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Impact of night trading sessions on volatility of USD futures market in Thailand

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Abstract. Prior to September 2021, USD Futures could only be traded during the regular hours in Thailand Futures Exchange (TFEX). An additional trading session at night, while trading in both London and New York exchanges is active, enables investors to better handle their foreign exchange exposure or speculative needs of the moment. However, understanding volatility behavior is crucial for achieving successful trading. Therefore, this study investigates the impact of night trading sessions on the USD Futures volatility using GARCH family models. The USD Futures market volatility is examined through comparative analysis before and after the introduction of the night trading session. Both TARCH and EGARCH models have revealed no existence of leverage effect over the sample period - from January 2, 2020 to December 30, 2022. The GARCH model has proved to be the most accurate model for describing USD Futures volatility. Following the launch of nighttime trading, USD Futures market has experienced higher and more persistent volatility. In response to an increase in the volatility of USD Futures, TFEX should increase its margin requirement and monitor the speculative movements in futures market for their possible destabilizing effect. Investors should also adjust their hedge ratio to manage risk more appropriately and incorporate an extended period of increased uncertainty into their trading strategies.

Keywords: Thailand's foreign exchange futures, futures price volatility, GARCH family models, trading hours

JEL Classification: G15, G23, G32, M21

1. INTRODUCTION

In recent years, both spot and derivatives foreign exchange markets have demonstrated upward trends. Unlike other markets, the foreign exchange market operates 24 hours a day during weekdays due to the different international time zones. In general, the most active trading hours are London and New York trading sessions, especially when these sessions cross. Together, London and New York accounted for about 57.5% of global foreign exchange volume in 2022. Despite almost 40% growth rate in 2022, currency derivatives accounted for only 9.2% of the global derivatives market. Currency derivatives traded on organized exchanges, almost equally split between currency futures and options, are used for hedging and gaining exposure to the foreign exchange rate risk. As illustrated in Figure 1, Asia accounted for a large share of the global foreign exchange derivatives (70.71%); it was followed by Latin America (14.53%), Europe (9.71%), North America (3.40%), and others (1.66%). While currency options were almost entirely traded in Asia (97.99%), currency futures were split between regions: Asia (48.39%), Latin America (26.30%), Europe (17.20%), North America (5.80%), and others (2.32%). Table 1 shows top ten exchanges by number of currency derivative contracts traded in 2022. These ten exchanges were responsible for 87.27% of the currency derivatives trading. In 2022, Thailand Futures Exchange (TFEX) entered the top ten list of derivatives exchanges based on currency derivative volumes for the first time. TFEX's ranking improved by six places from sixteenth to tenth with currency derivatives volume of 10,189,955 contracts, up 195.38% from the previous year. It had the biggest growth in currency derivatives contracts traded in 2022, compared to an average of 22.97% for the top nine exchanges. TFEX's introduction of nighttime trading hours for USD Futures on September 27, 2021 proved an effective move for improving its product and service and meeting investor demand. Before this, USD Futures as the first and only currency derivative could only be traded during regular trading hours from 9:45 am – 4:55 pm. It was not conducive for investors to speculate on the future direction of exchange rates or to mitigate foreign exchange risk caused by the market fluctuations at night. Since September 27, 2021 onwards, TFEX has added a night session for trading USD Futures, starting from 6:50 pm – 11:55 pm. The introduction of night trading session, while foreign exchange trading in both London and New York exchanges is active, provides investors the opportunity to absorb and react to global news instantly. In addition, investors can avoid overnight position-holding risks and manage their foreign exchange risk more efficiently.

However, there is a chance that the recent launching of night trading session affects USD Futures price volatility. According to Fung et al. (2016), the introduction of nighttime trading hours for commodity futures in China improves futures price efficiency and volatility. Since margin requirement setting and optimal hedge ratio are based on futures price volatility, it is necessary to analyze the effect of night trading session on the USD Futures volatility in Thailand. The goals of this paper are therefore to examine volatility behavior after extending trading hours at night and to construct a comparative analysis of the USD Futures market volatility before and after the introduction of night trading session. Although the launch of night trading session helps market participants assess the market and adjust their trading strategies at night, the empirical evidence from this study provides other developing countries with the possible adverse effect of the trading hours extension on futures market efficiency and volatility. To this end, there are several steps. First, the study focuses on the use of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family models augmented with dummy variable to investigate how the introduction of night trading session affects USD Futures volatility in Thailand using daily observations over a span of 3 years. If market volatility changes after the launch of nighttime trading hours, the coefficient of this dummy variable will be significantly different from zero. In addition, the most appropriate model in describing USD Futures volatility is chosen based on the lowest values of Akaike Information Criterion (AIC). Next, the selected volatility model is used to evaluate volatility persistence of USD Futures returns during pre- and post-night session trading periods. Although the GARCH processes is by far the most widely used approach in volatility modelling, the limitation is that the employed GARCH family models make the independently and identically distributed (IID) assumption. Violating the IID assumption results in inconsistent estimators.

