in the literature in Ghana by assessing the market risk of listed banks on the GSE using VaR and ES.

Purpose of Study

The purpose of this study is to model the exposure of the listed banks on the GSE to market risk following the 2017 financial reform of the banking industry using the Basel III regulatory framework for enhanced risk management.

Research Objectives

The following objectives would help assess the market risk level of the listed banks in Ghana:

1) To assess the nature of risk arising out of the returns distributions of listed banks;
2) To assess the risk of the listed banks using the quantitative measure of VaR and ES; and
3) To nominally rank the listed banks for investors' diversification purposes.

Research Questions

The research questions of the study are as listed as follows:

1) What is the nature of the distribution of the returns of the listed banks?

2) What is the risk of the listed banks using Value-at-Risk and Expected Shortfall?
3) What is the nominal rank of the listed banks for investors' diversification purposes?

Significance of the Study

Banks operate in a highly regulated environment laden with so much risk. The collapse of a single bank would send shivers down the market place and disrupt the country's economy. Therefore, regulators need the tools to monitor the health of these banks. Thus, the outcome of this study would inform bankers, management, shareholders, and investors, as well as the regulator on the effectiveness of using VaR and ES to capture bank risk. The risk estimates from GARCH-based VaR and ES has taken into account the stylised facts in the tails of the return distribution avoiding the underestimation of market risk. This would also provide additional information on the industry's risk level other than what is reported in financial statements, to guide investors' and management decisions. For banks, it would add to the tools used to assess their level of exposure to market risk. Lastly, this study could guide future researchers in assessing bank market risk.

Delimitation of the Study

There are many financial institutions in Ghana. Albeit, banks are the largest among financial institutions such as credit unions, rural banks and similarly non-bank financial institutions. The study was conducted on the listed banks from 2017 to 2021, using single-regmime conditional models for time-dependent regulatory downside risk measures.

Limitations of the Study

There are a few limitations to the study. The research is limited to only the listed banks in Ghana. The conditional volatility models used did not consider structural (regime) breaks. Also, the conditional volatility models used for the single predictions of VaR and ES are not time-varying. The ES risk predictions were not ranked because ES is inelicitable.

Organisation of the Study

This study is organised into five chapters: Chapter One is the introduction of the study providing evidence for the gap and the purpose of the study, the objectives and research questions to carry out the purpose, significance, delimitations, and limitations of the study, as well as the study background. Chapter Two presents the theories underpinning the study's objectives, conceptual and empirical reviews. Chapter Three describes the data collection procedure and instrument, the population and sampling, analytical tools and the philosophy and design backing the study; Chapter Four presents the results (descriptive and theoretical findings) which are discussed in relation to other literature. Chapter Five presents a summary of the study, conclusions and recommendations emanating from the theoretical findings as well as, recommendations for investors and banks.

CHAPTER TWO

LITERATURE REVIEW

Introduction

The study sought to assess the risk of listed banks in Ghana. This chapter presents the theoretical, empirical and conceptual reviews of this study. The theory of systemic risk and theory of financial regulation are the theories that underpin how systemic failure leads to the implementation of regulations intended to protect the banking system. The empirical review is on tail distributions and the regulatory risk measures of VaR and ES. The conceptual review sheds light on the market risk, the Ghanaian banking sector and market risk disclosure.

Theoretical Review

The theoretical connection among the research objectives was drawn using the theory of systemic risk and the theory of financial regulation. These two theories were reviewed because the risk in the banking system which is systemic, calls for regulations intended to limit the impact of the risk on the sector and economy to prevent financial crises. The efficient market hypothesis is also reviewed because this study assumes that the stock market is efficient; thus, stock returns can be used as a proxy for profit and loss data to model the market risk of the listed banks.

Theory of Systemic Risk

Systemic risk is a phenomenon that goes beyond a particular bank due to the systematic nature of banking operations and involves market wide connectedness (Diebold & Yılmaz, 2014). Diebold and Yilmax (2014) showed that systemic risk in banking is due to interconnectedness and contagion effects in the sector. Implicitly, financial institutions are more vulnerable to systematic risk than other sectors because of the structure of the accounts maintained by banks and the complexity of their network structure and its connectedness (Diebold & Yilmaz, 2014; Demirer et al., 2018). Systemic risk can cause the collapse of an entire financial system due to the system's connectedness and interdependence (Diebold & Yilmaz, 2014; Demirer et al., 2018; Scheibe & Blackhurst, 2018; Bricco & Xu, 2019; Jackson & Pernoud, 2021). In another vein, systemic risk is likely due to the activities of market participants in an interconnected financial market (Diebold & Yilmaz, 2014; Caccioli et al., 2018; Demirer et al., 2018; Bricco & Xu, 2019).

Following the 1929 stock market crisis, which triggered the Great Depression in the US, the theory of systemic risk was promulgated to explain the connectedness and interdependence between different levels of the financial system and institutions (Diebold & Yılmaz, 2014; Schwarcz, 2008; Scheibe & Blackhurst, 2018; Jackson & Pernoud, 2021). The theory of systemic risk illustrates how weaknesses in a financial system may set off a chain reaction that eventually leads to the system's collapse at a more cost than individual bank failure (Diebold & Yilmaz, 2014; Martinez-Jaramillo et al., 2010; Scheibe & Blackhurst, 2018; Jackson & Pernoud, 2021). The theory of systemic risk has been adopted in economics and finance to explain how regulated entities can cause instability that leads to financial upheavals in an economy (Acharya, 2009; Martinez-Jaramillo et al., 2010; Diebold & Yilmaz, 2014). So, in banking, for example, the theory of systemic risk has been proposed to explain banking crises and contagions (Acharya & Yorulmazer, 2002; Acharya & Steffen, 2013; Iannotta & Pennacchi, 2012; Bricco & Xu, 2019), the herding effects of banks (Acharya & Yorulmazer, 2007; Acharya & Steffen, 2013), and the probability of increased risk for banks holding correlated portfolios (Acharya & Yorulmazer, 2002).

In this research, the theory of systemic risk is proposed in the framework of a joint failure of banks due to contagion effects (Acharya & Yorulmazer, 2002; Summer, 2003; Iannotta & Pennacchi, 2012; Acharya & Steffen, 2013). Hypothetically, the theory of systemic risk is based on the inherent fragility and instability of the financial system and the interconnectedness of the banking system, which increase its potential to cause financial crisis (Currie, 2006; Diebold & Yılmaz, 2014). Hunter and Marshall (1999) proposed that systemic risk is substantially magnified by financial markets, leading to reduced investors' confidence; loss of economic output, or reduction in economic efficiency and ultimately calls for a policy response.

This study adopted the theory of systemic risk because of the theoretical implications that there is risk in banking and that this risk is systemic to the sector (Bolt & Tieman, 2004; Elsinger et al., 2006; Diebold & Yilmaz, 2014; Zins & Weill, 2017). The systemic risk in banking as theorised could cause substantial losses to the financial system and economy; hence regulators have sought to reduce the impact of systemic risk on the economy by implementing regulations (the Basel Accords). In implementing regulations, regulators intend to remedy the system and ensure stability amid the competitiveness of the financial system. Freixas and Santemero (2003, p. 2) assert that "regulation is the rational response of the government to these new market failures."

Theory of Financial Regulation

In theory, regulations in the financial industry are intended to protect the sector and the customers against systemic risk, promote confidence in the financial system and ensure a stable economy (Stigler, 1971; Davis, 1995; Goodhart, 1998). Diamond and Dybvig (1983) documented that a banking system without regulations frequently experience systemic failure which would lead to market and financial crises. Currie (2006) and more recently Battiston et al. (2016) suggested that the rationale for the theory of financial regulation is the need to recognise that financial regulation is required to promote a stable economic structure and to prevent the increasing price volatility that can lead to financial crises. Morgan and Yeung (2007) emphasised that with effective financial regulation, market failure is remediable. And this is what the BCBS seeks to achieve through the Basel Accord(s) intended to provide a standard for bank regulation.

The regulation in banking is subject to amendments because ineffective financial regulation can cause market failure (Uche, 2000; Freixas & Santomero, 2003; Currie, 2006; Asquer, 2018). Thus, to protect customers' and investors' interests, ensure solvency, safe and a sound financial system that promotes confidence, financial regulation should be successive and reassessed consecutively (Kane, 1997; Goodhart, 1998). The constant transition of financial regulations is a result of the adaptation and evolution of financial markets. Thus, financial regulation could be amended as a response to crises; keeping track of the varying financial risks; and closing gaps exposed in the financial system during crises (Freixas & Santomero, 2003; Currie, 2006; Brunnermeier et al., 2009).

The Basel Committee on Banking Supervision (BCBS), since 1988, was formed by the Bank for International Settlements (BIS) to provide a standard for bank regulation. The BCBS has promulgated three accords (I, II, III) in an attempt to strengthen banking regulation to ensure safety and solvency, and promote financial stability globally. The Basel I (BIS, 1992) was geared towards a minimum capital requirement for banks and Basel I (BIS, 1999) was amended to Basel II to include a supervisory review process and market disciplines of banks under normal market conditions. The Basel III (BCBS, 2013; BCBS, 2019) is a transition from Basel II consequent to the exposure of the financial system to the 2007-08 GFC to move from using VaR to ES and comparative backtest to measure the risk of a position by considering both the size and likelihood of losses above a certain confidence level and under stressed market conditions.

The theory of regulation supports this study's choice of risk measures for modelling market risk of the listed banks. In line with the Basel III supervisory and regulatory framework, financial institutions are expected to use VaR and ES as quantitative measures of market risk (BCBS, 2013). The VaR and ES account for the shortcomings in either risk measure to establish a more robust measure that can be used to monitor banks' risk exposure (Taylor, 2019; Owusu et al., 2021).

Efficient Market Hypothesis

A market is efficient when all material information related to the pricing of an asset is fully reflected in its price (Fama, 1965; Fama, 1970). Fundamentally, in an efficient market, it would be impossible to capitalise on information in the market to make abnormal profits (Fama, 1965; Fama, 1970;

Rossi & Gunardi, 2018). The extent to which asset prices reflect market- and stock-based information is hypothesised as weak, semi-strong and strong forms of market efficiency (Fama, 1965; Malkiel, 2003). The weak market efficiency states that, all past information about an asset is fully reflected in its price and follows a random walk process; semi-strong market efficiency hypothesises that asset prices fully reflect past and public information; and when stock prices reflect all available information (past, public and private) and it is impossible for an investor to capitalise on insider information, the market is considered a strong-form efficient market (Fama, 1965; Fama, 1970; Magnusson & Wydick, 2002).

Ghazani and Jafari (2021) reported that the reasoning behind market efficiency is that asset prices in an efficient market follow a random-walk process because all available information about prices is already mirrored in the asset price. Also, the efficient market hypothesis theorises that a stock market is efficient because investors act instantaneously on available information and stocks are traded at the fairest value making it impossible for any investor to make abnormal profits (Malkiel, 2003). The transmission of the available information in the market and on the asset as captured in assets' pricing is primarily reflected in the instantaneous demand and supply of the assets.

Fundamentally, news on assets and in markets (e.g., events, crises, dividend payouts and firm decisions) and how investors respond to such news determine the level of efficiency in the market (Shleifer, 2000). The cost of information to investors also determines their dynamic reactions in the market (Gilson & Kraakman, 1984). The value investors place on available information and at what cost shows the level of efficiency in the market. Gilson and Kraakman (1984) reported that the lower the cost of information on the market and asset, the easier it is to distribute to investors in the market. The variation in the asset prices based on the information in the market is also influenced by the relative importance attributed to the information and the investors' preference for risk in the market (Farmer & Lo, 1999).

In line with the efficient market hypothesis, this study uses stock returns as a proxy for profit and loss data of the listed banks in Ghana to assess their market risk (Su et al., 2011).

Conceptual Review

In this section, concepts that are important for understanding some of the terms used in the study are reviewed.

Risk and Risk Assessment

Risk is inherently controversial because the concept is subjective (Fischoff et al., 1984). Holton (2004) criticises researchers' intent to define risk, acknowledging that risk is uncertainty. The author argues that there is nothing like a true risk. Risk is perceived due to actions that expose one to an actual threat that is likely to reoccur due to uncertainty (Holton, 2004). Thus, perceived risk must be assessed based on actual risk. Apostolakis (2004) affirmed that it is more effective to make decisions that are implementable based on risk-informed data instead of risk-based data.

A risk that manifests as contagion in the banking system is seen as bad and therefore inexcusable (Elsinger et al., 2006; Das & Rout, 2020). Generally, in finance, risk arises because of investors' quest to capitalise on some investments and is further considered systemic in banking (Campbell, 1996; Malkiel & Xu, 1997; Elsinger et al., 2006; Cont & Moussa, 2010; Benoit et al., 2017; Zins & Weill, 2017; Das & Rout, 2020; Cornell, 2021). The systemic nature of bank risk arises from banking trading and operational activities (Iannotta & Pennacchi, 2012); competition (Kick & Prieto, 2015); and stakeholder expectations (Fortin et al., 2010). Furthermore, in banking, risk could be either systemic (systematic) or unsystematic depending on the bank's activity (Tursoy, 2008). There are types of risks that fall under either of these categories of systemic and unsystematic risk. Bank risk includes operational risk, liquidity risk, credit risk, default risk and market risk (Santomero & Babbel, 1997; Ekinci, 2016; Danisman & Demirel, 2019; Duho et al., 2020; Okafor & Fadul, 2019; Rabie, 2020). In the context of this research, risk is defined as the likelihood of loss in the value of stock prices (Holton, 2004; Elsinger et al., 2006; Das & Rout, 2020).

Risk assessment involves analytic techniques to quantify and create awareness to provide relative interventions for the benefit of decision making (National Research Council (NRC), 2009). With realistic risk assessments, accurate predictions can be made to avoid potential future effects and costs (Wilson & Crouch, 1987; Aven, 2016). However, risk assessment is subject to either overestimations or underestimations and could lead to unrealistic decision making that is bound to be ineffective (Gambrill & Shlonsky, 2000; English & Graham, 2000). This is why NRC (2009) opined that risk assessment should be done in a regulatory framework so that nothing is overlooked during an assessment.

When a realistic risk assessment is conducted, it reduces the likelihood of future risk based on the effective decisions that can be taken to reduce, avoid or manage the occurrence of risk (Wilson & Crouch, 1987). Studies on the risk assessment of banks such as Elsinger et al. (2005), Goodhart et al. (2005), Elsinger et al. (2006), van Greuning and Bratonovic (2009) and Gauthier and Souissi (2012) have used realistic models to assess the risks of banks. In all these studies, the authors provided realistic risk estimates that were relatively able to quantify bank risk. In the context of this study, risk assessment is defined as measuring risk analytically using a regulatory framework for bank risk assessment.

Market Risk

In banking, market risk is considered important because of its systemic nature (Scannella, 2018; Das & Rout, 2020; Polizzi & Scannella, 2020) and has received much attention from BCBS. BCBS has shown much interest in market risk which has been strengthened in the Basel II and Basel III Accords geared toward preventing financial crises as a result of market failure (BCBS, 2016). The BCBS defines market risk as "the risk of losses in on- and off-balance sheet positions arising from market prices including interest rates, exchange rates and equity values" (BCBS, 2016, p. 10).

A bank's market risk results from its inability to predict changes in credit spreads, foreign exchange, equity prices, interest rates and commodity prices in a capital market in its market-making activities (Rabie, 2020). Market risk also exists when a financial or non-financial entity or an individual suffers losses as a result of volatility in positions in an economic market, which is often connected to interest-sensitive debt instruments, equities, currencies, commodities, and credit spreads (van Greuning & Bratanovic, 2020). van Greuning and Bratanovic (2020) limited their definition of market risk to the banking sector and defined it as a loss in a bank's on- and off-balance sheet holdings due to changes in market prices (BCBS, 2016; Scannella, 2018; Scannella & Polizzi, 2018). Market risk is also the risk of losing money or loss in portfolio values due to changes in interest rates and prices, exchange rates, equities and commodity prices (Hirtle, 2003; BCBS, 2016; Ekinci, 2016; Ramirez, 2017).

According to van Greuning and Bratanovic (2020), interest rates, exchange rates, equities and commodity prices are the components of market risk. While investors try to diversify away from the components of market risk, each contributes to an increasing level of market uncertainty, causing an increase in the general level of market risk (van Greuning & Bratanovic, 2020). Moreover, Bugár and Ratting (2016) state that market risk is a comprehensive risk inherent in all investments and trading activities, confirming that market risk is systemic in the banking industry (Dowd, 2007; Das & Rout, 2020; Rabie, 2020). Studies have also shown that market risk is more pervasive and can lead to market failure and financial crises (Bugár & Ratting, 2016; Rabie, 2020).

The nature of market risk is such that whenever there are fluctuations in the financial market, the fair values of the financial instruments gyrate, leading to losses and thus affecting the value of a bank's position in the market (Scannella, 2018; Duho et al., 2021). Banks that trade in stock markets are subject to market risk due to the sensitivity of the trading instruments' market prices (Ramirez, 2017; Das & Rout, 2020). For this study, market risk is defined as banks' exposure to risk in the stock market due to fluctuations in their stock prices.

The Ghanaian Banking Industry, Transformation and Regulations

In 1920, banking was introduced in Ghana. From that period until the early 1950s, Ghana had two banks (Bank of British West Africa, now Standard Chartered Bank Ghana Ltd., and the former National Bank of South Africa now, Absa Bank Ghana Ltd.) providing financial needs to the colonial administration and their enterprises. However, in 1953, the GCB Bank Plc. was established to provide financial support to traders and farmers and to reduce autonomy and control from foreign banks. After Ghana gained independence in 1957, it established the BoG as its central bank (Obuobi et al., 2020; Amenu-Tekaa, 2021). The banking industry dominates the financial sector and currently, there are 23 commercial banks with eight banks listed on the GSE (Antwi-Asare & Addison, 2000; Owsu-Antwi, 2009; BoG, 2020).

Of all the 23 commercial banks, a minimum capital requirement of GH¢ 400 million is required for a license for operation and serves as good faith to the Regulator and customers that you are in a stable financial system. All the banks in Ghana are regulated by the Bank of Ghana. The Regulator of BoG is interested in ensuring a viable financial system. Though the primary control of banks is from the BoG, banks listed on the stock exchange are also required to comply with the Stock Exchange listing regulations as required by the Securities Industry Act, 2016. The ownership structure of the banks in Ghana is with respective shareholders at ratios of stock holding capacity. Thus, the ownership of most banks is not quite definite based on who has the highest holding power at a point in time. However, the Ghanaian government has 100% sole ownership of the Central Bank; gives the government full control over the country's resources.

As early as 1987, the sector had been subjected to reforms due to the financial crisis that broke out in the 1980s as a result of banks under capitalisation. In 1983, the Economic Recovery Program (ERP) was rolled out to revive the country's moribund industries and accelerate growth and development (Antwi-Asare & Addison, 2000). With literature reporting that the financial sector contributes to economic growth and development, the government also had to implement measures to strengthen the financial sector. In 1987, the Financial Sector Adjustment Programme (FINSAP) with the support of the Financial Sector Adjustment Credit (FSAC; World Bank) was put in place to ensure the liberalisation of the banking industry and markets, restructure the credit section of banks to regulate the level of non-performing loans, effectively manage for bank supervision, adopt a uniform accounting and auditing standard, and implement a regulatory framework toward financial stability (Antwi-Asare & Addison, 2000; Owusu-Antwi, 2009; Bokpin, 2016).

Long after the 1987 financial reform, the Financial Sector Strategic Plan (FINSSP) together with the FINSAP in 2003, contributed to financial mobilisation, increased levels of savings and deposits, and competition between the banks and generally contributed to strengthening bank positions (Frimpong, 2010; Biekpe, 2011; Bokpin, 2016; Kamasa et al., 2020). Several banking laws and regulations were implemented in-between these reforms. Bokpin (2016) claims that banking is the financial sector's most highly regulated industry because the central aim of the BoG is to implement comprehensive monetary policies that stabilise prices and provide an enabling environment for long-term growth and development (BoG, 2019). Several laws and global regulatory frameworks have also been passed and implemented to ensure a stable financial sector.

The laws introduced into the banking industry are the: Banking Law, 1989 (PNDCL 225) – revised under FINSAP (1989); BoG Law, 1992 (PNDCL 291) which – awarded supervisory roles to the central bank; Bank of Ghana Act 2002 (Act 612) – heighten the regulatory and supervisory role of the BoG, Banking Act, 2004 (Act 673) – replaced Banking Law, 1989 (PNDCL 225) to correct improper and unlawful bank practices; Banking Act 2004 (Amendment 783) replaced by Banking Amendment Act, 2007 (Act, 738) – ensuring stability and promoting offshore financial services; Foreign Exchange Act, 2007; Credit Reporting Act, 2008; Lenders and Borrowers Act, 2008; and the Banks and Specialised Deposit-Taking Institutions Act 930 and the Deposit Protection Act 931, all of 2016 (Alhassan & Ohene-Asare, 2016; Kamasa et al., 2020). Other global regulatory and supervisory frameworks adopted by banks in Ghana are the IFRS 9 and excerpts from Basel II and III (Amenu-Tekaa, 2021).

