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The impacts of Covid-19 pandemic on the smooth transition dynamics of stock market index volatilities for the Four Asian Tigers and Japan

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ABSTRACT

This rapid propagation of the Novel Coronavirus Disease (COVID-19) has caused the global healthcare system to break down. The infectious disease originated from East Asia and spread to the world. This unprecedented pandemic further damages the global economy. It seems highly probable that the COVID-19 recession changes stock market volatility. Therefore, this study resorts to the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model with a smooth transition method to capture the influences of the COVID-19 pandemic on the dynamic structure of the stock market index volatilities for some Asian countries (the Four Asian Tigers and Japan). The empirical results show that the shocks of the COVID-19 change the dynamic volatility structure for all stock market indices. Moreover, we acquire the transition function for all stock market index volatilities and find out that most of their regime adjustment processes start following the outbreak of the COVID-19 pandemic in the Four Asian Tigers except South Korea and Japan. Additionally, the estimated transition functions show that the stock market index volatilities contain U-shaped patterns of structural changes. This article also computes the corresponding calendar dates of structure change about dynamic volatility patterns. In the light of estimation of location parameters, we demonstrate that the structure changing the date of stock market index volatility for South Korea and Japan has occurred in late 2019.

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Introduction

The outbreak of COVID-19 brings about dramatic changes to the global financial markets. According to the record from Chicago Board Option Exchange's Volatility Index, namely VIX, the fear gauge of stocks surged past the prior peak in March 2020. Meanwhile, the stock markets in Europe and Asia have also plunged. (Narayan et al., 2021), (Sharma, 2020) and (Zhang et al., 2020) demonstrate that the COVID-19 pandemic really has impacts on global economies. Therefore, many countries adopt monetary, fiscal and containment policy one after another to response to the COVID-19 crisis. For example, the Federal Reserve (FED) reduced the federal funds rate to near zero and launched unlimited quantitative easing program for monetary policy. In addition, the U.S. fiscal policy provided some compensation for households and businesses. Even though both monetary and fiscal policy could be viewed as a way to stimulate economic development, (Teresiene et al., 2021) indicate that the monetary policy has limited possibilities to support the economy. On the other hand, the containment policy, including entry restrictions, social distancing mandates and put on lockdown, might damage the economic (Baldwin and Tomiura, 2020). All in all, some COVID-19 vaccines have authorized the use, as of 31 December, 2020, the number of confirmed cases still surpassed about 81 million, and confirmed deaths surpassed 1.79 million from the World Health Organization (WHO) website. Thus, it is fascinating to measure the impacts of infectious disease on dynamic volatility structure.

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During the period of early 1960s to 1990s, the economies of Hong Kong, Singapore, South Korea and Taiwan (also known as Four Asian Tigers) experience rapid industrialization and maintained exceptionally more than 7% high growth rates per year in the Asia-Pacific region. However, the Four Asian Tigers become developed countries by the early 21st century and contain different industrial structure advantages individually. For instance, Hong Kong and Singapore devote to become international financial center, whereas Taiwan and South Korea devote to developing and manufacturing electronic components. Therefore, we make an attempt to investigate whether the COVID-19 pandemic could trigger and bring distinct turmoil on volatility structure of stock market index for the Four Asian Tigers. Additionally, we also consider the stock market in Japan.

In this article, we first resort the modified GARCH model with exogenous trigger variable to fit the stock market index volatilities in the Four Asian Tigers and Japan, because this model specification is convenient to use as the break time is certain.¹ We further hire the smooth transition GARCH model (ST-GARCH for short) to fit the stock market index volatilities for the reason to prevent the biased estimates of structure change date. The specification of the ST-GARCH model could naturally reveal the regime switch date for stock market index as the volatility structure change actually exists.

All in all, our empirical findings report that the COVID-19 pandemic actually changes the dynamic unconditional volatility from the low level to high one for all stock market indices during entire sample period. In addition, we observe that the episode of COVID-19 pandemic causes the reactions of stock market index volatilities become more sensitive to information for Taiwan and Hong Kong. We further speculate that the US-China trade war dominates all reactions of information for the low volatility state.

The structure of this study is as follows. Section 2 discusses the related GRACH models and ST-GARCH model. Section 3 reports the empirical results and makes constructively discussions. Finally, section 4 concludes this paper.

