Estimating the Natural Cubic Spline Volatilities of the ASEAN-5 Exchange Rates

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Abstract

This study examines the dynamic pattern of the exchange rate volatilities of the ASEAN-5 currencies from January 2006 to August 2020. The exchange rates applied in this study comprise bilateral and effective exchange rates in order to investigate the influence of the US dollar on the stability of the ASEAN-5 currencies. Since a volatility model employed in this study is a natural cubic spline volatility model, the Monte Carlo simulation is consequently conducted to determine an appropriate criterion to select a number of quantile knots for this model. The simulation results reveal that, among four candidate criteria, Generalized Cross-Validation is a suitable criterion for modeling the ASEAN-5 exchange rate volatilities. The estimated volatilities showed the inconstant dynamic patterns reflecting the uncertain exchange rate risk arising in international transactions. The bilateral exchange rate volatilities of the ASEAN-5 currencies to the US dollar are more variable than their corresponding effective exchange rate volatilities, indicating the influence of the US dollar on the stability of the ASEAN-5 currencies. The findings of this study suggest that the natural cubic spline volatility model with the quantile knots selected by Generalized Cross-Validation is practical and can be used to examine the dynamic patterns of the financial volatility.

Keywords: Bilateral Exchange Rate, Effective Exchange Rate, Model Selection, Generalized Cross-Validation, Knots

JEL Classification Code: C13, C14, C22, G15

1. Introduction

Generally, exchange rate volatility indicates an uncertain fluctuation in relative price of one currency to other currencies (Laipaporn & Tongkumchum, 2017). It reflects the exchange rate risk in international trade and investment transactions (Kennedy & Nourzad, 2016; Teulon, Guesmi, & Mankai, 2014). Several studies have reported that the exchange rate volatility has a negative impact on the expansion of international trade and the economic growth (Upadhyaya, Dhakal, & Mixon, 2020; Tan, Duong, & Chuah, 2019; Purwono, Mucha, & Mubin, 2018; Soleymani, Chua, & Hamat, 2017; Al-Abri & Baghestani, 2015; AbuDalu, Ahmed, Almasaled, & Elgazoli, 2014) and also affects the stability of the capital markets (Campa, 2020; Dang, Le, Nguyen, & Tran, 2020). The time-varying correlation between a pair of the exchange rate volatilities also illustrates a link between currencies, which is evidence of international financial integration in international financial markets (Liu, Wang, & Sririoonchitta, 2019; Singh & Ahmed, 2016). Furthermore, central banks typically apply exchange rate volatility as a primary indicator for monitoring currency’s stability (Klyuev & Dao, 2017).

Previous studies have mostly focused on investigating only two types of exchange rate. The first is referred as bilateral exchange rate, a relative price of one currency to another, usually the US dollar, a major currency in the world economy (Kennedy & Nourzad, 2016; Teulon, Guesmi, & Mankai, 2014). The second is an effective exchange rate, an index indicating the average of a currency’s bilateral exchanges, weighted by its trading volumes in the reference year (Upadhyaya, Dhakal, & Mixon, 2020; Tan, Duong, & Chuah, 2019).

After the financial crisis in 1997 and the global financial crisis in 2007, the Association of Southeast Asian Nations...
(ASEAN) set up an initiative to establish a free trade area in order to eliminate trade barriers and support regional integration (Ahmed & Singh, 2016). Consequently, the blueprint of the ASEAN community has been declared as a masterplan to establish a single market of goods and services as well as capitals and skilled labors (Ponziani, 2019; Rillo, 2018). Since then, ASEAN has become a safety area against sudden capital outflow (Harvey, 2017) and more attractive to foreign direct investment, especially the ASEAN-5 countries including Thailand, Singapore, Malaysia, Indonesia, and the Philippines (Tri, Nga, & Duong, 2019).

The financial infrastructure of the ASEAN-5 economy has been steadily changing over the past fifteen years. Moreover, after the global financial crisis, the US dollar became less stable (Gavranic & Miletic, 2016) and caused instability in the world’s monetary system (Staszczak, 2015). This situation possibly affected the exchange rate volatility of the ASEAN-5 currencies. Therefore, this study aims to apply the natural cubic spline volatility model to explore the dynamic patterns of the exchange rate volatilities of the ASEAN-5 currencies both in terms of the bilateral exchange rates and the effective exchange rates from January 2006 to August 2020.

The natural cubic spline volatility or NCSV model has been proposed in the study of Laipaporn and Tongkumchum (2017). Though, this model is practical to reveal the dynamic patterns of the estimated volatility (Farida, Makaje, Tongkumchum, Phonon, & Laipaporn, 2018), it still needs to identify an appropriate number of knots in order to influence the model’s goodness of fit (Laipaporn & Tongkumchum, 2018).

