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MODELLING, AND FORECASTING THE RISK PREMIUM OF COMMERCIAL BANKS IN GHANA

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Abstract

To ascertain the risk premium of commercial banks in Ghana, a multifaceted evaluation of market conditions and risk factors are required. Using univariate ARCH and GARCH models, this paper simulates the behaviour of risk premium of commercial banks in Ghana from 1982 to 2023. Data was sourced from the World Development Indicators and Bank of Ghana database, and an index constructed through the utilization of factor analysis in order to quantify the risk premium exhibited by commercial banks in Ghana. ARCH, in addition to GARCH, GJR GARCH, and EGARCH models, were estimated to determining which model was most suitable for the research. It was resolved that the GARCH model was suitable for the estimation and forecasting of the data. Volatility clustering was evident, as periods of low volatility were succeeded by periods of low volatility, and periods of high volatility were also succeeded by periods of high volatility. The study found that, risk premium plot presents a mirrored representation of the *actual plots, the conditional variance remained constant over time, and aligns with that of the original series. Stable volatility was also observed in the predicted outcomes of both the dynamic and static forecasts, as the returns on the risk premium line fell within the standard error limits. In order to promote credit accessibility and financial inclusion, policymakers may opt to implement initiatives that target marginalized or underserved communities in particular. An area that warrants further examination is the potential influence of cognitive errors on risk perception, risk pricing in financial markets, and investment decision-making.*

Keywords: Risk premium, Inflation, Lending rate, Exchange rate, Volatility clustering, Default rate, Ghana

INTRODUCTION

The risk premium associated with commercial bank lending rates generally signifies the supplementary remuneration that lenders demand in exchange for the inherent risk they assume in extending loans (Marjohan & Andriani, Economic And Asymmetric Information As Moderation Variables, Credit Risk And Credit Prices, 2024; Alexander-Haw & Breitschopf, 2024; Rath, Basu, Govindan, & Mandal, 2024). Commercial banks evaluate the risk associated with lending to a specific borrower or sector by considering a multitude of factors. The borrower's credit history, the intended use of the loan, economic conditions, and the overall stability of the financial system are all potential determinants (Wibowo & Aripin, 2024; Pancotto & Williams, 2024). In response to increased lending risks perceived by financial institutions, lending rates are frequently increased to account for the risk premium. The purpose of this premium is to act as a safeguard against potential losses that may result from loan default or non-repayment. In essence, it provides the bank with protection against the risk of borrowers failing to fulfil their financial obligations (Owich & Mutswenje, 2021). Contingent on the economic climate or the perceived riskiness of the creditor, the magnitude of the risk premium may fluctuate. For example, banks may impose a greater risk premium in times of economic recession or instability as a means of compensating for the increased probability of loan defaults (Alhalabi et al., 2023). The risk premium and borrower default rate are fundamentally interconnected notions within the realm of finance, specifically with regard to investment and lending. Risk premium denotes the supplementary compensation or return that investors demand in exchange for assuming greater levels of risk in contrast to investments that are devoid of risk, such as government bonds (Jamaani & Alawadhi, 2023). It is the additional interest rate that lenders charge in the context of lending to mitigate for the risk of borrower default. As an alternative term for the default probability or default rate, the borrower default rate quantifies the probability that borrowers will default on their loans and fail to fulfil their debt obligations. Typically denoted as a percentage, it is subject to variation contingent upon economic conditions, borrower creditworthiness, and loan terms (Hiller & Jones, 2022). Thus, there is a clear correlation between the risk premium and borrower default rate; lenders perceive a greater risk in extending credit when the borrower default rate rises and as compensation, they demand a greater risk premium. Consequently, debtors who exhibit a greater propensity for loan default will generally be subjected to elevated interest rates (Brunnermeier & Krishnamurthy, 2020). Conversely, lenders might be more amenable to accepting a reduced risk premium in response to a decline in the borrower default rate, as the likelihood of default is diminished. Consequently, borrowers who possess solid credit profiles and have minimal likelihoods of defaulting may qualify for loans with reduced interest rates.

Determining the risk premium assessed on investments or loans is heavily reliant on the credit histories of debtors. The credit history of a consumer offers valuable information regarding their previous financial conduct, encompassing aspects such as their capacity and inclination to fulfil debt obligations (Ahmad, 2023; Abrantes-Braga & Veludo-de-Oliveira, 2020). Credit scores and credit reports are utilised by lenders to determine the creditworthiness of a borrower. Lower-risk borrowers are those who possess a robust credit history, which signifies a consistent track record of punctual payments and prudent financial administration. On the other hand, debtors who possess an unfavourable credit history marked by instances of non-payment, default, or insolvency are considered to be more hazardous. Lenders utilise the credit histories of consumers to ascertain the probability of default as part of their risk assessment procedure (Çall & Coşkun, 2021). A robust credit history is indicative of a reduced likelihood of default, whereas a weak credit history signifies an increased risk of default (Muñoz-Cancino et al., 2023). The risk premium imposed on loans or investments is modified by lenders in accordance with this evaluation. Credit-worthy borrowers generally qualify for reduced interest rates, as lenders perceive them to be a less significant risk. Borrowers with limited credit histories, on the other hand, might be subject to elevated interest rates as a means of offsetting the heightened default risk. An additional lending strategy is risk-based pricing, in which the interest rate applied to a loan is modified in accordance with the credit risk exhibited by the borrower. Lenders customise risk premiums in accordance with the hearsay evidence of credit risk associated with individual borrowers. This enables lenders to more precisely price loans in accordance with the corresponding level of risk, which is advantageous for both lenders and borrowers. In order to compensate for the increased risk, borrowers with poorer credit histories may be subject to higher interest rates, whereas borrowers with better credit histories may be granted preferential rates. The reason for the loan may have an impact on the risk premium that is assessed.

Lenders evaluate the intended use of the loan in order to ascertain the dangers involved. For instance, lenders might perceive a loan designated for business expansion as less hazardous due to the possibility that such an endeavour will augment the borrower's revenue and capacity to remit the loan. By virtue of the borrower already having financial obligations, loans obtained for the purpose of consolidating existing debts may be deemed riskier, thereby resulting in a potential reduction in the risk premium. As a risk offset, lenders might levy an increased risk premium. Start-up venture loans are frequently regarded as high-risk due to the inherent uncertainty that accompanies new enterprises. To offset the increased probability of business failure, lenders might impose a greater risk premium (Lerner & Nanda, 2020). Risk premiums for real estate investment loans may be adjusted proportionally to the degree of risk associated with the loans and the borrower's experience, among other variables (Akinci, 2021; Khair-Afham & Rosland, 2022).

The lending rate risk premium of commercial banks in Ghana is subject to the influence of a multitude of factors that are intrinsic to the economic environment of the nation. In calculating the risk premium, the general stability of Ghana's economy is a crucial factor. In addition to fiscal discipline, political stability or instability can influence investor confidence and risk perceptions. Inflation rates, exchange rate stability, and fiscal discipline are all factors that influence investor confidence and risk perception. Despite the fact that democratic governance in Ghana has been comparatively stable in recent years, political unrest or uncertainty can still have an effect on risk premiums. Lending rates are determined by commercial institutions with the creditworthiness of borrowers in mind. Increased perceived risks pertaining to non-payment or borrower default result in elevated risk premiums. Risk premiums are influenced by the liquidity of financial markets in Ghana. Lenders may perceive a greater degree of risk in the form of increased premiums as a result of diminished liquidity, which serves to offset potential losses. Commercial banks' risk management strategies and lending practices are impacted by the policies and regulations established by the Bank of Ghana. Regulatory mandate modifications have the potential to influence both lending costs and risk premiums. Volatility in commodity prices (e.g., cocoa and gold) and other global economic factors may have an effect on the economy of Ghana and, by extension, the risk premium on lending rates (Akomeah et al., 2020). Monetary policy determinations made by the Bank of Ghana, which encompass benchmark interest rate strategies, exert a direct influence on lending rates within the nation (Akosah et al., 2021). Varying policy rates have the potential to impact risk premiums. Lending rates and risk premiums are likewise impacted by the competition among commercial banks. As banks endeavour to attract borrowers, intense competition may result in lower premiums, whereas limited competition may enable banks to charge higher premiums (Matthews et al., 2023). Key performance indicators (KPIs), including GDP growth, unemployment rates, and the balance of payments position, offer valuable insights into the overall economic well-being and exert an impact on risk assessments and premiums.

