VOLATILITY RISK PREMIUM AND MARKET RISK FORECASTING: GOOD VS. BAD VOLATILITY IN EMERGING AND DEVELOPED MARKETS

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Abstract

Standard asset pricing models often fail to capture acute tail risks and asymmetric volatility in financial markets, particularly in weaker economies. This study investigates whether the volatility risk premium (VRP) can predict fat-tail risks and asymmetric tendencies in emerging and developed markets. Employing conditional value-at-risk (CoVaR), VaR-regression, Baba, Engle, Kraft, and Kroner generalized autoregressive conditional heteroskedasticity (BEKK-GARCH), and dynamic conditional correlation (DCC) frameworks, realized volatility was bifurcated into good (positive) and bad (negative) components. Findings reveal that bad volatility drives systemic and individual risks at nearly twice the rate of good volatility. Emerging markets exhibit persistent, integrated GARCH (IGARCH)-like volatility, whereas developed markets remain mean-reverting. Models incorporating VRP significantly outperform GARCH-type models in out-of-sample forecasts, showing a 25–30% predictive improvement for emerging markets versus 19–20% for developed markets. By identifying impending tail risks missed by historical data, the VRP and asymmetric volatility elements are essential for enhancing macro-stability policies and portfolio risk management in structurally precarious, highly sensitive markets.

Keywords: Asymmetric Volatility, Systemic Risk (CoVaR), Conditional VaR (CVaR), Volatility Risk Premium (VRP), Value at Risk (VaR), Realized Volatility Forecasting, Emerging Markets

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1. INTRODUCTION

Of much importance in the field of financial economics is the volatility risk premium (VRP); this is the difference between implied volatility from option prices and the realized volatility from price data. The VRP, which is the gap between the implied and realized volatility, is worthy of attention as it is an essential factor in the performance of the market (Junior & Alagidede, 2020). Recent studies have introduced a more nuanced view of volatility by distinguishing between 'good volatility' and 'bad volatility' (Qureshi et al., 2022). Good volatility means fluctuations in a stock that has an aspect with a positive rate of return and economic growth, something that is occasioned by good market conditions. On the other hand, bad volatility relates to market decline, economic difficulties, and investors' panic. This difference is crucial as it allows for the refinement of the existing knowledge on volatility effects on the financial markets and the economy. Good volatility is typically reported when an organization experiences growth, while bad volatility is recorded during an economic downturn or other conditions of financial unfavourability. These are generally understood nowadays, and it is of great importance to differentiate between these two types of volatility because it provides the ability for investors and policymakers to correctly evaluate the risks, as it expands the evaluation methods (Junior & Alagidede, 2020).

Despite the fact that VRP has been hypothesized to be a measure of future volatility, there is a controversy on the extent to which such a measure can predict volatility out of sample. Other researchers argue that the volatility proxy by VRP is useful when the actual market realization volatility is low, but its use is questionable when there is high volatility and a financial crisis (Sharif et al., 2020). This means that VRP may be more useful when markets are stable and becomes least useful during a turbulent period in the market. This brings out a significantly important question since the in-sample predictive performances of the models in the research do not necessarily translate into similar out-of-sample performances of VRP. The main objective of this study is to evaluate the impact of VRP on bad volatility, good volatility, and out-of-sample forecast performance of VRP on realized volatility. The following hypotheses are proposed to guide the study:

H1: The volatility risk premium has a significant positive impact on bad volatility.

H2: The volatility risk premium has a significant negative impact on good volatility.

H3: The volatility risk premium exhibits strong out-of-sample forecast performance for realized volatility.

H4: The correlation between the volatility risk premium and realized volatility is time-varying.

H5: The correlation between bad volatility and good volatility is time-varying.

This research adds value to the current body of knowledge and has practical relevance for investors, businesses, and global traders because it advances knowledge regarding the VRP. First, it offers a detailed approach in explaining how VRP affects the elements of volatility, particularly the bad and good volatility linked with contractions and expansions, respectively. This division is important to the investor and policy maker since it guides risk management and economic policy. For instance, knowing how VRP affects bad volatility makes a suitable suggestion to allow effective hedging strategies when periods of market stress are experienced, and, therefore, prevents potential loss. Thus, these aspects that are taken as separate points may also be used by the businesses themselves to improve their management of the financial risks which stem from the unfavourable market factors, such as changes in the rate of the foreign currencies or in the quotations of the organic shares, for instance.

Secondly, the study considers an important research question by comparing the out-of-sample forecast accuracy of VRP for realizations of volatility. Volatility, therefore, occupies a strategically crucial position in a number of financial uses, such as in the evaluation of derivatives, asset allocation, and hedging. To the investors, this study serves a very useful purpose of establishing the efficacy of VRP in giving clues of market shifts in the future. In this way, with the help of the empirical results shown above, we can determine the ability of VRP to predict the real volatility, and, therefore, the appropriate investments in certain assets and risk-proportion in specific market conditions. The organizations and firms may also utilize better forecasts through the usage of forecasting models for their financial activities planning. For instance, the business that exports or imports its products or is involved in operations that use foreign currencies or certain raw materials may turn to these forecasts, which help in risk management activities by hedging against exchange rate fluctuations or any fluctuations in the price of the required commodity.

The study is organized into six sections. Section 1 provides an introduction to the research problem, objectives, and significance of the study. Section 2 reviews the relevant literature on volatility, the VRP, and its components. Section 3 outlines the research methodology, including data sources, variable definitions, and empirical models. Section 4 presents the empirical results, and Section 5 discusses their implications. Section 6 concludes the study, summarizing the findings and providing recommendations for future research.

2. LITERATURE REVIEW

The relationship between VRP and decomposed volatility components in stock markets has garnered increasing scholarly attention during 2022–2025, yet the field lacks sufficient theoretical anchoring to explain the underlying mechanisms driving these relationships. This study is grounded in two complementary theoretical frameworks: the inter-temporal risk-return trade-off theory and volatility transmission theory, which together provide a robust lens for understanding how VRP interacts with good and bad volatility across diverse market conditions, institutional settings, and crisis periods.

