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Hedge Ratio and Hedging Effectiveness in Indian Currency Futures Markets

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ABSTRACT

The **purpose** of the study is to assess the efficacy of diverse hedge ratios computed **using** three econometric models: OLS, VECM, and BEKK-GARCH model. This investigation centres on minimizing variance for the USD/INR currency pair within the Indian currency market, specifically during two distinct periods: the pre-COVID era and the COVID-19 era. Out-of-sample comparisons are conducted using the last 10 days of observations for both phases. The **results** of in- and out-of-sample evaluations demonstrate that the hedge approach established on OLS model outperforms alternative models in both periods. These **findings** offer valuable insights for investors, aiding in the enhancement of risk management strategies and informed decision-making with the objective of minimizing portfolio volatility and maximizing long-term returns.

Keywords: hedge ratio; hedging effectiveness; Indian currency futures markets; OLS; VECM; BEKK-GARCH model

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INTRODUCTION

Companies use currency hedges to safeguard their finances from changes in exchange rates. This results in getting involved in the derivatives market and using different strategies and financial tools to protect themselves from the risks of foreign exchange (forex) fluctuations. Companies use currency hedges to safeguard their finances from changes in exchange rates. This result in getting involved in the derivatives market and using different strategies and financial tools to protect themselves from the risks of foreign exchange (forex) fluctuations. According to International Accounting Standards (IAS), a hedge is considered effective when alterations in the hedging instrument's revenue stream counteract variations in the hedged item's flow of cash. Therefore, treasurers of firms have to implement an effective hedging strategy to minimize exposure to exchange rate fluctuations. The increasing exposure of Indian companies to currency fluctuations, particularly the Indian Rupee (INR) against major world currencies such as the US Dollar (USD), Japanese Yen (JPY), Great Britain Pound (GBP), and EURO, is evident in *Fig. 1*, depicting the fluctuation of these currencies against the INR over the years. These fluctuations are attributed to factors such as an erratic inflow of foreign institutional investors (FII) and foreign direct investment (FDI), an unmanageable budget deficit, and a large trade imbalance. The Reserve Bank of India (RBI), in its 2012 Financial Stability Report, highlighted that those drastic swings in exchange rates complicate optimal business decision-making. Therefore, firms are encouraged to comprehend, and assess, as well as address embedded cash risks in their operations by employing suitable derivative instruments.

The RBI has taken steps to make the Indian foreign exchange market stronger. In 2015, they introduced cross-currency futures contracts and options as tools to help reduce the risks associated with forex exposure. In 2016, the RBI clarified hedging instructions for external commercial borrowings (ECBs), offering foreign companies a framework for managing forex risks. Multinational companies (MNCs) dealing with foreign exchange risks in India were granted flexibility in operations by the RBI in March 2017, and resident entities are able to simplify their FX hedging through approved banks. Alongside these modifications, the RBI and the Institute of Chartered Accountants of India (ICAI) unveiled Ind-AS, a revised accounting standard that will be required of all businesses starting in the 2016–2017 fiscal year. These standards, aligning with international accounting norms, necessitate companies to promptly conduct a hedging effectiveness test upon assuming a hedging position, followed by periodic reviews. The underlying philosophy is that securing coverage for financial exposure is insufficient, emphasizing the need for a systematic assessment of hedging strategy effectiveness. The standards mandate a comprehensive evaluation encompassing both qualitative and quantitative methods, leaving the specific quantitative approach to the discretion of each company in line with its risk management policies. In this evolving landscape of currency risk hedging, the lack of a precise quantitative method to gauge hedge efficacy underscores the importance of identifying a reliable method. Additionally, given the rising utilization of futures contracts as hedging instruments, understanding futures' efficacy as a hedge in controlling the risk of currencies becomes a pertinent consideration.

LITERATURE REVIEW

Numerous researches delved into the hedge ratio estimation and its effectiveness in the derivatives market. The literature features a range of static and dynamic models applied to calculate hedge ratios, highlighting different methodological approaches. Lien et al. [1] estimated the hedge ratios employing static OLS and a dynamic VGARCH model and found that the static model exhibited superior performance. Kenourgios et al. [2] assessed hedge effectiveness through various methods, indicating that the VECM method was most suitable for determining optimal hedge ratios (OHR). Bhaduri and Durai [3] investigated the effectiveness of hedge ratios across long- and short-term horizons, finding that dynamic GARCH performed better for longer time horizons. At the same time, the static OLS model was more effective for reduced temporal spans. Lai et al. [4], Czekierda and Zhang [5], and Fan [6] showed that the static OLS model outperformed the dynamic bivariate GARCH model. Wen et al. [7] found that the OLS hedge ratio reduced the most significant variance in the Chinese Index futures market. Similarly, Cotter and Hanly [8] explored short and long hedges in the spot and futures markets and showed that the OLS hedge outperformed the dynamic models. Moreover, Betancourt and Azzawi [9], Awang et al. [10] and Sahoo [11] contrasted OLS with BEKK and diagonal VECH models and found that the effectiveness of static models is superior. Kaur and Gupta [12] highlighted the superiority of constant hedge ratio models over time-varying models in the Indian currency futures market. Sharma and Karmakar [13] found that traditional regression models outperform GARCH-based models for hedging effectiveness across the various financial and non-financial assets of different countries. Similarly, Corbet et al [14] suggested that static models offered more stable hedge ratios than dynamic models with increased market volatility in CSI300 index futures.