Methodology

Related GARCH models

One of the broadly used dynamic volatility model is the GARCH model that developed by (Engle, 1982) and (Bollerslev, 1986). The GARCH(1,1) model could be applied to delineate the dynamic volatility process, that is,

$$\begin{aligned} R_t &= \varepsilon_t \\ h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \\ \varepsilon_t | \Omega_{t-1} &\sim N(0, h_t), \end{aligned}$$

where R_t is the underlying asset returns at time t , h_t is the conditional volatility at time t , ε_{t-1}^2 is the square residual at time $t-1$, and Ω_{t-1} is the information set at time $t-1$. The parameters, α_0 , α_1 and β_1 , can be explained as the inherent uncertainty level, short-term effect of volatility shocks, and long-term effect of volatility shocks, separately. The specification of classical GARCH(1,1) model could not discover the nonlinear structural breaks for dynamic volatility process. In this article, we attempt to comprehend the influence of COVID-19 pandemic on the stock market indices volatility process, therefore it is intuitively to consider an exogenous trigger variable into the equation (1). That is,

$$h_t = \alpha_0 + \varphi_0 D_t + \alpha_1 \varepsilon_{t-1}^2 + \varphi_1 D_t \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \varphi_2 D_t h_{t-1}$$

where D_t represents an exogenous trigger variable taking the value 1 post-event and 0 pre-event. We add three trigger terms, including a single trigger term and two cross-product terms, in the variance equation for capturing the complete processes. On the condition that the artificial break date contains correct and full information, this exogenous specification could be depicted the pattern of structure breaks. It shows that the imprecise definition of break date could lead to estimating results insignificant and biased.

The smooth transition GARCH model

From past study, introducing the framework of endogenous variable into nonlinear volatility model is superior to depict the structure break. The smooth transition model constructed by (Granger & Teräsvirta, 1993) and (Lin & Teräsvirta, 1994) can detect the regime switching date by itself. Some recent studies consider that combining the smooth transition method with GARCH model can obtain many advantages in parameter estimates of dynamic volatility model.² The ST-GARCH model provides relatively flexible approach to expand the volatility process with nonlinear regime switches. In addition, the ST-GARCH model could explicitly display the true date of structure breaks in the data generating process for dynamic volatility process. The generalized framework for detecting the

¹ We assume the exogenous trigger variable as the time of outbreak of the COVID-19. The given date of outbreak of COVID-19 is 26th December 2019.

² Also see (Hagerud, 1997), (González-Rivera, 1998), (Anderson et al., 1999), (Lee and Degennaro, 2000), (Lundbergh and Teräsvirta, 2002), (Lanne and Saikkonen, 2005), (Medeiros and Veiga, 2009), (Khemiri, 2011), (Chou et al., 2012), (Chen et al., 2017) and (Cheikh et al., 2020).

appropriateness of an estimated ST-GARCH type model is proposed by (Lundbergh and Teräsvirta, 2002). The ST-GARCH model can be shown as,

$$y_t = f(\mathbf{w}_t; \boldsymbol{\varphi}) + \varepsilon_t,$$

$$\varepsilon_t = z_t(h_t + g_t)^{1/2}$$

where $h_t = \boldsymbol{\eta}'s_t$, $g_t = \lambda's_tF(\tau_t; \gamma, \mathbf{c})$, \mathbf{w}_t denotes a regressor vector in mean, $\boldsymbol{\varphi}$ denotes the coefficient vector, $z_t \stackrel{iid}{\sim} (0,1)$, $s_t = (\mathbf{1}, \varepsilon_{t-1}^2, \dots, \varepsilon_{t-q}^2, h_{t-1}, \dots, h_{t-p})'$, $\boldsymbol{\eta} = (\alpha_0, \alpha_1, \dots, \alpha_q, \beta_1, \dots, \beta_p)'$, $\boldsymbol{\lambda} = (\bar{\alpha}_0, \bar{\alpha}_1, \dots, \bar{\alpha}_q, \bar{\beta}_1, \dots, \bar{\beta}_p)'$. In particular,

$$F(\tau_t; \gamma, \mathbf{c}) = (1 + \exp(-\gamma \prod_{i=1}^k (\tau_t - c_i)))^{-1}$$

where τ_t is the transition variable at time t , γ is the slope parameter ($\gamma > 0$), $\mathbf{c} = (c_1, c_2, \dots, c_k)$ is a location vector in which $c_1 \leq c_2 \leq \dots \leq c_k$, and k is the number of transitions. This specification implies transitions between two regimes, $F(\tau_t; \gamma, \mathbf{c}) = 0$ and $F(\tau_t; \gamma, \mathbf{c}) = 1$

