The Influence of Defense Industry Development Act on the Smooth Transition Dynamics of Stock Volatilities of Defense Industry

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Abstract

This study aims to investigate the impacts of the Defense Industry Development Act on the volatility of the defense industry as geopolitical risk is raised. Applying the smooth transition generalized autoregressive conditional heteroskedasticity (ST-GARCH) model for daily defense stocks, we demonstrate that the structure breaks in the volatility dynamics process of all defense stocks for Taiwan. The empirical findings show that most defense stocks started the adjustment process more than one year before the date of launch of Defense Industry Development Act except Magnate Technology Corporation (MTC) and China Ship Building Corporation Taiwan (CSBC). The model specification tests suggest two types of transition functions including U-shaped and Z-shaped for all defense stocks. The estimated parameters indicate that the volatilities of returns in defense stocks for Taiwan have inverted U-shaped and inverted Z-shaped patterns of structure breaks. The volatilities of defense enterprise stock return shift by the event of Defense Industry Development Act.

Keywords: Geopolitical, Defense industry, Volatility, Structure change, Defense Industry Development Act

JEL Classification: G00 , G14 , G18 , L52

1 Introduction

There are many reasons which could explain why Taiwan plays a critical role in global geopolitics. In the geographical aspect, Taiwan is located at the midpoint of the first island chain and guards the Taiwan Strait and Bashi Channel. Therefore, Taiwan occupies an important strategic position for the United States. In the economic field, the relationship between the U.S. and China has been deteriorating since the 2018 US-China trade war. Recently, the U.S. government promulgated sweeping restrictions on selling semiconductors and related equipment to China in late 2022. Additionally, according to the data from the Ministry of Economic Affairs, Taiwan manufactures over 60% of the world's semiconductors and about 90% of the most advanced ones. In view of the late closer relationship between the US and Taiwan, the Taiwan and China tensions are rising evidently and conflict risk is also growing.

Furthermore, the Taiwan geopolitical risk (GPR, for short) index constructed by Caldara and Iacoviello [1] shows in Fig. 1. The period of the monthly Taiwan geopolitical risk index is collected from January, 2010 to May, 2023, available open source from the website.[1] We could clearly observe that the GPR index became slightly volatile during 2016 to 2017, and then it turns into more and more volatile after 2018. Additionally, Lin et al. [2] consider that the tension across the Taiwan Strait became alleviated could be attributed to the cross-strait agreement. The cross-strait peace explains that the GPR index appears relatively stable from 2010 to 2016.

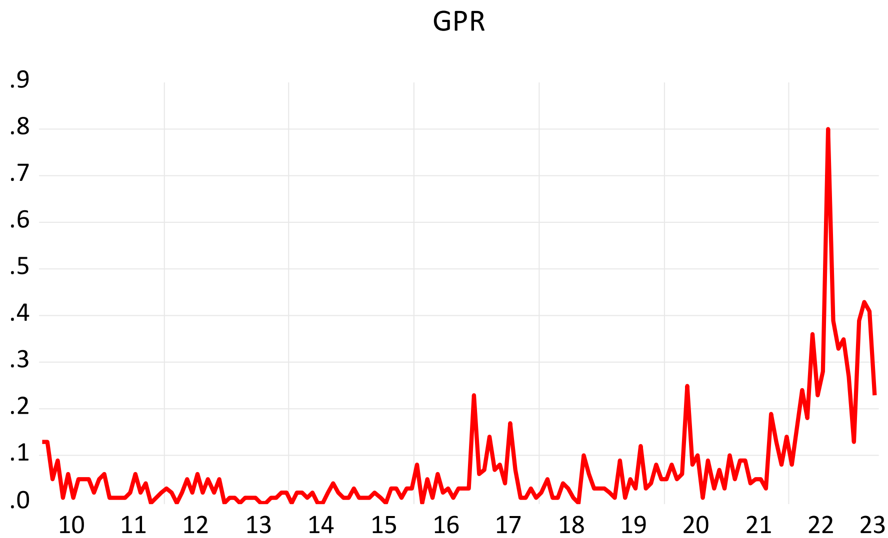

Fig. 1 Taiwan geopolitical risk from January 2010 to May 2023

All in all, the most volatile flashpoint between the U.S. and China is Taiwan. Therefore, national defense turns into a top issue for Taiwan. In order to improve the

