VOLATILITY DYNAMICS AND CORPORATE STRATEGY: A STATISTICAL ANALYSIS OF PRIVATE EQUITY INVESTMENTS IN EGYPT

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Abstract

This study examines the statistical properties and volatility dynamics of listed private equity (LPE) investments in Egypt from 2010 to 2020, focusing on their integration into corporate and business strategies. Advanced generalized autoregressive conditional heteroskedasticity (GARCH) family models uncover key patterns such as volatility clustering, leptokurtic distributions, and minimal long-term volatility asymmetries. While traditional valuation methods often underperform in fragmented markets (Damodaran, 2018), these advanced models effectively capture nuanced behaviors, emphasizing the predominance of internal market dynamics over external macroeconomic factors like gross domestic product (GDP) and inflation. The study highlights the Egyptian market's evidence of volatility linked to jump diffusions, with diagnostic tests confirming that internal dynamics significantly influence private equity investments more than external factors. Despite differing economic systems, no long-term volatility asymmetries were detected, indicating uniform market responses to shocks. These findings underscore the importance of integrating LPE investments into strategic frameworks, enabling businesses to optimize portfolio performance and enhance resilience, ultimately contributing to market stability (Brown & Kaplan, 2019). Policy implications include enhancing market transparency and adopting advanced modeling techniques to stabilize private equity markets. Future research should explore emerging technologies like artificial intelligence (AI) and blockchain and extend analyses to other emerging markets to uncover broader insights into portfolio management and risk mitigation.

Keywords: Listed Private Equity Investments, Statistical Modelling, Egypt, Generalized Autoregressive Conditional Heteroskedasticity Models, Vector Autoregression 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

Private equity has emerged as a pivotal investment class globally, offering unique risk-return profiles compared to public equities. However, the application of traditional valuation techniques to emerging markets like Egypt has revealed significant complexities. Listed private equity (LPE) investments exhibit distinct volatility dynamics influenced by country-specific risk factors such as gross domestic product (GDP) growth and inflation (Campbell, 2012). Despite their growing importance, the statistical properties and market behaviors of LPE investments in emerging economies remain underexplored, creating a critical gap in the literature.

Existing studies predominantly focus on developed markets, where market efficiency and liquidity are relatively high. In contrast, African markets, particularly Egypt, are characterized by fragmented conditions, liquidity constraints, and pricing challenges (Damodaran, 2018; Klonowski, 2013). Limited research has addressed how these factors interact with LPE investments, especially in the context of corporate and business strategy. This study addresses this gap by examining how LPE returns are influenced by internal market dynamics and external country-specific risks, offering insights for strategic decision-making.

This study aims to analyze the statistical properties and volatility dynamics of LPE investments in Egypt, integrating these findings into corporate and business strategy frameworks. The research addresses the following questions:

RQ1: Do listed private equity returns in Egypt exhibit non-normal distribution and volatility clustering?

RQ2: What role do country-specific risk factors, such as gross domestic product and inflation, play in shaping listed private equity returns?

RQ3: How can these insights inform corporate and business strategies for portfolio optimization?

The study leverages the global capital asset pricing model (CAPM) and generalized autoregressive conditional heteroskedasticity (GARCH) family models, integrating concepts of market inefficiencies, country-specific risks, and illiquidity premiums. This theoretical lens captures both short-term and long-term volatility dynamics, bridging the gap between financial theory and strategic application (Czasonis et al., 2019; Harasheh et al., 2020).

Understanding the behavior of LPE investments in emerging markets like Egypt has practical and academic implications. For investors, it provides a framework for risk assessment and portfolio diversification. For policymakers, it highlights the need for regulatory adjustments to enhance market efficiency and resilience. Strategically, businesses can leverage these findings to align their investment decisions with market conditions, ensuring long-term stability and growth (McKnight et al., 2023).

The study employs a comprehensive econometric approach, utilizing models such as GARCH (1,1), exponential GARCH (EGARCH), threshold GARCH (TGARCH), GARCH-in-mean, fractionally integrated GARCH (FIGARCH), fractionally integrated exponential GARCH (FIEGARCH), dynamic conditional correlation multivariate GARCH (DCC MGARCH), and vector autoregression (VAR) to capture volatility patterns and relationships between LPE returns and country-specific factors. Diagnostic tests validate the robustness of these models, offering nuanced insights into the market dynamics (Kapusuzoglu & Ceylan, 2018; Nelson, 1991).

The analysis reveals key stylized effects, such as volatility clustering and leptokurtic distributions, while confirming the minimal impact of external macroeconomic factors like GDP and inflation on LPE returns. Instead, internal market dynamics emerge as the dominant drivers. These findings challenge traditional assumptions about the pricing of country-specific risks in LPE markets and contribute to a deeper understanding of how volatility dynamics can be integrated into corporate and business strategies for portfolio optimization (Damodaran, 2012, 2018; Döpke & Tegtmeier, 2018).

This paper seeks to bridge the gap between financial modeling and strategic applications, offering actionable insights for stakeholders in Egypt's burgeoning private equity sector. By aligning the study's findings with strategic objectives, it provides a pathway for optimizing investment performance and enhancing market resilience.

The structure of this paper is organized as follows. Section 1 outlines the study's focus on the volatility dynamics of LPE investments in Egypt, addressing gaps in understanding their integration into corporate strategy, and highlights the relevance of advanced valuation techniques for emerging markets and in optimizing investment decisions. It also provides an overview of the research framework, setting the foundation for the analysis. Section 2 reviews the relevant literature, focusing on private equity investments, volatility dynamics, and the integration of these concepts into corporate and business strategy. Section 3 analyzes the methodological framework, detailing the econometric models and diagnostic tests used to analyze LPE returns in Egypt. Section 4 presents the empirical findings, discussing key results and their implications for corporate strategy and market behavior. Section 5 synthesizes the insights from the analysis, linking them to broader strategic and policy frameworks. Finally, Section 6 concludes the study by summarizing key contributions, highlighting limitations, and offering recommendations for future research.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

This Section synthesizes research on private equity valuation, focusing on the critical need to explore LPE investments in African markets. It is structured to address challenges in emerging markets, advances in volatility models, and the strategic applications of volatility analysis.

2.1. Challenges in emerging markets

Emerging markets like Egypt present unique challenges for private equity valuation due to fragmented markets, liquidity constraints, and limited exit strategies (Ismail & Medhat, 2019; Klonowski, 2013). Traditional valuation methods, such as the CAPM and discounted cash flow (DCF), fail to capture the nuanced risk-return profiles of LPE investments, prompting the need for alternative approaches (Damodaran, 2018). Data scarcity and regulatory gaps further exacerbate these issues, limiting the availability of consistent, reliable metrics for risk assessment (Zeilinga, 2020).