Market Risk Disclosure in the Banking Industry

In order to provide information on risk and how managers mitigate risk to make profits in their various institutions, they are required to disclose such risk information to stakeholders to inform their investment decisions (BCBS, 1996; Linsley et al., 2006; Nahar et al., 2016; Scannella, 2018; Polizzi & Scannella, 2020). Congruently, the Stock Exchange Commission (Securities and Exchange Commission, 2009) requires that market risk be disclosed to provide transparency to investors. However, the assessment and disclosure of bank market risk exposure is a critical problem for every bank shareholder because excessive risk exposure for one bank can negatively influence the overall stability of the financial system (Scannella, 2018; Polizzi & Scannella, 2020). Heinle and Smith (2017, p. 1463) aver that "from a theoretical perspective, systematic risk disclosure should have a greater impact on market prices". Implicitly, regulators would have to be sketchy about the amount of information they disclose about their risk profiles so that investors do not misinterpret (Linsley et al., 2006) because such disclosures could affect expected returns (Polizzi & Scannella, 2020).

Inadvertently, risk disclosure is important to stakeholders and management to ensure a stable financial system. The Securities and Exchange Committee, under the board and management structure and process, public institutions (of which banks) are required to disclose their risk management objectives, systems, and activities and indicate how they identify and manage risks that are in line with their operations (Securities Industry Act, 2016 (Act 929)). In addition, Basel III proposed to primarily mitigate the effect of market risk and stipulated that the predictions from the VaR and ES should be disclosed at regular intervals to stakeholders.

In Ghana, banks disclose their risk due to the increasing demands of the regulatory frameworks – IFRS 7 (Financial Instruments: Disclosure) and Basel II (Market Discipline) – and stakeholders' demand for transparency (Savvides & Savvidou, 2012; Nahar et al., 2016). From the annual financial reports of the listed banks, it is clear that risk disclosure is something they do not deal with lightly. In the various annual reports, readers would clearly understand the contents of bank risk, what the banks expect, how the risk comes about, and the quantified measure of risk (Buabeng, 2018). Banks generally fail to inform investors about how the risks are quantified and, what goes into their risk models. Also, an acceptable disclosure of risk offers a market signal of a bank's activity, which is helpful to the regulator(s) tasked with reducing bank(s) risk exposure (Buabeng, 2018).

Over time, the regulator must carry out an AQR to assess banks' risk and sustainability levels. The AQR, though a strategic review of loans, reveals any other risk that a bank could be exposed to, and shows the sustainability of a financial system. In 2015-16, the regulator of BoG undertook an asset quality review on Ghanaian banks and concluded that several banks were under capitalised, and a couple of banks were operating under false licenses among other factors like non-performing loans, poor management and supervision of operations revealing the vulnerability of the banking sector (BoG, 2017; Aboagye, 2020; Affum, 2020). The aftermath of this was the sectoral clean-up that resulted in many mergers, liquidations and takeovers intended to strengthen banks and ensure a more healthy and stable banking sector. Correspondingly, the regulator assured the Ghanaian economy that through the restructuring of the industry, the sector would perform better and this increased the level of confidence in the sector again (PwC, 2019; Affum, 2020; Amenu-Tekaa, 2021).

Empirical Literature

Here, literature on tail risk, VaR and ES as used in other studies were discussed based on the study's objectives. Thus, earlier literature on tail distribution risks as captured by stylised facts and how they are modelled and literature that have used conditional models to estimate VaR and ES predictions were reviewed.

Tail Distributions of Returns

Over decades, asset returns were theorised as having normal tail distributions (de Moivre, 1733; Gauss, 1809). But asset returns are heteroscedastic, non-normal, fat-tailed, and often skewed (Mandlebrot, 1963; Theodossiou, 1998; Bollerslev, 1986; French et al., 1987; Engle & Gonzalez-Rivera, 1991; Engle, 2004). Literature has proven that investor characteristics in the markets are a factor contributing to the non-normality of return distributions. The efficiency of the market (Fama, 1965) and investor response to news on the changing market conditions as theorised by the adaptive (Lo, 2004) and the need of investors at particular times as in the heterogeneous (Müller et al., 1997) market hypotheses contribute to why the distributions of returns are far from normal distributions. As a result of investor reaction to the news on the market, the tails of distributions are not normally distributed and this leads to the likelihood of tail risks (Peiro, 1999; Härdle & Mungo, 2008; Karoglou, 2010; Blau, 2017; Bessembinder, 2018). The stylised facts such as heteroscedasticity, non-normality, fat-tails and skewness are present in the tails of the distributions of an asset return and need not be ignored because its compounded effect could be aggravating.

The tails of a return's distribution provide additional information on assets which guides investment decision making and can predict the risk of assets. The tail risk of returns distributions can predict the pricing of an asset and theoretically, this is reflected in investor demand for the assets based on the stylised facts that the tails seem to show (Kraus & Litzenberg, 1976; You & Diagler, 2010; Kelly & Jiang, 2014; Van Oordt & Zhou, 2016; Wang, 2016). Tail risk may be underestimated but its effect over a long horizon could be large and overwhelming to the market and investors because of its predictive power (Wang, 2016). Thus, for every market, the tail distribution of the assets should be critically studied to avoid extreme shocks (Liu & Wang, 2021).

Empirical evidence has shown that financial assets' tail distributions are mostly skewed and heavy-tailed (Harvey, 1995; Bekaert & Harvey, 1997; McNeil & Frey, 2000; Engle, 2004; Cajueiro & Tabak, 2004; McNeil et al., 2015). Because investor reactions are unpredictable, it is quite unnerving to just assume the nature of the tails of return distributions. Over time, higher moments such as skewness and kurtosis have been espoused to assess the level of tail risk in a distribution (Harvey, 1995; Bekaert & Harcey, 1997; Reiss & Thomas, 1997; Mabitsela et al., 2015). Babikir et al. (2019) opined that higher moments of kurtosis and skewness provide additional information on the distributions of data series that pre-inform conditional innovations to accurately fit the distributions of a model (Nolan, 2003; Yan, 2005). Wilhelmsson (2009) showed that for the tail distributions of asset returns, skewed leptokurtic returns distribution is what should be considered in assessing the nature of the tail risk.

The higher moments of kurtosis and skewness as argued by Engle (1982) are time-dependent and most accurately good for conditional volatility models. Using conditional volatility models, assumptions are made as to how to capture stylised facts in the tails of a distribution. Thus, using the higher moments of kurtosis and skewness, choosing innovations to capture the stylised facts in a tail distribution would be much easier. Also, in some cases, kurtosis and skewness are moments used to explore the interdependence and contagion among assets due to their characteristics in explaining tail risk (Hadar & Seo, 1990; Chang et al., 2013; Amaya et al., 2015; Barinov, 2018; Bessembinder, 2018; Müller & Wagner, 2018). These moments are used to describe return distributions, especially in the tails to avoid the assumptions of any structural restrictions (Hansen, 1994). However, these higher moments have implications on how to model risk; thus, several distributional innovations are modelled to fully capture the stylised facts in the tails of a distribution.

Based on the distributional characteristics of financial asset returns, several studies have pioneered distributional innovations that can be assumed in conditional volatility models to capture the tail risk of a series so as not to underestimate risk. The symmetric and asymmetric distributional innovations such as the Gaussian (-norm) (Gauss, 1809; Bollerslev et al., 1994), Student-*t* (-std) (Gosset, 1908), generalised error distribution (-ged) (McDonald & Newey, 1988; Nelson, 1991), normal inverse gaussian (-nig), Johnson Su's family (-jsu) (Shenton & Bowman, 1975; Johnson, 1949), generalised hyperbolic skew-t distribution (-ghst) (Aas & Haff, 2006), generalised hyperbolic distribution (-ghyp) (Barndorff-Nielsen, 1978), generalised pareto distribution (-gpd) (Holmes & Moriarty, 1999), skewed Gaussian (-snorm) (de Moivre, 1733; Gosset, 1908; Hansen, 1994), skewed studen-t (-sstd) (Fernández & Steel, 1998), skewed generalised error distribution (-sged) (Theodossiou, 1998) are among the distributions that have been used to capture asymmetry and fat-tails (Galanos & Kley, 2022). Each of these innovations has a finite feature that contributes to capturing asymmetry, fat-tails and volatility clustering.

Researchers have successfully used these distribution innovations and have discovered their effectiveness in capturing fat-tails, large kurtosis and skewness in the tails of distributions. Hung et al. (2008) conducted a study using energy commodities and sought to explore the VaR of crude oil (Brent and WTI), heating oil, propane and gasoline. To construct a realistic conditional model that can capture the tails of these commodities, they used GARCH with Gaussian, Student-*t* and heavy-tailed (-ht) distribution innovations. They were able to show that energy commodities are heavily-tailed because the GARCH-ht was more accurate in modelling the returns of the energy commodities. Another study by Lyu et al. (2017) also showed that asymmetric distributions (skewed GED, generalised hyperbolic skewed Student-*t* and generalised asymmetric Student-*t*) produce accurate risk estimates for energy commodities using the crude oil (Brent and WTI) market returns.

Lin and Shen (2006) also wanted to find out whether Gaussian, Student-*t* and extreme value theory (EVT) innovations could estimate accurate VaR predictions using stock returns (1990-2993). Among all the distributions used to model the tails, Student-*t* was more accurate in making the VaR predictions for the S&P500, FTSE100, NASADQ and DAX stock returns. Mabitsela et al. (2015) sought to model the VaR of four stocks on the Johannesburg stock exchange and the S&P500 and FTSE/JSE40 stock indexes. Because VaR underestimated risk during the GFC based on its assumption of normality, the stock returns of these stocks were modelled comparatively using the normal inverse gaussian distribution against the Gaussian, Student-*t* and skewed Student-*t* distributions. Their results proved that the normal inverse gaussian, Student-*t* and skewed Student-*t* distributions captured the heavy tails in the stock returns.

Nadarajah and Kwofie (2022) found that the Ghanaian automobile industry data show heavy-tailed distributions as shown by the kurtosis. Nadarajah and Kwofie (2022) used a composite lognormal distribution (Nadarajah & Bakar, 2013) that models the risk in the body and tails of the distribution based on several embedded distributions and reported that the inverse Burr distribution –takes into account the shape and parameters of the entire distribution– was more suitable for modelling the tails based on the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Nortey et al. (2015) adopted the conditional theory of extreme values and fitted the tail distributions of the GSE all share indexes from 2000 to 2010 based on the ARMA-GARCH model. Using the GDP based on the peak over threshold (POT) and the extreme values in the all share index; they successfully modelled the heavy-tails of the all share index and further used it for assessing VaR and ES. Their adoption of the GPD was based on the risk level in the left tail as opposed to the right tail risk.

Korkpoe and Kawor (2018) undertook a study using the Bayesian Threshold GARCH (TGARCH) in the single and regime-switching states and fitted the conditional model with skewed Student-*t* and *i*-*t* innovations. They used the GSE all share index returns in both the single and switching regime because a number of the literature were reporting that the regime-switching conditional models are better at modelling the returns of an asset. Upon their analysis, they found that the tails of the GSE all share index were fat-tailed and the skewed Student-*t* distributions could better model the returns in the single and regime switching states comparatively. Korkpoe and Howard (2019) further explored the volatility model of sub-Saharan African stock exchanges using conditional regime-switching models. They found that the skewed Student-*t* was a better fit for Ghanaian stocks in the regime-switching GJR-GARCH(1,1). For other stock exchanges as the Nairobi and Botswana stock exchange indexes, the EGARCH skewed Student-*t* was also the most suitable for modelling the distributions in the tail. The Nigerian stock exchange tail distribution was best captured by the Student-*t* distribution in the GJR-GARCH regime-switching conditional models (Korkpoe & Howard, 2019). The results show that the African stock market is mostly characterised by skewed heavy tails as also proved by Korkpoe and Owusu Junior (2018) in the Johannesburg stock exchange tail distributions.

There is a consensus in literature proving that the distributions of returns are fat-tailed and asymmetric. While conditional models with both symmetric and asymmetric innovations better capture the tails of return distributions, in line with their stylised facts, no literature has explicitly identified superior distribution innovations (Angelidis & Benos, 2008; Lechner & Ovaert, 2010; Rachev et al., 2010). This is because the level of asymmetry and fatness in tails defers across assets and is time-dependent based on investor response (Rachev et al., 2010). Modelling the stylised facts in the tails of the distributions helps to predict accurate estimates of risk measures because it avoids underestimation of risk (Angelidis & Benos, 2008; Hung et al., 2008; Lechner & Ovaert, 2010; Rachev et al., 2010; Lyu et al., 2017; Nadarajah & Kwofie, 2022). In the Ghanaian banking industry, no study has looked at the characteristics of the tails of their distributions. Using the higher moments of kurtosis and skewness would pre-inform the selection of which distribution innovations to use in the conditional models to provide accurate risk predictions and avoid underestimation of risk.

GARCH-based VaR and ES

The interrelatedness and complex nature of the banking system can lead to crises. Banking is one of the most regulated sectors in the financial system. The Basel Committee on Banking Supervision (BCBS) is globally recognised for implementing supervisory and regulatory frameworks for banks. Based on the aftermath of the GFC in 2007-08, the Basel Committee moved from using VaR to ES as a risk measuring tool for market risk. This section presents a review of the use of VaR and ES in measuring risk (market risk) in finance and other disciplines.

VaR has been a *de rigueur* risk measure and portfolio risk management criterion for many years. However, as a risk metric, it was unable to predict the GFC. This resulted in the promulgation of ES as in the Basel III framework to measure market risk in stressed market conditions by moving from VaR to ES (Fissler et al., 2015; Kellner & Rösch, 2016; Owusu Junior & Alagidede, 2020; Wang & Zitikis, 2021). In line with the requirements and framework of the Basel Accords (I, II – VaR, and III - VaR and ES) are used for regulatory internal risk modelling. Literature has explored the shortcomings of both risk measures and showed that jointly, both measures are effective in modelling risk (Fissler et al., 2015). VaR is not coherent (Artzner, 1997) but elicitable (Patton et al., 2019), and is insensitive to tail risk because it ignores losses beyond a certain level unlike ES (Chang et al., 2019; Owusu Junior et al., 2019) and also, does not conform to sub-additivity risk property

(Yamai & Yoshiba, 2002). For all the shortcomings in either risk measure, the other makes up for.

Although the ES risk measure is not elicitable (Fissler et al., 2015), the BCBS has pushed for its use. The ES risk measure is coherent, but because of its inelicitability, most literature do not backtest the ES forecasts (Aloui & Ben Hamida 2015; Owusu Junior et al., 2021). However, Fissler et al. (2015) argued from the regulatory sense that ES is a risk measure in a regulatory sense and should be backtested to prove that the forecasts are accurate and meet the condition of a strictly consistent scoring function ensuring elicitability. Following that, several studies have several methods to backtest the accuracy of ES forecasts (Fissler et al., 2015, Fissler & Ziegel, 2016; Wang & Zitikis, 2021; Pradha & Tiwari, 2020; Maciel, 2021).

Also, since it had become important for regulators to transition from VaR to ES, Wang and Zitikis (2021) undertook a study and reviewed the axiomatic foundation of ES. To show that ES has theoretical characteristics of risk measures, specifically in the context of a portfolio, capital calculation, risk management and decision making this study was conducted. ES is a coherent risk measure (Artzner, 1997) used in current financial regulation and has some theoretical properties such as – monotonicity, law invariance, prudence, and no reward for concentration. Wang and Zitikis also concluded from a series of reviews that ES rewards portfolio diversification and penalises risk concentration, especially and intuitively, not shared by any other risk measure.

Kellner and Rösch (2016) also explored how a shift from VaR to ES would better predict market risk since VaR had failed to predict the GFC. In doing so, the authors compared VaR at 99% to ES at 97.5% as proposed in the

BCBS III to analyse the possible consequences of the shift in risk measures. Kellner and Rösch used negative log returns to measure the level of sensitivity of the VaR (99%) and ES (97.5%) for S&P 500, Dax and Nikkei 225, Euro and US Dollars as well as Euro and Yen from 2005 to 2015 and backtested the predictions of ES based on the test statistic of Acerbi and Szekely (2014). The results showed that ES is more sensitive to regulations and misspecification of predictions than VaR at 97.5% and reaffirmed the tail sensitivity of ES (Chang et al., 2019).

Lazar and Zhang (2020) explored the effectiveness of VaR and ES during the COVID-19 pandemic when the market was in a stressed condition after the passage of Basel III. They sought to explore and compare the market risk position of equities and commodities markets from 2001 to 2020 during the GFC and the COVID-19 pandemic. Their empirical analysis showed that market risk was overestimated during the COVID-19 pandemic using ES compared to the GFC because regulatory capital increased after the GFC. Implicitly, the market risk estimates obtained over a short period was more reasonable than those obtained over a longer period because of the contagion effect of information from the shorter time range due to tail risk (Bessembinder, 2018; Müller & Wagner, 2018).

By applying VaR and ES to S&P 500 index (January 1995 to December 2020), Boţoroga et al. (2021) also explored three crises that had a greater impact on market risk. The crises that were taken into consideration are the dot com bubble, the housing market bubble 2006-2010 (GFC), and the healthcare crisis of the COVID-19 pandemic. The authors used Generalised Autoregressive Conditional Heteroscedasticity (GARCH(1,1)) fitted with

Gaussian and Student-*t* distributions at the 95% and 99% confidence levels. The results revealed that the housing market bubble of 2006, among other crises, had a more damaging effect than other crises. Theoretically, both risk measures were effective in capturing market risk.

Empirically, several works of literature have used time-dependent-conditional-volatility GARCH model forecasts for predicting VaR and ES estimates due to their effectiveness in modelling returns. Earlier studies from Harmantzis et al. (2006), explored which conditional volatility models would accurately predict VaR and ES when returns are heavy-tailed. The data used were sampled from 1990 to 2003 on exchange rates (USD/Yen, USD/Canadian, USD/Euro and Pound/USD) and six stock markets (TSE300 (Canada), S&P500 (US), FTSE100 (UK), CAC40 (France), Nikkei225 (Japan), DAX (Germany)). They used GARCH models fitted with the Gaussian (norm), Generalised Pareto (peak over threshold (POT) (following EVT approach) and stable Paretian distribution (both symmetric and skewed innovations) at 95% and 99% confidence levels (for VaR and ES). At comparative confidence levels, the authors ran an analysis at 126, 251 and 502 rolling window sizes. Comparatively, the VaR backtest results proved that fat-tailed models capture risk effectively as opposed to ES (Chang et al., 2019; Owusu Junior et al., 2019). Irrespective, they found that ES predictions were more accurate in non-fat-tail models such as the POT and historical approaches. This is because the fat-tailed risk models overestimate the ES predictions – ES is sensitive to tail risk (Kellner & Rösch, 2016).

In order to test the effectiveness of Basel III, as proposed to be more effective in a stressed market condition, Zueli and Carvalhal (2018) backtested the Basel III market risk measures using the 2002 Brazilian pre-election crisis (as the stressed market condition). The data used included the Brazilian Reais quoted against the US Dollar (PTAX); currency exchange swaps contracts, VIX and S&P500. Using GARCH to model any stylised fact (heteroskedasticity), the authors further sought to capture any structural break using a one-dimensional regime-switching GARCH and iterative cumulative sum of squares to measure volatility. The GARCH models were fitted with Gaussian and Student-*t* distributions to capture the unexpected unconditional variance in the data. Theoretically, their study supports the use of ES to model market risk because it was more suitable to model the risk during the Brazilian pre-election crisis. Also, among the conditional variance models, regime-switching GARCH models were found to be more suitable for modelling VaR and ES than the single regime.

Berggren (2017) also used GARCH models to estimate VaR and ES. Berggren sampled the data from January 1996 to November 2016. The VaR and ES predictions were based on GARCH models (Exponential GARCH (EGARCH), Glosten-Jagannathan-Runkle GARCH (GJR-GARCH), Integrated GARCH (IGARCH), Non-linear Asymmetry GARCH (NAGARCH), and Asymmetric GARCH (AGARCH)) fitted with Gaussian, Student-*t*, skewed Student-*t*, and GED innovation distributions at 97.5% confidence level. The researcher's empirical analysis showed that fitting the distributions with Student-*t* provided more accurate predictions than the other distribution innovations for computing ES and VaR. Also, unlike other studies that did not backtest ES, Berggren asserted that backtesting ES is not intuitively direct compared to VaR; however, under certain circumstances, it could be possible. Therefore, following the test statistic of Acerbi and Szekely (2014), Berggren computed the average ratio of loss on a violation day and the predictions of the ES for backtesting. The backtested results from the ES were much more difficult to compute than VaR and which is why more empirical studies do not backtest ES and also because it is inelicitable.

