The impact of COVID-19 pandemic on the smooth transition dynamics of broad-based indices volatilities in Taiwan

Abstract

This study adopts the smooth transition Generalized Autoregressive Conditional Heteroscedastic (GARCH) model to depict the influences of the Novel Coronavirus Disease (COVID-19) on the dynamic structure of the broad-based indices volatility in Taiwan. The empirical results show that the episode of the COVID-19 switches the volatility structure for the most of indices volatilities except two industrial sub-indices, the building materials and construction index and the trading and consumer goods index. Furthermore, we obtain the transition function for all indices volatilities and catch that their regime adjustment processes start prior to the outbreak of COVID-19 pandemic in Taiwan except two industrial sub-indices, the electronics index and the shipping and transportation index. Additionally, the estimated transition functions show that the broad-based indices volatilities have U-shaped patterns of structure changes except the trading and consumer goods sub-indices. This study also calculated the corresponding calendar dates of regime change about dynamic volatility pattern.

Keywords: COVID-19, ST-GARCH, volatility, structure change.
JEL Classification: G00, G10.

Introduction

For the recent decade, global financial markets have suffered several dramatic shocks including the 911 attacks in 2001, subprime crisis in the fall of 2007, Lehman Brothers collapse on September 2008, 2009 European sovereign-debt crisis and 2018-2019 US-China trade war etc. Most of these financial shocks could be directly attributed to equities or capital market decline. However, it is rare to observe that the infectious disease episodes cause the financial market turmoil. In addition, the volatility is widely used in asset pricing and hedge, risk management, portfolio selection and the other financial events. For this reason, we attempt to detect whether the COVID-19 pandemic incident will trigger the dynamic volatility changes.

The COVID-19 pandemic distribute from a regional disease in East Asia to a global infectious disease. According to the outbreak situation from the World Health Organization (WHO) website, the confirmed cases are about 4 million, and confirmed deaths are about 300 thousand as of 10th May 2020. In the face of this serious infection, many governments adopt entry restrictions, social distancing mandates and put on lockdown. However, the above containment policy might directly decrease the labor inputs and further harm the economic, as argued by Baldwin and Tomiura (2020). The characters of infectious disease episodes are dissimilar to that of economic crisis. Governments usually use the containment policy bringing economic damage to deal with the former mishap, but take the quantitative easing policy stimulating economic growth to handle the latter incident. Therefore, it is reasonable to comprehend the influences of the containment policy promulgated by infectious disease on dynamic volatility structure are significant or not.

In this study, firstly, we apply the modified GARCH model with threshold variable to fit the broad-based indices volatility in Taiwan, since this model is easy to use as the break time is certain.[1] To avoid the biased estimates of regime-switching date, we further employ the smooth transition GARCH model (ST-GARCH for short) to capture the broad-based indices volatility. By the specification of the ST-GARCH model, we could effortlessly explore the regime break date for broad-based indices as the volatility structure change is truly being.

Generally speaking, the grave epidemic might lead to stocks plummet and market volatility surges. However, we discover that the COVID-19 pandemic switches the dynamic volatility from the high level to low case for the most of indices during our sample period. We conjecture that this phenomenon could be attributed to two factors. Firstly, the government seems succeeded in increasing the COVID-19 treatment efficiency and diminishing the spillover effect to economy. The relative evidences refer to the statistical data from Deep Knowledge Group website. Secondly, the event of US-China trade war dominated the indices volatility in Taiwan. According to the official statistical data, Taiwan gains the most trade diversion effects about 4.2 billion from the US-China trade war. For this reason, the impact of the US-China trade war drives the dynamic volatility in high regime.

The rest of this paper is arranged as follows. In section 2 we introduce the related GRACH models and ST-GARCH model. The empirical analysis is reported in section 3. Finally section 4 summarizes the results and presents the concluding remarks.

2. Methodology

2.1 Related GARCH models

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

[1] We assume the threshold variable as the time of outbreak of the COVID-19. In Taiwan the date of outbreak of COVID-19 is 21th January 2020.

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

where R_t denotes the underlying asset returns at time t, h_t denotes the conditional volatility at time t, ε_{t-1}^2 denotes the square residual at time $t-1$, and Ω_{t-1} denotes the information set at time $t-1$. The parameters, α_0, α_1 and β_1, can be regarded as the inherent uncertainty level, short-run impact of volatility shocks, and long-run effect of volatility shocks, respectively. The specification of standard GARCH(1,1) model could not detect the nonlinear structural changes for dynamic volatility process. In this study, we concern about the influence of COVID-19 pandemic on the indices volatility process, therefore it is nature to incorporate a threshold variable into the equation (1). That is,

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

where D_t represents a threshold variable taking the value 1 post-outbreak and 0 pre-outbreak. We consider three threshold terms, including a single threshold term and two cross-product terms, in the variance equation for capturing the complete processes. On the condition that the given break date contains correct and full information, the exogenous adjustment could be explored the data structure change. It means that inaccurate definition of break date could cause estimating results insignificant and biased.

