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Modelling Range Volatility in Currency Bid - Ask Spreads: Implications for Financial Resilience and Sustainable Development in Emerging Market Economies

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Abstract:

This study introduces a novel methodological approach to modelling volatility in currency bid - ask spreads, comparing classical and modern volatility models to assess currency resilience among emerging market economies and categorize them based on relative strength of the estimated parameters. Utilising historical price range data from currency bid–ask spreads, we analyse 27 currencies in the post-global recession period, excluding extraordinary events such as the global oil price plunge in 2014, outbreak of the COVID-19 pandemic and Russia – Ukraine War in 2023. Employing Thomson Reuters daily historical range data, we estimate classical return-based and modern range-based volatility models.

Our results indicate that the range-based volatility model outperforms the return-based standard volatility model in terms of significant estimated parameters and model selection criteria. By leveraging full price range information, the range-based volatility model yields more accurate results. We categorize currencies based on their performance, identifying distinct currency regimes across 27 emerging market economies. This study contributes to the literature by attempting volatility modelling for bid – ask spreads in the currency market. Our findings provide policymakers with a deeper understanding of currency price determination and adjustment, enabling countries to implement safeguard measures to protect their exchange rates from potential volatility spillovers.

Keywords: currency; range; volatility; spillover; GARCH; RGARCH.

JEL Classification: C58, C22, G17.

Introduction

Emerging market economies (EMEs) have become increasingly integral to the global economy, accounting for a substantial share of international trade and investment. However, high currency volatility poses significant challenges to these economies, impacting trade, investment, and economic stability (Ishfaq, 2022; Yıldırım et al., 2022). A stable currency environment is crucial for attracting foreign direct investment, promoting economic development, and supporting infrastructure projects. Moreover, understanding currency volatility is essential for emerging markets engaging with sustainable finance mechanisms, such as Environmental, Social, Governance (ESG) investments.

Financial resilience is critical for EMEs, enabling them to endure external shocks, maintain economic stability, and promote sustainable development. By maintaining a resilient financial system, emerging markets can reduce vulnerability to shocks, improve risk management, increase investor confidence, and support the achievement of sustainable development goals (SDGs). Sustainable development in the context of financial resilience integrates economic, social, and environmental dimensions to foster stability, resilience, and long-term economic development. Ultimately, financial resilience enhances emerging markets' ability to endure shocks, promote sustainable economic growth, and achieve sustainable development (Chen et al., 2020).

Economic policy uncertainty (EPU) significantly impacts currency ask-bid spreads in emerging markets, influencing market dynamics and risk perceptions (Abid, 2020; Muzaffar et al., 2024). EPU increases exchange rate volatility, leading to wider bid-ask spreads, with far-reaching consequences for trade, investment, and economic stability in emerging markets (Fasanya et al., 2021). Historical price range data, which includes open, high, low, and close prices (OHLC data), can provide valuable insights into currency market dynamics, allowing researchers to better understand the impact of EPU on currency ask-bid spreads (Pan et al., 2021).

The relationship between exchange rate volatility and bid-ask spreads in emerging markets is complex and multifaceted. Research has shown that exchange rate volatility has a significant impact on bid-ask spreads, primarily by affecting market liquidity, risk perceptions, and trading behaviours (Henao-Londono et al., 2022). This study aims to contribute to the existing literature on modelling range volatility in currency ask-bid spreads, focusing on emerging market economies. By examining currency market dynamics and the impact of range volatility on ask-bid spreads, this research seeks to provide critical insights that enhance financial resilience in EMEs.

The remainder of this paper is organized as follows. Section 1 provides a comprehensive literature review, covering the existing research on volatility spillover and currency volatility. Section 2 outlines the motivation behind this research, highlighting the gaps in the existing literature. Section 3 presents the objectives of this study, while Section 4 describes the methodology employed. The research findings are presented in Section 5, and the conclusions drawn from the study are discussed in last Section.

1. Literature Review

(a) Literature of Volatility Spillover

Volatility models can be broadly classified into two types: classical volatility models and modern volatility models. Classical volatility models, such as the Autoregressive Conditional

Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models, are widely used to study volatility clustering and autocorrelations among error terms. Engle (1982) contributed the ARCH model, which was further extended and generalized by Bollerslev (1986) to model spillover in prices of an asset. Such classical volatility models consider only close price and ignore other information such as open price, high price, and low price while building its model.

Modern volatility models try to incorporate and utilize full price range information. Empirical evidence suggests that close-to-close return-based volatility models are inaccurate and inefficient, failing to use the information contents inside the reference price range (difference between daily high and low price) of an asset. In contrast, modern volatility models, such as range-based volatility models, incorporate full price range information to extract more information from the unexplained error component (Chou et al., 2010; Fałdziński et al., 2024).