Egypt's private equity sector has experienced significant growth since 2004, driven by domestic and regional funds (Central Intelligence Agency [CIA], 2008; Errais & Gritly, 2022; Fritzen, 2012; Gompers & Lerner, 1999, 2001; Gujarati & Porter, 2009). By 2008, 13 private equity firms managed 36 funds with over $6.4 billion in committed capital, establishing Egypt as a key player in the Middle East and North Africa (MENA) region (CIA, 2008). However, persistent issues such as underdeveloped exit strategies and inconsistent pricing hinder effective market analysis and impede the strategic integration of private equity into broader corporate planning frameworks (Ismail, 2009; Aarts et al., 2012).

2.2. Advances in volatility models

Advances in econometric modeling, particularly the development of GARCH-type models, have proven effective in addressing the complexities of LPE investments in emerging markets. Studies by Baillie et al. (1996) and Damodaran (2018) emphasize the utility of these models for analyzing volatility dynamics, including clustering, asymmetry, and long-memory behavior. EGARCH and FIGARCH models allow for the assessment of asymmetric shocks and persistence, making them well-suited for the fragmented and volatile nature of Egypt's financial markets (Harasheh et al., 2020; Nelson, 1991).

Additional methodologies, such as DCC MGARCH, provide insights into spillover effects between markets, while FIGARCH and FIEGARCH models capture long-memory behavior in volatility patterns (Atenga & Mougoué, 2021; Abu Afifa et al., 2025). These approaches are critical for understanding how internal market dynamics and external macroeconomic factors interact, enabling more accurate valuation and strategic decision-making.

2.3. Strategic applications of volatility analysis

The integration of advanced volatility models into corporate and business strategies has significant implications for portfolio management and risk mitigation. For instance, GARCH-type models offer valuable insights into how volatility clustering and asymmetric effects influence investment outcomes, enabling firms to optimize diversification strategies and align long-term growth plans with market conditions (Döpke & Tegtmeier, 2018; McKnight et al., 2023).

Studies highlight the importance of diversification as a strategy to mitigate volatility in LPE investments (Tegtmeier, 2023). Furthermore, integrating corporate social responsibility (CSR) into private equity strategies fosters investor confidence and long-term stability (Debnath et al., 2024). Emerging technologies, such as artificial intelligence (AI) and blockchain, present further opportunities for improving analytics, risk assessment, and operational efficiency (Abu Afifa et al., 2025).

Institutional governance and regulatory frameworks also play a critical role in stabilizing markets. Policymakers are urged to strengthen these mechanisms to reduce information asymmetry, enhance transparency, and foster sustainable growth in Egypt's LPE sector (Miralles-Quirós et al., 2024).

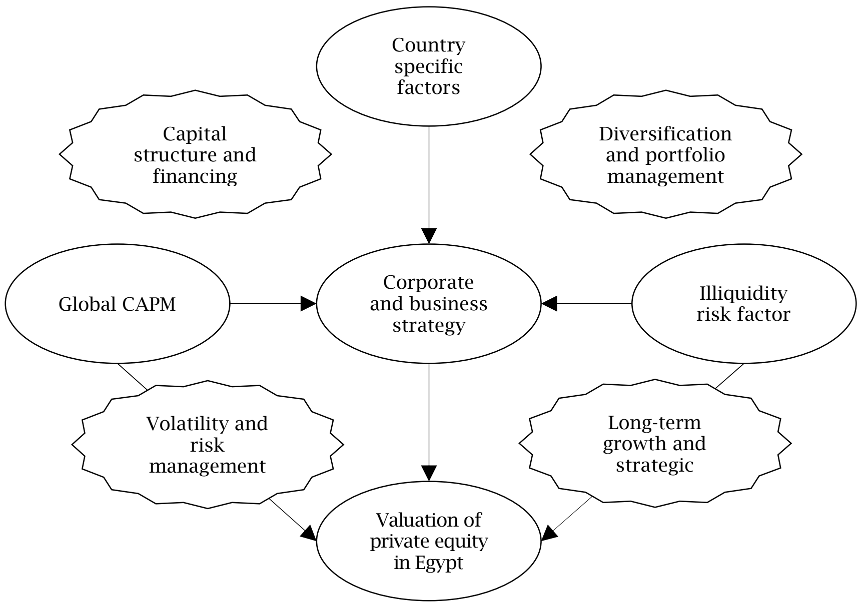
2.4. Model estimation in the context of Egyptian private equity investments

The study framework in Figure 1 integrates the global CAPM, country beta, and an illiquidity coefficient to address the unique liquidity challenges of private equity investments. This model emphasizes the following aspects:

- Volatility and risk management: Insights from market volatility inform corporate risk management frameworks.
- Long-term growth and strategic planning: Aligning strategic plans with market dynamics allows businesses to capitalize on growth opportunities amidst volatility.
- Capital structure and financing: Risk-return profiles derived from the model guide financing decisions, ensuring alignment with investment risk.
- Diversification and portfolio management: Statistical outputs from the model support diversification and portfolio optimization strategies.

Figure 1 illustrates this integrated approach, ensuring that corporate and business strategies are informed by the unique dynamics of private equity valuation in Egypt.

Figure 1. Study framework



Source: Authors' elaboration.

By incorporating country-specific risks into equity premium valuations, the framework ensures that market openness, liquidity constraints, and diversification opportunities are adequately addressed. While CAPM remains a fundamental tool, its limitations in emerging markets like Egypt underscore the need for advanced models that better align with corporate strategy (Damodaran, 2018; Klonowski, 2013). This study's application of GARCH-type models offers valuable insights for optimizing risk management and driving sustainable growth in Egypt's LPE sector.

2.5. Theoretical framework and hypotheses development

This section connects theoretical concepts with empirical analysis, generating hypotheses that align with corporate and business strategies. A solid theoretical framework ensures research is grounded in established theories, providing valuable insights (Cresswell & Creswell, 2017; Imenda, 2014). Market models better account for financial irregularities prevalent in emerging markets compared to dividend discount models (Harasheh et al., 2020). GARCH models are particularly useful in capturing volatility dynamics in LPE returns, where market inefficiencies and segmentation are common in African markets.