To address the question of whether accounting for long memory in the conditional variance specification improves the accuracy of VaR and ES forecasts, particularly for longer time horizons, Degiannakis et al. (2013) conducted a study to explore the accuracy of the short and long forecasting predictions of VaR and ES based on conditional volatility models of GARCH and FIGARCH (to distinguish between short and long memory data). The FIGARCH allows for long memory; thus the authors used multiple- and one-step-ahead forecasts for the developed stock market indices at a 95% confidence level. Using data across 20 stock markets from January 1989 to February 2009, the FIGARCH model does not seem to increase the accuracy of VaR and ES predictions for the 1-day, 10-day, and 20-day horizons compared to the short memory specification of the GARCH model. As a result, they found that a long memory volatility model does not appear to enhance VaR and ES forecasting compared to a short memory GARCH model contrary to findings from Rossignolo et al. (2012) who showed that long memory models with asymmetric properties capture volatility in returns better than normal GARCH models.

Also, Taylor (2019) used an intraday dataset of CAC40, DAX30, FTSE100 and NIKKEI225 from 1993 to 2017, with combined forecasts of scoring functions approach to predict the estimates for VaR and ES because the researcher assumed that an approach based on useful information would provide better predictions than individual conditional volatility models. Taylor used quantile regression for the conditional variance models (GJRGARCH – fitted with Student-*t* innovation distributions; conditional autoregressive VaR and historical simulation approach) to individually model the VaR and ES predictions. For the combined forecasts, parametric, non-parametric and semiparametric time series methods were used. The individual model forecasts were further combined using the minimum scoring function (estimates based on the difference between VaR and ES estimates – spacing), relative score combining (combining the mean of the forecast to set the weights to the mean squared error) and historical simulation of the relative and minimum scores to produce sets of weights to account for their respective weakness. Jointly, as the ES is elicitable with VaR (Fissler et al., 2015), the author used asymmetric laplace (AL) for the scoring function of Fissler-Zigler by enforcing a consistent scoring function density with time varying location and scale parameters. The results from the five stock indices showed that combining models outperformed all the individual methods for the 1% and 5% probability levels for VaR and ES.

Caporale and Zekokh (2019) selected the best model or a superior set of models for modelling the volatility of cryptocurrencies (Bitcoin, Ethereum, Ripple and Litecoin) from July 2010 to April 2018 on a rolling window basis. Several GARCH models were fitted at the one-step ahead VaR and ES using the log returns of the currency rates in USD and fitted with the Student-*t*, skewed Student-*t*, GED and Gaussian innovation distributions. In selecting the most suitable risk measure for modelling risk for the respective cryptocurrencies, the authors backtested the VaR and ES forecasts and used a Model Confidence Set (MCS) for their loss functions. The VaR predictions were backtested using conditional and unconditional coverage tests. The ES predictions were also backtested based on a series of regressions using asymptotic covariance following the ES Regression of Bayer-Dimitriadis. Based on the VaR and ES backtested results, the AGARCH, EGARCH, GJR-GARCH and Markov-switching GARCH models were considered more suitable for modelling volatility in the cryptocurrency markets as compared to standard GARCH models which most likely are bound to produce unfitting VaR and ES predictions leading to ineffective risk assessment.

Patton et al. (2019) adopted a semiparametric approach in line with a dynamic model for risk mapping from past information to remove any misspecification in the conditional density of the models for VaR and ES. Using data on S&P500, the Japanese stock, the Dow Jones Industrial Average and NIKKEI 225 sampled from January 1990 to December 2016, Patton et al. imposed a parametric structure on VaR and ES dynamics using information from their lag variables. This was intended toward testing the elicitability of ES through the joint modelling of VaR and ES as proposed by Fissler et al. (2015). Beyond regularity conditions on the distributions of the returns and the Fissler et al. (2015) minimisation loss function, the semiparametric models were more suitable than GARCH models because they impose conditions on the parameters and leave little room for assumptions.

Le (2020) also applied quantile regression to exploit the serial dependence of horizons for 24 developed and 18 emerging markets from January 1996 to December 2017. To capture the serial dependence on the short-term series in the data sampled, Le applied Mixed Data Sampling (MIDAS) quantile regression to forecast VaR and ES, while using semiparametric specifications to eliminate restrictive assumptions on the conditionality of the distributions (returns of the stock markets). Because the author followed Fissler et al. (2015) that VaR and ES are jointly elicitable, he used the asymmetric laplace (AL) density function to address serial dependence in the ES so that the VaR and ES are forecasted at the horizons (1-day, 5-day and 10-day). The forecasts of the VaR and ES were further backtested to ensure accuracy, using unconditional coverage and dynamic quantile tests for the VaR estimates and the conditional and unconditional coverage tests as well as the discrepancy test for the ES estimates (to standardise any violations between the VaR and ES). For comparison, GJRGARCH, GARCH, and CaViaR (symmetric absolute value and asymmetric slope) of the historical and filtered historical simulation approaches were used. The empirical analysis proved that MIDAS outperformed the semiparametric, individual and GARCH models in forecasting VaR and ES across quantiles and horizons.

Pradha and Tiwari (2020) sought to understand the ES backtesting approach. They modelled the market risk of clean energy technology production firms by backtesting the ES on a regression-based approach and the VaR measure. The data were sampled from January 2001 to August 2018 using WilderHill Clean energy index. As a prerequisite, the AR(1)-GARCH (1,1) was fitted with Student-*t* distributions to model the tail of stock returns for VaR and ES predictions. The multi-quantile regression approach was used to backtest ES by integrating VaR predictions as explanatory variables. The results indicated that ES forecasts can validate the VaR results and identify inaccuracies in the characteristics of risk modelling, including variance, mean, tail, and several dynamic misspecifications. Also, the backtest results confirmed that ES forecasts can accurately measure market risk during financial uncertainty.

Of the literature that have applied VaR and ES in capturing risk, Rabie (2020) is among the first to use it in banks. The objective was to measure market risk as a standalone risk using different approaches of both traditional VaR and ES for 42 banks in Europe, Asia and Africa to calculate the banks' required regulatory capital according to Basel using VaR and ES. The VaR and ES forecasts were made based on the ARMA-GARCH (1,1) conditional volatility models. Intuitively, Rabie sought to asses market risk regulatory capital according to Basel regulations. The findings show that ES encourages holding higher capital than VaR driven by the distributional characteristics of the model. The theoretical implication of choosing ES as a method of determining regulatory capital is more beneficial than VaR because ES is not sub-additive, which means that it accounts for integration in managing the risks of the bank.

Maciel (2021) sought to explore whether the conditional variance model in its single (GARCH, EGARCH and TGARCH) or multiple regimes (Markov-Switching GARCH/ MS-GARCH) – in the medium and long term – would effectively predict VaR and ES at risk levels of 1%, 5% and 10% for cryptocurrencies (Bitcoin, Dashcoin, Ethereum, Litecoin, Monero and Ripple) from 2013 to September 2018. At VaR and ES of risk levels of 1%, 5%, and 10%, the conditional models were fitted with several distribution innovations such as the standard normal, Student-*t* and the GED as well as skewed versions of the three innovations. The estimates from the MSGARCH, EGARCH, TGARCH and GARCH models for the VaR and ES estimates were backtested using the unconditional coverage (UC) test of Kupiec (1995) and the dynamic quantile (DQ) test of Engle and Manganelli (2004). Maciel found that regime-switching models provide better forecasts for VaR and ES.

Aside from Rabie (2020) who used the VaR and ES in banks, Ochieng (2021) sought to explore whether Kenyan banks had adopted excerpts from the Basel III framework and if there were any challenges in using the predictions to manage market risk. Ochieng found through primary descriptive studies that the Basel III accord had enhanced Kenyan banks' strategies in managing market risk. Irrespective, Ochieng reported that Kenyan banks had to suffer from high costs for implementation, technology and system infrastructure, as well as issues stemming from model and validation issues. Aside from all the challenges, Ochieng acknowledged that it is important for banks to adopt and implement Basel III in their risk management strategies to avoid shocks and vulnerability in the system.

Research has also shown that a risk measure should be useful for forecast comparison and ranking for model estimation and selection to be possible (Fissler et al., 2015; Caporale & Zekokh, 2019; Patton et al., 2019). Owusu Junior et al. (2022) used the VaR model to predict, forecast and rank the tail risk of gold and white precious metals: gold, silver and palladium. The data sampled include the pre- and post-Eurozone and global financial crises (January 2000 to April 2018) to facilitate a time-varying assessment of the variables of different market conditions at the 5% and 1% probability levels.

The Model Confidence Set (MCS) – which supports multivariate robustness tests – was used to rank and choose Superior Set Models (SSMs) of predicted GARCH and GAS models based on the Fissler-Ziegel loss (FZL) function. The authors primarily used the GARCH and GAS – to exploit the complete density of the returns – models. The authors traditionally employed GARCH (EGARCH, Asymmetric Power ARCH, Absolute Value- (AVGARCH), GJR-GARCH, Component sGARCH, Threshold- (TGARCH, NAGARCH, Non-linear GARCH (NGARCH)) fitted with Gaussian, Student t, Skewed Student t, and Johnson's U innovations and the GAS model fitted with Gaussian, Student t, Skewed Student t, asymmetric Laplace, asymmetric Student-*t* with two tail decay parameters, and asymmetric Student-*t* with one tail decay parameter innovations. The GARCH and GAS models were fitted to avoid single model misspecification and to increase forecasting performance. The authors used three approaches to comparatively backtest the outcomes from the SSM; correct unconditional coverage (UC), correct conditional coverage (CC) and dynamic quantile (DQ). The findings were inclined toward the variables used in the study instead of the efficiency of the models.

Financial markets are risky due to uncertainty, excess volatility, and contagion effects (Naeem et al., 2019). Also, financial asset returns are conditionally heteroskedastic, generally non-normally distributed, fat-tailed and often skewed (Harvey, 1995; Bekaert & Harvey, 1997; Engle, 2004; Cajueiro & Tabak, 2004; McNeil & Frey, 2000; Harmantzis et al., 2006; Mcneil et al., 2015). These features must be considered to produce accurate forecasts for VaR and ES and to avoid underestimation (Gunay & Khaki, 2018; Lazar & Zhang, 2020; Owusu Junior et al., 2022). Studies on VaR forecasting indicate that returns demonstrate most of the well-known stylised facts of assets, such as – fat tails, leptokurtosis, volatility clustering, and leverage effects (Fissler et al., 2015; Braione & Scholtes, 2016; Berggren, 2017; Degiannakis, & Potamia, 2017; Owusu Junior et al., 2022).

The heteroscedastic models for stock markets as used in literature have been proven to provide the most accurate VaR and ES forecasts (Degiannakis & Potamia, 2017; Aloui, & Ben Hamida, 2015; Berggren, 2017; Zueli & Carvalhal, 2018; Caporale & Zekokh, 2019; Pradha & Tiwari, 2020). The empirical literature has in their respective scenarios and instances proved different conditional volatility (non-parametric or semiparametric) measures in either single- or multiple-regimes which they consider most appropriate for modelling VaR and ES. Other studies have adopted different approaches to backtest their ES results although it not elicitable (Fissler et al., 2015, Fissler & Ziegel, 2016; Wang & Zitikis, 2021; Pradha & Tiwari, 2020; Maciel, 2021). Also, the review shows that most researchers use GARCH models to forecast VaR and ES. Along the GARCH models are several distribution innovations, such as the Student-*t*, skewed Student-*t*¸ Gaussian and Johnson's U innovation distributions to improve the forecasting performance of the conditional variance models.

Also, from the above literature, barely is there any research on financial institutions aside from Rabie (2020) and Ochieng (2021) who have used VaR and ES across 42 banks in Europe, Asia and Africa and Kenyan banks respectively. In Ghana, there are studies from Nortey et al. (2015) (on GSE all share index), Kyei-Boadu (2015) (on Fan milk limited and GSE composite index) and Osei (2017) (on six unnamed stocks) applied VaR but not primarily to the banks on the GSE. The lack of literature on using VaR and ES for modelling the market risk in line with a regulatory framework for financial institutions in Ghana is what this study seeks to do.

Chapter Summary

This chapter reviews the theories and concepts used and the empirical literature on VaR and ES risk measures. The theory of systemic risk explains the phenomenon of an entire system failure owing to the interrelatedness and complexity of the financial sector. This systemic failure leads to the implementation of regulations intended to mitigate the extent of the impact that comes with a total collapse of the financial system and thus, the theory of financial regulation. Assuming that the GSE is efficient, the stock prices of the banks should capture all valid information that can be used to measure market risk and that it is the efficient market hypothesis. Concepts that are important to understanding the implications of the study were also presented on risk, market risk, the Ghanaian banking sector, its transformation, and the implications of risk disclosure to stakeholders. The empirical review for the study was based on the methods for measuring market risk as proposed by the Basel Committee and how other researchers have adopted the method differently.

CHAPTER THREE

RESEARCH METHODS

This chapter presents the philosophy, the approach toward the research, the research design, the study area and population of the data sample and the sampling technique for assessing the market risk of the listed banks in Ghana. Also, the data collection procedure and suitable theoretical models for analysing the data for the study and the chapter summary are presented.

Research Philosophy

Research philosophy sets the fundamental framework for how data is gathered, analysed, and used based on the source, nature and the belief that structures the knowledge of a researcher; which is not built on values and related moral content (Hallebone & Priest, 2008; Saunders et al., 2009; Žukauskas et al., 2018). The research paradigm allows researchers to understand the topic within its descriptive framework as per the philosophical direction (Aaker et al., 2018). Also, research philosophy helps a researcher develop ideas into contextual knowledge that reflects the assumptions made in his or her research (Saunders et al., 2009). Per the researcher's reflexivity, this study adopts the positivist philosophy because it supports the author's assumptions, approach, and methodology that is suitable for this study (Creswell & Creswell, 2017; Saunders et al., 2009).

The study adopts the positivist philosophy to come out with objective generalisable findings that are not influenced by the researcher's interpretation (Saunders et al., 2009). The positivism paradigm involves researching an objective social observation and arriving at conclusions and generalisations (Cooper & Schindler, 2008). The positivist research paradigm is based on the view that social sciences research can replicate scientific or natural sciences research methods (Pring, 2000). Positivist philosophy is empirically adopted when a researcher wants to mathematically present an objective finding (Ryan, 2006). Justifiably, the positivist philosophy is used with the intent to capture an objective market risk level of the respective banks on the GSE. Specifically, the positivism paradigm involves the collection of data, analysis of collected data using statistical tests of significance, and presenting findings in a highly structured quantitative approach (Ryan, 2018; Zyphur & Pierides, 2020).

Research Design

Intuitively, the research design sets the decorum for data collection and analysis to arrive at answers to a study's objective (Grey, 2014) and primarily, determine the feasibility and reliability of a study (Plonsky, 2017). The confidence an author puts out in his or her study is subject to the strategic framework that serves as a bridge for planning, implementing and executing to provide answers to research questions (Durrheim, 2006). According to Saunder et al. (2009), research can be conducted using exploratory, descriptive, or explanatory research designs.

This study adopted a descriptive research design to explore the market risk level of listed banks in Ghana. A descriptive research design would help provide an in-depth explanation of the market risk to which banks are exposed (Thomlison, 2001; Atmowardoyo, 2018). The descriptive research design aids in describing reality in its completeness (Lans & Van der Voordt, 2002; Hooker, 2004); is suitable for modelling one variable –market risk– and prevents manipulation of findings (Hooker, 2004; Siedlecki, 2020). Because this research is geared toward providing objective findings to assess the market risk that banks face, a descriptive research design is more appropriate.

Research Approach

The approach to the research is quantitative. Creswell and Creswell (2017) define a research approach as a framework that provides guidelines to efficiently and systematically carry out a study by providing guidelines to determine the philosophy and design of the research. Though there are other approaches to research, such as qualitative and mixed approaches, the quantitative approach is considered acceptable because it enables the researcher to collect data based on highly organised research instrument(s) and well-defined study concepts (Creswell, 2009; Creswell et al., 2017). Also, quantitative research is associated with variables through systematic collection procedures and statistical processing using computational techniques to ensure the objectiveness of the findings (Patel & Davidson, 2003; Creswell, 2009; Zikmund et al., 2013).

Bryman and Bell (2003) explained that quantitative research attracts a low cost of gathering data, requires little time for gathering data; has no data inconsistency, and, compared to qualitative research, has no respondent effect. On the contrary, quantitative research fails to capture very important human aspects, such as the respondent's emotions, behaviour, feelings, and perception which could be instrumental in understanding the human attributes of risks exposure to the financial system (Rahman, 2020). Notwithstanding, a quantitative research approach is appropriate for the assessment of phenomena (Rahman, 2020). Also, to obtain an objective measure of banks' market risk that reflects the reality of risk exposure, the quantitative research approach is more suitable to avoid any personal bias (Savela, 2018).

Population

A study population has been described as "including all elements that are fundamentally instrumental in understanding a phenomenon" and where necessary, the study selects a representative sample (Kazerooni, 2001; Cooper & Schindler, 2008). A research population is specified in terms of some combination of geographic- and demographic-specific characteristics (Hair et al., 2010). The study population consists of all commercial banking institutions in Ghana. Currently, the BoG regulates 23 commercial banks in the financial sector of the Ghanaian economy (BoG, 2020, p. 4). Due to the financial crisis that resulted in a clean-up in 2016, some of these banks had been subject to mergers, takeovers and restructuring, but all the banks have rebased their minimum capital requirement – as a sign of good faith for a stable financial system (Aboagye, 2020; Affum, 2020).

Sampling Procedure

Sampling is necessary when the population is too large, data is not available to the entire population, or collecting data would be costly and time consuming, and may even result in misleading results (Bluman, 2009; Phrasisombath, 2009; Garson, 2012). Also, sampling should be done effectively to ensure that the sample is representative of the population to ensure the generalisation of the findings (Randall & Nielsen, 2012). Purposive sampling was adopted in this research. Purposive sampling allows a researcher to choose the most suitable case to answer the research questions and achieve respective objectives (Saunders et al., 2009).

This sampling method was chosen because the study sought to assess the market risk of listed banks using stock returns. Though there are 23 commercial banks in Ghana, only eight (8) (as shown in Table 1) are listed on the GSE with daily data (high-frequency data) that can be used to compute their respective profits and losses. Because the downside risk measures used in line with regulatory framework (VaR and ES) seek to measure the relative changes in stock prices in assessing market risk, the listed banks were the most suitable case as the other banks neither have daily profit and loss statements nor stock prices. The secondary data of commercial banks available to the public (aside from the data on the stock exchange) are published annual reports of the respective banks. Hence, based on the availability of daily stock prices for the listed banks, they were duly sampled to assess the market risk of banks in Ghana. Thus, based on the efficient market hypothesis, assuming the stock market is efficient the author sampled daily stock prices that would reflect the volatility in the stock market subject to banks that do not trade on the GSE (Su et al., 2011). Thus, the purposive sampling technique is more suitable for this study.

Table 1: Banks Listed on the Ghana Stock Exchange (GSE)

Bank Name	Symbol	Date Listed	Market Capital ('000)	Issued Shares (GHS Mil.)	Authorised Shares ('000)
Access Bank Ghana PLC	ACCESS	21/12/2016	GHS400,000	118.09	173,947.596
Agricultural Development Bank PLC	ADB	12/12/2016	-	-	-
CalBank PLC	CAL	05/11/2004	GHS400,000	548.26	1,000,000
Ecobank Ghana Limited	EGH	06/2006	GHS416,641	293.23	500,000
GCB Bank PLC	GCB	17/05/1996	GHS500,000	265	1,500,000
Republic Bank (Ghana) PLC	RBGH	17/03/1995	GHS401,191	1	1,000,000
Standard Chartered Bank Ghana PLC	SCB PREF	23/08/1991	GHS400,000	115.52 (OS) 17.48 (PS)	250,000
Societe General Ghana Limited	SOGEGH	13/10/1995	GHS404,242.257	429.06	500,000

Source: Ghana Stock Exchange (2022) (https://gse.com.gh/listed-companies/)
Note: PLC is Public Company Limited by Shares as per the Company's Act 2019 (Act 992); OS is ordinary shares; PS is preference shares

Data Collection Procedure

This study is geared toward capturing the market risk of banks listed on the GSE. Thus, this study used secondary data. Secondary data can either be raw or published summaries (Saunders et al., 2009). Secondary data for banks can be found in their financial statements which are required by the company act (Act 992) to be published to ensure transparency and promote confidence in the industry and the stock prices published by the GSE. This study used the weekly stock prices of the listed banks on the GSE from January 2017 to December 2021. The data for this study were gleaned from the Ghana Stock

Exchange Market Statistics website (https://gse.com.gh/daily-shares-and-etfs-trades/).