The concept of range volatility has its roots in the work of Mandelbrot (1971), with subsequent academic research on range-based volatility estimators commencing in the 1980s. Parkinson (1980) made a significant contribution by developing a more efficient measure of volatility, which surpassed classical return-based estimators in terms of accuracy. Recent studies have extended range-based volatility models to multivariate frameworks, such as the DCC-CARR model proposed by Chou, Wu, & Liu (2009). Empirical results have shown that range-based DCC models outperform return-based models in estimating and forecasting covariance matrices (Fiszeder et al., 2019). Furthermore, studies have shown that range-based volatility models can capture more information from the price range data compared to return-based models (Molnar, 2016).

(b) Literature on Currency Volatility

The existing literature on currency market volatility is vast and diverse, encompassing a wide range of theoretical and empirical studies. However, this study focuses specifically on the currency market, examining the dynamics of bid-ask spreads and their relationship with volatility. Two primary types of volatility models have emerged in the currency market literature: multivariate stochastic volatility modelling and transaction cost-based bid-ask spread analysis.

Multivariate stochastic volatility models have been widely employed in the currency market literature, providing a flexible framework for modelling the complex dynamics of currency markets. Studies such as Andersen et al. (2001), Alizadeh et al. (2002), and Andersen et al. (2003) have utilized realized volatility to estimate currency market volatility. This approach involves taking the sum of squares and cross-products of intra-day high-frequency returns to estimate volatility. Range volatility models have also been applied in the currency market literature, providing an alternative approach to estimating currency market volatility. Alizadeh et al. (2002) were among the first to utilize range volatility in the context of currency markets. This approach defines range volatility as the difference between the high and low prices of a security.

Transaction costs and market microstructure bias have also been examined in the currency market literature, highlighting the importance of considering the underlying market structure when modelling currency market volatility. Roll (1984) made a seminal contribution to the literature by estimating transaction costs associated with bid-ask spreads. This model has been extended by subsequent researchers; however, no further effort has been made to estimate volatility between bid-ask spreads.

Recent studies have investigated various aspects of financial markets, including exchange rate volatility and bid-ask spreads. For instance, Yıldırım et al. (2022) analysed time-varying volatility spillovers between real exchange rates and real commodity prices in emerging markets, providing new insights into the volatility transmission mechanisms between these variables. The relationship between exchange rate volatility and international trade has also been examined. Lal et al. (2023) found that exchange rate fluctuations have a significant impact on trade flows, shedding light on the complex dynamics between these variables. In addition, research has focused on the determinants of bid-ask spreads in financial markets. Pan & Misra (2021) conducted a comprehensive study on bid-ask spreads in the Indian market, providing a detailed analysis of the factors influencing bid-ask spreads. The behaviour of foreign exchange markets has also been investigated. Henao-Londono & Guhr (2022) examined price responses and spread impacts in foreign exchange markets, providing new insights into the dynamics of these markets. Furthermore, Ishfaq et al. (2022) analysed the behaviour of options volatility and bid-ask spreads around macroeconomic announcements, providing new evidence on the impact of macroeconomic news on foreign exchange market volatility and liquidity. Finally, research has explored the connection between oil prices, global foreign exchange markets, and economic policy uncertainty. Fasanya et al. (2021) found that economic policy uncertainty plays a significant role in the relationship between oil prices and exchange rates, providing new insights into the complex relationships between these variables.

This study aims to address the gap in the literature by modelling volatility spillover in bid-ask spreads of the currency market. By examining the dynamics of bid - ask spreads and their relationship with volatility, this study seeks to provide a more nuanced understanding of currency market volatility. The findings of this study will contribute to the existing literature on currency market volatility, providing valuable insights for policymakers, practitioners, and researchers seeking to better understand the complex dynamics of currency markets.

2. Motivation of this Research

This study is motivated by three primary gaps in the existing literature on volatility modelling. Firstly, despite the established superiority of range volatility models, their application has been predominantly confined to stock markets, with limited extensions to other financial markets, including currency markets. This oversight underscores the need for exploring the efficacy of range volatility models in the context of currency markets.

Secondly, the existing literature has primarily focused on modelling volatility using market clearing prices, which is more relevant to stock and commodity markets. In contrast, this study aims to model volatility on bid-ask spreadsheets, which is more pertinent to currency markets.

Thirdly, the existing literature has largely neglected the impact of economic shocks in large emerging economies on other emerging economies. This study seeks to address this knowledge gap by empirically examining the impact of economic shocks in large emerging economies on other emerging economies, with a specific focus on currency markets.

3. Objectives

The primary objective of this paper is to investigate whether classical volatility models or modern volatility models can effectively capture the volatility of bid - ask spreads in the currency market. Additionally, this study aims to categorize currency bid - ask spreads based on the estimated coefficients of the best-fitted volatility model. This categorization will provide understanding into the underlying currency regime and price adjustment mechanisms in the foreign exchange market, particularly among Emerging Market Economies (EMEs).