Using time series analysis Arthur-Nunoo et al. (2023) predicted the exchange rate between the Ghana cedi and the US dollar and concluded that the Ghana cedi is depreciating against the US dollar. Chugunov et al. (2021) examined the determinants of exchange rate behaviour in Ghana and conclusion that government spending is a significant predictor of exchange rate movements; thus, short-term exchange rate volatility should be mitigated by regulating government spending. Zhang et al. (2024) conducted a study on interest rate forecasting and reached the conclusion that the Kalman filter is the most effective model. Nevertheless, as a well-established technique in the field of econometrics, it hardly requires special promotion. Using asymmetric GARCH models, Fang et al. (2020) estimated and predicted the volatility of financial markets. Sari et al. (2023) concluded that the CGARCH and TGARCH models appear to be preferable for modelling the velocity of financial instruments in Turkey. In addition, they stated that return series encompass leptokurtosis, asymmetry, volatility clustering, and long memory across all markets.

Liu et al. (2021) explored modelling and prediction of short-term interest rate volatility and discovered that the semi-parametric approach yielded more accurate in-sample forecasts of short rate change volatility in comparison to the prevalent single-factor diffusing models. Khan et al. (2024) employed time series and neural network methodologies to forecast exchange rates, and discovered that the ANN-based model outperformed the GARCH model in terms of exchange rate prediction. Lahboub and Benali (2024) utilised GARCH models to forecast the volatility of the exchange rate and found that TGARCH model is deemed to deliver the most precise forecasts due to its incorporation of all essential stylized facts of financial data, including persistent volatility, GARCH, asymmetric models, and exchange rates. Ruan et al. (2024) predicted the dynamics of exchange rates in developing nations and reach the conclusion that negative news has a greater impact on exchange rates volatility than positive news. Zhang et al. (2024) reached the conclusion that it is crucial to include public search queries from search engines in order to accurately forecast exchange rate. Limited quantitative research has been conducted to model and forecast the risk premium of commercial banks in Ghana. Consequently, this study models and forecasts the risk premium of commercial banks in Ghana in order to establish the impact of risk premium on the credit operations of commercial banks and to bridge the knowledge gap in this area. Various scholars have employed distinct econometric models to calculate interest rates and exchange rates. However, the existing body of literature regarding the application of the ARCH and GARCH family models to estimate risk premiums remains ambiguous. This study endeavours to address this methodological gap and make a scholarly contribution to the field. The following sections of the manuscript are structured into four distinct parts. Section two comprises a literature review that examines the present state of research on risk premium in financial institutions, theories relevant to the subject, and the framework or variables that link the study's concepts. The methodology to be utilised in estimating the research model is discussed in the third section. The results of the analysis are presented in the fourth section, and the paper is concluded in the final section.

LITERATURE REVIEW

In finance, mean-variance theory is a prevalent framework for analysing uncertain investment decisions. According to Markowitz (1976) investors have the ability to construct an ideal portfolio by taking into account the trade-off between risk and anticipated returns, which is quantified by the standard deviation or variance of returns. Mean-variance theory may be utilised to comprehend the portfolio management decisions of commercial institutions. Typically, commercial banks maintain an assortment of assets, such as reserves, securities, and loans (Fabozzi & Markowitz, 2011). The objective is to minimise the risk of losses while maximising the return on assets. Credit risk is the risk that borrowers will default, interest rate risk is the risk that interest rate fluctuations will affect the value of assets and liabilities, and liquidity risk, the risk that indicate the inability to meet short-term obligations, are all types of risk that commercial banks encounter. Commercial banks must evaluate the risk associated with each asset in their portfolio and adjust their expected returns accordingly in order to ascertain the risk premium (Angbazo, 1997). They employed mean-variance analysis-based models to assess the risk-return trade-offs of various assets and allocate capital in a manner that maximises the return-risk ratio. The risk premium demanded by commercial institutions may be impacted by markets, regulatory requirements, economic conditions, and other variables. In times of financial instability or economic uncertainty, banks may opt to raise their risk premiums as a means of mirroring the heightened perceived risks within the market (Saunders, 2000; Ahmad & Ariff, 2008; Koehn & Santomero, 1980). On the contrary, risk premiums may diminish in stable economic environments as financial institutions gain greater assurance regarding the future of their investments (Merton, 1990; Park & Kim, 2020). In general, mean-variance theory offers a valuable conceptual structure for comprehending the risk management practices of commercial banks and the calculation of the necessary risk premium for their investment endeavours. Through meticulous risk-return management, financial institutions can maximise the performance of their portfolios and accomplish their financial goals (Adusei, 2022; Iqbal & Mirakhor, 1999).

A foundational concept in finance, the Capital Asset Pricing Model (CAPM) establishes a correlation between the anticipated return and systematic risk of an asset (Rossi, 2016). The expected return on an investment, according to Miller (1999) the CAPM consists of two elements: the risk-free rate and a risk premium. The risk-free rate, which is commonly represented by the yield on government bonds, signifies the rate of return on an investment that entails no risk. Investors are compensated with the risk premium for assuming systematic risk, which is unavoidable through diversification. CAPM utilises systematic risk, which is alternatively referred to as market risk or non-diversifiable risk, to assess risk. Systematic risk is inherent to the complete market or a specific asset class and therefore cannot be eliminated via diversification. Beta is a metric utilised to quantify the systematic risk of an asset in relation to the market as a whole. A beta value of 1 signifies perfect correlation between the asset's price movement and the market (Aıt-Sahalia, Wang, & Yared, 2001). A beta value exceeding 1 indicates increased volatility, whereas a beta value falling below 1 indicates decreased volatility (Blitz & Van Vliet, 2007). The market risk premium signifies the supplementary rate of return that investors anticipate attaining in exchange for assuming systematic risk, as opposed to the risk-free rate. It signifies the mean return of the market in excess of the risk-free rate. The size of the market risk premium is influenced by factors such as economic conditions, investor sentiment, and market volatility (Verma & Soydemir, 2009; He, He, & Wen, 2019). The CAPM equation is expressed as follows: $E(Ri)=Rf+\beta i\times(E(Rm)-Rf)$ Where: $E(Ri)$ = Expected return on the asset, Rf = Risk-free rate, βi = Beta of the asset, $E(Rm)$ = Expected return on the market.

The Security Market Line, which illustrates the relationship between expected return and systematic risk for individual assets, is frequently used to graphically represent CAPM. The slope of the SML, a linear function that compares expected returns to betas, is equivalent to the market risk premium (Cloninger et al., 2004). The CAPM has numerous significant ramifications for financial decision-makers and investors. It proposes that incentivizing investors to assume systematic risk is warranted, and that asset valuation should reflect the expected returns in relation to such risk. Additionally, CAPM assists in determining the cost of capital for investment initiatives and serves as a standard against which investment performance can be measured. Although the CAPM has had a significant impact on financial theory and practice, its limitations have been highlighted by critics (Levy, 2010; Ross, 1978). This includes the dependence on historical data to estimate betas, assumptions regarding market efficiency, and the reliability of the risk-free rate (DeJong & Collins, 1985). Despite this, CAPM continues to be a fundamental principle in contemporary finance and a useful instrument for comprehending the correlation between return and risk when making investment decisions.