Lundbergh and Teräsvirta (2002) believe that the ST-GARCH model contains several vantages. First, the timing decision for regime switch in parameters is endogenesis in estimation and this decisive manner is more adaptable than artificially given a priori. Second, the specification of GARCH model with exogenous trigger variable belong to a special case as the slope parameter (γ) reaches to infinity. Finally, the transition function in equation (4) provides another flexible specification in modeling to determine the patterns of structural breaks. For instance, equation (4) reduces to a special case of a chow's structural change as $\gamma \rightarrow \infty$ and $k = 1$. In another case, if the slope parameter $\gamma \rightarrow \infty$ and $k = 2$, equation (4) come to be a double step function.

On the foundation of the suggestion from (Lundbergh and Teräsvirta, 2002), we inspect the hypothesis of parameter constancy in GARCH model before estimation of the ST-GARCH model. Assuming the null model is $g_t = 0$ and let $\bar{\mathbf{x}}_t' = \hat{h}_t^{-1} \partial \hat{h}_t / \partial \boldsymbol{\eta}'$ under the null. Furthermore, we regard the transition variable as time, $\tau_t = t$, in order to take an assessment for the impacts of COVID-19 pandemic for the stock market index volatility in the Four Asian Tigers and Japan. Let, $\mathbf{v}_{it} = t^i s_t$, $\hat{\mathbf{v}}_{it} = t^i \hat{s}_t$, and $\hat{\mathbf{v}}_{it} = (\hat{\mathbf{v}}_{1t}, \hat{\mathbf{v}}_{2t}, \hat{\mathbf{v}}_{3t})'$ for $i = 1, 2$, and 3 .

The step of statistical test can be implemented by an artificial regression as below. Firstly, estimate the parameters of the conditional

model under the null. Let $SSR_0 = \sum_{t=1}^T (\hat{\varepsilon}_t^2 / \hat{h}_t - 1)^2$, and then regress $(\hat{\varepsilon}_t^2 / \hat{h}_t - 1)$ on $\bar{\mathbf{x}}_t', \hat{\mathbf{v}}_t'$ and gather the sum of squared residuals, SSR_1 . The LM test statistic can be calculated by $LM = T(SSR_0 - SSR_1) / SSR_0$. On the other hand, the F test statistic can be computed by $F = ((SSR_0 - SSR_1) / k) / SSR_1 / (T - p - q - 1 - k)$. Finally, we take the statistics to ascertain an appropriate k to specify the ST-GARCH models. The choosing criterion of k value is the smallest p-values.

Data and empirical results

In our research, we concern about the stock market index volatility for the COVID-19 pandemic in the Four Asian Tigers and Japan. We select stock index of the Four Asian Tigers and Japan, including Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), Hang Seng Index (HSI), Korea Stock Exchange KOSPI Index (KSI), Straits Times Index (STI), and Nikkei 225 (NIKKEI). These daily data of five stock market index could be obtained from Yahoo Finance (<http://finance.yahoo.com/>) and the sample period starts from April 2, 2015 to July 3, 2020. The daily closing prices for all stock market indices are separately plotted in Figure 1. The daily stock market indices returns are computed by using the first difference of the logarithmic prices. Descriptive statistics for these daily stock market index returns are shown in Table 1. We divide the entire period into two sub-sample periods by the infectious disease outbreak of COVID-19. Most of the items of summary statistics for the pre- and post-outbreak phase seem dissimilar. It is

intriguing to detect whether the difference is significantly existence or not. In the line of the significance of the Ljung-Box Q^2 statistics for all stock market indices returns, we can conclude that it is appropriate to fit them by the GARCH family model.

