Effectiveness of Futures Contracts as Hedging Instruments for Rubber Price Risk: Evidence from Thailand

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Abstract

This study investigates whether the Thailand Futures Exchange (TFEX) listed futures contracts can be effectively used to transfer rubber price risks. Using auction price data of natural rubber ribbed smoke sheet no. 3 (RSS3) and daily settlement prices of highly liquid TFEX-listed futures contracts from 2007 to 2019, the results from the two different methods used to estimate static and dynamic optimal hedge ratios are consistent. The most effective futures contract for hedging RSS3 price risk is the RSS3 futures contract, which can reduce RSS3 price volatility by approximately 4-6%. Single-stock futures are more effective than SET50 index futures as hedging instruments. Specifically, the single stock futures contract of a company with a rubber-related business, STA, is the most effective futures contract, reducing 1-2% of RSS3 price volatility.

Keywords : Rubber Price Risk; TFEX; Futures Contract; SET50 Index Futures, Single Stock Futures, Hedging, Cross Hedge

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1. Introduction

High price volatilities are commonly found in the agricultural sector. The rubber industry is no exception to this trend. There is a high fluctuation in the prices of natural rubber ribbed smoke sheet no. 3 (RSS3) in the rubber spot or cash market in Songkhla, which is one of the most important rubber markets in Thailand. For instance, the average price of RSS3 decreased from 103.94 baht per kilogram in July 2008 to 38.83 baht per kilogram in December 2008. In February 2011, the average price was 180.18 baht per kilogram, the highest level since 2006, and declined almost 50% to 93.69 baht per kilogram by November of the same year (Rubber Authority of Thailand, 2019). This price volatility directly affects either revenues or costs of agricultural businesses, and hence operating performance, which consequently impacts income and the standard of living of stakeholders. The need to stabilize price volatility makes risk management crucial. Among the existing instruments, futures contracts are a simple way to manage price risk. It is a straightforward instrument. If the underlying asset of a futures contract is the same as an asset in a cash position, and their prices are closely related to each other, taking the opposite position in both spot and futures markets can reduce the overall price risk (Hull, 2015).

The Thailand Futures Exchange (TFEX) is the only futures exchange in Thailand. The overall market liquidity is relatively low with a variety of asset classes. The most actively traded contracts are the SET50 index and single stock futures, accounting for almost 95% of the total volume traded. RSS3 is the only agricultural product available on TFEX. With choices of either cash settlement (RSS3) or physical delivery (RSS3D), none of them are actively traded. However, RSS3D contracts are more active than RSS3 contracts (Thailand Futures Exchange, 2019). This may reflect the need for risk management in cash positions in the rubber market.

For hedging purposes, liquid contracts with highly correlated price are desirable (Cuny, 1993; Tashjian, 1995). As RSS3 and RSS3D futures contracts are illiquid, this study investigates whether SET50 Index futures, single stock futures, US dollar futures, and gold futures traded on the TFEX can be as effective as RSS3 futures contracts in hedging against rubber price fluctuations. It focuses on the price fluctuations of RSS3 in the Songkhla Rubber Market, Thailand, and the prices of futures contracts listed on the TFEX in a normal situation. The underlying assets of interest are the SET50 Index, single stock, US dollar, gold, and RSS3. To ensure that futures prices accurately reflect information and that hedgers can enter or close their positions as needed, only actively traded contracts were considered in the analysis. The study period is from 2007 to 2019 to represent normal situation in financial market. The period of COVID-19 crisis is excluded because of its significant impact on global financial markets, including Thailand (Akhtaruzzaman et al., 2021; He et al., 2020; Jindal and Gupta, 2022; Okorie and Lin, 2021; Tiwari et al., 2022; Topcu and Gulal, 2020; Vo et al., 2022; Zaremba et al., 2021; Zhao et al., 2023).

This study complements previous literature, such as Ali et al. (2020), Belousova and Dorfleitner (2012), Bessler and Wolff (2015), Chunhachinda et al. (2019), Mensi et al. (2021), Nguyen et al. (2020), and

Satyanarayan and Varangis (1996), who investigate the hedging effectiveness of adding commodities into equity portfolios as a diversification tool. The results of this study provide valuable insights for agricultural hedgers, including businesses, cooperatives, and farmers, operating in emerging markets with underdeveloped futures exchanges and a limited range of available futures contracts. This study sheds light on the efficacy of employing alternative futures contracts as hedging instruments in such contexts.

