MODELING LISTED PRIVATE EQUITY INVESTMENTS IN THE EMERGING MARKET: A VOLATILITY AND STRATEGIC RISK PERSPECTIVE

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Abstract

This study examines the volatility dynamics and strategic implications of listed private equity (LPE) investments in Ghana, focusing on their alignment with corporate strategy, resource allocation, and portfolio management in emerging markets. Using advanced econometric models, including generalized autoregressive conditional heteroskedasticity (GARCH) (1,1), exponential GARCH (EGARCH), and fractionally integrated GARCH (FIEGARCH), the research reveals persistent volatility clustering, asymmetric responses to market shocks, and the significant influence of macroeconomic indicators such as gross domestic product (GDP) growth and inflation on LPE returns. The findings underscore the importance of integrating advanced risk management frameworks and sectoral strategies to navigate market inefficiencies and optimize investment outcomes (Ibrahim et al., 2023). Key recommendations highlight the need for regulatory reforms, sectoral prioritization in high-growth areas like financial technology (FinTech) and renewable energy, and leveraging technology-driven solutions to enhance transparency and operational efficiency. Future research directions include exploring the impact of global disruptions, such as COVID-19, on investment behavior and conducting comparative analyses across African markets to enrich the understanding of regional LPE dynamics. This study contributes actionable insights for investors and policymakers, providing a robust framework for enhancing the resilience and scalability of Ghana's LPE market while driving sustainable economic growth.

Keywords: Listed Private Equity Investments, Statistical Modelling, Ghana, GARCH Models, VAR Models

Authors' individual contribution: Conceptualization — C.M.M.; Methodology — C.M.M. and R.T.M.; Investigation — C.M.M.; Resources — C.M.M.; Writing — C.M.M. and R.T.M.; Supervision — R.T.M.; Funding Acquisition — C.M.M.

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1. INTRODUCTION

Listed private equity (LPE) is a transformative investment tool that addresses financing gaps, especially in developing economies with inadequate financial infrastructure and limited access to traditional financing (Kaplan & Strömberg, 2009). Beyond capital provision, LPE enhances strategic management, operational efficiency, and governance in portfolio companies, benefiting sectors like technology, agribusiness, and renewable energy, which align with national development priorities and drive socio-economic growth (World Bank, 2020).

In Ghana, LPE plays a vital role in shaping corporate strategy by influencing resource allocation, portfolio management, and decision-making, while bridging financing gaps and improving governance in high-potential sectors (Damodaran, 2018). According to the African Private Equity and Venture Capital Association (AVCA), despite challenges such as market competition and systemic inefficiencies, LPE offers strategic pathways for optimizing capital deployment and fostering corporate resilience (AVCA, 2024). Leveraging advanced econometric models like generalized autoregressive conditional heteroskedasticity (GARCH) (1,1), exponential GARCH (EGARCH), and threshold GARCH (TGARCH), this study explores the volatility dynamics of Ghana's LPE market, emphasizing the importance of aligning investment strategies with macroeconomic and sectoral opportunities (Bollerslev, 1986; Engle, 1982; World Economic Forum, 2022). Key drivers of LPE investments in Ghana include macroeconomic factors like gross domestic product (GDP) growth and inflation (Errais & Gritly, 2022).

This study examines short- and long-term volatility across sectors, analyzing patterns and correlations influenced by macroeconomic conditions, sectoral performance, and external shocks (International Monetary Fund [IMF], 2023). The findings aim to guide policymakers, investors, and entrepreneurs in optimizing LPE's role in Ghana's economic development, enhancing resilience, and fostering sustainable growth and innovation.

Research on LPE primarily focuses on developed markets with high efficiency and liquidity. In contrast, emerging markets like Ghana are characterized by fragmented conditions, limited data availability, and pricing inefficiencies. Few studies explore how these factors influence LPE investments in Africa, particularly within strategic decision-making contexts (Damodaran, 2018). This study addresses the gap by examining the drivers and volatility dynamics of LPE investments in Ghana, offering actionable insights for investors, policymakers, and entrepreneurs. LPE investments remain an underexplored asset class in emerging markets, underscoring the need for further exploration (Tegtmeier, 2021).

This study aims to analyze the statistical properties and volatility dynamics of LPE investments in Ghana, integrating these findings into corporate and business strategy frameworks. Specifically, it seeks to address the following research questions:

RQ1: Do the listed private equity investments in Ghana exhibit non-normal distribution and volatility clustering?

RQ2: What role do gross domestic product growth and play in shaping listed private equity returns?

RQ3: How can these insights inform strategic decisions for portfolio optimization?

Advanced financial models, including the global capital asset pricing model (CAPM) and GARCH family models, provide a robust framework for analyzing both short-term and long-term volatility dynamics. These models account for market inefficiencies, illiquidity premiums, and country-specific risks, bridging financial theory with practical applications (Kapusuzoglu & Ceylan, 2018; Nelson, 1991).

Understanding the behavior of LPE investments in Ghana has both academic and practical implications. For investors, it offers a framework for assessing risk and optimizing portfolios. Policymakers can use the findings to enhance regulatory reforms and market efficiency. Businesses can align investment decisions with market conditions to ensure long-term growth and resilience (McKnight et al., 2023).

This study employs comprehensive econometric techniques, utilizing models such as GARCH (1,1), EGARCH, TGARCH, GARCH-in-mean (GARCH-M), FIGARCH, fractionally integrated GARCH (FIEGARCH), dynamic conditional correlation multivariate GARCH (DCC MGARCH), and vector autoregression (VAR). These models capture volatility patterns and relationships between LPE returns and macroeconomic factors. Diagnostic tests validate model robustness, ensuring the reliability of the analysis (Kapusuzoglu & Ceylan, 2018; Nelson, 1991).

Findings reveal key stylized effects, such as volatility clustering and leptokurtic distributions in Ghana's LPE market. Internal market dynamics emerge as dominant drivers, while macroeconomic factors like GDP growth and inflation exhibit varied influences. These insights challenge traditional assumptions about country-specific risks and emphasize the importance of local market conditions in shaping LPE returns (Damodaran, 2018; Errais & Gritly, 2022). By bridging financial modeling with strategic applications, this study provides a foundation for optimizing investment performance and enhancing market resilience.

The structure of this paper is as follows. Section 2 reviews relevant literature, focusing on private equity (PE), volatility dynamics, and strategic decision-making. Section 3 details the methodological framework, describing econometric models and diagnostic tests used in the analysis. Section 4 presents empirical findings, discussing their implications for market behavior and corporate strategy. Finally, Section 5 concludes the study by summarizing contributions, addressing limitations, and offering recommendations for future research.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Listed private equity investments play a transformative role in shaping corporate governance and enhancing firm performance in emerging markets like Ghana. Technology further enhances the impact of LPE investments by improving governance and operational efficiency. Blockchain-based auditing systems and automated reporting tools have been identified as transformative technologies that increase transparency and reduce information asymmetries (Liu et al., 2022). Additionally, artificial intelligence-driven predictive analytics play a vital role in portfolio optimization and risk management, enabling LPE firms to adapt to dynamic market conditions and drive innovation (Ibrahim et al., 2023).