2.2 The smooth transition GARCH model

From past study, using the endogenous variable to nonlinear volatility model is better to capture the structure change. The smooth transition model proposed by Granger and Teräsvirta (1993) and Lin and Teräsvirta (1994) can diagnose the break point by itself. A series of recently literature consider that combining the smooth transition method with GARCH model can obtain many benefits in parameter estimates of dynamic volatility model.[2] The ST-GARCH model provides relatively flexible approach to widen the volatility process with nonlinear regime changes. Furthermore, the ST-GARCH model could explicitly point out the true date of structure changes in the data generating process for volatility process. The generalized framework for examining the appropriateness of an estimated ST-GARCH type model is built by Lundbergh and Teräsvirta (2002). The ST-GARCH model can be illustrated as,

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

$$\varepsilon_t = z_t (h_t + g_t)^{1/2} , \qquad (3)$$

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

$$F(\tau_t;\gamma,\boldsymbol{c}) = (1 + \exp(-\gamma \prod_{i=1}^{k} (\tau_t - c_i)))^{-1} , \qquad (4)$$

---

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

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

Lundbergh and Teräsvirta (2002) consider that the ST-GARCH model contains some vantages. Firstly, the timing decision for regime change in parameters is endogenesis in estimation and this decisive manner is more adaptable than artificially given a priori. Secondly, the specification of GARCH model with threshold 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 changes. For example, equation (4) reduces to a special case of a chow's structural change as $\gamma \to \infty$ and *k* = 1. In another case, if the slope parameter $\gamma \to \infty$ and *k* = 2, equation (4) turn out to be a double step function.

On the basis of the suggestion from Lundbergh and Teräsvirta (2002), we examine 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 $\bar{\boldsymbol{x}}_t' = \hat{h}_t^{-1} \partial \hat{h}_t / \partial \boldsymbol{\eta}'$ under the null. Furthermore, we consider the transition variable to be time, $\tau_t = t$, in order to take an evaluation for the impacts of COVID-19 pandemic for the broad-based indices volatility in Taiwan. Let, $\boldsymbol{v}_{it} = t^i \boldsymbol{s}_t$, $\hat{\boldsymbol{v}}_{it} = t^i \hat{\boldsymbol{s}}_t$, and $\hat{\boldsymbol{v}}_{it} = (\hat{\boldsymbol{v}}_{1t}, \hat{\boldsymbol{v}}_{2t}, \hat{\boldsymbol{v}}_{3t})'$ for i = 1, 2, and 3.

The procedure of statistical test can be executed by an artificial regression as below. First, 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 $\overline{x}_t'$, $\hat{v}_t'$ and collect the sum of squared residuals, SSR_1. The LM-version test statistic can be computed by $LM = T(SSR_0 - SSR_1)/SSR_0$. On the other hand, the F-version test statistic can be calculated by $F = ((SSR_0 - SSR_1)/k / SSR_1/(T - p - q - 1 - k))$. We adopt the statistics to ascertain an appropriate k to specify the ST-GARCH models. The choosing criterion of k value is the smallest p-values.

3. Data and empirical results

In this article, we concern about the broad-based indices volatility for the COVID-19 pandemic in Taiwan. We select several broad-based indices including TAIEX, Electronics (ELEC), Plastic and chemical (CHEM), Food (FOOD), Iron and steel (STEEL), Building materials and construction (BUILD), Tourism (TOUR), Finance and insurance (FIN), Trading and Consumer goods (TRAD), Biotechnology and medical care (BIO) and Shipping and transportation (SHIP). Daily data of 11 broad-based indices for the period 2 April 2015 to 1 April 2020 are adopted and collected from Taiwan Stock Exchange (TWSE). In Figure 1, the daily closing prices for all broad-based indices are respectively graphed. The daily indices returns are calculated by taking the first difference of the logarithmic prices. Descriptive statistics for these daily indices returns are reported in Table 1. We separate the whole period into two sub-sample periods by the infections disease outbreaks of COVID-19. Most of the items of summary statistics for the pre- and post-outbreak phase seem different. It is necessary for us to check whether the difference is significantly existence or not. According to the significance of the Ljung-Box Q^2 statistics for all indices returns, we can infer that the GARCH family model is proper to fit them.

[Figure 1]

[Table 1]

In order to handle more easily for volatility data with structure change in it, we employ the modified GAHCH model with threshold variable. The threshold variable is embedded respectively in the intercept term, lagged squared residual term and lagged conditional variance term for the adaptability of model specification. Table 2 expresses the parameter estimation results of this model. According to the significance of parameter estimates and Ljung-Box Q^2 statistics, we can infer that the impacts of COVID-19 pandemic change the most of the indices volatilities except the TRAD industrial sub-indices. For the reason of explicitly point out the true date of volatility structure changes of COVID-19 pandemic, it is intuitive to employ an endogenous deciding framework, the ST-GARCH model.

[Table 2]

Before using the ST-GARCH model to estimate, we have to test the parameter constancy by the LM test developed by Lundbergh and Teräsvirta (2002). We calculate the LM statistics for k = 1, 2, and 3. Furthermore we assume that the null model is standard GARCH(1,1) model. Table 3 reports that the parameter constancy is violated for all broad-based indices. That is to say the regime change in dynamic volatility process is certainly being against the corresponding GARCH model. In addition, we also detect that the parameter, k = 2, has the smallest p-value for the most of broad-based indices except the TRAD sub-indices. Theses empirical results can support us to adopt the ST-GARCH(1,1) model with k =2 to diagnose the dynamic volatility process. Our detailed model specification is given by,

$$
\begin{aligned}
R_t &= \varepsilon_t, \\
\varepsilon_t &= z_t (h_t + g_t)^{1/2}, \qquad (5) \\
h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}, \\
g_t &= (\overline{\alpha}_0 + \overline{\alpha}_1 \varepsilon_{t-1}^2 + \overline{\beta}_1 h_{t-1}) F(t;\gamma,\boldsymbol{c}),
\end{aligned}
$$

where $F(t;\gamma,\boldsymbol{c}) = (1+\exp(-\gamma \prod_{i=1}^{k} (\tau_t - c_i)))^{-1}$. We list the parameter estimates for the ST-GARCH(1,1) model in Table 4. Meanwhile, the estimated results for the GARCH(1,1) model are provided in Table 5 for the purpose of comparison.