Daily spot price data were collected from 2007 to 2019, while daily futures prices have been collected since the introduction of contracts to the market. Using the Ordinary Least Squares (OLS) estimation of the Simple Linear Regression and the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to estimate the hedge ratio, consistent results were found. The most effective futures contracts for hedging RSS3 price volatility are RSS3D and STA (Sri Trang Agro-Industry) stock futures, respectively. The hedged portfolios exhibit enhanced performance characterized by both risk reduction and an increase in average returns. These findings align with the recommendation of Hull (2015) that utilizing the same or highly correlated underlying asset is advisable when employing hedging strategies. In addition, the results are consistent with prior research findings (Ali et al., 2020; Belousova and Dorfleitner, 2012; Bessler and Wolff, 2015; Chunhachinda et al., 2019; Mensi et al., 2021; Nguyen et al., 2020; Satyanarayan and Varangis, 1996) suggesting that incorporating equities and other diverse assets can enhance the performance of investment portfolios. Inconsistent with the result of Chotinuchittrakul and Boonvorachote (2013) regarding the efficacy of the models used to estimate hedge ratios, the findings of this study were inconclusive. Specifically, the OLS estimated hedge ratio proves to be more effective in reducing the risk of an unhedged position for STA stock futures compared to the GARCH (1,1) estimated hedge ratio. The opposite is found for RSS3D futures, in that the GARCH (1,1) estimated hedge ratio leads to more effective risk reduction than the OLS estimated hedge ratio.

The remainder of this paper is organized as follows. Section 2 describes the hedging transactions, optimal hedge ratios, and hedging effectiveness. Section 3 describes the data and methodology used in this study. Section 4 presents the empirical results. Finally, Section 5 presents the conclusions of this study.

2. Hedging, Optimal Hedge Ratio, and Hedging Effectiveness

2.1 Hedging

Hedging, an investment transaction that attempts to reduce the price volatility or price risk of an asset, is always performed at the cost of profit reduction by taking an offsetting position in the related asset or instrument (Howard & D'Antonio, 1984). The potential profit from a hedging transaction compensates for the potential loss from the asset position, and vice versa.

A perfect hedge occurs when the price risk of the asset position is eliminated completely. With futures contracts, this is done by taking the opposite position in the futures and spot markets. Identical assets are required in both markets to ensure perfect correlation and convergence of prices at the expiration date of the futures contract. However, executing a perfect hedge is difficult, for several reasons. First, not all types of assets are offered as underlying assets in the futures markets. Second, futures markets may not provide hedgers with the desired expiration dates. Third, hedgers must accurately predict the future timing of spot positions. If these conditions do not hold, hedgers cannot control the basis risk—the time variation of the difference between the spot and futures prices of the asset (Hull, 2015).

Given these challenges, a more common practice is cross-hedging, in which the underlying asset of futures contracts differs from the asset being hedged. In a cross-hedge, the prices of the assets in both positions are not perfectly correlated, and they may not necessarily converge at expiration. This can lead to a higher level of risk compared with an unhedged position. Consequently, a cross-hedge is generally considered less effective than a perfect hedge in terms of risk reduction (Eaker & Grant, 1987). However, in more recent work, i.e. Felix et al. (2023), shows that gold futures are more effective than oil futures in hedging airline stock price. Therefore, cross-hedging strategy can be used to enhance stock investment portfolio returns.

2.2 Optimal Hedge Ratio

Identifying the appropriate or optimal number of futures contracts for hedging positions is the primary task for hedgers to meet their risk management objectives. An optimal hedge ratio is defined as the proportion of positions in futures contracts to positions in the asset to be hedged to meet the hedger's investment objective. Based on the previous theoretical literature, see Chen et al. (2003) for a review, various objective functions have been used to determine the optimal hedge ratio.

The simplest and most widely used objective is to minimize the variance of change in the value of a hedged portfolio, a combination of positions in asset and futures contracts (Ederington, 1979; Myers & Thompson, 1989). This optimal hedge ratio is called the minimum-variance hedge ratio. It is based on the relationship between changes in the spot prices of the hedged asset and changes in the futures prices of the underlying asset. Unfortunately, the minimum variance hedge ratio ignores the consideration of the expected return of the hedged portfolio and expected utility function of hedgers. This is inconsistent with either the mean–variance framework or the maximization of hedgers' utility. (Cecchetti et al., 1988; Howard & D'Antonio, 1984; 1987)

By incorporating both the expected return and variance into the objective function, the optimal hedge ratio is derived by maximizing the expected return for a given level of variance of a hedged portfolio. Howard and D'Antonio (1984, 1987) derive the optimal hedge ratio by maximizing the Sharpe ratio, assuming that hedgers are risk averse. Hsin et al. (1994) estimated the optimal hedge ratio by maximizing the utility function that incorporates risk and returns into the hedger's utility function. Similarly, Cecchetti et al. (1988) determine the optimal hedge ratio by maximizing the expected utility function represented by the logarithm of the terminal wealth. The difficulty arises in identifying the hedge ratio, as the level of risk aversion and the utility function must be known.

Under specific conditions, especially when hedgers exhibit infinite risk aversion and the expected return on the hedged portfolio is zero, the optimum mean-variance hedge ratio aligns with the minimum variance hedge ratio (Chen et al., 2003).