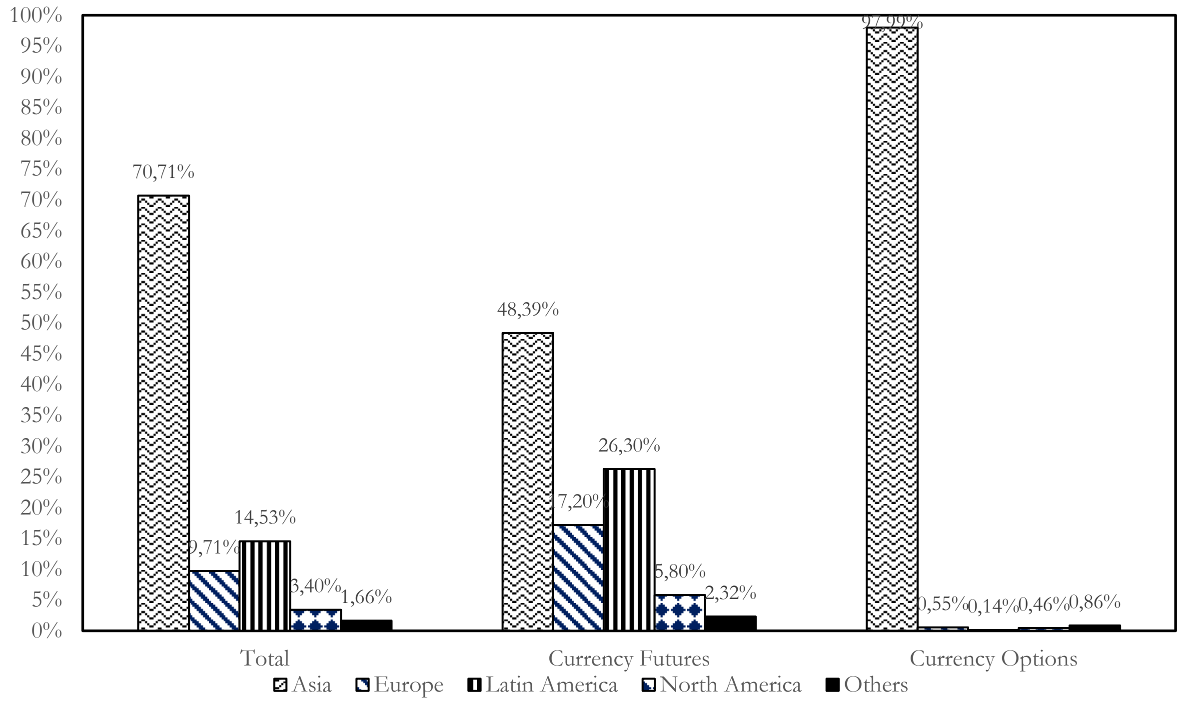

Figure 1. Share of Volume in 2022 by Region

Source: Futures Industry Association (2023)

Table 1

Top 10 Exchanges by Number of Currency Derivatives Contracts Traded in 2022

Exchange	Volume	Share of Volume	YoY Change
National Stock Exchange of India	4,331,844,491	56.04%	91.03%
B3 - Brasil Bolsa Balcão	908,625,035	11.75%	17.76%
Moscow Exchange	789,053,884	10.21%	-12.98%
CME Group	247,803,161	3.21%	23.13%
Matba Rofex	173,787,133	2.25%	56.89%
Korea Exchange	127,420,424	1.65%	27.14%
Borsa Istanbul	70,794,375	0.92%	-27.01%
Johannesburg Stock Exchange	52,431,596	0.68%	0.84%
Singapore Exchange	34,514,045	0.45%	29.90%
Thailand Futures Exchange	10,189,955	0.13%	195.38%
Others	984,055,530	12.73%	-2.07%
Grand Total	7,730,519,629	100.00%	39.49%

Source: World Federation of Exchanges (2023); Authors' calculations

The empirical findings do not detect the existence of leverage effect in USD Futures market. This implies that good news has the same effect on USD Futures volatility as bad news. The GARCH (1,1) model is considered the best fitting model. Controversial to some of the findings in metal futures market (see for example, Fung et al., 2016; Jiang et al., 2020; Yao et al., 2020), the estimation results of this study show that launching of nighttime trading increases the volatility of USD Futures market in Thailand. It is possible that extending trading hours in USD Futures market attracts more uninformed speculative investors and thus destabilizes USD Futures market. Return volatility tends to be higher in a more liquid market, with a larger trading volume. In response to an increase in the volatility of USD Futures, investors should adjust their hedge ratio more appropriately to manage risk. TFEX should also increase its margin requirement and monitor the speculative movements in USD Futures market for their possible destabilizing effect. Furthermore, the persistence of volatility increases significantly, following the launching of nighttime trading. This suggests that investors should incorporate an extended period of volatility shocks into their trading strategies. Although no one can ensure the wholly universal nature of the results, empirical evidence from this study may provide other developing countries some lessons for the improving trading on their futures markets.

The remainder of this paper is conducted as follows. Section 2 provides literature review on futures market volatility. Section 3 describes the data and the GARCH family models. Section 4 presents estimation results of the GARCH family models and analysis. Finally, section 5 concludes the findings of this paper and offers corresponding suggestions.

2. LITERATURE REVIEW

Previous literature on futures market contains a number of theoretical and empirical studies explaining factors affecting futures price volatility. Theoretical paper by Samuelson (1965) shows that volatility of futures prices increases as the futures contract approaches its maturity date. It is widely known as the "Samuelson hypothesis". Several studies empirically check for the validity of the Samuelson hypothesis, but the evidence is mixed. The maturity effect in agricultural futures is analyzed by Anderson (1985), Milonas (1986), Khoury & Yourougou (1993), Karali & Thurman (2010), Verma & Kumar (2010), Silveira et al. (2017), and Amit (2022). Their results in general show the support of the Samuelson hypothesis. Jongadsayakul (2014) employs both linear regression model and the GARCH(1,1) model and finds the empirical support of the Samuelson hypothesis in Thailand's gold futures. Mukherjee & Goswami (2017) collect the data from MCX India and investigate the maturity effect in potato, gold, crude oil, and mentha oil futures. Their estimation results of the GARCH(1,1) model reveal that only price returns volatility of gold futures increases when the futures contract approaches expiration. Some other evidence to support the Samuelson hypothesis can be found for energy futures contracts traded in the NYMEX (Serletis, 1992). Floros & Vougas (2006) use both linear regression models and the GARCH family models to show that the Samuelson hypothesis holds in the FTSE/ASE-20 stock index futures during the period of August 1999-August 2001 and in the FTSE/ASE Mid 40 stock index futures during the period of January 2000-August 2001. Kenourgios & Ketavatis (2011) also reach a similar conclusion about the phenomenon of maturity effect in the Greek index futures. Madarassy Akin (2003) examines the Samuelson hypothesis by applying a GARCH framework to financial futures and finds strong support for currency futures, but not for stock index futures and interest rate futures. According to Daal et al. (2006), the Samuelson hypothesis is more likely to hold for commodity futures than for financial futures. Using intraday data of agricultural, metals, energy, and financial futures in US and non-US markets, Duong & Kalev (2008) conduct the non-parametric test, the linear regression model with realized volatility, and the GARCH(1,1) model and find supportive evidence for the Samuelson hypothesis in only agricultural futures, except the CBOT Soybean meal futures.

