Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi:10.13106/jafeb.2021.vol8.no2.0685

The Stochastic Volatility Option Pricing Model: Evidence from a Highly Volatile Market

Woraphon WATTANATORN[1], Kedwadee SOMBULTAWEE[2]

Received: November 05, 2020 Revised: January 05, 2021 Accepted: January 15, 2021

Abstract

This study explores the impact of stochastic volatility in option pricing. To be more specific, we compare the option pricing performance between stochastic volatility option pricing model, namely, Heston option pricing model and standard Black-Scholes option pricing. Our finding, based on the market price of SET50 index option between May 2011 and September 2020, demonstrates stochastic volatility of underlying asset return for all level of moneyness. We find that both deep in the money and deep out of the money option exhibit higher volatility comparing with out of the money, at the money, and in the money option. Hence, our finding confirms the existence of volatility smile in Thai option markets. Further, based on calibration technique, the Heston option pricing model generates smaller pricing error for all level of moneyness and time to expiration than standard Black-Scholes option pricing model, though both Heston and Black-Scholes generate large pricing error for deep-in-the-money option and option that is far from expiration. Moreover, Heston option pricing model demonstrates a better pricing accuracy for call option than put option for all level and time to expiration. In sum, our finding supports the outperformance of the Heston option pricing model over standard Black-Scholes option pricing model.

Keywords: Stochastic Volatility, Option Pricing Models, Performance Comparison, Heston Option Pricing Model, Nonconstant Volatility

JEL Classification Code: G10, G11, G13

1. Introduction

In 1973, Black and Scholes developed a model to price contingent claim named Black-Scholes option pricing model (Black & Scholes, 1973). This option pricing is well known among both academicians and practitioners due to an easiness to use. As a consequence, the Black-Scholes (BS) model is useful and convenient to value option price for both portfolio management and risk management purposes. However, due to its reliance on strict assumptions, the BS model assumes that underlying asset prices follow a geometric Brownian motion (GBM) process with known, and constant of mean and variance. Besides, BS assumes a constant risk-free rate, no transaction costs, and continuous trading. Based on mentioned unrealistic assumptions for the real world, the pricing accuracy of the BS model is questionable. Further, many empirical studies report that the BS hardly predicts option price correctly, principally because its assumption of constant volatility is incorrect. Volatility is not constant; it moves stochastically over time (Geske, 1979; Johnson & Shanno, 1987; Rubinstein, 1985; Scott, 1987; Wiggins, 1987). Regarding this stochastic volatility, the BS model's assumption of constant volatility is inaccurate and the model will misprice. Hence, the hedging parameters obtained by the BS model can lead to low hedging efficiency. To capture the inconsistent nature of volatility, an alternative stochastic volatility option pricing model is more appropriate (Ball & Roma, 1994).

Over the past decades, stochastic volatility option pricing models have become more popular, e.g., Hull and White (1987), Stein and Stein (1991) and Heston (1993). However,

[1]First Author and Corresponding Author. Lecturer in Finance, Department of Finance, Thammasat Business School, Thammasat University, Thailand [Postal Address: 2 Phra Chan Road, Phra-Borom Maha-Ratchawang, Phra-Nakhon, Bangkok 10200, Thailand] Email: woraphon@tbs.tu.ac.th
[2]Assistant Professor in Marketing, Department of Marketing, Thammasat Business School, Thammasat University, Thailand. Email: kedwadee@tbs.tu.ac.th

the drawback of stochastic volatility option pricing models is that they are theoretical difficulty as well as difficult to apply (Papi, Pontecorvi, & Donatucci, 2017). Therefore, in this study, we aim to explore the pricing performance of the most widely used stochastic volatility option pricing model – the Heston option pricing model (Alfeus, Overbeck, & Schlögl, 2019) because the Heston option pricing model is the modified version of the BS model that accommodates the stochastic volatility of asset returns and derive a model with a closed-form pricing formula. Several studies in developed markets show the superior pricing accuracy of Heston model over BS (Bakshi, Cao, & Chen, 1997; Fiorentini, Leon, & Rubio, 2002). Although the emerging markets are known for the higher volatility than developed markets (Kearney, 2012; Jantadej & Wattanatorn, 2020; Luu & Luong, 2020), there is a limited study of stochastic volatility option pricing model in emerging context. Hence, in this study, we focus on Thailand market – one of the important emerging markets due it economic size and it has exhibited rapid expansion over the past decades (Wattanatorn & Nathaphan, 2019, 2020). Therefore, the aim of this study is to explore the effectiveness of Heston option pricing model in the emerging market, Thailand.

This study contributes to the existing literature in four main ways. Firstly, it finds that asset volatility moves stochastically in the Thai market, thus, a model using stochastic volatility assumption is more consistent with the data. Secondly, it finds that stochastic volatility significantly affects the performance of option pricing formulas. Thirdly, based on the model comparison using SET 50 index option prices, the study finds that the Heston model gives smaller pricing errors and less biased theoretical prices for both put and call options. Fourthly, although volatility smiles exist in the Heston model, they are less severe than those exhibited by the BS model.

The remainder of the study is organized as follows. Section 2 provides a related literature review. Section 3 presents the research methods and data used in this study, while section 4 analyzes the findings and discussion. The last section is a conclusion and summary.