2.3 Estimation Methods of Minimum Variance Hedge Ratio

The econometric models used to identify the minimum variance hedge ratio can be broadly categorized into static and dynamic estimation approaches. Among the methodologies used for estimating the static minimum variance hedge ratio, the Ordinary Least Squares (OLS) method is the simplest and easiest to estimate and understand. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method is widely adopted for the estimation of the dynamic minimum variance hedge ratio (see Chen et al., 2003; Yao & Wu, 2012).

The OLS method is a conventional approach first introduced by Ederington (1979) to estimate the minimum variance hedge ratio. This method involves a simple linear regression between the changes in spot and futures prices. The OLS method relies on several assumptions regarding error terms: the errors have a zero mean, the variance of errors is constant and finite across all values of independent variables, the errors are linearly independent of one another, there is no relationship between errors and independent variables, and errors are normally distributed (Brooks, 2014). Previous empirical studies have provided evidence that violates these assumptions. For example, Herbst et al. (1989) and Herbst et al. (1993) show that spot and futures prices are cointegrated, indicating an autocorrelation problem. Additionally, there is evidence of heteroskedasticity, in which the variance of the error terms varies across times. While the presence of serial correlation and heteroskedasticity is acknowledged, it is not a major concern in this study because OLS estimators remain linearly unbiased, consistent, and asymptotically normally distributed (Stock and Watson, 2020).

In general, time-series data on asset prices are nonstationary and time varying. Transforming it to a return series eliminates the non-stationary problem, but does not resolve the issue of time-varying volatility. The use of the slope of an ordinary least squares regression as an optimal hedge ratio is inefficient because of the presence of heteroskedasticity (Andersen et al., 2009). Many studies, such as Buyukkara et al. (2022), Chunhachinda et al. (2019), Kroner and Sultan (1993), Lien and Luo (1994), and Moschini and Myers (2002), adopt a bivariate generalized autoregressive conditional heteroskedasticity (GARCH) model to capture time-varying correlation features and solve the heteroskedasticity problem in OLS estimations.

The GARCH model facilitates the conditional variance and covariance of spot and futures prices to estimate the conditional hedge ratios. Allowing the conditional correlation matrix to be time-varying, Engle (2002) introduced dynamic conditional correlation (DCC) as a two-step approach to estimate the conditional variance and covariance between two time-series data. The first step involved estimating the condition variance from the univariate GARCH (1,1) model. In the second step, the conditional correlation matrix of the standardized disturbance was estimated. The conditional variance and conditional correlation matrix are then used to construct the DCC conditional variance and covariance matrix, which is later used to estimate the optimal hedge ratio.

2.4 Hedging Effectiveness

Hedging effectiveness is defined as the proportion of risk measured by variance, which is mitigated through hedging. Prior studies have proposed various hedging effectiveness measures. For instance, Ederington (1979) uses R^2 from a regression model of changes in spot prices against changes in futures prices as a measure of hedging effectiveness. However, the presence of a serial correlation problem can lead to an overestimation of the R^2 of the OLS regression model. A more reliable measure of hedging effectiveness is the reduction in variance of the hedged position. Herbst et al. (1989) used the variance of residuals, as it is inversely related to the reduction in the variance of a hedged position. The smaller the variance of residuals, the larger the reduction in the variance of the portfolio return.

Many empirical studies, such as those conducted by Butterworth and Holmes (2001), Chunhachinda et al. (2019), In and Kim (2006), Koulis et al. (2018), and Sanders and Manfredo (2004), use straightforward measures of overall risk reduction. In these studies, overall risk is measured as either the standard deviation or variance of portfolio returns.

3. Data and Methodology

3.1 Data

The data used in this study were the daily prices of natural rubber ribbed smoke sheet no. 3 from 2007 to 2019. Spot price data are auction prices from the centered rubber market in Songkhla, collected manually from the official website of the Rubber Authority of Thailand. Futures price data are daily settlement prices of closet-to-delivery contracts retrieved from the Thailand Futures Exchange (TFEX) database.

Only futures contracts with acceptable liquidity are included in this study to prevent the potential illiquidity problems faced by traders. Trading volume was used in the data screening process. To be included, each contract must be traded on at least 80% of the yearly trading days, on average, with at least one contract per day. Additionally, the contract must be available in the market for at least one full year, until the end of 2019.

From the six categories of underlying assets, namely equity, precious metals, interest rate, energy, currency, and agriculture, the futures contracts considered in this study are the SET 50 index, 13 single stocks in agribusiness, food, petrochemicals, and energy sectors, gold, US dollar, and natural rubber ribbed smoke sheet no. 3, as shown in Table 1.

In Table 1, Panel A shows equity futures, including SET 50 and selected single stock futures contracts. Panel B shows the gold, USD, and RSS3D futures contracts. The sample period for each contract is from the first trading day to the end of 2019. % of Trading Day is the number of days the contract is being traded as proportion to its total trading days. The trading Volume is the average number of contracts traded daily across the sample period.