[Table 4]

[Table 5]

Comparing the figures of parameter estimates in Table 4 and 5, we find that the existence of serial correlation up to the 10^{th} order in the standardized residuals and residuals squared for both models exhibit almost insignificant for all broad-based indices. In Table 4, the volatility persistent effect for regime 1 is stronger than that for regime 2 except the BUILD sub-indices. This finding indicates that the episode of the COVID-19 pandemic weaken the persistence of shocks for volatility. In addition, we observe that the volatility persistent effect of the GARCH model is relatively excessive than that of the ST-GARCH model. Figure 2 plots the estimated transition function, F(t). Apart from F(t) for the TRAD sub-indices, the others display the U-shaped. In terms of regime specification, we define the upper regime as F(t) = 1, and the lower regime as F(t) goes to its minimum value. The minimum values of estimation of smooth transition function are zero for all broad-based indices.

[Figure 2]

We use the persistence coefficients reported in Table 4 and 5 to measure the dynamic volatility half-life. This could be explained as the time taken for the dynamic volatility to move halfway back to its own unconditional volatility. All in all, the period of the outbreak of COVID-19 pandemic contains low volatility half-life. This finding implied that the impact of shocks has been rapidly reflected in unconditional volatility after the COVID-19 pandemic.

[Table 6]

Our article also uses the estimation of location parameters, c_1 and c_2, to point out the relatively objective structure change date for the dynamic volatility process, which is shown in Table 7. The responses of volatilities changes for half of broad-based indices (TAIEX, CHEM, FOOD, STEEL, FIN and BIO) are happening before the episode of the COVID-19 in Taiwan. This finding indicates that employing the modified GARCH model with threshold variable to fit the volatility process might use a subjective and biased determination in break time. In addition, Table 7 also reports some intriguing phenomena that the impacts of the outbreak of COVID-19 pandemic seem inexistence for BUILD and TRAD.

[Table 7]

Figure 3 further shows the time varying unconditional volatility for all broad-based indices. We could explicitly displays the shifting pattern of volatility structure by this illustration. The dynamic unconditional volatilities for most of broad-based indices switch from a lower level to a higher case and then it goes back to a lower one. As to the graphs for the TRAD sub-indices in Figure 3, the switching pattern obviously differs from that of others. We infer that the unconditional volatility structure change for the TRAD could be attributed to the economy slowing during the period from August, 2018 through March, 2020. Furthermore, the TRAD sub-indices have high connection to the business indicators. In Table4 the large coefficients of slope parameter, γ, could lead to all of the switching pattern experience sharper shifts. We clarify that the dynamic volatility process goes upwards by the US-China trade war during our sample period. Afterward, the outbreak of COVID-19 pandemic should rocket downwards the volatilities for broad-based indices including the TAIEX, ELEC, CHEM, FOOD, STEEL, TOUR, FIN, BIO and SHIP. The structure change of unconditional volatility for BUILD industrial sub-indices could be attributed to the adjustment of housing tax policy from government.

[Figure 3]

The estimation of ST-GARCH model in this study also has some valuable implications. Firstly, the modified GARCH model with threshold variable seems appropriate for fitting the dynamic volatility process. However, using the ST-GARCH model to fit dynamic volatility process can obtain more precise estimates of the break time dating. Lastly, the impacts of the outbreak of COVID-19 pandemic are really being and can switch the volatility structure of broad-based indices.

4. Conclusion

In this study, we document that the impact of the outbreak of COVID-19 pandemic triggered structure change in volatility process for broad-based indices in Taiwan. This study employs the standard GARCH model, the modified GARCH model with threshold variable, and the ST-GARCH model to depict the dynamic volatility process, respectively.

From the empirical results, we demonstrate statistically significant volatility structure change in Taiwan’s broad-based indices by the parameter estimates of both modified GARCH and ST-GARCH model. We find that the estimates of volatility persistent effect from the standard GARCH model could show the relatively higher value, as the dynamic volatility structure contains a regime change. The outbreak of COVID-19 pandemic weakens the persistence of shocks for volatility process and brings lower volatility half-life. Moreover, the estimates for the modified GARCH model with threshold variable might provide biased regime-switching date in the same situation. We also illustrate that the dynamic volatility structure for the most of broad-based indices embedded two regime change points by the LM test presented by Lundbergh and Teräsvirta (2002).

This article uses the estimation results of ST-GARCH model to graph the time varying unconditional volatilities and to calculate the calendar day of break time for all broad-based indices. The patterns of unconditional volatility for the most of broad-based indices appear the similar inverted U-shaped. We infer that the upwards switching in volatility could be attributed to the US-China trade war, and the declines in volatility could be triggered by the outbreak of COVID-19 pandemic. The empirical results show that the dynamic volatility switching dates are earlier than the outbreak of COVID-19 pandemic for the most of broad-based indices.