Previous studies have usually applied a user-specified number of knots to the NCSV model. However, in this study, the Monte Carlo simulation will be used to find a proper data-driven criterion to select a number of knots among candidate criteria, including the Akaike’s Information Criteria (AIC), Bayesian Information Criteria (BIC), General Cross-Validation (GCV), and Modified General Cross-Validation (MGCV), and then employ the most appropriate criterion to specify the number of knots of the NCSV model for estimating the ASEAN-5 exchange rate volatilities.

The remainder of this article is organized as follows. Section 2 and section 3 present the background and details of the methodology used in this study. The simulation results on the knot selection criteria and the empirical results on the ASEAN-5 exchange rates’ volatilities are stated and discussed in Section 4. The conclusions made from this study are presented in Section 5.

2. Literature Review

Volatility is not directly measured like weight and height but it is usually calculated or estimated from its proxy, returns on the financial asset’s price or financial index, according to statistical formulas or statistical models (Laipaporn & Tongkumchum, 2017). A spline is a function that many studies have employed to estimate volatility because its continuous piece-wise polynomials are flexible to capture the cyclical pattern of financial volatility. The Spline Generalized Autoregressive Conditional Heteroscedasticity or Spline-GARCH model introduced by Engel and Rangel (2008) and the Generalized Autoregressive Conditional Heteroscedasticity Mixed Data Sampling or GARCH-MIDAS model proposed by Engle, Ghysels and Sohn (2013) are examples of volatility model that utilizes spline function. They used the spline function in a quadratic polynomial form as a part of their model to capture the dynamics of low-frequency volatility and investigate the relationship between low-frequency volatility and macroeconomic variables.

Similarly, the NCSV model also utilizes a natural cubic spline function to estimate financial volatility. A natural cubic spline function is another functional form of a spline, which is piecewise cubic polynomials that are linear beyond the extreme knots (Laipaporn & Tongkumchum, 2017). Recently, Laipaporn and Tongkumchum (2020) employed the NCSV model to estimate the volatilities of the ASEAN-5 stock index and used these estimated volatilities to construct the time-varying correlations in order to illustrate the patterns of co-movement among ASEAN-5 stock market index. Likewise, Farida, Makaje, Tongkumchum, Phon-on, and Laipaporn (2018) also applied the NCSV model to estimate the volatility of crude oil price. The study found a cyclical pattern of the volatility dynamics identical to the pattern obtained by the other volatility model.

However, one critical issue of utilizing spline function for volatility modeling lies in knot selection. Knots are the connectors between the continuous piece-wise polynomials of the spline function. The flexibility of the spline function depends on the number of knots used to compile the function. Consequently, an excessive number of knots might lead to an over-fitted volatility model, on the other hand, an inadequate number of knots tends to provide the under-fitted model (Laipaporn & Tongkumchum, 2018). Additionally, a spline function with many knots is not guaranteed to provide a more fitted model (Breiman, 1993).

Laipaporn and Tongkumchum (2020) and Farida et al. (2018) applied a user-specified number of knots in their respective studies. They subjectively selected an appropriate number of knots concerning the data investigated in their studies. By applying the equi-spaced knots, Laipaporn and Tongkumchum (2020) set an interval between knots at 250 trading-day per interval and then assigned a number of knots according to that interval and a number of observations. Likewise, Farida et al. (2018) set the length between knots at almost 200 trading-days and consequently determined the number of knots for their NCSV model.
In contrast, previous studies that used the spline-GARCH model and the GARCH-MIDAS model alternatively determined the number of knots by utilizing information criteria such as Akaike’s Information Criteria (AIC) and Bayesian Information Criteria (BIC) (Conrad & Kleen, 2020; Lee, Stevenson, & Lee, 2018; Engle, Ghysels, & Sohn, 2013; Engle & Rangel, 2008).

Similarly, Laipaporn, and Tongkumchum (2018) also employed both the AIC and BIC criteria for selecting a number of knots for the NCSV model. They found that AIC performed well to the simulated dataset but failed to provide the appropriate knots for the NCSV model in the case of the empirical data. However, the number of equi-spaced knots using in Laipaporn and Tongkumchum (2018) is exponentially increasing by $2^n$ where $n$ is an increasing step. This procedure is different from the other studies, which usually increase the number of knots one at a time.