2. Literature Review

2.1. Stochastic Volatility

Prior studies support the important role of stochastic volatility in asset pricing (Geske, 1979; Johnson & Shanno, 1987; Rubinstein, 1985; Scott, 1987; Wiggins, 1987). In addition, much evidence demonstrates that the stochastic volatility has a mean reversion property (Scott, 1987; Stein & Stein, 1991). Beside equity market, the more recent literature documents the stochastic volatility in option market called volatility smile. For example, Jones (2003) shows that there is volatility smile on S&P100 option index based on sample between 1986 and 2000. Like Jones (2003), Yakoob and Economics (2002) reported volatility smiles in options on the S&P100 and S&P500 indexes based samples between 2000 and 2001.

Although the Heston model has provided a closed-form option pricing formula since 1993, its popularity has been impacted by how difficult it is to use. In 1997, Bakshi et al. studied alternative option pricing models, including the Heston model, for S&P500 options between June 1, 1988, and May 31, 1991. They found volatility smiles violate the BS model's assumptions. Hence, they concluded that the Heston model's price calculations are more accurate than those of the BS model. To support the existence of stochastic volatility, many researchers point to evidence of stochastic volatility in other developed markets. For example, studies of Nikkei 225 options demonstrated a volatility smile after the Asian crisis (Fukuta & Ma, 2013). Further, Larkin et al. (2012) reported a positive relationship between stochastic processes and sampling frequency of asset prices. Using ultrahigh frequency data, they reported an asymmetric volatility smile for options on the ASX200. They further demonstrated that the call options only exhibited a volatility smile during a bear market. Evidence of volatility smiles is also reported in the smaller developed markets. For example, Beber (2001) studied the implied volatility of options on the Italian Stock Market – MIBO30 between 1995 and 1998. MIBO30 is the most liquid option traded on the Italian stock market. Beber demonstrated a U-shaped relationship between its volatility and its moneyness by showing that the volatility changes in relation to the level of moneyness on both short and long expiration options. The same stochastic volatility is reported on the Spanish option index – IBEX-35 (Peña, Rubio, & Serna, 1999).

Despite emerging markets demonstrating higher volatility than developed markets, few studies on stochastic volatility are conducted in emerging markets. For example, Singh (2013) reported evidence of volatility smiles in the Indian option market. He further reported that, although no option pricing model can replicate the market price, volatility-based option pricing models such as the Heston model and Deterministic Volatility Function (DVF) are among the best estimation models compared with other option pricing models. Expanding on the work of these researchers, we further examine the effect of volatility smiles on the SET50 index using both put and call options.

2.2. Stochastic Volatility Option Pricing Model

Prior literature demonstrates that volatility exhibits a mean reversion pattern: it always reverts to a long-run mean whenever its current level deviates from the mean value (Hull & White, 1987; Scott, 1987; Stein & Stein, 1991;

Wiggins, 1987). Previous researchers' models allow for another source of risk, such as changing volatility, but the results are mixed. For example, Nandi (1998) used high frequency data to study S&P500 index options and found that the stochastic volatility option pricing model offered better pricing performance than the BS model for out of the money options. Sigh (2013) demonstrated that the volatility smile is linked to the inefficiency of the BS model. Fiorentini et al. (2002) discussed how volatility smiles exist in the Spanish market and demonstrated that the stochastic volatility option pricing model is marginally better than the BS model based on the IBEX-35 stock index.

2.3. The Heston Option Pricing Model.

The Heston option pricing model is the primary closed form stochastic option pricing model. Like stock prices, which normally follow a Geometric Brownian motion (GBM), the Heston model allows volatility to follow stochastic process defined by Cox-Ross-Ingersoll (CIR) (1985). Theoretically, the Heston model allows correlation between the stochastic term of asset price and volatility. While the BS model only allows for a single source of risk (underlying asset), the Heston model allows changing volatility as another source of risk. Thus, the Heston model utilizes two sources of risk to derive the price of the option. The underlying processes of asset price and its volatility are as follows:

$$dS_t = \mu S_t dt + \sqrt{v_t} S_t dZ_{1,t} \tag{1}$$

$$dv_t = \kappa(\theta - v_t)dt + \sigma\sqrt{v_t} dZ_{2,t} \tag{2}$$

$$E^p[dZ_{1,t}, dZ_{2,t}] = \rho dt \tag{3}$$

where κ, θ, and σ are the mean reversion speed, mean reversion long-run level, and volatility of the variance respectively and v_t is the level of variance at time t. These parameters are assumed to be positive values.

In general, the Heston option price, $V = V(v_t, S_t, T, K, R_f, \sigma, \kappa, \theta, \lambda, \rho)$, is a function of current asset price and its volatility, time to expiration, strike price, risk-free rate, variance parameters of asset price and its volatility of the underlying asset, mean reversion speed, mean reversion level for the variance, volatility risk premium, and the correlation between two processes as shown in Eq (3).

3. Research Methods and Data

3.1. Data and Sample Selection

In this study, we based our analysis on daily data of SET50 index options between May 2011 and September 2020. Our sample consisted of 440 call options and 476 put options. We gather daily SET50 option price, exercise price (strike price), option expiration date from Thomson Reuter DATASTREAM database. Like prior study, we obtain SET50 index, which is the underlying asset of SET50 index option and one-month Thailand treasury bills as a proxy for risk-free rate provided by Thomson Reuter DATASTREAM database and Thai bond association respectively (Jantadej & Wattanatorn, 2020). In addition, we apply the actual number of trading day in our analysis to correctly formulate the time to maturity. Table 1 summarizes variable definition in this study.