Table 1 List of selected futures contracts traded on TFEX

Panel A: Equity Contracts				
Underlying Asset		Beginning Period	% of Trading Day	Trading Volume
INDEX	SET 50	3/1/2007	100.00%	64,689.02
AGRO: AGRI	STA	21/3/2011	75.91%	47.50
AGRO: FOOD	CBG	5/10/2015	84.67%	49.69
AGRO: FOOD	CPF	21/3/2011	93.80%	48.77
INDUS: PETRO	IVL	21/3/2011	97.02%	77.92
INDUS: PETRO	PTTGC	18/3/2013	95.05%	39.78
RESOURC: ENERG	BANPU	22/6/2009	87.99%	157.06
RESOURC: ENERG	CKP	5/10/2015	90.16%	188.97
RESOURC: ENERG	GUNKUL	16/1/2017	80.00%	54.46
RESOURC: ENERG	IRPC	21/3/2011	99.39%	368.17
RESOURC: ENERG	PTG	16/1/2017	97.52%	131.02
RESOURC: ENERG	PTT	24/11/2008	98.19%	41.88
RESOURC: ENERG	PTTEP	24/11/2008	99.93%	86.59
RESOURC: ENERG	TOP	21/3/2011	81.73%	19.26
Panel B: Other Contracts				
Underlying Asset		Beginning Period	% of Trading Day	Trading Volume
GOLD	GF10	2/8/2010	100%	9,950.62
CURRENCY	USD	5/6/2012	100%	1,621.32
AGRICULTURE	RSS3D	16/5/2016	73.71%	112.20

Source: Thailand Futures Exchange (2019) and from calculation by author

Among these, the SET50 index futures are the most active, followed by gold and USD futures. The average daily trading volume are 64,689, 9,950, and 1,621 contracts, respectively. For single-stock futures, stocks in the energy sector are more active than those in other sectors. Note that STA and RSS3D futures are included in this study because their prices may be closely related to the RSS3 spot price.

3.2 Methodology

To determine the effectiveness of the selected futures contracts in reducing the price risk of natural rubber in the spot market and to identify the best instrument for this purpose, this study considers both static and dynamic relationships between spot and futures prices when estimating a minimum-variance hedge ratio.

The minimum-variance hedge ratio is the ratio of the size of the futures position to the size of the cash market position that minimizes the variance of the hedged or combined position. The ratio was calculated using Equation (1).

$$h^* = -\rho_{S,F}\frac{\sigma_S}{\sigma_F} \tag{1}$$

where h^* is the minimum variance hedge ratio, σ_S is the standard deviation of the spot price, σ_F is the standard deviation of the futures price, and $\rho_{S,F}$ is the correlation coefficient between these two prices. A negative sign indicates a short position in futures contracts required for hedging when the correlation coefficient between the two prices is positive.

As it is commonly known that price series are non-stationary, return series are used. The return is a percentage change in price, which is defined as the difference in the natural logarithms of daily price, as shown in equation (2).

$$R_t = \ln(\mathrm{P}_t) - \ln(\mathrm{P}_{t-1}) \text{ or } R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (2)$$

where R_t is the return at any time t, and P_t and P_{t-1} are the prices at time t and the previous time, respectively.

Estimate Static Minimum-Variance Hedge Ratio

The static minimum variance hedge ratio is commonly estimated as the beta coefficient from the regression model of spot returns against futures returns, as shown in equation (3).

$$R_{s,t} = \alpha + \beta R_{F,t} + \varepsilon_t \quad (3)$$

where $R_{s,t}$ and $R_{F,t}$ are spot and futures returns, respectively, at time t calculated using equation (2). α is the intercept, β is the slope or beta coefficient, and ε is the error term of the regression line.

Estimate Dynamic Minimum-Variance Hedge Ratio

The dynamic minimum-variance hedge ratio, h_t^*, defined in Equation (1), is calculated using Equation (4).

$$h_t^* = \frac{\sigma_{sF,t}}{\sigma_{FF,t}} \quad (4)$$

where h_t^* is the time – varying hedge ratio; $\sigma_{sF,t}$ is the conditional covariance between spot and futures returns at time t; and $\sigma_{FF,t}$ is the conditional variance of futures returns at time t.

To determine the time-varying variance-covariance matrix, Engle's (2002) two-step estimation approach was adopted. First, I estimate the condition variance from the univariate GARCH (1,1) model, as shown in equations (5) and (6).

$$\sigma_{ss,t} = c_{ss} + \alpha_{ss}\varepsilon_{s,t-1}^2 + \beta_{ss,t-1}\sigma_{ss,t-1} \quad (5)$$
$$\sigma_{FF,t} = c_{FF} + \alpha_{FF}\varepsilon_{F,t-1}^2 + \beta_{FF,t-1}\sigma_{FF,t-1} \quad (6)$$

where $\sigma_{ss,t}$ and $\sigma_{ss,t-1}$ are the conditional variance of the errors $\varepsilon_{s,t}$ at time t and one lag period, respectively. $\sigma_{FF,t}$ and $\sigma_{FF,t-1}$ are the conditional variances of the errors $\varepsilon_{F,t}$ at time t and one previous period, respectively. $\varepsilon_{s,t-1}^2$ and $\varepsilon_{F,t-1}^2$ are the squared values of $\varepsilon_{s,t-1}$ and $\varepsilon_{F,t-1}$, respectively.