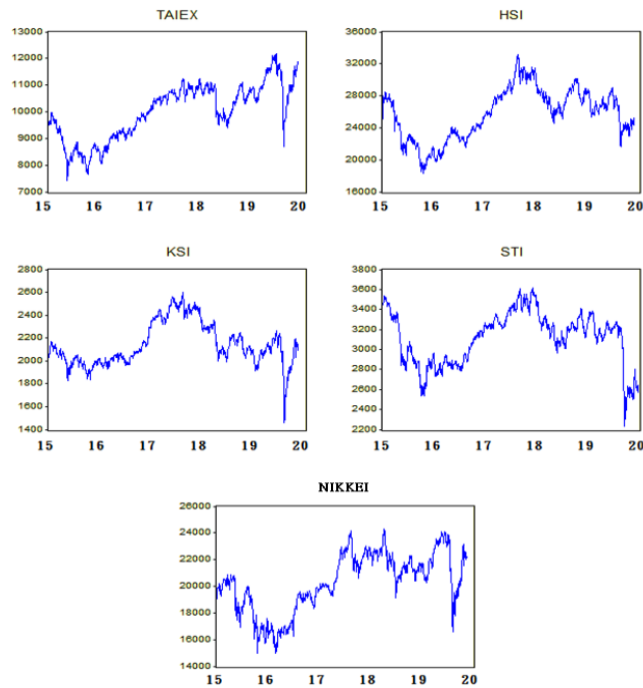


Figure 1: Daily closing prices for stock market indices of the Four Asian Tigers and Japan over the period April 2, 2015 to July 3, 2020.

Table 1: Descriptive Statistics

Before COVID-19 pandemic (2 April 2015 to 25 December 2019)							
	Mean	St.D	Skewness	Kurtosis	Maximum	Minimum	$Q^2(10)$
TAIEX	0.020	0.838	-0.880	6.309	3.518	-6.521	311.57*
HSI	0.009	1.130	-0.334	2.181	4.125	-6.018	287.06*
KSI	0.003	0.813	-0.586	2.491	3.473	-4.541	326.31*
STI	-0.006	0.763	-0.233	1.944	2.656	-4.391	285.65*
NIKKEI	0.019	1.236	-0.337	6.267	7.426	-8.253	328.88*
After COVID-19 pandemic (26 December 2019 to 3 July 2020)							
TAIEX	-0.007	1.667	-0.587	3.633	6.173	-6.005	57.715*
HSI	-0.074	1.767	-0.472	1.286	4.925	-5.720	66.224*
KSI	0.026	2.547	-0.065	2.420	8.251	-8.767	45.936*
STI	-0.152	1.978	0.712	3.733	5.894	-7.637	72.642*
NIKKEI	-0.051	2.072	0.289	2.416	7.731	-6.274	50.160*

Notes:

1. This table shows the descriptive statistics for the logarithmic stock returns before and after the starting of the COVID-19 pandemic. $Q^2(10)$ is the Ljung-Box test for serial correlation up to 10th order in the squared standardized residuals.
2. The return is calculated as $100 \times [\log(p_t) - \log(p_{t-1})]$. Significant at the 1% level is denoted by *.

By handling more simply for volatility data with regime change in it, we hire the modified GAHCH model containing an exogenous trigger variable. The trigger variable is embedded individually in the intercept, lagged squared residual and lagged conditional variance term for the adaptability of model specification. Table 2 reports the parameter estimation results of this model. In the light of the significance of parameter estimates and Ljung-Box Q^2 statistics, we could observe that the shocks of COVID-19 pandemic

seem to change all the stock market index volatilities in the Four Asian Tigers and Japan. At first sight, using the modified GARCH model with trigger variable could roughly depict the impacts of COVID-19 pandemic. However, it is nature to use an endogenous deciding model, the ST-GARCH model, to directly capture the true date of volatility regime changes of COVID-19 pandemic.

Table 2: The modified GARCH(1,1) model with exogenous trigger variables estimation

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\phi}_0$	$\hat{\phi}_1$	$\hat{\phi}_2$	Q(10)	Q ² (10)	LogL
TAIEX	0.055*	0.129*	0.799*	0.271*	0.017	-0.104*	7.722	4.649	-1594.841
	[<0.001]	[<0.001]	[<0.001]	[0.001]	[0.708]	[0.013]	[0.656]	[0.913]	
HSI	0.012*	0.033*	0.957*	0.147*	0.002	-0.047*	8.983	12.486	-1990.553
	[<0.001]	[<0.001]	[<0.001]	[0.019]	[0.917]	[0.028]	[0.534]	[0.254]	
KPI	0.042*	0.079*	0.861*	0.283*	0.106	-0.138*	10.947	8.127	-1608.980
	[<0.001]	[<0.001]	[<0.001]	[0.017]	[0.062]	[0.002]	[0.362]	[0.616]	
STI	0.014*	0.058*	0.918*	0.074*	0.097*	-0.115*	17.692	11.520	-1527.687
	[<0.001]	[<0.001]	[<0.001]	[0.004]	[0.012]	[<0.001]	[0.060]	[0.318]	
NIKKEI	0.078*	0.141*	0.811*	0.174	0.052	-0.069	5.934	8.403	-2006.827
	[<0.001]	[<0.001]	[<0.001]	[0.080]	[0.490]	[0.442]	[0.821]	[0.590]	