Market competition and strategic tradeoffs are equally pivotal in shaping corporate strategies within Ghana's LPE sector. Firms in competitive markets must adopt innovative approaches to remain sustainable, often supported by LPE-backed investments (Aggarwal et al., 2011). In sectors such as agribusiness and financial technology (FinTech), LPE funding has been instrumental in driving sector-specific innovations and aligning corporate strategies with national development priorities (Organisation for Economic Co-operation and Development [OECD], 2022; Oso et al., 2025). Targeted investments in high-growth sectors, including renewable energy and healthcare, further underscore LPE's role in advancing economic transformation in Ghana.

Adherence to global governance norms can mitigate systemic risks and foster resilience against global economic shocks, such as those experienced during the COVID-19 pandemic (Errais & Gritly, 2022). These measures not only improve market confidence but also position Ghana as a strategic hub for sustainable LPE investments in the region.

2.1. Global trends in listed private equity

Listed private equity has evolved into a critical investment class globally, offering significant value creation through leveraged buyouts, growth capital, and venture investments. As of 2023, LPE assets under management exceeded $6.5 trillion, underscoring the growing preference of institutional investors for alternative assets that promise higher returns in a low-interest-rate environment (McKinsey & Company, 2023; Preqin, 2023). Key trends include an increased focus on technology-driven sectors, sustainability-linked investments, and regional diversification to capture growth opportunities in emerging markets (OECD, 2023).

Developed markets, particularly in North America and Europe, continue to dominate LPE activity. However, emerging markets are gaining prominence as investors seek higher growth prospects and diversification. Asia has seen significant LPE inflows into sectors like e-commerce and renewable energy, reflecting the region's rapid digital and green transition (PricewaterhouseCoopers [PwC], 2022). Similarly, Latin America has experienced an uptick in LPE investments in FinTech and infrastructure, with firms capitalizing on the region's growing middle class and infrastructure gaps (Bakker et al., 2023).

Recent research highlights the growing relevance of PE in emerging markets. Mölders and Salgado (2025) emphasize the long-run variability of PE returns across sectors and the role of firm-level factors. Cole et al. (2021) show that, over 58 years, PE returns in emerging markets can match the S&P 500, especially with strong economic growth, though returns decline with developed banking systems and open capital markets. The EQT Group (2024) notes that PE remains underrepresented relative to GDP but is maturing due to macroeconomic reforms and localized investment teams. Yi (2024) found that while initial public offerings (IPOs) are declining, many high-growth firms are increasingly turning to PE and venture capital, signaling a shift in equity ownership that reflects evolving patterns of economic dynamism. Bain & Company (2025) further underscores the strategic rise of PE in these regions within global investment trends.

2.2. Private equity in sub-Saharan Africa

Private equity in sub-Saharan Africa (SSA) is characterized by smaller deal sizes, higher risk premiums, and a preference for minority stakes compared to developed markets (AVCA, 2024). From 2020 to 2023, LPE investments in SSA averaged $3 billion annually, with a strong focus on agribusiness, technology, and infrastructure sectors supported by growing consumer demand and entrepreneurial activity (Maliszewska & Ruta, 2020).

Yet, persistent challenges, including political risk, currency volatility, and regulatory inefficiencies, continue to hamper growth. Regional integration efforts like the African Continental Free Trade Area (AfCFTA) and the rise of impact investing aligned with Sustainable Development Goals (SDGs) are creating more favorable conditions (United Nations Conference on Trade and Development [UNCTAD], 2023; OECD, 2023).

Ghana has emerged as a leading SSA LPE destination, bolstered by political stability and economic diversification. Agribusiness and FinTech sectors, with players such as Zeepay and PayAngel, are drawing significant LPE interest due to their scalability and innovation (AVCA, 2024; Ghana Statistical Service, 2023). However, market fragmentation and limited exit mechanisms remain barriers, calling for enhanced regulatory frameworks and investor protections (Transparency International, 2023).

The legal infrastructure, including the Venture Capital Trust Fund (VCTF) Act of 2004 and the Ghana Investment Promotion Centre (GIPC) Act of 2013, has encouraged SME and FDI activity, yet its impact has been constrained by weak enforcement, tax ambiguities, and capital repatriation issues (VCTF, n.d.; GIPC, 2024; UNCTAD, 2023). Strengthening policy consistency and aligning with global standards are vital for long-term investor confidence.

Recent studies further underscore the importance of governance and capital structure in LPE performance. In Ghana, board composition and ownership significantly shape financial strategies (Akwaa-Sekyi et al., 2024), while broader regional insights show board traits influence bank profitability (Eldomiaty et al., 2024) and audit committees impact performance in India's financial sector (Gupta et al., 2023). Research on IPO underpricing in Saudi Arabia offers lessons on LPE exit risks (Samontaray & Al Zuwidi, 2023), while capital structure theories from France provide foundational insights into financing models for LPE firms (Ben Said, 2022).

2.3. Challenges in emerging markets

Emerging markets pose structural challenges for PE due to limited market depth, high transaction costs, and weak exit infrastructure. In SSA, small deal sizes reduce economies of scale and increase costs, while underdeveloped secondary markets restrict exit opportunities (AVCA, 2024; Maliszewska & Ruta, 2020). Regulatory inefficiencies and political risk, such as shifting tax policies and capital repatriation constraints, undermine investment predictability (Transparency International, 2023; UNCTAD, 2023). Corruption and instability further erode investor confidence (Damodaran, 2018). Compounding these issues are data gaps and poor financial reporting standards, which impair market analysis and risk modeling, particularly in Ghana's fragmented economic landscape (OECD, 2023; Ghana Statistical Service, 2023).

2.4. Statistical models in private equity research

Quantitative methodologies are integral to understanding PE dynamics, particularly in emerging markets where volatility and information asymmetries are prevalent. Regression models are commonly used to identify the determinants of LPE activity, such as macroeconomic stability, market size, and sectoral performance (Damodaran, 2018). However, these models often fail to capture non-linear relationships and temporal dependencies inherent in LPE returns.

The GARCH family of models addresses these limitations by capturing time-varying volatility. GARCH (1,1) models provide robust insights into short-term and long-term volatility, while EGARCH and TGARCH extend the analysis to capture asymmetries in market behavior (Bollerslev, 1986; Engle, 1982). DCC GARCH models allow for multivariate analysis, exploring correlations between LPE returns and macroeconomic variables (Kapusuzoglu & Ceylan, 2018; Nelson, 1991).