Model Specification

The stock market volatility is time varying; as such, a suitable model for analysing financial asset returns would be one that can effectively capture the distribution, volatility clustering, and leverage effects (Rossetti, Nagano, & Meirelles; Yousef, 2020). Thus, the study adopted the family of Generalised Autoregressive Conditional Heteroscedastic (GARCH) models because the models have been successful in describing financial data and capturing the features of stock returns (Karmakar, 2005; Korkpoe & Junior, 2016). In building a GARCH model, there must be an Autoregressive Conditional Heteroscedasticity (ARCH) effect that indicates risk or volatility (Engle, 1982). The ARCH model allows the conditional variance of time series and econometric models to change over time as a function of past errors, leaving the unconditional variance constant (Engle, 1982; Bollerslev, 1986; Bollerslev et al., 1992).

Vrontos et al, (2000) acknowledge that GARCH and Exponential GARCH (EGARCH) are the most useful ARCH parameterisations in overcoming some of the shortcomings of ARCH models, such as overfitting and breach of non-negativity constraints (Yousef, 2020). The most prevalent conditional volatility models that fully capture the key stylised facts of financial assets are GARCH, E-GARCH and GJR-GARCH (Berggren, 2017; Korkpoe & Howard, 2019). The family of GARCH models used in this study were of order (1,1). In literature high frequency data of order (1,1) provide increased volatility insights and produce enhanced precision for estimates (Zivot, 2009).

Generalised ARCH Model (GARCH)

The GARCH model permits past conditional variance, whose effect on current volatility declines over time (Karmakar, 2005). The GARCH model is most appropriate for recording the conditional volatility in stock returns of the listed banks under study (Karmakar, 2005; Chaudhary, Bakhshi, & Gupta, 2020). Also, Zivot (2009) avers that GARCH (1,1) is optimal for high frequency data in practice.

$$r_t = lo\,g\left(\frac{p_t}{p_{t-1}}\right) \quad (1)$$

$$r_t = u_t + \varepsilon_t \quad (2)$$

$$\varepsilon_t = \sigma_t z_t \quad (3)$$

$$z_t \sim f[E(z_t) = 0, V(z_t) = 1; 0] \quad (3.1)$$

Let; p_t represent the closing price of the trading day t of the listed banks on the GSE; z_t be the independent and identically distributed process that captures the behaviour of the tail of the returns with a mean (0) and variance (1); and r_t be the returns of the stock prices. To test for the ARCH effect, the following hypothesis was set:

$$\varepsilon_t^2 = \lambda_0 + \sum_{i=1}^{q} \beta_1 \varepsilon_{t-1}^2 \quad (4)$$

$$H_0: \beta_0 = \cdots = \beta_n = 0 \quad (4.1)$$

$$H_1: \beta_0 \neq \cdots \neq \beta_n \neq 0 \quad (4.2)$$

This study further specifies the GARCH (1,1) model as follows (Engle, 1982; Bollerslev, 1986):

$$\sigma_t^2 = \lambda_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (5)$$

For conditional variance stationarity; $\alpha_1 + \beta_1 < 1$

For a positive conditional variance, the parameters are restricted to; $\lambda > 0; \alpha_1 > 0;\ \beta_1 \geq 1$

Exponential GARCH (EGARCH)

The study also adopts EGARCH to accommodate the leverage effect in stock prices arising from good and bad news (Black 1976; McAleer & Hafner, 2014; Korkpoe & Howard, 2019; Hung, 2021) based on a logarithmic expression of the conditional variance of the variable under analysis (Beggren 2017; Karmakar, 2005). Karmakar (2005) asserts that EGARCH has a restrictive effect on the asymmetric response to positive (good news) and negative (bad news) shocks on financial assets by ensuring that no positive condition is imposed on the parameters (Hung, 2021). The study specifies the EGARCH model (Black, 1976; Nelson, 1991):

$$ln(\sigma_t^2) = \lambda_0 + \alpha_1|z_{t-1}| + \gamma_1 z_{t-1} + \beta_1 ln(\sigma_{t-1}^2) \qquad (6)$$

Regularity condition: $\gamma < 0;\ \gamma < \alpha < -\gamma$

Stationarity condition: $\beta_1 < 1$

Where, $z_{t-1} = \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$; adequately captures asymmetry

γ; permits an asymmetric effect

To test for leverage effect; $\gamma_1 < 0$

Glosten-Jagannathan-Runkle GARCH (GJR-GARCH)

The GJR-GARCH models the conditional variance directly and empirically considered the best estimation of positive and negative shocks on volatility (Karmakar, 2005; Berggren, 2017). Also, Su et al. (2011) assert that the GJR-GARCH model works very well in VaR forecasting. To capture any asymmetry in stock prices for this study, the GJR-GARCH is adopted (Glosten et al., 1993):

$$\sigma_t^2 = \lambda_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + (\Pi_0 I_{t-1})\varepsilon_{t-1}^2 \qquad (7)$$

For conditional variance stationarity; $\alpha_1 + \beta_1 + \frac{1}{2}\Pi_0 < 1$

For a positive conditional variance, the study restricts the parameters to; $\lambda > 0; \alpha_1 \geq 0; \beta_1 \geq 0;\ \alpha_1 + \Pi \geq 0$

For positive news; $\varepsilon_{t-1}^2 > 0$ and negative news; $\varepsilon_{t-1}^2 < 0$

Degiannakis et al. (2013) and Yamai and Yoshiba (2002) empirically provide reasonable arguments for using GARCH forecasts for the VaR and ES estimates. Literature has also proven that returns of financial data sets are not normally distributed (Peiro, 1999; Härdle & Mungo, 2008; Karoglou, 2010; Blau, 2017), thus this study uses GARCH, EGARCH and GJR-GARCH models to prefilter the data (Le, 2020) to avoid mimicking the unconditional non-stationarity and volatility clouding effect present in stock prices (Rossignolo et al., 2012).

Distributional Innovations

To capture any stylised fact(s) in the returns of the listed banks, the study imposed the Gaussian, Student-*t* and skewed Student-*t* distribution assumptions on the conditional variance in the heteroscedasticity models. These distributional assumptions have parameters that are flexible and can incorporate stylised facts such as symmetry, asymmetry and fat-tails in the analysis of the VaR and ES to avoid underestimations of risk.

Gaussian (-norm)

The Gaussian distribution assumption imposes that the distributions of the returns are normally distributed (Gauss, 1809):

$$f(\varepsilon_t) = \frac{1}{\sqrt{2\pi}} e^{(-\frac{\varepsilon_t^2}{2})} \tag{8}$$

Student-t (-std)

The Student-*t* distribution assumptions can capture any fat-tails in the distributions of the listed banks (Gosset, 1908; Hansen, 1994):

$$f(\varepsilon_t, v, \sigma_t^2) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{\pi(v-2)\,\sigma_t^2}}\left(1 + \frac{\varepsilon_t^2}{(v-2\,\sigma_t^2)}\right)^{\frac{(v+1)}{2}} \tag{9}$$

where $v > 2$ (leptokurtic distribution); $v < 2$ (platykurtic distribution).

Skewed Student-t (-sstd)

The skewed Student-*t* distribution assumptions impose parameters that can capture any such fat-tails and skewness in the distributions of the listed banks (Fernández & Steel, 1998):

$$f(\varepsilon_t, v, \sigma_t^2, \gamma) = \begin{cases} pq\left(1 + \frac{1}{v-2}\left(\frac{p\varepsilon_t + \sigma_t y}{\sigma_t(1-\gamma)}\right)^2\right)^{-\frac{v+1}{2}}, \varepsilon_t < -\frac{y}{p} \\ pq\left(1 + \frac{1}{v-2}\left(\frac{p\varepsilon_t + \sigma_t y}{\sigma_t(1+\gamma)}\right)^2\right)^{\frac{v+1}{2}}, \varepsilon_t \geq -\frac{y}{p} \end{cases} \tag{10}$$

where $2 < v < \infty$; $-1 < \gamma < 1$ (captures asymmetry); $y = 4\gamma c(\frac{v-2}{v-1})$; $p^2 = 1 + 3\gamma^2 - a^2$; $q = \frac{\Gamma(\frac{v+1}{2})}{\sqrt{\pi(v-2)}\Gamma(\frac{v}{2})}$.

Backtesting the Conditional Models

Backtesting is a requirement of the BCBS (1996) – for validation purposes – for a financial risk model to ensure that the risk predictions made are accurate. Backtesting is a statistical procedure that compares actual profits and losses to the corresponding risk-predicted estimates to avoid inaccurate estimation of risk and prove the robustness of the risk models (Korkpoe & Howard, 2019; Korkpoe, 2020; Chinhamu et al., 2015). To backtest the risk models, the unconditional coverage test (UC) (Kupiec, 1995) and conditional coverage test (CC) (Christoffersen, 1998) were used. The CC test validates both independence and unconditional coverage for the predictions given that the risk estimate exceedances are both independent and non-autocorrelated (Carporale & Zekokh, 2019; Korkpoe & Howard, 2019; Chinhamu et al., 2015). For backtest 33% of the data was used for the validation and reliability of the conditional models.

$$LR_{uc} = 2\ln\left(\left(\frac{\vartheta^x}{N}\right)^{\vartheta^x} * \left(1 - \frac{\vartheta^x}{N}\right)^{N-\vartheta^x}\right) - 2\,ln\left(\xi^{\vartheta^x}(1-\mathfrak{p})^{N-\vartheta^x}\right) \quad (11)$$

$$LR_{ind} = 2ln\frac{[(1-\mathfrak{C}_0)^{\phi_{00}}\mathfrak{C}_0{}^{01} * (1-\mathfrak{C}_1)^{\phi_{10}}\mathfrak{C}_1{}^{11}]}{\ln[((1-\mathfrak{C})^{\phi_{00}+\phi_{10}} * \mathfrak{C}^{\phi_{01}+\phi_{11}})]} \quad (12)$$

$$LR_{cc} = LR_{uc} + LR_{ind} \quad (13)$$

where $\frac{\vartheta}{N}$ is the tolerance level for the model; $N - \vartheta^x$ and ϑ^x is the number 1 and 0 indicator in the estimate of $\frac{\vartheta}{N}$; ϕ_{00}, ϕ_{10} is the number of observations with value 1 when predictions are violated and 0 when otherwise; and $\mathfrak{C}_0$ is the probability of having an exception that is conditional on its lag.

The null hypothesis of the respective tests are as follows;

LR_{uc}; H_0: correct exceedances

LR_{cc}; H_0: correct exceedances and independent of failure

Failure to reject the tests proves the validity, accuracy and robustness of the risk model and its predictions.

Risk Measure Estimates: Value-at-Risk (VaR) and Expected Shortfall (ES)

The best GARCH model based on the lowest information criterion is used for the VaR and ES predictions. The VaR and ES are in line with the Basel III framework for modelling market risk (BCBS, 2016; Lönnbark, 2016; Taylor 2019; Owusu Junior et al., 2021). Empirically, VaR and ES are effective in capturing market risk measures (Harmantzis et al., 2006; Jorion, 2007; Chinhamu et al., 2015; Lönnbark, 2016; Degiannakis & Potamia, 2017) while complementing and substituting the shortcomings – subadditivity, coherence and elicitability – in each other (Dowd, 2007; Fissler & Ziegel, 2016; Berggren, 2017; Taylor, 2019; Owusu Junior et al., 2021). Variations in the VaR and ES estimates reflect variations in market risk (Hirtle, 2003; Lönnbark, 2016) while quantitatively summarising the potential market risk allowing regulators to put in place measures to mitigate market risk (Jorion, 2002).

VaR is an estimate of the maximum possible loss from market movements given a level of confidence at a defined period of time and probability (Jorion, 2002; Jorion, 2007; Braione & Scholtes, 2016; Lönnbark, 2016; Degiannakis & Potamia, 2017). ES is a risk measure for the conditional expectation of exceeding the expected return on an asset given a confidence level (Berggren, 2017; Taylor, 2019). In line with Basel III's regulatory framework, this study adopted both risk measures to get accurate and effective findings.

At a $100(1-\alpha)\%$ confidence level, the VaR and ES are defined as:

$$\alpha = \int_{-\infty}^{-VaR(\alpha)} f_q(x)dx \tag{14}$$

$$VaR_{\alpha,t} = \varphi_t \phi^{-1}(\alpha) \tag{15}$$

$$ES_\alpha = \frac{1}{1-\alpha} \int_{\alpha}^{1} VaR_x dx \tag{16}$$

Models for Ranking the Risk for the Respective Banks

The study used the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and symmetric Mean Absolute Percentage Error (sMAPE) to rank the banks (Barnston, 1992; Hamner et al., 2018). The MAE, RMSE and sMAPE quantify the accuracy of the actual data to the predicted data. The study adopted sMAPE because, although the data frequency was converted to a lower frequency in an attempt to correct for thin trading, the returns were relatively close to zero. Thus, sMAPE was used to automatically capture such shortcomings. MAE and RMSE are both negatively oriented scores that the study adopted to capture any effect of negative returns (Willmott & Kenji, 2005).

$$MAE = \left[\frac{1}{s}\sum_{i=1}^{s} |r_{oi} - r_{fi}|\right] \tag{17}$$

$$RMSE = \left[\frac{1}{s}\sum_{i=1}^{s} (r_{oi} - r_{fi})^2\right]^{0.5} \tag{18}$$

$$sMAPE = \frac{1}{s}\sum_{i=1}^{s} \frac{|r_{oi} - r_{fi}|}{\frac{r_{oi} + r_{fi}}{2}} \tag{19}$$

where s, r_{oi} ; r_{fi} are the observation, actual values (bank returns) and forecasted values (GARCH-VaR), respectively.

Data Processing and Analysis

The study used closing offer prices with the assumption of an efficient market, where there was no trading, the immediate previous recorded stock price was repeated. To correct thin trading, daily returns were transformed into weekly returns to avoid biases in the empirical results for an efficient market (Lo & MacKinlay, 1988; Miller et al., 1994). The stock returns of the listed banks were computed as;

$$r_t = lo\,g\left(\frac{p_t}{p_{t-1}}\right) \times 100 \qquad (20)$$

where r_t is the continuously compounded return; p_t represent the closing price of the trading day t of the listed banks and p_{t-1} represent the closing price of the trading day $t-1$.

The data were analysed using R programming software version 4.0.2. The rugarch package was used for the GARCH models (Galanos & Kley, 2022); the evir package was used to assess the risk estimates (VaR and ES) (Pfaff et al., 2022) and the metrics package was used to rank the listed banks (Hamner et al., 2018).

Chapter Summary

This chapter outlined the research methodology. The study is a quantitative descriptive study intended to provide an objective, generalisable finding, thus, the positivist research philosophy. The listed banks were sampled purposively due to data availability and outlined that GARCH-, EGARCH-, and GJRGARCH-based VaR and ES would be used to assess the market risk of listed banks. The best GARCH model for VaR and ES would be backtested using UC and CC backtesting hypotheses and absolute forecast errors. Lastly, the study used MAE, RMSE and sMAPE to rank the risk of the listed banks. The limitation of this study is that there are no daily P & L data; therefore, the study used stock prices (returns) based on the hypothesis that the market is efficient and any information on the stock prices should depict information on their profit and loss. However, the daily stock prices were characterised by thin trading thus, the data were transformed from high-frequency data (daily) to low frequency data (weekly) in an attempt to correct thin trading.

CHAPTER FOUR

RESULTS AND DISCUSSION

Introduction

The study sought to model the risk of the banks listed on the GSE. This chapter presents the analyses of the data toward answering the research questions. The chapter is in five sections. The characteristics of the listed banks' stock returns are discussed using descriptive statistics and graphical representations. The analysis of the respective objectives and discussions: the nature of the tails of the returns; the market risk of the banks using VaR and ES, and lastly, the banks are ranked according to statistical risk metrics. The chapter is presented chronologically followed by a chapter summary.

Data Description and Summary Statistics

The fluctuations in stock returns are not the same across assets. Stocks in developing countries have low trading volumes (relatively small number of buyers and sellers) and wide bid-ask spreads causing increased volatility and high transaction costs (Mlambo & Biekpe, 2005; Korkpoe, 2020). Mlambo and Biekpe (2005) found that thin trading in the African stock market is a common issue. Their findings were theorised to reflect how stock prices in African stock markets are recorded. In their submission, if a stock in the market does not trade, the transaction price (mostly the closing price) of the stock is recorded for subsequent days until the stock is traded again. In other cases, thin trading is identified when stocks trade at every consecutive interval but not necessarily at the close of each trading day (Kuttu, 2012). This is what is reflected in the stocks on the GSE (Korkpoe & Junior, 2016; Korkpoe & Howard, 2019) and, in particular, the listed banks.

For each listed bank, weekly log returns from January 2017 to December 2021 were used instead of daily P & L statements (Su et al., 2011). Aside from Republic which was listed in 2018, the other seven banks sampled for the study were either listed earlier than the sampled period or in 2016. The study uses the weekly log returns of the listed banks.

Table 2 presents the summary statistics, stationarity, normality and heteroscedasticity tests of the returns of the listed banks. The first panel presents the descriptive statistics of the respective banks. On average, the mean of the returns is close to zero. On a stock market that is characterised by thin-trading, this is an indication of illiquid stocks which are more suspectible to price volatility and pose higer risk of investor losses in an efficient market (Amihud & Mendelson, 1986; Brennan et al., 1998). Averagely, investors in the listed banks make little or no returns. Investors of SOGEGH however, make higher returns compared to the other banks at a mean of 0.2256, with investors in RBGH and Access suffering a loss in the market (-0.3946 and -0.1018 respectively). The level of returns in the banks conforms to the low volume of trade characterised in African stock markets (Mlambo & Biekpe, 2005; Kuttu, 2012; Korkpoe & Owusu Junior, 2016; Korkpoe & Howard, 2019).

The standard deviation is a symmetric risk measure (Rockafellar et al., 2002). The standard deviation measures indicate fluctuations in time and can be used to explain the total volatility in the returns of the distribution.

Table 2: Descriptive Statistics

	Access	ADB	CAL	EGH	GCB	RBGH	SCB	SOGEGH
Mean	-0.1018	0.1535	0.0446	0.0604	0.0676	-0.3946	0.1586	0.2256
Min.	-14.4846	-12.8013	-13.2377	-15.8706	-51.4952	-18.9757	-16.9419	-19.6264
Max.	17.4152	19.1653	17.5694	19.7359	59.1933	17.0697	26.5452	17.3663
Std. dev.	3.9833	2. 4456	4. 2354	4.3575	21.3734	4.1132	4.7380	4.2331
Normality Test								
Jarque-Bera	244.4500***	6920.8000***	81.9180***	169.4500***	1083.8000***	213.3000***	678.7100***	193.1500***
Shapiro-Wilk	0.8701***	0.3047***	0.9546***	0.9021***	0.9878**	0.8712***	0.8433***	0.9131***
Stationarity Test								
KPSS	0.0761	0.2334	0.1013	0.0653	0.0120	0.4014	0.1700	0.1268
ADF	-6.4681**	-6.0910***	-6.9615**	-7.0360***	-10.4490***	-5.8619**	-5.8619**	-4.5754***
PP	-207.9300**	-182.8000***	-188.6400***	-224.2000***	-309.6100***	-156.6500***	-189.6200**	- 165.8500***
Heteroscedasticity Test								
ARCH LM [-12]	57.6910***	39.4730***	22.1620**	17.9990**	31.5720***	45.9630**	20.0550*	30.3220***
Obs.	259	259	259	259	259	192	259	259

Source: Author's Construct (2022)

Note: Access (Access Bank Ghana Plc.); ADB (Agricultural Development Bank Plc.); CAL (CalBank Plc.); EGH (Ecobank Ghana Ltd.), GCB (GCB Bank Plc.), RBGH (Republic Bank (Ghana) Plc.), SCB (Standard Chartered Bank Ghana Plc.); SOGEGH (Societe General Ghana Ltd.). Plc. is Public Company Limited by Shares. Descriptive statistics are presented for 8 listed banks and (***); (**); (*) denote significance at 1%, 5% and 10% respectively. Std. dev is the standard deviation and Obs. is the sample observations.

Also, from the estimated standard deviation values, the data series are spread out away from the mean. From Table 2, the standard deviation ranges from 2 (ADB) to 22 (GCB) but most of the banks are centered around 4. This shows that the observations of the listed banks are highly volatile and far dispersed from the mean. Statistically, these estimates indicate that the risk level of listed banks is high. GCB has the highest risk level at a standard deviation of 21.3734, followed closely by Standard Chartered, CAL, Ecobank, Republic, Societe Generale, and Access with ADB (2.4456) having the least standard deviation measure.