Besides, considering whether the futures price volatility is affected by the maturity, other research examines the mixture of distribution hypothesis proposed by Clark (1973). It is expected that information flow affects futures volatility due to the market reaction to new information. Either trading volume as a proxy for information or open interest as a proxy for market depth is incorporated in the volatility model. Xin et al. (2005) first estimate a residual-based volatility using a two-pass procedure and then conduct OLS regressions to examine the volatility behavior of copper, aluminum, soybean, and wheat futures in China. Their estimation results show a support of positive relationship between trading volume and volatility in all futures contracts. In addition, a significantly negative relationship between open interest and futures volatility can be found in copper, soybean, and wheat futures. Ripple & Moosa (2009) collect daily data of crude oil futures from the NYMEX during the period from January 1995 to December 2005 and compute volatility using high and low prices. They employ the linear regression model for the contract-by-contract analysis and the autoregressive distributive lag methodology for the full-period time series analysis. Their results support earlier findings of a significantly positive role for trading volume and a significantly negative role for open interest. They also argue that supportive evidence for the Samuelson hypothesis in previous studies may have really been capturing the influence of open interest. Consistent with previous empirical evidence, a positive coefficient of trading volume and a negative coefficient of open interest in explaining futures price volatility are founded in Greek index futures market (Kenourgios & Ketavatis, 2011), Thai gold futures market (Jongadsayakul, 2014), Turkish futures market (Kadioğlu et al., 2016), and Indian agricultural futures market (Amit, 2022). A greater amount of information, embedded in volume, yields greater volatility while a high level of open interest enhances market depth and mitigates volatility. Feng & Chuan-zhe (2008) develop the GARCH(1,1) model in explaining Chinese wheat futures price volatility and document supportive evidence for the mixture of distribution hypothesis. They also find that futures volatility is higher on Monday and lower on Friday.

In addition, another group of existing literature evaluates the impact of major events on futures price volatility. The research by Ye et al. (2014) shows that the events, including the Asian financial crisis in 1997, OPEC's production cut in 1999, the U.S. invasion of Iraq in 2003, the bankruptcy filing of Lehman Brothers in 2008, have statistically significant effects on crude oil futures price volatility. Evidence of a decline in gold futures volatility after global financial crisis is also observed by Sinha & Mathur (2016). Lamouchi & Badkook (2020) show that gold futures returns exhibit more volatility spikes during the 1987 stock market crash, the first Gulf War, the 2001 terrorist attacks, and the COVID-19 outbreak. Conversely, the volatility in gold futures prices shows a high level of persistence during the Asian and global financial crises. More recently, other research has focused on the impact of COVID-19 on futures volatility such as Zhang & Wang (2022) and Selvan & Ramraj (2022). Further, a number of works consider the release of a new product or service as a cause of changing futures market volatility. Bin & Wen (2014) use EGARCH model to show a reduction in the volatility of aluminum and cathode copper futures contracts caused by the emergence of new metal futures contracts under the conditions that no systemic crisis happens. Jongadsayakul (2020) uses GARCH family models and finds that that there is a statistically significant decrease in volatility of 50 Baht Gold Futures and 10 Baht Gold Futures after the introduction of Gold-D. Fung et al. (2016) show that the introduction of nighttime trading hours for commodity futures in China improves futures price efficiency and volatility. Jiang et al. (2020) use data for the Shanghai Futures Exchange (SHFE) gold and silver futures to show that prices are less volatile at the opening period of daytime trading in China after the introduction of night trading. According to Yao et al. (2021), the SHFE gold futures market witnesses large fluctuations before the introduction of night trading sessions because of the overnight fluctuation in the global gold market. After the introduction of night trading sessions, realized volatility is moderate. In addition, the ARCH and GARCH coefficients remain almost the same as they were before the launching of nighttime trading, meaning that the features of volatility are not affected by the introduction of night trading sessions.

The previous studies on night trading sessions limit the analysis to metal futures market. Since a few studies specifically explore the determinants of futures price volatility in Asian emerging markets, the contribution of this paper lies in its investigation of USD Futures volatility after the introduction of a night session by Thailand Futures Exchange. The empirical evidence from this study provides other developing countries with important information about the response of futures market volatility to extending trading hours at night.

3. DATA AND METHODOLOGY

This study collects daily settlement prices of USD Futures in Thailand Futures Exchange from January 2, 2020 to December 30, 2022, covering the period before and after the introduction of night trading session on September 27, 2021. The data set is retrieved from the website of SETSMART for the quarterly month contracts with 725 sample data points. The quarterly month contract is chosen in this study since it is the most active contract in Thai USD Futures market. The construction of the data set is to switch or roll over from the expiring quarterly month contract to the next quarterly month contract when trading volume and open interest of the expiring quarterly month contract are lower than those of the next quarterly month contract.

In common with previous literature, the futures returns are obtained by taking the first difference in the logarithms of the daily future prices, $R_t = \ln F_t - \ln F_{t-1}$, where F_t represents the settlement price for USD Futures on day t. Therefore, this return series consists of 724 observations (over the whole observation period), of which 419 observations pertain to the period before the introduction of night trading session (January 3, 2020 – September 27, 2021), and the remaining 305 observations belong to the period after the introduction of night trading session (September 28, 2021 – December 30, 2022). The subsamples before and after the introduction of night trading session are called the pre- and post-night session trading, respectively. It is essential to test all the return series (pre- and post-night session trading and whole sample) for stationarity via Augmented Dickey-Fuller (ADF) test. The ADF test was created by Dickey & Fuller (1981) to test the null hypothesis of a unit root (H_0: $b = 0$) against the alternative hypothesis of stationarity (H_a: $b < 0$). Here are three cases of the test equation.