The study shows that option volatility change by the level of moneyness (Bakshi et al., 1997). In this analysis, we define the level of moneyness into five groups. For call option, when the underlying asset price equals to its strike price (S = K), we define it is an at the money option (ATM). To be more specific, we define the option as ATM when its S/K ratio is between 0.97 and 1.03. Further, the option is out-of-the-money (OTM) when the underlying asset price is less than its strike price (S < K). We define the option as OTM when the S/K ratio laid between 0.94 and 0.97. Conversely, if the underlying asset price is more than its strike price (K < S), the option is in-the-money (ITM). Hence, we define the option as ITM when the S/K ratio is between 1.03 and 1.06. We further classify option into deep out-of-the-money (DOTM) and deep in-the-money (DITM). We define options that have a S/K ratio of less than 0.94 as DOTM and define options that have S/K ratio over 1.06 as DITM. In the same ways, we use K/S ratio to define the level of moneyness for put option and apply the same criteria as call option

Table 1: Variables definition

Variable	Description
V_t	Option price
S_t	SET50 index
K	Option strike price
R_f	1-month Thailand treasury bills
σ	Volatility of variance
v	Level of volatility
κ	Mean reversion speed
θ	Mean reversion of variance
λ	Volatility risk premium
ρ	Correlation coefficient between Weiner process

In the Thai market as well as other emerging market study, the market liquidity issues is an important concern (Wattanatorn, Padungsaksawasdi, Chunhachinda, & Nathaphan, 2020; Wattanatorn & Tansupswatdikul, 2019). Therefore, we take care of this liquidity issue following Bakshi et al. (1997). We further class further classify our sample into six groups based on day to expiration between seven days and two months since the near expiration options are more likely to suffer from liquidity-related bias to alleviate the liquidity-related bias concern. Table 2 shows the average option value and number of samples after the time-to-expiration criterion is used as a filter. Panel A shows the call options while Panel B shows the put options. There were a total of 2,220 option prices, comprised of 1,060 call prices and 1,160 put prices.

Both call and put options are more likely to trade at ATM. There are 425 call option traded at ITM and DITM while there are 323 option traded at OTM and DOTM. Also, we find a similar trend for put option.

3.2. Model Estimation and Calibration

To estimate model parameters, we apply model calibration technique to accurately estimate Heston model's parameters. The objective of model calibration is to obtain the best fit model parameter which yield minimum different between model predicted price and market prices (Bakshi et al., 1997; Beliaeva & Sanjay, 2010; Cui, del Baño Rollin, & Germano, 2017). As suggested by prior studies, we apply the minimize sum-square-error (SSE) between the market price, C_{mkt}, and model price, C_{heston}, as shown:

$$\begin{aligned}&\text{error}(\boldsymbol{\sigma}, \boldsymbol{\nu}, \boldsymbol{\kappa}, \boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\rho})\\ &= C_{\text{mkt}} - C_{\text{heston}}(S_t, T, K, R_f; \boldsymbol{\sigma}, \boldsymbol{\nu}, \boldsymbol{\kappa}, \boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\rho})\end{aligned} \tag{4}$$

$$\text{SSE} = \min \sum_{n=1}^{N} |\text{error}(\boldsymbol{\sigma}, \boldsymbol{\nu}, \boldsymbol{\kappa}, \boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\rho})|^2 \tag{5}$$

For each day, we minimize the objective function shows in Eq. 5 and employ numerical method to estimate the value of model parameter including $\boldsymbol{\sigma}, \boldsymbol{\nu}, \boldsymbol{\kappa}, \boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\rho}$. We then predict the option price based on estimated parameter in next section.

3.3. Model Performance

To compare the model performance between Black-Schole option pricing and Heston option pricing, we employ two methods to evaluate model performance. First, we employ the traditional model evaluation method – the root means square error (RMSE) as our second model performance measurement (Bakshi et al., 1997; Bhat, 2019; Singh & Dixit, 2016). RMSE is the absolute fit of the model and market date. The notorious advantage of RMSE is that the RMSE squares the error term. Hence, RMSE gives the greater weight to large error and thus penalized the large error model. As the result, RMSE reduces the tendency toward overfit of the model. And we expect the better model can show low RMSE, which reflect the good fit of the model.

$$\text{RMSE} = \sqrt{\frac{\sum_1^n \left(C_{\text{mkt}} - C_{\text{model}}\right)^2}{n}} \tag{6}$$

Second, we apply mean pricing error (MPE) to gauge the model performance (Bakshi et al., 1997; Bhat, 2019; Feng, Hung, & Wang, 2016). MPE is the mean percentage price different between the mean actual market price and model price as shown in Eq. 6. Since MPE based their calculation on the actual value, MPE can indicate the direction of biasness from the model (Bhat, 2019; Wilson & Keating, 2001).

$$\text{MPE} = \frac{1}{n}\sum_1^n \frac{C_{\text{mkt}} - C_{\text{model}}}{C_{\text{mkt}}} \tag{7}$$

4. Results and Discussion

4.1. Summary statistic

In this section, we report the empirical finding of the study. Table 2 reports basic summary statistic of the sample under study. Table 2 report cross-sectional option price and standard deviation for each level of moneyness and time to expiration. Panel A shows the result for call option. The table shows that the value of option increase as it becomes in-the-money. In addition, the value of call option declines as it approaches the expiration date. In a similar pattern, we find that the value of put option increase as it becomes in-the-money option as well as it increases as if the option is far from expiration date.