In the second step, the conditional correlation matrix of the standardized disturbance is the estimation of, as shown in equation (7).

$$\rho_{sF,t} = \bar{\rho}(1-\alpha-\beta) + \alpha\epsilon_{s,t-1}\epsilon_{F,t-1} + \beta\rho_{sF,t-1} \tag{7}$$

where $\rho_{sF,t}$ and $\rho_{sF,t-1}$ are the conditional correlations of the standardized disturbances at time t and one previous period, respectively. $\bar{\rho}$ is the unconditional correlation coefficient; $\epsilon_{s,t-1}$ and $\epsilon_{F,t-1}$ are the one lag values of the standardized error terms for asset's return s and F, respectively. The standardized error terms, $\epsilon_{s,t}$, is calculated as $\varepsilon_{s,t}/\sigma_{s,t}$, and $\epsilon_{F,t}$, is calculated as $\varepsilon_{F,t}/\sigma_{F,t}$. α and β are scalars.

The DCC conditional variance-covariance matrix can be represented as a matrix multiplication in equation (8).

$$M_t = D_t R_t D_t \tag{8}$$

where M_t is the conditional variance and covariance matrix; D_t is the diagonal matrix of time – varying standard deviation estimated from the GARCH (1,1) model; and R_t is the conditional correlation matrix of the standardized disturbances.

Measure the Effectiveness of Futures Contract as Hedging Instrument

Similar to previous empirical studies, such as Butterworth and Holmes (2001), Chunhachinda et al. (2019), In and Kim (2006), Koulis et al. (2018), Sanders and Manfredo (2004), the measure of hedging effectiveness used in this study is defined as the proportion of overall risk eliminated by hedging. Overall risk is measured as the variance in the portfolio return. For the unhedged portfolio, the return is the daily change in spot price calculated using equation (2). The overall risk of the unhedged portfolio is simply the variance of the daily spot return $\sigma^2_{S,t}$ over the sample period. For the hedged portfolio, the return of the combined position in the spot and futures markets is calculated as the weighted average of the difference in the natural logarithms of daily spot prices and daily futures prices, as given in equation (9).

$$R_{H,t} = ln\left(\frac{S_t}{S_{t-1}}\right) - h^*_t ln\left(\frac{F_t}{F_{t-1}}\right) \tag{9}$$

where $R_{H,t}$ is the hedged portfolio's return at time t. $ln\left(\frac{S_t}{S_{t-1}}\right)$ and $ln\left(\frac{F_t}{F_{t-1}}\right)$ are the returns of the spot asset and futures contracts, respectively, at time t. h^*_t is the optimal hedge ratio at time t.

The overall risk or variance of return for the hedged portfolio is calculated using Equation (10).

$$\sigma^2_{H,t} = \sigma^2_{S,t} + (h^*_t)^2\sigma^2_{F,t} + 2h^*_t\sigma_{SF,t} \tag{10}$$

where $\sigma^2_{H,t}$ is the conditional variance of the hedged portfolio's return at time t, $\sigma^2_{S,t}$ and $\sigma^2_{F,t}$ are the conditional variances of an asset's return at time t for spot and futures returns, respectively. $\sigma_{SF,t}$ is the conditional covariance between spot and futures returns at time t, and h^*_t is the optimal hedge ratio at time t.

The overall risk reduction is calculated as the proportion of the standard deviation of the unhedged portfolio return, which can be reduced by taking a hedged position, as shown in Equation (11).

$$HE = \left(\frac{\sigma_U - \sigma_H}{\sigma_U}\right) \times 100 \quad (11)$$

where HE measure of hedging effectiveness and σ_U and σ_H are the standard deviations of the returns for the unhedged and hedged portfolios, respectively.

4. Empirical Results

4.1 Descriptive Statistics

The distribution of returns for each sample asset, given by descriptive statistics, is presented in Table 2. The table shows that the returns on each asset are highly volatile during the sample period. The median daily returns are zero, except for the RSS3 spot returns and SET50 index futures returns. The average returns are close to zero, ranging from -0.238% to 0.075%. Standard deviations, representing the volatility of daily mean returns, vary from 0.30% to 2.91%. Among the assets, USD futures exhibit the least volatility, whereas CBG stock futures display the highest volatility.