Notes:

- The figures in brackets are p-value. Q(10) denotes the Ljung-Box statistic for serial correlation test with 10 lags, Q2(10) is the Ljung-Box statistics for serial correlation up to 10th order in the squared standardized residuals. Significant at the 5% level is denoted by *.
- Before 25, Dec., 2019, the trigger variable D_t is 0. After 26, Dec., 2019, the trigger variable D_t is 1.

$$R_t = \varepsilon_t$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha_0 + \phi_0 D_t + \alpha_1 \varepsilon_{t-1}^2 + \phi_1 D_t \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \phi_2 D_t h_{t-1}$$

Before estimating the ST-GARCH model, we need to check the parameter constancy by the LM test proposed by (Lundbergh and Teräsvirta, 2002). First, we make an assumption that the null model is standard GARCH(1,1) model. Then, we computer the LM statistics for k = 1, 2, and 3. Finally, we list the estimated results in Table 3. We demonstrate that the parameter constancy is violated for all stock market indices. In other words, the structure break in dynamic volatility process is actually being against the corresponding GARCH(1,1) model. Moreover, we also observe that the parameter, k = 2, provides the smallest p-value for all stock market index in the Four Asian Tigers and Japan.

Table 3: LM tests of parameters constancy for k=1, 2, and 3

	k		
	1	2	3
TAIEX	2.076	6.693	9.044
	[0.557]	[0.350]	[0.669]
HSI	2.408	7.103	7.353
	[0.492]	[0.311]	[0.626]
KPI	12.333	22.020	22.732
	[0.006]	[0.001]	[0.009]
STI	3.545	9.812	10.171
	[0.315]	[0.133]	[0.366]
NIKKEI	2.252	5.806	8.514
	[0.522]	[0.445]	[0.759]

Notes: The number in brackets is p-value.

These evidences can sustain us to resort the ST-GARCH(1,1) model with $k=2$ to detect the volatility structure. The detailed model specification could be shown as,

$$LM = T \frac{(SSR_0 - SSR_1)}{SSR_0}$$

$$R_t = \theta_1 R_{t-1} + \varepsilon_t,$$

$$\varepsilon_t = z_t (h_t + g_t)^{1/2},$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1},$$

$$g_t = (\bar{\alpha}_0 + \bar{\alpha}_1 \varepsilon_{t-1}^2 + \bar{\beta}_1 h_{t-1}) F(t; \gamma, \mathbf{c}),$$

$$F(t; \gamma, \mathbf{c}) = (1 + \exp(-\gamma \prod_{i=1}^k (\tau_i - c_i)))^{-1}$$

where . The estimated results for the ST-GARCH(1,1) model are reported in Table 4. Meanwhile, the parameter estimates for the GARCH(1,1) model are also listed in Table 5 for the purpose of comparison.

Table 4: The ST-GARCH model estimation

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	\hat{k}	$\hat{\gamma}$	\hat{c}_1	\hat{c}_2	$\hat{\bar{\alpha}}_0$	$\hat{\bar{\alpha}}_1$	$\hat{\bar{\beta}}_0$	Q(10)	Q ² (10)	LogL	Regime 1	Regime 2
TAIEX	0.061* [<0.001]	0.152* [<0.001]	0.754* [<0.001]	2	3053.56 [0.949]	0.241* [<0.001]	0.907* [<0.001]	0.208* [0.010]	-0.027 [0.464]	-0.078 [0.3854]	10.742 [0.378]	0.090 [0.999]	-1590.669	0.906	0.801
HSI	0.012* [0.015]	0.026* [<0.001]	0.961* [<0.001]	2	2456.98 [0.928]	0.158* [<0.001]	0.912* [<0.001]	0.581 [0.102]	0.124 [0.060]	-0.340 [0.068]	12.589 [0.248]	1.441 [0.999]	-1969.624	0.987	0.771
KSI	0.034* [0.004]	0.047* [<0.001]	0.898* [<0.001]	2	2339.82 [0.885]	0.277* [<0.001]	0.897* [<0.001]	0.012 [0.574]	0.139* [<0.001]	-0.105* [0.025]	9.355 [0.499]	1.534 [0.999]	-1609.111	0.945	0.979
STI	0.007* [0.012]	0.024* [<0.001]	0.960* [<0.001]	2	1540.06 [0.831]	0.146* [<0.001]	0.914* [<0.001]	0.074* [0.038]	0.260* [<0.001]	-0.253* [<0.001]	7.590 [0.669]	4.603 [0.916]	-1521.000	0.984	0.991
NIKKEI	0.050* [<0.001]	0.069* [<0.001]	0.876* [<0.001]	2	2409.91 [0.948]	0.317* [<0.001]	0.902* [<0.001]	0.127* [0.005]	0.140* [<0.001]	-0.125* [0.002]	12.770 [0.237]	2.759 [0.987]	-1994.881	0.945	0.960