4.2. Volatility Smile

In this section, we demonstrate the existence of stochastic volatility. Figure 1 illustrates a clear picture of stochastic volatility in SET50 index for call option. We find that both BS implied volatility and Heston implied volatility vary by the level of moneyness at all time to expiration. The existence of this smile volatility violates the basic assumption of BS model. Hence, our finding – the longest prior of study in Thailand, confirms the existing of smile volatility in SET50 index in Thailand. We further compare the smile volatility for BS and Heston model. We find that the BS demonstrates larger curvature than the Heston model at all time to expiration. In addition, Figure 2 shows similar pattern of volatility smile for put option.

Table 2: Reports cross-sectional average of option price and number of samples (parenthesis). The sample period spans May 2011 – September 2020. The samples are classified into five moneyness categories and six times to expiration. Panel A report the sample average for call option and Panel B report the sample average for put option

Panel A: Call option							
Moneyness		**Day to expiration**					
		7	**10**	**15**	**20**	**40**	**60**
DOTM	(S/K < 0.94)	0.646	0.577	0.373	0.812	1.518	3.290
		(1.284)	(1.075)	(0.402)	(1.152)	(1.586)	(4.168)
OTM	(0.94 < S/K < 0.97)	0.723	1.190	1.296	2.928	6.291	9.056
		(0.691)	(2.186)	(1.161)	(3.233)	(3.618)	(8.393)
ATM	(0.97 < S/K < 1.03)	8.911	10.550	10.260	11.000	18.356	22.471
		(8.532)	(9.266)	(9.056)	(9.430)	(9.134)	(15.972)
ITM	(1.03 < S/K < 1.06)	31.476	37.868	34.330	36.177	36.455	49.155
		(16.451)	(17.256)	(18.893)	(15.481)	(16.948)	(17.881)
DITM	(S/K > 1.06)	81.320	86.376	71.764	76.437	79.092	85.129
		(36.426)	(38.204)	(41.507)	(36.724)	(32.951)	(42.528)
Panel B: Put option							
Moneyness		**Day to expiration**					
		7	**10**	**15**	**20**	**40**	**60**
DOTM	(K/S < 0.94)	0.590	1.000	0.588	1.140	3.471	9.514
		(1.644)	(1.841)	(0.845)	(1.620)	(2.635)	(7.738)
OTM	(0.94 < K/S < 0.97)	1.562	1.867	1.789	3.669	7.964	12.567
		(3.051)	(3.159)	(1.900)	(3.467)	(4.443)	(10.070)
ATM	(0.97 < K/S < 1.03)	8.612	10.832	9.533	12.021	21.360	29.527
		(8.509)	(10.092)	(8.281)	(10.111)	(9.545)	(15.730)
ITM	(1.03 < K/S < 1.06)	37.500	40.243	39.311	40.771	49.363	56.050
		(19.245)	(20.168)	(19.675)	(18.364)	(7.629)	(4.762)
DITM	(K/S > 1.06)	135.843	127.785	75.339	81.416	89.222	103.077
		(101.309)	(88.849)	(51.243)	(64.129)	(56.288)	(32.002)

Furthermore, we find that the volatility smile becomes more severe as options approach their expiration for both call and put option. Figure 1 and Figure 2 show that the volatility is flatter for 60 days before expiration than the near expiration. Clearly, it becomes more curvature, particularly at 7 and 10 days before expiration. Also, the volatility is higher for OTM option than ATM and ITM. In addition, we find that BS volatility shows larger curvature than Heston model in all time to expiration. As BS based their pricing model on the assumption of constant volatility, we conjecture that BS model faces a more severe in model mispricing. Hence, the Heston option pricing model – the alternative option pricing which can accommodate the changing volatility can accommodate this problem due to an ability of the model that allows volatility to move stochastically over time. Therefore, the Heston model may improve pricing and hedging performance when trading options on the Thai market

4.3. Parameter Estimation

We further estimate and calibrate Heston model's parameters. We employ the method shown in section 3.2 to estimate the six-model parameter including $\sigma, \nu, \kappa, \theta, \lambda, \rho$ which are volatility of variance, level of volatility, mean reversion speed, mean reversion of variance, Volatility risk premium, and correlation coefficient between Weiner process respectively. We then report the result of estimation and calibration in Table 3 and Table 4.