Contrary to modern portfolio theory, where investors expect the maximum return for a certain level of risk (Markowitz, 1952), ADB has the lowest standard deviation risk level with a relatively high average return as compared to SOGEGH which has the highest mean (0.2256). This is partly attributable to the fact that from the 2020 financial statement report, ADB made massive profits during the COVID-19 pandemic as compared to the other banks.

To test for normality in the return distribution, the Jarque-Bera and Shapiro-Wilk tests were used (Gel et al., 2007; Hui et al., 2008). The Jarque-Bera test determines whether the sample data have skewness and kurtosis of a normal distribution. The outputs in Table 2 show that the sampled data for the listed banks are not normally distributed and this is the first motivation for using conditional models to capture the stylised facts in their tails. The Shapiro-Wilk output also affirms the Jarque-Bera test statistics showing that the error terms of the listed banks are not normally distributed. Thus, the study rejects the null hypothesis for normality for both normality tests in the listed banks at the 1% significance level. The stationarity tests were conducted for the listed banks and reported at the 1% significant level using the KPSS, ADF, and PP tests. The alternate hypothesis for the ADF and PP tests is stationary whereas the null hypothesis of KPSS states that the series is stationary (Dickey & Fuller, 1979; Phillips & Perron, 1988; Kwiatkowski et al., 1992). At the 1% confidence level, the study rejects the null hypothesis for stationarity for the KPSS test and fails to reject the ADF and PP non-stationarity tests. This means that the weekly returns of the listed banks are neither normally distributed nor stationary.

From the graphical representations in Figures 1 and 2, the price and log return plots for the listed banks are presented. In terms of volatility, they differ across the sample periods. Volatility clusters that correspond to expected price fluctuations can also be seen in the log returns (Figure 2). In addition, the graphical presentations of the daily prices show that the stocks of the listed banks are neither stationary nor normal.

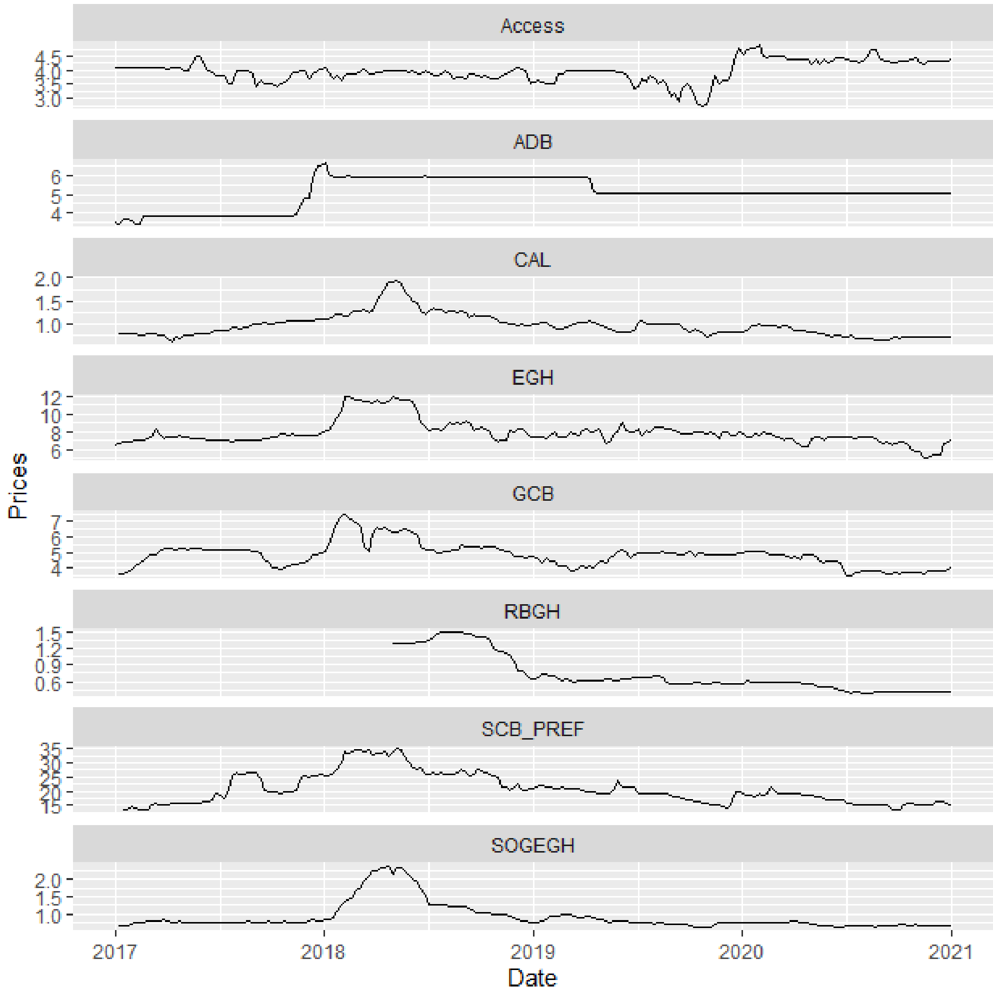

Figure 1: Plot of Weekly Closing Prices of Listed Banks

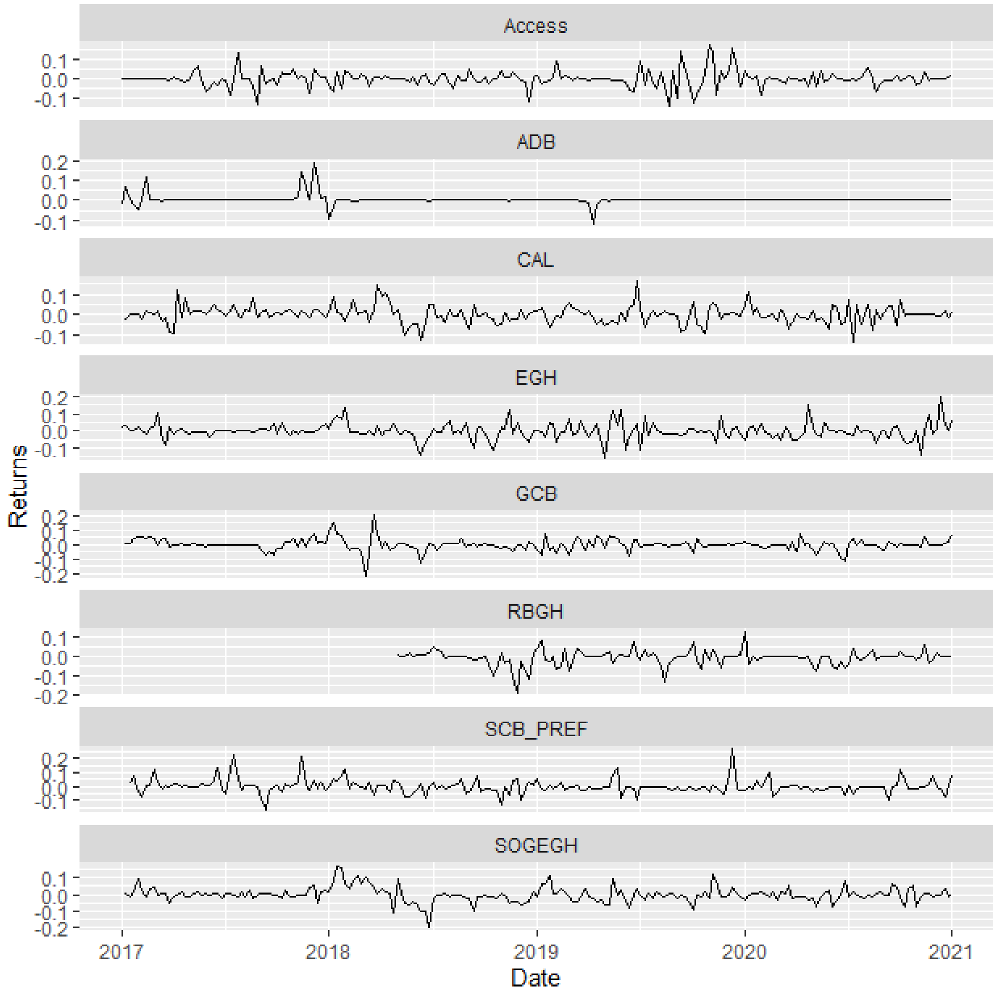

Figure 2: Plots of Weekly Log Returns of Listed Banks

Empirical Results

Objective 1

The nature of risk arising from the returns distribution of the listed banks

Earlier literature examining the nature of stock returns has theorised that stock returns have excess kurtosis and are skewed (Mandelbrot, 1963; Fama, 1965; Bollerslev, 1987; French et al., 1987; Engle & Gonzalez-Rivera, 1991; Mills, 1995; Corrado & Su, 1996; Peiro, 1999). Several studies have contributed to the widespread consensus in the literature that asset returns are asymmetric and fat-tailed (You & Diagler, 2010; Kelly & Jiang, 2014; McNeil et al., 2015; Babikir et al., 2019; Van Oordt & Zhou, 2016; Wang, 2016). Literature has also shown that the nature of the returns of developed markets depict a more efficient market (almost normal) than emerging or stock markets in developing economies (Cajueiro & Tabak, 2004; Ushad et al., 2008; Risso, 2009). The returns of assets in developing countries (markets) as shown by Ushad et al. (2008), Nortey et al. (2015), Korkpoe and Kawor (2018), Korkpoe and Owusu Junior (2018), Korkpoe and Howard (2019), Owusu Junior (2020) and Nadarajah and Kwofie (2022) are consistent with stylised facts (asymmetric and fat-tailed).

To assess the nature of the risk arising from the distribution of the tails of the returns of the listed banks thereof, this study adopted higher moments of skewness and kurtosis to identify any stylised fact (Harvey, 1995; Joanes & Gill, 1998; Bekaert & Harvey, 1997; Engle, 2004; Cajueiro & Tabak, 2004; McNeil & Frey, 2000; Mcneil et al., 2015; Wong, 2016; Bessembinder, 2018). Kurtosis compares extreme values in both tails (fatness of tail), whereas skewness compares extreme values in one tail to the other (asymmetry of distribution) (Park, 2015; McNeil et al., 2015; Wong, 2016; Bessembinder, 2018). A large observed skewness makes the normality of the population doubtful as a result of the drawn statistics and indicates asymmetry (Doane & Seward, 2011). A negative co-efficient represents a negatively skewed distribution while a positive co-efficient represents a positively skewed distribution of the data under study (Brys et al., 2004; Bessembinder, 2018). The statistical measure of kurtosis was used to measure the heaviness of the tails of the distribution. A high kurtosis means that the tails of the related distribution are heavily tailed but a low kurtosis shows either no or few outliers in the distribution and less extreme than in the tail of a normal distribution (You & Daigler, 2010; Kenton, 2022). Also, a kurtosis above three (3) shows high peaks and fat tails (leptokurtic), suggesting non-normality. A kurtosis statistic of less than three (3) means the data sets have lighter tails than a normal distribution, lack outliers, and are platykurtic (Albuquerque, 2012).

On average, stock markets are expected to show negative skewness due to investors' risk-taking characteristics and the efficiency of stock markets (Albuquerque, 2012). The coefficients for skewness of the respective banks as shown in Table 3 reflect positive skewness but for GCB (-0.4528). With positive skewness, investing in the listed banks is expected to produce positive returns (You & Daigler, 2010). Investors who are more risk averse may thus prefer to invest in stocks with positive skewness with the assumption that there would be more stable gains as compared to losses (Wang, 2016; Bessembinder, 2018). In Ghana, Frimpong and Oteng-Abayie (2006) also found that stocks on the GSE showed positive skewness using daily data from the databank stock index (DSI). Another study by Coffie (2015) also reported a positive skewness for the GSE broad market index as compared to stocks on the Nigerian stock exchange (which are negatively skewed).

Table 3: Moments of the Listed Banks

	Access	ADB	CAL	EGH	GCB	RBGH	SCB	SOGEGH
Skewness	0.3437	2. 5619	0.4543	0.4374	-0.4528	0.0786	1.4528	0.4457
Excess Kurtosis	4.6495	27.5392	2.5676	3.8239	9.0483	5.0764	7.2923	4.0715

Source: Author’s Construct (2022)

Note: Access (Access Bank Ghana Plc.); ADB (Agricultural Development Bank Plc.); CAL (CalBank Plc.); EGH (Ecobank Ghana Ltd.), GCB (GCB Bank Plc.), RBGH (Republic Bank (Ghana) Plc.), SCB (Standard Chartered Bank Ghana Plc.); SOGEGH (Societe General Ghana Ltd.). Plc. is Public Company Limited by Shares.

The positive skewness in this study is theorised by Beedles and Skimkowitz (1980). Beedles and Skimkowitz (1980) reported in contradiction to other studies that had shown that asset returns have stylised that, financial returns were symmetrical by finding that over the past “three decades, securities have displayed a persistent propensity to positive asymmetry”. Also, the positive co-efficient of the asymmetry implies that investors react more to good news than to bad news related to the listed banks and are more risk averse. A positive skewness also implies that investors are rewarded with low returns over long intervals. In addition, positive asymmetry could imply a fat or thin tail that corresponds to outsized profits or losses that are less likely (Ilmanen, 2012) and is reflected in the kurtosis measure.

The kurtosis of the respective banks shows that their tails are heavily tailed and leptokurtic (Fama, 1965). The minimum recorded kurtosis is CAL (2.7256) and platykurtic but ADB has the heaviest tail (27.5392 – leptokurtic).

The estimated leptokurtic statistics show that the listed banks are extremely risky due to the magnitude of the estimates. An extremely leptokurtic distribution, as shown in Table 3, is more predisposed to a greater likelihood of events and broader fluctuations, resulting in a greater potential for extremely low or high returns (Ivanovski et al., 2015). Risk averse investors would rather not invest in assets that have large kurtosis or fat tails (You & Daigler, 2010; Wang, 2016).

Given the leptokurtic nature of the returns, the average returns of the distributions reflect low returns as compared to ADB which has a high return. The analysis shows that the listed banks on the GSE have heavy and fat-tailed distributions (Nortey et al., 2015; Korkpoe & Owusu Junior, 2016; Korkpoe & Howard, 2019). According to Korkpoe and Kawor (2018, p.4), "the presence of heavy tails in return distributions indicates the likelihood of extreme outcomes, which represent real risks and should not be ignored in volatility modelling". In line, the fat-tails depict that the listed banks are risky (Harmantzis, et al., 2006; Chang et al., 2019). This study thus contributes to the literature that states that asset returns deviate from normality and are asymmetric and fat-tailed (Fama, 1965; Mandlebrot, 1963; Peiro, 1999; Brys et al., 2004; Frimpong & Oteng-Abayie, 2006; Wilhelsson, 2009; Mandlebrot & Hudson, 2010; Coffie, 2015; Korkpoe, 2017; Korkpoe & Owusu Junior, 2016; Korkpoe & Kawor, 2018; Korkpoe & Howard, 2021).

As the nature of the distribution of the tails of the returns analysis has proven, the listed banks show tail risks (fat tails and are skewed retrospectively). The fatness and asymmetry in the tails of the listed banks show that there is risk in the banking industry. The asymmetry and fat-tails in the distributions of the returns are important to informing investors of the severity of the risk in the listed banks. The asymmetry and fat-tails also explain investors' response to information on the market and how the banks on the GSE are showing traces of thin trading. Contrary to what investors would want for holding assets that have tail risks (high returns), the average returns of the listed banks do not compensate for due to the relatively low mean (Wang, 2016).

Selecting the Best ARCH Model

The basis of selecting the most suitable GARCH model for the VaR and ES are discussed in this section. The tails of the listed banks are leptokurtic and asymmetric. With conditional models that allow symmetric and asymmetric innovations to capture the risk in the tails of return distributions, in line with their stylised facts, the author explores the optimal GARCH model for assessing the risk in the listed banks. This would provide realistic VaR and ES predictions and avoid underestimating the risk in the listed banks (Gambrill & Shlonsky, 2000; English & Graham, 2000). GARCH models are more suitable for modelling stylised facts such as leptokurtosis, skewness, and volatility clustering which the return distributions show (Engle, 1982; Bollerslev, 1986).

With non-zero skewness and leptokurtic returns, this study tested for the presence of heteroscedasticity using the ARCH LM test (Engle, 1982). The null hypothesis of the test states that there is no ARCH effect (Engle, 1982). If the ARCH effect is present, GARCH can be used to model such volatility. This test is important for reducing errors in the forecasts and predictions for the VaR and ES estimates. In Table 2, the ARCH LM test shows that there are

ARCH effects at a lag of 12 for all banks indicating the presence of heteroscedasticity in the returns.

To capture the volatility, asymmetry and leverage effects, the returns of the respective listed banks were modelled using EGARCH(1,1), GJR-GARCH(1,1) and standard GARCH(1,1). GARCH models aim to reduce forecasting errors and improve the accuracy of ongoing predictions (Braione & Scholtes, 2016; Owusu Junior et al., 2022).

The values of skewness and kurtosis of the listed banks in Table 3 show that the banks have asymmetric and leptokurtic distributions. Thus, with more flexible distributional assumptions, the GARCH models performance would improve (Braione & Scholtes, 2016). Also, to integrate the stylised facts of the listed banks returns in estimating and forecasting VaR and ES, some distributional innovations were used to fit the GARCH models to avoid univariate model misspecification, risk underestimation and to improve forecasting performance (Fernández & Steel, 1998). Thus, the GARCH models were fitted with Student-*t* (-std), skewed Student-*t* (-sstd), and Gaussian (-norm) distribution innovations based on the asymmetric and leptokurtic distributions (de Moivre, 1733; Gauss, 1809; Gosset, 1908; Hansen, 1994; Fernández & Steel, 1998).

Based on the lowest Akaike Information Criterion (AIC), the best model for forecasting VaR and ES is selected (Korkpoe & Owusu Junior, 2016; Korkpoe & Howard, 2019; Korkpoe & Howard, 2021). The study used AIC because it measures information leakage from a model specified by a log-likelihood function and is relatively used to determine the quality of a model (Akaike, 1973, Burnham & Anderson, 2004; Wagenmakers & Farrell, 2004;

Arnold, 2010; Owusu Junior et al., 2022). Table 4 presents the family of ARMA-GARCH(1,1) models for the respective listed banks. The GARCH order used in this study was (1,1). In financial series analysis, it is the most appropriate order proven to capture the dynamics of a market condition (Korkpoe & Owusu Junior, 2016; Miah & Rahman, 2016; Zivot, 2016; Korkpoe, 2017; Korkpoe & Howard, 2019; Korkpoe & Howard, 2021).

Aside from ADB returns, the banks' tail distributions were best captured by GARCH(1,1) with Student-*t* distribution assumptions. ADB has the heaviest tails and largest asymmetry among the banks. Hence, GARCH(1,1) with skewed Student-*t* proved appropriate to capture the tail distributions based on the AIC. The findings of this study are in line with those of Sarpong (2015), Korkpoe and Owusu Junior (2016), and Korkpoe and Amarteifio (2018). Because the data series are not normally distributed but characterised by heavy tails, the Student-*t* fully captures any leverage, volatility, and clustering effects (Mandlebrot, 1963; Fama, 1965; Verhoven & McAleer, 2004; Berggren, 2017). The weighted ARCH LM test of the squared standardised residuals at lag five (5) shows that the ARCH effect has been captured. Table 5 presents the optimal parameters for the best model. These parameters meet the restrictions for conditional variance stationarity (Engle, 1982; Bollerslev, 1986).