Case 1: a pure random walk:

$$\Delta R_t = bR_{t-1} + \sum_{j=2}^{l} \gamma_j \Delta R_{t-j+1} + u_t \tag{1}$$

Case 2: random walk with intercept:

$$\Delta R_t = c + bR_{t-1} + \sum_{j=2}^{l} \gamma_j \Delta R_{t-j+1} + u_t \tag{2}$$

Case 3: random walk with intercept and linear time trend:

$$\Delta R_t = c + bR_{t-1} + \sum_{j=2}^{l} \gamma_j \Delta R_{t-j+1} + dt + u_t \tag{3}$$

The difference between the three equations concerns the presence of the deterministic elements c (an intercept) and d (a linear time trend). In all cases (pre- and post-night session trading and whole sample), case 2 (random walk with intercept) is chosen since d is not statistically different from zero. Schwarz information criterion is also conducted to select the optimal lag length equal to zero. The ADF unit root test result for the whole sample shows that the test statistic and p-value come out to be equal to -26.2852 and 0.0000 respectively. Moreover, the ADF unit root tests report a test statistic value of -18.0118 with a p-value of 0.0000 for the pre-night session trading and a test statistic value of -18.0373 with a p-value of 0.0000 for the post-night session trading. Since the p-value in each case is less than 0.01, hence the null hypothesis is rejected. It implies that the futures returns series is stationary at the 1 percent level of significance in all cases.

Figure 2 plots the daily futures returns for the period January 3, 2020 to December 30, 2022, which shows volatility clustering. To find whether Autoregressive Conditional Heteroskedasticity (ARCH) effect exists in the data, this study conducts the Lagrange Multiplier (LM) test for all residuals up to lag 2. Using the data for the whole sample, the LM test statistic is 16.1497, and its corresponding p-value is 0.0003. This outcome leads to rejecting the null hypothesis of no ARCH effect at the 1 percent level of significance. Therefore, it is more appropriate to model the futures returns series using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model by Bollerslev (1986) in the presence of time-varying volatility.

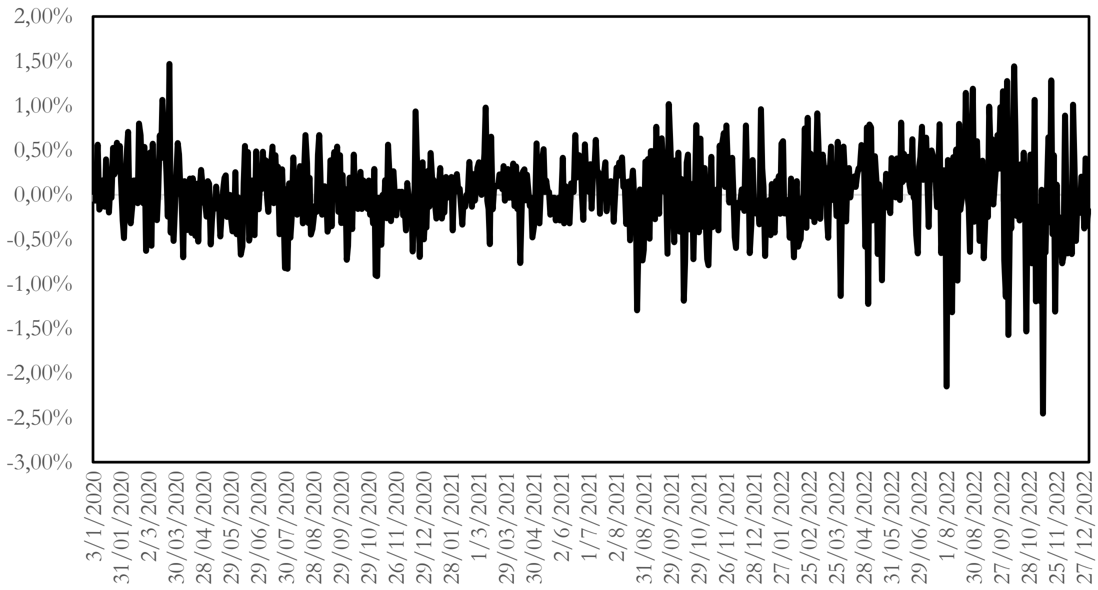

Figure 2. Daily USD Futures returns from the 3/1/2020 to the 30/12/2022

Source: own calculation

The GARCH (p,q) model is represented as follows:

$$\mathrm{R}_t = E_{t-1}\left[\mathrm{R}_t\right] + \varepsilon_t \tag{4}$$

$$\varepsilon_t \left| \mathrm{I}_{t-1} \sim \mathrm{N}\left(0, h_t^2\right)\right. \tag{5}$$

$$h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}^2 \tag{6}$$

where $E_{t-1}[\cdot]$ represents expectation conditional on information available at time t-1, h_t^2 is the conditional variance, $\alpha_0 > 0, \alpha_i \geq 0, i = 1,...,q-1, \alpha_q > 0, \beta_i \geq 0, i = 1,..., p-1, \beta_p > 0$, p is the order of the GARCH terms, and q is the order of the ARCH terms. The sum of ARCH and GARCH coefficients must be less than one in order to have a mean reverting variance process and a constant long-term unconditional variance equal $\alpha_0 \Big/ 1 - \sum_{i=1}^{q} \alpha_i - \sum_{i=1}^{p} \beta_i$.

The GARCH model assumes symmetry in volatility, but negative shocks are assumed to have bigger impact on volatility than positive shocks in many financial markets. To capture the leverage effect, this paper considers two asymmetric specifications of the conditional variance equation, including the Threshold ARCH (TARCH) specification introduced by Zakoian (1994) and Glosten et al. (1993) and the Exponential GARCH (EGARCH) specification introduced by Nelson (1991). The TARCH model can be written as

$$h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i d_{t-i} \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}^2 \tag{7}$$

where d_{t-i} takes a value of 0 if $\varepsilon_{t-i} \geq 0$ and a value of 1 if $\varepsilon_{t-i} < 0$. If the sign of γ_i is positive, negative changes will have bigger effect than the positive changes.