The specific objectives of this study are:

- To determine whether the Range Generalized Autoregressive Conditional Heteroskedasticity (RGARCH) model outperforms the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in capturing volatility.
- To investigate whether the estimated coefficients of the RGARCH (1,1) model provide more significant results compared to the GARCH model.
- To categorize countries based on their bid–ask range volatility, providing a framework for understanding the underlying dynamics of currency markets.

4. Methodology

Financial time series data typically consists of open, high, low, and close prices (OHLC data) for a specified time interval. This data is often used to model spillover in prices and volatility using various econometric models. We retrieve historical OHLC daily bid - ask spread of currency spreadsheet consisting of open price, high price, low price and close price from Thomson Reuters DataStream for 27 currencies (standardized in $) viz. Argentina (ARS), Brazil (BRL), Chile (CLP), China (CNY), Colombia (COP), Czech Republic (CZK), Egypt (EGP), Hong Kong (HKD), Hungary (HUF), India (INR), Indonesia (IDR), Korea (KRW), Malaysia (MYR), Mexico (MXN), Pakistan (PKR), Philippines (PHP), Poland (PLN), Qatar (QAR), Russia (RUB), Saudi Arabia (SAR), Singapore (SDG), South Africa (ZAR), Taiwan (TWD), Thailand (THB), Turkey (TRY), United Arab Emirates (AED) and Vietnam (VND).

This study examines the dynamics of 27 currencies from various countries, focusing on the period between January 2016 and September 2019. This timeframe was chosen to provide a relatively stable and calm period, allowing for the isolation of the effects of China's structural rebalancing program on currency dynamics. The period preceding this, marked by the global financial crisis and its aftermath, and the period following, marked by the COVID-19 pandemic and the Russia-Ukraine war, were characterized by extraordinary circumstances and supply-side shocks that profoundly impacted currency rates. By focusing on the chosen timeframe, this study aims to provide a robust analysis of currency dynamics, utilizing daily data to mitigate concerns related to loss of degrees of freedom.

Return and Range

To facilitate the analysis, we perform the following transformations on the selected variables:

- Open-to-Close Return: The open-to-close return is calculated as the logarithmic difference between the closing price and the opening price;
- Open-to-Close Return = log(Close/Open).

This transformation allows us to capture the daily price movements and facilitates the estimation of volatility models.

- The Parkinson (1980) range volatility proxy is calculated as the squared logarithmic difference between the high and low prices, divided by 4 times the logarithm of 2;
- Parkinson Range Volatility Proxy = (log(High/Low))^2 / (4 * log(2)).

This proxy provides a robust estimate of volatility, which is less sensitive to outliers and noise in the data.

Volatility Models

$$\text{GARCH}(1,1) = \omega + \alpha * \text{RETURN}^{\wedge}2(-1) + \beta * \text{GARCH}(-1) \quad (1)$$

$$\text{RGARCH}(1,1) = \omega + \alpha * \text{PARK}(-1) + \beta * \text{GARCH}(-1) \quad (2)$$

We estimate the coefficients of two volatility models: GARCH (1,1) using open-to-close return and RGARCH (1,1) using Parkingson (1980) volatility proxy to capture daily intraday high low fluctuations. The GARCH (1,1) model is a widely used volatility model that captures the clustering and leverage effects in financial time series. The RGARCH (1,1) model is an extension of the GARCH model that incorporates range-based volatility. To evaluate the performance of these models, we employ several model selection criteria, including: Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Criterion (HQC). These criteria provide a quantitative measure of the relative goodness of fit of each model, allowing us to select the best-performing model from Table 1 and Table 2 (see Appendix).

Comparison of estimated Coefficients for α and β

To gain a deeper understanding of the volatility dynamics of the 27 currencies, we conduct a comparison of the ask and bid coefficients for α and β. Specifically, we examine whether the estimated coefficients for ask and bid are greater than, less than, or equal to each other. This comparison allows us to identify patterns and differences in the volatility dynamics of the ask and bid sides of the market. The results of the comparison are presented in Table 3 (see Appendix), which shows the estimated α and β coefficients for ask and bid, as well as the comparison of these coefficients.

Categorization of Currencies

Based on the estimated α and β coefficients for ask and bid respectively, we categorize the currencies into different groups. Specifically, we identify three categories for estimated β: (i) currencies with $\beta_{ask} > \beta_{bid}$, (ii) currencies with $\beta_{ask} < \beta_{bid}$, and (iii) currencies with $\beta_{ask} = \beta_{bid}$ and three categories for estimated α: (i) currencies with $\alpha_{ask} > \alpha_{bid}$, (ii) currencies with $\alpha_{ask} < \alpha_{bid}$, and (iii) currencies with $\alpha_{ask} = \alpha_{bid}$. The results of the categorization are presented in Table 4, which shows the categorization of currencies based on the estimated α and β coefficients for ask and bid.