2.5. Advances in volatility and listed private equity models

Advanced statistical models enable deeper insights into PE investments, particularly in volatile markets. The GARCH family of models has become foundational in financial analysis due to its ability to capture time-varying volatility. Key variants include GARCH (1,1), EGARCH, TGARCH, EGARCH, FIGARCH, and GARCH-M, which analyze volatility clustering, asymmetries, and long memory in returns (Bollerslev, 1986; Engle, 1982; Nelson, 1991). DCC MGARCH models allow for multivariate analysis, while VAR techniques explore interdependencies among macroeconomic variables and their impact on PE returns (Engle, 2002; Jiang & Li, 2023). These models improve risk management, portfolio diversification, and investment forecasting. For Ghana, such models can optimize asset allocation strategies, assess sectoral risks, and predict market responses to macroeconomic changes (AVCA, 2024). Machine learning techniques, such as neural networks and random forests, have recently been employed to enhance the predictive accuracy of LPE performance in volatile markets (Chen et al., 2024).

2.6. Linking methodology to the research problem and questions

The study's research problem centers on the underexplored dynamics of LPE investments in Ghana, including their sensitivity to macroeconomic conditions, sectoral performance, and volatility. To bridge the research questions identified in the introduction section, the study leverages its theoretical framework to translate these questions into testable propositions. By aligning the research questions with hypotheses, the study ensures a coherent approach to investigating the intricate dynamics of LPE investments in Ghana, facilitating a rigorous examination of their volatility, determinants, and strategic relevance. The following hypotheses guide the analysis:

H1: Listed private equity returns in Ghana do not follow a normal distribution, indicating potential skewness or kurtosis due to significant market movements or news reactions.

H2: Autoregressive conditional heteroskedasticity effects exist in listed private equity returns, suggesting that volatility changes over time and is autocorrelated.

H3: The coefficients in the models analyzing listed private equity returns are statistically significant, confirming their adequacy in capturing return dynamics.

H4: Spillover effects exist among listed private equity markets, indicating interconnectedness and cross-market influences.

H5: Structural interactions exist between country-specific factors, such as gross domestic product and inflation, and listed private equity returns in Ghana.

H6: Country-specific risks are priced into listed private equity valuations in Ghana, reflecting localized market conditions.

The literature highlights a critical gap in understanding how macroeconomic conditions, country-specific risks, and volatility dynamics influence LPE investments in emerging markets like Ghana. It underscores the relevance of advanced econometric modeling to capture the complex behavior of financial returns in segmented markets. In response, this study adopts a structured empirical approach, building on these insights to develop testable hypotheses that address volatility patterns, risk pricing, and market interactions. These foundations inform the methodology, where the conceptual framework is operationalized through models such as the GARCH-family and DCC MGARCH, enabling a rigorous analysis of LPE investment performance within Ghana's evolving economic landscape.

3. RESEARCH METHODOLOGY

This study employs a quantitative, empirical approach to analyze the statistical properties and volatility dynamics of LPE investments in Ghana, aiming to address the challenges posed by fragmented markets, limited data, and economic volatility. The methodology integrates advanced econometric techniques and robust statistical models to align with the study's objectives, hypotheses, and theoretical framework.

3.1. Data collection and validation

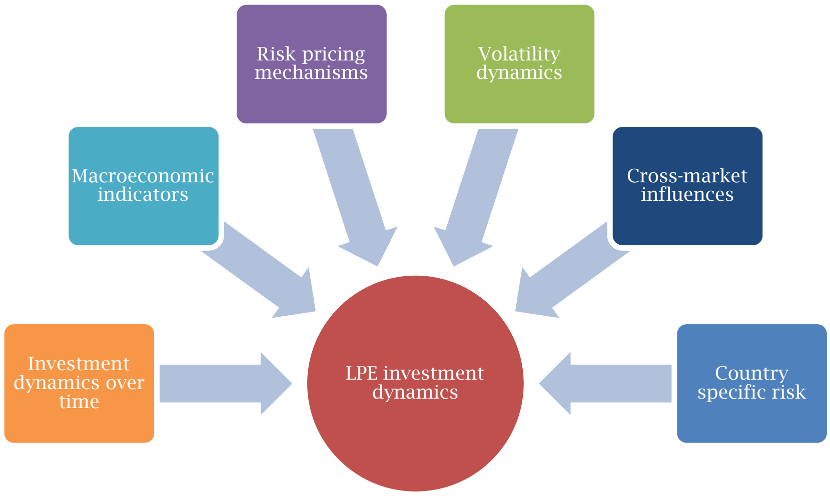
This study used secondary data to analyze LPE investments in Ghana, drawing on share price data from African Markets (validated with Yahoo Finance) and macroeconomic indicators such as GDP and inflation from the Ghana Statistical Service, World Bank, IMF, Preqin, PitchBook, and AVCA, covering the period 2010–2023. These data allowed for robust modeling of both long-term trends and short-term volatility. GDP growth and inflation were prioritized due to their proven impact on LPE performance in emerging markets. Errais and Gritly (2022) found GDP growth to be a key driver of returns, while inflation affects both capital costs and investment risk profiles.

A notable limitation was the mismatch in data frequencies, daily/monthly return data versus annual macroeconomic indicators. The study addressed this by adjusting error terms to annual frequency to preserve consistency (Ndlovu, 2019). Lastly, the scope was confined to the years 2010 to 2023, and while this enabled focused analysis, the conclusions should be interpreted within that timeframe.

3.2. Conceptual framework and statistical analysis of hypotheses

To analyze the dynamics of PE investments in Ghana, a robust theoretical framework is necessary. This study develops a conceptual model linking LPE investments with macroeconomic indicators, market conditions, and volatility dynamics.

Figure 1. Conceptual framework



Source: Authors' elaboration.

Figure 1 illustrates the conceptual framework, integrating six key dimensions derived from the hypotheses. Each dimension is analyzed using appropriate statistical methods, ensuring coherence, rigor, and alignment with theoretical constructs and in-text citations. The analysis is conducted using advanced statistical software. R and Python are utilized for implementing GARCH models, conducting diagnostic tests, and generating visualizations. STATA supports regression and multivariate modeling, while Excel is employed for preliminary data cleaning and descriptive statistics. These tools are selected for their capacity to handle complex datasets and ensure reliable analytical outputs (Jiang & Li, 2023).