The conceptual framework highlights the integration of corporate and business strategy with volatility dynamics for optimal decision-making. Traditional models like the Gaussian random walk are inadequate for future financial decisions (Kapusuzoglu & Ceylan, 2018). By combining GARCH models with adjusted CAPM, which incorporates additional risk factors beyond the CAPM beta, deeper insights into equity returns can be gained (Acheampong & Swanzy, 2016; Andrei et al., 2023; Bekaert & Harvey, 2002; Damodaran, 2012, 2018). The CAPM framework serves as a baseline for understanding risk-adjusted returns, but its limitations in fragmented markets like Egypt necessitate the use of GARCH models. These models, by capturing volatility clustering and asymmetric shocks, enable firms to align their investment strategies with market dynamics, improving resilience and long-term growth potential. This approach emphasizes how LPE valuations in Egypt align with corporate strategy, providing a unique investment profile compared to more integrated markets. The subsequent hypotheses are investigated:

H1: Egypt's listed private equity returns are not normally distributed, as demonstrated by skewness and kurtosis, likely resulting from significant market movements and reactions to external news, where country-specific factors and market volatility play a critical role in shaping return distributions.

H2: The presence of autoregressive conditional heteroskedasticity (ARCH) effects in Egypt's listed private equity returns indicates time-varying and autocorrelated volatility.

H3: The coefficients in models analyzing Egypt's listed private equity returns are statistically significant, confirming the models' ability to adequately capture the complexities of returns.

H4: Spillover effects among listed private equities in Egypt highlight inter-market connections and potential cross-market influences.

H5: Structural interactions between country-specific factors such as gross domestic product and inflation and listed private equity returns in Egypt emphasize the significant influence of regional economic conditions on private equity performance.

H6: Egypt's listed private equity valuations reflect country-specific factors, indicating that investors incorporate these risks into their investment decisions.

By formulating key hypotheses, the Section sets the stage for an in-depth investigation into the volatility and returns of LPEs, advancing the understanding of their role as a distinct asset class in Egypt. The upcoming section outlines the methodologies used to test these hypotheses, contributing to the discourse on corporate and business strategy considerations on private equity valuation in emerging markets.

3. RESEARCH METHODOLOGY

This Section outlines the econometric approach employed to analyze the volatility dynamics and statistical properties of LPE investments in Egypt. It consolidates the discussion of econometric techniques into two primary subsections: the GARCH family models and supplementary techniques.

3.1. GARCH family models

To comprehensively analyze the volatility dynamics of LPE investments, the study employs a range of GARCH family models. These models provide a robust framework for understanding the statistical properties of LPE returns, capturing phenomena such as volatility clustering, asymmetry, and persistence. Each model offers distinct advantages tailored to different aspects of volatility analysis.

- *GARCH (1,1)*: The GARCH model is the foundational approach for modeling time-varying volatility. It captures periods of high volatility clustering, where volatility persists over time (Bollerslev, 1986). Its simplicity and efficiency make it indispensable for understanding risk dynamics and informing corporate strategies related to resource allocation and risk management (McKnight et al., 2023; Nelson, 1991).
- *EGARCH*: The EGARCH model accounts for asymmetric effects, allowing the study to distinguish between the impacts of positive and negative shocks on volatility (Nelson, 1991; Shanthi & Thamilsevan, 2019). This feature is particularly relevant in fragmented markets like Egypt.
- *TGARCH*: The TGARCH model evaluates the threshold effect, where the magnitude of shocks impacts volatility differently based on whether the shocks are positive or negative (Glosten et al., 1993; Shanthi & Thamilsevan, 2019).
- *GARCH-in-mean*: The GARCH-in-mean model incorporates volatility directly into the mean equation, enabling an analysis of how risk influences return. This model underscores the importance of incorporating volatility into return predictions, making it a valuable tool for strategic investment planning in emerging markets (Engle et al., 1987; McKnight et al., 2023).
- *FIGARCH and FIEGARCH*: These models capture long-memory behavior in volatility, where past shocks influence current volatility over extended periods (Baillie et al., 1996). The FIEGARCH model further incorporates asymmetries, making it ideal for exploring the nuanced dynamics of LPE markets.

3.2. Supplementary techniques

In addition to the GARCH family models, the study incorporates supplementary techniques to explore broader structural relationships and interactions within the Egyptian LPE market:

- *DCC MGARCH:* This model captures volatility spillovers and interdependencies between markets, providing insights into cross-market interactions and their implications for diversification strategies (Engle, 1982).
- *VAR*: The VAR model assesses the structural relationships between LPE returns and macroeconomic factors such as GDP and inflation. It enables the examination of endogenous variables and their dynamic interdependencies (Karunanayake, 2014). Impulse response functions (IRFs) are also employed to evaluate how shocks to one variable propagate through the system (Damodaran, 2018; Döpke & Tegtmeier, 2018).
- *Diagnostic tests:* To ensure the robustness and reliability of the models, the study employs a series of diagnostic tests for identifying residual biases and to ensure the reliability and validity of the findings (Miralles-Quirós et al., 2024; Abu Afifa et al., 2025; Shanthi & Thamilsevan, 2019):

1) Ljung-Box test: Assesses autocorrelation in the residuals (Ljung & Box, 1980).
2) Nyblom parameter stability test: Evaluates model stability and the absence of structural breaks (Nyblom, 1989).
3) Sign bias tests: Identifies biases in the residuals of volatility models (Engle & Ng, 1993).

3.3. Justification for method selection

The choice of econometric models reflects the unique characteristics of Egypt's LPE market. The GARCH family models are well-suited for capturing the conditional heteroskedasticity and clustering effects prevalent in emerging markets. Meanwhile, supplementary techniques like VAR and DCC MGARCH address the structural relationships and spillover effects critical to understanding the broader market dynamics. By consolidating these methodologies, the study provides a comprehensive framework for analyzing LPE investments in Egypt, ensuring that both short-term volatility and long-term structural interactions are effectively captured.

The GARCH family models were selected for analysis due to their robustness in capturing volatility clustering, long memory, and asymmetric effects in financial time series. These models were validated through diagnostic tests, including stationarity and parameter stability assessments, ensuring their suitability for analyzing the nuanced dynamics of Egypt's LPE market. The selected econometric models are well-suited to the study's objectives, particularly in addressing the complexities of fragmented and emerging markets like Egypt. These models, with their capacity to capture conditional heteroskedasticity and volatility clustering, are ideal for analyzing financial time series and aligning with strategic corporate decision-making (Ismail & Medhat, 2019; Cresswell & Creswell, 2017). The integration of these models into the study's conceptual framework highlights the interplay between internal market dynamics, country-specific risks, and corporate strategies, ensuring that portfolio performance optimization and market resilience remain central to the analysis (Miralles-Quirós et al., 2024; Abu Afifa et al., 2025).

By employing a combination of advanced econometric techniques and alternative methodologies, the study provides a comprehensive framework for analyzing LPE investments in Egypt. This approach offers actionable insights for investors, policymakers, and corporate strategists, enabling informed decision-making and effective navigation of the complexities of LPE markets while optimizing long-term growth strategies.