5. Research Findings

A comprehensive understanding of the data is gained through the conduct of diagnostic tests and descriptive statistics. Descriptive statistics (mean, median, max, min, std dev, skewness, kurtosis, and Jarque-Bera) are calculated for each of the 27 currencies, separately for ask and bid spreads. Graphical representations of open-to-close for each currency are examined. To ensure data suitability for modelling, Augmented Dickey Fuller (ADF) tests are conducted to check for stationarity in each currency, separately for ask and bid spreads.

Model Estimation and Comparison

The GARCH (1,1) and RGARCH (1,1) models are estimated to address the first research objective. The performance of these models is compared using three model selection criteria: Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HQC). The results, presented in Tables 1 and 2, indicate that the RGARCH (1,1) model outperforms the GARCH (1,1) model across all 27 currencies. The estimated α coefficient is examined to address the second research objective. The results show that the estimated α coefficient is consistently higher for the RGARCH (1,1) model.

The estimated α and β coefficients for the RGARCH (1,1) model are examined. The results indicate that these coefficients are statistically significant, suggesting that the RGARCH (1,1) model is an appropriate specification. The estimated α and β coefficients are compared between bid and ask spreads for each currency to address the third research objective. The results, presented in Table 3, show that these coefficients differ significantly between bid and ask spreads. A categorization matrix, presented in Table 4, is used to further analyse the differences in volatility dynamics between bid and ask spreads. This matrix allows for the identification of different currency regimes or price adjustment mechanisms for each currency.

An analysis of the categorization matrix reveals three possibilities for the estimated α coefficient: (i) Bid > Ask, indicating demand-driven intraday fluctuations; (ii) Bid = Ask, indicating demand-supply neutral intraday fluctuations; and (iii) Bid < Ask, indicating supply-driven intraday fluctuations. Similarly, three possibilities are observed for the estimated β coefficient: (i) Bid > Ask, indicating demand-driven variability; (ii) Bid = Ask, indicating demand-supply neutral variability; and (iii) Bid < Ask, indicating supply-driven variability.

The findings suggest that both systematic and non-systematic patterns exist among currency fluctuations from Emerging Market Economies (EMEs). For instance, a systematic pattern is observed for China, India, and South Africa, whereas Brazil and Russia exhibit non-systematic patterns. The observed patterns can be attributed to the differing market structures and economic conditions of each country.

The empirical observations reveal that the estimated α and β coefficients differ significantly between the ask and bid sides of the market for most currencies. The differences in the estimated coefficients can be attributed to the varying levels of market liquidity, trading activity, and economic conditions across currencies.

The categorization of currencies based on the estimated α and β coefficients provides valuable insights into the underlying market dynamics. For example, currencies such as the Chinese renminbi (CNY) and the Indian rupee (INR) exhibit demand-driven fluctuation, whereas currencies such as the Brazilian real (BRL) and the Russian rubble (RUB) exhibit supply-driven fluctuation. These findings have significant implications for investors, policymakers, and researchers seeking to understand the complex dynamics of currency markets. Empirical observations are made for the remaining 22 currencies, revealing distinct patterns in demand-driven variability and fluctuation. It is observed that:

- Demand-driven variability and demand-supply neutral fluctuation are exhibited by Argentina (ARS), Poland (PLN), and Egypt (EGP), likely due to the relatively stable economic conditions and market structures in these countries.
- Demand-driven variability and supply-driven intraday fluctuations are exhibited by Hong Kong (HKD), Indonesia (IDR), Saudi Arabia (SAR), Malaysia (MYR), and United

Arab Emirates (AED), possibly resulting from the high trading activity and market liquidity in these countries.

- Neutrality for both demand-supply variability and intraday fluctuation is exhibited by Korea (KRW), Singapore (SDG), South Africa (ZAR), India (INR), Thailand (THB), and Mexico (MXN), which may be attributed to the balanced market conditions and economic stability in these countries.
- Supply-driven volatility and demand-driven intraday fluctuations are exhibited by Taiwan (TWD), Colombia (COP), Turkey (TRY), Philippines (PHP), Qatar (QAR), Chile (CLP), Czech Republic (CZK), and Pakistan (PKR), potentially resulting from the relatively high market volatility and economic uncertainty in these countries.
- Supply-driven volatility and demand-supply neutral intraday fluctuations are exhibited by Vietnam (VND) and Hungary (HUF), which may be due to the relatively stable market conditions and economic growth in these countries.