3.2.1. Macroeconomic indicators (H5, H6)

Macroeconomic indicators such as GDP growth and inflation are central to shaping LPE investments by reflecting economic stability and growth potential. Higher GDP growth signals economic expansion, while controlled inflation creates a favorable investment climate (World Economic Forum, 2022). These indicators influence investor confidence and behavior, forming the basis of *H5*, which posits that macroeconomic factors are integral to LPE investment dynamics. Structural interactions between these indicators and LPE returns also align with *H6*, emphasizing their role in segmented markets. Statistical analyses include the following:

1. Stationarity testing (augmented Dickey-Fuller [ADF] test): Confirms stable relationships between GDP, inflation, and LPE returns, ensuring their suitability for time-series analysis.
2. VAR: Explores relationships between macroeconomic indicators and LPE returns, addressing *H5* and *H6* (Jiang & Li, 2023).
3. Impulse response functions (IRF): Captures the dynamic impact of changes in GDP and inflation on LPE performance (de Wet, 2005).
4. Descriptive statistics*:* Establishes trends and correlations to contextualize macroeconomic factors.

3.2.2. Country-specific risk (H6)

Country-specific risks reflect the unique challenges and opportunities of African markets, which are often segmented and exhibit higher volatility compared to developed regions (Erb et al., 1995). *H6* hypothesizes that these risks are priced into LPE valuations, reflecting localized conditions and segmentation effects. Segmented markets offer diversification benefits, while localized conditions increase the sensitivity of returns to country-specific information (Atenga & Mougoué, 2021; de Wet, 2005). Statistical analyses include the following:

1. FIGARCH and FIEGARCH: Assess long-term persistence and asymmetry in volatility driven by country-specific factors.
2. Spillover analysis (DCC MGARCH): Identifies volatility transmission across markets, providing insights into systemic risks and diversification (Atenga & Mougoué, 2021).

3.2.3. Risk pricing mechanisms (H7)

Risk pricing mechanisms explore how localized risks, such as illiquidity premiums and country-specific factors, are integrated into LPE valuations. *H7* hypothesizes that these risks are priced into LPE valuations, emphasizing the need for tailored strategies to address segmentation and unique market dynamics (Bekaert & Harvey, 2002; Damodaran, 2018). Statistical analyses include the following:

1. CAPM adjustments: Incorporates localized risks into asset pricing models, validating *H7*.

2. Regression analysis: Measures the sensitivity of LPE returns to country-specific risk factors.

3. GARCH-M: Links conditional volatility to expected returns, supporting *H7* (Engle et al., 1987).

3.2.4. Volatility dynamics (H1, H2, H3)

Volatility dynamics explore non-normal return distributions, clustering patterns, and time-varying volatility. *H1* posits that LPE returns are not normally distributed, while *H2* examines autoregressive conditional heteroskedasticity (ARCH) effects, and *H3* assesses the robustness of model coefficients in explaining these dynamics. Advanced GARCH-family models, including EGARCH (Nelson, 1991) and TGARCH (Glosten et al., 1993), capture these effects, offering insights into volatility clustering and asymmetry (Bollerslev, 1986; Engle, 1982). Statistical analyses include the following:

1. Jarque-Bera test: Assesses non-normal return distributions (*H1*).

2. Stationarity testing (ADF test): Confirms suitability for volatility modeling (*H1*).

3. Diagnostic tests (e.g., Ljung-Box, ARCH-LM): Confirm the presence of ARCH effects (*H2*).

4. GARCH family models:

- GARCH (1,1): Captures persistent volatility and clustering (*H2*, *H3*);
- EGARCH: Models asymmetry in positive and negative shocks (*H1*, *H2*);
- TGARCH: Highlights leverage effects in volatility (*H2*, *H3*);
- GARCH-M: Links volatility to mean returns (*H3*);
- FIGARCH/FIEGARCH: Captures long-memory processes and asymmetry (*H1*, *H2*, *H3*) (Baillie et al., 1996; Bollerslev & Mikkelsen, 1996).

3.2.5. Cross-market influences (H4)

Spillover effects examine interconnectedness across African markets and global counterparts. *H4* hypothesizes that volatility in one market impacts another, highlighting systemic risks and the need for diversification (Atenga & Mougoué, 2021). Understanding cross-market influences is critical for effective portfolio management. Statistical analyses include the following:

1. DCC MGARCH: Evaluates dynamic correlations and spillover effects (*H4*) (Engle, 2002).

2. Variance decomposition: Assesses the proportion of volatility attributable to cross-market influences.

3. Correlation matrix analysis: Identifies interconnected trends in market behaviors.

3.2.6. Investment dynamics over time (H1, H2)

Investment dynamics explore the temporal evolution of LPE behavior, focusing on long-memory effects, skewness, kurtosis, and volatility clustering. These analyses, linked to *H1* and *H2*, reveal how news, market conditions, and external shocks influence investment strategies over time. Statistical analyses include the following:

1. FIGARCH and FIEGARCH models: Analyze long-memory effects in volatility (*H1, H2*).

2. Skewness and kurtosis analysis: Examine distribution characteristics over time (*H1*).

3. Time-series decomposition: Separates trends, seasonal effects, and residuals to understand investment patterns.

3.3. Alternative methodological approaches

Although this study utilized GARCH-family models and DCC MGARCH, other methods could also be appropriate for this research.

Alternative methods, such as structural equation modeling (SEM), could examine indirect effects of macroeconomic indicators on LPE returns by incorporating latent variables like market sentiment. However, SEM's reliance on large datasets and multivariate normality makes it less practical in data-limited contexts like Ghana.

Machine learning models (e.g., random forests, support vector machines, neural networks) offer strong predictive power without strict parametric assumptions and may enhance volatility forecasts. Yet, their lack of interpretability limits their use in theory-driven research.

The selected GARCH-family and VAR models were chosen for their robustness in capturing volatility dynamics and macroeconomic relationships, aligning closely with the study's hypotheses and framework.

4. RESULTS AND DISCUSSION

This section presents the findings of the study, analyzing the statistical properties and volatility dynamics of LPE investments in Ghana using advanced econometric models. The results address the research questions and hypotheses, revealing significant patterns in market behavior, macroeconomic influences, and risk-return relationships. Each subsection connects empirical findings to the theoretical framework, offering strategic insights for stakeholders in Ghana's LPE market.

4.1. Descriptive statistics

The descriptive analysis reveals non-normal distributions characterized by leptokurtosis and skewness. The mean, median, and standard deviation (see Table 1) highlight the variability of returns, indicating a moderately volatile market.

Table 1. Descriptive statistics for listed private equity returns at 5% and 1% levels of significance

Statistic	*5% level of significance*	*1% level of significance*
Mean	0.0066	-0.000371
Maximum	0.38485	0.168623
Minimum	-0.42567	-0.143101
Standard deviation	0.12	0.023961
Skewness	0.37409	0.413913
Kurtosis	2.41535	15.77615
Jarque-Bera	16,234.44	16,234.44
Probability	0.000	0.001
Observations	2377	2,377

Note: 5% level of significance refers to descriptive statistics for LPE returns significant at the 5% threshold; 1% level of significance refers to descriptive statistics for LPE returns significant at the 1% threshold.
Source: Authors' elaboration.