While EGARCH and TGARCH models theoretically capture asymmetry and threshold effects, they were excluded due to stationarity issues identified through Nyblom parameter stability and diagnostic tests (see Table 3). These limitations underscore the fragmented nature of Egypt's market, reinforcing the need for stable, long-memory models like FIGARCH. The exclusion of these models ensures that the analysis remains both statistically rigorous and contextually relevant.

3.4. Alternative methodologies: Synthesis and recommendations

While the GARCH family models effectively capture the volatility dynamics of LPE investments in Egypt, alternative methodologies could enhance future research by addressing specific limitations.

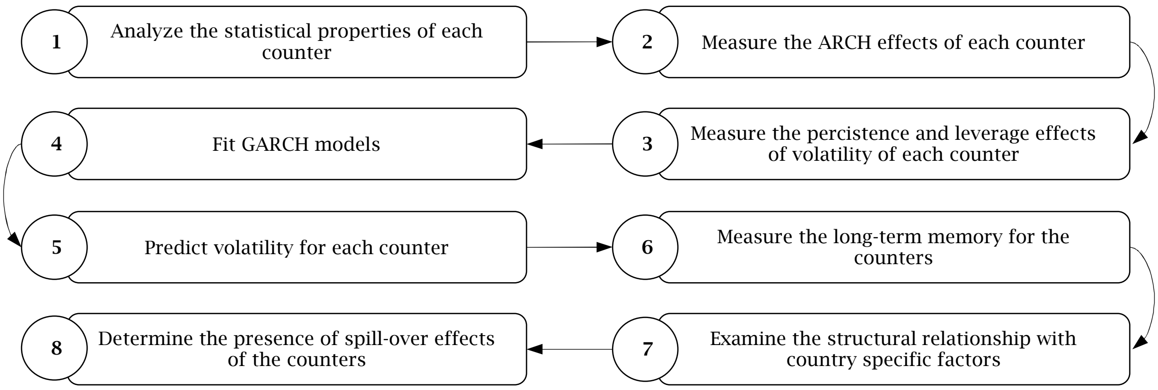
1. Machine learning techniques: Algorithms like random forests and support vector machines can identify non-linear relationships and latent patterns, making them valuable for predictive modeling in LPE markets. However, their reliance on large datasets and limited interpretability restricts their application in data-scarce environments like Egypt (Debnath et al., 2024).
2. Bayesian econometrics: By incorporating prior information, Bayesian methods refine volatility forecasts and support adaptive modeling in uncertain settings. Their flexibility makes them particularly suited for fragmented markets, presenting a promising avenue for future studies to enhance data-limited analyses (Tegtmeier, 2023).
3. Agent-based modeling (ABM): ABM simulates interactions among market participants and external shocks, providing insights into systemic risks and market contagion. While excluded due to computational complexity, ABM could be employed in future studies to evaluate the effects of policy interventions on market stability (Abu Afifa et al., 2025).
4. Panel data analysis: Comparing Egypt's LPE market with other emerging economies through fixed-effects or random-effects models could uncover inter-market influences and enrich regional trend analyses. This approach was not used due to the study's single-market focus but could inform broader comparative research (Harasheh et al., 2020).
5. Scenario and stress testing: These methods assess LPE resilience under adverse conditions, offering insights for risk mitigation and strategic planning. Scenario testing could complement econometric models by exploring potential market disruptions, and guiding policymakers and investors in preparing for future volatility (Miralles-Quirós et al., 2024).
6. Justification for exclusion: These methodologies were excluded due to data limitations, computational demands, and the study's focus on econometric models addressing volatility dynamics. Their integration would require broader datasets and expanded research objectives beyond

the current scope. Future research could incorporate these methodologies to address gaps in LPE analysis, enhancing predictive accuracy, policy evaluation, and cross-market insights and provide a deeper understanding of LPE investments, thus informing strategies for navigating volatile and emerging markets like Egypt.

3.5. Analytical framework

The analytical framework for LPE investments in Egypt, as depicted in Figure 2, is designed to analyze their statistical properties, volatility dynamics, and the relationship with macroeconomic factors such as GDP and inflation.

Figure 2. Analytical framework



Source: Authors' elaboration.

This framework employs a structured approach to evaluate LPE investments, beginning with statistical metrics like mean, variance, skewness, and kurtosis to understand return distributions. Tests for ARCH effects assess the influence of past volatility on future patterns, including persistence and asymmetric impacts. Key models such as GARCH (1,1) and FIGARCH are used to capture time-varying volatility and long-term memory, respectively, while DCC MGARCH explores cross-market spillovers. Structural relationships with macroeconomic factors are analyzed using the VAR model and IRFs. Key statistical tools and models applied include descriptive and trend analysis, normality tests (Jaque-Bera), autocorrelation tests (augmented Dickey-Fuller, ADF), and diagnostic tests to validate data properties.

This methodological framework aligns with the study's objectives to provide insights for refining investment strategies and deepening the understanding of LPE market dynamics in Egypt. It captures key economic changes from 2010 to 2020, a period influenced by post-global financial crisis developments in emerging markets.

4. RESEARCH RESULTS

The analysis of LPE investments in Egypt using advanced econometric models revealed key insights into their volatility dynamics and statistical properties. GARCH (1,1) models identified significant conditional heteroskedasticity, confirming the presence of volatility clustering, where periods of high volatility are followed by high volatility, and low volatility periods follow each other. Diagnostic tests, including the Ljung-Box test, Nyblom parameter stability test, and sign bias tests, validated the robustness of the selected models, ensuring the reliability of the findings. The FIGARCH model highlighted long memory in volatility, while the DCC MGARCH model showed limited spillover effects between markets, emphasizing the localized nature of volatility in Egypt's LPE sector.

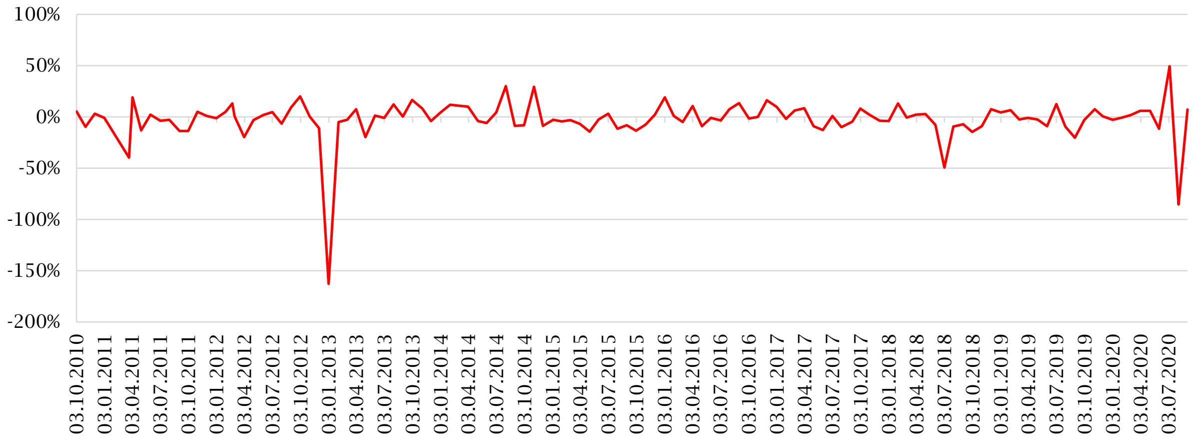
4.1. Volatility dynamics and statistical properties of LPE investments in Egypt