Table 4: Categorization matrix between bid – ask spread based on estimated α and β coefficient

Tranche	$\alpha_{Bid} > \alpha_{Ask}$ (Demand driven fluctuation)	$\alpha_{Bid} = \alpha_{Ask}$ (Demand Supply neutral fluctuation)	$\alpha_{Bid} < \alpha_{Ask}$ (Supply driven fluctuation)
$\beta_{Bid} > \beta_{Ask}$ (Demand driven variability)	*China (CNY)*	Argentina (ARS) Poland (PLN) Egypt (EGP)	Hong Kong (HKD) *Brazil (BRL)* Indonesia (IDR) Saudi Arabia (SAR) Malaysia (MYR) United Arab Emirates (AED)
$\beta_{Bid} = \beta_{Ask}$ (Demand Supply neutral variability)		Korea (KRW) Singapore (SDG) *South Africa (ZAR)* *India (INR)* Thailand (THB) Mexico (MXN)	
$\beta_{Bid} < \beta_{Ask}$ (Supply driven variability)	Taiwan (TWD) Colombia (COP) Turkey (TRY) Philippines (PHP) Qatar (QAR) Chile (CLP) Czech Republic (CZK) Pakistan (PKR) *Russia (RUB)*	Vietnam (VND) Hungary (HUF)	

Source: Authors calculation based on Thomson Reuter DataStream data.

Conclusion

This study contributes to the existing literature on currency market volatility by developing new methodological aspects of modelling volatility in currency bid-ask spreads. Empirical results suggest that the RGARCH (1,1) model outperforms the GARCH (1,1) model across all 27 currencies, separately for both bid spread and ask spread. The estimated α coefficient is consistently higher for the RGARCH (1,1) model compared to the GARCH (1,1) model, indicating that the RGARCH (1,1) model is better equipped to capture the volatility clustering and leverage effects in the data.

Systematic and non-systematic patterns among currency fluctuations from Emerging Market Economies (EMEs) and BRICS are revealed through analysis. It is found that China, India, and South Africa follow a systematic pattern, whereas Brazil and Russia follow a non-systematic pattern. Furthermore, analysis of the remaining 22 currencies of EMEs reveals that 4 currencies (Korea, Singapore, Thailand, and Mexico) follow a symmetric pattern, while the remaining 18 currencies follow a non-symmetric pattern.

The findings of this study have important implications for policymakers, practitioners, and researchers seeking to better understand the complex dynamics of currency markets. It is suggested that the RGARCH (1,1) model is a more appropriate specification for modelling currency market volatility, particularly in the context of EMEs and BRICS. The importance of considering the underlying market structure and volatility dynamics when modelling currency market volatility is also highlighted.

Future research directions are identified, including carrying out in-depth analysis to identify other factors that influence currency volatility, as well as exploring the possibility of synergy among sets of currencies among BRICS and next BRICS. Additionally, multivariate models or spillover models, such as DCC - CARR or DCC - RGARCH, can be employed to examine the possibility of volatility spillover and its direction from one currency to another.

Credit Authorship Contribution Statement

The corresponding author takes full responsibility for this research paper, encompassing all aspects of the project, including conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, supervision, validation, visualization, and writing under the guidance and overall supervision of the second author. This includes originating the research idea, collecting, and analysing data, overseeing the project timeline and resources, and composing and revising the manuscript for publication. This preliminary study aims to comprehend the existing dynamics of the currency market, serving as a foundational precursor to inform the selection of respective sub-samples for the subsequent PhD chapter of the first author.

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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APPENDIX: Table 1: Estimated coefficients of GARCH (1,1) and RGARCH (1,1) for Currency Bid Spread for 27 emerging economies currency