Return distributions are symmetric for most sample assets, with a skewness of -0.5 to 0.5. Five assets–spot RSS3, RSS3 futures, gold futures, GUNKUL stock futures, and STA stock futures–have a left-skewed distribution. In addition, the kurtosis of each asset's return is greater than three, indicating a leptokurtic distribution, a distribution with fatter tails than a normal distribution.

The last column of Table 2, the correlation coefficients between spot RSS3 and each futures contract. A consistently low positive correlation was observed, ranging from 0.0003 to 0.2914, indicating that their prices move in the same direction to each other. As expected, RSS3 futures and STA stock futures show the highest correlations with RSS3 spot returns. Only three contracts have low negative correlation with spot RSS3, namely USD, CBG and GUNKUL.

The Table 2 shows the distributions of sample daily return, calculated as $\ln(P_t) - \ln(P_{t-1})$, from January 1, 2007, to December 31, 2019. The number presented are maximum, minimum, median, mean, standard deviation, skewness, and kurtosis of sample returns, all expressed in percentage term. The total number of observations is provided, along with the correlation coefficient between spot RSS3 and each futures contract.

Table 2 Descriptive Statistics

	# Obs	Max	Min	Median	Mean	SD	Skew	Kurt	Corr
Spot Asset:									
S-RSS3	3718	19.67	-22.59	0.081	-0.015	1.83	-1.40	24.72	1.0000
Futures Contracts:									
RSS3	889	9.82	-21.87	0	-0.013	2.24	-1.64	19.26	0.2914
GOLD	2302	4.33	-11.75	0	0.008	0.86	-1.45	24.32	0.0418
USD	1853	1.65	-2.43	0	-0.003	0.30	-0.36	7.88	-0.0238
SET50	3718	11.46	-14.19	0.045	0.027	1.51	-0.27	11.08	0.0715
STA	2145	18.41	-36.89	0	-0.045	2.54	-1.47	28.86	0.1726
CBG	1036	30.81	-30.79	0	0.075	2.91	-0.11	28.48	-0.0105
CPF	2145	9.37	-10.86	0	0.005	1.90	0.17	5.94	0.0517
IVL	2145	12.34	-13.12	0	-0.019	2.46	0.02	5.47	0.0875
PTTGC	1657	9.57	-9.07	0	-0.016	1.76	0.05	5.44	0.0524
BANPU	2573	20.23	-23.02	0	-0.039	2.18	-0.38	17.91	0.0502
CKP	1036	8.41	-8.07	0	0.068	1.91	0.02	5.44	0.0044
GUNKUL	724	6.32	-16.56	0	-0.103	1.97	-1.75	15.70	-0.0013
IRPC	2145	9.50	-12.30	0	-0.238	1.95	-0.11	6.40	0.1000
PTG	724	9.44	-12.53	0	-0.092	2.66	-0.58	5.80	0.0003
PTT	2710	9.66	-9.77	0	0.043	1.72	0.16	6.65	0.0734
PTTEP	2710	12.88	-11.76	0	0.016	1.95	0.16	7.08	0.0632
TOP	2145	10.64	-9.52	0	-0.008	1.93	0.14	5.59	0.0822

4.2 Static Hedge Ratio

Using the OLS estimation of the minimum – variance hedge ratio, the findings in Table 3 indicate that RSS3D is the most effective instrument for hedging RSS3 spot price volatility. This aligns with the general suggestion that an appropriated hedging instrument is the one where the underlying asset exactly matches the asset being hedged (Hull, 2015). Using RSS3D futures as a hedging instrument, with an estimated hedge ratio of 0.2377, reduces the overall risk by 4.3413%. The standard deviation of returns decreases from 1.8287% to 1.7493% around the average returns, and the average returns improve. The average negative daily return decreases from -0.0460% to -0.0429%. However, this result is far from what is meant by a perfect hedge, as shown in Table 2 that RSS3 spot and futures prices are not perfectly correlated,

The Table 3 presents the results of the OLS estimation of the minimum - variance hedge ratio using data from the full sample period. The optimal hedge ratio is defined as the beta coefficient of the simple linear regression between spot and futures returns, $R_{s,t} = \alpha + \beta R_{F,t} + \varepsilon_t$. The average return and standard deviation of both the unhedged and hedged portfolios, as well as risk reduction, are expressed as daily percentages. For an unhedged portfolio, the average return and standard deviation are calculated for the corresponding period, with futures contracts used for hedging. For a hedged portfolio, the average return is calculated as $R_{H,t} = ln\left(\frac{S_t}{S_{t-1}}\right) - h_t^* ln\left(\frac{F_t}{F_{t-1}}\right)$, and the standard deviation is calculated as the square root of variance, where $\sigma_{H,t}^2 = \sigma_{S,t}^2 + (h_t^*)^2\sigma_{F,t}^2 + 2h_t^*\sigma_{SF,t}$. Finally, risk reduction is calculated as the percentage change in the standard deviation from the unhedged portfolio: $HE = \left(\frac{\sigma_U - \sigma_H}{\sigma_U}\right) \times 100.$ Statistical significance at the 1% (***), 5% (**), and 10% (*) levels is reported for estimated hedged ratios.