The EGARCH model can be written as

$$\ln\left(h_t^2\right) = \alpha_0 + \sum_{i=1}^{q} g\left(e_{t-i}\right) + \sum_{i=1}^{p} \beta_i \ln\left(h_{t-i}^2\right) \tag{8}$$

where $g\left(e_{t-i}\right) = \gamma_i e_{t-i} + \alpha_i \left[\left|e_{t-i}\right| - E\left|e_t\right|\right], \mathrm{i} = 1,...,q$, and $e_t = \dfrac{\varepsilon_t}{h_t}, e_t \sim N\left(0,1\right)$. The term $\gamma_i e_{t-i}$ determines the sign effect of the shocks on volatility, and the term $\alpha_i \left[\left|e_{t-i}\right| - E\left|e_t\right|\right]$ determines the size effect of the shocks on volatility. If the sign of γ_i is negative, negative shocks will have bigger impact on volatility than positive shocks. In addition, the conditional variance is constrained to be non-negative by the assumption that $\ln\left(h_t^2\right)$ is a function of passed e_t's. However, the EGARCH model does not capture leverage effect when the sign of γ_i is positive.

In general, a GARCH (1,1) model and its TARCH (1,1) and EGARCH (1,1) extensions are often sufficient for the empirical modelling of financial time series (see for example, Lim & Sek, 2013; Zabiulla, 2015; Ausloos et al., 2020; Jongadsayakul, 2021; Wang, 2021). To capture the effect of night trading session on the USD Futures volatility, all models have a dummy variable (NT_t) in the conditional variance equation. That is,

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 + a\mathrm{N}T_t \tag{9}$$

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 d_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 + a\mathrm{N}T_t \tag{10}$$

$$\ln\left(h_t^2\right)=\alpha_0+\gamma_1 e_{t-1}+\alpha_1\left[\left|e_{t-1}\right|-E\left|e_t\right|\right]+\beta_1\ln\left(h_{t-1}^2\right)+aNT_t \qquad (11)$$

where NT_t takes a value of 0 for the period from January 3, 2020 to September 27, 2021 and a value of 1 for the period from September 28, 2021, to December 30, 2022.

The above-mentioned three models make the independently and identically distributed (IID) assumption. However, violating the IID assumption results in inconsistent estimators. The appropriate volatility model for futures return series is carefully chosen based on the significance of the explanatory variables and the Ljung-Box Q-statistics of both standardized residuals and standardized squared residuals. The LM test is also conducted to ensure that no ARCH effect left in the standardized residuals. The appropriate volatility model should provide no evidence of autocorrelation between residuals and no evidence of ARCH effect. The best representation is the model with the lowest value of Akaike Information Criterion (AIC).

In addition, the selected model without the dummy variable (NT_t) in the conditional variance equation is used to make a comparative analysis of the USD Futures market volatility before and after the introduction of night trading session. The ARCH coefficient (α_1) represents the impact of past innovation on the conditional variance, and the GARCH coefficient (β_1) indicates the degree of persistence in the volatility. Therefore, comparing these coefficients in the pre- and post-night session trading allows us to discover how the introduction of night session trading has an impact on the USD Futures market volatility and to what extent. An increase in the ARCH coefficient (α_1) implies that futures prices respond faster to new information whereas a decrease in α_1 indicates a slower information transmission into futures prices. In addition, an increase in the GARCH coefficient (β_1) specifies that information have a higher persistent effect on futures price changes whereas a decline in β_1 signifies lesser persistence.

4. EMPIRICAL RESULTS AND DISCUSSION

With the existence of ARCH effect in the data, this paper models USD Futures returns series for the whole sample using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family models. Table 2 presents the findings of three volatility models (GARCH (1,1), TARCH (1,1), and EGARCH (1,1)). In all, the dummy variable (NT_t) is added in the conditional variance equation to analyze how the launching of nighttime trading on September 27, 2021 has the impact on the volatility of USD Futures market.

Table 2

Estimation Results of the GARCH Family Models for USD Futures Market Volatility

Model	**GARCH (1,1)**		**TARCH (1,1)**		**EGARCH (1,1)**	
Variance Eq.	**Coefficient**	**P-Value**	**Coefficient**	**P-Value**	**Coefficient**	**P-Value**
Intercept (α_0)	9.91E-07	**0.0136****	9.29E-07	**0.0166****	-0.684250	**0.0255****
ARCH (α_1)	0.080356	**0.0030*****	0.086973	**0.0099*****	0.138742	**0.0015*****
Asym. (γ_1)			-0.015257	0.5938	0.016351	0.3037
GARCH (β_1)	0.843815	**0.0000*****	0.850297	**0.0000*****	0.948906	**0.0000*****
Dummy (*a*)	1.17E-06	**0.0428****	1.09E-06	**0.0533***	0.039398	**0.0958***
Q (36)	40.8802	0.2647	41.1377	0.2557	41.6424	0.2386
Q^2 (36)	27.7462	0.8361	27.4054	0.8477	28.6005	0.8051
ARCH-LM (1)	0.19934	0.6553	0.16055	0.6887	0.00082	0.9772
AIC value	**-8.140773**		-8.138305		-8.135567	

Source: Authors' results. * indicates significance level at 0.10 level, ** indicates significance level at 0.05 level, *** indicates significance level at 0.01 level.