Currency	Country	GARCH (1,1)						RGARCH (1,1)					
		ω	α	β	AIC	SIC	HQC	ω	α	β	AIC	SIC	HQC
CNY	China	0.487249	-0.011388	0.518431	2.844713	2.865964	2.852829	7.87E-07***	0.394843***	0.552647***	-9.446461	-9.430509	-9.440368
HKD	Hong Kong	0.488873	-0.009837	0.520044	2.844343	2.864622	2.852066	-3.08E-10***	0.063239***	0.931042***	-13.09501	-13.07979	-13.08921
KRW	Korea	0.485271	-0.014721	0.516475	2.846562	2.866824	2.854278	-5.90E-08	0.039007***	0.961310***	-7.692090	-7.676881	-7.686298
SGD	Singapore	0.485141	-0.014815	0.516322	2.846538	2.866800	2.854254	1.03E-09	0.039313***	0.956572***	-8.866394	-8.851185	-8.860602
BRL	Brazil	0.485055	-0.014888	0.516235	2.846632	2.867063	2.854416	5.32E-05***	0.530314***	-0.046468	-6.522529	-6.507192	-6.516685
TWD	Taiwan	0.488380	-0.008382	0.519248	2.841632	2.861827	2.849321	2.27E-07*	0.164323***	0.719139***	-8.859258	-8.844099	-8.853486
ZAR	South Africa	0.485187	-0.014786	0.516376	2.846544	2.866807	2.854260	1.28E-06	0.025847**	0.959707***	-6.256199	-6.240990	-6.250407
INR	India	0.484985	-0.014950	0.516143	2.846568	2.866914	2.854318	7.74E-07***	0.198011***	0.730075***	-8.858805	-8.843532	-8.852987
IDR	Indonesia	0.440320	0.063211	0.478081	2.805126	2.826659	2.813356	2.75E-07***	0.260704***	0.754211***	-9.196754	-9.180589	-9.190575
SAR	Saudi Arabia	0.075147	0.066128	0.855172**	2.795178	2.812306	2.801634	2.39E-10***	0.112393***	0.755887***	-15.65285	-15.63999	-15.64800
THB	Thailand	0.488195	-0.009800	0.519214	2.843043	2.863305	2.850759	-5.51E-08	0.041305***	0.953025***	-8.955241	-8.940032	-8.949449
MXN	Mexico	0.483219	-0.016304	0.514150	2.846303	2.866565	2.854019	6.47E-06***	0.239742***	0.674507***	-6.833660	-6.818451	-6.827868
MYR	Malaysia	0.489627	-0.008824	0.520789	2.843693	2.865074	2.851862	1.92E-07***	0.209163***	0.788677***	-9.187557	-9.171506	-9.181424
COP	Colombia	0.485283	-0.014706	0.516486	2.846582	2.866894	2.854318	3.01E-06***	0.157645***	0.814864***	-6.889990	-6.874743	-6.884183
TRY	Turkey	0.488779	-0.008070	0.519771	2.842148	2.862410	2.849864	1.83E-05***	0.438751***	0.383658***	-6.487472	-6.472263	-6.481680
ARS	Argentina	0.458542	0.033163	0.494371	2.815573	2.835920	2.823323	4.55E-07**	0.451188***	0.718785***	-6.483994	-6.468722	-6.478177
PHP	Philippines	0.485019	-0.014925	0.516188	2.846543	2.866822	2.854266	2.38E-06***	0.114583***	0.612753***	-8.697497	-8.682275	-8.691700
PLN	Poland	0.485233	-0.014753	0.516434	2.846570	2.866849	2.854293	1.16E-06	0.078453***	0.879661***	-7.462031	-7.446809	-7.456234
QAR	Qatar	0.486356	-0.011064	0.517360	2.841309	2.857675	2.847461	6.53E-10***	0.135555***	0.741289***	-11.17055	-11.15826	-11.16593
CLP	Chile	0.485328	-0.014670	0.516537	2.846579	2.866875	2.854309	1.66E-06*	0.110344***	0.849273***	-7.436072	-7.420837	-7.430270
CZK	Czechia	0.485319	-0.014679	0.516528	2.846563	2.866825	2.854279	2.76E-05***	0.104220**	-0.255171	-7.783174	-7.767965	-7.777382
PKR	Pakistan	0.489050	-0.008247	0.519844	2.841729	2.861793	2.849365	1.66E-07***	0.531336***	0.607546***	-8.704340	-8.689280	-8.698608
EGP	Egypt	0.481212	-0.017125	0.513720	2.842302	2.861256	2.849490	7.15E-06***	0.000224	0.975893***	-5.276352	-5.262126	-5.270956
AED	UAE	0.018037	0.041153	0.939362***	2.760820	2.778401	2.767457	-8.53E-11*	0.053206***	0.855877***	-16.15682	-16.14363	-16.15184
VND	Vietnam	0.032179	0.072581	0.893531***	2.761289	2.782032	2.769199	1.77E-08***	0.418793***	0.567634***	-11.50782	-11.49225	-11.50188
HUF	Hungary	0.483936	-0.015805	0.514958	2.846429	2.866708	2.854152	2.14E-06	0.034843**	0.888657***	-7.538425	-7.523203	-7.532628
RUB	Russia	0.485159	-0.014803	0.516347	2.846526	2.866755	2.854228	5.99E-06***	0.231641***	0.672285***	-6.866730	-6.851546	-6.860948

Note: *** , ** and * represents 1%, 5% and 10 level of significance respectively. Source*:* Authors calculation based on Thomson Reuter DataStream data.

APPENDIX: Table 2: Estimated coefficients of GARCH (1,1) and RGARCH (1,1) for Currency Ask Spread for 27 emerging economies currency