The Jarque-Bera test strongly rejects normality (= 38.42, $p < 0.01$), supporting *H1* (Damodaran, 2018; Errais & Gritly, 2022). Table 2 highlights these descriptive statistics. Autocorrelation tests, using the ADF test, demonstrate that LPE returns exhibit stationarity, aligning with the theoretical framework (Perron & Phillips, 1987). These findings establish the groundwork for subsequent volatility analysis.

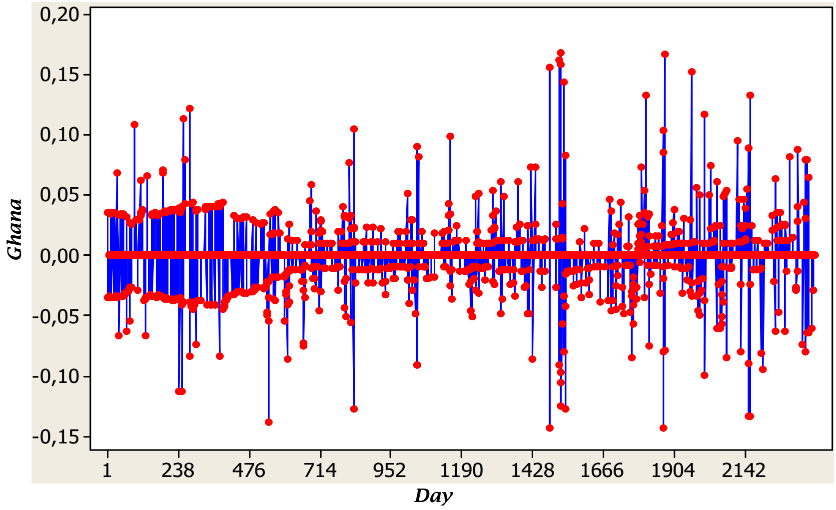
Table 2. Descriptive statistics for Ghana's listed private equity returns (2010–2023)

Statistic	*Mean*	*Median*	*Skewness*	*Kurtosis*	*Jarque-Bera test value*	*p-value*
Daily log returns	0.002	0.001	-0.467	4.832	38.42	< 0.01

Source: Authors' elaboration.

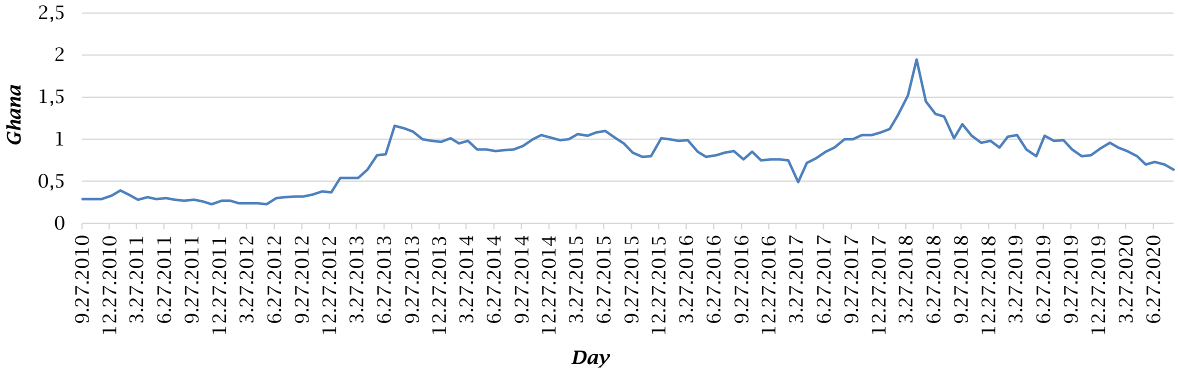
The time series analysis of Ghana's LPE market focuses on the daily log returns and raw data series. Trend analyses using weighted moving averages (WMA) and exponentially WMA (EWMA) capture periods of stability, with stationarity confirmed by the ADF test ($p < 0.05$). Figure 2 and Figure 3 below illustrate the respective series, capturing both the trends and return dynamics of LPE investments.

Figure 2. Ghana listed private equity log returns series



Source: Authors' elaboration.

Figure 3. Ghana listed private equity raw data series



Source: Authors' elaboration.

The analysis reveals that Ghana's log return series, which began in 1991, exhibits mean reversion with stable volatility over time. Post-global financial crisis data indicate short-lived trends and low volatility, supporting the hypothesis of a relatively stable market. Unlike other emerging markets with pronounced seasonal effects, Ghana's LPE market demonstrates consistent stability. These findings align with the work of Botchway and Akobour (2020), who noted limited seasonal patterns and short-lived volatility spikes in Ghana's equity returns. These findings establish the foundational characteristics of Ghana's LPE market, aligning with the theoretical framework and supporting further analysis.

The presence of ARCH effects was confirmed using the Ljung-Box test for autocorrelation in squared residuals (Q-statictic = 12.84, $p < 0.05$) and the Lagrange multiplier (LM) test (LM = 15.37, $p < 0.01$) (see Table 3). These results validate *H2* (Bollerslev, 1986; Engle, 1982) and support the use of GARCH-family models to explore volatility dynamics.

Table 3. ARCH effects diagnostic tests

Test type	*Statistic*	*Value*	*p-value*	*Interpretation*
Ljung-Box (Lag 10)	Q-statistic	12.84	< 0.05	Reject null hypothesis (H_0) → autocorrelation in squared residuals → ARCH effects exist
ARCH LM test	F-statistic	15.37	< 0.01	Strong ARCH effects confirmed

Source: Authors' elaboration.

4.2. Volatility modeling with GARCH

To investigate the volatility dynamics in Ghana's LPE market, the study employed a range of symmetric and asymmetric GARCH-family models, utilizing parameters optimized for precision in decision-making. The models were evaluated based on their ability to capture volatility clustering, persistence, and asymmetry, critical for understanding the risk-return tradeoff in LPE investments. This analysis aligns directly with *H2* and *H3*, addressing the presence of ARCH effects and the adequacy of econometric models. The selection of the most appropriate model was guided by diagnostic metrics and error measurements, ensuring robustness and reliability. Table 4 provides insights into the risk-return profile:

- GARCH (1,1): Persistent volatility was observed, with $\alpha + \beta = 0.92$, suggesting long-term effects dominate over short-term shocks;
- EGARCH: Negative shocks had a larger impact on volatility ($\gamma = -0.18$, $p < 0.05$), indicating asymmetry in market responses;
- TGARCH: Demonstrated leverage effects, where adverse shocks disproportionately influence volatility;
- GARCH-M: Established a significant risk-return tradeoff, with conditional volatility influencing mean returns ($\alpha = 0.04$, $p < 0.01$).