Notes: The figures in the brackets are p-value. Q(10) denotes the Ljung-Box statistic for serial correlation test with 10 lags, Q2(10) is the Ljung-Box statistic for serial correlation up to 10th order in the squared standardized residuals. The regime 1 and 2 shows the persistent rate for upper and lower regime, individually. Significant at the 5% level is denoted by *.

$$R_t = \varepsilon_t$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + [\bar{\alpha}_0 + \bar{\alpha}_1 \varepsilon_{t-1}^2 + \bar{\beta}_1 h_{t-1}] F(t)$$

$$F(t) = (1 + \exp(-\gamma \prod_{i=1}^k (\tau_i - c_i)))^{-1}$$

Table 5: The GARCH(1,1) model estimation

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	Q(10)	Q²(10)	LogL	Persistence
TAIEX	0.060*	0.125*	0.808*	6.128	2.555	-1616.550	0.934
	[<0.001]	[<0.001]	[<0.001]	[0.804]	[0.990]		
HSI	0.018*	0.050*	0.937*	8.860	9.486	-1996.601	0.987
	[0.001]	[<0.001]	[<0.001]	[0.546]	[0.487]		
KSI	0.041*	0.112*	0.841*	11.076	9.415	-1618.754	0.953
	[<0.001]	[<0.001]	[<0.001]	[0.352]	[0.493]		
STI	0.026*	0.109*	0.858*	18.598	18.832	-1539.660	0.967
	[<0.001]	[<0.001]	[<0.001]	[0.046]	[0.042]		
NIKKEI	0.080*	0.152*	0.806*	6.115	8.549	-2013.150	0.957
	[<0.001]	[<0.001]	[<0.001]	[0.805]	[0.575]		

Notes: The figures in the brackets are p-value. Q(10) denotes the Ljung-Box statistic for serial correlation test with 10 lags, Q²(10) is the Ljung-Box statistic for serial correlation up to 10th order in the squared standardized residuals. The persistence rate is calculated by sum of short- and long-term effect. Significant at the 5% level is denoted by *.

$$R_t = \varepsilon_t$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

In the light of parameter estimates in Table 4 and 5, we discover that the existence of serial correlation up to the 10th order in the standardized residuals and residuals squared for both models express almost insignificant for all stock market indices. In Table 4, the estimated volatility persistent effect for regime 1 is stronger than that for regime 2 in Taiwan and Hong Kong. It means that the event of the COVID-19 pandemic diminish the persistence of shocks for dynamic volatility. Furthermore, we observe that the estimated volatility persistent effect of the GARCH model is different to that of the ST-GARCH model. The estimated transition function, F(t), is plotted in Figure 2. It is clearly to observe that the illustrations of F(t) display inverted U-shaped patterns for all stock market indices in the Four Asian Tigers and Japan. According to the model specification, the upper regime could be shown as F(t) = 1, and the lower regime as F(t) gets to its minimum value. The minimum values of estimation of smooth transition function are zero for all stock market indices in the Four Asian Tigers and Japan.