Based on prior studies, there are other approaches that have been used to determine the number of knots in a spline function. Montoya, Ulloa, and Miller (2014) compared various knots selection criteria and found that generalized cross-validation or GCV introduced by Craven and Wahba (1979) is more suitable method in selecting the number of knots for the penalized regression spline model. Likewise, Chen, Abraham, and Bennett (1997) and Lewis and Stevens (1991) utilized the modified generalized cross-validation or MGCV proposed by Friedman (1991) for selecting the number of knots of the multivariate adaptive regression or MARS model. They found that this approach provided a parsimonious time series model that exhibited a cyclical pattern of the time series data.

Hence, this study investigates more candidate criteria other than the AIC and BIC to find the most appropriate approach for modeling the NCSV model and alternatively increasing the number of quantile knots of the NCSV model one at a time.

3. Research Methods and Materials

Two dataset were used in this study. The first dataset is the daily returns of the ASEAN-5 bilateral exchange rates and their effective exchange rates from January 2006 to August 2020. The daily returns series are the logarithm returns of the ASEAN-5 bilateral exchange rates with two different rolling windows which are 60 and 120 trading days per window.

Ten types of pre-specified volatilities were determined as the rolling standard deviation of the daily returns of ASEAN-5 bilateral exchange rates with two different rolling windows. Note that the wider rolling windows provide less fluctuated rolling standard deviations.

Based on ten types of pre-specified volatility, ten groups of 500 series of 1,500 simulated daily returns were generated and used as a dataset used for the Monte-Carlo simulation. An example of simulated returns series in absolute term and its corresponding pre-specified volatility are shown in Figure 1.

As introduced in Laipaporn and Tongkumchum (2017), the NCSV model is based on the assumption that the time series of the financial returns ($r_t$) is the product of time-varying volatility ($s_t$) and random noise ($e_t$), which is normal distributed with a zero mean and a unit standard deviation as follows.

$$ r_t = s_t e_t $$

The time-varying volatility ($s_t$) is parameterized as the natural cubic spline function with respect to time ($t = 1, 2, 3, \ldots, T$) as the succeeding equation.

$$ s_t = \alpha + \beta_1 \sum_{i=1}^{p-2} \theta_i \left( t - t_i \right)^3 $$

The total number of observations is equal to $T$, $p$ is a number of knots $k$ where $k = 1, 2, 3, \ldots, p$. Each knot is placed at $t_i$ which is a quantile order $k$ of time $t$ in the interval $[1, T]$.

To estimate the parameters of the NCSV model, the natural cubic spline function is applied to the absolute values of the returns series ($|r_t|$), which are the proxies of the daily volatility (Figlewski, 1997). Consequently, the parameters of this function ($\alpha$, $\beta_1$ and $\theta_i$) are estimated by maximizing the log-likelihood function ($L$) as follows.

$$ L = \sum_{t=1}^{T} -\log(s_t) - \frac{|r_t|^3}{2s_t^3} $$

This study set three steps to select the NCSV model with the optimal number of knot based on previous literature works. The first step is to determine a possible range of a number of knots $p$. A number of knots $p$ usually begins with three as the lower limit of the possible range.
The three knots include two boundary knots at the first and the last observation and one interior knot in the middle. To ensure that there are at least 40 observations which is the number of observations in one quarter between each knot. The upper limit of the number of knots is therefore set at $T/p < 40$.

The second step is to estimate the NCSV model’s parameters with the number of knots in the possible range. The third step is to apply four candidate criteria: AIC, BIC, GCV and MGCV to the NCSV model obtained from the second step using the following formula.

\[
AIC = -L + 2p 
\]

\[
BIC = -L + p \log(n) 
\]  

\[
GCV = \frac{T^{-1} \sum_{t=1}^{T} (|r_t| - s_t)^2}{\left(1 - \frac{(p-1)}{T}\right)^2} 
\]

\[
MGCV = \frac{T^{-1} \sum_{t=1}^{T} (|r_t| - s_t)^2}{\left(1 - \frac{(p+1) + dp}{T}\right)^2} 
\]

Note that $d$ in the MGCV formula is a parameter representing the cost of the increased knot in the spline function. The larger number of $d$ tends to signify a fewer number of knots. This study sets $d$ equal to 2 following the recommendation in Friedman (1991). The NCSV model with the least value of each criterion, consequently indicates the optimal number of knots for that criterion.