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Table 1: Descriptive Statistics

	Mean	St.D	Skewness	Kurtosis	Maximum	Minimum	$Q^2(10)$
Before COVID-19 pandemic (2 April 2015 to 20 January 2020)							
TAIEX	0.020	0.830	-0.870	6.358	3.518	-6.521	317.75*
ELEC	0.028	1.000	-0.547	3.904	4.449	-6.868	273.76*
CHEM	0.004	0.887	-0.881	7.783	4.085	-7.661	250.05*
FOOD	0.031	0.941	-0.479	3.525	3.816	-6.611	247.41*
STEEL	0.002	0.912	0.073	5.686	4.927	-5.613	242.22*
BUILD	0.004	0.808	-1.340	14.291	4.197	-7.962	382.23*
TOUR	-0.016	0.978	-0.212	3.635	3.844	-6.768	309.68*
FIN	0.018	0.834	-0.429	5.338	4.547	-5.062	287.92*
TRAD	0.006	1.050	-0.986	6.803	3.873	-7.614	293.37*
BIO	-0.012	1.150	-1.044	6.467	4.081	-8.206	262.35*
SHIP	-0.031	0.939	-0.588	7.452	4.064	-8.076	271.37*
After COVID-19 pandemic (21 January 2020 to 1 April 2020)							
TAIEX	-0.515	2.370	0.041	1.077	6.173	-6.005	13.277
ELEC	-0.491	2.508	0.162	0.965	6.782	-6.173	11.907
CHEM	-0.622	2.460	-0.194	1.045	5.231	-7.105	46.364*
FOOD	-0.292	1.811	0.175	1.285	5.039	-4.480	9.188
STEEL	-0.500	1.866	-0.365	2.378	5.383	-5.443	11.382
BUILD	-0.468	2.326	-0.690	2.416	4.907	-8.168	10.137
TOUR	-0.776	2.873	-0.654	1.071	5.277	-8.435	11.124
FIN	-0.509	2.297	-0.128	1.759	6.300	-7.053	14.659
TRAD	-0.162	1.532	-1.193	1.781	2.583	-4.617	6.295
BIO	-0.464	2.711	-1.139	1.780	4.431	-9.280	19.563
SHIP	-0.685	2.368	-0.796	1.267	4.219	-7.683	12.627

Notes:

1. This table reports 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 10^{th} order in the squared standardized residuals.
2. Return is defined as $100\times[\log(p_t)-\log(p_{t-1})]$. Significant at the 1% level is denoted by *.

Table 2: The estimation of modified GARCH(1,1) model with threshold variables

$$R_t = \varepsilon_t$$
$$\varepsilon_t \left| \Omega_{t-1} \sim N(0, h_t) \right.$$
$$h_t = \alpha_0 + \varphi_0 D_t + \alpha_1 \varepsilon_{t-1}^2 + \varphi_1 D_t \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \varphi_2 D_t h_{t-1}$$

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\varphi}_0$	$\hat{\varphi}_1$	$\hat{\varphi}_2$	Q(10)	$Q^2(10)$	LogL
TAIEX	0.060	0.097	0.827	0.294	0.184	-0.311	6.281	1.556	-1512.101
	[<0.001]	[<0.001]	[<0.001]	[0.034]	[0.073]	[0.008]	[0.791]	[0.999]	
ELEC	0.101	0.083	0.815	0.488	0.135	-0.281	7.317	2.106	-1738.132
	[<0.001]	[<0.001]	[<0.001]	[0.059]	[0.121]	[0.029]	[0.695]	[0.995]	
CHEM	0.052	0.089	0.853	0.255	0.199	-0.350	5.130	1.556	-1571.540
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.019]	[<0.001]	[0.882]	[0.999]	
FOOD	0.031	0.040	0.926	0.404	0.207	-0.567	19.428	2.745	-1658.020
	[<0.001]	[<0.001]	[<0.001]	[0.015]	[0.023]	[0.016]	[0.035]	[0.987]	
STEEL	0.016	0.070	0.915	0.189	0.200	-0.355	14.238	2.353	-1543.541
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.001]	[<0.001]	[0.162]	[0.993]	
BUILD	0.055	0.155	0.783	0.260	0.345	-0.411	21.992	2.105	-1426.792
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.002]	[<0.001]	[0.015]	[0.995]	
TOUR	0.131	0.097	0.782	0.424	0.221	-0.437	5.266	5.507	-1730.938
	[<0.001]	[<0.001]	[<0.001]	[0.004]	[0.098]	[0.016]	[0.873]	[0.855]	
FIN	0.037	0.125	0.834	0.173	0.200	-0.283	6.061	2.861	-1459.292
	[<0.001]	[<0.001]	[<0.001]	[0.004]	[0.020]	[0.001]	[0.810]	[0.985]	
TRAD	0.107	0.117	0.793	0.119	-0.160	0.225	8.800	3.204	-1756.537
	[<0.001]	[<0.001]	[<0.001]	[0.568]	[0.030]	[0.214]	[0.551]	[0.976]	
BIO	0.080	0.162	0.791	0.277	0.257	-0.298	16.478	6.144	-1817.726
	[<0.001]	[<0.001]	[<0.001]	[0.010]	[0.012]	[<0.001]	[0.087]	[0.803]	
SHIP	0.552	0.138	0.405	0.244	0.275	-0.172	16.844	12.581	-1693.704
	[<0.001]	[<0.001]	[<0.001]	[0.173]	[0.038]	[0.039]	[0.078]	[0.248]	

Notes:

1. The number in brackets is p-value. Normality tests are based on the Bera-Jarque statistics. Q(10) is the Ljung-Box (1978) test for serial correlation up to the 10^{th} order in the standardized residuals, $Q^2(10)$ is the Ljung-Box test for serial correlation up to 10^{th} order in the squared standardized residuals.
2. Before 20, Jan., 2020, the threshold variable D_t is 0. After 21, Jan., 2020, the threshold variable D_t is 1.