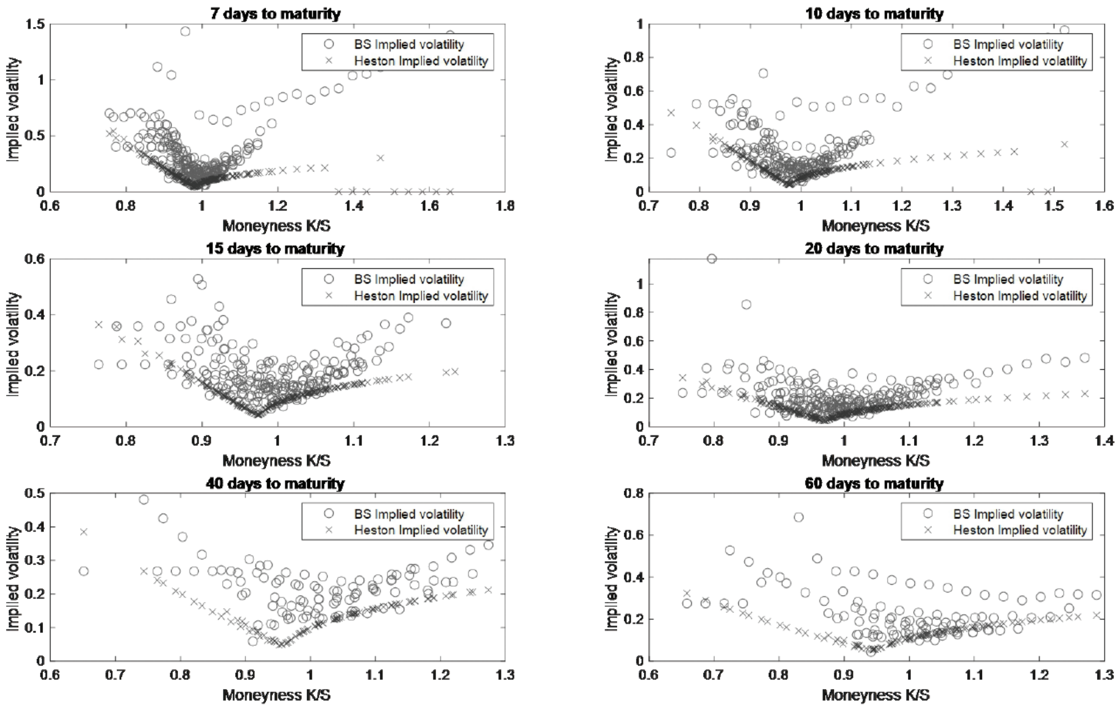

Figure 1: Shows implied volatility to level of moneyness for call options at 7, 10, 15, 20, 40, and 60 day to expiration

Source: Author

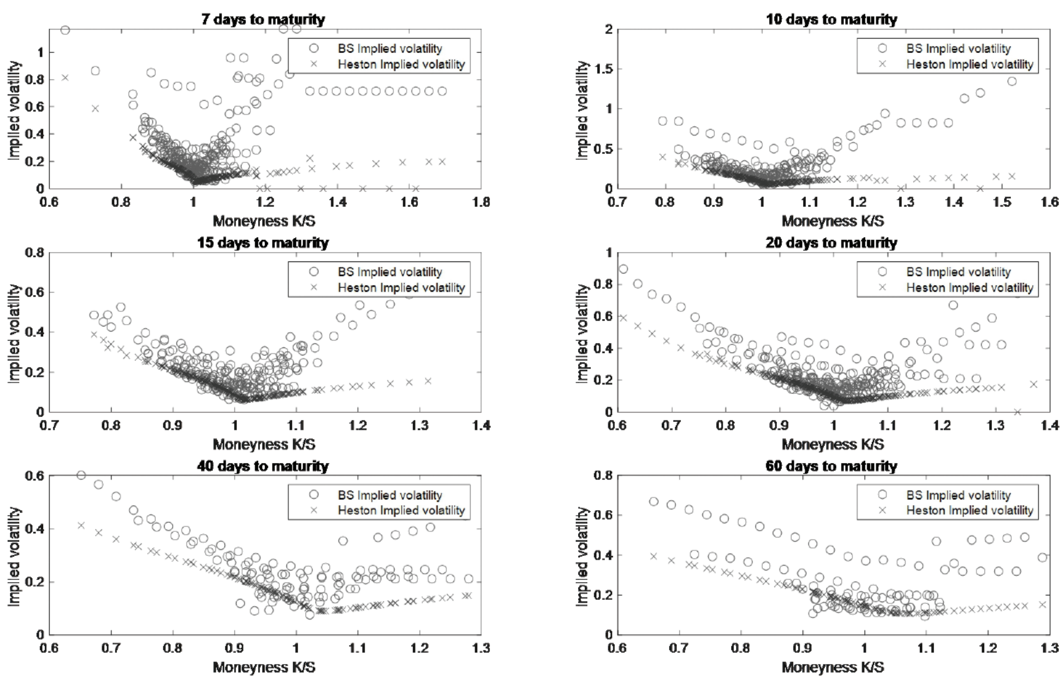

Figure 2: Shows implied volatility to level of moneyness for put options at 7, 10, 15, 20, 40, and 60 day to expiration

Source: Author

Table 3: Shows parameters for call options by time to expiration

Days to Expiration	Kappa	Theta	Lamda	Roh	Sigma	V_0
7	0.014	0.333	0.000	0.236	4.072	0.258
10	0.444	0.620	0.000	0.405	36.249	0.055
15	5.047	1.297	0.000	0.404	15.583	0.218
20	1.727	0.855	0.000	0.147	8.670	0.231
40	0.047	1.810	0.000	–0.173	47.110	0.027
60	0.160	4.044	0.000	0.195	12.874	0.606

Table 4: Reports the model's put option parameters for each time to expiration

Days to Expiration	Kappa	Theta	Lamda	Roh	Sigma	V_0
7	0.075	0.399	0.000	0.886	13.228	0.019
10	0.016	0.469	0.000	0.783	5.131	0.011
15	2.125	0.705	0.000	0.755	32.142	0.005
20	0.520	0.676	0.000	0.681	44.152	1.364
40	0.049	1.338	0.000	0.617	6.132	0.056
60	3.105	2.442	0.000	0.825	13.862	0.219

Table 3 shows the estimated parameter for call option. The results show that the speed of convergence, level of long-run volatility, and volatility of variance falls as option approach expiration date. Furthermore, the positive correlation for two Weiner processes suggests that the risk from the stochastic movement of the underlying asset and stochastic volatility move in the same direction, and the impact of both risks moves closely as options approach expiration.