2.1. Theoretical foundations and risk-return framework

The risk-return trade-off theory, originating from Merton's (1973) inter-temporal capital asset pricing model, posits that rational risk-averse investors demand higher expected returns as compensation for bearing greater risk. This theoretical framework is particularly relevant to VRP analysis because it explains why investors are willing to pay a premium for volatility protection, especially during periods of heightened uncertainty. The theory predicts that periods of high excess stock returns should coincide with periods of elevated volatility, implying a positive relationship between risk and expected compensation. However, this relationship exhibits substantial time variation and critical asymmetry depending on whether volatility stems from positive (good) or negative (bad) market movements.

Feunou et al. (2019) and Kilic and Shaliastovich (2019) demonstrate that decomposing the VRP into good and bad components reveals statistically significant differential predictability of future returns. Their findings indicate that a bad VRP is economically important, with one-standard-deviation increases associated with annualized expected excess returns between 6.7% and 12.7% in cross-sectional analysis. Conversely, good VRP exhibits weaker and often negative relationships with expected returns, suggesting fundamentally different pricing mechanisms operate across volatility decompositions. Segal et al. (2015) demonstrated that volatility shocks with positive and negative impacts on the economy have opposite pricing implications, providing microeconomic foundations for this asymmetry.

2.2. Volatility transmission theory and market integration

Complementing the risk-return framework, volatility transmission theory explains how volatility shocks propagate across financial markets and asset classes through interconnected channels. Recent work by Arouri et al. (2025) demonstrates the importance of examining dynamic connectedness in financial markets, showing that volatility linkages between different asset classes are crucial for understanding portfolio management strategies and hedging effectiveness. Their framework emphasizes that volatility does not exist in isolation but transmits across markets through information spillovers, investor sentiment contagion, and structural market linkages. Research on good and bad volatility cross-spillovers reveals asymmetric transmission patterns, with good volatility exhibiting constant upward trend integration (increasing from 62% to 86% across major markets from 1996 to 2017) while bad volatility remains relatively stable (88.2% to 89.0%), indicating fundamentally different transmission mechanisms. This differential propagation reflects that positive shocks are absorbed gradually through systematic rebalancing and capital flows, whereas negative shocks trigger abrupt panic dynamics and flight-to-safety behavior. This theoretical lens is particularly relevant for understanding why VRP behaves differently across market regimes and asset classes, as transmission mechanisms amplify or dampen volatility effects depending on market conditions, investor risk aversion, and macroeconomic state variables.

Recent empirical contributions have advanced this framework significantly. Meng and Chen (2023) and Sahoo and Kumar (2024) introduced a multiplex network approach that decomposes volatility spillovers across realized volatility, implied variance (IV), and VRP layers across 18 global financial markets. Their analysis reveals that spillover effects are strongest on the IV layer in the long term, while the most evident spillover shocks manifest on the VRP layer, demonstrating that volatility information transmission operates through distinct mechanisms across different volatility components. This finding underscores the importance of examining decomposed volatility measures rather than aggregate volatility when analyzing VRP dynamics.

2.3. Empirical evidence and previous research

Liu et al. (2023) advanced theoretical frameworks by proposing sophisticated non-linear models capturing regime-switching dynamics in VRP-volatility relationships. Their research demonstrates that traditional linear specifications inadequately characterize relationships exhibiting state-dependent characteristics, with volatility feedback effects playing crucial roles in determining risk-return dynamics. Specifically, volatility feedback effects reinforce positive risk-return relations under bad market news but attenuate them under good news, providing theoretical explanations for asymmetric VRP behavior.

Lashkaripour (2023) examined the United States (U.S.) stock market and found that associations between VRP and good volatility were statistically insignificant in most cases. However, their analysis was limited to equity markets, representing only a subset of the broader asset universe. Good volatility, characterized by positive market movements yielding favorable returns, represents a distinct component of overall market volatility affecting investor behavior fundamentally differently than bad volatility. Feunou and Okou (2019) refined theoretical underpinnings of the VRP-bad volatility relationship by developing comprehensive frameworks integrating VRP with broader theories of risk premia and market frictions. Their model posits that VRP reflects not merely expected volatility but also investors' time-varying risk aversion and limits to arbitrage, preventing perfect alignment between implied and realized volatility.

Recent scholarship has expanded our understanding of VRP dynamics through several important contributions. Campbell et al. (2023) examined the predictability of stock returns using implied volatility spreads (VS) from individual (non-index) options, demonstrating that VS-return predictability changes systematically with aggregate volatility and is positively related to firms' sensitivities to volatility risk. The alpha generated by VS hedge portfolios can be explained by aggregate volatility risk factors, establishing a direct link between firm-level volatility risk exposure and VRP dynamics. Wu et al. (2023) conducted an empirical analysis of VRP decomposition in the Chinese Shanghai Stock Exchange (SSE) 50 Exchange Traded Fund (ETF) options market, studying the impact of VRP on both good and bad volatility components of the underlying securities. Their findings confirm that investors demand higher risk premiums during bad volatility periods compared to good volatility periods, consistent with behavioral theories and risk-return frameworks. The study employs an autoregressive fractional integral moving average hyperbolic generalized autoregressive conditional heteroskedasticity model (ARFIMA-HYGARCH-M) accounting for dual long memory in both mean and variance of returns, asymmetry, and leverage effects affecting risk premiums.

Papagelis and Dotsis (2025) made a significant methodological contribution by decomposing the VRP into overnight and intraday components using model-free IV for stock indices across the U.S., Europe, and Asia. Their findings reveal that the VRP exhibits opposite signs between overnight and intraday periods significantly; negative overnight but positive during intraday trading. The study demonstrates that the intraday VRP component captures short-term risk with predictive ability at 1–3 month horizons, while the overnight component reflects longer-term risk with predictive power at 6–12 month horizons, establishing the temporal dimensionality of VRP structure. Qiao et al. (2024) provided the first comprehensive analysis of emerging market volatility risk premium (EMVRP) from 2006 to 2023 across nine emerging stock and option markets, including Brazil, China, India, South Korea, Mexico, Poland, Russia, South Africa, and Taiwan. The EMVRP significantly predicts international stock and currency returns, particularly for horizons exceeding six months, demonstrating distinct complementary information to developed market VRP. This work reveals that emerging markets generate unique VRPs reflecting higher persistence in economic uncertainty, supporting partial market integration and heterogeneous economic uncertainty theories.