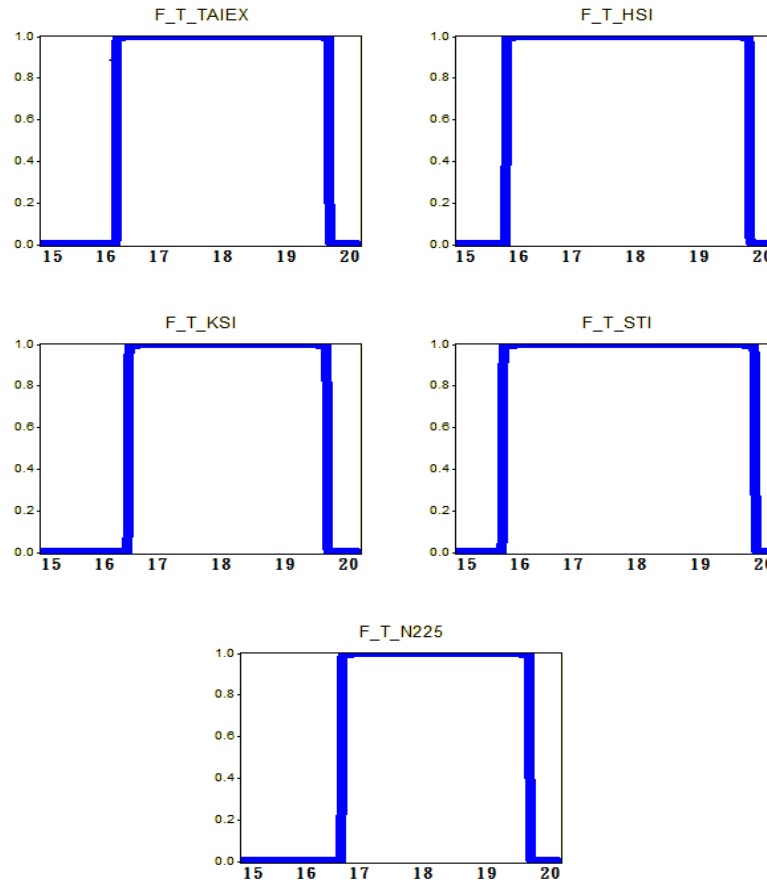


Figure 2: Estimation of smooth transition functions for stock market indices of the Four Asian Tigers and Japan.

In Table 6, we calculate the dynamic volatility half-life by the persistence coefficients reported in Table 4 and 5. The volatility half-life could be interpreted as the time taken for the volatility to move halfway back to its own unconditional volatility. In brief, the period of the outbreak of COVID-19 pandemic has low volatility half-life for Taiwan and Hong Kong, but contains high case for South Korea, Singapore and Japan. This finding implied that the impact of shocks has been rapidly reflected in unconditional volatility after the COVID-19 pandemic for the stock market index in Taiwan and Hong Kong. We infer that the different estimated results for volatility half-life in TAIEX and HSI could be attributed to the experience of severe acute respiratory syndrome (SARS) outbreak in 2003. The outbreak of SARS hits the economy of Taiwan and Hong Kong seriously. Thus, the volatilities of TAIEX and HIS become more sensitive as the similar infectious disease outbreak.

Table 6: The estimation of volatility half-life for different regimes of ST-GARCH model

Stock market indices	ST-GARCH model		GARCH model
	Regime 1 half-life	Regime 2 half-life	Half-life
TAIEX	7	3	10
HSI	53	3	53
KSI	12	33	14
STI	43	77	21
NIKKEI	12	17	16

Notes: The half-life could be calculated by $\frac{1}{2} = e^{y \times \ln(\rho)}$.

This study also uses the estimation of location parameters, C_1 and C_2 , to measure the relatively objective structure break date for the volatility process, which is expressed in Table 7. The responses of volatility regime changes for South Korea and Japan occurred before the outbreak of the COVID-19 pandemic. However, the responses of volatility regime changes for Taiwan, Hong Kong and Singapore arose after the outbreak of the COVID-19 pandemic. These findings demonstrate that using a subjective and biased determination in structure break time to fit the dynamic volatility process might obtain inconsistent estimated results.

Table 7: The estimation of location parameters and corresponding calendar dates

Stock market indices	C_1	Date	C_2	Date
TAIEX	0.241	July 7, 2016	0.907	January 3, 2020
HSI	0.158	January 29, 2016	0.912	January 16, 2020
KSI	0.277	September 7, 2016	0.897	December 19, 2019
STI	0.146	January 19, 2017	0.914	January 17, 2020
NIKKEI	0.317	December 1, 2016	0.902	December 25, 2019

By the illustration of the time varying unconditional volatility for all stock market indices in Figure 3, we could clearly display the shifting pattern of volatility structure. The dynamic unconditional volatilities for all stock market indices switch from a higher level to a lower one and then it goes back to a higher case. We deduce that the event of US-China trade war rockets down the dynamic unconditional volatility process during our sample period. Subsequently, the outbreak of COVID-19 pandemic could raise the volatilities for all stock market indices.