Fig. 1. **Performance of INR to other Major Currencies over a Period of 5 Years**

Source: URL: https://www.google.com/finance/quote/USD-INR?comparison=EUR-INR, JPY-INR, GBP-INR&window=5Y (accessed on 09.01.2025).

In contrast, Yang and Allen [15], Casillo [16] and Choudhry [17] assessed hedge ratios employing various constant models, including OLS, VAR, VECM, and a dynamic multivariate GARCH model. The authors found that the dynamic model surpassed the OLS model. Floros and Vougas [18] and Kumar et al. [19] compared static and dynamic models and found that M-GARCH is superior in reducing variance. Yang and Pavlov [20] compared OLS, VAR, VECM and VAR-MGARCH models and showed that VAR-GARCH model yielded superior outcomes. Jampala [21] and Gupta et al. [22] found that dynamic hedging with VECM and BEKK is better regarding both mean return and variance reduction in the Indian commodity futures market. Singh [23] demonstrated the portfolio variance reduction with OLS and EGARCH models on NSE indices. Kharbanda and Singh [24] showed that the CCC–MGARCH model better-evaluated hedge effectiveness in the currency futures market. Buyukkara et al. [25] concluded that the dynamic GARCH model significantly outperformed the static OLS model in variance reduction in the Turkish foreign exchange market. Despite extensive research on hedge ratio estimation and effectiveness, no clear consensus exists on whether static or dynamic models perform better. Studies show mixed results regarding the effectiveness of different models across asset classes, time horizons, and market conditions. Moreover, the impact of major economic disruptions, viz. COVID-19 on hedging performance, remains under explored, particularly in the Indian currency market. Analyzing intraday hedging effectiveness using real-time data in the USD/INR foreign exchange market will be immensely helpful to investors and regulators due to the changing structure and increased participation. The present study throws light on evaluating the efficacy of OLS, VECM, and BEKK-GARCH models for the USD/INR currency pair across pre-COVID and COVID-19 periods.

METHODOLOGY

This research examines 1-minute real-time data of futures and spot prices for USD/INR on NSE in India. The time-series data is divided into two distinct periods: the pre-COVID-19 Phase (August 1, 2019, to January 24, 2020) and the COVID-19 Phase (January 25, 2020, to August 31, 2020). Specifically, the last ten days' observations for each period are used to conduct a comparison of an out-of-sample hedge ratio productivity. Tick-by-tick information for these prices are acquired from Accelpix Solutions Pvt. Ltd., an NSE Authorized Vendor in Equity, Index, Futures, and Options.

Model 1: The traditional regression technique

The study uses a conventional method to compute the one-period Minimum Variance Hedge Ratio (MVHR) by utilizing a linear regression analysis to assess fluctuations in spot prices against alterations in futures prices. The formula for determining the one-period MVHR is expressed as follows:

$$\Delta S_t = \alpha + \beta \Delta F_t + \varepsilon_t. \qquad (1)$$

In the context of OLS estimation, the error term is denoted as ε_t. Additionally, ΔS_t signifies the alterations in spot prices, while ΔF_t represents the adjustments in futures prices within currency markets. The coefficient β corresponds to the estimated OHR.

Model 2: The Vector Error Correction Model

This model calculates the hedging ratio to manage non-stationary level series of integrated futures and spot prices at level one.

$$r_{st} = \alpha_s + \sum_{i=1}^{m} \beta_{si} r_{st-i} + \sum_{j=1}^{n} \gamma_{si} r_{ft-i} + \lambda_s Z_{t-1} + \varepsilon_{st}, \qquad (2)$$

$$r_{ft} = \alpha_f + \sum_{i=1}^{m} \beta_{fi} r_{st-i} + \sum_{j=1}^{n} \gamma_{fi} r_{ft-i} + \lambda_f Z_{t-1} + \varepsilon_{ft}. \qquad (3)$$

In the context where the error correction term is represented as $Z_{t-1} = S_{t-1} - \delta F_{t-1}$, with $(1-\delta)$ serving as the cointegrating vector, and adjusting parameters denoted as λ_s and λ_f. Upon estimating the equation, the residuals are generated for vecm $(\varepsilon_{st}) = \sigma_s$, vecm $(\varepsilon_{ft}) = \sigma_f$, and cov $(\varepsilon_{st}, \varepsilon_{ft}) = \sigma_{sf}$. Consequently, the minimum hedge ratio h^* is calculated as $\frac{\sigma_{sf}}{\sigma_f}$.

Model 3: The BEKK-GARCH Model

Traditional models assume constant variances and covariances of residuals, while GARCH models consider that conditional variance is influenced by past values and squared innovations. M-GARCH models, widely used for forecasting MVHRs, have shown efficacy in capturing complexities in financial time series Harris et al [26]. Studies Kroner and

Sultan [27] and Myers [28] have extensively employed M-GARCH models for this purpose. The dynamic hedging ratios, influenced by conditional variability and covariance, are established by these models. In our study, the BEKK-GACRH model was used to determine the hedge ratio.

$$\begin{bmatrix} h_{ss,t} \\ h_{sf,t} \\ h_{ff,t} \end{bmatrix} = \begin{bmatrix} c_{ss,t} \\ c_{sf,t} \\ c_{ff,t} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{s,t\text{-}1} \\ \varepsilon_{s,t-1}, \varepsilon_{f,t-1} \\ \varepsilon^2_{f,t-1} \end{bmatrix} + \\ + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} h_{ss,t\text{-}1} \\ h_{sf,t\text{-}1} \\ h_{ff,t\text{-}1} \end{bmatrix}.$$