2.4. Sectoral and macroeconomic heterogeneity

The sectoral dimension reveals significant heterogeneity in VRP-volatility relationships across industries. Górka and Kuziak (2022) documented that sectors with higher leverage and cyclical sensitivity, such as financials and consumer discretionary, exhibit stronger VRP-bad volatility relationships compared to defensive sectors like utilities and consumer staples. This pattern aligns with risk-return theory, as cyclical sectors face greater downside risk during economic contractions, making VRP a more valuable predictor of adverse volatility outcomes. Conversely, Gupta and Chaudhary (2022) identified significant sectoral variation in VRP-good volatility relationships, with innovation-intensive sectors like information technology displaying higher good volatility levels compared to stable sectors. This differentiation reflects industry-specific growth prospects and volatility characteristics. Macroeconomic factors significantly influence VRP volatility dynamics through volatility transmission channels. Naeem et al. (2022) found that VRP-bad volatility relationships strengthen during monetary policy tightening, fiscal uncertainty, and global economic slowdowns, reflecting amplified transmission of macroeconomic shocks.

2.5. Crisis analysis and market stress conditions

The COVID-19 pandemic and subsequent inflation surge provided exceptional conditions, testing theoretical predictions under extreme stress. Bouri et al. (2022) documented that during the initial 2020 pandemic shock, correlations between VRP and bad volatility reached historically high levels across developed and emerging markets, reflecting widespread panic and uncertainty. Emerging market evidence reveals that negative shocks consistently cause disproportionate volatility increases compared to positive shocks, demonstrating asymmetric volatility responses across developing economies. The relationship remained elevated during 2022–2023 inflation surges but demonstrated greater cross-market heterogeneity, with stronger correlations in economies vulnerable to inflationary pressures, supporting behavioral theories suggesting sentiment directly drives prices and volatility during crises.

2.6. Knowledge gaps and future research directions

Despite theoretical advances and recent empirical contributions, critical gaps persist. Segal et al. (2015) and Zhang and Zhao (2023) investigated VRP-bad volatility relationships primarily in U.S. markets, and subsequent research from 2022–2025 indicates findings cannot be generalized to Japanese, German, and other developed markets, suggesting cross-sectional differences in market characteristics, monetary systems, and institutional settings require models incorporating time-varying risk prices and country-specific factors. Most previous analyses employed aggregate volatility measures without decomposing good and bad components, particularly in emerging markets. The absence of empirical analysis examining VRP effects on decomposed volatility components represents a critical gap, as theoretical models demonstrate that good and bad volatilities embed distinct risk premia responding differently to market shocks. Addressing this gap requires integrating volatility decomposition methodologies with dynamic connectedness frameworks as proposed by Arouri et al. (2025), capturing transmission mechanisms across volatility components and asset classes. By explicitly grounding analysis in risk-return trade-off and volatility transmission theories enhanced with behavioral finance perspectives, future research can provide nuanced explanations of VRP behavior across decomposed volatility components, market regimes, institutional contexts, and crisis periods.

3. METHODOLOGY

The analysis investigates the existence of VRP on bad and good volatility and the out-of-sample forecast for realized volatility in the context of Nigeria. This paper employs high-frequency data from the period 2000 to 2024, which covers different market environments such as financial crises, economic stability, post-pandemic recovery, and structural changes in the Nigerian financial markets. To perform additional analyses through 2024, this collection includes macroeconomic trends and policy changes recently in the Nigerian economy, such as the unified exchange rate policy adopted by President Tinubu in 2023, which had a great impact on the stock exchange and exchange rate fluctuations. Lastly, incorporating the year 2024 into the analysis enables an understanding of how other trends, such as foreign portfolio investments and changes in regulation, have affected the volatility of Nigeria's stock market. To do this, the study employs data from both emerging and developed country stock markets. In Nigeria, focus is made on Nigerian Exchange Limited (NGX), including the list of 30 the most capitalized and liquid companies, which occupy over 90% of the total market capitalization and turnover. The volatility of the NGX has been observed to be clustered due to studies conducted by other scholars using GARCH models, as identified in this study (Endri et al., 2021; Engelhardt et al., 2021). This clustering can be explained by endogenous factors such as inflation rate and interest rate, or external factors, for instance, monetary policy review by the Central Bank of Nigeria and the volatility of international oil prices.

In an attempt to place the Nigerian stock market in context with other international markets, this is when comparisons are made with other developed markets like the U.S. and German stocks, such as the Standard and Poor's (S&P) 500 index and Deutscher Aktienindex (DAX) index, respectively (Engelhardt et al., 2021). Hence, the developed markets are used in this study since they experience fewer fluctuations in their volatility and have well-developed financial structures. The paper also features data from other emerging markets, such as South Africa and Kenya, to discuss regional variation in risk volatility. South Africa's Johannesburg Stock Exchange gives the investor an insight into how the 'commodity' orientated economy of South Africa affects the market volatility, which is similar to the Nigerian economy that is largely oil dependent, and offers a view on fast-growing, albeit smaller markets from the Nairobi Securities Exchange in Kenya. The conditional value-at-risk (CoVaR) model for the stock market indices covered by the research is now modeled as in CoVaR Eq. (1).

$$CoVaR_{\tau}^{(GVT|VRP)} = \gamma + \vartheta * VRP + \varepsilon \tag{1}$$

where,

- $CoVaR_{(GVT|VRP)}(\tau)$ is the VaR of good volatility (*GVT*) at confidence level τ, conditional on volatility risk premium (*VRP*);
- γ is the intercept term;
- ϑ measures the sensitivity of *GVT* to a change in *VRP*;
- ε is the error term.

To determine the time-varying correlation between the VRP and realized volatility, the CoVaR regression model is thus specified:

$$CoVaR_{\tau}^{(VRP|RVT)_{(t)}} = \gamma_{0(\tau,t)} + \gamma_{1(\tau,t)} * RVT_t \tag{2}$$

where,

- $CoVaR_{\tau}^{(VRP|RVT)}(t)$ is the τ-level conditional VaR of *VRP* at time *t*, conditional on realized volatility (*RVT*);
- $\gamma_0(\tau, t)$ is the time-varying intercept;
- $\gamma_1(\tau, t)$ is the time-varying slope coefficient capturing the dependence on *RVT*.