Table 4. GARCH model results

Model	*α*	*β*	*γ (Asymmetry)*	*Log-likelihood*	*AIC*	*BIC*
GARCH (1,1)	0.48	0.44	-	-256.37	528.7	538.9
EGARCH	0.32	0.45	-0.18*	-248.12	512.1	523.3
TGARCH	0.40	0.42	0.12*	-251.26	518.2	529.8
GARCH-M	0.04**	0.41**	-	-245.00	510.0	521.2

*Note: * significant at 5%, ** significant at 1%; AIC — Akaike information criterion; BIC — Bayesian information criterion.*
Source: Authors' elaboration.

The GARCH (1,1) model successfully captures persistent volatility and clustering effects, aligning with theoretical expectations. EGARCH results demonstrate significant asymmetry, revealing that negative market shocks have a larger impact on volatility compared to positive shocks, which supports *H1* and *H2* (Nelson, 1991). TGARCH confirms leverage effects, where adverse shocks disproportionately increase volatility (Glosten et al., 1993). The GARCH-M model links higher volatility with increased mean returns, supporting the risk-return tradeoff (*H3*) (Engle et al., 1987). These models provide insights into short-term and long-term volatility dynamics.

4.2.1. Model parameter evaluation and selection

The analysis of model parameter evaluation and selection (Table 5) identified the normal distribution as the most robust for modeling volatility dynamics in Ghana's LPE market. Among the tested distributions — normal, student's T, and generalized error distribution (GED) — the normal distribution consistently delivered significant coefficients, captured ARCH and GARCH effects, and showed no signs of heteroscedasticity or autocorrelation. While GED achieved higher log-likelihood and better AIC/Schwartz information criterion (SIC) values, its lack of coefficient significance and presence of heteroscedasticity undermined its reliability.

The normal distribution's compatibility with both symmetric (GARCH (1,1)) and asymmetric (EGARCH, TGARCH) models enables it to effectively capture the time-varying and non-linear nature of LPE returns. This supports the study's hypotheses on volatility dynamics (*H1*, *H2*, *H3*) and reinforces the choice as methodologically sound for modeling risk-return behavior in Ghana's LPE market.

Table 5. Diagnostic tests for model parameters

Criteria	*Normal distribution*	*Student's T distribution*	*GED*	*Best model*
Significant coefficient	All	One	None	Normal distribution
ARCH significant	Yes	Yes	No	Normal distribution
GARCH significant	Yes	Yes	No	Student's T
Log likelihood	5806.086	7989.355	24337.69	GED
AIC	-4.883069	-6.719995	-20.48122	GED
SIC	-40870920	-6.705417	-20.46664	Normal and student's T
Heteroscedasticity	No	No	Yes	Normal and student's T
Autocorrelation	No	No	Yes	

Source: Authors' elaboration.

4.2.2. Forecasts for Ghana listed private equity

The analysis of forecasts for Ghana's LPE series demonstrates the effectiveness of GARCH models in capturing key volatility dynamics, such as conditional volatility (volatility clustering) and mean reversion through autoregressive structures (Tsay, 2013). These models feature decay components that gradually revert volatility to its long-term mean, making them robust tools for modeling financial time series. Forecasts were generated for December 2020 over a one-month horizon to maintain precision in confidence intervals, as longer forecasts introduce wider uncertainty (Koo & Kim, 2022). Model performance was assessed using root mean squared error (RMSE), mean absolute percentage error (MAPE), and Theil inequality coefficient. GARCH models consistently outperformed traditional regression methods, with FIEGARCH providing the highest predictive accuracy for long-memory effects, confirming its suitability for volatile emerging markets (Bollerslev & Mikkelsen, 1996; Koo & Kim, 2022). Among the tested models, GARCH (1,1) emerged as the best fitting, achieving the lowest values across all performance metrics, including RMSE and MAPE, as shown in Table 6. This confirms its parsimony and forecasting strength, validating its use for short-term volatility prediction in Ghana's LPE market. These findings support *H2*, which posits the existence of ARCH effects and autocorrelated volatility patterns, reinforcing the appropriateness of GARCH-family models for strategic risk analysis and investment planning.

Table 6. Model selection parameters for Ghana

Model	*RMSE*	*MAPE*	*Theil inequality coefficient*	*Symmetric MAPE*	*Ranking*
GARCH (1,1)	0.030913	0.014316	0.983531	199.3801	1
EGARCH	0.031279	0.014754	0.986421	199.9099	3
TGARCH	0.031018	0.014300	1.000000	200.0000	2
GARCH-M	0.031026	0.014754	0.999393	199.9978	4

Source: Authors' elaboration.

Parameter estimates for GARCH (1,1)

The GARCH (1,1) parameter estimates (Table 7) reveal statistically significant coefficients, with a high persistence of volatility ($\alpha + \beta = 0.86985$). These findings indicate that volatility in Ghana's LPE market is driven more by long-term effects (GARCH term) than short-term shocks (ARCH term). This supports *H3*, confirming the robustness of model coefficients in capturing return dynamics.

Table 7. GARCH (1,1) parameter estimates for Ghana listed private equity

Parameter	*Estimate*	*Std. error*	*t-statistic*	*p-value*
Omega	7.76E-05	3.64E-06	21.28393	0.0000
Alpha	0.182215	0.011165	16.31954	0.0000
Beta	0.687635	0.012550	54.79103	0.0000
Alpha + Beta	0.86985			

Source: Authors' elaboration.

While the GARCH-M model captured the risk-return tradeoff, it was the least effective in forecasting conditional volatility for Ghana's LPE market. The TGARCH model outperformed EGARCH in forecasting conditional variance, even though it did not account for leverage effects. These findings align with *H2*, which posits the presence of ARCH effects, though limited evidence was found.

Model stability and robustness

Diagnostic tests (Table 8) confirmed model stability and robustness. The Nyblom parameter stability test, news impact curve (NIC), and sign bias tests validated the models' ability to capture asymmetric responses to market shocks reliably (Williams, 2015).