The revised model, denoted by h_{ss} and h_{ff} represents the conditional variance of errors for spot and futures market returns at the same time.It includes mean equations errors ($\varepsilon_{st}, \varepsilon_{ft}$), and incorporates variability over time through matrices α and β. The diagonal elements of h_{ss} and h_{ff} and the covariance element h_{sf} are mathematicallydepicted as:

$$h_{ss,t} = c_{ss} + \alpha_{11}\varepsilon^2_{s,t\text{-}1} + \beta_{11} h_{ss,t\text{-}1}, \quad (4)$$

$$h_{sf,t} = c_{sf} + \alpha_{22}\varepsilon_{s,t\text{-}1}\varepsilon_{f,t\text{-}1} + \beta_{22} h_{sf,t\text{-}1}, \quad (5)$$

$$h_{ff,t} = c_{ff} + \alpha_{33}\varepsilon^2_{ft\text{-}1} + \beta_{33} h_{ff,t\text{-}1}. \quad (6)$$

Additionally, h_{sf} signifies the conditional covariance between spot and futures market returns at time t. The ratio of $h_{sf,t}$ to $h_{ff,t}$ expresses the covariance of spot and futures prices relative to the variance of futures prices, providing a measure of time-varying hedge ratio. This method offers a more precise representation of the dynamic changes in the hedging ratio over time.

Estimating Effectiveness of Hedging

To assess hedging methods, we measured efficiency by creating two portfolios: one without hedging and another using a mix of futures and spot contracts. Variance reduction between unhedged and hedged portfolios was compared to gauge the success of the hedging approach. Portfolio returns can be summarized as follows.

$$R_{unhedged} = S_{t+1} - S_t, \quad (7)$$

$$R_{hedged} = (S_{t+1} - S_t) - h^*(F_{t+1} - F_t). \quad (8)$$

The variable R_{hedged} signifies the returns on a hedged portfolio, while $R_{unhedged}$ represents the returns on an unhedged portfolio. S_t and F_t indicates the natural logarithm of spot and futures prices at time t. OHR is denoted by h^*. Additionally, the variances of the hedged and unhedged portfolios are articulated below:

$$Var_{unhedged} = \sigma^2_s, \quad (9)$$

$$Var_{hedged} = \sigma^2_s + h^{*2}\sigma^2_f - 2h^*\sigma_{sf}. \quad (10)$$

Evaluate hedging effectiveness by comparing variances of hedged (Var_{hedged}) and unhedged ($Var_{unhedged}$) portfolios. Standard deviations of futures and spot prices, along with their covariance, determine these variances. This aligns with Ederington's 1979 methodology. The percentage decrease in variance indicates the efficacy of the hedge, calculated through the formula below.

$$Hedging\ Effectiveness = 1 - \frac{Var_{hedged}}{Var_{unhedged}}. \quad (11)$$

Hedged portfolio exhibits lower volatility compared to unhedged, showcasing risk reduction. Hedge Efficiency (HE) of 1 indicates complete variance reduction, while HE of 0 implies ineffective risk mitigation. Higher HE signifies superior hedging performance. This study evaluates hedge ratio and its effectiveness in both in- and out-of-sample time frames.

RESULTS AND ANALYSIS

Descriptive Statistics

Table 1 displays the time series' descriptive data. Average values of futures and spot returns, expressed as percentages, are reported. Both the mean returns and standard deviations exhibit proximity to zero in both phases. Notably, the positive skewness values suggest a positive skew in both returns, while the elevated kurtosis values indicate fat-tailed distributions for both return series.

Unit Root and CointegrationTests

KPSS Unit Root Test Results

Table 2 presents the results of the KPSS test, which examines the null hypothesisof no unit root. The critical values corresponding to the 1%, 5%, and 10% significance levels are 0.7390, 0.4630, and 0.3470.

Table 3 presents Johansen's cointegration test to investigate the enduring connection between spot prices and index prices in both phases. The normalized cointegrating vector for spot prices signifies statistically significant long-term coefficients related to futures prices, suggesting a lasting linkage between spot and futures values of currencies in India during both analysis stages.

First, the optimal hedge ratio is derived from the OLS regression (1) where the spot return is regressed on the futures return. *Table 4* presents the results of this regression framework in both in- and out-of-sample timeframes for both phases.

Determining OHR through a bivariate VAR model involves selecting an appropriate lag length for unbiased and homoscedastic residuals, determined using the SIC. The VECM model includes error correction terms, and the estimates from Equations (2) and (3) are depicted in *Table 5*. Analysis shows a statistically significant and positively signed error correction coefficient Z_{t-1} in futures, suggesting quicker adaptation to equilibrium fluctuations in the preceding period compared to the spot price series. These findings underscore the importance of aligning futures prices with current spot prices on contract delivery dates.

Table 6 presents the outcomes obtained by calculating the OHR through the VECM, utilizing variance and covariance of residual series derived from Equations (2) and (3).

The study assesses VECM efficacy by examining standardized squared residuals, evaluating ARCH effects as proposed by McLeod and Li in 1983 through sample autocorrelation functions (ACF). A significant Q-statistic at a specific lag suggests the presence of ARCH effects. To identify serial connections in squared values, a common practice for conditional heteroskedasticity, the study analyses ACF and Partial ACF for normalized squared residuals. The Ljung-Box Q statistics are applied at a particular lag k to discern the presence of autocorrelation. This aligns with Ding et al [29] suggestion to examine absolute returns. *Table 7* displays ACF and PACF for standardized squared residuals, contributing to the investigation of conditional heteroskedasticity presence in the data.