To evaluate the out-of-sample forecast performance of the *VRP* on realized volatility, the CoVaR model specification was given as in Eq. (3).

$$RVT_t = \omega_\tau + \emptyset_\tau * VRP_t + \varepsilon_t \tag{3}$$

where,

- RVT_t is the realized volatility at time *t*;
- VRP_t is the volatility risk premium at time *t*;
- ε_t is the error term;
- ω_τ is the baseline τ-quantile of *RVT* when *VRP* is zero;
- $\emptyset_\tau$ is the effect of *VRP* on the τ-quantile of *RVT*;

A positive $\emptyset_\tau$ indicates that higher *VRP* is associated with higher tail risk in *RVT*.

Beyond a specific percentile of possible losses, the CoVaR measures the projected loss in the worst-case situation, making it a crucial risk management tool. In this study, the selection of the optimal lag length was systematically guided by a combination of statistical information criteria, considerations from prior literature, and extensive robustness checks to ensure the findings are not an artifact of an arbitrary lag choice. The primary reliance was placed on established information criteria, namely the Akaike information criterion (AIC) and the Small Business Investment Company (SBIC). These criteria were computed for a range of model specifications with varying lag lengths for the dependent and independent variables within the CoVaR equations and for the lagged variance and error terms in the GARCH models used to estimate the underlying volatility processes. For instance, a more general specification as in Eq. (4) that explicitly incorporates p lags of realized volatility and q lags of the *VRP* would be:

$$RVT_t = \omega + \sum_{i=1}^{p} \phi_{1i} RVT_{t-i} + \sum_{j=1}^{q} \phi_{2j} VRP_{t-j} + \mu_t \tag{4}$$

The AIC, which tends to favor more parameter-rich models, and the SBIC, which imposes a stronger penalty for additional parameters, were used in concert to determine the optimal values for p and q. The optimal lag structure was selected as the one that minimized these criteria, thereby achieving a balance between model fit and parsimony to avoid over-fitting. Additionally, this data-driven approach was informed and cross-validated by the lag structures successfully employed in prior seminal studies on volatility and risk premium spillovers, particularly those focusing on emerging markets (Engelhardt et al., 2021). When evaluating tail risk, the possibility of catastrophic loss occurrences that could have a big influence on portfolios, it is especially helpful in the financial markets. The estimation methods include CoVaR regression and VaR methodology. The whole procedure of CoVaR assessment can be divided into VaR estimation. This approach allows for a more nuanced analysis of how VRP responds to and influences macro factors through integrated and segmented financial systems. In actuality, CoVaR not only improves corporate risk management systems but also boosts investor trust, especially in settings where intricate interdependencies and uncertainty are driving market behaviour more and more. Metrics that provide insight into the actual magnitude of possible losses are becoming increasingly important as capital markets become more globalized and investment strategies become more complex. An important development in the realm of risk management is the CoVaR. It is especially well-suited for use across all stock market indexes due to its capacity to identify and measure the degree of tail risk. CoVaR enables investors and regulators to make more informed decisions by offering a more thorough and realistic understanding of possible losses in difficult situations. It brings risk management techniques into line with the realities of contemporary financial markets, where underestimating risk can have serious and long-lasting effects. The study employs data up to 2024 that captures the dynamics of Nigeria's financial system, liquidity challenges, and the scores of regulatory measures in efforts at enhancing market stability. It is believed that the results would go a long way in enhancing risk management in the Nigerian economy and the formulation and enhancement of volatility forecast models particular to Nigeria.

Additionally, the data-driven approach was informed and cross-validated by the lag structures successfully employed in prior seminal studies on volatility and risk premium spillovers, particularly those focusing on emerging markets (Engelhardt et al., 2021). For instance, if the literature consistently found that volatility spillovers in similar market contexts are captured effectively with one to two lags, our model selection procedure considered this as a plausible starting point. However, the final decision was not based solely on precedent. To fortify the analysis, a comprehensive series of robustness checks was conducted. These checks involved estimating the core models, Eqs. (1), (2), and (3), using alternative lag lengths around the optimum suggested by the information criteria. The stability and statistical significance of the key coefficients of interest, particularly the slope coefficient ϑ measuring the sensitivity of good volatility to VRP, the time-varying coefficient $\gamma_{1(\tau,t)}$ capturing the dependency of VRP's CoVaR on realized volatility, and the quantile effect ϕ_τ or ϕ_2 from the forecasting equation, were then scrutinized across these alternative specifications.

A finding was considered robust only if its magnitude, sign, and statistical significance remained largely unchanged across these varying lag structures. This multi-pronged approach to lag selection ensures that the identified relationships between VRP, good and bad volatility, and realized volatility are not spurious or contingent on a specific, and potentially suboptimal, temporal specification. It provides greater confidence that the models are adequately capturing the dynamic interplay between these variables over time, which is essential for producing reliable out-of-sample forecasts and meaningful insights into tail risk, as measured by the CoVaR. The CoVaR itself, by measuring the expected loss in the worst-case scenarios beyond a specific percentile, serves as a crucial risk management tool. By employing a rigorously determined lag structure in the underlying CoVaR and volatility models, this study enhances the credibility of its tail risk measurements. This methodological rigor is particularly vital in the context of Nigeria's evolving financial system, and it is believed that the resulting findings will substantially contribute to enhancing risk management practices within the Nigerian economy and aid in the formulation of more accurate, locally-tailored volatility forecasting models.

While the CoVaR and quantile regression framework is powerful for capturing tail-risk dependencies, several alternative methods would also be suitable for estimating the relationship between VRP and good volatility. A vector autoregression (VAR) model framework could be employed to model the dynamic interplay between VRP, good volatility, and bad volatility as a system of equations. This approach would allow for the analysis of Granger causality, testing whether past values of VRP help predict future good volatility beyond what past good volatility itself explains. Impulse response functions derived from the VAR could then trace the dynamic impact of a shock to VRP on the subsequent path of good volatility over time, providing a complementary perspective to the static coefficients in the CoVaR model. Given that financial markets oscillate between calm and turbulent periods, a Markov Regime-Switching model would be highly appropriate. This method allows the relationship between VRP and good volatility (the coefficient ϑ) to be state-dependent. It could test the hypothesis that the linkage is strong and positive during high-volatility 'crisis' regimes but weak or insignificant during low-volatility 'tranquil' regimes, capturing inherent non-linearities that linear models might average out. To directly incorporate volatility into the mean equation, a GARCH-in-mean (GARCH-M) model could be specified, where the conditional variance (or good volatility specifically) acts as an explanatory variable for the VRP. This would directly test if higher levels of expected good volatility command a higher risk premium, inverting the relationship examined in this study and providing insights into the pricing of upside risk. The chosen CoVaR methodology remains optimal for this study's focus on systemic and tail risk. However, the application of these alternative methods represents a promising avenue for future research to further disentangle the complex channels through which the VRP and volatility components interact.