Gregory (2024) investigated the relationship between credit history and risk premiums in the corporate bond market and discovered that credit history has a substantial impact on risk premiums. Investors generally assign lower risk premiums to bonds issued by companies that possess more robust credit histories, as this signifies their trust in the issuers' capacity to fulfil their debt responsibilities (Okimoto & Takaoka, 2024). On the contrary, risk premiums are elevated for bonds issued by companies with less reputable credit histories as a means of compensating investors for the heightened likelihood of default (Khan et al., 2024). Palmieri and Geretto (2024) examined the correlation between credit history and mortgage risk premiums and the results underscored the criticality of credit history in the mortgage market as a determinant of risk premiums. Mortgage loans with reduced interest rates are accessible to borrowers who possess superior credit scores and lengthy credit histories, which signify a diminished perception of default risk. Higher risk premiums manifest as elevated interest rates for borrowers with inferior credit profiles, which are a reflection of the heightened default risk associated with such loans. Elkamhi and Nozawa (2024) investigated the relationship between insurance risk premiums and credit history and discovered that credit history has a substantial impact on corporate bond market risk premiums. Investors generally assign lower risk premiums to bonds issued by companies that possess more robust credit histories, as this signifies their trust in the issuers' capacity to fulfil their debt responsibilities. Risk premiums on bonds issued by companies with less resolute credit histories are elevated in order to offset the heightened default risk perceived by investors.

Lane (2024) investigated small business loan risk premiums and credit history, and discovered that firms with more robust credit histories are eligible for loans featuring reduced interest rates, which can be attributed to a diminished perception of default risk. On the contrary, lenders assess greater risk premiums against small businesses that possess less favourable credit profiles in an effort to offset the heightened default risk associated with such debtors. Arayssi and Yassine (2024) discovered that individuals with more stable incomes have a tendency to request reduced risk premiums when investing, based on their research on income stability and risk premium. This implies that the stability of income has a substantial impact on the way in which investors perceive and value assets in terms of risk. The impact of income stability on asset pricing was examined by Mitragotri (2024) and the study indicated that risk premiums for securities of companies with more stable earnings streams are generally lower in comparison to those with volatile income streams. The significance of income stability in influencing investor perceptions of risk and return is highlighted by these results. Additionally, Kaya (2024) examined the relationship between risk aversion, bond yields, and income stability; the findings of the study indicated that investors prefer government bonds with more stable income levels. This indicates that investor risk aversion and the pricing of fixed-income securities on global financial markets are influenced by income stability. Rigamonti et al. (2024) investigated the correlation between equity risk premium and income uncertainty. The researchers utilised behavioural finance principles to analyse the relationship between these two variables. The research demonstrates, by experimental methodologies and surveys that individuals confronted with greater income uncertainty demand higher risk premiums and exhibit greater risk aversion when investing in equities. The psychological factors that underlie investor decision-making and asset pricing dynamics are illuminated by these results.

The relationship between the purpose of loans and the attendant risk premiums was examined by Fadun (2024) using sizable dataset of loans issued by a variety of financial institutions is utilised for the study. The results indicate that the intention behind a loan has a substantial impact on the risk premiums. In general, risk premiums for loans designated for business investment are lower than those utilised for consumer expenditure or real estate acquisition. This suggests that financial institutions consider business loans to be of lower risk; potentially as a result of the opportunities they present to generate revenue and foster economic expansion. On the same note, lenders may impose higher interest rates on loans intended for real estate or consumer expenditures due to the increased perceived risk involved. Breitschopf and Alexander-Haw (2024) performed a cross-national examination to determine the correlation between the intent of loans and the risk premiums associated with them in the banking systems of various nations. Mansour et al. (2024) investigated the impact of economic, regulatory, and cultural elements on lenders' risk assessments and the pricing of loans; the study identifies correlations and patterns between loan purposes and risk premiums. The research reveals that although there are consistent patterns in the relationship between purpose and risk premiums, there are also notable discrepancies among nations. Economic conditions, cultural norms, and legal frameworks all significantly influence the risk perceptions of borrowers and lenders. Business loans in nations characterised by stable economies and robust legal systems may entail reduced risk premiums as a result of enhanced contract enforcement and diminished macroeconomic uncertainty (Palmieri et al., 2024). Furthermore, business loans may incur greater risk premiums in nations with weakened institutions or more volatile economies. Furthermore, specific loan purposes deviate substantially from anticipated risk premiums in a few anomalous cases identified by the study, highlighting the significance of contextual factors in influencing lending practices.

Han (2024) examined the premium for inflation risk and the correlation between inflation and anticipated equity returns. Future stock returns are found to be negatively correlated with unexpected inflation, the authors discovered. Additionally, it was observed that the correlation is more evident in the case of value equities as opposed to growth stocks. Haider et al. (2024) investigated the relationship between unexpected inflation and nominal interest rates, and discovered evidence of a positive correlation between the two variables. This suggests that investors are willing to accept greater risk premiums in order to offset the uncertainty associated with inflation and real returns. Ikeobi (2024) study on inflation, nominal returns, and the equity premium and discovered a positive correlation between unexpected inflation and nominal stock returns. This finding implies that investors might require a greater equity risk premium to offset the potential recompense for inflation risk. Inflation risk and the inflation risk premium are time-varying and positively correlated with inflation uncertainty (Dergunov, Meinerding, & Schlag, 2023). This suggests that when inflation uncertainty is significant, investors demand greater risk premiums. The determinants of credit spreads, which are the yield differences between corporate bonds and Treasury securities of comparable maturities (Huang, Liu, & Shi, 2023). Standard structural models, according to the authors, inadequately account for the magnitude and fluctuation of credit spreads. In order to better capture the dynamics of credit spreads, they propose a model that integrates both observable and unobservable factors, including changes in market liquidity and default risk. Tlemsani et al. (2023) examined the equity risk premium and proposed an explanation for the equity risk premium conundrum, which pertains to the incongruity between the forecasts of conventional financial models and the actual returns of stocks over time. The authors posit that the substantial equity risk premium witnessed in financial markets may be accounted for by investors' extreme risk aversion. A model is constructed wherein agents possessing logarithmic utility functions are compelled to pay substantial risk premiums in order to retain inventories, owing to the unpredictability linked to future consumption.

METHODOLOGY

The empirical section of the study employed a quantitative approach and utilised simple random sampling to obtain a representative sample from which statistical inferences could be drawn regarding the chosen variables. The research utilised time series data sourced from the World Development Indicators (WDI) of the World Bank, covering the period 1982 to 2023. The rationale behind selecting data spanning 1982 to 2023 is that such data can offer a more comprehensive historical record, which is advantageous and helps to generate the desire results. Additionally, such data may encompass out-dated patterns or trends that have ceased to be pertinent. In addition to high frequency data, this time period permits the examination of more complex fluctuations. The specific country of interest is Ghana. The research modelled the variance of the risk premium of commercial banks in Ghana, and to determine the most suitable estimator for the study, the autoregressive conditional heteroscedasticity (ARCH) and ordinary least squares methods are employed. In the realm of financial econometrics, the ARCH (Autoregressive Conditional Heteroskedasticity) method, in conjunction with its extensions GARCH (Generalised Autoregressive Conditional Heteroskedasticity), EGARCH (Exponential GARCH), and TGARCH (Threshold GARCH), is commonly employed for time series analysis (Siddiqui & Shamim, 2024). It is frequently observed, when analysing time series data, particularly financial data, which periods of high volatility tend to congregate after periods of low volatility. Modelling this phenomenon is facilitated by the ARCH method, which permits the conditional variance to be explicitly dependent on previously squared error terms. The concept of heteroskedasticity pertains to the action of time on the variability of a given variable. Heteroskedasticity is a phenomenon frequently observed in financial time series, wherein the variance of asset returns fluctuates over time. This time-varying volatility is ideally adapted for modelling with the ARCH method. It is frequently noted that the reaction of volatility in financial markets to positive and negative events exhibits an asymmetric pattern. Negative returns, for instance, may result in greater subsequent volatility than positive returns of equivalent magnitude. By extending the ARCH framework, models such as EGARCH and TGARCH are capable of capturing this asymmetry. ARCH models are employed by financial practitioners and researchers to simulate and predict volatility, a critical component in comprehending and mitigating risk within financial markets. ARCH models assist in the effective pricing of financial derivatives, portfolio construction, and risk exposure management through the precise modelling of volatility dynamics. ARCH models are utilised to predict future volatility by analysing past data. For the purposes of risk management and scenario analysis, which evaluate the impact of prospective market shocks on portfolio performance; these forecasts are invaluable (Kothandapani, 2023). The assumption of constant volatility, which underpins numerous financial models, is called into question by the existence of heteroskedasticity and volatility clustering in financial data. The utilisation of ARCH models to examine the existence of such phenomena carries significance for the efficient market hypothesis as well as the soundness of numerous financial models. In general, the ARCH method is extensively employed in time series analysis, specifically within the finance sector, to capture and simulate the intricate dynamics of financial market volatility.