Currency	Country	GARCH (1,1)						RGARCH(1,1)					
		ω	α	β	AIC	SIC	HQC	ω	α	β	AIC	SIC	HQC
CNY	China	0.488583	-0.012235	0.520150	2.839926	2.861177	2.848042	2.43E-06***	0.150904***	0.414883**	-9.320652	-9.304700	-9.314560
HKD	Hong Kong	-9.320652	-9.304700	-9.314560	2.846491	2.866770	2.854214	-1.71E-10	0.659257***	0.414362***	-13.24494	-13.22972	-13.23915
KRW	Korea	0.485298	-0.014698	0.516505	2.846563	2.866826	2.854279	-9.61E-08	0.042106***	0.957625***	-7.692761	-7.677552	-7.686969
SGD	Singapore	0.485313	-0.014680	0.516519	2.846559	2.866821	2.854274	8.28E-09	0.040171	0.956030	-8.866683	-8.851474	-8.860891
BRL	Brazil	0.485011	-0.014922	0.516185	2.846628	2.867059	2.854412	5.46E-05***	0.542871***	-0.071980	-6.523090	-6.507754	-6.517247
TWD	Taiwan	0.484463	-0.015363	0.515547	2.846428	2.866624	2.854117	1.21E-07	0.140675***	0.764876***	-8.855890	-8.840731	-8.850118
ZAR	South Africa	0.485199	-0.014776	0.516390	2.846547	2.866809	2.854263	1.36E-06	0.027669***	0.956866***	-6.264545	-6.249336	-6.258753
INR	India	0.484474	-0.015377	0.515574	2.846542	2.866888	2.854292	7.80E-07***	0.201899***	0.725119***	-8.857618	-8.842346	-8.851801
IDR	Indonesia	0.205870	0.079936	0.708818	2.821433	2.842967	2.829664	5.23E-07***	0.432198***	0.604439***	-9.167573	-9.151409	-9.161395
SAR	Saudi Arabia	0.079680	0.128293**	0.786550***	2.771265	2.788393	2.777721	8.33E-11**	0.212394***	0.651065***	-15.63895	-15.62610	-15.63411
THB	Thailand	0.488277	-0.009630	0.519260	2.842872	2.863135	2.850588	-5.00E-08	0.043695***	0.948943***	-8.944639	-8.929430	-8.938847
MXN	Mexico	0.482874	-0.016548	0.513757	2.846233	2.866495	2.853949	6.49E-06***	0.238935***	0.671893***	-6.839448	-6.824239	-6.833656
MYR	Malaysia	0.484368	-0.015492	0.515409	2.847009	2.868391	2.855178	4.54E-07***	0.504841***	0.537595***	-9.138696	-9.122646	-9.132564
COP	Colombia	0.483353	-0.016237	0.514271	2.846316	2.866629	2.854052	9.05E-07	0.013078	0.974144***	-6.779393	-6.764146	-6.773586
TRY	Turkey	0.488767	-0.008907	0.519948	2.842103	2.862365	2.849819	5.27E-06***	0.142542***	0.804514***	-6.330582	-6.315373	-6.324790
ARS	Argentina	0.481918	-0.017105	0.512712	2.845854	2.866200	2.853603	9.31E-05***	0.455046***	-0.079652	-6.152116	-6.136844	-6.146299
PHP	Philippines	0.488841	-0.008373	0.519714	2.842206	2.862485	2.849929	2.22E-06**	0.086584**	0.672069***	-8.663769	-8.648548	-8.657972
PLN	Poland	0.484699	-0.015178	0.515814	2.846486	2.866748	2.854202	1.50E-06**	0.082802***	0.862928***	-7.456679	-7.441470	-7.450887
QAR	Qatar	0.446072	0.075503	0.475309	2.837268	2.853634	2.843419	1.84E-09***	0.091023***	0.831332***	-10.21471	-10.20243	-10.21010
CLP	Chile	0.485229	-0.014759	0.516426	2.846576	2.866872	2.854305	1.37E-06*	0.095867***	0.870360***	-7.432262	-7.417027	-7.426459
CZK	Czechia	0.483420	-0.016149	0.514351	2.846319	2.866581	2.854035	1.08E-07	0.011850***	0.980059***	-7.788271	-7.773062	-7.782479
PKR	Pakistan	0.027090	0.114755	0.855710***	2.758046	2.778109	2.765681	4.00E-09***	0.006929***	0.999403***	-8.287134	-8.272074	-8.281402
EGP	Egypt	0.483617	-0.015879	0.514937	2.845124	2.864078	2.852313	0.000372	-0.003243***	0.170998	-5.041517	-5.027291	-5.036122
AED	UAE	0.018285	0.046069	0.932197***	2.702574	2.720155	2.709211	1.09E-09***	0.060291***	0.642328***	-16.18154	-16.16835	-16.17656
VND	Vietnam	0.034715	0.095998	0.867570***	2.786236	2.806980	2.794147	4.81E-09***	0.418839***	0.635194***	-11.42021	-11.40464	-11.41428
HUF	Hungary	0.485217	-0.014765	0.516411	2.846554	2.866816	2.854270	1.93E-06	0.034373**	0.894009***	-7.544269	-7.529060	-7.538477
RUB	Russia	0.484025	-0.015703	0.515062	2.846394	2.866623	2.854097	5.35E-06***	0.215415***	0.698376***	-6.855320	-6.840136	-6.849539

Note: ***, ** and * represents 1%, 5% and 10 level of significance respectively *Source:* Authors calculation based on Thomson Reuter DataStream data.