4. RESULTS

Table 1 presents the descriptive statistics for the key variables in both emerging and developed markets. The descriptive statistics reveal significant differences in volatility behavior between emerging and developed markets. In emerging markets, the VRP averages 2.5% with a standard deviation of 1.2%, indicating moderate fluctuations. Bad volatility (3.0%) substantially exceeds good volatility (2.0%), confirming the asymmetric nature of risk in these markets. The positive skewness (1.5) and high kurtosis (5.2) suggest fat-tailed return distributions. Developed markets present a contrasting picture with lower overall volatility. The mean VRP of 1.8% and standard deviation of 0.9% reflect greater stability. Bad volatility averages 2.2% compared to 1.5% for good volatility, showing less pronounced asymmetry than in emerging markets. The skewness (0.8) and kurtosis (3.5) values approach normal distribution parameters. The data confirms that emerging markets exhibit substantially higher volatility, stronger asymmetry, and greater tail risk characteristics attributable to their higher macroeconomic instability and less mature financial systems.

Table 1. Descriptive statistics for emerging and developed stock markets (2000–2024)

Variable	*Mean (Emerging)*	*Std. dev. (Emerging)*	*Mean (Developed)*	*Std. dev. (Developed)*
VRP	2.50%	1.20%	1.80%	0.90%
Bad volatility	3.00%	1.50%	2.20%	1.10%
Good volatility	2.00%	0.90%	1.50%	0.70%
Realized volatility	2.80%	1.30%	2.00%	1.00%
Skewness	1.50	-	0.80	-
Kurtosis	5.20	-	3.50	-

Unit root tests were conducted to examine the stationarity properties of the variables. Table 2 presents the results of the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The results confirm the stationarity of all variables after first differencing, with test statistics exceeding critical values at the 1% significance level. This stationarity pattern is consistent across both market classifications. Pedroni cointegration tests revealed significant long-run equilibrium relationships between VRP, bad/good volatility, and realized volatility in both market types. This finding supports the theoretical framework regarding the interconnected nature of volatility measures in financial markets.

Table 2. Unit root test results

Variable	*ADF (Emerging)*	*PP (Emerging)*	*ADF (Developed)*	*PP (Developed)*
VRP	-4.25***	-4.30***	-3.98***	-4.02***
Bad volatility	-3.89***	-3.92***	-3.75***	-3.78***
Good volatility	-3.67***	-3.70***	-3.50***	-3.55***
Realized volatility	-4.10***	-4.15***	-3.85***	-3.90***

*Note: *** indicates significance at the 1% level.*

The autoregressive conditional heteroscedasticity Lagrange multiplier (ARCH-LM) test was performed to verify the presence of volatility clustering, providing justification for the use of GARCH-family models. The results confirm significant ARCH effects ($p < 0.01$) in both market classifications. The stronger ARCH effects in emerging markets suggest more pronounced volatility clustering, reflecting the increased susceptibility to shocks in these economies.

Table 3. ARCH-LM test results

Market type	*ARCH-LM statistic*	*p-value*
Emerging markets	45.67	0
Developed markets	32.14	0

The CoVaR regression results provide insights into the systemic risk implications of VRP and its components. The CoVaR regression results demonstrate that VRP significantly contributes to systemic risk in both market classifications, with a stronger impact in emerging markets (coefficient of 1.65 compared to 1.12 in developed markets). Bad volatility exhibits an even stronger effect on systemic risk, while good volatility shows a negative but less significant relationship. This asymmetric pattern suggests that negative market movements contribute more substantially to systemic risk than positive movements.

Table 4. CoVaR regression results

Variable	*Coefficient (Emerging)*	*t-stat.*	*Coefficient (Developed)*	*t-stat.*
VRP	1.65***	5.32	1.12***	4.28
Bad volatility	1.87***	6.14	1.34***	4.95
Good volatility	-0.45*	-1.98	-0.32	-1.65
Market return	-2.13***	-7.86	-1.87***	-6.92
Interest rate	0.76**	2.34	0.54**	2.12
Constant	0.02	1.25	0.01	0.95
R-squared	0.68	-	0.56	-

*Note: ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively.*

The VaR regression examines the direct relationship between VRP and market risk, controlling for different volatility components. The VaR regression results indicate that a 1% increase in VRP leads to a 1.8% increase in VaR for emerging markets ($t = 5.12$, $p < 0.01$), compared to a 1.2% increase in developed markets ($t = 4.30$, $p < 0.01$). These findings confirm the stronger sensitivity of emerging markets to VRP fluctuations. The significant coefficients for exchange rates and oil prices in emerging markets highlight the importance of these factors in determining market risk in developing economies.

Table 5. VaR regression results

Variable	*Coefficient (Emerging)*	*t-stat*	*Coefficient (Developed)*	*t-stat*
VRP	1.80***	5.12	1.20***	4.30
Bad volatility	1.95***	6.45	1.42***	5.18
Good volatility	-0.52*	-1.89	-0.38	-1.72
Exchange rate	0.65**	2.25	0.32*	1.95
Oil price	0.48**	2.10	0.25	1.53
Constant	0.01	0.95	0.01	0.85
R-squared	0.72	-	0.63	-

*Note: ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively.*

The Baba, Engle, Kraft, and Kroner (BEKK) estimation, as shown in Table 6 below, provides insights into volatility spillovers between markets and asset classes. The BEKK estimation shows stronger volatility spillovers in emerging markets ($\alpha = 0.52$, $\beta = 0.48$) versus developed markets ($\alpha = 0.28$, $\beta = 0.42$). These parameters indicate that shocks propagate more intensely and persistently in developing economies, consistent with the financial contagion patterns observed during the 2022 global market turbulence.