[1] Data downloaded from https://www.matteoiacoviello.com/gpr.htm on June 10, 2023

national defense forces, the Taiwan government passed Defense Industry Development Act on May 31, 2019. The national defense independent policy aims to accelerate public-private partnerships to build internally manufactured weapons, especially in shipbuilding, aerospace, and information security, thereby aiding the country in accomplishing its goal of defense autonomy. According to the former research, military spending could stimulate employment in the long term in Taiwan [3]. In the light of the official information of the Ministry of National Defense, the act could not only take into consideration the need of national defense security and economic development but also attract firms to invest and expand the national defense market size. Hence, this policy might mainly and directly benefit the military industry enormously.[2] Briefly speaking, the implementation of Defense Industry Development Act could integrate industrial resources and create synergy. These advantages could be mirrored in the related information flow. Ross [4] demonstrates that in the absence of arbitrage, the market volatilities will move up as the concerned information flows get more exposure. In this article, we believe that the announcement of Defense Industry Development Act could not only increase the revelation of information flows but change the volatility state. Consequently, we surmise that the act could alter the dynamic volatility process of defense stock return.

This paper firstly detects whether the volatility structure change is existence or not. Secondly, we hire the smooth transition approach to discover the regime-switching date as it is a presence. According to the related public news, we conjecture that the structure breaking date could arrive before the promulgation of Defense Industry Development Act.[3] For this reason, using the threshold method to depict the policy impacts of volatility might be biased. Our analysis verifies this viewpoint later.

The previous literature has utilized threshold, smooth transition, and Markov switching methods to deal with the structure change problem. In this study, we choose the smooth transition mechanism to investigate the endogenous structure break of the dynamic volatility process. The smooth transition method is more suitable for this topic because the influence of planned acts on volatility structure is picked up by a process of osmosis. Regarding the Markov switching approach, it is appropriate to describe the effect of unexpected shocks. Granger and Teräsvirta [5] and Lin and Teräsvirta [6] propose the smooth transition approach and introduce this nonlinear concept into the mean equation. A lot of subsequent studies employ the smooth transition mechanism in the variance equation further, such as Hagerud [7], González-Rivera [8], Anderson et al. [9], Lundbergh and Teräsvirta [10], Liau and Yang[11], Chou et al. [12], Chen et al. [13], Ho et al. [14], and Li et al. [15]. Considering the purpose of this research is to find out the endogenous structure break point of volatility, we hire the smooth transition GARCH model proposed by Lundbergh and Teräsvirta [10] to fit the dynamic volatility process. In the light of estimated results of the parameter consistency test, almost all defense stock volatilities contain an inverted U-shaped pattern except for

[2] The main related defense companies of the military industry include Aerospace Industrial Development Corporation (AIDC), Magnate Technology Corporation (MTC), National Aerospace Fasteners Corporation (NAFCO), China Ship Building Corporation Taiwan (CSBC), Lanner Electronics Incorporation (LE) and TOPKEY Corporation (TK). AIDC, MTC, and NAFCO manufacture the aerospace components. CSBC, LE, and TK produce ship, advanced network appliances, and aviation products individually.

[3] The earliest published news about the national defense independent policy is on October 10, 2018, from the wealth magazine (https://www.wealth.com.tw/articles/79386c21-338b-4dfd-b128-832fb9950c78).

the National Aerospace Fasteners Corporation (NAFCO). We have evidence that the regime change date for all defense stock return volatilities begins ahead of the act besides MTC. Additionally, the empirical findings show that the long-term unconditional volatilities shift from a lower volatility state to a higher one and then return to the lower case except NAFCO.

We can perceive that nongovernmental defense communication activities become more active in the last few years. In accordance with the recent data from the Taiwan Defense Industry Development Association, there are 50 domestic companies and legal persons who joined the member.[4] It indirectly explains that the development for military industry chain seems boosted by the implementation of Defense Industry Development Act. Therefore, we attempt to clarify this amusing influence of the policy for Taiwan's national defense industry.

The remainder of this paper is organized as follows. Section 2 introduces the methodology including the classical GARCH model, GARCH model with threshold variable, and smooth transition GARCH model. Section 3 presents the data and empirical results. Section 4 concludes this paper.