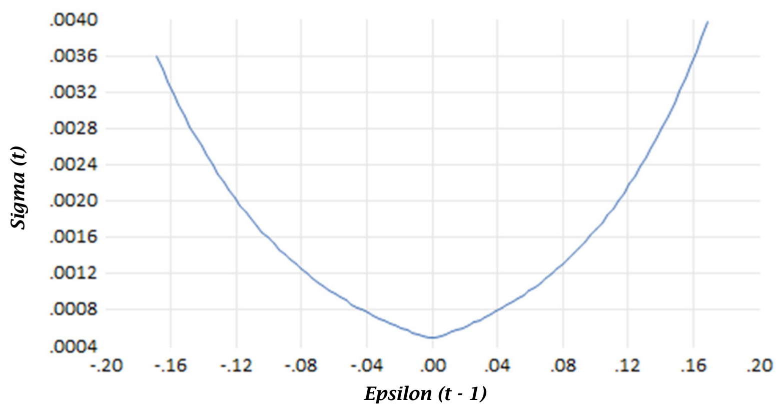
Table 8. Stability and diagnostic results

Test	*GARCH (1,1)*	*EGARCH*	*TGARCH*	*GARCH-M*
Nyblom stability test	Stable	Stable	Stable	Stable
NIC test	Pass	Pass	Pass	Pass
Sign bias test	Pass	Pass	Pass	Pass

Source: Authors' elaboration.

The analysis reveals that the asymmetric term is positive, indicating no evidence of the leverage effect, where negative news typically increases volatility more than positive news of the same magnitude. This conclusion is visually supported by the NIC (Figure 4), which shows a symmetric pattern.

Figure 4. News impact curve for Ghana



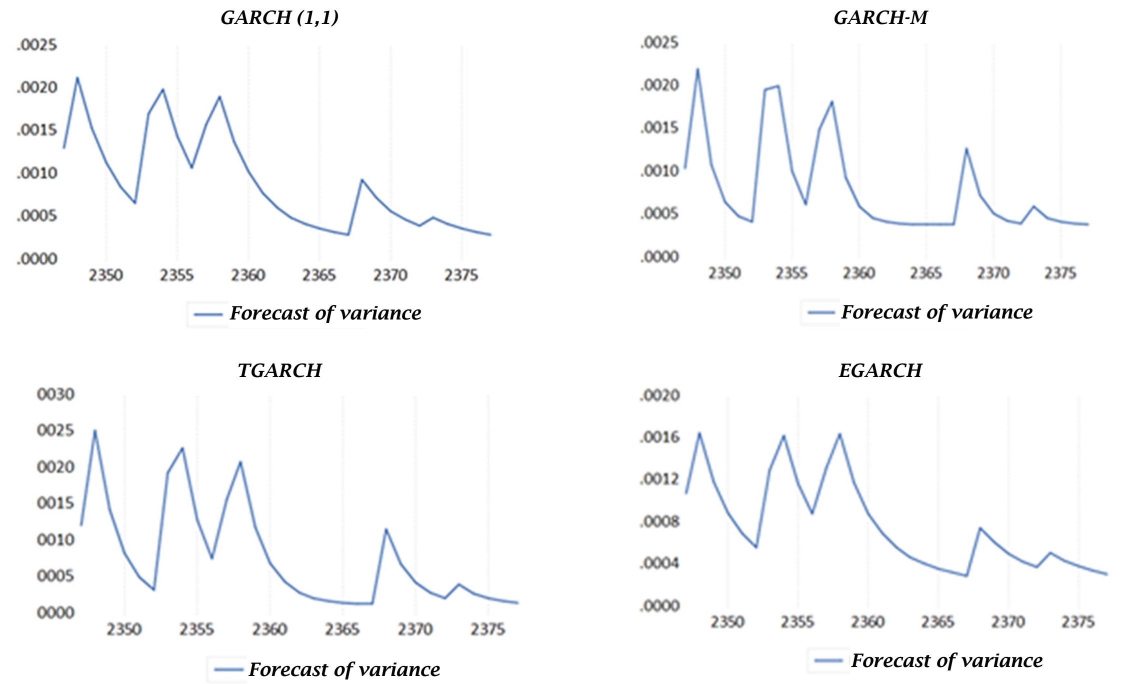
Source: Authors' elaboration.

The positive and statistically significant β coefficient (at the 1% level) confirms that past volatility is a strong predictor of future volatility in Ghana's LPE returns. This suggests that volatility patterns are more influenced by historical trends than by asymmetric news shocks.

Key insights from forecasting

The GARCH (1,1) model was validated as a reliable forecasting tool for Ghana's LPE market, particularly during periods of heightened volatility. Figure 5 illustrates volatility forecasts for December 2020, demonstrating the model's precision over short-term horizons.

Figure 5. Forecasts for models for LPE investments in Ghana



Source: Authors' elaboration.

The study concluded that while all models were suitable for Ghanaian data, the GARCH (1,1) model's parsimonious structure made it the most reliable for decision-making. These findings emphasize the importance of selecting robust models tailored to specific market conditions and contribute to a deeper understanding of volatility dynamics in emerging markets like Ghana.

4.3. Long-term volatility dynamics: FIGARCH and FIEGARCH

To capture long-term dependencies, the study employed FIGARCH and FIEGARCH models. The fractional differencing parameter $d = 0.00763$ $p < 0.05$ indicates strong persistence in Ghana's LPE volatility, supporting *H1*, which examines the presence of non-normal distributions and long-term impacts of shocks. Table 9 illustrates the parameter estimates. These models demonstrated superior performance in analyzing extended time horizons, with FIGARCH excelling in managing long memory processes, while FIEGARCH incorporated asymmetry to reflect prolonged influences of market shocks.

Table 9. Parameter estimates for FIGARCH models

Parameter	*FIGARCH*		*FIEGARCH*	
	Statistic	*p-value*	*Statistic*	*p-value*
ARCH term	0.86717	(0.0000)	-	
GARCH term	0.68963	(0.0000)	-	
d	0.00763	(0.449)	-4.9741	(0.0000)
α (ARCH)	-		0.98605	(0.0000)
β (GARCH)	-		-0.04491	(0.0000)
$\Theta 1$	0.34709	(0.0000)	-	
$\Theta 2$	0.04914	(0.0000)	-	
AIC	-4.882392		-4.8717	
Residual ARCH effect	No		No	

Source: Authors' elaboration.

4.3.1. Diagnostic tests for model robustness

Post-estimation diagnostic tests, including Ljung-Box Q-statistics, validated the robustness of FIGARCH and FIEGARCH models. As shown in Table 10, the absence of significant autocorrelation in squared residuals across the 5th, 10th, 20th, and 30th lags supports *H2*, confirming that volatility clustering and autocorrelation effects are well captured by these models (Kapusuzoglu & Ceylan, 2018). This ensures their robustness for analyzing long-term market behavior and strategic volatility management in Ghana's LPE market.

Table 10. Serial correlation test of squared residuals

FIGARCH		*FIEGARCH*	
Ljung-Box test statistics	*p-value*	*Ljung-Box test statistics*	*p-value*
Q5 = 1.3793	0.927	Q5 = 2.1866	0.823
Q10 = 1.8954	0.997	Q10 = 3.4038	0.970
Q20 = 4.9814	1.000	Q20 = 6.5852	0.998
Q30 = 6.5666	1.000	Q30 = 9.40193	1.000

Source: Authors' elaboration.