Table 4 reports the result for put option. We find that the level of variance increases as options approach expiration. The results are consistent with the results found in Figure 2. As options approach expiration, all else remaining equal, they become more volatile. The level of volatility (V_0) increases as the options expire; the volatility of variance (sigma) representing the long-run mean of variance likewise increases. These findings support the hypothesis of high volatility closer to expiration.

4.4. Model Performance

Table 5 compares option pricing performance between BS and Heston option pricing mode using MPE and RMSE. The finding in this section demonstrates that the Heston model outperforms the BS model for all times to expiration and all degrees of moneyness. Panel A shows that both BS and Heston model provide a good result of pricing for OTM and DOTM option for all expiration periods. For example, at 7 days prior expiration, Heston gives only 1.040% error on DOTM option pricing comparing with 2.028% generate by BS model. However, this superior performance decline for longer days to expiration. For example, at 60 days prior expiration, Heston generates 4.013% prediction error comparing with 4.297% predicted by BS model for the same DOTM option. Although we find that the Heston option pricing yields a better pricing result in all level of moneyness and time to expiration, we further find that as option moves to ITM and DITM, the superior performance of Heston option pricing declines. For example, at 7 days prior expiration, Heston provides 37.298% pricing error for DITM option while BS generates 38.856% pricing error. Moreover, the superior performance declines for longer day to expiration as we found in DOTM. Moreover, the results show that both BS and Heston model generate large pricing error for the longer day to expiration option. One possible explanation of this large error is the liquidity issue supported by several studies (Brenner, Eldor, & Hauser, 2001; Peña et al., 1999). In addition, this liquidity issue is found to be an important issue in the Thai market (Pojanavatee, 2020; Wattanatorn et al., 2020).

Consistent with Panel A, the findings for put option shown in Panel B provide the similar results. Although, Heston model for put option provides lower pricing error in all level of moneyness and time to expiration like call option, we find that the levels of error are not far better than BS like in call option pricing. This findings are similar to those of call option. In sum, our results demonstrate the superior performance of the Heston model over BS in emerging market context. The findings here are consistent with the evidence found in develop markets (Bakshi et al., 1997; Fiorentini et al., 2002). Also, we find the same superior performance of Heston model over BS as in Indian stock index option (Singh & Dixit, 2016). More recently, our results go along with Bhat (2019) who shows the superior pricing performance of Heston model over BS model in currency option.

Table 6 reports the result of model performance based on MPE. Panel A reports the result for call option while Panel B reports the result for put option. Consistence with prior section, in Panel A, we find that Heston model outperforms BS model for all level of moneyness and time to expiration. Based on MPE, we can see the direction of bias of pricing error. The result reported by Table 6 clearly shows that the Heston option pricing model predicts pricing error toward undervaluing. Unlike Heston model, the BS model provides overvalue estimation for all moneyness and time to expiration. Although in previous section we find the RMSE are large for both the Heston and BS model, MPE is obviously lower for Heston model. In Panel B, we find the similar results for put option.

Table 5: Reports model pricing performance-based root mean square error—RMSE (Eq. 6). Panel A reports the result for call option while Panel B report the result for put option

Panel A: Call option							
Moneyness	**Model**	**Day to expiration**					
		7	**10**	**15**	**20**	**40**	**60**
DOTM	Heston	1.040	1.000	0.407	1.102	1.101	4.013
	BS	2.028	1.559	1.323	1.766	3.017	4.297
OTM	Heston	0.628	2.084	1.131	3.023	3.027	7.011
	BS	1.396	2.139	2.152	2.759	4.816	7.260
ATM	Heston	6.369	6.003	6.145	7.915	7.277	12.071
	BS	7.280	6.426	9.140	10.640	10.185	12.802
ITM	Heston	17.342	17.123	16.630	13.629	17.621	19.646
	BS	20.155	17.790	20.130	18.148	22.241	21.768
DITM	Heston	37.298	34.698	46.320	47.871	67.025	79.755
	BS	38.856	35.363	47.150	50.609	68.457	84.625
Panel B: Put option							
Moneyness	**Model**	**Day to expiration**					
		7	**10**	**15**	**20**	**40**	**60**
DOTM	Heston	1.661	1.898	0.805	1.577	2.134	5.894
	BS	2.144	1.971	1.313	2.112	3.190	6.332
OTM	Heston	3.097	2.127	1.900	3.091	3.724	6.086
	BS	1.648	3.137	2.023	3.517	4.798	6.589
ATM	Heston	6.813	6.114	7.496	7.986	6.374	10.001
	BS	7.320	7.160	8.672	8.862	7.677	13.143
ITM	Heston	20.506	20.123	16.597	15.454	6.012	5.429
	BS	21.104	21.801	17.503	17.429	6.351	14.927
DITM	Heston	39.117	31.148	59.026	71.635	73.279	46.321
	BS	40.690	33.361	60.270	73.082	75.518	57.556