Table 7 displays the 5th, 10th, and 15th order sequential associations for squared normalized residuals in Equations (2) and (3) across different

Table 1

Descriptive Statistics

Pre-COVID Phase	Spot Return	Futures Return
Mean	0.00155	0.00152
Std. deviation	0.0041	0.0042
Skewness	13.419	13.106
Kurtosis	1047.1	1017.5
Observations	45080	45080
COVID Phase	**Spot Return**	**Futures Return**
Mean	0.00116	0.00118
Std. deviation	0.0050	0.0051
Skewness	6.8862	9.9415
Kurtosis	1281.3	1633.2
Observations	55984	55984

Source: Author's calculation.

Table 2

KPSS Test

	Variables	Levels	First Difference	Inference on Integration
Pre-COVID Phase	Spot	0.8093*	0.2328	I (1)
	Futures	0.7314*	0.2366	
COVID Phase	Spot	12.028*	0.5089	I (1)
	Futures	11.170*	0.5376	

Source: Author's calculation.

Note: * Indicates significance at 1% level. The Schwarz Information Criteria (SIC) for the Augmented Dickey-Fuller test is used to determine the optimal lag length.

Table 3

Johansen's Cointegration Test Results

Phase	Cointegrating Vector (*r*)	Maximal Eigen-Value (λ_{max})	Trace Test Statistics (λ_{trace})
In-Sample Period			
Pre-COVID Phase	$r = 0$	20.927**	24.746**
	$r = 1$	3.8191	3.8191
COVID Phase	$r = 0$	20.088**	21.041**
	$r = 1$	0.9535	0.9535
Out-of-Sample period			
Pre-COVID Phase	$r = 0$	79.384**	80.069**
	$r = 1$	0.6851	0.6851
COVID Phase	$r = 0$	108.82**	110.54**
	$r = 1$	1.7210	1.7210

Source: Author's calculation.

Note: R is the number of cointegrating vectors under the null hypothesis. Critical values for trace test statistics are 15.494 and 3.8414 and for the max eigen values are 14.264 and 3.8414 for r = 0 and r = 1, respectively. ** denotes the significance at 5% level.

phases of the currency market. These correlations are highly significant, providing strong evidence of ARCH effects, indicating heteroskedasticity within the VECM. Subsequently, the research estimated the BEKK-GARCH model, considering covariance and conditional variance among spot and futures returns. This model offers a compatible and adaptable scheme for calculating the time-varying hedging ratio. *Figures 2–5* depict the conditional covariance of pre-COVID and COVID-19 in-sample and out-of-sample periods. The result shows the relationship and risk between variables that change over time during these periods. It highlights the patterns with occasional spikes during pandemics.

Further, *Table 8* findings show all parameter estimates are positive, definite, and statistically significant, highlighting the crucial role of current market information in forecasting conditional variances. The notable significance of estimated parameters suggests the effectiveness of the GARCH error in capturing dynamic patterns within variances of combined spot and futures returns.

Table 4

OLS Regression Model

Period	Pre-COVID Phase		COVID Phase	
	Variable	Coefficient	Variable	Coefficient
In-sample Period	c	1.15E – 08 (6.58E – 08)	c	1.45E – 08 (8.37E – 08)
	ΔF_t	0.9370* (0.0015)	ΔF_t	0.9221* (0.0016)
	R^2	**0.9005**	R^2	**0.8506**
Out-of-sample Period	c	8.94E – 08 (1.88E – 07)	c	–5.10E – 07 (5.20E – 07)
	ΔF_t	0.7259* (0.0106)	ΔF_t	0.7645* (0.0109)
	R^2	**0.5903**	R^2	**0.6850**

Source: Author's calculation.

Note: Standard errors are in the parentheses; and * shows that the outcome is significant at 1% level.

Optimal Hedge Ratio

Table 9 details the estimated OHRs from VECM for both in-sample and out-of-sample periods. The results show that, in both phases, the hedge ratio derived through covariance and time-shifting conditional variation is consistently lower compared to alternative methods. Notably, the OLS method yields the highest hedge ratios in both phases. This suggests that the hedge ratio assessed through the time-varying BEKK-GARCH method is less effective in minimizing the risk associated with spot prices.

Effectiveness of Hedging

The efficacy of three types of hedge ratios is assessed across in- and out-of-sample timeframes. Out-of-sample analysis uses the last ten days' observations from each period to compare hedge ratios' productivity.

The findings in *Table 10* indicate that OLS model-based hedging with fluctuating ratios over time is more effective in reducing conditional variability for currency market assets in both phases. This observation suggests that the static OLS model-based hedging strategy is most successful in cutting down on the hedged portfolio's conditional variability. It is important to note that even though the in-sample results were successful during the pandemic, this doesn't guarantee the same success in future out-of-sample periods. Unpredictable events like sudden lockdowns, supply chain disruptions, and changes in consumer behaviour make it challenging to accurately forecast and hedge against future risks.