The analysis of LPE investments in Egypt employed GARCH models to capture the volatility dynamics and statistical properties essential for financial time series analysis. Daily and monthly log returns were analyzed to reveal key trends, volatility characteristics, and return behaviors, with a specific focus on their implications for corporate and business strategy (McKnight et al., 2023; Nelson, 1991). Figures and tables illustrate the nuanced behaviors of LPE returns across different time horizons.

4.2. Time series analysis of the private equity return series

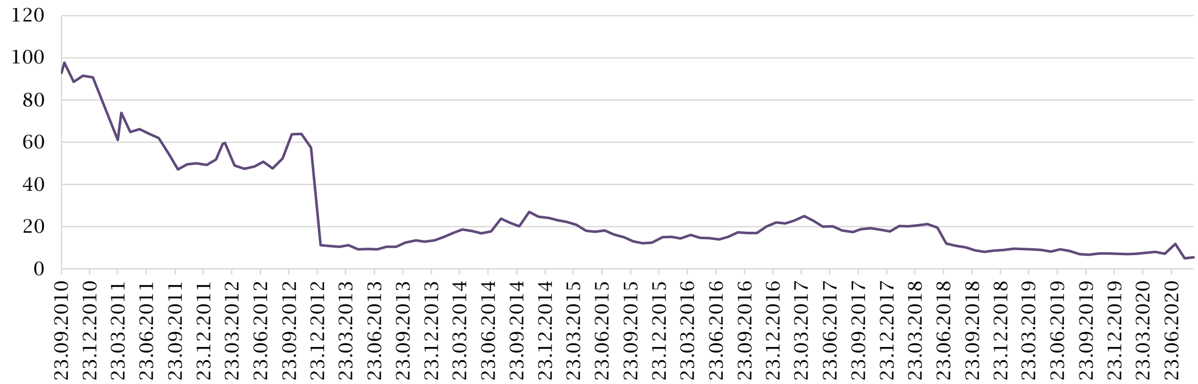
The time series analysis revealed critical trends and patterns in Egypt's LPE returns, particularly during the 2011 revolution. Weighted moving averages (WMA) and exponentially weighted moving averages (EWMA) highlighted resilience in the market, which stabilized quickly post-revolution despite significant volatility spikes (Paciello, 2010). Figure 3a shows Egypt's log returns, while Figure 3b presents the raw data series, emphasizing the market's capacity for mean reversion and low volatility around the mean, respectively.

Figure 3a. Trends in LPE returns and volatility (2010–2020)



Source: Authors' elaboration.

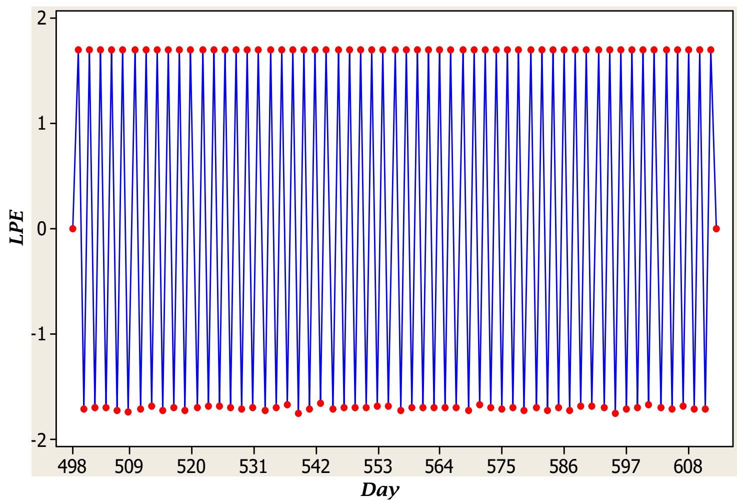
Figure 3b. Trends in LPE actual returns (2010–2020)



Source: Authors' elaboration.

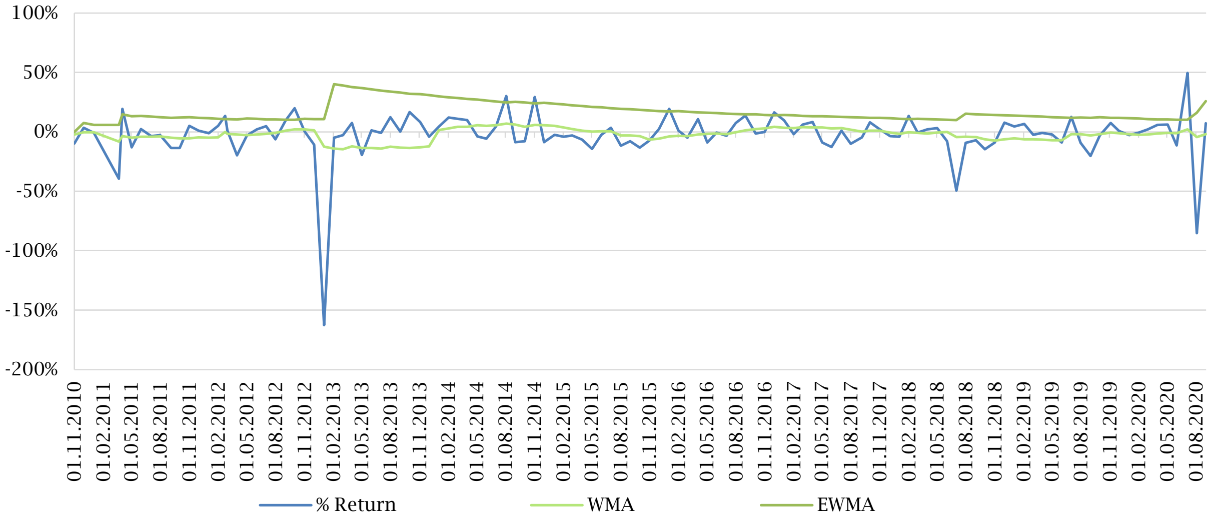
The market's behavior during the political upheaval underscores its ability to recover from external shocks, aligning with the findings from Figure 4a, which captured trends during the period of January 25, 2011, to November 30, 2011. Figure 4b further depicts the stability in returns using WMA and EWMA, showing mean reversion tendencies and resilience in volatility patterns.