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

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

	k		
	1	2	3
TAIEX	1.917	8.632	11.029
	[0.590]	[0.195]	[0.472]
ELEC	3.231	9.989	12.870
	[0.357]	[0.125]	[0.351]
CHEM	1.115	5.632	8.721
	[0.774]	[0.466]	[0.776]
FOOD	1.281	4.749	5.146
	[0.733]	[0.576]	[0.856]
STEEL	1.786	6.393	11.195
	[0.618]	[0.381]	[0.700]
BUILD	0.054	6.345	7.561
	[0.997]	[0.386]	[0.705]
TOUR	1.963	5.093	6.196
	[0.580]	[0.532]	[0.826]
FIN	4.116	14.180	15.826
	[0.249]	[0.028]	[0.116]
TRAD	0.659	1.893	4.414
	[0.883]	[0.929]	[0.993]
BIO	1.910	6.940	8.258
	[0.591]	[0.326]	[0.643]
SHIP	0.271	6.724	8.292
	[0.965]	[0.347]	[0.666]

Note: The number in brackets is p-value.

Table 4: The estimation of the ST-GARCH model

$$R_t = \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + [\overline{\alpha}_0 + \overline{\alpha}_1 \varepsilon_{t-1}^2 + \overline{\beta}_1 h_{t-1}]F(t)$$
$$F(t) = (1 + \exp(-\gamma \prod_{i=1}^{k} (\tau_i - c_i)))^{-1}$$

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{k}$	$\hat{\gamma}$	$\hat{c}_1$	$\hat{c}_2$	$\hat{\overline{\alpha}}_0$	$\hat{\overline{\alpha}}_1$	$\hat{\overline{\beta}}_0$	Q(10)	$Q^2(10)$	LogL	Regime 1	Regime 2
TAIEX	0.059	0.147	0.760	2	17519.77	0.094	0.355	0.291	0.002	-0.167	6.051	2.948	-1497.197	0.907	0.742
	[<0.001]	[<0.001]	[<0.001]		[0.937]	[<0.001]	[<0.001]	[0.009]	[0.961]	[0.156]	[0.811]	[0.983]			
ELEC	0.162	0.052	0.814	2	1310.840	0.556	0.978	-0.121	0.049	0.042	7.829	3.320	-1733.604	0.957	0.866
	[0.017]	[0.002]	[<0.001]		[0.915]	[<0.001]	[<0.001]	[0.083]	[0.061]	[0.563]	[0.645]	[0.973]			
CHEM	0.029	0.093	0.868	2	17704.82	0.061	0.652	0.843	0.238	-0.665	5.806	1.454	-1541.703	0.961	0.534
	[0.764]	[0.295]	[<0.001]		[0.103]	[<0.001]	[0.999]	[0.011]	[0.085]	[0.010]	[0.831]	[0.999]			
FOOD	0.023	0.034	0.937	2	1492.512	0.027	0.357	0.406	0.148	-0.331	17.646	4.193	-1651.251	0.971	0.788
	[0.001]	[<0.001]	[<0.001]		[0.725]	[0.001]	[<0.001]	[0.086]	[0.160]	[0.078]	[0.061]	[0.938]			
STEEL	0.017	0.049	0.915	2	13299.46	0.151	0.357	0.279	0.184	-0.336	13.180	5.169	-1534.114	0.964	0.812
	[0.005]	[<0.001]	[<0.001]		[0.826]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.214]	[0.880]			
BUILD	0.345	0.220	0.566	2	6543.094	0.006	0.076	-0.229	0.029	0.017	23.812	1.525	-1422.122	0.786	0.832
	[0.091]	[0.013]	[0.007]		[0.517]	[0.365]	[<0.001]	[0.263]	[0.746]	[0.936]	[0.008]	[0.999]			
TOUR	0.016	0.017	0.951	2	3477.490	0.267	0.361	0.495	0.297	-0.655	7.187	5.427	-1720.584	0.968	0.610
	[0.062]	[0.157]	[<0.001]		[0.027]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.708]	[0.861]			
FIN	0.071	0.191	0.666	2	15799.67	0.094	0.357	0.321	-0.030	-0.053	7.459	3.365	-1426.526	0.857	0.774
	[<0.001]	[<0.001]	[<0.001]		[0.878]	[<0.001]	[<0.001]	[0.022]	[0.644]	[0.694]	[0.682]	[0.971]			
TRAD	0.184	0.147	0.703	1	238.701	0.672		-0.141	-0.067	0.182	7.392	2.910	-1755.774	0.965	0.850
	[<0.001]	[<0.001]	[<0.001]		[0.744]	[<0.001]		[0.007]	[0.054]	[0.016]	[0.688]	[0.983]			
BIO	0.170	0.249	0.595	2	20387.97	0.086	0.409	0.586	0.018	-0.103	20.027	6.859	-1799.619	0.844	0.759
	[0.008]	[0.036]	[<0.001]		[0.975]	[<0.001]	[0.964]	[0.097]	[0.897]	[0.606]	[0.029]	[0.739]			
SHIP	0.20	0.207	0.622	2	4697.755	0.067	0.366	0.557	-0.055	-0.091	9.560	0.797	-1587.503	0.829	0.683
	[<0.001]	[<0.001]	[<0.001]		[0.982]	[<0.001]	[0.978]	[0.292]	[0.333]	[0.754]	[0.480]	[0.999]			

Note: The number in brackets is p-value. Normality tests are based on the Bera-Jarque statistics. Q(10) is the Ljung-Box (1978) test for serial correlation up to the 10^{th} order in the standardized residuals, $Q^2(10)$ is the Ljung-Box test for serial correlation up to 10^{th} order in the squared standardized residuals. The regime 1 and 2 shows the upper and lower regime individually.