2 Methodology

2.1 Related GARCH models

The GARCH model introduced by Engle [16] and Bollerslev [17] is one of the widely applied dynamic volatility models. The classical GARCH $(1,1)$ model could be used to measure the dynamic volatility process, that is,

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

where R_t denotes the underlying asset returns at time t, h_t denotes the conditional volatility at time t, ε_{t-1}^2 represents the square residual at time $t-1$, and Ω_{t-1} represents the information set at time $t-1$. The parameters, α_0, α_1, and β_1, can be shown as the intrinsic uncertainty level, short-run effect of volatility shocks, and long-run effect of volatility shocks, individually. The specification of the conventional GARCH $(1,1)$

[4]The members involve ChenFull Precision Co., Jong Shyn Shipbuilding Co., China Steel Corporation, Chung-Hsin Electric and Machinery Manufacturing Corp., TAIWAN AEROSPACE Corporation, CSBC Corporation, Zyxel Communications Corp, Apex Flight Academy Inc., CyCarrier Co., Hung Shen Propeller Co., Air Asia Company, DragonCloud Technology Co., SGD Engineering Co., Topkey Corporation, Loop Telecommunication International, Kolik Enterprise Co., Athemaster Co., Kolead Aerospace Co., Ship and Ocean Industries R & D Center, National Chung-Shan Institute of Science and Technology, Vivian & Vincent International Trading Company, Geosat Aerospace & Technology Inc., Aerospace Industrial Development Corporation, Data Force System Ltd., Ming Rong Yuan Business Co., LungTeh Shipbuilding Co., Trend Micro Incorporated, Chan Ta Machinery & Electric Mfg.,Co., Shengan Marine Co., Yung Chi Paint & Varnish Mfg. Co., Karmin International Co., Tri-Force International Inc., ADLINK Technology Inc., Digicentre Company Limited, Kun Yi Engineering Co., Tron Future Tech Inc., KeyXentic Inc., Gbit Technology Corporation, Wavefidelity Inc., Funz-San Industry Co., Value Valves Co., MiTwell, Inc., Orient Semiconductor Electronics Limited, Twoway Communications Inc., Gong Wei Co., Accton Technology Corporation, U & U Engineering Inc., F Time Technology Industrial Co., InfoKeyVault Technology Co. and Skylink Technology Co..

model could not expose the nonlinear structural breaks for the dynamic volatility process. In this paper, we focus on the influence of Defense Industry Development Act on the defense stocks volatility process, thence it is natural to apply an exogenous threshold variable to Eq. (1). That is,

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + D_t(\theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 h_{t-1}), \tag{2}$$

where D_t denotes an exogenous dummy variable allowing the value 1 post-case phase and 0 pre-case phase. We put three threshold terms, containing a single threshold term and two cross-product terms, in the variance equation for catching the entire process. On the condition that the given break date implies correct and full information, this exogenous specification could be delineated in the form of regime changes. It means that the erroneous definition of break date could bring about insignificant and biased estimating consequences.

2.2 The smooth transition GARCH model

From previous literature, applying the endogenous variable to a nonlinear volatility model is superior to delineating the regime change. The smooth transition model built by Granger and Teräsvirta [5] and Lin and Teräsvirta [6] could examine the structure change data through itself. Several recent literature indicate that combining the smooth transition mechanism with the GARCH model can receive many vantages in parameter estimates of the dynamic volatility model.[5] The ST-GARCH model offers the dynamic volatility process with nonlinear state switches. Furthermore, the ST-GARCH model could clearly capture the actual date of regime changes in the data-generating process for the dynamic volatility process. Lundbergh and Teräsvirta [10] constructed the generalized framework for detecting the appropriateness of an estimated ST-GARCH type model. The ST-GARCH model could be presented as,

$$\begin{aligned} \mathrm{y_t} &= f(\mathbf{w_t}; \boldsymbol{\psi}) + \varepsilon_t \\ \varepsilon_t &= \mathrm{z_t}(h_t + \mathrm{g_t})^{1/2}, \end{aligned} \tag{3}$$

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

$$F(\tau_t; \gamma, \boldsymbol{\nu}) = (1 + \exp(-\gamma \prod_{i=1}^{k} (\tau_t - v_i)))^{-1}, \tag{4}$$

where τ_t is the transition variable at time t, γ shows the slope parameter ($\gamma > 0$), $\boldsymbol{\nu} = (\nu_1, \nu_2, ..., \nu_k)$ shows a location vector in which $\nu_1 \leq \nu_2 \leq ... \leq \nu_k$, and k shows the number of transition systems. The model specification means transitions between two states, $F(\tau_t; \gamma, \boldsymbol{\nu}) = 0$ and $F(\tau_t; \gamma, \boldsymbol{\nu}) = 1$.

[5] Also see [7], [8], [9], [10], [11], [12], [13], [14], and [15].