APPENDIX: Table 3: RGARCH Coefficient Comparison between Currency Bid and Currency Ask Spreadsheet

Currency	Country	Currency Bid			Currency Ask			Comparison of α between Bid & Ask	Comparison of β between Bid & Ask
		ω	α	β	Ω	α	β		
CNY	China	7.87E-07***	0.394843***	0.552647***	2.43E-06***	0.150904***	0.414883**	Bid > Ask	Bid > Ask
HKD	Hong Kong	-3.08E-10***	0.063239***	0.931042***	-1.71E-10	0.659257***	0.414362***	Bid < Ask	Bid > Ask
KRW	Korea	-5.90E-08	0.039007***	0.961310***	-9.61E-08	0.042106***	0.957625***	Bid = Ask	Bid = Ask
SGD	Singapore	1.03E-09	0.039313***	0.956572***	8.28E-09	0.040171	0.956030	Bid = Ask	Bid = Ask
BRL	Brazil	5.32E-05***	0.530314***	-0.046468	5.46E-05***	0.542871***	-0.071980	Bid < Ask	Bid > Ask
TWD	Taiwan	2.27E-07*	0.164323***	0.719139***	1.21E-07	0.140675***	0.764876***	Bid > Ask	Bid < Ask
ZAR	South Africa	1.28E-06	0.025847**	0.959707***	1.36E-06	0.027669***	0.956866***	Bid = Ask	Bid = Ask
INR	India	7.74E-07***	0.198011***	0.730075***	7.80E-07***	0.201899***	0.725119***	Bid = Ask	Bid = Ask
IDR	Indonesia	2.75E-07***	0.260704***	0.754211***	5.23E-07***	0.432198***	0.604439***	Bid < Ask	Bid > Ask
SAR	Saudi Arabia	2.39E-10***	0.112393***	0.755887***	8.33E-11**	0.212394***	0.651065***	Bid < Ask	Bid > Ask
THB	Thailand	-5.51E-08	0.041305***	0.953025***	-5.00E-08	0.043695***	0.948943***	Bid = Ask	Bid = Ask
MXN	Mexico	6.47E-06***	0.239742***	0.674507***	6.49E-06***	0.238935***	0.671893***	Bid = Ask	Bid = Ask
MYR	Malaysia	1.92E-07***	0.209163***	0.788677***	4.54E-07***	0.504841***	0.537595***	Bid < Ask	Bid > Ask
COP	Colombia	3.01E-06***	0.157645***	0.814864***	9.05E-07	0.013078	0.974144***	Bid > Ask	Bid < Ask
TRY	Turkey	1.83E-05***	0.438751***	0.383658***	5.27E-06***	0.142542***	0.804514***	Bid > Ask	Bid < Ask
ARS	Argentina	4.55E-07**	0.451188***	0.718785***	9.31E-05***	0.455046***	-0.079652	Bid = Ask	Bid > Ask
PHP	Philippines	2.38E-06***	0.114583***	0.612753***	2.22E-06**	0.086584**	0.672069***	Bid > Ask	Bid < Ask
PLN	Poland	1.16E-06	0.078453***	0.879661***	1.50E-06**	0.082802***	0.862928***	Bid = Ask	Bid > Ask
QAR	Qatar	6.53E-10***	0.135555***	0.741289***	1.84E-09***	0.091023***	0.831332***	Bid > Ask	Bid < Ask
CLP	Chile	1.66E-06*	0.110344***	0.849273***	1.37E-06*	0.095867***	0.870360***	Bid > Ask	Bid < Ask
CZK	Czechia	2.76E-05***	0.104220**	-0.255171	1.08E-07	0.011850***	0.980059***	Bid < Ask	Bid > Ask
PKR	Pakistan	1.66E-07***	0.531336***	0.607546***	4.00E-09***	0.006929***	0.999403***	Bid < Ask	Bid > Ask
EGP	Egypt	7.15E-06***	0.000224	0.975893***	0.000372	-0.003243***	0.170998	Bid > Ask	Bid = Ask
AED	UAE	-8.53E-11*	0.053206***	0.855877***	1.09E-09***	0.060291***	0.642328***	Bid > Ask	Bid < Ask
VND	Vietnam	1.77E-08***	0.418793***	0.567634***	4.81E-09***	0.418839***	0.635194***	Bid < Ask	Bid = Ask
HUF	Hungary	2.14E-06	0.034843**	0.888657***	1.93E-06	0.034373**	0.894009***	Bid < Ask	Bid = Ask
RUB	Russia	5.99E-06***	0.231641***	0.672285***	5.35E-06***	0.215415***	0.698376***	Bid < Ask	Bid > Ask

Note: *** , ** and * represents 1%, 5% and 10 level of significance respectively *Source:* Authors calculation based on Thomson Reuter DataStream data.