Table 3 OLS Estimated Hedge Ratio and Hedging Effectiveness

Futures Contracts	Hedge Ratio	Unhedged Portfolio RSS3 Spot		Hedged Portfolio RSS3 Spot + Futures		Risk Reduction (%)
		Avg Return (%)	SD	Avg Return (%)	SD	
RSS3D	0.2377***	-0.0460	1.8287	-0.0429	1.7493	4.3413
GOLD	0.0886**	-0.0396	1.8205	-0.0403	1.8190	0.0875
USD	-0.1313*	-0.0471	1.6692	-0.0475	1.6687	0.0283
SET50	0.0867***	-0.0148	1.8319	-0.0171	1.8272	0.2556
STA	0.1153***	-0.0626	1.6969	-0.0575	1.6715	1.5001
CBG	-0.0066	-0.0052	1.8081	-0.0047	1.8080	0.0056
CPF	0.0460**	-0.0626	1.6969	-0.0629	1.6947	0.1335
IVL	0.0604***	-0.0626	1.6969	-0.0615	1.6904	0.3836
PTTGC	0.0505**	-0.0413	1.6924	-0.0405	1.6901	0.1376
BANPU	0.0411**	-0.0090	1.7838	-0.0074	1.7816	0.1260
CKP	0.0042	-0.0052	1.8081	-0.0055	1.8081	0.0010
GUNKUL	-0.0012	-0.1042	1.8348	-0.1043	1.8348	0.0001
IRPC	0.0870***	-0.0626	1.6969	-0.0606	1.6684	0.5012
PTG	0.0002	-0.1042	1.8348	-0.1042	1.8348	0.0000
PTT	0.0785***	-0.0034	1.8401	-0.0067	1.8352	0.2696
PTTEP	0.0595***	-0.0034	1.8401	-0.0043	1.8365	0.2000
TOP	0.0723***	-0.0626	1.6969	-0.0620	1.6912	0.3382

The STA stock futures contract is the second-best instrument for hedging the RSS3 spot price volatility. With an estimated hedge ratio of 0.1153, the overall risk is reduced by 1.5001%. The standard deviation of the return decreases from 1.6969% to 1.6715%, and the average return also improves, with the average negative daily return decreasing from -0.0626% to -0.0575%. The remaining contracts slightly decrease the volatility of the RSS3 spot price. Some of these, such as gold, USD, SET50, BANPU, CPF, IRPC, IVL, PTT, PTTEP, PTTGC, and TOP, can reduce the risk by less than 1%. Others, including CBG, CKP, GUNKUL, and PTG, provided minimal help in risk reduction. Hedging with CBG, IVL, PTTGC, BANPU, IRPC, and TOP results in improved average returns.

4.3 Dynamic Hedge Ratio

Using the DCC-GARCH (1,1), the minimum – variance hedge ratio is allowed to change daily. The results in Table 4 are quite consistent with the results in the static case. RSS3D futures and STA stock futures are the first and second most effective instruments, respectively, for hedging RSS3 price risk. The overall risk can be reduced by 4.7750% and 1.3388% using RSS3D and STA futures contracts, respectively. Specifically, with RSS3D futures, the standard deviation decreases from 1.8287% for the unhedged portfolio to 1.7413% for the hedged portfolio. With STA stock futures, the standard deviation decreases from 1.6969% for the unhedged portfolio to .6742% for the hedged portfolio. Other contracts that help in reducing the overall price risk of RSS3, though only slightly by less than 1%, include CBG, CKP, GUNKUL, IRPC, IVL, PTG, PTT, PTTEP, PTTGC, TOP, gold, USD, and SET50 futures. However, CPF and BANPU futures slightly increase the volatility and returns of the hedged portfolio. For most of these contracts, that is, CBG, GUNKUL, IRPC, IVL, PTG, PTTEP, PTTGC, RSS3D, STA, not only is the risk decreased, but the average return also increases.

The Table 4 presents the results of the DCC-GARCH (1,1) estimation of the minimum – variance hedge ratio. The dynamic conditional variance – covariance matrix is estimated using the DCC-GARCH (1,1) model. The optimal hedge ratio is then calculated as the ratio of covariance between spot and futures returns to the variance of futures returns: $h_t^* = \frac{\sigma_{SF,t}}{\sigma_F^2}$. The reported hedge ratio is the average of daily estimated hedge ratios. The average return and standard deviation of the unhedged and hedged portfolios as well as risk reduction are expressed in daily percentage terms. For an unhedged portfolio, the average return and standard deviation are calculated for the corresponding period, with futures contracts used for hedging. For a hedged portfolio, the average return is calculated as $R_{H,t} = ln\left(\frac{S_t}{S_{t-1}}\right) - h_t^* ln\left(\frac{F_t}{F_{t-1}}\right)$, and the standard deviation is calculated as the square root of variance: $\sigma_{H,t}^2 = \sigma_{S,t}^2 + (h_t^*)^2\sigma_{F,t}^2 + 2h_t^*\sigma_{SF,t}$. Finally, risk reduction is calculated as the percentage change in the standard deviation from the unhedged portfolio: $HE = \left(\frac{\sigma_U - \sigma_H}{\sigma_U}\right) \times 100.$