Table 4: ARMA-GARCH (1,1) Models for Listed Banks

Model	AIC	BIC	Q^2[5]	AIC	BIC	Q^2[5]	AIC	BIC	Q^2[5]	AIC	BIC	Q^2[5]
	Access			ADB			CAL			EGH		
GARCH-norm	5.3043	5.3592	0.9040(0.88)	3.6506	3.7330	0.0580(1.00)	5. 6914	5. 7601	7.7550(0.03)	5.6456	5.7006	0.8603(0.89)
GARCH-std	**4.7977**	**4.8938**	0.4948(0.96)	-20.5880	-20.478	0.0195(1.00)	**5.4411**	**5.5235**	2.2014(0.57)	**5.2908**	**5.3732**	2.0740(0.60)
GARCH-sstd	4.8658	4.9482	0.8904(0.88)	**-21.903**	**-21.780**	0.0194(1.00)	5.4461	5.5423	2.2650(0.14)	5.3455	5.4279	1.3426(0.75)
eGARCH-norm	5.3038	5.3724	0.9007(0.88)	3.6582	3.7544	0.0573(1.00)	5.5681	5.6505	1.2523(0.80)	5.5994	5.6681	0.5541(0.95)
eGARCH-std	4.9626	5.0316	1.7787(0.67)	-17.7600	-17.6510	0.0009(1.00)	5.4360	5.5322	2.2018(0.57)	5.3412	5.4099	1.3142(0.79)
eGARCH-sstd	4.9651	5.0475	1.8224(0.66)	-18.8560	-18.733	0.0129(1.00)	5.4422	5.5510	2.2047(0.57)	5.2940	5.3902	2.1740(0.58)
gjrGARCH-norm	5.3056	5.3743	0.9616(0.87)	3.5330	3.6291	0.0253(1.00)	5.5925	5.6749	1.4626(0.75)	5.6185	5.6872	0.2687(0.99)
gjrGARCH-std	4.9635	5.0459	1.8152(0.66)	-5.7253	-5.6154	0.0121(1.00)	5.4429	5.5390	2.0375(0.61)	5.3364	5.4188	0.7899(0.91)
gjrGARCH-sstd	4.9635	5.0021	3.2460(0.09)	-15.3230	-15.227	0.0195(1.00)	5. 4491	5.5590	2.0335(0.61)	5.3424	5.4385	0.8474(0.90)
	GCB			RBGH			SCB			SOGEGH		
GARCH-norm	4.8696	4.9383	1.1097(0.83)	5.4061	5.5418	1.1076(0.83)	5. 9086	5. 9772	4.3500(0.21)	5.5621	5.6582	9.1020(0.12)
GARCH-std	**4.5588**	**4.6549**	2.2183(0.57)	**5.0166**	**5.1863**	1.6900(0.88)	**5. 3467**	**5. 4428**	1.7997(0.67)	**5.2637**	**5.3735**	1.5254(0.73)
GARCH-sstd	4.5635	4.6734	2.1672(0.58)	5.1108	5.2805	1.7026(0.92)	5. 3537	5. 4636	1.8995(0.64)	5.2645	5.3881	1.8040(0.67)
eGARCH-norm	4.7601	4.8425	0.7834(0.91)	5.3506	5.5033	1.0430(0.85)	5. 7053	5. 7877	1.1344(0.83)	5.4404	5.5503	0.5051(0.96)
eGARCH-std	4.6361	4.7185	1.4495(0.75)	5.1052	5.2579	1.3661(0.77)	5. 4645	5. 5469	2.6560(0.47)	5.2669	5.3904	1.3411(0.78)
eGARCH-sstd	4.6424	4.7386	1.5245(0.73)	4.9931	5.1797	1.3209(0.78)	5. 4573	5. 5534	2.3340(0.54)	5.2689	5.4063	1.2899(0.79)
gjrGARCH-norm	4.8403	4.9227	0.9747(0.87)	5.4410	5.5937	1.2758(0.79)	5. 9111	5. 9935	4.7100(0.18)	5.5518	5.6617	5.7280(0.10)
gjrGARCH-std	4.6331	4.7292	1.3164(0.78)	5.1131	5.2828	1.2511(0.80)	5.4443	5.5404	1.8490(0.65)	5.2729	5.3965	1.4539(0.75)
gjrGARCH-sstd	4.6376	4.7474	1.3211(0.78)	5.1192	5.3058	1.2468(0.80)	5. 4517	5. 5616	1.7890(0.67)	5.3267	5.4640	5.2360(0.14)

Source: Author's Construct (2022)

Note: Access (Access Bank Ghana Plc.); ADB (Agricultural Development Bank Plc.); CAL (CalBank Plc.); EGH (Ecobank Ghana Ltd.), GCB (GCB Bank Plc.), RBGH (Republic Bank (Ghana) Plc.), SCB (Standard Chartered Bank Ghana Plc.); SOGEGH (Societe General Ghana Ltd.). All models are GARCH (1,1) specifications. eGARCH is Exponential-GARCH, gjrGARCH is the Glosten-Jagannathan-Runkle GARCH model. The parameter innovations used for the models are norm (Gaussian), std (Student-t) and sstd (Skewed Student-t). Q^2[5] is the weighted ARCH LM test of the squared standardised residuals at lag 5 and p-values are in (). The best GARCH models are shown in bold based on the lowest AIC.

Table 5: Optimal Parameters of the Best Model

	Estimate	Std. Error	t-value	p-value	Estimate	Std. Error	t-value	p-value
	Access				ADB			
μ	-0.0489	0.0925	-0.5285	0.5972	0.0000	0.0000	0.0000	0.96605
λ	1.2083	0.6420	1.8821	0.0598	3.9537	0.0000	0.0000	0.0000
α	0.4417	0.1213	3.6427	0.0003	-0.0000	0.0000	-2.9046	0.0000
β	0.5573	0.0874	6.3757	0.0000	0.8790	0.0004	2.4438	0.0000
v	2.6659	0.2396	11.1269	0.0000	2.0157	0.0002	1.0901	0.0000
	CAL				EGH			
μ	-0.0079	0.1445	-0.0549	0.9562	-0.1308	0.1144	-1.1438	0.2527
λ	6.2890	2.0186	3.1155	0.0018	3.2599	1.5741	2.0710	0.0384
α	0.8407	0.3473	2.4207	0.0155	0.5719	0.1737	3.2919	0.0010
β	0.1503	0.0992	1.5148	0.1298	0.4271	0.1058	4.0381	0.0001
v	3.4307	0.8156	4.2064	0.0000	2.6899	0.28379	9.4787	0.0000
	GCB				RBGH			
μ	-0.0513	0.0578	-0.8884	0.3744	-0.0413	0.0843	-0.4897	0.6244
λ	0.7518	0.2730	2.7542	0.0059	3.7488	1.7919	2.0921	0.0364
α	0.7565	0.1280	5.9084	0.0000	0.7946	0.2468	3.2193	0.0013
β	0.2425	0.0618	3.9244	0.0001	0.2044	0.1122	1.8220	0.0685
v	3.3755	0.3602	9.3720	0.0000	2.6290	0.2625	10.0168	0.0000
	SCB				SG			
μ	-0.0979	0.0527	-1.8575	0.0632	-0.1233	0.1830	-0.6738	0.5004
λ	0.6261	0.7153	0.8753	0.3814	4.3186	1.8848	2.2913	0.0220
α	0.4524	0.1016	4.4516	0.0000	0.7072	0.2532	2.7936	0.0052
β	0.5466	0.0563	9.7098	0.0000	0.2918	0.1620	1.8012	0.0717
v	2.5508	0.1366	18.6778	0.0000	2.8581	0.3834	7.4545	0.0000

Source: Author's Construct (2022)

Note: Access (Access Bank Ghana Plc.); CAL (CalBank Plc.); EGH (Ecobank Ghana Ltd.), GCB (GCB Bank Plc.), RBGH (Republic Bank (Ghana) Plc.), SCB (Standard Chartered Bank Ghana Plc.); SOGEGH (Societe General Ghana Ltd.). Mu (μ); Omega (λ); Alpha1 (α); Beta1 (β); Shape (v).

Also Figures 3 to 10 show that GARCH(1,1)-std captures the stylised facts in the returns of the listed banks (Brooks, 2014). From the respective figures, the QQ plots show that the returns deviates from normality implying the presence of skewness and the likelihood of fat-tails. This is also reflective in the sigma plots of the residuals of each banks which are reflecting the extent of fluctuations in the data. It can be inferred that there is the presence of conditional heteroscedasticity in the returns of the listed banks. However, the ACF of squared standardised residual plots show the presence of positive correlation across the returns for all the listed banks. This shows that the most suitable conditional model for the listed banks (GARCH(1,1)-std and

GARCH(1,1)-sstd (ADB only)) has effectively captured the stylised facts in the tails of the return distributions and the presence of ARCH has been effectively modelled. The 1% VaR limit plots are an indication of losses in the respective banks. Implicitly, this shows the presence of downside risk in the returns of the listed banks.

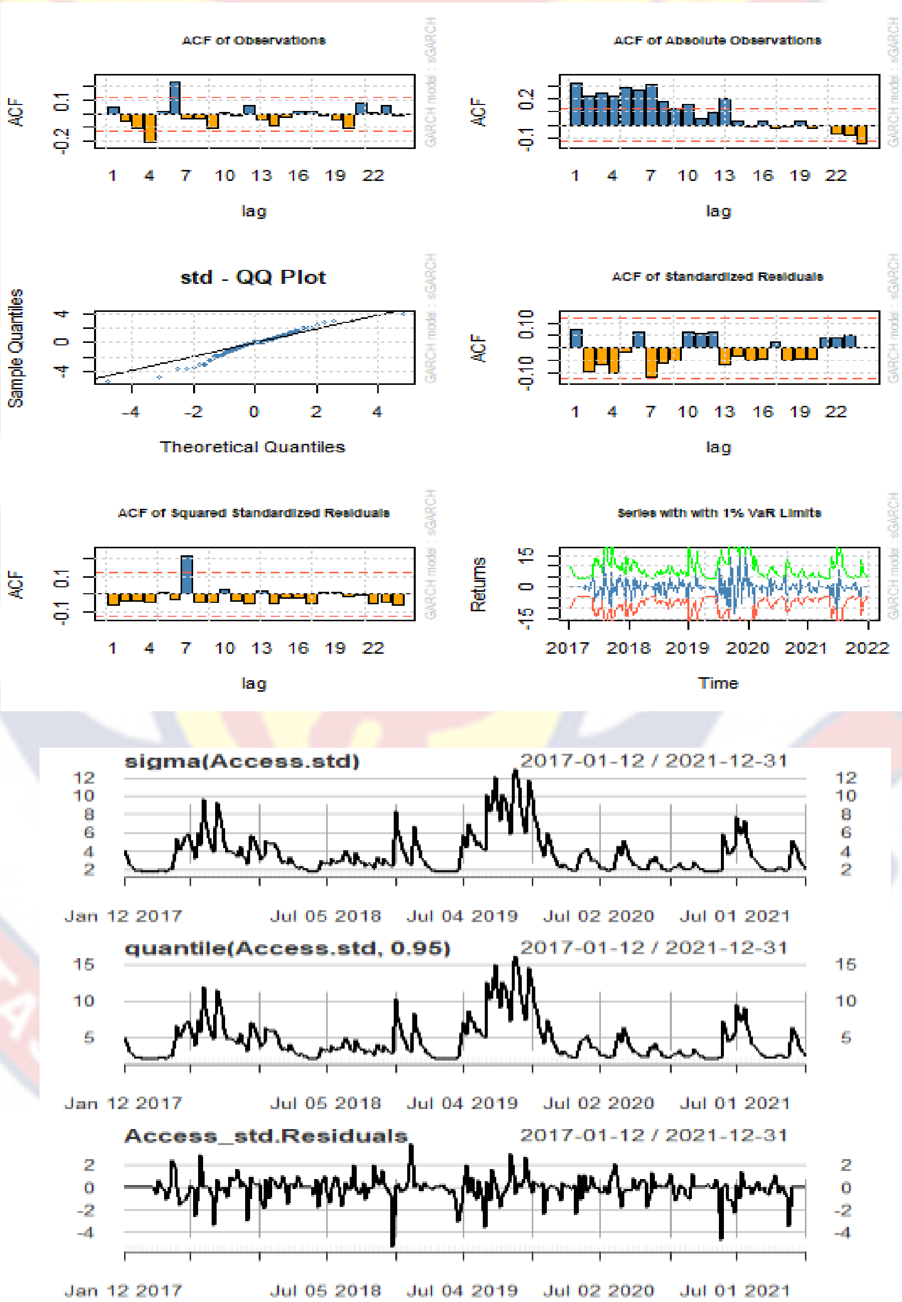

Figure 3: The Autocorrelation Function (ACF) of observations, ACF of Standardised Observations, ACF of Standardised Residuals, ACF of Squared Standardised Residuals, QQ-plot, VaR Backtest, Time Varying, and Residual plots for the best model for Access

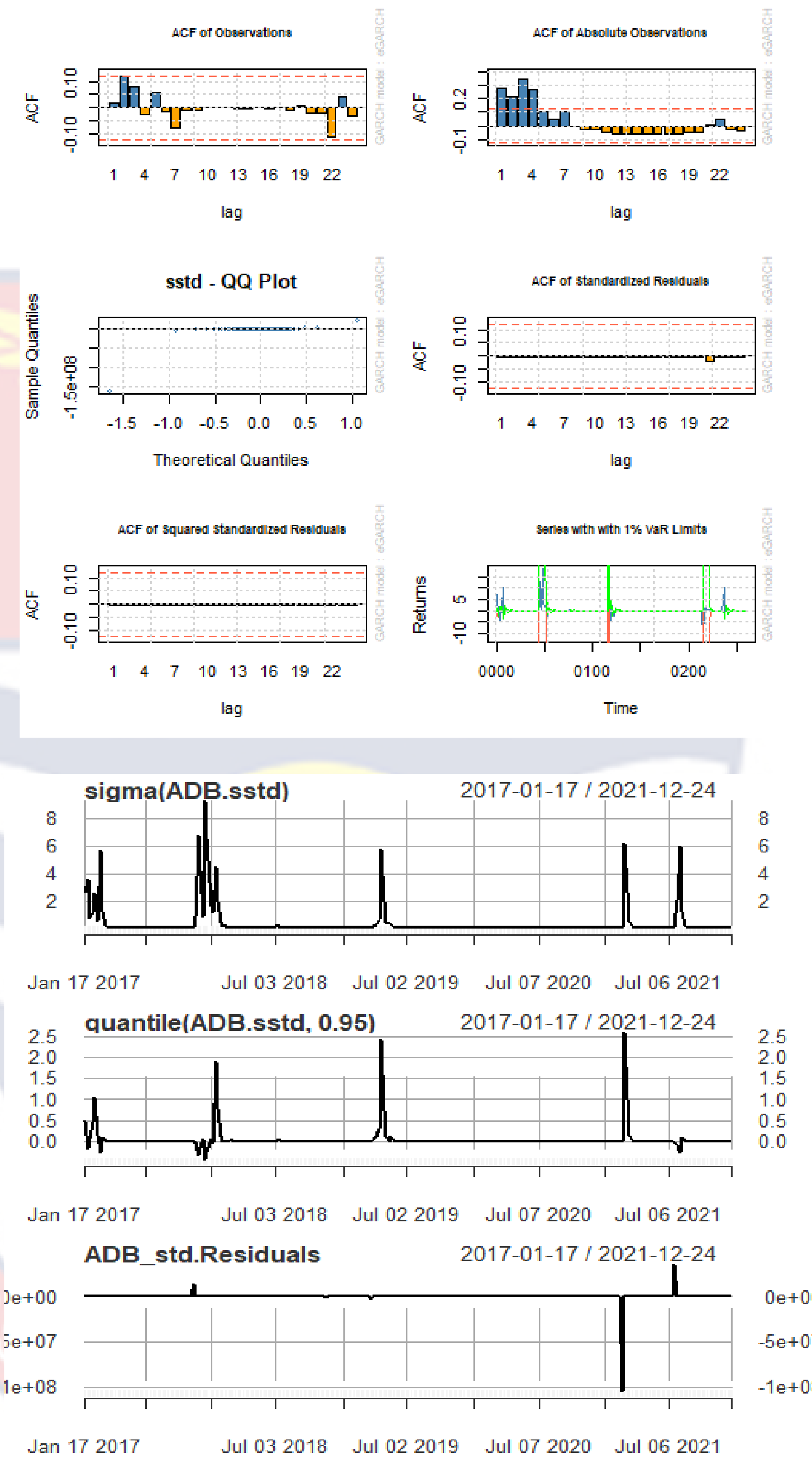

Figure 4: The Autocorrelation Function (ACF) of observations, ACF of Standardised Observations, ACF of Standardised Residuals, ACF of Squared Standardised Residuals, QQ-plot, VaR Backtest, Time Varying, and Residual plots for the best model for ADB

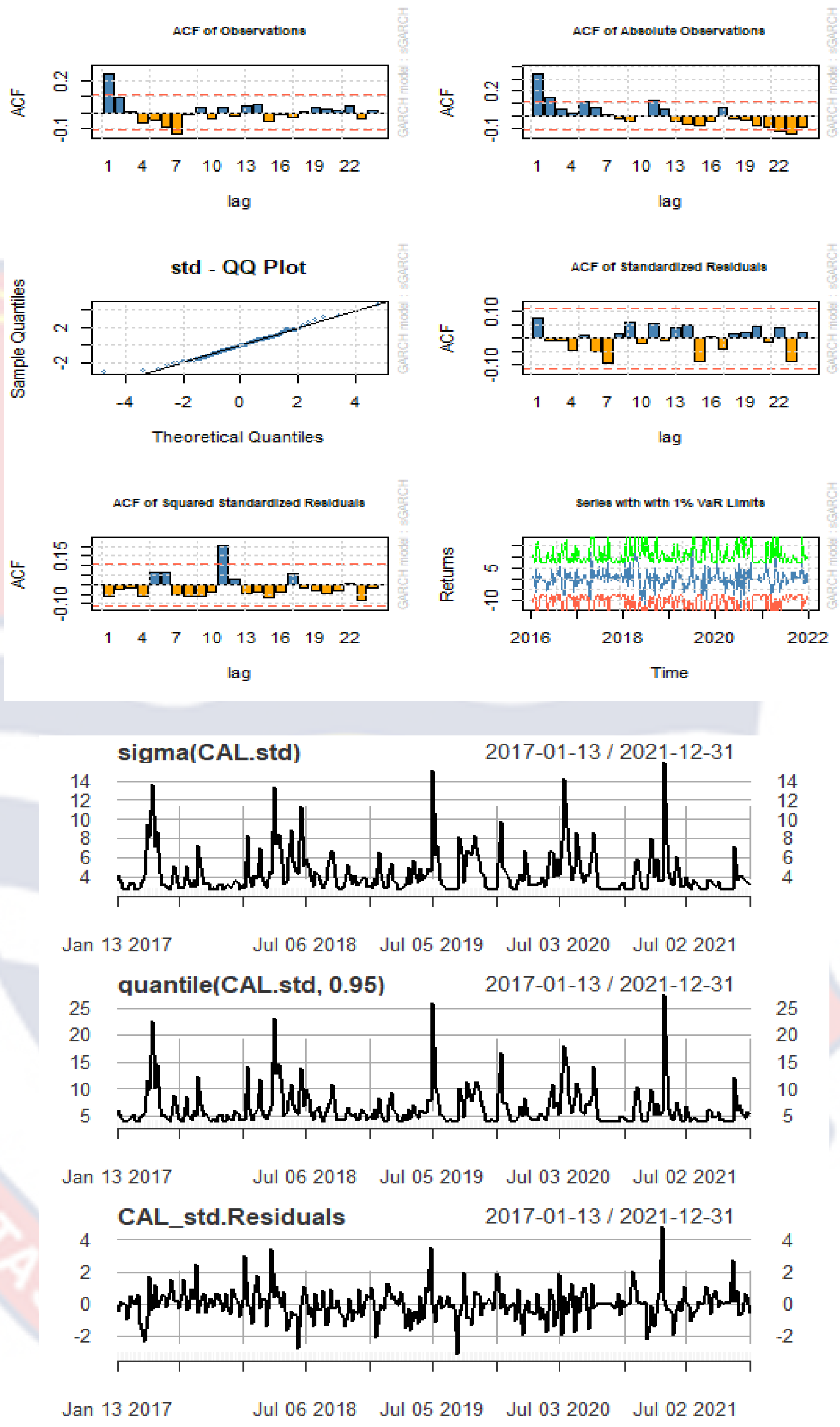

Figure 5: The Autocorrelation Function (ACF) of observations, ACF of Standardised Observations, ACF of Standardised Residuals, ACF of Squared Standardised Residuals, QQ-plot, VaR Backtest, Time Varying, and Residual plots for the best model for CAL