CONCLUSION AND IMPLICATIONS

This study explores the effectiveness of various econometric models — OLS, VECM, and time-varying BEKK-GARCH — in determining hedge ratios within currency markets. The evaluation, based on variance minimization, covers both in- and out-of-sample timeframes across two distinct phases: the pre-COVID-19 phase and the COVID-19 phase. Empirical results reveal that, in both phases, the static OLS regression model consistently outperforms models derived from VECM and time-varying BEKK-GARCH methods regarding the minimization of variance. Specifically, during the out-of-sample period, OLS regression consistently demonstrates superior risk minimization, underscoring the pivotal role of investor risk aversion in selecting an OHR. The implication is that, when prioritizing risk aversion, the conventional OLS regression model proves economically and statistically superior, helping to lower the hedged portfolio's conditional variability. The research has significant implications for hedgers, guiding the selection of optimal hedging models based on performance criteria in the Indian context during the pandemic. The disruptions caused by the pandemic, along with increased volatility, have led to unexpected correlations, liquidity challenges, and changes in investor behaviour. In such dynamic environments, making hedging decisions requires careful consideration of evolving market dynamics to effectively manage risk and improve portfolio performance. The findings indicate that an investor's risk aversion level may play a crucial role in determining the most suitable hedge ratio.

Table 5

Short-Run Coefficient Estimates

Dependent variable	Pre-COVID Phase (In-sample)		COVID Phase (In-sample)		Pre-COVID Phase (Out-of-sample)		COVID Phase (Out-of-sample)	
	ΔS	ΔF	ΔS	ΔF	ΔS	ΔF	ΔS	ΔF
ΔS_{t-1}	−0.2641 (0.019)	0.5386 (0.020)	−0.0849 (0.011)	0.2004 (0.011)	−0.2133 (0.045)	0.4654 (0.046)	−0.0660 (0.038)	0.0271 (0.041)
ΔS_{t-2}	−0.2152 (0.025)	0.4455 (0.025)	−0.0245 (0.012)	0.0677 (0.012)	−0.1040 (0.049)	0.4208 (0.049)		
ΔS_{t-3}	−0.1424 (0.028)	0.4050 (0.028)	−0.0141 (0.012)	0.0344 (0.011)	−0.1289 (0.050)	0.2640 (0.050)		
ΔS_{t-4}	−0.0903 (0.029)	0.3660 (0.030)	−0.0035 (0.011)	0.0408 (0.011)	−0.1294 (0.048)	0.1287 (0.049)		
ΔS_{t-5}	−0.0604 (0.031)	0.3257 (0.031)	0.0174 (0.011)	0.0342 (0.011)	−0.0894 (0.043)	0.0680 (0.044)		
ΔS_{t-6}	−0.0357 (0.031)	0.2820 (0.032)			−0.0685 (0.034)	0.0096 (0.035)		
ΔS_{t-7}	−0.0121 (0.032)	0.2578 (0.032)						
ΔS_{t-8}	0.0253 (0.032)	0.2521 (0.032)						
ΔS_{t-9}	−0.0002 (0.032)	0.2006 (0.032)						
ΔS_{t-10}	0.0021 (0.031)	0.1798 (0.032)						
ΔS_{t-11}	0.0266 (0.031)	0.1646 (0.031)						
ΔS_{t-12}	−0.0362 (0.029)	0.0688 (0.030)						
ΔS_{t-13}	−0.0120 (0.028)	0.0740 (0.028)						

Table 5 (continued)

Dependent variable	Pre-COVID Phase (In-sample)		COVID Phase (In-sample)		Pre-COVID Phase (Out-of-sample)		COVID Phase (Out-of-sample)	
	ΔS	ΔF	ΔS	ΔF	ΔS	ΔF	ΔS	ΔF
ΔS_{t-14}	−0.0692 (0.025)	−0.0063 (0.025)						
ΔS_{t-15}	−0.0308 (0.019)	0.0001 (0.019)						
ΔF_{t-1}	0.2551 (0.019)	−0.5427 (0.019)	0.0719 (0.011)	−0.2125 (0.011)	0.1802 (0.044)	−0.4699 (0.045)	0.0949 (0.035)	0.0494 (0.038)
ΔF_{t-2}	0.2118 (0.024)	−0.4416 (0.025)	0.0188 (0.012)	−0.0692 (0.012)	0.1245 (0.048)	−0.3880 (0.048)		
ΔF_{t-3}	0.1430 (0.027)	−0.4010 (0.028)	0.0100 (0.012)	−0.0420 (0.011)	0.1370 (0.049)	−0.2514 (0.049)		
ΔF_{t-4}	0.0878 (0.029)	−0.3694 (0.030)	0.0064 (0.011)	−0.0402 (0.011)	0.1167 (0.047)	−0.1465 (0.047)		
ΔF_{t-5}	0.0683 (0.030)	−0.3166 (0.030)	−0.0262 (0.011)	−0.0398 (0.011)	0.0921 (0.042)	−0.0768 (0.042)		
ΔF_{t-6}	0.0365 (0.030)	−0.2807 (0.031)			0.0357 (0.032)	−0.0356 (0.033)		
ΔF_{t-7}	0.0037 (0.031)	−0.2661 (0.032)						
ΔF_{t-8}	−0.0193 (0.032)	−0.2478 (0.032)						
ΔF_{t-9}	−0.1959 (0.031)	0.0021 (0.032)						
ΔF_{t-10}	0.0017 (0.031)	−0.1734 (0.032)						
ΔF_{t-11}	−0.0252 (0.030)	−0.1644 (0.031)						
ΔF_{t-12}	0.0358 (0.029)	−0.0697 (0.029)						

Table 5 (continued)