Prior to interpreting the results, the estimated models are checked for serial correlation and additional ARCH effect in the standardized residuals. According to Table 2, the Ljung–Box Q test statistic associated with the p-values is not significant, which shows no sign of serial correlation in the residuals of the GARCH (1,1), TARCH (1,1), and EGARCH (1,1) models. All the p-values are greater than the 5% significance level. Testing for the null hypothesis of no ARCH effect shows the p-values from the Ljung–Box test of the squared residuals above 0.05 and the p-values from the ARCH-LM test for the residual series above 0.05. The test results show no evidence against the null hypothesis of no ARCH effect. In other words, the residuals of the GARCH (1,1), TARCH (1,1), and EGARCH (1,1) models are homoscedastic, and there is no additional ARCH effect. Therefore, the variance equations of these three different GARCH models are correctly specified.

The results of three different GARCH models (GARCH (1,1), TARCH (1,1) and EGARCH (1,1)) presented in Table 2 show that the coefficients of ARCH (α_1) and GARCH (β_1) terms in the conditional variance equation are statistically significant at 1% level. The GARCH (1,1) and TARCH (1,1) models satisfy the nonnegativity constraints of the estimated parameters ($\alpha_1 > 0$ and $\beta_1 > 0$). The sum of the estimated GARCH (1,1) parameters indicates a strong degree of persistence in the conditional variance process. Interestingly, the results of the TARCH (1,1) and EGARCH (1,1) models do not show the presence of leverage effect in USD Futures market since the asymmetric coefficient (γ_1) which captures this presence is statistically insignificant in each model. This implies that the positive and negative shocks exert the same impact on the conditional variance process. The GARCH (1,1) model also provides the minimum value of AIC, so the GARCH (1,1) model outperforms other two volatility models. The estimated coefficient on dummy variable in all three volatility models is positive and significant implying that the introduction of night trading session resulted in an increase in the USD Futures market volatility. This result is in opposition to existing literature (see for example, Fung et al., 2016; Jiang et al., 2020; Yao et al., 2020), which provides the evidence of negative relationship between launching of nighttime trading and volatility of metal futures. However, this can be explained by market microstructure theory. That said, after the launch date of the night trading session, return volatility tends to be higher in a more liquid market, with a larger trading volume. In response to an increase in the volatility of USD Futures, investors should adjust their hedge ratio more appropriately to manage risk. TFEX should also increase its margin requirement.

The whole sample is divided into two subsamples on September 27, 2021, the starting date for night trading in USD Futures market. The GARCH (1,1) model is used next to explore how GARCH estimations change after the introduction of night trading session. Table 3 shows the estimation results of the GARCH (1,1) models for pre- and post-night session trading. Since the residuals of the GARCH (1,1) model should be white noise, this paper performs diagnostic tests for serial correlation and remaining ARCH effect. To test autocorrelation, the Ljung–Box Q-test on the residuals is applied. In both cases (pre- and post-night session trading), the Ljung-Box test results show that the p-values are all greater than a significance level of 5%, signalling that the residuals do not have autocorrelation. To check for ARCH effect, the Ljung–Box Q-test on the squared residuals and the ARCH-LM test are applied. In both cases (pre- and post-night session trading), the associated p-values are all greater than 5%, indicating strong evidence of accepting the null hypothesis of no ARCH effect. There is reason to believe that the variance equations of the GARCH (1,1) models for pre- and post-night session trading are correctly specified.

The GARCH (1,1) estimation results for pre- and post-night session trading shown in Table 3 indicate the significance of the coefficients of ARCH (α_1) and GARCH (β_1) and satisfy the nonnegativity constraints ($\alpha_1 > 0$ and $\beta_1 > 0$). The GARCH (1,1) model also requires that $\alpha_1 + \beta_1$ is less than 1 for the volatility process to be stationary. The estimation outcomes show $\alpha_1 + \beta_1 = 0.879418$ for the pre-night session trading period and $\alpha_1 + \beta_1 = 0.967112$ for the post-night session trading period, verifying that that the GARCH process is stationary. An increase in the sum of these coefficients indicates the higher persistence of volatility shocks. Because of the unconditional variance = $\alpha_0 / (1-\alpha_1-\beta_1)$, the unconditional variance (or long-run average variance) increases from 0.0000126 (pre-night session trading) to 0.0000298 (post-night session trading). Moreover, the ARCH coefficient (α_1) goes down from 0.097859 (pre-night session trading) to 0.056703 (post-night session trading). The existence of night trading session decreases the rate at which new information is incorporated into USD Futures prices. On the other hand, the GARCH coefficient (β_1) increases from 0.781559 (pre-night session trading) to 0.910409 (post-night session trading). An increase in the GARCH coefficient during the post-night session trading period indicates that it takes longer period of time for volatility to die out compared to the pre-night session trading period. These results imply that the launching of nighttime trading changes the features of USD Futures volatility. The introduction of night session trading increases market volatility and decreases market efficiency. Since foreign exchange futures market has a higher degree of leverage than spot foreign exchange market does, it is possible that extending trading hours in USD Futures market attracts more uninformed speculative investors and thus destabilizes USD Futures market. The findings suggest authorities to carefully monitor the consequences of the speculative movements and the potential for destabilizing effects in USD Futures. Investors should also incorporate an extended period of increased uncertainty into their trading strategies.

Table 3

Estimation Results of the GARCH (1,1) Model for USD Futures Market Volatility Before and After Night Session Introduction on September 27, 2021

Time Period	**Pre-Night Session Trading (3/1/2020 – 27/9/2021)**		**Post-Night Session Trading (28/9/2021 – 30/12/2022)**	
Variance Eq.	**Coefficient**	**P-Value**	**Coefficient**	**P-Value**
Intercept (α_0)	1.52E-06	0.0513*	9.79E-07	0.2352
ARCH (α_1)	0.097859	0.0303**	0.056703	0.0957*
GARCH (β_1)	0.781559	0.0000***	0.910409	0.0000***
Q (36)	38.6196	0.3521	37.6221	0.3948
Q^2 (36)	26.2372	0.8838	19.8813	0.9865
ARCH-LM (1)	0.02523	0.8738	0.58728	0.4435

Source: Authors' results. * indicates significance level at 0.10 level, ** indicates significance level at 0.05 level, *** indicates significance level at 0.01 level.