Figure 4a. Egypt LPE series (January 25, 2011, to November 30, 2011)



Source: Authors' elaboration.

Figure 4b. Returns, WMA, and EWMA for Egypt



Source: Authors' elaboration.

4.3. Descriptive statistics and diagnostics tests

Table 1 presents descriptive statistics for LPE returns, highlighting key metrics such as mean, skewness, kurtosis, and the Jarque-Bera test results. Egypt's returns exhibited positive skewness at the 1% level and negative skewness at the 5% level, indicating frequent small gains and occasional large losses. The leptokurtic distribution of returns reinforces the non-normality of return distributions, supporting *H1* (Czasonis et al., 2019).

Table 1. Descriptive statistics for LPE returns

Significance	*Mean*	*Max.*	*Min.*	*Std. dev.*	*Skewness*	*Kurtosis*	*Jarque-Bera*	*Probability*	*Obs.*
5%	-0.024	0.495037	-1.62703	0.204452	-4.58527	33.65053	31849.1	0	2442
1%	0.0012	2.100644	-2.056563	0.377279	0.030935	20.69207	31849.1	0.001	2442

Source: Authors' elaboration.

Diagnostic tests, including the ADF test, confirmed stationarity across most cases (see Table 2). These results validate the suitability of GARCH models for analyzing volatility and emphasize the importance of understanding the dynamic nature of returns for strategic investment decisions.

Table 2. Unit root test results for private equity returns

Series	*Intercept*	*Intercept with trend*	*No intercept*
Statistic 1%	-29.60824***	-29.60339***	-29.56734***

*Note: *** $p < 0.001$.*
Source: Authors' elaboration.

By using descriptive statistics and diagnostic tests, investors glean insights from skewness, kurtosis, and volatility to assess performance and risk for portfolio construction and risk management, while policymakers can evaluate market stability and efficiency, potentially prompting regulatory reviews. These analyses provide essential insights into the return distributions and dynamics of Egypt's LPE markets, aiding comprehensive financial analysis.

4.4. Volatility dynamics and model validation

The GARCH models identified volatility clustering, confirming *H2*, which suggests that periods of high volatility are followed by high volatility and vice versa. Table 3 presents the results of Durbin-Watson (DW) tests for ARCH effects, supporting the presence of time-varying and autocorrelated volatility in Egypt's LPE market.

Table 3. ARCH effects

Model	*DW stat test*	*ARCH LM test*
ARCH	2.068200	20.31098 [0.000] ***

*Note: *** 1% significance level, LM — Lagrange multiplier.*
Source: Authors' elaboration.

The GARCH (1,1) parameter estimates revealed significant p-values and coefficients for omega (0.000392), alpha (7.332084), and beta (0.012977) further validating the robustness of the model.

Volatility forecasts for Egypt demonstrated the model's predictive accuracy, with metrics such as the root mean squared error (RMSE) and mean absolute error (MAE) indicating reasonable deviations from actual values. The findings reinforce the importance of integrating advanced econometric techniques into corporate strategies for risk assessment and portfolio optimization (Miralles-Quirós et al., 2024; Abu Afifa et al., 2025).

4.5. Modelling long-run volatility

The FIGARCH and FIEGARCH models captured long-memory volatility in Egypt's LPE market, with significant fractional difference parameters indicating sustained trends over time (Baillie et al., 1996). Table 4 illustrates the parameter estimates, showing that FIEGARCH outperformed FIGARCH in fitting Egypt's volatility data due to its ability to capture asymmetric and leverage effects.

Table 4. Parameter estimates for FIGARCH models

Parameter	*FIGARCH*	*FIEGARCH*
ARCH term	0.329022 (0.2040)	-
GARCH term	0.005910 (0.9741)	-
d	0.520088 (0.0000)	-0.719029 (0.0000)
α (ARCH)	-	-1.008334 (0.0000)
β (GARCH)	-	0.985105 (0.00000
Θ_1	-	0.950257 (0.0000)
Θ_2	-	-0.462182 (0.0000)
AIC	-0.276708	-4.003491
Residual ARCH effect	NO	NO

Note: P-value is given in parenthesis. All models estimated on EViews 12 are a fractional difference parameter that measures the degree of long memory behavior: α — FIGARCH ARCH term; β — FIGARCH GARCH term; Θ_1 — leverage effects; Θ_2 — asymmetric term, AIC — Akaike information criterion.
Source: Authors' elaboration.

The diagnostic tests for the FIGARCH and FIEGARCH models (see Table 5) confirm their accuracy in modeling LPE returns for Egypt. Residuals' p-values for the 5th, 10th, 20th, and 30th lags exceeded 5%, indicating no serial autocorrelation and validating the models at a 5% confidence level. The Q-statistics for both models showed p-values of 0.944 to 1.000 across all lags, reinforcing the absence of autocorrelation. Additionally, the Nyblom parameter stability test confirmed model stability and the absence of structural breaks, affirming their robustness and reliability (Bawa et al., 2023; Tsiaras, 2020).

Table 5. Q-statistic for FIGARCH and FIEGARCH models

Q-statistic	*FIGARCH*	*FIEGARCH*
Q_5	Q_5 = 0.4072(0.995)	Q_5 = 1.2051(0.944)
Q_{10}	Q_{10} = 0.4361(1.000)	Q_{10} = 1.2263(1.000)
Q_{20}	Q_{20} = 0.4658(1.000)	Q_{20} = 1.327(1.000)
Q_{30}	Q_{30} = 0.4903(1.000)	Q_{30} = 1.4026(1.000)

Note: P-value is given in parenthesis; Q(n) is the n-th lag Ljung-Box test statistics. All lags provide evidence of the absence of autocorrelation of residuals.
Source: Authors' elaboration.

The diagnostic tests for the FIGARCH and FIEGARCH models (see Table 6) validate their robustness in modeling LPE returns for Egypt. The sign-bias t-test, negative and positive size bias t-tests, and the joint test all yielded non-significant p-values, indicating no systematic biases in the model residuals. Additionally, the Nyblom parameter stability test confirmed parameter stability and the absence of structural breaks, reinforcing the models' reliability. These findings align with standards set by Bawa et al. (2023) and Tsiaras (2020), emphasizing the importance of parameter stability in financial modeling.