Dependent variable	Pre-COVID Phase (In-sample)		COVID Phase (In-sample)		Pre-COVID Phase (Out-of-sample)		COVID Phase (Out-of-sample)	
	ΔS	ΔF	ΔS	ΔF	ΔS	ΔF	ΔS	ΔF
ΔF_{t-13}	0.0232 (0.027)	−0.0643 (0.028)						
ΔF_{t-14}	0.0682 (0.024)	0.0044 (0.025)						
ΔF_{t-15}	0.0345 (0.019)	0.0040 (0.019)						
Wald−χ^2 statistics	201.90* [0.0000]	780.94* [0.0000]	46.248* [0.0000]	313.72* [0.0000]	18.706* [0.0047]	114.84* [0.0047]	7.0795* [0.0078]	0.4282 [0.5128]

Panel B: Long-Run Coefficient Estimates

Parameter	Pre-COVID Phase (In-sample)		COVID Phase (In-sample)		Pre-COVID Phase (Out-of-sample)		COVID Phase (Out-of-sample)	
	ΔS	ΔF	ΔS	ΔF	ΔS	ΔF	ΔS	ΔF
Z_{t-1}	−0.0025* (0.001)	−0.2641* (0.001)	−0.0010* (0.001)	0.0001* (0.001)	−0.0213* (0.035)	0.1493* (0.036)	−0.0323** (0.016)	0.0698* (0.017)
c	5.90E−07* (8.9E−07)	5.90E−07* (8.9E−07)	9.01E−07* (9.3E−07)	9.09E−07* (9.3E−07)	1.52E−06* (1.2E−06)	1.48E−06* (1.3E−06)	−8.48E−06** (4.0E−06)	−7.88E−06*** (4.3E−06)

Source: Author's calculation.

Notes: In Panel A, currency futures and spot returns, the variables are listed in the first column. Probability values and t-statistics are denoted by the numbers in parenthesis () and []. A significance level of 1%, 5%, or 10% is indicated by the symbols *, **, and ***, respectively.

Table 6

OHR from the VECM

	Pre-COVID Phase		COVID Phase	
Parameters	In-sample Period	Out-of-sample Period	In-sample Period	Out-of-sample Period
Covariance (ε_{st}, ε_{ft})	3.22E – 08	4.38E – 09	4.39E – 08	3.09E – 08
Variance (ε_{ft})	3.34E – 08	5.17E – 09	4.72E – 08	3.95E – 08
Optimal Hedge Ratio	**0.9641**	**0.8472**	**0.9301**	**0.7823**

Source: Author's calculation.

Table 7

Autocorrelation Function for VECM

Phase	Lags	Spot Equation (2)				Futures Equation (3)			
		AC	PAC	Q-Statistics	Prob.	AC	PAC	Q-Statistics	Prob.
In-sample									
Pre-COVID	5	0.007	0.007	13.08	0.023	0.009	0.008	28.54	0.000
	10	0.004	0.004	18.62	0.045	0.005	0.005	28.54	0.000
	15	0.004	0.004	26.38	0.034	0.005	0.005	38.02	0.001
COVID	5	−0.007	−0.007	22.96	0.000	−0.007	−0.007	42.12	0.000
	10	0.007	0.007	31.79	0.000	0.004	0.004	53.75	0.000
	15	0.003	0.003	40.85	0.000	−0.001	−0.001	61.97	0.000
Out-of-sample									
Pre-COVID	5	0.004	0.002	16.88	0.005	−0.002	−0.004	23.13	0.000
	10	−0.017	−0.018	27.29	0.002	−0.019	−0.016	26.80	0.003
	15	−0.012	−0.013	30.58	0.010	−0.016	−0.017	29.37	0.014
COVID	5	0.028	0.026	5.686	0.338	−0.007	−0.012	12.87	0.025
	10	0.003	−0.003	18.82	0.043	−0.014	−0.018	16.43	0.088
	15	0.036	0.033	28.38	0.019	0.051	0.050	32.45	0.006

Source: Author's calculation.

Note: Q (5), Q(10) and Q(10) represent Ljung and Box (1978). Q-statistics for the standardized squared residuals are obtained from VECM.

Table 8

BEKK-GARCH Model Estimates

Variables	Pre-COVID Phase	COVID Phase	Pre-COVID Phase	COVID Phase
	In-sample		Out-of-sample	
Conditional mean equation				
C(1)	9.74E – 09* (1.54E – 10)	8.06E – 10* (8.69E – 12)	8.37E – 11* (1.30E – 11)	2.72E – 11* (4.31E – 12)
C(2)	8.31E – 09* (1.35E – 10)	6.91E – 10* (8.73E – 12)	6.87E – 11* (1.09E – 11)	1.76E – 11* (3.06E – 12)
C(3)	1.00E – 08* (1.71 – E10)	7.33E – 10* (1.14E – 11)	1.04E – 10* (2.25E – 11)	2.08E – 11* (3.61E – 12)
C(4)	0.4436* (0.0073)	0.4620* (0.0069)	0.3185* (0.0257)	0.3549* (0.0167)
C(5)	0.4295* (0.0071)	0.4503* (0.0068)	0.2628* (0.0255)	0.3324* (0.0155)
C(6)	0.2499* (0.0186)	0.0145 (0.0153)	0.7580* (0.0369)	0.9238* (0.0056)
C(7)	0.2710* (0.0191)	0.3203* (0.0130)	0.7559* (0.0550)	0.9338* (0.0049)
Conditional variance equation				
M(1,1)	9.74E – 09 (1.54E – 10)	8.06E – 10 (8.69E – 12)	8.37E – 11 (1.30E – 11)	2.72E – 11 (4.31E – 12)
M(1,2)	8.31E – 09 (1.35E – 10)	6.91E – 10 (8.73E – 12)	6.87E – 11 (1.09E – 11)	1.76E – 11 (3.06E – 12)
M(2,2)	1.00E – 08 (1.71E – 10)	7.33E – 10 (1.14E – 11)	1.04E – 10 (2.25E – 11)	2.08E – 11 (3.61E – 12)
A1(1,1)	0.4436 (0.0073)	0.4620 (0.0069)	0.3185 (0.0257)	0.3549 (0.0167)
A1(2,2)	0.4295 (0.0071)	0.4503 (0.0068)	0.2628 (0.0255)	0.3324 (0.0155)
B1(1,1)	0.2499 (0.0186)	0.0145 (0.0153)	0.7580 (0.0369)	0.9238 (0.0055)
B1(2,2)	0.2710 (0.0191)	0.3203 (0.0130)	0.7559 (0.0550)	0.9338 (0.0049)
Diagnostictest				
$Q^2(5)$	0.7515 (0.386)	1.9741 (0.410)	0.5324 (0.114)	1.9020 (0.570)
Q^2 (10)	0.8662 (0.648)	1.6859 (0.338)	0.8075 (0.227)	1.4906 (0.119)
Q^2 (15)	0.9291 (0.818)	1.9174 (0.110)	0.8254 (0.430)	1.7882 (0.361)
ARCH-LM statistics	0.3761 (0.539)	1.1566 (0.282)	0.4355 (0.687)	1.0116 (0.914)