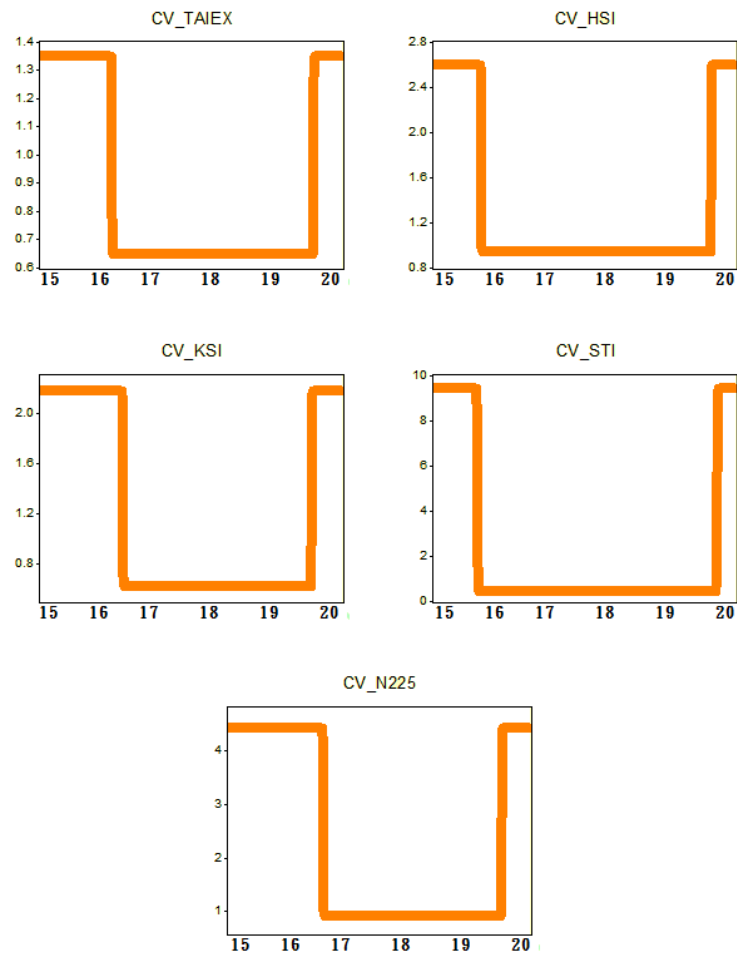


Figure 3: Estimation of unconditional variance under ST-GARCH model for stock market indices of the Four Asian Tigers and Japan.

In this article, the estimation of ST-GARCH model also contains some valuable meaning. First, the modified GARCH model with trigger variable seems suitable for fitting the dynamic volatility process. However, employing the ST-GARCH model to fit dynamic volatility process can acquire more realistic estimates of the break time dating. Finally, the impacts of the outbreak of COVID-19 pandemic really exist and can switch the volatility structure of stock market indices in the Four Asian Tigers and Japan.

Conclusions

In this article, we detect that the shocks of the outbreak of COVID-19 pandemic triggered regime shift in volatility process for all stock market indices in the Four Asian Tigers and Japan. We apply the classical GARCH model, the modified GARCH model with exogenous trigger variable, and the ST-GARCH model to depict the dynamic volatility process, individually.

The empirical findings report statistically significant volatility structure change in stock market indices for the Four Asian Tigers and Japan by the estimation of both modified GARCH and ST-GARCH model. We further discover that the estimated volatility persistent effect calculated from the classical GARCH (1,1) model could contain a single and invariable value, as the dynamic volatility contains structure breaks. The episode of COVID-19 reduces the volatility persistent rate and half-life for TAIEX and HSI. Moreover, the estimation of the modified GARCH model with exogenous trigger variable might offer a biased regime change date in the same time. This study also demonstrates that the dynamic volatility structure for all stock market indices in the Four Asian Tigers and Japan embedded two regime switch points by the LM test proposed by (Lundbergh and Teräsvirta, 2002).

In addition, we use the estimation of ST-GARCH model to plot the time varying unconditional volatilities and to compute the calendar day of break time for all stock market indices. The shapes of unconditional volatility for all stock market indices appear the similar U-shaped. We deduce that the downwards switching in unconditional volatility could be attributed to the US-China trade war, and the rises in that could be attributed to the outbreak of COVID-19 pandemic. The empirical results display that the dynamic volatility change dates are later than the outbreak of COVID-19 pandemic for the most of stock market indices in the Four Asian Tigers except South Korea and Japan.

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