Model specification

In order to successfully model the conditional variance and past values of risk premium, the ARCH model proposed by Engle and Patton (2007) to capture the volatility clustering phenomenon observed in time series data is used. It assumes that the variance of a time series is a function of its own past variances, with the conditional variance following an autoregressive process. The ARCH (p) model is expressed as:

$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \alpha_1\epsilon_{t-2}^2 + \cdots + \alpha_p\epsilon_{t-p}^2$ --------- (1)

Where; the conditional variance at time t is σ_t^2, $\in_t$ is the error term at time t, $\alpha_0, \alpha_1, \alpha_2, and \ldots\ldots\ldots.\alpha_p$ are the model's parameters.

After the ARCH test, if there is the need to capture the long term persistent of volatility, the GARCH model may be specified. The GARCH model was introduced by Bollerslev (1986) extending the ARCH model by incorporating lagged conditional variances in addition to lagged squared error terms. The GARCH (p q) model is expressed as follows:

$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\alpha_i\,\epsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_i\,\sigma_{t-j}^2$ -------------------- (2)

Where; σ_t^2 is the conditional variance at time t, $\in_t$ is the error term at time t, $\alpha_0, \alpha_1, \alpha_2, and \ldots\ldots\ldots.\alpha_p$ are ARCH parameters, $\beta_1, \beta_1, \ldots\ldots\ldots\beta_q$ are GARCH parameters.

The ARCH term captures the short-term clustering of volatility, whilst the GARCH term captures the long-term persistence of volatility.

Also if there are asymmetric effects of past shocks on future volatility, the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model which is an extension of the GARCH model may be used. Introduced by Nelson (1991) as a way to capture the leverage effects observe in financial markets, where negative returns tend to lead to higher subsequent volatility than positive returns of the same magnitude. The EGARCH model is specified as follows:

Log $(\sigma_t^2) = \omega + \sum_{i=1}^{p}\alpha_i\,|\in_{t-i}| + \sum_{j=1}^{q}\beta_j\log(\sigma_{t-j}^2) + \sum_{k=1}^{r}\gamma k(\epsilon_{t-k} - \mu_t)$ ---------- (3)

Where; σ_t^2 is the condition variance at time t, $\in_t$ is the error term at time t, ω is a constant, α_i are parameters governing the impact of past shocks on future volatility, $\beta_j are\ GARCH$ parameters, γ_k are parameters capturing the asymmetry in the volatility response to positive and negative shocks, μ_t is the conditional mean.

Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) model is a variation from the GARCH model which incorporates a threshold effect (Sun & Yu, 2020). It allows for the conditional variance to respond differently depending on whether past returns exceed a certain threshold level. The TGARCH model is specified as follow.

$\sigma_t^2 = \omega + \sum_{i=1}^{p}\sigma_i\,\epsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j\,\sigma_{t-j}^2 + \sum_{k=1}^{r}\gamma_k\,(\epsilon_{t-k} - \lambda_k)^2$ ------------- (4)

Where; σ_t^2 is the conditional variance at time t, $\in_t$ is the error term at time t, ω is a constant, σ_i and β_j are GARCH parameters, γ_k are parameters capturing the effect of squared shocks exceeding a threshold, and λ_k is the threshold level.

Definition of variables and measurements

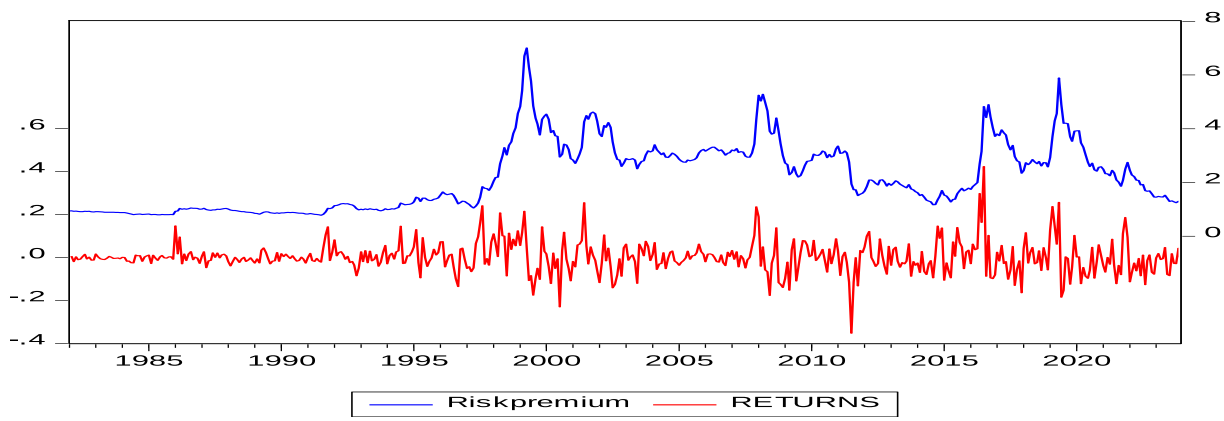
To effectively quantify risk premium, an index is constructed through the application of factor analysis, utilising data obtained from the World Bank's World Development Indicators and the Bank of Ghana's interest rates. Principal component analysis was used to calculate an index representing the risk premium based on the monthly average 364-day Treasury bill interest rate equivalent, the average commercial banks' lending rate (%), the interbank weighted average (%), and the monetary policy rate (%). The average lending rate denotes the rate of interest that commercial banks impose on consumer loans; generally financial institutions augment their lending rates with a risk premium in order to offset a range of liabilities linked to lending, such as credit risk, interest rate risk, and liquidity risk. A rise in the mean lending rate signifies that financial institutions are imposing elevated interest rates on loans, potentially attributable to an escalation in lending expenses or an elevated perception of credit risk. The elevated lending rate engenders an increased risk premium for commercial institutions. The interbank weighted average rate is indicative of the benchmark interest rate utilised by banks when conducting interbank lending transactions. It operates as a standard against which institutions lend and borrow on a short-term basis. Variations in the interbank weighted average rate have the potential to influence the profitability and funding expenses of institutions. Banks may transfer the increased borrowing costs to their clients in the event of an interbank rate hike, which could result in elevated lending rates and potentially increased risk premiums. An equivalent interest rate on 364-day Treasury bills signifies the rate of return on government securities maturing in 364 days. Assumed to represent the risk-free rate of return. Commercial banks frequently calculate loan rates and evaluate the risk premium with reference to the risk-free rate. An investor's opportunity costs will increase in response to a higher risk-free rate, which may cause banks to adjust their lending rates and risk premiums. Monetary policy rate fluctuations have an impact on the borrowing costs of institutions, liquidity conditions, and the broader monetary environment. Monetary policy rate fluctuations are closely observed by banks due to the direct influence they have on their funding expenses and overall profitability. Monetary policy rate fluctuations may prompt banks to modify their lending rates and risk premiums in reaction to alterations in market conditions and the monetary policy position.