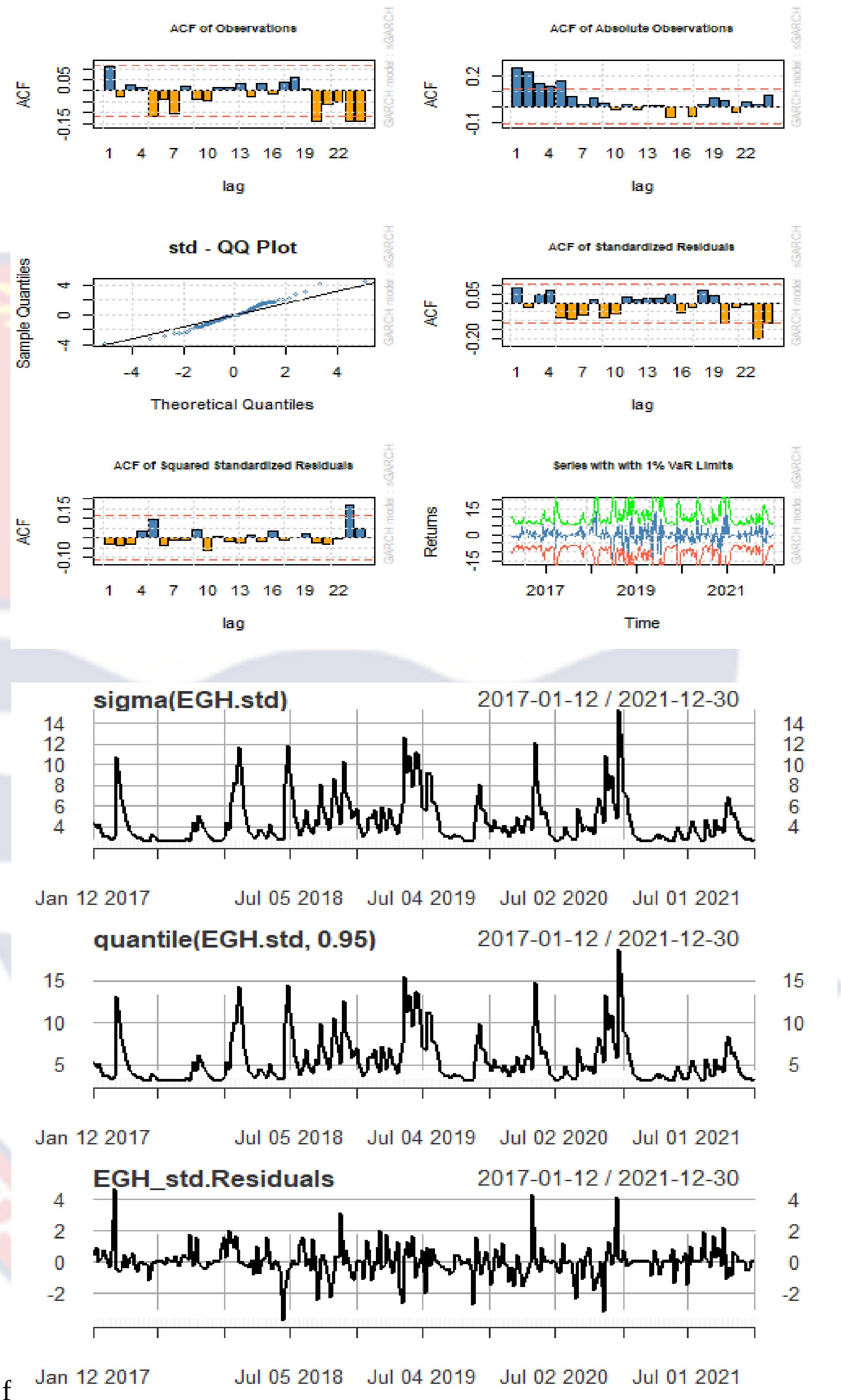

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Figure 6: The Autocorrelation Function (ACF) of observations, ACF of Standardised Observations, ACF of Standardised Residuals, ACF of Squared Standardised Residuals, QQ-plot, VaR Backtest, Time Varying, and Residual plots for the best model for EGH

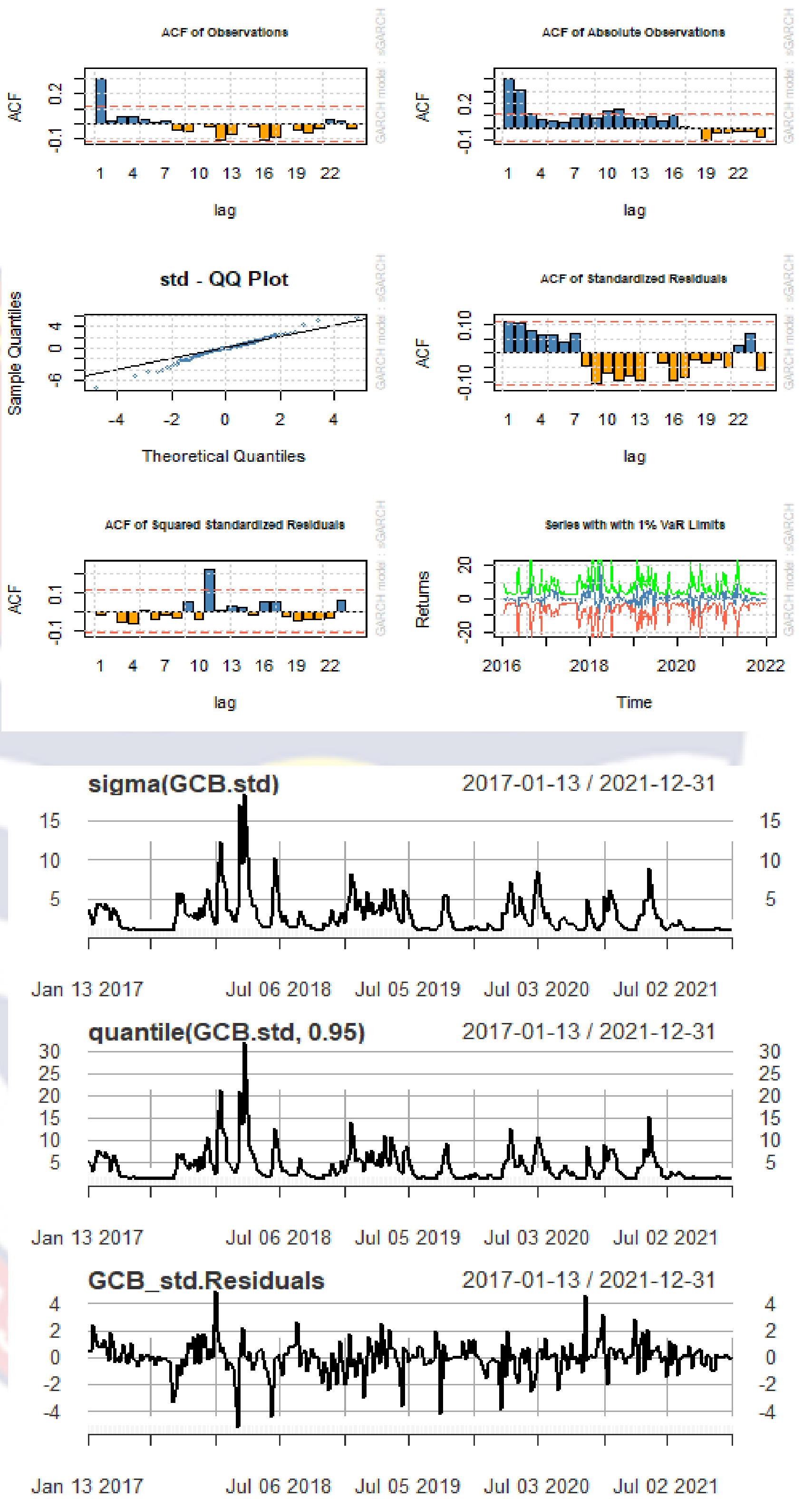

Figure 7: The Autocorrelation Function (ACF) of observations, ACF of Standardised Observations, ACF of Standardised Residuals, ACF of Squared Standardised Residuals, QQ-plot, VaR Backtest, Time Varying, and Residual plots for the best model for GCB

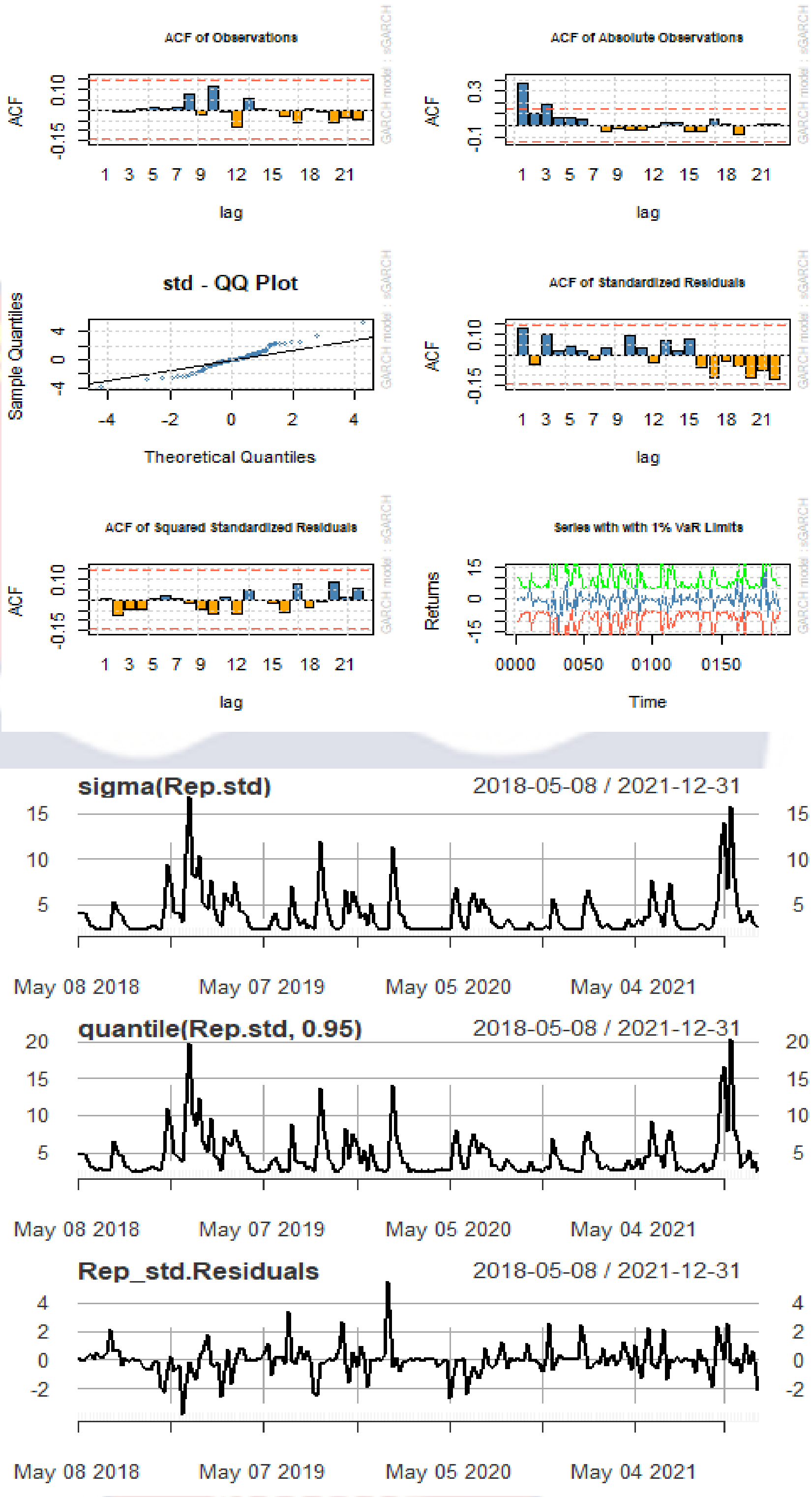

Figure 8: The Autocorrelation Function (ACF) of observations, ACF of Standardised Observations, ACF of Standardised Residuals, ACF of Squared Standardised Residuals, QQ-plot, VaR Backtest, Time Varying, and Residual plots for the best model for RBGH

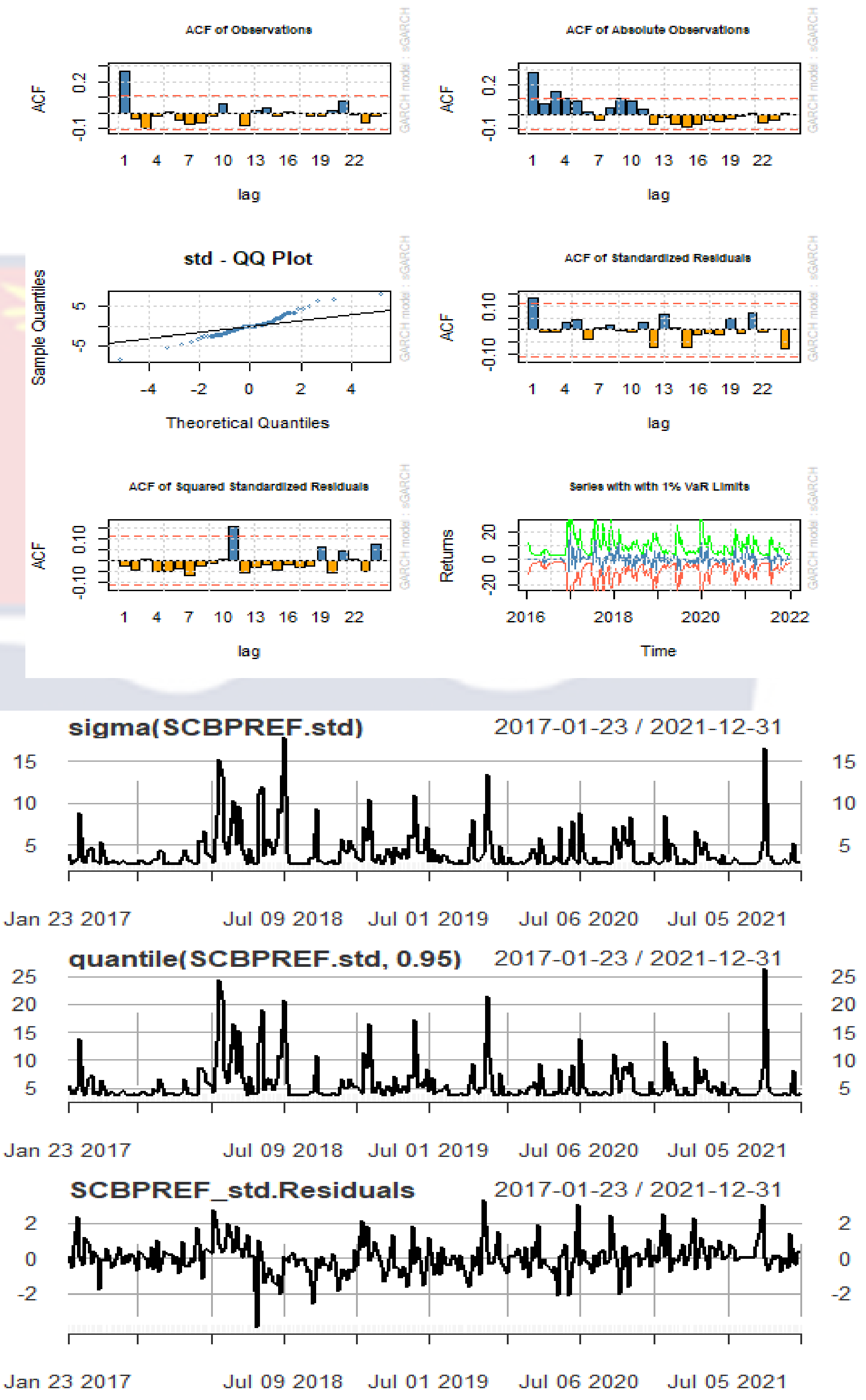

Figure 9: The Autocorrelation Function (ACF) of observations, ACF of Standardised Observations, ACF of Standardised Residuals, ACF of Squared Standardised Residuals, QQ-plot, VaR Backtest, Time Varying, and Residual plots for the best model for SCB PREF

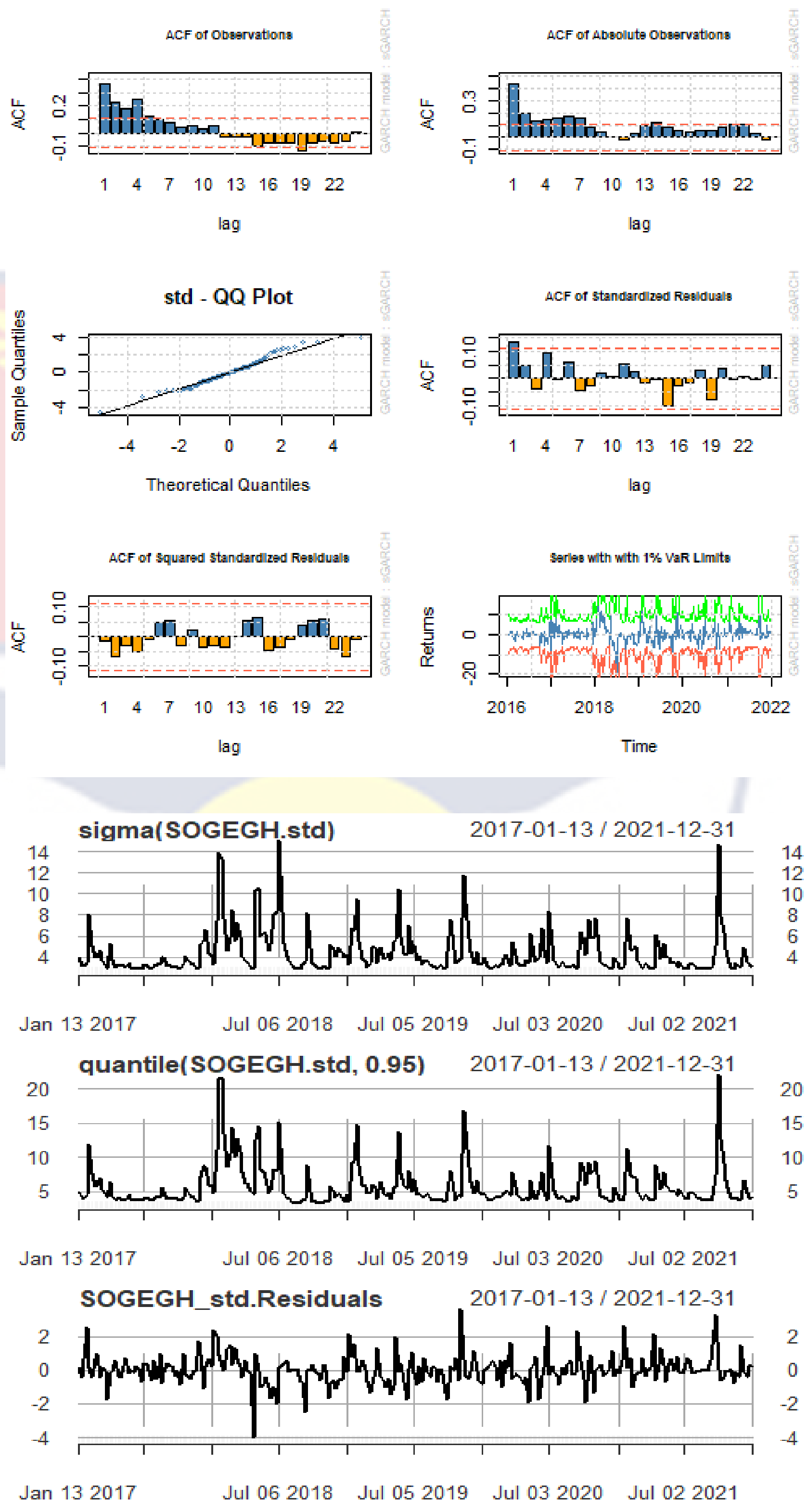

Figure 10: The Autocorrelation Function (ACF) of observations, ACF of Standardised Observations, ACF of Standardised Residuals, ACF of Squared Standardised Residuals, QQ-plot, VaR Backtest, Time Varying, and Residual plots for the best model for SOGEGH

In Table 6, the backtest results for the best models are presented at 1% and 5% significance levels. The unconditional coverage (Kupiec, 1995) and conditional coverage (Christoffersen, 1998) were used to check for the accuracy of the GARCH (1,1)-std and GARCH (1,1)-sstd models for all the listed banks under study. The p-values of the respective banks show that the null hypotheses for UC and CC should not be rejected, indicating that the best models (GARCH (1,1)-std) have correct exceedances, are independent, and are non-autocorrelated. Thus, the models can be used to accurately predict VaR and ES estimates for the listed banks.

Table 6: Backtest Results of Selected GARCH(1,1) Model

	Conditional Coverage		Unconditional Coverage		Expected(Actual) Observations	
	1%	5%	1%	5%	1%	5%
Access	0.6560 (0.7200)	1.3220 (0.5160)	0.5820 (0.4450)	0.3700 (0.5430)	1.1(2)	5.6(7)
ADB	3.5689 (0.5113)	5.8889 (0.1119)	3.0983 (0.4470)	4.9362 (03544)	2.6(2)	13.1(9)
CAL	1.3310 (0.5140)	4.2000 (0.1220)	1.3240 (0.2500)	2.4700 (0.1160)	2.6(1)	13.1(19)
Ecobank	2.1620 (0.3390)	4.2970 (0.1170)	1.9570 (0.1620)	1.5400 (0.2150)	2.5(5)	12.5(17)
GCB	7.2830 (0.2260)	5.2850 (0.1710)	5.4240 (0.1200)	5.0000 (0.1250)	2.5(7)	8.1(15)
RBGH	0.6400 (0.7260)	1.2670 (0.5310)	0.5660 (0.4520)	0.9610 (0.3270)	1.1(2)	5.6(8)
SCB	0.7570 (0.6850)	1.1340 (0.5670)	0.6320 (0.4270)	1.1220 (0.2900)	2.6(4)	13.1(17)
SG	1.3310 (0.5140)	1.2520 (0.5350)	1.3240 (0.2500)	0.3740 (0.5410)	2.6(1)	13.1(11)

Source: Author's Construct (2022)

Note: p-values and actual observations for the models are presented in parenthesis. Access (Access Bank Ghana Plc.); CAL (CalBank Plc.); EGH (Ecobank Ghana Ltd.), GCB (GCB Bank Plc.), RBGH (Republic Bank (Ghana) Plc.), SCB (Standard Chartered Bank Ghana Plc.); SOGEGH (Societe General Ghana Ltd.).