Lundbergh and Teräsvirta [10] believe that the ST-GARCH model has several superiorities. First, the timing determination for state alteration in parameters is endogenous in estimation and this critical mode is more suitable than artificially given a priori. Second, the specification of the GARCH model with threshold variable could be viewed as a special case as the slope parameter (γ) gets to infinity. Lastly, the transition function, $F(\tau_t; \gamma, \boldsymbol{\nu})$, offers another flexible model specification to define the forms of structure changes. For example, Eq. (4) reduces to a special case of a chow's state break as $\gamma \to \infty$ and $k = 1$. In another case, as the slope parameter $\gamma \to \infty$ and $k = 2$, Eq. (4) becomes a double-step function.

Before estimating the ST-GARCH model, we consider the suggestion from [10] to examine the hypothesis of parameter constancy in GARCH model. We assume the null model as $g_t = 0$ and let $\bar{\boldsymbol{x}}'_t = \hat{h}_t^{-1}\partial\hat{h}_t/\partial\boldsymbol{\eta}'$ under the null. In addition, we regard the transition variable as time, $\tau_t = t$, in order to take an assessment of the impacts of Defense Industry Development Act on the defense stocks volatility in Taiwan. Let, $\omega_{it} = t^i s_t$, $\hat{\omega}_{it} = t^i \hat{s}_t$, and $\omega_{it} = (\hat{\omega}_{1t}, \hat{\omega}_{2t}, \hat{\omega}_{3t})'$ for $i = 1$, 2, and 3.

The statistical test procedure can be estimated by an artificial regression as below. First, estimate the parameters of the conditional model under the null. Let $SSR_0 = \sum_{t=1}^{T}(\varepsilon_t^2/\hat{h_t} - 1)^2$, and then regress $(\varepsilon_t^2/\hat{h_t} - 1)$ on $\bar{\boldsymbol{x}}'_t$, $\hat{\omega'}_t$ 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 calculated by $F = ((SSR_0 - SSR_1)/k/SSR_1/(T - p - q - 1 - k))$. Lastly, we use the statistics to find out a suitable k to fit the ST-GARCH models. The choosing criterion of k value is the smallest p-values.

3 Data and empirical results

In our article, we are concerned about the defense stocks volatility for Defense Industry Development Act in Taiwan. We chose defense stocks, containing Aerospace Industrial Development Corporation (AIDC), Magnate Technology Corporation (MTC), National Aerospace Fasteners Corporation (NAFCO), CSBC Corporation, Taiwan (CSBC), Lanner Electronics Incorporation (LE) and TOPKEY Corporation (TK).[6] These daily data of defense stocks could be gathered from Yahoo Finance[7] for the sample period starting from October 24, 2014 to May 5, 2023. The daily closing prices for all defense stocks are separately plotted in Fig. 2. At first glance, the daily closing prices for all defense stocks seem to become more volatile after 2018. We use the first difference of the logarithmic closing prices to calculate the daily defense stock returns. Table 1 shows the descriptive statistics for these daily defense stock returns. We separate the entire period into two sub-sample periods by the event of Defense Industry Development Act. Most of the items of descriptive statistics for the pre-and post-launch period seem different, especially the standard deviation for all defense

[6] The purpose of this paper is to examine the influence of Defense Industry Development Act released in May 31, 2019 on defense stock return volatility. Consequently, the chosen defense companies have to trade in the stock market during our research period. We skip AEWIN Technologies Co., CASwell Inc., Lungteh Shipbuilding Co., and Aero Win Technology Co.

[7] See http://finance.yahoo.com/.

stock returns. After publishing Defense Industry Development Act, the standard deviation of whole defense stock returns increase. It is necessary to check whether the discrepancy is considerably existing or not. In accordance with the significance of the Ljung-Box [18] Q^2 statistics for all defense stock returns, we could conjecture that it is suitable to estimate them by the GARCH family model.