ANALYSIS AND DISCUSSION OF RESULTS

Stationarity Test

Conducting stationarity testing on time series data is an essential component of time series analysis, as it guarantees the dependability of statistical models and predictions (Priestley & Rao, 1969). The statistical properties of a time series, including its mean, variance, and autocorrelation structure, are said to be stationary if they remain constant over time, which is there is no heteroskedasticity in the model. An array of techniques can be utilised to determine the stationarity of time series data. In order to visually examine the series for trends, seasonality, or irregular patterns, it is possible to plot the data. It should appear as though a stationary series fluctuates irrationally about a constant mean over time. To determine whether or not data is stationary, one can compute summary statistics, including mean and variance, for various time periods or moving windows. Significant fluctuations in these statistics over time indicate the presence of non-stationarity. The ADF test is a statistical procedure utilised to determine whether a time series dataset contains a unit root. The presence of a unit root signifies non-stationarity. The null hypothesis of the test posits that the time series exhibits non-stationarity due to the presence of a unit root, and therefore the null hypothesis is rejected when the p-value of the test falls below a predetermined significance level (e.g., 0.05). The KPSS test is a frequently employed statistical method for examining the stationarity of time series data. In contrast to the ADF test, the KPSS test assumes the time series to be stationary as its null hypothesis. Non-stationarity is indicated when the p-value is less than the significance level, which rejects the null hypothesis of stationarity. Comparable to the ADF test, the DF-GLS test examines time series datasets for the presence of unit roots. It is especially beneficial when addressing serial correlation. An additional unit root test that can be substituted for the ADF test is the PP test. Multiple tests are frequently used to evaluate stationarity, given that each test may have unique advantages and disadvantages. In addition, statistical analyses, it is invariably accompanied by visual inspection in order to obtain a holistic comprehension of the behaviour of the data. The present research employs the graphical method to assess the stationarity of the collected data.

Figure 1. Stationarity Test



The risk premium is depicted in the initial graph (blue) of figure 1. This graph comprises the raw data that was aggregated for the purpose of visualisation and stationarity testing, employing both the graphical method and the augmented dickey Fuller test. The data were non-stationary, as determined by the unit root test involving a trend and a constant at first difference; thus, the data lack statistical significance. Upon performing a first difference on the data, specifically the returns, it is observed that the data is statistical significance. This suggests the absence of a unit root, and as depicted in Figure 1, the data are presently considered stationary.

Lag order selection

Table 1. Determination of the lag order

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.299	0.299	45.281	0.000
.|* |	.|. |	2	0.145	0.061	55.980	0.000
.|. |	.|. |	3	0.037	-0.025	56.665	0.000
.|. |	.|. |	4	-0.033	-0.051	57.227	0.000
*|. |	*|. |	5	-0.095	-0.079	61.848	0.000
.|. |	.|. |	6	-0.045	0.013	62.869	0.000
.|. |	.|. |	7	0.019	0.053	63.055	0.000
.|. |	.|. |	8	0.011	-0.005	63.115	0.000
.|* |	.|* |	9	0.099	0.092	68.143	0.000
.|. |	.|. |	10	0.065	0.003	70.289	0.000

The determination of the lag order p and q for an Arima-Garch model involves an analysis of the correlogram, autocorrelation function (acf), and partial autocorrelation function (pacf) of the squared residuals (residuals ^2) in order to ascertain the potential lag length, as illustrated in table 1. The squared residuals in the acf plot exhibit a distinct decline following a portion of the lags, followed by a gradual reduction to statistically significant levels. This behaviour indicates that the volatility follows an autoregressive (AR) structure. The lag order q, for the garch procedure, is determined by the lag at which the acf terminates. By examining the pacf plot of the squared residuals, one can determine the lag order p of the autoregressive (ar) component. The pacf plot exhibited a progressive decline of the significant partial autocorrelations until they reached insignificant levels. P represents the value that these partial autocorrelations indicate for the arch component. Hence, as shown in table 1, the bars surpassing the confidence limits correspond to possible lag orders. Nevertheless, for the sake of parsimony, the Arima (111) model is preferred. It is essential to conduct diagnostic tests after determining the lag values of p and q in order to verify the correct specification of the model and the independence, identical distribution (iid), and absence of autocorrelation and heteroscedasticity in the residuals.

Estimating the equation of the mean, AR and MA components

Table 2. Mean Equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000536	0.004879	0.109866	0.0000
AR(1)	0.440252	0.094515	4.658015	0.0000
MA(1)	0.554686	0.239977	0.314709	0.0000
SIGMASQ	0.004679	0.000182	25.69004	0.0000
R-squared	0.092237		Mean dependent var	0.000566
Adjusted R-squared	0.086780		S.D. dependent var	0.071863
S.E. of regression	0.068674		Akaike info criterion	-2.510772
Sum squared resid	2.353352		Schwarz criterion	-2.477208
Log likelihood	635.4591		Hannan-Quinn criter.	-2.497605
F-statistic	16.90099		Durbin-Watson stat	2.005119
Prob(F-statistic)	0.000000			
Inverted AR Roots	.44			
Inverted MA Roots	.15			

The mean equation in an ARIMA (Autoregressive Integrated Moving Average) model signifies the deterministic aspect of the time series, encompassing both the overall trend and any seasonal variations inherent in the data. The magnitude of the mean equation may differ based on the particular configuration of the ARIMA model. In table 2, The AR, and MA components, and the standard deviation are statistically significant, indicating that they are appropriate or the lag orders are appropriately selected, the prob (F-statistic) which shows the overall significance of the model is also appropriate. The ARIMA model is represented in its general form as ARIMA (p, d, q), where: p denotes the number of lagged observations incorporated into the model and is the autoregressive (AR) order. The differencing order, denoted as d, specifies the quantity of differencing operations required to attain stationarity for the data. The moving average (MA) order, denoted as q, signifies the quantity of lagged forecast errors incorporated into the model. The expression for the mean equation of an ARIMA model is as follows:

$\mu t=\alpha+\beta 1Xt-1+\beta 2Xt-2+\ldots+\beta pXt-p$---(5)

Where: μt is the mean of the time series at time t. $Xt-1$, $Xt-2,\ldots$, $Xt-p$ are lagged values of the time series up to lag order p, α is the intercept term, representing the average value of the time series when all lagged values are zero, $\beta 1$, $\beta 2,\ldots$, βp are coefficients corresponding to the lagged values of the time series. The ARIMA model presupposes that the differenced series is stationary and its mean remains constant over time, even after differencing. As a result, any long-term trends or seasonal patterns that are present in the data are captured by the mean equation. The autoregressive and moving average components, denoted as AR and MA, respectively, in the mean equation, reflect the linear dependence of the current observation on previous observations and forecast errors. Model diagnostics are commonly employed to determine p, d, and q. This involves assessing the model's goodness of fit using information criteria such as AIC or BIC and examining ACF and PACF plots of the differenced data. It is possible to make iterative adjustments until the model meets the requirement.

Table 3. Heteroskedasticity Test: ARCH

F-statistic	24.01530	Prob. F(1,500)		0.0000
Obs*R-squared	23.00635	Prob. Chi-Square(1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003685	0.000534	6.905174	0.0000
RESID^2(-1)	0.214051	0.043679	4.900541	0.0000
R-squared	0.045829	Mean dependent var		0.004688
Adjusted R-squared	0.043921	S.D. dependent var		0.011296
S.E. of regression	0.011045	Akaike info criterion		6.169727
Sum squared resid	0.060994	Schwarz criterion		6.152920
Log likelihood	1550.602	Hannan-Quinn criter.		6.163133
F-statistic	24.01530	Durbin-Watson stat		2.000046
Prob(F-statistic)	0.000001			

The obtained p-values are statistically significant, suggesting the presence of the ARCH effect in the model. Consequently, we reject the null hypothesis that no ARCH effect exists prior to the designated lag order. Given that the p-value is below 0.05, the null hypothesis (Ho) is rejected in favour of the ARCH effects being confirmed. The coefficient becomes statistically significant after one (1) lag is incorporated; suggesting that the inclusion of one (1) lag is indeed significant and that the heteroscedasticity test concludes that the ARCH effect exists. ARCH effects, which stand for Autoregressive Conditional Heteroskedasticity, pertain to the existence of volatility clustering or time-varying volatility within a given time series. These effects suggest that the variance of the error term (or squared residuals) in a regression model displays patterns of heteroskedasticity rather than remaining constant over time.