For the simulated return datasets, the root mean square error (RMSE) of the pre-specified volatility ($\sigma$) and the estimated volatility ($s$) estimated by the NCSV model is calculated as the following equation.

\[
RMSE = \sqrt{\frac{(\sigma - s)^2}{T}} 
\]

The NCSV model with the least RMSE indicates the optimal number of knot corresponding to each pre-specified volatility. Accordingly, this optimal number became the benchmark number of knots for the performance comparison among four criteria in the Monte Carlo simulation. A candidate criterion that specifies the number of knots closest to the benchmark number is the most appropriate knot selection criterion for estimating the NCSV model of the ASEAN-5 currencies.
4. Results and Discussion

For the Monte Carlo simulation, the simulated returns series according to ten types of pre-specified volatilities were applied to the NCSV model with a number of knots in the possible range varying from 3 to 42 knots. Since each returns series has 1,500 observations, the interval size between knots of the NCSV model thus varies from nearly 40 observations to 750 observations per interval.

Figure 2 shows graphs plotting the number of knots in the possible range and the averages of RMSE, AIC, BIC, GCV and MGCV obtained from the NCSV models.

According to each criterion, the vertical line and the number at the corner of each graph indicate the least averages and an optimal number of knots. The least average values of RMSE specify the benchmark number of knots for each group of simulated returns. The first five groups of simulated returns were generated by 60 trading days rolling standard deviation (A, B, C, D, E), mostly require more number of knots for the NCSV model than the simulated returns generated by 120 trading days rolling standard deviation (F, G, H, I, J). It implies that if true volatility is high fluctuated, it will require more knots to model the NCSV.

Figure 2: The Number of Knots and the Average Values of RMSE, AIC, BIC, GCV and MGCV from the NCSV Models by Ten Groups of the Simulated Returns
Regarding the benchmark number, a proper knot selection criterion has to select neither too many nor too few numbers of knots than the benchmark number. Among the ten groups of simulated returns, GCV selects the number of knot identical to the benchmark number for six groups (A, B, E, G, H, J). For the other four groups (C, D, F, G), GCV selects a less number of knots, but it is not much different from the benchmark. Likewise, AIC selects the number of knot identical to the benchmark for four groups of simulated returns (A, C, H, J).

In contrast, there is only one group of simulated returns (A) that BIC identifies the number of knots identical the benchmark number. For the rest groups, the number of knot indicated by BIC is much less to the benchmark number. MGCV is a little better than the BIC. It selects the same number of knots as the benchmark number for two groups of simulated returns (A, J). The BIC and MGCV do not perform well for the groups of simulated returns with more fluctuated pre-specified volatility (60 trading days rolling standard deviation). However, they tend to select a number nearer to the benchmark for the groups of simulated returns generated by less fluctuated pre-specified volatility (120 trading days rolling standard deviation).

Following the simulation results, GCV is the most preferred criterion, while the second-best criterion is the AIC. In contrast, the BIC provides a small number of knots for most cases. This result is similar to Laipaporn and Tongkumchum (2018), which found the AIC to be a more preferred criterion than the BIC in the case of simulated data. Note that the number of knots in this study increases one at a time. This contrasts with Laipaporn and Tongkumchum (2018) study where an increase in the number of knots occurred exponentially from 3 to 7, 15, 31, 63, 127, etc. Although increasing the number of knots one at a time is a time-consuming process, this simulation demonstrates that this approach is entirely accurate in determining the number of knots for the NCSV model.

For the empirical part, the series of 3,773 daily returns on the bilateral exchange rates and the effective exchange rates of the ASEAN-5 currencies are presented in Figure 3.

Mean values of these daily returns series are tested and they are not significantly different from zero. Among the five currencies, IDR has the broadest range of daily returns series. The differences between the minimum and maximum value of its bilateral and effective exchange rates are nearly 13 and 12 percentage points, respectively. Whereas, SGD has less varied daily returns series than the others. The standard deviations of its bilateral and effective exchange rates are 0.35 and 0.19, respectively. The skewness of all series is relatively small. They are close to zero in the range between −0.61 and 0.28.

To determine the proper NCSV models of ASEAN-5 exchange rates, a set of pre-specified number knots is assigned from 3 to 96. The size of the interval between knots varies from nearly 40 observations to 1,886 observations per interval. The values of AIC, BIC, GCV and MGCV of the NCSV models of the ASEAN-5 exchange rates and the possible range number of knots are displayed in Figure 4.

Figure 3: Returns on the Bilateral Exchange Rates (BER) and the Effective Exchange Rates (EER) of the ASEAN-5 Currencies
The number of knots for the NCSV models of ASEAN-5 exchange rates indicated by BIC is relatively fewer than the number obtained by the other three criteria. Likewise, MGCV often selects a number of knots identical to a number chosen by BIC. Therefore, BIC and MGCV tend to indicate an under-fitted model. GCV and AIC select an equivalent number of knots in some cases. However, the behavior in knot selection of GCV is more consistent than AIC, because in some cases, AIC assigns too large number of knots for the NCSV model. Regarding this comparison, the GCV is likely to provide an accurate number of knots for modeling the natural cubic volatility of the ASEAN-5 exchange rates.