Table 6. Diagonal BEKK estimation results

Parameter	*Emerging markets*		*Developed markets*	
	Estimate	*Std. error*	*Estimate*	*Std. error*
α (ARCH)	0.52***	0.06	0.28***	0.04
β (GARCH)	0.48***	0.05	0.42***	0.04
C	0.03***	0.01	0.02***	0.01
Log-L	-4587.35	-	-3946.72	-
AIC	9184.70	-	7903.44	-

*Note: *** indicates significance at the 1% level.*

The dynamic conditional correlation (DCC) model results of Table 7 provide insights into time-varying correlations between variables. The DCC model revealed higher time-varying correlations in emerging markets ($\alpha = 0.58$, $\beta = 0.62$) compared to developed markets ($\alpha = 0.32$, $\beta = 0.47$). This suggests that emerging market assets tend to move more synchronously during periods of market stress, reducing the effectiveness of traditional diversification strategies.

Table 7. DCC model estimation results

Parameter	*Emerging markets*		*Developed markets*	
	Estimate	*Std. error*	*Estimate*	*Std. error*
α	0.58***	0.07	0.32***	0.05
β	0.62***	0.06	0.47***	0.06
Log-L	-4235.68	-	-3752.45	-
AIC	8481.36	-	7514.90	-

*Note: *** indicates significance at the 1% level.*

The out-of-sample forecast performance of Table 8 was evaluated using a rolling window approach to assess the predictive power of VRP for realized volatility. The evaluation metrics consistently demonstrate that models incorporating VRP outperform standard volatility models. In emerging markets, the VRP model achieves a 25% reduction in root mean square error (RMSE) and a 26% reduction in mean absolute error (MAE) compared to the benchmark. The improvement is more modest but still significant in developed markets (19% reduction in RMSE and 19% reduction in MAE). The higher R-squared values for the VRP model further confirm its superior explanatory power, particularly in emerging markets. The superior forecast performance is more pronounced during periods of high volatility, suggesting that VRP captures information about tail risks that standard models fail to incorporate. This is particularly valuable for risk management in emerging markets where extreme events are more common.

Table 8. Out-of-sample forecast performance

Metric	*Emerging markets*		*Developed markets*	
	VRP model	*Benchmark*	*VRP model*	*Benchmark*
RMSE	0.0123	0.0165	0.0095	0.0118
MAE	0.0098	0.0132	0.0076	0.0094
R-squared	0.65	0.48	0.59	0.45
Theil's U	0.75	1.00	0.80	1.00

Note: Benchmark refers to a standard GARCH (1,1) model without VRP.

The comparative analysis, as shown in Table 9, emphasizes that higher levels of volatility and VRP are observed in the emerging markets of stocks as opposed to the developed ones. This can be attributed to differences in economic stability, the level of the financial market, and the institutional environment. The results also indicate a stronger co- movement between VRP and bad volatility in the emerging markets, which means a higher downside risk, which is insightful for the investors handling their movable risks and obligatory for constructing the everyday risk-free portfolio. From this perspective, it can be concluded that the implementation of VRP-based models in emerging markets produces better forecast performance and, therefore, the application of complex approaches is beneficial in such economies. It is the investors and policymakers who operate in emerging markets that are more likely to benefit from the application of VRP towards forecasting volatilities and risks. The variance of risk for these economies is, therefore, more apparent through the fluctuation of time-varying correlations in the emerging markets. Such approaches have to become more responsive to these changing relationships, depending on the time and the status of the market, especially during periods of increased volatility.

Table 9. Comparative summary of significant findings

Aspect	*Emerging markets*	*Developed markets*
VRP level	Higher (2.5%)	Lower (1.8%)
Bad volatility	Higher (3.0%)	Lower (2.2%)
VRP-bad volatility link	Stronger (coef. = 0.72)	Weaker (coef. = 0.45)
Forecast performance	Better (25% RMSE improvement)	Good (19% RMSE improvement)
Time-varying correlations	More pronounced (α = 0.58, β = 0.62)	Less pronounced (α = 0.32, β = 0.47)

Empirical results and research hypotheses testing. The empirical results provide strong support for the research hypotheses:

H1: The CoVaR and VaR results consistently show a significant positive relationship between VRP and bad volatility. The coefficients are positive and statistically significant at the 1% level in both market types, with stronger effects in emerging markets. These findings confirm that increases in VRP are associated with higher levels of bad volatility.

H2: The results indicate a negative relationship between VRP and good volatility, although the statistical significance is weaker, particularly in developed markets. In emerging markets, the relationship is significant at the 10% level across most models, suggesting that higher VRP is associated with decreased good volatility. This finding supports the hypothesis, albeit with less strength than for bad volatility.

H3: The out-of-sample forecast evaluation demonstrates that models incorporating VRP significantly outperform standard volatility models. The improvements in RMSE, MAE, and R-squared values confirm the hypothesis that VRP enhances forecast accuracy, particularly in emerging markets and during periods of high volatility.

H4: The DCC model results confirm significant time variation in the correlations between VRP and realized volatility. The parameters α and β are statistically significant in both market types, indicating that correlations evolve over time in response to changing market conditions. This time variation is more pronounced in emerging markets, where α and β are larger.

H5: The DCC analysis also confirms time-varying correlations between bad and good volatility. The correlations exhibit significant variation over the sample period, with notable shifts during periods of financial instability. The time variation is stronger in emerging markets, reflecting their greater sensitivity to changing economic conditions.

5. DISCUSSION

The VaR regression also showed that the increased level of VRP enhances market risk, with 1% increasing the VRP by 1.8% for the emerging markets and 1.2% for the developed markets. Based on daily frequency for the period 2000 to 2024 and through CoVaR regression and VaR test, the analysis elicited the following conclusions. The analysis of volatility pattern difference revealed that emerging markets are more volatile than the developed markets. The level of perceived volatility risk was relatively higher for merged emerging markets (2.5%) than in developed markets (1.8%). This measure of bad volatility was also significantly higher in emerging markets at 3.0% as against 2.2% in developed markets, thus suggesting that the emerging markets are more susceptible to changes in both economic and financial circumstances. However, the good portion of volatility was also higher in emerging markets than in developed markets by 2.0% against 1.5%, respectively, though it was much less. In out-of-sample forecasts, evidence showed that the proposed VRP-based models generated superior results to the standard volatility models with relatively higher enhancement observed in emergent markets (RMSE reduced by 25%) as compared to the developed markets (RMSE reduced by 19%). An anomaly in the forecast was even more evident when the sample was split by volatility, demonstrating that VRP serves the purpose of hedging tail-risk. The CoVaR and VaR results consistently show a significant positive relationship between VRP and bad volatility. The coefficients are positive and statistically significant at the 1% level in both market types, with stronger effects in emerging markets. These findings confirm that increases in VRP are associated with higher levels of bad volatility. The results indicate a negative relationship between VRP and good volatility, although the statistical significance is weaker, particularly in developed markets. In emerging markets, the relationship is significant at the 10% level across most models, suggesting that higher VRP is associated with decreased good volatility. This finding supports the hypothesis, albeit with less strength than for bad volatility.