Table 6. Diagnostic tests for FIGARCH and FIEGARCH models for Egyptian LPE returns

Method	*Test*	*Sign-bias t-test*	*Negative size bias t-test*	*Positive size bias t-test*	*Joint test*
FIGARCH	Statistic p-value	1.101484 (0.2708)	-1.353517 (0.1760)	1.172165 (0.2412)	4.101614 (0.2510)
FIEGARCH	Statistic p-value	0.818864 (0.4129)	0.212269 (0.8319)	0.246058 (0.8057)	0.832458 (0.8417)

Source: Authors' elaboration.

The Nyblom parameter stability tests (see Table 7) evaluate the FIGARCH and FIEGARCH models for Egyptian LPE returns, focusing on *H3*. The FIGARCH model exhibits instability, with all coefficients exceeding critical values, indicating structural breaks and inadequate representation of LPE return dynamics. In contrast, the FIEGARCH model shows greater stability, with most coefficients below critical values, although instability persists in Theta 1 and Theta 2 parameters. These findings highlight the robustness of the FIEGARCH model and the importance of careful model selection in volatile markets like Egypt (Bawa et al., 2023; Tsiaras, 2020).

Table 7. Nyblom parameter estimates for FIGARCH and FIEGARCH models

Variables	*Value*
FIGARCH	
Constant	23.16752
ARCH	4.034751
GARCH	2.38636
D-parameter	6.880559
FIEGARCH	
Constant	0.147048
Omega	0.141732
Alpha	0.108072
Beta	0.321307
Theta 1	2.035492
Theta 2	1.133064
D-parameter	0.642485

Note: 1% critical value = 0.748; 5% critical value = 0.47; 10% critical value = 0.353. All coefficients are unstable pointing towards evidence of structural breaks.
Source: Authors' elaboration.

4.6. News impact on Egypt using GARCH models

Diagnostic tests and the news impact curve, following methodologies outlined by Benzai et al. (2022), and Paul and Birthal (2021) were conducted using the GARCH-in-mean model. The GARCH-in-mean model revealed a positive variance term but an insignificant mean term, indicating an inverse risk-return relationship. Overall, this model was determined to be the most appropriate for analyzing Egypt's LPE investments, as it showed no significant asymmetric effects of news on conditional volatility for this asset class.

4.7. Structural relationships with country risk factors

The study examines the structural relationship between private equity investments and country-specific risk factors like GDP and inflation in Egypt using a VAR model, where all variables are endogenous and depend on past values. The VAR model helps interpret asset price fluctuations and forecast variances, providing insights for optimizing corporate investment strategies in emerging markets, particularly by linking market volatility to economic factors (Jiang et al., 2021; Karunanayake, 2014; Mpofu, 2011).

The stationarity of *GDP*, returns (*RTN*), and inflation (*INF*) was assessed using the ADF test (see Table 8). *GDP* was stationary at level, *INF* achieved stationarity after the first differencing, and *RTN* required a second differencing to become stationary. These findings validate the application of the VAR model.

Table 8. Tests for stationarity

Variable	*Level*	*1st differencing*	*2nd differencing*
GDP	-4.022197 (0.0106)	-8.053597 (0.0000)	No need to test
RTN	-1.634842 (0.4382)	-3.99181 (0.5435)	-7.688940 (0.0001)
INF	-2.762155 (0.0906)	-4.193337 (0.0089)	No need to test

Source: Authors' elaboration.

Trace values from Table 9 confirm contemporaneous interactions among *GDP, RTN*, and *INF*, ensuring a robust foundation for the VAR model and emphasizing these interactions' role in understanding and predicting private equity returns.

Table 9. Trace value vs critical values for the data (*GDP, RTN, INF*)

Hypothesis	*Trace value*	*5% critical value*	*P-value*
H1	35.35746	29.79707	0.0103
H2	12.966.06	15.49471	0.1161
H3	3.717853	3.841165	0.0538

Note: H1: At most one cointegrating relationship; H2: At most two cointegrating relationships; H3: At most three cointegrating relationships.
Source: Authors' elaboration.

The VAR model below — see Eq. (1) — includes three variables — volatility of returns (*EGPTRTN*), GDP (*EGPTGDP*), and inflation (*EGPTINF*) — to capture their dynamic interrelationships.

$$\begin{bmatrix} EGPTRTN \\ EGPTGDP \\ EGPTINF \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \phi_{1,1} & \phi_{1,2} & \phi_{1,3} \\ \phi_{2,1} & \phi_{2,2} & \phi_{2,3} \\ \phi_{3,1} & \phi_{3,2} & \phi_{3,3} \end{bmatrix} \begin{bmatrix} EGPTRTN_{t-1,1} \\ EGPTGDP_{t-1,2} \\ EGPTINF_{t-1,3} \end{bmatrix} + \begin{bmatrix} w_{t,1} \\ w_{t,2} \\ w_{t,3} \end{bmatrix} \quad (1)$$

where,

- α — constant terms for each variable;
- ϕ — coefficients representing the impact of lagged values of each variable on the current value;
- w — error terms capturing the shocks to each variable;
- *EGPTRTN* — this represents the natural log of real broad money in Egypt;
- *EGPTGDP* — this represents the real GDP of Egypt;
- *EGPTINFL* — this represents the inflation rate in Egypt.

Variance decomposition highlights that *EGPTRTN*'s variance is initially driven by its own shocks but gradually influenced by GDP and inflation over time. IRFs illustrate how *EGPTRTN* self-influences in the short term, with GDP and inflation playing a more significant role in the long term. Table 10 presents the VAR coefficients, indicating the dynamic interdependencies among these variables.

Table 10. VAR and variance decomposition for Egypt

Lagged variables	*EGPTRTN*	*EGPTGDP*	*EGPTINF*
EGPTRTN (-1)	0.197834	0.001375	0.03194
Standard errors	-0.31776	-0.01915	-0.06716
t-values	0.6226	0.07182	0.47559
EGPTGDP (-1)	1.659502	-0.487091	1.05997
Standard errors	-5.19394	-0.31297	-1.0978
t-values	0.31951	-1.55636	0.96554
EGPTINFL (-1)	0.82192	-0.142553	0.78041
Standard errors	-1.14111	-0.06876	-0.24119
t-values	0.72028	-2.07322	3.23573

Source: Authors' elaboration.

Table 11 shows that while *EGPTRTN* is largely self-driven in the short term, GDP and inflation exert growing influence over time. Inflation's variance remains predominantly influenced by its own past values, with minimal contributions from GDP and *EGPTRTN*.