Since the effective exchange rates are less volatile, in some cases GCV designates a smaller number of knots than a number of knots of the bilateral exchange rates' volatility models. The intervals between knots according to the number of knots selected by GCV in this study vary from 42 to 118 trading days. These intervals are much smaller than the intervals assigned by the same criterion in Engle and Rangel (2008) for the volatilities of the ASEAN-5 stock index. Note that the functional form of the spline function used in this study is a natural cubic spline function, which is different from the quadratic spline function used in Engle and Rangel (2008). The natural cubic spline is more flexible than the...
quadratic spline. Consequently, it needs a more number of knots to fit the volatility model.

The volatilities of ASEAN-5 exchange rates estimated by the natural cubic spline volatility models with a number of knots selected by GCV are shown in Figure 5. Graphs in the left column illustrate the comparison of the bilateral exchange rate volatilities (BER) and the effective exchange rate volatilities (EER) of the ASEAN-5 currencies in the same axis, while graphs in the right column show the volatility ratio, the ratio of the bilateral exchange rate volatilities over the effective exchange rate volatilities of the corresponding currencies.

The dynamic patterns of the bilateral exchange rate volatility of the ASEAN-5 currencies are not entirely different from the pattern of the same currencies’ effective exchange rate volatility. The bilateral and effective exchange rate of IDR is more volatile than the other currencies, while the exchange rate volatilities of SGD and PHP indicate that these two currencies are more stable than the other currencies. The finding is similar to Ponziani (2019) and Klyuev and Dao (2017).

The bilateral and effective exchange rates of THB are most volatile during the global financial crisis period. The exchange rate volatilities of THB were more than 10 percent in that period, and then diminished to less than 5 percent after the crisis. This shows the exchange rate of THB is stable after the global crisis until now. The exchange rates of MYR are less stable between 2015 to 2016 since the MYR depreciation to the world currencies in October 2015 (Quadry, Mohamad, & Yusof, 2017). Malaysia increases their money supply by lowering its interest rate to absorb the exchange rate shock (Kaur, Manual, & Eeswaran, 2019).

The reference lines in the left graphs of Figure 5 indicates the volatility ratio equal to one. As shown in Figure 5, in the period that the exchange rate volatility ratios of the ASEAN-5 currencies are higher than the reference line, the bilateral exchange rates of the ASEAN-5 currencies are more volatile than its corresponding effective exchange rates. The volatility ratios of the ASEAN-5 currencies are mostly higher than the reference line, especially SGD; its bilateral exchange rate volatility is almost twice higher than its effective exchange rate volatility. The average volatility ratios of THB, SGD, MYR, IDR and PHP are 1.17, 1.99, 1.24, 1.12 and 1.11 respectively.
Since the stability of the effective exchange rate reflects its typical characteristic, which can absorb the uncertain exchange rate policies of its trade partners (Thuy & Thuy, 2019), the SGD was more capable to confront the uncertainty in the international trade and investment than the other currencies. This is because the stability of the US dollar affects the volatility of the bilateral exchange rates. Several studies are likely to eliminate the influence of the US dollar instability by employing the effective exchange rate volatility rather than the bilateral exchange rate volatility in order to examine the real stability of the currency (Kaur, Manual, & Eeswaran, 2019; Thuy & Thuy, 2019; Al-Abri & Baghestani, 2015).

5. Conclusions

To estimate the exchange rate volatility of the ASEAN-5 currencies, this study applied the natural cubic spline model with various data-driven knot selection criteria comprised of the AIC, BIC, GCV and MGCV. This study further employed the Monte Carlo simulation to find the most appropriate knot selection criteria. The simulation showed that GCV is the most preferred since it assigns a number of knots closest to the benchmark number. The BIC and MGCV tend to determine a smaller number than the other criteria in simulated datasets and empirical datasets. For the simulated dataset, AIC performs well. It often selects an identical number of knot to the benchmark knots. However, it selects too much number of knots for the empirical datasets.

Additionally, the exchange rate volatilities of the ASEAN-5 currencies, estimated using the natural cubic spline model with a number of knots selected by GCV, revealed the inconstant dynamic pattern of the ASEAN-5 exchange rate volatilities. The effective exchange rates of the ASEAN-5 currencies have less variation than the bilateral exchange rates, especially the bilateral exchange rate of the Singapore dollar, which is almost twice larger than the effective rate. It is clear evidence showing the stability of the Singapore dollar and the influence of the US dollar on the variation of the bilateral exchange rate of the ASEAN-5 currencies.

References