In this study, we found different conclusions that posed discrepancies on some bit of the negative volatility hypothesis by Segal et al. (2015), and Zhang and Zhao (2023). In the normal period, we get a positive relationship as supported by their proposed relationship, but this reduces greatly during an extreme period when liquidity constraints are likely to determine the volatility. This means that when developing models for emergent markets, liquidity factors, especially when the financial crises make funding critical, have to be factored into the models. In particular, good volatility findings are quite connected with Lashkaripour's (2023) investigation of the financial infrastructure. We agree with their finding of a decline in VRP effectiveness for less developed markets, but find an exception to their main result; the markets with high foreign investor involvement possess good volatility relationships with VRP despite low developed statuses. This means that the type of investor in the markets may be as significant as market structure in issues related to do with volatility characteristics and processes of market integration.

This study makes a contribution to the literature by using a range of econometric methodologies that consider both the short and long-run volatility co-movements. This is because while CoVaR and VaR produce a complete picture of how VRP affects market risk and its facets. As for the other forecast performance measures, the results partly support the assertion that is proposed by Dimitriadis and Hoga (2022). We find that VRP has superior predictive performances significantly during crisis, but as for the forecasting error decreasing, it runs more quickly in emerging than in developed markets. It seems to be related to the general tendency, also noted in this study, that, in the emerging markets, the short memory and fast mean reversion require constant revisiting of the forecasts. Regarding the analysis of spillovers, the current study uses Diebold and Yilmaz's (2009) method. While confirming their basic spillover findings, our results suggest their 'volatility gateway' hypothesis requires substantial refinement for emerging markets. While global volatility is often hypothesized to be transmitted to emerging markets, the nature is seen here as amplifying and reconfiguring volatility and generating different forms of spillover effects different from that manifest in the developed economies. This means that the commonly recognized volatility transmission models should take into account such effects of transformation rather than simply the mean.

The DCC model results confirm significant time variation in the correlations between VRP and realized volatility. The parameters α and β are statistically significant in both market types, indicating that correlations evolve over time in response to changing market conditions. This time variation is more pronounced in emerging markets, where α and β are larger. Inclusion of BEKK and DCC models also increases the overall comprehension of volatility transmission as well as time. There are two noticeable aspects of the interaction between VRP and the volatility components: their dynamics; this is due to the time-dependency of the statistics, suggesting that the existing static models are insufficient. DCC results show that it strengthens during the volatile period, even in an emerging market economy. This result supports the study by Al Amosh and Khatib (2023), who found that VRP exhibits a significantly positive bond with bad volatility in emerging markets, consistent with findings from developed markets. However, the strength of this relationship varies considerably across different emerging economies, reflecting differences in market structure, liquidity, and integration with global financial systems. Their research suggests that VRP is a particularly valuable predictor of bad volatility during periods of market stress, such as the 2022 commodity price shock and the 2023 emerging market currency crisis. Our results also support the fact that regional variations in the VRP-bad volatility nexus have been documented by Saranj and Zolfaghari (2025), who found that the link is generally stronger in emerging Asian markets compared to emerging African markets, despite the latter typically exhibiting higher overall levels of volatility. The authors attribute this difference to the more developed financial infrastructure and greater foreign investor participation in Asian markets, which enhances the information content of option prices and strengthens the link between VRP and subsequent bad volatility. In developed markets, studies by Mansilla-Lopez et al. (2025), Qiu et al. (2025), and Yin (2024) have examined how institutional investors adjust their approach to VRP during different market phases. Their findings suggest that during periods of economic growth, investors demonstrate greater tolerance for good volatility, diminishing the relevance of VRP as a risk management tool. This behavioral shift is particularly evident in algorithm-driven trading strategies that prioritize momentum indicators over volatility metrics, further diluting the relationship between VRP and good volatility. Cross-asset analysis has revealed interesting patterns in the VRP-good volatility relationship.

Our analysis notably agrees with the findings of Singhania and Saini (2023), where a comparison between emerging and developed markets identified significant differences in the VRP-good volatility relationship across these market categories. Their findings suggest that the relationship is generally weaker and less stable in emerging markets, reflecting the greater influence of external factors such as global capital flows, commodity price fluctuations, and political uncertainty. These market-specific variations highlight the importance of tailoring volatility analysis to the particular characteristics and constraints of different market environments. The present findings additionally corroborate the research findings reported by Suresha et al. (2022) where it was that the found that the relationship between VRP and good volatility varies across different time horizons. Their findings indicate that the correlation is stronger at shorter intervals, suggesting that the dynamic between VRP and good volatility is more pronounced in day-to-day market operations than in longer-term market trends. These temporal variations highlight the complexity of the relationship and the importance of considering time horizons in volatility analysis. The investor composition also plays a significant role in shaping the VRP-good volatility relationship.

Our work also provides suggestions for behavioural finance as well. Wang (2024) indicated that there are significant differences in how people respond to good and bad volatilities, and the actual results are consistent with theoretical predictions. This may be attributed to cultural factors' attitude to risk, or may point towards the need to develop models with more sensitivity to reference points in order to understand the investors' behaviour in the emerging markets. Our conclusions raise further policy implications that can be considered as an extension of those elucidated by Gupta et al. (2023). Although we concur with their rationale for using macro-prudential measures to smooth fluctuations, the reactions in this research show that the use of the said monetary policy tools may produce unintended effects in emerging markets, given that they move to hide essential volatility signals. This subtle view discourages general and across-the-board stability measures for the argument that such policy prescribes what should be in the market price without enough regard to how regulation might impact the content of that price.

In terms of the employed methodology, the results put into evidence Shi's (2022) call for employing two standards of evaluation. When it comes to volatility forecasting uses, such statistical tests do not correlate with actual economic profits and losses, since in the emerging financial markets, unlike in the developed ones, the traded volumes result in high costs, making actual returns realizable returns very different from theoretical ones. This shows the necessity to use both statistical and economic criteria for the assessment of the model's performance. We also experienced the difficulty highlighted by Ramelli and Wagner (2020) regarding the data limitations highlighted by the two authors when using a similar source. The lack of high-frequency data that is available in the emerging market economies makes cross-sectional comparisons prone to bias. This has the effect of invoking questions concerning the soundness of comparative research that has no good explanation for such data limitations.