Table 11. Variance decomposition by variable

Period	*Std. err.*	*EGPTRTN*	*EGPTGDP*	*EGPTINFL*
Variance decomposition of EGPTRTN				
1	6.2902	100	0	0
2	6.5019	96.8875	0.4021	2.7102
3	6.5597	95.6727	0.3952	3.9319
Variance decomposition of EGPTGDP				
1	0.3790	7.1643	92.8357	0
2	0.4478	5.9315	76.8825	17.1859
3	0.4551	6.7311	75.2762	17.9927
Variance decomposition of EGPTINFL				
1	1.329	0.9043	3.1427	95.9529
2	1.6966	1.8365	3.3634	94.7999
3	1.8247	3.1768	2.9185	93.9045

Note: Cholesky one standard deviation (d.f. adjusted); Cholesky ordering: EGPTRTN, EGPTGDP, EGPTINFL.
Source: Authors' elaboration.

The analysis reveals that LPE returns are predominantly influenced by their own past values in the short term, as evidenced by the variance decomposition results (see Table 11). This suggests a low sensitivity to GDP and inflation fluctuations in the immediate term, underscoring the need for micro-level risk management strategies for LPE investors in Egypt. Over time, these macroeconomic factors play a more significant role, yet their influence remains secondary to *EGPTRTN*'s own past values. These findings refute *H6*, which posits that country-specific risks significantly affect LPE valuations in the short term. This suggests that investors place limited emphasis on GDP and inflation in their immediate strategic decisions regarding LPE investments in Egypt.

5. DISCUSSION

The conceptual framework presented in Figure 1 is reaffirmed by the study's findings, which demonstrate that integrating volatility dynamics into corporate strategy can optimize portfolio performance and align long-term planning with market conditions. For instance, the framework's emphasis on diversification and capital structure is supported by the predictive capabilities of FIGARCH and FIEGARCH models. The findings of this study provide critical insights for shaping corporate and business strategy, particularly in the context of LPE investments in emerging markets like Egypt. The identification of long-memory volatility through FIGARCH models suggests that firms should adopt long-term diversification strategies to mitigate prolonged market shocks. These key implications for corporate and business strategy can be categorized into the following areas.

5.1. Dynamic risk management

The findings highlight the importance of dynamic risk management strategies in volatile environments like Egypt's LPE market (Baillie et al., 1996; McKnight et al., 2023). Advanced models, such as FIEGARCH, allow firms to adapt to high-frequency market changes, enabling proactive decision-making (Abu Afifa et al., 2025) and portfolio optimization.

5.2. Strategic focus on internal market dynamics

Results indicate the primacy of internal market factors over macroeconomic indicators in shaping LPE returns. This underscores the need for firms to prioritize operational efficiency, innovation capacity, and sector-specific drivers in their strategic planning (Damodaran, 2018; Döpke & Tegtmeier, 2018). As Debnath et al. (2024) emphasize, aligning corporate strategy with internal dynamics enhances resource allocation and builds resilience against external shocks.

5.3. Leveraging advanced volatility models for portfolio diversification and growth

Advanced volatility models, including FIGARCH and FIEGARCH, provide valuable insights into long-term trends, helping firms optimize diversification strategies and allocate resources effectively. These models should be integrated into corporate strategic frameworks to enhance resilience against market shocks (Miralles-Quirós et al., 2024; Abu Afifa et al., 2025). Additionally, firms can enhance their resilience against volatility shocks by integrating these insights into long-term strategic planning frameworks (Baillie et al., 1996; Tegtmeier, 2023).

5.4. Technological integration and predictive analytics

Emerging technologies, including AI and blockchain, present further opportunities for improving the strategic application of these findings. Abu Afifa et al. (2025) highlight how AI-driven predictive analytics can enhance the accuracy of volatility forecasts and support real-time decision-making in private equity markets. Incorporating these tools into corporate strategy allows firms to adapt more effectively to market changes and optimize investment outcomes. Furthermore, blockchain technology can improve transparency and trust in LPE investments, a critical factor for attracting global investors in emerging markets.

5.5. Policy implications and governance structures

From a policy perspective, the findings suggest a need for regulatory frameworks that support the integration of advanced modeling techniques into corporate practices. Strong institutional governance structures can stabilize private equity markets and foster investor confidence, as noted by Miralles-Quirós et al. (2024). Policymakers in Egypt should consider developing tailored regulations that encourage transparency, data availability, and the adoption of innovative risk management tools.

These insights collectively highlight the interconnectedness of these elements in shaping effective corporate and business strategies for LPE investments. By aligning strategic objectives with these findings, firms operating in Egypt's LPE market can navigate uncertainties more effectively, capitalize on long-term opportunities, and contribute to the broader stability and growth of the private equity sector in emerging economies.

6. CONCLUSION

This study provides critical insights into the volatility dynamics and strategic implications of LPE investments in Egypt. The findings emphasize the importance of integrating risk management frameworks that address both internal market dynamics and external economic factors. Inflation emerges as a key driver of LPE valuations, while global risk factors remain largely unpriced in the short term. Firms that align their strategies with these insights are better equipped to navigate uncertainties, optimize investments, and enhance resilience against volatility shocks.

The GARCH-in-mean model effectively captured Egypt's LPE volatility, showing stable long-term dynamics and highlighting inflation's stronger influence on returns compared to GDP. These findings align with prior research (Damodaran, 2018; Döpke & Tegtmeier, 2018; Naumoski, 2012) and validate the importance of advanced modeling techniques in fragmented markets. Key implications include the need for corporate strategies that incorporate extreme outcomes (Czasonis et al., 2019), utilize GARCH models for cycle-aligned decision-making, and employ advanced techniques like FIEGARCH to predict outcomes in volatile contexts (McKnight et al., 2023). The absence of long-term volatility asymmetries supports stable growth planning, while the limited short-term impact of GDP and inflation underscores the primacy of internal market dynamics.

The study acknowledges limitations, including reliance on historical data that may not capture post-COVID-19 dynamics, an exclusive focus on Egypt, and the complexity of applying advanced econometric models in data-constrained settings. These limitations highlight opportunities for future research to broaden geographic scope, integrate real-time data, and explore technological impacts on LPE valuation.

From a policy perspective, the findings advocate for enhanced market transparency, strengthened governance frameworks, and the adoption of predictive analytics and blockchain to boost investor confidence and operational efficiency. Policymakers should prioritize reducing information asymmetry and fostering innovative financial models tailored to Egypt's LPE market (Miralles-Quirós et al., 2024; Abu Afifa et al., 2025).

In conclusion, this study underscores the pivotal role of volatility dynamics and internal market factors in shaping LPE investment outcomes. Leveraging these insights enables firms and policymakers to navigate the complexities of emerging markets, optimize portfolios, and drive sustainable growth. Future research should explore machine learning, broader African contexts, and the long-term impacts of global disruptions like COVID-19, particularly on investor sentiment, liquidity, and macroeconomic indicators. These developments are especially relevant for emerging markets where systemic shocks can have enduring effects.

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