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

$$R_t = \varepsilon_t$$
$$\varepsilon_t \left| \Omega_{t-1} \sim N(0, h_t)\right.$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	Q(10)	$Q^2(10)$	LogL	Persistence
TAIEX	0.057	0.128	0.810	6.800	1.850	-1520.700	0.938
	[<0.001]	[<0.001]	[<0.001]	[0.744]	[0.997]		
ELEC	0.050	0.098	0.864	7.643	2.979	-1744.309	0.962
	[0.001]	[<0.001]	[<0.001]	[0.664]	[0.982]		
CHEM	0.073	0.125	0.800	7.310	1.076	-1581.951	0.925
	[<0.001]	[<0.001]	[<0.001]	[0.696]	[0.999]		
FOOD	0.064	0.071	0.863	16.568	2.863	-1665.322	0.934
	[<0.001]	[<0.001]	[<0.001]	[0.084]	[0.984]		
STEEL	0.027	0.107	0.872	15.108	3.513	-1556.743	0.979
	[<0.001]	[<0.001]	[<0.001]	[0.128]	[0.967]		
BUILD	0.075	0.213	0.715	24.751	1.824	-1434.666	0.928
	[<0.001]	[<0.001]	[<0.001]	[0.006]	[0.998]		
TOUR	0.221	0.155	0.649	6.208	4.298	-1739.621	0.804
	[<0.001]	[<0.001]	[<0.001]	[0.797]	[0.933]		
FIN	0.042	0.163	0.801	6.578	2.920	-1468.427	0.964
	[<0.001]	[<0.001]	[<0.001]	[0.795]	[0.983]		
TRAD	0.118	0.129	0.775	7.754	3.291	-1758.215	0.904
	[<0.001]	[<0.001]	[<0.001]	[0.653]	[0.974]		
BIO	0.101	0.213	0.739	18.784	5.163	-1825.177	0.952
	[<0.001]	[<0.001]	[<0.001]	[0.043]	[0.880]		
SHIP	0.066	0.114	0.828	14.341	0.711	-1650.804	0.942
	[<0.001]	[<0.001]	[<0.001]	[0.158]	[0.999]		

Notes:

The number in brackets is p-value. Normality tests are based on the Bera-Jarque statistics. Q(10) is the Ljung-Box (1978) test for serial correlation up to the 10^{th} order in the standardized residuals, $Q^2(10)$ is the Ljung-Box test for serial correlation up to 10^{th} order in the squared standardized residuals.

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

	ST-GARCH model		GARCH model
Board-based indices	Regime 1 half-life	Regime 2 half-life	Half-life
TAIEX	7	2	11
ELEC	16	5	18
CHEM	17	1	9
FOOD	24	3	10
STEEL	19	3	33
BUILD	3	4	9
TOUR	21	1	3
FIN	4	3	19
TRAD	19	4	7
BIO	4	3	14
SHIP	4	2	12

Notes: The half-life could be calculated by $0.5 = e^{y \times \ln(\rho)}$.

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

Board-based indices	c_1	Date	c_2	Date
TAIEX	0.094	July 6, 2016	0.355	January 3, 2020
ELEC	0.556	January 5, 2018	0.978	February 25, 2020
CHEM	0.061	January 22, 2016	0.652	January 17, 2020
FOOD	0.027	August 12, 2015	0.357	January 15, 2020
STEEL	0.151	April 14, 2017	0.357	January 14, 2020
BUILD	0.006	May 6, 2015	0.076	April 13, 2016
TOUR	0.267	October 29, 2018	0.361	February 12, 2020
FIN	0.094	July 11, 2016	0.357	January 13, 2020
TRAD	0.672	August 8, 2018		
BIO	0.086	May 31, 2016	0.409	January 20, 2020
SHIP	0.067	March 1, 2016	0.366	January 31, 2020