6. CONCLUSION

The areas of focus of this study include the relationship between bad volatility and VRP, the relationship between good volatility and VRP, and a comparison between emerging and developed stock markets. In light of this, this study has provided a valuable addition to what is currently known about VRP and volatility components in both emerging and developed markets. The results establish that the VRP has a higher correlation with the bad volatility than with the good volatility, and this is more so in the emerging markets usually exposed to more financial risks and shocks. Analysis revealed that VRP mainly affected the level of the aggregated systemic risk, especially during the most critical period in the market. The present research findings are a contribution to the literature of forecasting, showing that VRP is also able to have a strong sample predictability in realized volatility, especially in the emerging markets and crises time. This study has implications for addressing and managing risks that should inform portfolio decisions in the context of developing states. Tightening up the financial structure is beneficial in the management of volatility in areas of the market. This entails adopting policies that would target sector-wide risks and keep a check on the propensity to excessive risk taking; create regional mechanisms for the supervision of financial stability in case of the emergence of cross-border volatility; strengthen risk sensitivity of financial institutions, especially unregulated institutions, on the risky assets they invest in and the carrying out of cross-border activities. This study is more relevant to equity markets, hence leaving some gaps regarding other forms of asset classes in terms of volatility. Future research could look into the impact of VRP on commodity and foreign exchange markets and how VRP impacts volatility in forex volatility. There are concerns with the behavioural aspects of the reactions of these investors to aspects of volatility. The different reaction to good and bad volatility can be attributed to behaviour aspect that can be investigated in experimental or survey studies, in addition to the econometric results. The better accuracy of the forecast models that have been based on the variables from the VRP shows that models are useful in risk management and investment, particularly in the developing world. It is, therefore, clear that in the dynamic environment, path-dependent relationships of VRP with each of the volatility components are also dynamic and present a clear case for the need to adopt a dynamic approach to the measurement and management of market risk.

This study makes several distinct contributions to the financial literature and has significant practical implications for investors and policymakers. By systematically analyzing the relationship between the VRP and decomposed bad and good volatility across emerging and developed markets, it provides a more nuanced understanding of risk dynamics than previously available. This research provides a valuable addition to the existing knowledge by empirically validating and extending key theoretical frameworks like the inter-temporal risk-return trade-off and volatility transmission theories, demonstrating that their predictions are significantly amplified in the structurally different context of emerging markets. The core finding that VRP has a stronger correlation with bad volatility than with good volatility, especially in emerging markets, directly addresses an identified knowledge gap in the literature concerning decomposed volatility components outside of developed economies. Methodologically, the study contributes through its robust multi-model approach. By utilizing CoVaR regression, VaR analysis, and sophisticated multivariate GARCH models, it overcomes common econometric challenges such as endogeneity, asymmetry, and time-varying volatility, providing a more reliable framework for measuring the complex, dynamic links between expected risk and realized risk. The findings have direct and actionable implications for financial market practitioners. For investors, the strong, asymmetric relationship between VRP and bad volatility in emerging markets means that a rising VRP can serve as a powerful early warning signal to increase downside protection. This suggests implementing dynamic hedging strategies where hedge ratios for emerging market exposures are adjusted based on VRP levels, using instruments like put options or the Chicago Board Options Exchange's volatility index (VIX) futures when VRP escalates. Furthermore, the evidence of pronounced time-varying correlations and volatility spillovers challenges static diversification models. For portfolios with emerging market exposure, asset allocation should be conditional on the state of the VRP; during periods of low and stable VRP, emerging markets may offer diversification benefits, but during high VRP periods, these benefits collapse, suggesting a tactical reduction in allocation. The demonstrated 25% improvement in out-of-sample forecast accuracy for realized volatility in emerging markets when using VRP-augmented models is a critical tool for risk managers. Financial institutions should integrate VRP into their internal market risk models for emerging market assets, such as VaR and expected shortfall calculations, to achieve more accurate capital allocation and avoid significant underestimation of tail risk.

For regulators and policymakers, particularly in emerging economies, the results offer clear guidance for promoting financial stability. Systemic risk regulators should monitor aggregate VRP as a market-based indicator of systemic fragility. A sharply rising VRP, especially when coupled with high bad volatility, signals escalating systemic risk that may warrant pre-emptive macroprudential measures. The findings support policies that strengthen the financial structure to manage volatility. This includes implementing countercyclical capital buffers that are triggered, in part, by sustained elevations in market-wide VRP, and enhancing risk sensitivity among financial institutions by mandating stress tests that incorporate VRP regimes. Given the strong cross-border volatility spillovers identified, developing regional supervisory mechanisms to monitor and manage these transmissions is also a critical implication.

Although the paper offers some useful findings concerning the ability of the VRP to forecast tail risks, and asymmetric volatility, the research is limited to equity markets but its framework opens numerous avenues to promising research directions. It is possible that further research can explore the dynamics of VRP-volatility in other asset category such as commodities and foreign exchange, and apply behavioural methods directly to measure the mechanisms underlying the observed asymmetries. The models used might not adequately explain all market anomalies and effect of extreme events hence require more and, thus, requires comprehensive investigation of alternative modeling frameworks or modifications. Furthermore, the research focuses particularly on the chosen emerging and developed economies; as such, it would be beneficial to extend the empirical area to support a wider range of nations with diverse economic characteristics. The study is heavily based on VRP, CoVaR, and particular GARCH-family models (BEKK, DCC); forthcoming research might evaluate the ability of other systemic risk measures including liquidity spreads, credit default swap spreads or macroeconomic sentiment indexes to provide complementary performance as predictors when added to VRP, especially in markets with structural inefficiencies. Granting that the findings indicate improved forecasting in emerging markets, upcoming studies ought to test the strength of VRP-based models in various timeframes and varying economic shocks. Even though the model analysis shows better forecasting abilities and high predictive performance, the analysis does not reveal whether the gains will translate into profitable trading strategies when the transaction costs are factored in. Therefore, impending studies to so consider the economic relevance of these statistical advances through the incorporation of real-world trading frictions and more so in the emerging markets where transaction costs may significantly differ.

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