Objective 2

To assess the risk of the listed banks using quantitative measure of VaR and ES

The VaR was the regulatory risk measure adopted by regulators and financial institutions for measuring market risk until the 2007-08 GFC which led to its revision. VaR has been the regulatory measure of the market risk of financial institutions, to inform portfolio risk managers for many years. However, because VaR assumes normality, it was unable to accurately predict risks such as the GFC. To make accurate predictions for VaR estimates, there should be assumptions of asymmetry since asset returns are not normally distributed but depict stylised facts such as heteroscedasticity, non-normality, fat-tailed, and often skewed (Harvey, 1995; Bekaert & Harvey, 1997; Engle, 2004; Cajueiro & Tabak, 2004; Mcneil et al., 2015). Extensively, the literature has adopted parametric and non-parametric VaR models to test its applicability in predicting risk in emerging and developed stock markets across assets (Kellner & Rösch, 2016; Naeem et al., 2019; Caporale & Zekokh, 2019; Owusu Junior et al., 2022; Trucious & Taylor, 2022). For this study, conditional volatility GARCH(1,1)-std VaR was used to predict the market risk of listed banks on the GSE (Kellner & Rösch, 2016).

VaR is a non-negative risk prediction that reflects the quantile of the distribution of maximum gains and losses at a time (Jorion, 2007). In Table 7, the VaR estimates for respective banks are listed at 95%, 97.5% and 99% respectively. At each level, an average of three is added to the magnitude of the previous risk prediction; however, for this study, the analysis for VaR predictions at 99% according to BCBS reassessment of the Bassel Accord II to III is discussed (BCBS, 2013).

Table 7: Results of GARCH-based VaR and ES Predictions

	Probability	VaR	ES
Access	0.950	9.5784	12.5115
	0.975	11.9927	**14.3304**
	0.990	**14.4491**	16.1811
ADB	0.950	5.9777	10.3230
	0.975	9.5474	**13.0218**
	0.990	**13.1928**	15.7777
CAL	0.950	7.9495	11.0063
	0.975	9.8824	**13.2216**
	0.990	**12.7142**	16.4672
EGH	0.950	9.5023	12.8075
	0.975	12.1539	**14.8980**
	0.990	**14.9813**	17.1271
GCB	0.950	7.3098	11.0599
	0.975	9.7370	**13.7491**
	0.990	**13.2077**	17.5943
RBGH	0.950	9.1268	12.4604
	0.975	11.5835	**14.6923**
	0.990	**14.5787**	17.4132
SCB	0.950	10.1757	15.8897
	0.975	13.4073	**20.2199**
	0.990	**18.6519**	27.2475
SG	0.950	8.7232	11.6135
	0.975	10.9977	**13.4672**
	0.990	**13.5044**	15.5101

Source: Author's Construct (2022)
Note: The bold font represents the Basel III proposed probability for quantifying the VaR (99%) and ES (97.5%). Access (Access Bank Ghana Plc.); CAL (CalBank Plc.); EGH (Ecobank Ghana Ltd.), GCB (GCB Bank Plc.), RBGH (Republic Bank (Ghana) Plc.), SCB (Standard Chartered Bank Ghana Plc.); SOGEGH (Societe General Ghana Ltd.)

Table 7 presents the maximum level of loss values that the respective banks are exposed to on the stock market. The respective loss in value for the banks is a prediction of the actual losses at a 99% confidence level. Thus investors in these banks, over a 5-year period, should expect a respective loss in value at a 99% confidence level as shown. Hence, a portfolio holder who invests in these banks has the likelihood of loosing these respective values for holding their stocks. An investor in Access bank, has the likelihood of loosing

GH¢ 14.4491 at a 1% probability level. Subsequent to the tail distribution of the returns of Access bank, there is an indication that investors are sensitive to risk. This level of predicted risk would deter investors from buying the stocks of Access bank. Investors in ADB, CAL bank, GCB and Societe General have the likelihood of making losses in value of between GH¢12.00 to GH¢14.00. The returns of these banks also show the sensitivity in the tail distribution of the assets indicating that investors would not appreciate to make such losses as compared to the returns they are getting. Averagely, Ecobank, Republic bank, and SCB investors also have the probability of losing in value of GH¢14.00 to GH¢19.00 over the five-year period of investing in the banks.

Ultimately, this is not motivating enough to trade in the stocks of these banks and that contributed implicitly to the unattractiveness of the stocks on the GSE. At 99%, the maximum loss in value expected from the downside risk measures for the respective banks shows their market risk levels. The maximum loss that banks listed on the GSE could encounter if the market is in a normal condition, on average, over five years is relatively higher than the level of average returns (mean) these banks offer to respective investors. This indicates that investors on the GSE are not sufficiently rewarded for the level of risk of investing in the banks as theorised in the modern portfolio theory (Makorwitz, 1952). The average risk of the banking institution if measured by the standard VaR shows that although some banks show a higher risk or loss, the difference in magnitude is not excessively large. Moreover, the magnitude of the loss predicted in the banks is on average high across the respective banks.

If VaR predictions for a bank are consistently higher than the returns, it suggests that the bank’s risk exposure is significant and potentially problematic. This indicates that the banks’ potential losses exceed its returns at the specified confidence level, highlighting a potential risk of sustaining significant losses. Such a situation calls for a thorough assessment of the bank's risk management strategies and a reevaluation of its investment and portfolio composition to align with the desired risk-return trade-off.

After the GFC, it was found that VaR could capture loss only under normal market conditions and not when the market condition was in turmoil (Fissler et al., 2015; Kellner & Rösch, 2016). Thus, the Basel Committee moved from VaR to ES to capture maximum tail losses in a stressed market condition – the Conditional VaR (CVaR) (BCBS, 2013). The ES was proposed to strengthen the shortfall of VaR as exposed by GFC. Basel III proposed that ES be computed at 97.5% to calibrate capital requirements and rationalise financial markets. Kellner and Rösch (2016) showed that ES is more sensitive to regulations and misspecification of predictions. Although ES has been espoused as a better measure of risk, its sensitivity to tail risks can lead to greater periodic capital charges based on the magnitude of estimated risk predictions in an attempt to predict the worst that could happen under stressed conditions (Artzner, 1997) and rarely varies under misspecification (Kellner & Rösch, 2016).

In Table 7, the risk predictions for ES at 97.5% are presented in bold font. Under extreme market conditions, as captured by the Student-*t* distributions, the banks also show large losses for the respective banks. Financial risks are usually well-captured by skewed and leptokurtic distributions (Kellner & Rösch, 2016). As shown in Table 3, it is evident that the tails of the listed banks are heavy and fat; – thus, large ES predictions are expected. The ES captures risks under the assumption that it is a coherent tail risk measure. The risk level for the listed banks as measured by ES at 99% is quite close to the predictions of VaR at 97.5% as proposed by the Basel Committee. It is worth noting that at the same confidence level, ES predicts expected losses that exceed VaR risk predictions.

For the respective banks at 97.5% the likelihood in loss of value show how much investors would lose over a five-year period of holding stocks in the listed banks. Arguably, just as for the VaR loss predictions, the respective banks have shown that investors are not been compensated enough for investing in them. At 2.5% probability level, investors are showing series of high losses, higher than the total risk (standard deviation) in value. For Access bank, there is a loss in value of GH¢14.3301, followed by Republic in value of GH¢14.6923, Ecobank (GH¢14.8980) with SCB having the highest loss in value at GH¢20.2199 over the five-year period. The other banks have less loss in value of relatively GH¢13.

Comparing the results of VaR and ES at respective probability levels, it is clear that the ES loss predictions are larger than those of VaR. Aside from the tail characteristics of the listed banks that may have contributed to such large risk predictions, ES is a non-sub-additive risk measure (Artzner, 1997). As such, integrations that also account for large risk predictions, and in this case, for the listed banks (Rabie, 2020), are taken into consideration. From Table 7, the risk predictions for ES, just as the VaR, show that the maximum loss for the respective listed banks beyond a probability level indicates that the banks are risky.

A financial system that has tail risk is characterised by a synchronous market risk which would deter investors from trading in such assets. In the analysis, the results have shown that investors are first and foremost not being compensated for investing in the listed banks and this has been reflected in the asset pricing due to thin trading on the GSE (Kelly & Jiang, 2014; Van Oordt & Zhou, 2016; Wang, 2016). With the presence of tail risk as shown by the skewness and kurtosis, the ES measure theoretically confirms that the Ghanaian banking system faces risk.

Objective 3

To rank the listed banks nominally for investors' diversification purposes

The VaR and ES regulatory risk measures have been used extensively in developed and emerging stock markets to capture market risk. For this objective, the study used the VaR predictions of the respective banks as the forecast values to compare how far off the actual returns are from the VaR losses. Research shows that a risk measure should be useful for forecast comparison and ranking for model estimation and selection to be possible (Fissler et al., 2015; Caporale & Zekokh, 2019; Sadik et al. 2019; Patton et al., 2019). Because the returns of the listed banks are asymmetric and fat-tailed (tail risk), the best model for capturing such stylised facts across the banks was GARCH(1,1)-std. Across the banks, model estimation and selection were the same making it possible to nominally rank the listed banks.

Unlike VaR, ES is inelicitable making it impossible to rank its predictions (BCBS, 2017). Irrespective, Basel III theoretically holds that the

VaR at 99% and ES at 97.5% are approximately the same. Table 7 shows that the VaR and ES predictions at 99% and 97.5%, respectively, are almost indifferent (BCBS, 2013). Thus, the elicitable VaR risk measure was used to nominally rank the listed banks in this study and can be generalised for the ES predictions (Patton et al., 2019; Liu & Wang, 2021; Owusu Junior et al., 2022). Hence, using the VaR predictions at 99% as forecasted values, the listed banks were ranked based on MAE, RMSE, and sMAPE risk metrics (Hamner et al., 2018; Bezerra & Albuquerque, 2017; Sadik et al., 2019; Owusu Junior, 2020; Owusu Junior et al., 2021; Rehman et al., 2022), as shown in Table 8. The selection criterion is the metric with the least co-efficient in an independent case (Hamner et al., 2018; Bezerra & Albuquerque, 2017; Owusu Junior, 2020). However, in this study, the best model across the banks is GARCH (1,1)-std; thus, the study ranks the banks based on their respective metrics.

The metrics in Table 8 show the mean of absolute error (MAE), the square root of the mean (RMSE), and the percentage (sMAPE) of the difference between the actual returns and the forecasted VaR values at 99%. The banks are ranked from 1 (lowest metric coefficient) to 8 (highest metric coefficient) across metrics. The coefficient of the MAE metric shows that the bank with the least risk is ADB (2.8139) and Societe General (11.5843) ranked the highest. This shows that the absolute difference between the returns and non-negative losses is quite high for GCB, Republic, Access, Standard Chartered, Ecobank and CAL (listed in ascending order). The RMSE metric is the standard deviation of the predicted errors among the banks. From Table 8, ADB has the lowest RMSE metric coefficient, but Societe Generale has the highest coefficient and is thus ranked highest. Also, the sMAPE metric shows that the percentage of the banks' respective errors is lowest for GCB and highest for ADB.

Table 8: Ranking of GARCH-based VaR of Listed Banks

	MAE	$Rank_{MAE}$	RMSE	$Rank_{RMSE}$	sMAPE	$Rank_{sMAPE}$
Access	9.4222	4	11.7797	4	1.6636	4
ADB	2.8139	1	4.7735	1	1.9896	8
CAL	11.4899	7	13.5294	7	1.6450	2
EGH	11.4673	6	13.4898	5	1.6765	5
GCB	7.7203	2	10.7944	2	1.6233	1
RBGH	9.2501	3	11.3985	3	1.6520	3
SCB	11.2860	5	12.2542	6	1.6233	6
PREF						
SOGEGH	11.5843	8	13.4976	8	1.6773	7

Source: Author's Construct (2022)

Note: Access (Access Bank Ghana Plc.); CAL (CalBank Plc.); EGH (Ecobank Ghana Ltd.), GCB (GCB Bank Plc.), RBGH (Republic Bank (Ghana) Plc.), SCB (Standard Chartered Bank Ghana Plc.); SOGEGH (Societe General Ghana Ltd.)

The nominal rank of the listed banks across the metrics is consistent for at least two of the metrics. Republic and Access are persistently ranked 3rd and 4th respectively while the other banks change across the metrics. ADB and Societe were consistently ranked 1st and 8th respectively, contrary to Ofosu-Hene and Amoah (2016), where Societe Generale had the lowest risk index. GCB is a government bank listed on the stock exchange and is reported to have a good risk profile and as shown, ranked 2nd among the other banks (Adu-Mensah et al., 2015). Gozah et al. (2020) found that GCB could be used for diversification if an investor is interested in the financial institutions listed on the GSE. ADB is also a government-owned development and commercial bank. Thus, ownership structure could be a contributing factor to this finding from the political and social front of the government (looking at the data sampled, there has been one party in power since 2017). Stiglitz (1993) theorised that government-owned banks implement measures intended to reduce market failures and improve social welfare. Other studies have found that this is true because government-owned banks have low market (bank) risk (Iannotta et al., 2013; Aymen, 2014).

Chapter Summary

This chapter is presented in order of the objectives of the study. The descriptive statistics of the respective banks showed that investors in the listed banks get “little” compensation for risk in the market (standard deviation). The nature of the tails of the return distributions showed stylised facts of returns. The findings showed that the returns are asymmetric and leptokurtic. Following that, GARCH models were used to model the asymmetry and leptokurtic tail distributions of the respective banks. For all the banks but ADB (GARCH(1,1)-sstd), GARCH (1,1)-std was more suitable for modelling the stylised facts. The GARCH (1,1)-std was backtested to ensure accurate predictions because the accuracies of VaR and ES estimations depend on how well a selected model portrays the extreme data observations. Feeding GARCH(1,1)-std (GARCH(1,1)-sstd for ADB) into the VaR and ES risk measures, objectives 2 and 3 were answered the VaR and ES predictions were made. The predictions showed the presence of risk in the listed banks. Finally, the risks of the listed banks were ranked and the results show that ADB(SOGEH) across the metrics (MAE and RMSE) is the least(highest) risky listed bank in Ghana.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Introduction

The study sought to assess the risk of the listed banks on the GSE. Thus, in this chapter, a summary of the study, the conclusions deduced from the findings, recommendations for the theoretical and practical implications of the findings, and suggestions for further studies are presented.

Summary

The study aimed to assess the risk in the listed banks after the sectoral clean-up. Inherently, because economies are interconnected, irrespective of economic differences there is the likelihood of a system failure coming out of the actions, operation or the risks in a bank as theorised in the theory of systemic risk. Thus, per the theory of financial regulation, it is important that banks use regulatory frameworks to ensure a stable and confident financial system. The literature on risk in the Ghanaian financial sector has extensively been on the nexus between risk and performance, risk and profitability and management. None of the literature in Ghana has however adopted the regulatory framework for measuring risk and barely do the banks report on using VaR and ES to measure their market risk. To bridge this gap, this study used the Basel III framework for modelling market risk. The following objectives were set:

1) To assess the nature of risk arising out of the returns distributions of listed banks;
2) To assess the risk of the listed banks using the quantitative measure of VaR and ES;

3) To nominally rank the listed banks for investors' diversification purposes.

To be able to describe the downside risk in the listed banks, these questions were deduced:

1) What is the nature of the distribution of the returns of the listed banks?
2) What is the risk of the listed banks using Value-at-Risk and Expected Shortfall?
3) What is the nominal rank of the listed banks for investors' diversification purposes?

The study adopted a quantitative research approach and a descriptive research design to assess the risk in the listed banks. The weekly returns of the listed banks were purposively sampled from 2017 to 2021 based on the positivist philosophy. The study used higher moments of skewness and kurtosis to examine the stylised facts in the tails of the returns distributions of the banks. The conditional volatility GARCH models (GARCH, EGARCH and GJRGARCH) were used for the VaR and ES predictions and lastly, metrics for risk model selection were adopted to nominally rank the risk in the listed banks.

The results of the first objective showed that the tails of the returns distribution of the listed banks are fat and asymmetrically distributed. The returns of the listed banks were leptokurtic and positively skewed. This shows the presence of tail risk in the listed banks. Generally, this pre-informed the distribution assumptions that can be made to avoid underestimation of the risk in the listed banks. Using symmetric and asymmetric distribution innovations, the study finds that for the listed banks but ADB (GARCH(1,1)-sstd), GARCH(1,1) with Student-*t* distribution innovation was appropriate for modelling the stylised facts in the tails distributions.

In line with the Basel framework for measuring market risk, the VaR predictions were made for the respective banks. Using the 99% VaR probability level for measuring market risk under Basel III, the risk in the banks was assessed. The results from the analysis based on the GARCH (1,1)-std across banks showed that over the five-year period there is risk. Using ES at a 97.5% probability level, the same deductions were made for objective three. Because ES is sensitive to tail risks, the predictions at a lower probability level (97.5%) are similar to the VaR estimates at 99%. Across the banks also, each of the VaR and ES proves that risk has been effectively predicted based on the closeness of the predictions at different probability levels.

In the last objective, the closeness of the risk predictions across the banks prompted the objective to nominally rank the risk of the banks using MAE, RMSE and sMAPE risk metrics. Across at least two of the metrics, ADB is the least risky bank and SOGEGH was ranked the highest. The study is limited to only listed banks in Ghana and used a single regime conditional models for the VaR and ES predictions.

Conclusions

Based on the findings of the study, the following conclusions are made:

The conclusions from objective one is that the tails of the listed banks are asymmetric and fat indicating a high likelihood of tail risks. The asymmetry and fat tails reflect the theoretical response of investors to information on the markets as in the efficient, heterogenous and adaptive market hypotheses. Investors' response to efficiency at different levels leads to asymmetry in returns. For a realistic risk prediction, the risk in the tails of the return distributions should not be ignored. Theoretically, if the risk in the tails were not analysed, there could have been an underestimation of risk.

The conclusion from objective two shows that VaR and ES has captured the downside risk in the listed banks. This shows that there is systemic risk in banking as in theory of systemic risk which leads to financial regulations intended to mitigate these level of risks. The VaR and ES are interpretable and provide a time-dependent risk prediction. Banks can use the predictions to assess their risk levels at consecutive times; which can inform the banks of their involvement in reducing risk.

The last objective concludes that banks that barely trade and have government ownership are less risky (as seen in the case of ADB and GCB). Banks that barely trade have less price movements indicating the presence of low volatility. Also, banks that have a percentage of government ownership are less prone to risk due to the consecutive decision making toward ensuring a stable economy.

Recommendations

The following recommendations are made based on the conclusions from the findings of the study:

From the nature of the tail risks, banks should use well-planned public relations strategies to prevent panic in the wake of seemingly negative news. The heaviness in the tails shows how sensitive and extreme investors are on the market. Thus, without effective public relations strategies, negative news could cause extreme losses in the market. Also, the Governor of BoG should enforce that banks comply with regulatory standards of measuring downside risk for enhanced risk measurement. Banks should adopt healthy practices (such as defining their risk tolerance; disclosing exposure to risk; and dveleoping risk management framework) that seek to limit risky operations and ultimately reduce bank risk levels.

Furthermore, to be able to compare risk predictions from internal risk models with regulatory risk models, it is important that the models used by the banks or financial institutions are rankable. This is because it can help stakeholders prioritise their resources in mitigating and diversify against risk. Thus, it is recommended that risk levels should be ranked. Lastly, investors who want to diversify on the stock markets should include government owned banks for diversification benefits.

Suggestions for Further Studies

Due to the connectedness of the operations of the banking industry, a further study could explore the interconnectedness of risk in the industry using copula VaR. To capture the impact of structural breaks (regime switch) in the assessment of risk, a similar study can be conducted using regime-switching-GARCH-based VaR and ES. Also, the jointly elicitable VaR and ES (VaR,ES) could be used for predicting risk, and compared against the risk predictions of VaR and ES only.

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