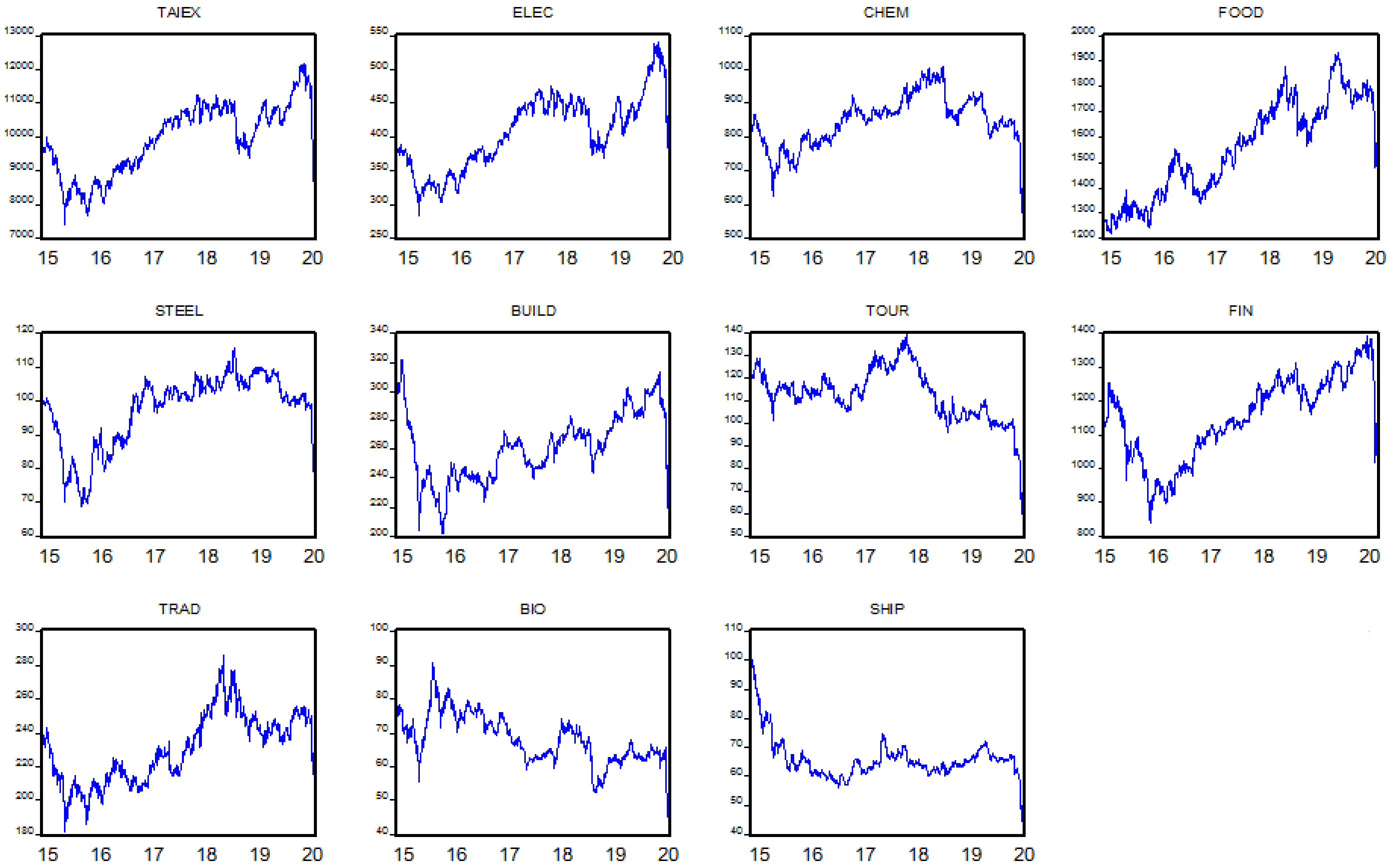

Figure 1: Daily closing prices for broad-based indices over the period 2 April 2015 to 1 April 2020