Comparing ARCH (1) and GARCH (1, 1) Models

Table 4. Model Selection Criteria

Model Selection Criteria			
Criteria	**Model**		**Best Model**
	Model A ARCH(1)	**Model B GARCH(1 1)**	
Log likelihood	681.1764	726.1560	A
Akaike	2.893461	2.861170	B
Schwarz	2.831209	2.793950	B
Hannan-Quinn	2.868961	2.834803	B

Table 4 demonstrates that the GARCH(11) model produces significantly more favourable outcomes in comparison to the ARCH(1) model. The GARCH model's Akaike, Schwarz, and Hannan-Quinn information criteria exhibit a marked improvement over those of the ARCH(1) model; therefore, it is appropriate to employ the GARCH(11) for estimation purposes.

Table 5. Estimation of GARCH (11) Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.231545	0.003712	62.37742	0.0002
AR(1)	0.424192	0.168889	2.511657	0.0120
MA(1)	0.232274	0.180297	1.288285	0.0000
Variance Equation				
C	0.000132	5.59E-05	2.356405	0.0185
RESID(-1)^2	0.202274	0.029373	6.886516	0.0000
GARCH(-1)	0.208721	0.019701	10..59443	0.0000
EXCHANGE	0.332273	0.018463	18.02892	0.0000
INFLATION	0.242533	0.018262	13.28074	0.0000

Table 5…

R-squared	0.091816	Mean dependent var	0.000554
Adjusted R-squared	0.088176	S.D. dependent var	0.071934
S.E. of regression	0.068690	Akaike info criterion	2.861179
Sum squared resid	2.354415	Schwarz criterion	2.793950
Log likelihood	726.1560	Hannan-Quinn criter.	2.834803
Durbin-Watson stat	2.000434		
Inverted AR Roots	.42		
Inverted MA Roots	.14		

$Returns_t = 0.231545Return_{t-1} + 0.232274\epsilon_{t-1} + \epsilon_t$ ……..………………………………… (6)

$h_t = 0.000132 + 0.202274h_{t-1}^2 + 0.208721h_{t-1}^2$……………………………………….. (7)

The results presented in Table 5 unequivocally demonstrate the existence of conditional volatility of risk premium returns that varies with time. With p-values of 0.000, both the ARCH and GARCH parameters exhibit high levels of significance. Furthermore, the sum of the coefficients for parameters (0.2022 + 0.208) less than 1, indicating that disturbances to the conditional variance will not have a substantial and enduring impact. Given the statistical significance of the GARCH parameter, a substantial excess return value, whether positive or negative, will result in protracted periods of elevated variance forecasts in the future. Consequently, during periods of extreme volatility, the GARCH model holds greater predictive accuracy than the ARCH model.

Model Diagnostics

Table 6. Heteroskedasticity Test: ARCH

F-statistic	0.078792	Prob. F(1,463)		0.7791
Obs*R-squared	0.079119	Prob. Chi-Square(1)		0.7785
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.013727	0.127399	7.957074	0.0000
WGT_RESID^2(-1)	0.113046	0.046477	2.432299	0.7791
R-squared	0.780170	Mean dependent var		1.000652
Adjusted R-squared	0.641989	S.D. dependent var		2.554503
S.E. of regression	2.557043	Akaike info criterion		4.719872
Sum squared resid	3027.310	Schwarz criterion		4.737687

Log likelihood	1095.370	Hannan-Quinn criter.	4.726884
F-statistic	0.078792	Durbin-Watson stat	1.996105
Prob(F-statistic)	0.000066		

Table 6…

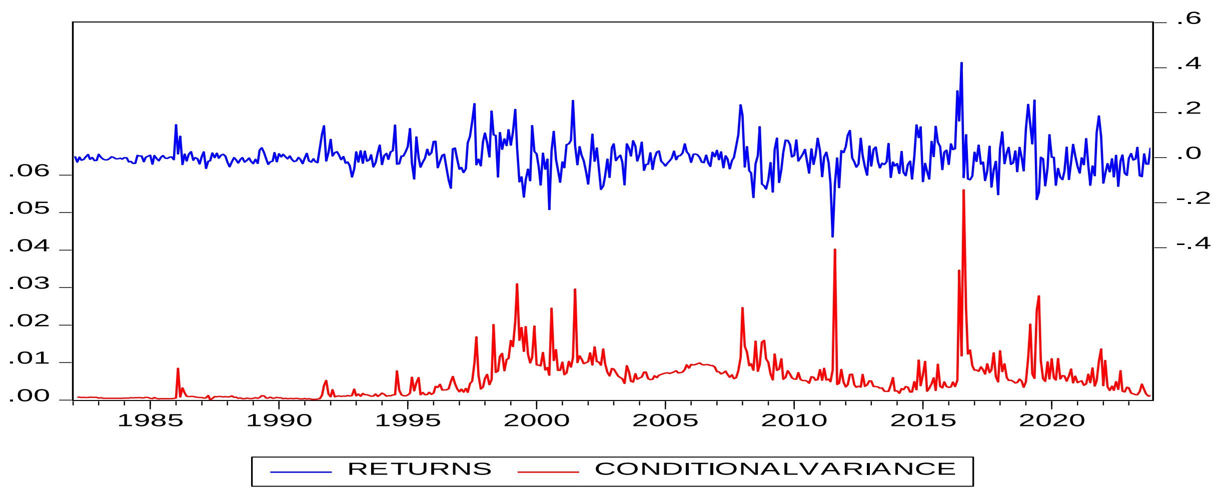
Table 7. Autocorrelation test

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.013	-0.013	0.0798	0.778
.|* |	.|* |	2	0.133	0.133	8.3923	0.015
.|. |	.|. |	3	0.025	0.029	8.6887	0.034
.|. |	.|. |	4	-0.016	-0.034	8.8137	0.066
.|. |	.|. |	5	-0.005	-0.013	8.8238	0.116
.|. |	.|. |	6	-0.022	-0.016	9.0508	0.171
.|. |	.|. |	7	0.017	0.021	9.1945	0.239
.|. |	.|. |	8	-0.016	-0.011	9.3189	0.316
.|. |	.|. |	9	-0.006	-0.011	9.3354	0.407
.|. |	.|. |	10	0.020	0.022	9.5260	0.483
.|. |	.|. |	11	0.038	0.043	10.227	0.510
.|. |	.|. |	12	0.007	0.002	10.248	0.594
.|. |	.|. |	13	0.010	-0.002	10.295	0.670
.|. |	.|. |	14	0.051	0.048	11.539	0.643
.|. |	.|. |	15	-0.010	-0.007	11.587	0.710
.|. |	.|. |	16	-0.004	-0.017	11.597	0.771
.|. |	.|. |	17	0.020	0.021	11.796	0.812
.|. |	.|. |	18	-0.019	-0.013	11.964	0.849
.|. |	.|. |	19	0.049	0.047	13.143	0.831
.|. |	.|. |	20	-0.013	-0.007	13.226	0.867

Note: *Probabilities may not be valid for this equation specification.