5. CONCLUSION

Past studies investigate metal futures volatility after the introduction of a night session. This study adds to the existing literature by analyzing the effect of night trading session on the USD Futures volatility in Thailand. Like most previous literature, GARCH family model is employed to analyze the time varying volatility of USD Futures returns from January 3, 2020 to December 30, 2022. The empirical findings reveal that the GARCH (1,1) model outperforms other models in capturing the volatility of USD Futures market. The estimation results of TARCH (1,1) and EGARCH (1,1) do not find any evidence of leverage effect in USD Futures market, implying that bad news does not confer higher volatility more than good news of the same magnitude. Adding dummy variable for the night trading session to conditional variance equation shows the statistically significant positive relationship between the launching of nighttime trading and USD Futures volatility. The GARCH (1,1) model is also used to analyze whether the volatility behavior of USD Futures changes significantly after the launching of nighttime trading. Results from a sub-sample analysis (pre- and post-night session trading) suggest that the existence of night trading session decreases the rate at which new information is incorporated into USD Futures prices and increases the persistency of volatility shocks. Therefore, following the introduction of nighttime trading, TFEX, should increase its margin requirement and monitor the speculative movements in futures market for their possible destabilizing effect. The results also help investors by increasing their information regarding the adverse effect of the introduction of night trading session on futures volatility and thus support them to implement their hedging strategies effectively. In addition, investors should recognize the issue of hight volatility persistence after the introduction of night trading session and incorporate it into trading strategies.

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REFERENCES

Amit, S. (2022). Determinants of Futures Price Volatility: A Study of Agricultural Market. *Ekonomicko-Manazerske Spektrum*, *16*(1), 1–11. Retrieved from https://ems.uniza.sk/wp-content/uploads/EMS_1_2022_01_Amit.pdf

Anderson, R. W. (1985). Some Determinants of the Volatility of Futures Prices. *Journal of Futures Markets*, *5*(3), 331–348. https://doi.org/10.1002/fut.3990050305

Ausloos, M., Zhang, Y., & Dhesi, G. (2020). Stock Index Futures Trading Impact on Spot Price Volatility. The CSI 300 Studied with a TGARCH Model. *Expert Systems with Applications*, *160*, 1–12. https://doi.org/10.1016/j.eswa.2020.113688

Bin, W., & Wen, L. (2014). Analysis on the Effect of New Futures Contract Coming into Market: Taking the Related Metal Futures in SHFE for Example. *Procedia Computer Science*, *31*, 175 – 183. https://doi.org/10.1016/j.procs.2014.05.258

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Clark, P. B. (1973). Uncertainty, Exchange Risk, and the Level of International Trade. *Western Economic Journal*, *11*(3), 302–313. https://doi.org/ 10.1111/j.1465-7295.1973.tb01063.x

Daal, E., Farhat, J. & Wei, P. P. (2006). Does Futures Exhibit Maturity Effect? New Evidence from an Extensive Set of US and Foreign Futures Contracts. *Review of Financial Economics*, *15*(2), 113–128. https://doi.org/10.1016/j.rfe.2005.03.001

Dickey, D. A, & Fuller, W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with Unit Root. *Econometrica*, *49*(4), 1057–1072. https://doi.org/10.2307/1912517

Duong, H. N., & Kalev, P. S. (2008). The Samuelson Hypothesis in Futures Markets: An Analysis Using Intraday Data. *Journal of Banking & Finance*, *32*(4), 489–500. https://doi.org/10.1016/j.jbankfin.2007.06.011

Feng, W., & Chuan-zhe, L. (2008). *Determinants of the Volatility of Futures Markets Price Returns: The Case of Chinese Wheat Futures*. 2008 International Conference on Management Science and Engineering 15th Annual Conference Proceedings. Long Beach, CA. https://doi.org/10.1109/ICMSE.2008.4668988

Floros, C., & Vougas, D. (2006). Index Futures Trading, Information and Stock Market Volatility: The Case of Greece. *Journal of Derivatives and Hedge* Funds, *12*(1-2), 146–166. https://doi.org/10.1057/palgrave.dutr.1840047

Fung, H. -G., Mai, L., & Zhao, L. (2016). The Effect of Nighttime Trading of Futures Markets on Information Flows: Evidence from China. *China Finance and Economic Review*, *4*(7), 1–16. https://doi.org/10.1186/s40589-016-0032-0

Futures Industry Association. (2023). ETD Tracker. Retrieved May 4, 2023, from https://www.fia.org/fia/etd-tracker

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, *48*(5), 1779–1801. https://doi.org/10.2307/2329067

Jiang, Y., Kellard, N., &Liu, X. (2020). Night Trading and Market Quality: Evidence from Chinese and US Precious Metal Futures Markets. *Journal of Futures Markets*, 40(10), 1486–1507. https://doi.org/10.1002/fut.22147

Jongadsayakul, W. (2014). Determinants of the Gold Futures Price Volatility: The Case of Thailand Futures Exchange. *Applied Economics Journal*, *21*(1), 59–78. Retrieved from https://so01.tci-thaijo.org/index.php/AEJ/article/download/57237/47444

Jongadsayakul, W. (2020). The Effect of New Futures Contracts on Gold Futures Price Volatility: Evidence from the Thailand Futures Exchange. *Cogent Economics & Finance*, *8*(1). 1–14. https://doi.org/10.1080/23322039.2020.1802807

Jongadsayakul, W. (2021). Value at Risk Estimation of the SET50 Index: Comparison between Stock Exchange of Thailand and Thailand Futures Exchange. *Journal of International Studies*, *14*(1), 227-240. https://doi.org/10.14254/2071-8330.2021/14-1/16

Kadioğlu, E., Kılıç, S., & Öcal, N. (2016), Determinants of Price Volatility of Futures Contracts: Evidence from an Emerging Market. *Journal of Applied Finance & Banking*, *6*(2), 103–115. Retrieved from https://ssrn.com/abstract=3971806