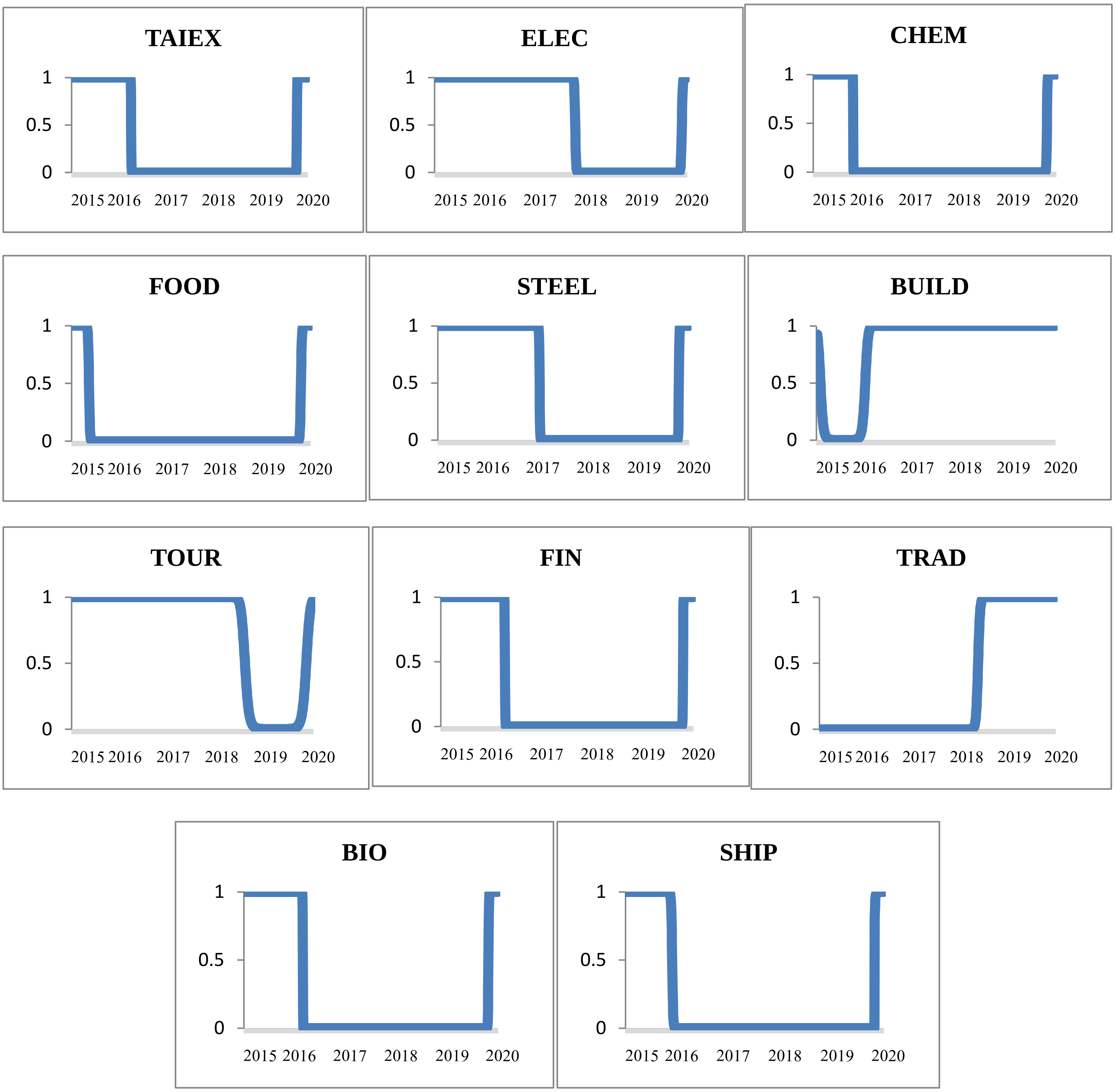

Figure 2: Estimated smooth transition functions for broad-based indices

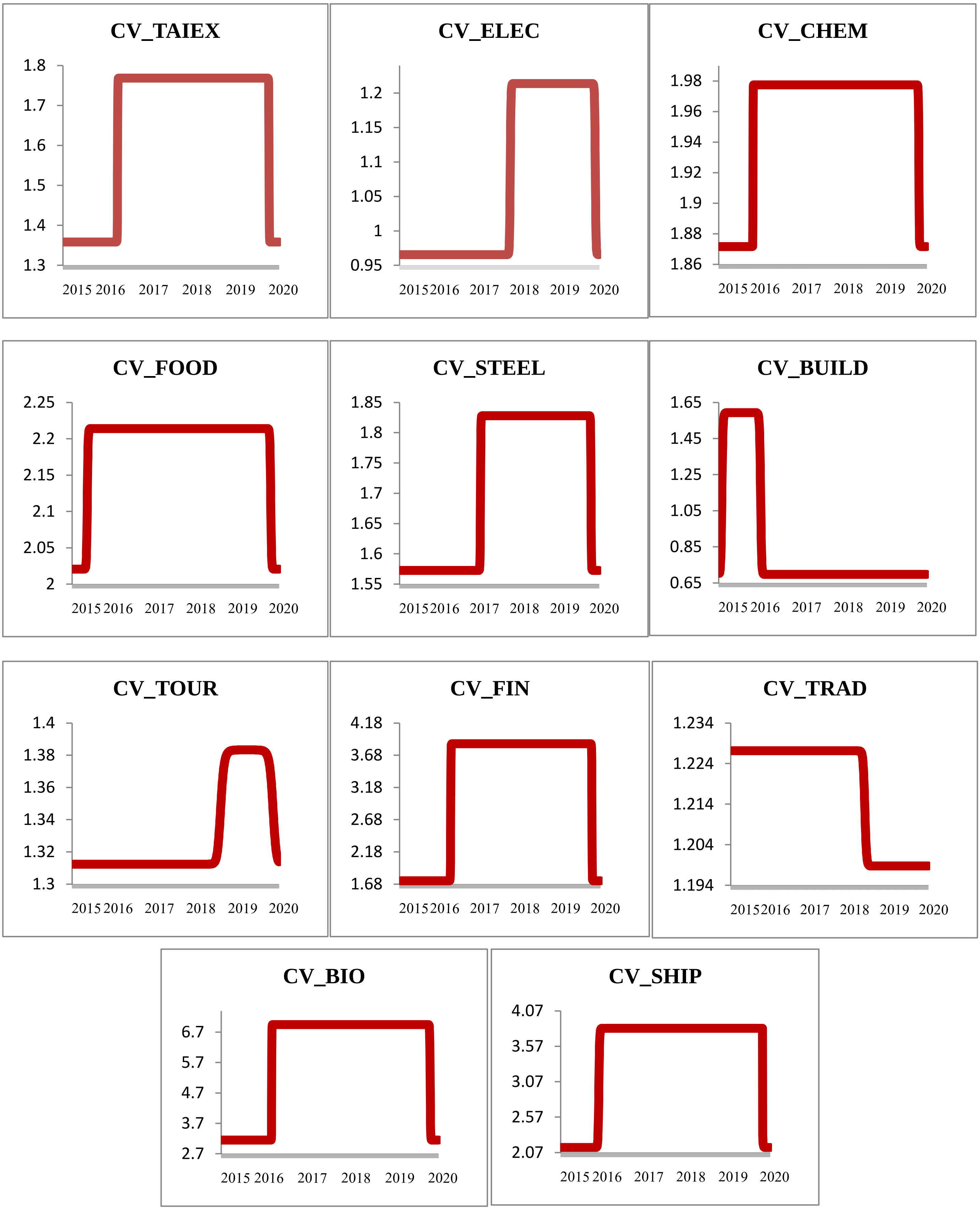

Figure 3: Estimated unconditional variance under ST-GARCH model for broad-based indices