Table 6 and 7 indicates the diagnostics conducted on the residuals of the GARCH$_{(11)}$ model and the results for both heteroscedasticity and autocorrelation indicates that there is no ARCH effect in the model. The p-values are more than 0.05, indicating that, there is no heteroscedasticity and autocorrelation in the model. The lack of ARCH effects in the GARCH$_{(11)}$ model indicates that the variance of the error term, also known as the squared residuals, remains relatively constant over time. This suggests that the data might demonstrate homoscedasticity, which denotes the absence of systematic clustering patterns or variance variations in the time series volatility. The absence of ARCH effects indicates that the time series volatility is relatively consistent, devoid of significant intervals of elevated or diminished volatility. The lack of substantial autocorrelation in the squared residuals of the GARCH model suggests that previous squared residuals do not exert a substantial influence on the present volatility. When ARCH effects are absent, it may be possible to conclude that the GARCH model captures the volatility dynamics in the data adequately, obviating the necessity for additional autoregressive terms. This indicates that the observed volatility patterns are sufficiently explained by the current model specification; therefore, introducing further lags is unnecessary. Also the lack of ARCH effects may be construed as support for the GARCH model's robustness. This signifies that the selected model specification effectively captures the volatility process in a concise manner, preventing over fitting and unnecessary intricacy. The lack of autocorrelation observed in the residuals of the GARCH model indicates that there is no substantial interdependence in volatility among repeated observations. This signifies a process of stable volatility in which the present level of volatility remains unaffected by previous levels of volatility. The absence of autocorrelation observed in the residuals of the GARCH model indicates that the temporal dependencies inherent in the volatility process are sufficiently accounted for in the current model specification. This suggests that the autoregressive and moving average components of the GARCH model accurately represent the volatility dynamics with the selected lag structure, obviating the necessity for supplementary lags.

Figure 2. description of the conditional variance



Analysis of the conditional variance

The stability of the data over time is evident in figure 2. The actual returns of the risk premium plot provide a mirrored representation of the data, and the conditional variance from 1985 to 2023 coincides with that of the original series plot. This indicated that periods of significant low fluctuations in the returns of the risk premium are succeeded by periods of low fluctuations, and vice versa, and thus, the data exhibit a period of volatility clustering (Elyasiani & Mansur, 2017). The return of risk premium plots and the initial risk premium plots are symmetrical and remain constant over time. The Market Risk Premium Regime implemented in 1983, as a component of Ghana's wider economic reforms of the time, was to promote investment and stabilise the economy. In accordance with the Market Risk Premium Regime, interest rates and other financial incentives were modified to reflect the perceived risk of investing in the Ghanaian market. The government sought to increase investment in the country by providing investors with higher returns in order to offset the perceived risk. Nevertheless, the efficacy and consequences of such a regime would have been contingent on a multitude of elements, encompassing its implementation efficiency, the nation's comprehensive economic stability, and the risk aversion exhibited by investors worldwide and domestically. Ghana encountered substantial economic obstacles during this time period, including high inflation and external debt, and this resulted in the volatility of the risk premium from 1983 to 1985 as indicated in figure 2.

In order to tackle these obstacles and incentivize essential investment to bolster economic development and expansion, economic reforms were then executed, which included the Market Risk Premium Regime. Similar to any economic policy, the efficacy of Ghana's Market Risk Premium Regime would have been a matter of contention, and its consequences would have been contingent upon the particular circumstances and wider economic situation of the era.

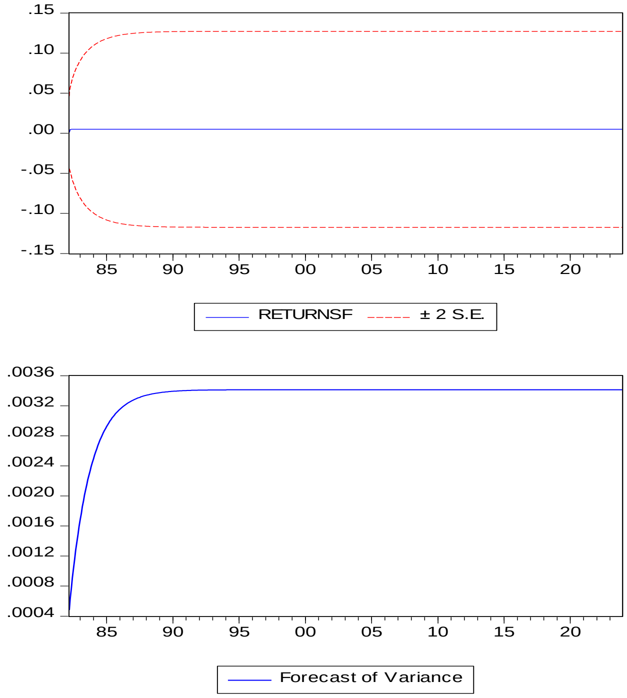
Beyond substantial economic reforms implemented with the objective of promoting growth and stabilisation, Ghana encountered a number of economic obstacles between 1995 and 2005. The volatility of risk premiums in banks and other financial institutions during Ghana's protracted struggle with high inflation rates in the 1990s and early 2000s is illustrated in Figure 2. Long-term economic planning was impeded, consumer confidence was diminished, and inflation eroded purchasing power. Significant number of organisations, particularly small and medium-sized businesses, encountered challenges in obtaining credit from financial institutions due to high interest and inflation rates. The inaccessibility of credit information systems, high interest rates, and stringent collateral requirements all hindered the availability of capital for investment and expansion. The prevalence of hardship persisted despite economic expansion, especially in rural regions.

During this time, Ghana was saddled with a substantial external debt burden, which constrained the country's ability to finance investments in infrastructure, social services, and economic development. The debt service incurred a significant expenditure of the government's budget. The government encountered fiscal deficits, which occurred when expenditure surpassed revenues. Frequently, borrowing was utilised to finance these deficits, which contributed to the nation's debt burden and macroeconomic instability. The presence of insufficient infrastructure, encompassing networks for transportation, energy, and telecommunications, presented substantial obstacles to both economic progress and competitiveness. Inadequate infrastructure impeded operational efficiency, soared expenditures on production, and limited entry into markets. For export revenue, Ghana's economy continued to be highly dependent on primary commodities such as timber, gold, and cocoa. The country was vulnerable to external disruptions and revenue volatility due to fluctuations in commodity pricing on the global market. Deteriorations afflicted the labour market, including underemployment and high unemployment rates, which were especially pronounced among young people and women.

Figure 2 illustrates how the global financial crisis, which commenced in 2007-2008, had substantial effects on emergent markets such as Ghana. A decline in investor confidence resulted in heightened aversion to risk and elevated perceived risk premiums with regard to investments made in developing nations. Due to its heavy dependence on commodity exports including gold, cocoa, and oil, Ghana's economy was susceptible to external disruptions. Investments exhibited increased risk perceptions as a result of commodity price fluctuations, especially during the period of global economic uncertainty. Ghana encountered fiscal difficulties, which encompassed enduring budget deficits and escalating levels of public debt. Anxieties regarding the government's fiscal sustainability and its capacity to efficiently administer its finances exacerbated investor apprehensions regarding risk. Political unpredictability, specifically with regard to electoral processes and matters of governance, escalated the perceived hazards for investors. Political transitions and election-related tensions in Ghana between 2007 and 2009 were influential factors in the increase in risk premiums. Potential apprehensions regarding the trajectory of economic expansion, the stability of financial systems, and geopolitical strife could have prompted investors to demand increased risk premiums on investments in developing economies, including Ghana.

Figure 2 also demonstrated that, the COVID-19 pandemic, between 2019 and 2020 had a significant impact on economies across the globe, including Ghana. Uncertainty and economic contraction resulted from supply chain disruptions, travel restrictions, and lockdown measures resulting in high interest and exchange rates in financial markets.