Source: Author's calculation.

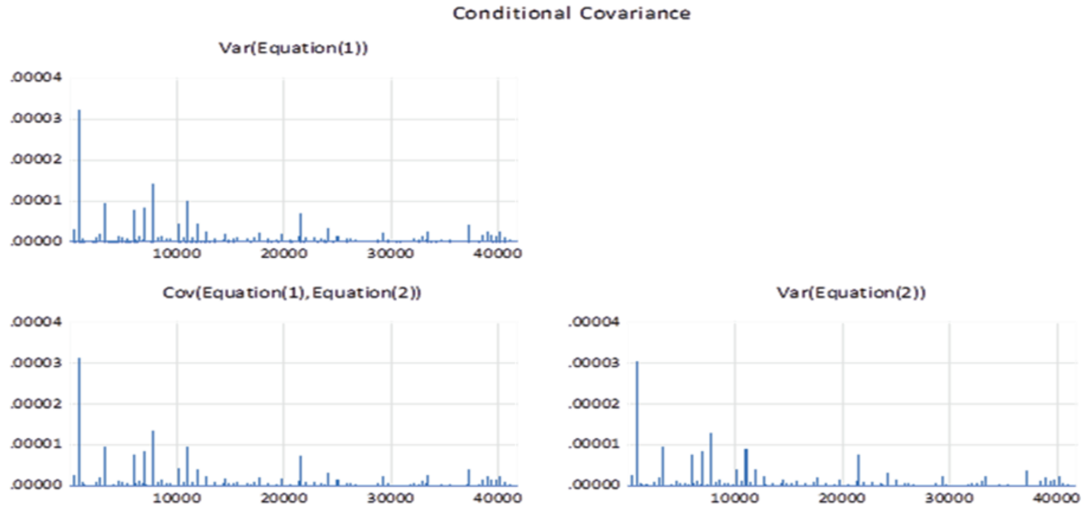

Fig. 2. **Conditional Covariance for Pre-COVID Phase (In-sample)**
Source: Author's calculation.

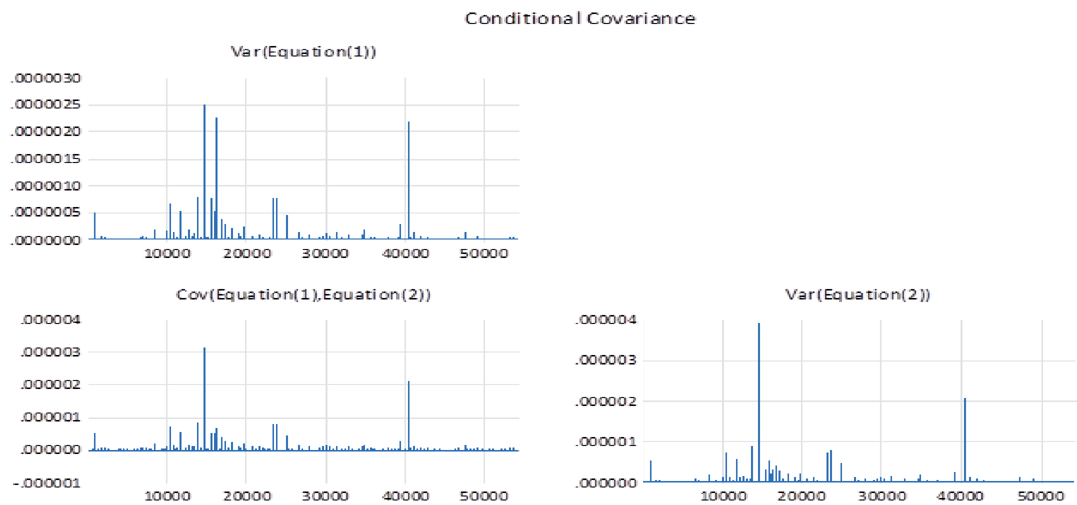

Fig. 3. **Conditional Covariance for COVID Phase (In-sample)**
Source: Author's calculation.