Table 4 DCC GARCH (1,1) Estimated Hedge Ratio and Hedging Effectiveness

Futures Contracts	Hedge Ratio	Unhedged Portfolio RSS3 Spot		Hedged Portfolio RSS3 Spot + Futures		Risk Reduction (%)
		Avg Return (%)	SD	Avg Return (%)	SD	
RSS3D	0.2250	-0.0460	1.8287	-0.0256	1.7413	4.7750
GOLD	0.0797	-0.0396	1.8205	-0.0408	1.8192	0.0750
USD	-0.1129	-0.0471	1.6692	-0.0477	1.6689	0.0135
SET50	0.0823	-0.0148	1.8319	-0.0148	1.8286	0.1830
STA	0.1176	-0.0626	1.6969	-0.0526	1.6742	1.3388
CBG	-0.0080	-0.0052	1.8081	-0.0051	1.8073	0.0444
CPF	0.0410	-0.0626	1.6969	-0.0623	1.6970	-0.0048
IVL	0.0522	-0.0626	1.6969	-0.0608	1.6929	0.2394
PTTGC	0.0417	-0.0413	1.6924	-0.0394	1.6909	0.0908
BANPU	0.0394	-0.0090	1.7838	-0.0063	1.7867	-0.1588
CKP	0.0030	-0.0052	1.8081	-0.0055	1.8080	0.0047
GUNKUL	0.0019	-0.1042	1.8348	-0.1040	1.8346	0.0076
IRPC	0.0805	-0.0626	1.6969	-0.0592	1.6901	0.4039
PTG	0.0037	-0.1042	1.8348	-0.1037	1.8347	0.0041
PTT	0.0674	-0.0034	1.8401	-0.0067	1.8385	0.0860
PTTEP	0.0521	-0.0034	1.8401	-0.0024	1.8370	0.1860
TOP	0.0617	-0.0626	1.6969	-0.0626	1.6913	0.3349

5. Conclusions

This study uses the daily settlement prices of highly liquid futures contracts traded on the TFEX from the establishment of the contract to 2019 to identify the most effective futures contracts for hedging fluctuations in RSS3 spot prices. The results for the static hedge ratio reveal that RSS3D and STA stock futures are the most effective tools for hedging RSS3 price volatility. They not only decrease volatility, but also increase the average return of the hedged position compared to the unhedged position. Consistent results were found in the case of the dynamic hedge ratio. RSS3D and STA stock futures are the most effective tools.

The results from both static and dynamic cases are consistent with (Hull, 2015), suggesting that, to minimize basis risk in hedging, the price of the asset underlying the futures contract should be closely related to the price of the asset that needs to be hedged. Additionally, they support findings in the literature, such as Ali et al. (2020), Belousova and Dorfleitner (2012), Bessler and Wolff (2015), Chunhachinda et al. (2019), Nguyen et al. (2020), and Satyanarayan and Varangis (1996), regarding the ability of equity futures contracts as a hedging instrument for commodity portfolios. This study provides evidence from emerging markets, in which futures exchanges are still in the developing stage, offering a limited variety of contract choices. Finally, the results show that the effectiveness of a hedging instrument depends on the model used to estimate the hedge ratio. For RSS3D futures, the hedge ratio estimated from the DCC-GARCH (1,1) model leads to a higher risk reduction than the hedge ratio estimated from the OLS method. Conversely, for STA stock futures, the opposite result is found, where the hedge ratio estimated from the OLS method leads to a higher risk reduction than the hedge ratio estimated from the DCC-GARCH (1,1) model. This finding aligns with (Chotinuchittrakul & Boonvorachote, 2013), who find that OLS estimated hedge ratios can more effectively reduce the risk of an unhedged position than GARCH (1,1) estimated hedge ratios.

As the estimated optimal hedge ratio is very low, it might be difficult for hedgers with relatively small positions in the spot rubber market to hedge their positions using TFEX-listed futures contracts. Notably, the contract size of the RSS3D futures is 5,000 kg. With an average DCC-GARCH (1,1) estimated optimal hedge ratio of 0.2250, a hedger would need approximately 22,222 kg in the RSS3 cash position for each RSS3D futures contract. To promote liquidity and effective price discovery in the futures market, the TFEX might consider increasing participation from individuals or entities who need to hedge their small positions in the rubber cash market by introducing smaller RSS3D futures.

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