Table 6: Reports model pricing performance based on mean pricing error—MPE (Eq. 7). Panel A reports the result for call option while Panel B report the result for put option

Panel A: Call option							
Moneyness		**Day to expiration**					
		7	**10**	**15**	**20**	**40**	**60**
DOTM	Heston	0.655	–1.239	–0.767	–1.120	–0.785	–1.626
	BS	1.451	1.435	1.127	1.536	2.571	3.624
OTM	Heston	–0.843	–1.692	–1.329	–1.001	–0.581	–6.013
	BS	1.198	1.962	1.779	2.461	4.606	–11.898
ATM	Heston	–2.219	–1.322	–2.273	–1.274	–1.031	–7.989
	BS	4.568	4.066	6.510	7.749	8.924	11.427
ITM	Heston	–2.399	–2.844	–2.139	–0.738	–1.139	–0.364
	BS	14.027	10.626	12.431	12.755	14.390	16.409
DITM	Heston	–1.742	–2.782	–2.441	–4.332	–0.887	–2.187
	BS	26.536	20.808	30.025	31.748	49.448	67.791
Panel B: Put option							
Moneyness		**Day to expiration**					
		7	**10**	**15**	**20**	**40**	**60**
DOTM	Heston	–1.128	–1.716	–1.087	–1.108	–0.812	–1.264
	BS	2.383	1.591	1.697	2.450	3.225	5.345
OTM	Heston	–1.706	–2.291	–0.914	–1.336	–0.339	–0.909
	BS	0.925	1.396	1.032	1.566	2.884	5.246
ATM	Heston	–1.461	–1.201	–1.750	–1.815	–0.903	–2.150
	BS	4.737	4.363	5.524	5.532	4.700	5.762
ITM	Heston	–1.429	–2.685	–7.803	–5.863	–5.764	–0.251
	BS	23.971	20.222	38.918	49.622	45.857	36.066
DITM	Heston	–3.760	–4.653	–2.877	–2.093	–0.002	–0.002
	BS	11.785	13.143	10.007	10.374	3.064	7.800

5. Conclusion

In general, derivatives are widely used as an instrument to manage risk (Park & Park, 2020) while the one of the most popular instrument used to manage portfolio risk is an option on index. Particularly, in Thailand, SET 50 index options are designed to help investors hedge their investment risks. It is crucial for both hedging processes to obtain the correct option price. The general way is to generate from a theoretical model. Empirically, many studies report inaccurate option pricing produced by BS model, though it is the most popular model. One major drawback of BS is that the volatility changes stochastically, which violates the standard BS model assumption. As the result, BS yields a large mispricing.

In this study, we challenge the BS model by alternative option pricing model, namely, the Heston option pricing model. This Heston option pricing model allows volatility to change stochastically. Therefore, it can accommodate the issue that the BS model can hardly handle. To be more specific, we compare the performance of the BS model against the Heston model based on their pricing error. Our finding demonstrates that the Heston model outperforms the BS model for all measures and conditions.

References

Alfeus, M., Overbeck, L., & Schlögl, E. (2019). Regime switching rough Heston model. *Journal of Futures Markets, 39*(5), 538–552. doi:10.1002/fut.21993

Bakshi, G., Cao, C., & Chen, Z. (1997). Empirical performance of alternative option pricing models. *The Journal of Finance, 52*(5), 2003–2049.

Ball, C. A., & Roma, A. (1994). Stochastic volatility option pricing. *Journal of Financial and Quantitative Analysis, 29*(04), 589–607.

Beber, A. (2001). *Determinants of the implied volatility function on the Italian Stock Market*. LEM Papers Series 2001/05, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Beliaeva, N. A., & Sanjay K., N. (2010). A Simple Approach to Pricing American Options Under the Heston Stochastic Volatility Model. *The Journal of Derivatives, 17*(4), 25–43. doi:10.3905/jod.2010.17.4.025

Bhat, A. P. (2019). An empirical exploration of the performance of alternative option pricing models: the case of Indian currency options. *Journal of Indian Business Research*, *11*(1), 23–49.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy, 81*(3), 637–654.

Brenner, M., Eldor, R., & Hauser, S. (2001). The Price of Options Illiquidity. *The Journal of Finance, 56*(2), 789–805. doi:10.1111/0022-1082.00346

Cui, Y., del Baño Rollin, S., & Germano, G. (2017). Full and fast calibration of the s stochastic volatility model. *European Journal of Operational Research, 263*(2), 625–638.

Feng, S.-P., Hung, M.-W., & Wang, Y.-H. (2016). The importance of stock liquidity on option pricing. *International Review of Economics & Finance, 43*, 457–467. doi:https://doi.org/10.1016/j.iref.2016.01.008

Fiorentini, G., Leon, A., & Rubio, G. (2002). Estimation and empirical performance of Heston's stochastic volatility model: the case of a thinly traded market. *Journal of Empirical Finance, 9*(2), 225–255.

Fukuta, Y., & Ma, W. (2013). Implied volatility smiles in the Nikkei 225 options. *Applied Financial Economics, 23*(9), 789–804. doi:10.1080/09603107.2013.767975

Geske, R. (1979). The valuation of compound options. *Journal of Financial Economics, 7*(1), 63–81. doi:http://dx.doi.org/10.1016/0304-405X(79)90022-9

Hull, J., & White, A. (1987). The pricing of options on assets with stochastic volatilities. *The Journal of Finance, 42*(2), 281–300.