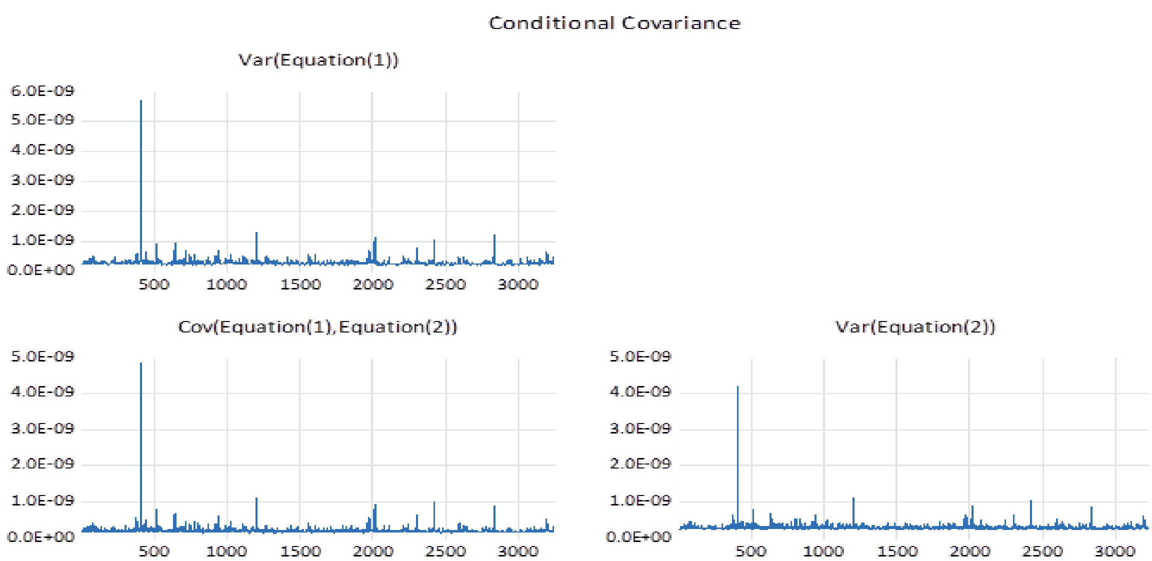

Fig. 4. **Conditional Covariance for Pre-COVID Phase (Out-of-sample)**

Source: Author's calculation.

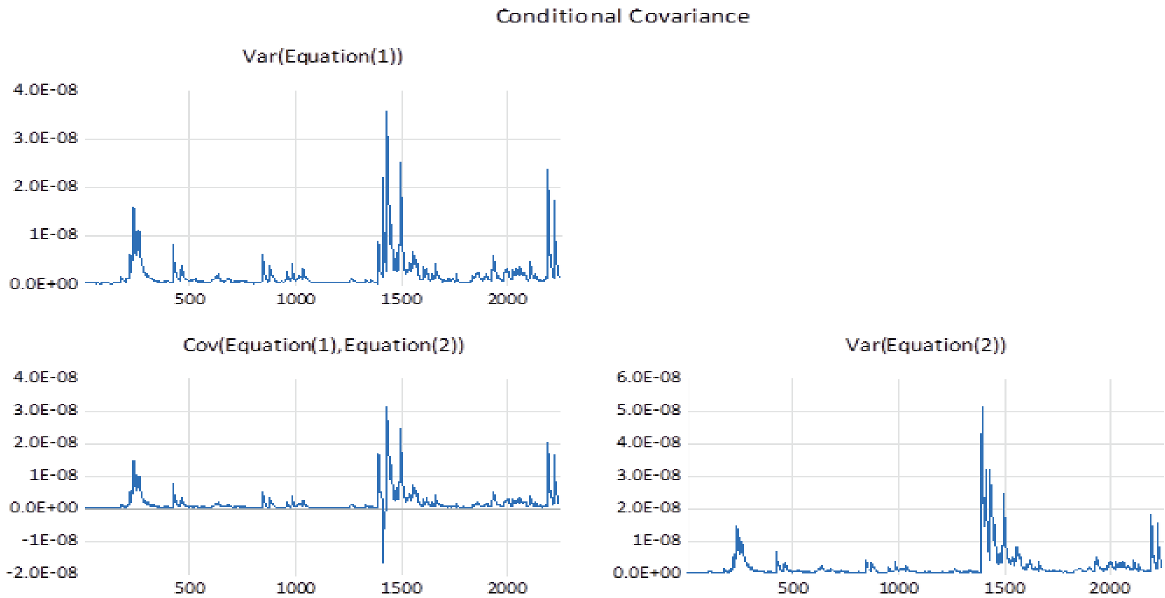

Fig. 5. **Conditional Covariance for COVID Phase (Out-of-sample)**

Source: Author's calculation.

Table 9

Estimates of OHR

Phase	Period	OLS	VECM	BEKK-GARCH
Pre-COVID phase	In-sample	0.9370	0.9610	0.9360
COVID phase		0.9220	0.9300	0.9252
Pre-COVID phase	Out-of-sample	0.7259	0.8433	0.7260
COVID phase		0.7645	0.7748	0.7650

Source: Author's calculation.

Table 10

Optimal Hedging Effectiveness

Phase	Period	OLS	VECM	BEKK-GARCH
Pre-COVID phase	In-sample	0.9005^{H}	0.6579	0.6293^{L}
COVID phase		0.8506^{H}	0.2983	0.2794^{L}
Pre-COVID phase	Out-of-sample	0.5904^{H}	0.5174	0.5075^{L}
COVID phase		0.6850^{H}	0.2860	0.2799^{L}

Source: Author's calculation.

Note: ^{L} Lowest variance reduction and ^{H} Highest variance reduction.

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