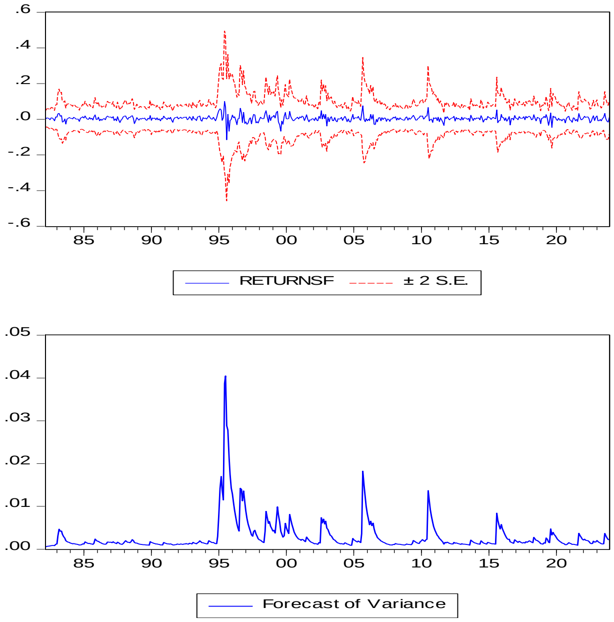
Figure 3. Dynamic forecast



Forecast: RETURNSF	
Actual: RETURNS	
Forecast sample: 1982M01 2023M12	
Adjusted sample: 1982M03 2023M12	
Included observations: 502	
Root Mean Squared Error	0.057818
Mean Absolute Error	0.037819
Mean Abs. Percent Error	NA
Theil Inequality Coefficient	0.923235
Bias Proportion	0.003527
Variance Proportion	0.990604
Covariance Proportion	0.005869
Theil U2 Coefficient	NA
Symmetric MAPE	161.4927

The dynamic forecast demonstrated stable volatility, as evidenced by the returns on the risk premium line remaining within the standard error bands (Figure 3). Volatility could have been mitigated if government implement prudent macroeconomic policies with the objective of stabilising the economy. Stability could potentially be enhanced through the implementation of fiscal discipline, monetary policy adjustments, and regulatory measures. Economic stability could potentially be achieved through the maintenance of stable prices and demand for essential commodities such as oil, gold, and cocoa. By effectively managing these resources and the revenues they generate, economic fluctuations can be mitigated. The economy may be influenced by favourable international trade conditions and global economic stability. A reduction in global market volatility might have contributed to the stabilisation of the economy over the period. International organisations' investment, foreign aid, and support have the potential to enhance the economic stability of developing nations. The introduction of structural reforms with the objective of enhancing governance, infrastructure, and the business environment has the potential to bolster economic stability and entice investment. Expanding economic diversification beyond conventional sectors such as mining and agriculture has the potential to mitigate reliance on unstable industries and foster a more stable global environment.

Figure 4. Static forecast graph



Forecast: RETURNSF	
Actual: RETURNS	
Forecast sample: 1982M01 2023M12	
Adjusted sample: 1982M03 2023M12	
Included observations: 502	
Root Mean Squared Error	0.055672
Mean Absolute Error	0.036279
Mean Abs. Percent Error	NA
Theil Inequality Coefficient	0.741536
Bias Proportion	0.002127
Variance Proportion	0.538194
Covariance Proportion	0.459679
Theil U2 Coefficient	NA
Symmetric MAPE	146.7467

The static forecast time series plot exhibits no temporal variation, volatility remains constant, and falls within the standard error bands (see figure 4). Consequently, investors may choose to retain their assets throughout the examined period. In order to generate a stable static forecast for Ghana spanning the years 2020 to 2023, it is imperative to take into account a multitude of economic indicators and trends that transpire throughout the timeframe. Ghana has exhibited comparatively robust rates of GDP growth in recent years, primarily propelled by its agricultural and service sectors, in addition to its natural resources industry, which is notably focused on oil and gas. The historical volatility of inflation rates in Ghana can be attributed to various factors, including external disruptions, currency depreciation, and fiscal deficits. The government and central bank's efforts to stabilise prices may, nevertheless, result in a moderate inflation rate. The Ghanaian cedi (GHS) has undergone volatility in relation to significant currencies such as the US dollar. Ghana has garnered substantial foreign direct investment, particularly in its extractive sectors. Sustained foreign direct investment (FDI) inflows could be predicted with a degree of predictability owing to fluctuations in commodity prices and worldwide economic conditions. Throughout the forecast period, stable policies that encourage investment, reduce fiscal deficits, and enhance infrastructure may contribute to overall economic stability. Ghana's economy is susceptible to the impact of external factors, including geopolitical events, world economic trends, and commodity prices (particularly oil). These variables and the assumption of a relatively stable global environment throughout the period may be incorporated into the forecast.

CONCLUSION, RECOMMENDATIONS AND POLICY IMPLEMENTATIONS

The research utilized a univariate time series model to predict and analyze the movement of the risk premium of commercial banks in Ghana spanning the years 1982 to 2023. Secondary data was sourced from the Bank of Ghana database and the World Development Indicators and used for the analysis. Arch1 to arch5 were estimated for selection including Garch, GJR Garch, and EGarch. Upon careful evaluation, it was determined that the Garch model was considerably more suitable for estimation and forecasting purposes. As a result, it was chosen for the research. A mirrored representation of the data is indicated by the plot of the conditional variance and the actual risk premium returns; the conditional variance aligns with that of the initial plot. This indicated the presence of volatility clustering, which occurs when periods of low fluctuations are succeeded by periods of low fluctuations, and periods of high fluctuations are succeeded by periods of high fluctuations in the data. Over time, both the risk premium and the original plots have maintained their asymmetrical returns. As shown in Figure 3, the dynamic forecast from 1982 to 2023, on the other hand, exhibited stable volatility. Nonetheless, investor confidence in the system had increased as a result of the stability of inflation, exchange rates, and other economic variables within the forecasted period. Additionally, as depicted in figure 4, the forecast indicates that there is no temporal variation, volatility has remained constant over time, and it is contained within the standard error bands. This implies that investors have the option to retain their investments throughout the period being evaluated. According to the research, there are a greater number of periods with high volatility risk premiums from 1982 to 2023 than periods with low volatility risk premiums. In order to diminish the premium added to the risk-free rate, banks require a discernible reduction in loan default rates and an increase in lending confidence, which would subsequently lead to a decrease in risk premiums.

In order to increase financial stability, policymakers may elect to enact measures such as monitoring systemic risks and remediating potential vulnerabilities within the banking system. This may entail the implementation of early warning systems, strengthened supervisory frameworks, and risk mitigation strategies to address the vulnerabilities that arise from the interdependence of financial institutions. In order to advance financial inclusion and credit accessibility, policymakers may choose to implement initiatives that specifically target underserved or marginalized communities. Potential strategies to address this issue include the implementation of targeted lending initiatives, provision of incentives for banks to cater for low-income communities, and endeavors to diminish obstacles for new entrants into the market. Credit demand and macroeconomic conditions may be influenced by fiscal policy measures, including tax incentives and government expenditure programs. To further stabilize and expand the economy, policymakers may modify fiscal policies, thereby exerting an indirect impact on the banking sector's risk premiums. Policy objectives that seek to safeguard consumers and promote equitable lending practices may have an indirect impact on the risk premiums that commercial banks levy. Efforts aimed at augmenting financial literacy, fostering transparency in lending terms, and averting predatory lending practices have the potential to positively impact the efficiency and competitiveness of the banking industry.

Future research on the functions of behavioural biases in the construction of risk premiums may yield valuable insights regarding the details of the market and the behaviour of investors. Another avenue for research could be the impact of cognitive mistakes on investment decisions, risk pricing in financial markets, and risk perception. The correlation between credit risk and risk premiums may provide insight into how default risk is priced in lending markets. Further investigation is warranted to determine how changes in credit quality, loan attributes, and macroeconomic variables influence the magnitude of risk premiums imposed by lenders. An alternative area worthy of investigation would be the relationship between market frictions and information transmission and pricing of risk premiums on financial markets. Examination of risk premiums across various nations and regions may facilitate the identification of variations in risk perceptions, market structures, and regulatory frameworks that exist between countries.

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