Karali, B., & Thurman, W. N. (2010). Components of Grain Futures Price Volatility. *Journal of Agricultural and Resource Economics*, *35*(2), 167–182. https://doi.org/10.22004/ag.econ.93205

Kenourgios, D., & Katevatis, A. (2011). Maturity Effect on Stock Index Futures in an Emerging Market. *Applied Economics Letters*, *18*(11), 1029–1033. https://doi.org/10.1080/13504851.2010.522512

Khoury, N., & Yourougou, P. (1993). Determinants of Agricultural Futures Price Volatilities: Evidence from Winnipeg Commodity Exchange. *Journal of Futures Markets*, *13*(4), 345–356. https://doi.org/10.1002/fut.3990130403

Lamouchi, R. A., & Badkook, R. O. (2020). Gold Prices Volatility among Major Events and During the Current COVID-19 Outbreak. *Journal of Statistical and Econometric Methods*, *9*(4), 39–52. Retrieved from http://www.scienpress.com/Upload/JSEM%2fVol%209_4_4.pdf

Lim, C. M., & Sek, S. K. (2013). Comparing the Performances of GARCH-type Models in Capturing the Stock Market Volatility in Malaysia. *Procedia Economics and Finance*, *5*, 478–487. https://doi.org/10.1016/S2212-5671(13)00056-7.

Madarassy Akin, R. (2003). *Maturity Effects in Futures Markets: Evidence from Eleven Financial Futures Markets*. UC Santa Cruz Economics Working Paper No. 03-6. https://doi.org/10.2139/ssrn.410381

Milonas, N. T. (1986). Liquidity and Price Variability in Futures Markets. *Financial Review*, *21*(2), 211–238. Retrieved from https://ideas.repec.org/a/bla/finrev/v21y1986i2p211-37.html

Mukherjee, I., & Goswami, B. (2017). The Volatility of Returns from Commodity Futures: Evidence from India. *Financial Innovation*, *3*(15), 1–23. https://doi.org/10.1186/s40854-017-0066-9

Nelson, D. B. (1991) Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, *59*(2), 347–370. https://doi.org/10.2307/2938260

Ripple, R. D., & Moosa, I. A. (2009). The Effects of Maturity, Trading Volume, and Open Interest on Crude Oil Futures Price Range-Based Volatility. *Global Finance Journal*, *20*(3), 209–219. https://doi.org/10.1016/j.gfj.2009.06.001

Samuelson, P. A. (1965). Proof that Proper Anticipated Prices Fluctuate Randomly. *Industrial Management Review*, *6*(2), 41–49. Retrieved from https://capital-gain.ru/wp-content/uploads/Proof-that-properly-anticipated-prices-fluctuate-randomly.pdf

Selvan, S. C. B. S. A., & Ramraj, G. (2022). The Impact on Gold Spot and Futures Prices Volatility During the COVID-19: An Event Study. *Journal of the Asiatic Society of Mumbai*, *95*(32), 95–100. Retrieved from https://www.researchgate.net/publication/358497825_THE_IMPACT_OF_COVID-19_ON_GOLD_SPOT_PRICE_VOLATILITY_IN_THE_INDIAN_COMMODITY_MARKET

Serletis, A. (1992). Maturity Effects in Energy Futures. *Energy Economics*, *14*(2), 150–157. https://doi.org/10.1016/0140-9883(92)90008-2

Sinha, P., & Mathur, K. (2016). *Impact of Global Financial Crisis and Implied Volatility in the Equity Market on Gold Futures Traded on Multi Commodity Exchange, India*. Munich Personal RePEc Archive (MPRA) Paper No. 72966. Retrieved from https://mpra.ub.uni-muenchen.de/id/eprint/72966

Silveira, R. L. F., dos Santos Maciel, L., Mattos, F. L., & Ballini, R. (2017). Volatility Persistence and Inventory Effect in Grain Futures Markets: Evidence from a Recursive Model. *Revista de Administracao*, *52*(4), 403–418. https://doi.org/10.1016/j.rausp.2017.08.003

Verma, A., & Kumar, C. V. R. S. V. (2010). An Examination of the Maturity Effect in the Indian Commodities Futures Market. *Agricultural Economics Research Review*, *23*, 335–342. Retrieved from https://core.ac.uk/download/pdf/6455750.pdf

Wang, C. (2021). Different GARCH Model Analysis on Returns and Volatility in Bitcoin. *Data Science in Finance and Economics*, *1*(1), 37–59. https://doi.org/10.3934/DSFE.2021003

World Federation of Exchanges. (2023). Statistics Portal. Retrieved May 4, 2023, from https://statistics.world-exchanges.org/ReportGenerator/Generator

Xin, Y., Chen, G., & Firth, M. (2005). The Determinants of Price Volatility in China's Commodity Futures Markets. *China Accounting and Finance Review*, *7*(1), 124–145. Retrieved from http://hdl.handle.net/10397/60080

Yao, X., Hui, X., & Kang, K. (2021). Can Night Trading Sessions Improve Forecasting Performance of Gold Futures' Volatility in China?. *Journal of Forecasting*, *40*(5), 849–860. https://doi.org/10.1002/for.2748

Ye, S., Karali, B., & Ramirez, O. A. (2014). *Event Study of Energy Price Volatility: An Application of Distributional Event Response Model.* 2014 Annual Meeting. Minneapolis, MN. https://doi.org/10.22004/ag.econ.170207

Zabiulla. (2015). Volatility Clustering and Leverage Effect in the Indian Forex Market. *Global Business Review*, *16*(5), 785–799. https://doi.org/10.1177/0972150915591453

Zakoian, J. M. (1994). Threshold Heteroskedastic Model. *Journal of Economic Dynamics and Control*, *18*(5), 931–955. https://doi.org/10.1016/0165-1889(94)90039-6

Zhang, Y., & Wang, R. (2022). COVID-19 Impact on Commodity Futures Volatilities. *Finance Research Letters*, *47*, 1–6. https://doi.org/10.1016/j.frl.2021.102624