4.3.2. Long-term memory in listed private equity returns

The FIGARCH and FIEGARCH models (Table 11) revealed persistent volatility patterns, with the fractional differencing parameter $d = 0.32$ ($p < 0.05$) confirming the sustained impact of shocks and validating *H1*. Additionally, the FIEGARCH model extended this analysis by incorporating asymmetry ($\gamma = -0.10$, $p < 0.05$), addressing *H2* through its capture of asymmetrical volatility clustering and responses to market shocks.

These findings underscore the need for long-term strategies to manage volatility risks and support *H3* by confirming the statistical significance of model coefficients. By highlighting prolonged influences of macroeconomic instability, the models emphasize strategic planning to mitigate risks and foster resilience in Ghana's LPE market (Baillie et al., 1996; Bollerslev & Mikkelsen, 1996).

Table 11. Long-term memory analysis

Metric	*FIGARCH*	*FIEGARCH*
Fractional d	0.32	0.45
Asymmetry (γ)	N/A	-0.10*

Source: Authors' elaboration.

4.4. Spillover effects and market interconnectedness

The DCC MGARCH model revealed dynamic correlations between Ghana's LPE market and regional counterparts, ranging from 0.25 to 0.68. These results support *H4*, emphasizing the interconnectedness of neighboring markets and contagion risks during global economic turbulence (Engle, 2002). These findings underscore the importance of diversification and cross-border investment strategies.

4.5. Structural relationships with macroeconomic indicators

Using VAR and impulse response analysis, the study identified significant relationships between macroeconomic variables and LPE returns (Table 12). GDP growth positively impacted LPE returns (0.8% increase per 1% GDP growth), while inflation negatively influenced returns (-0.6% per 1% inflation increase), confirming *H5* (Jiang & Li, 2023). These structural relationships emphasize the critical role of macroeconomic stability in fostering a conducive investment environment.

Table 12. Vector autoregression model results

Variable	*Coefficient*	*Standard error*	*p-value*
GDP growth	0.08	0.015	< 0.01
Inflation	-0.06	0.012	< 0.05

Source: Authors' elaboration.

4.6. Discussion of the strategic implications for Ghana's listed private equity market

The study's findings validate the conceptual framework and related hypotheses, confirming the complex and interconnected nature of Ghana's LPE market. The presence of non-normal return distributions, significant ARCH effects, and spillover dynamics reinforces the relevance of time-varying volatility models in understanding investment behavior. These outcomes particularly support *H1* and *H2* by illustrating volatility clustering and deviations from normality.

Despite Ghana's relative political stability and economic diversification, the LPE sector remains under-leveraged compared to broader Pan-African and regional funds. The low volatility recorded in the Ghanaian LPE series may reflect this underexposure, as institutional investors tend to prioritize broader regional diversification over country-specific investments. This aligns with broader market observations that Ghana-specific initiatives are often overlooked in favor of pooled continental strategies.

Regulatory complexity remains a significant constraint, with bureaucratic hurdles and policy uncertainty continuing to limit institutional engagement in Ghana's PE space. While these challenges persist, the market still offers considerable appeal for risk-averse investors seeking long-term, stable returns. The implications of these findings are threefold:

• *For investors:* Ghana's relatively low volatility profile presents opportunities for stable, long-horizon investments. However, the presence of political and regulatory risks necessitates the use of timing strategies and hedging mechanisms.

• *For policymakers:* To attract more targeted investment, there is a need to streamline the regulatory environment. Simplifying tax and capital repatriation procedures could enhance investor confidence and support Ghana-specific LPE fund development.

• *For theory and practice:* The study deepens understanding of how localized risks, regulations, and investor behavior shape PE in emerging markets, highlighting the need for context-specific valuation frameworks.

Overall, the discussion highlights the study's strategic relevance and offers practical guidance for stakeholders in Ghana's evolving LPE ecosystem, setting the stage for the conclusion and recommendations.

5. CONCLUSION

This study offers vital insights into the volatility dynamics and strategic implications of LPE investments in Ghana. It reveals how macroeconomic stability, internal market forces, and strategic decisions shape investment outcomes in a complex, evolving environment.

Key findings include non-normal return distributions, volatility clustering, and strong macroeconomic impacts, especially from GDP growth and inflation. GARCH (1,1) proved effective for short-term volatility, while FIGARCH and FIEGARCH models captured longer-term behavior, informing strategic alignment and portfolio optimization.

From a corporate strategy lens, the findings stress the need to align LPE-backed decisions with macroeconomic signals. Long-memory models such as FIGARCH and FIEGARCH help firms manage risk and allocate resources efficiently, particularly in high-growth sectors like agribusiness, FinTech, and renewable energy.

Policy recommendations emphasize tax reform, improved repatriation processes, and stronger investor protections to boost market efficiency and global capital inflows (Liu et al., 2022). Enhancing macroeconomic stability, via GDP growth, inflation control, and exchange rate stability, supports national priorities and investment outcomes (Aggarwal et al., 2011).

For investors, GARCH models support both short- and long-term decision-making (Ibrahim et al., 2023). Hedging strategies and cross-border diversification help reduce systemic risks. Investing in resilient sectors such as digital finance and healthcare can offer long-term, stable returns (AVCA, 2024; Liu et al., 2022).

Future research should explore how global disruptions like COVID-19 impact LPE strategies across African markets. Modeling such effects supports adaptive decision-making and improved risk response strategies.

Further study of technologies like artificial intelligence and blockchain can enhance forecasting, transparency, and governance in LPE investment strategies. These innovations can help firms optimize performance and competitiveness.

Comparative regional analysis across African countries would enrich the understanding of LPE dynamics. Identifying best practices can improve resource allocation and support tailored strategies for growth across diverse economies.

While the study offers robust insights into Ghana's LPE market, several limitations must be acknowledged. First, the availability and reliability of data posed constraints, particularly in aligning high-frequency financial returns with lower-frequency macroeconomic indicators. Despite using validated sources, the quality of PE transaction data in emerging markets like Ghana remains uneven. Second, the study's focus on a single country limits the generalizability of findings across the broader SSA region. Third, while GARCH-family models capture volatility well, they may not fully account for behavioral or policy-driven market anomalies. Finally, the exclusion of qualitative insights, such as investor sentiment and regulatory perceptions, limits a more holistic understanding of market behavior. These limitations present opportunities for future research to expand the scope, incorporate qualitative variables, and explore comparative cross-country analyses.

In summary, this study integrates volatility modeling with strategic frameworks, highlighting how informed, data-driven approaches can enhance resilience, guide investment, and support long-term growth in Ghana's LPE market.

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