Jantadej, K., & Wattanatorn, W. (2020). The Effect of Corporate Governance on the Cost of Debt: Evidence from Thailand. *The Journal of Asian Finance, Economics, and Business, 7*(9), 283–291. https://doi.org/10.13106/JAFEB.2020.VOL7.NO9.283

Johnson, H., & Shanno, D. (1987). Option Pricing when the Variance is Changing. *The Journal of Financial and Quantitative Analysis, 22*(2), 143–151. doi:10.2307/2330709

Jones, C. S. (2003). The dynamics of stochastic volatility: evidence from underlying and options markets. *Journal of Econometrics, 116*(1–2), 181–224. doi:http://dx.doi.org/10.1016/S0304-4076(03)00107-6

Kearney, C. (2012). Emerging markets research: Trends, issues and future directions. *Emerging Markets Review, 13*(2), 159–183. doi:http://dx.doi.org/10.1016/j.ememar.2012.01.003

Larkin, J., Brooksby, A., Lin, C. T., & Zurbruegg, R. (2012). Implied volatility smiles, option mispricing and net buying pressure: evidence around the global financial crisis. *Accounting & Finance, 52*(1), 47–69. doi:10.1111/j.1467-629X.2011.00419.x

Luu, Q. T., & Luong, H. T. T. (2020). Herding Behavior in Emerging and Frontier Stock Markets During Pandemic Influenza Panics. *The Journal of Asian Finance, Economics, and Business, 7*(9), 147–158. https://doi.org/10.13106/JAFEB.2020.VOL7.NO9.147

Papi, M., Pontecorvi, L., & Donatucci, C. (2017). Weighted average price in the Heston stochastic volatility model. *Decisions in Economics and Finance, 40*(1), 351–373. doi:10.1007/s10203-017-0197-5

Park, H.-Y., & Park, S. Y. (2020). Does Hedging with Derivatives Affect Future Crash Risk? *The Journal of Asian Finance, Economics, and Business, 7*(4), 51–58. https://doi.org/10.13106/JAFEB.2020.VOL7.NO4.51

Peña, I., Rubio, G., & Serna, G. (1999). Why do we smile? On the determinants of the implied volatility function. *Journal of Banking & Finance, 23*(8), 1151–1179. doi:https://doi.org/10.1016/S0378-4266(98)00134-4

Pojanavatee, S. (2020). Tests of a Four-Factor Asset Pricing Model: The Stock Exchange of Thailand. *The Journal of Asian Finance, Economics, and Business, 7*(9), 117–123. https://doi.org/10.13106/JAFEB.2020.VOL7.NO9.117

Rubinstein, M. (1985). Nonparametric Tests of Alternative Option Pricing Models Using All Reported Trades and Quotes on the 30 Most Active CBOE Option Classes from August 23, 1976 through August 31, 1978. *The Journal of Finance, 40*(2), 455–480. doi:10.1111/j.1540-6261.1985.tb04967.x

Scott, L. O. (1987). Option Pricing when the Variance Changes Randomly: Theory, Estimation, and an Application. *The Journal of Financial and Quantitative Analysis, 22*(4), 419–438. doi:10.2307/2330793

Singh, S., & Dixit, A. (2016). Performance of the Heston's stochastic volatility model: a study in Indian index options market. *Theoretical Economics Letters, 6*(2), 151–165.

Stein, E. M., & Stein, J. C. (1991). Stock price distributions with stochastic volatility: an analytic approach. *Review of Financial Studies, 4*(4), 727–752. Retrieved from http://rfs.oxfordjournals.org/content/4/4/727.abstract

Wattanatorn, W., & Nathaphan, S. (2019). Do bank-affiliated funds perform better than the others: the higher moment approach. *Asia-Pacific Journal of Accounting & Economics*, 1–15. doi:10.1080/16081625.2019.1658528

Wattanatorn, W., & Nathaphan, S. (2020). A new dimension of investment forecasting: evidence from Thailand. *International Journal of Business Innovation and Research, 22*(3), 429–446.

Wattanatorn, W., Padungsaksawasdi, C., Chunhachinda, P., & Nathaphan, S. (2020). Mutual fund liquidity timing ability in the higher moment framework. *Research in International Business and Finance, 51*, 101–105. doi:https://doi.org/10.1016/j.ribaf.2019.101105

Wattanatorn, W., & Tansupswatdikul, P. (2019). An ability to forecast market liquidity – Evidence from South East Asia Mutual fund industry. *The Journal of Finance and Data Science, 5*(1), 22–32. doi:https://doi.org/10.1016/j.jfds.2018.10.002

Wiggins, J. B. (1987). Option values under stochastic volatility: Theory and empirical estimates. *Journal of Financial Economics, 19*(2), 351–372. doi:http://dx.doi.org/10.1016/0304-405X(87)90009-2

Wilson, J. H., & Keating, B. (2001). *Business Forecasting with ForecastX*: McGraw-Hill Higher Education.

Yakoob, M. Y., & Economics, D. U. D. (2002). *An Empirical Analysis of Option Valuation Techniques Using Stock Index Options*. Duke University, Durham, NC.