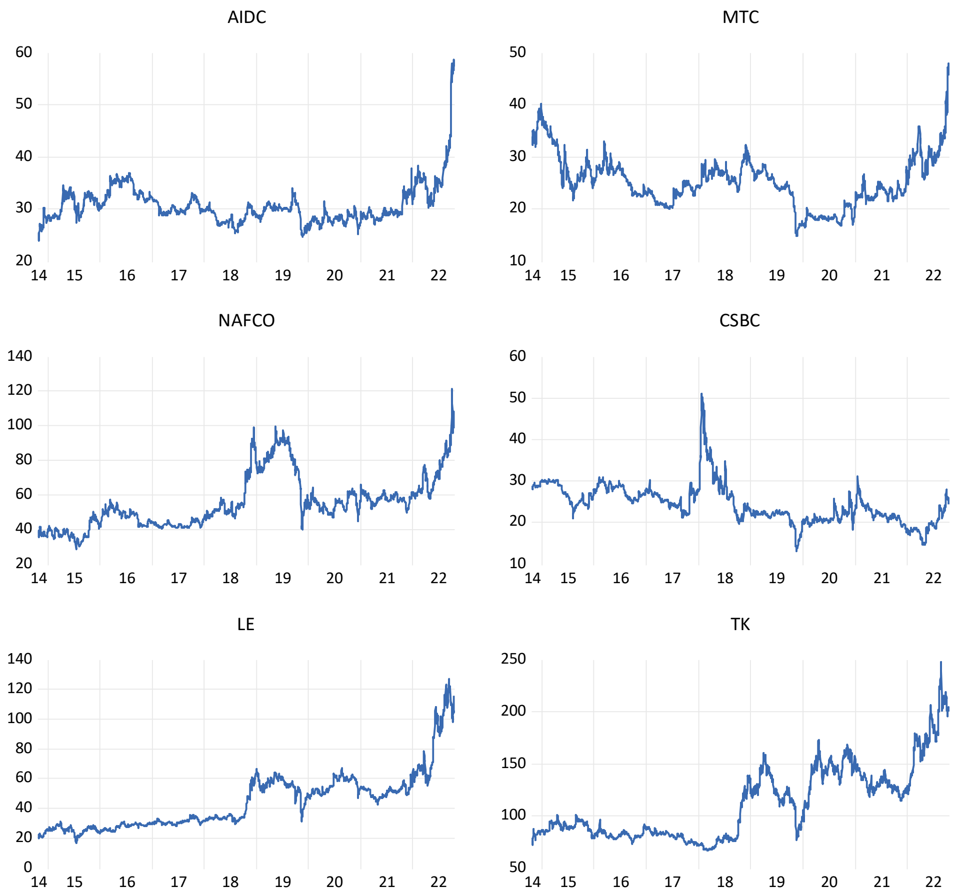

Fig. 2 Daily closing prices for defense stocks over the period October 24 2014 to May 5 2023

By dealing more commonly with volatility data with structural change, we employ the adjusted GAHCH model embedded in an exogenous variable. A more flexible volatility model specifies the exogenous variable separately into the intercept, lagged squared residual, and lagged conditional variance term. The parameter estimation results of the adjusted GARCH model are shown in Table 2. According to the significance of parameter estimates and Ljung-Box [18] Q^2 statistics, we could find out

Table 1 Descriptive Statistics

	Mean	SD	Skewness	Kurtosis	Maximum	Minimum	$Q^2(10)$
Before Defense Industry Development Act (October 24, 2014 to May 30, 2019)							
AIDC	0.013	1.310	0.356	8.397	8.071	-10.104	315.94*
MTC	-0.019	1.983	0.903	5.199	9.531	-9.132	259.06
NAFCO	0.058	2.166	0.682	5.616	9.531	-10.507	314.39*
CSBC	-0.023	2.130	0.855	7.526	9.531	-10.495	234.57*
LE	0.086	1.994	0.087	3.507	9.518	-9.848	246.76*
TK	0.045	1.578	0.438	4.524	9.300	-8.038	293.02*
After Defense Industry Development Act (May 31, 2019 to May 5, 2023)							
AIDC	0.067	1.648	0.588	8.252	9.500	-10.478	245.50*
MTC	-0.057	2.170	0.654	5.293	9.531	-10.423	253.86*
NAFCO	0.030	2.405	0.455	4.423	9.531	-10.536	289.70*
CSBC	0.011	2.264	0.669	4.658	9.531	-10.447	305.47*
LE	0.077	2.477	-0.062	3.054	9.517	-10.536	276.38*
TK	0.049	2.394	0.298	2.509	9.476	-10.524	283.15*

Notes:

[1]This table reports the summary statistics for the logarithmic stock returns before and after the introducing of the Defense Industry Development Act. The Ljung-Box [18] test for serial correlation up to 10^{th} order in the squared standardized residuals reports as $Q^2(10)$.

[2]Return is defined as $100\times[log(p_t) - log(p_{t-1})]$. Significant at the 1% level is expressed as *.

the impacts of Defense Industry Development Act appear to affect all defense stock volatilities. At first glance, adopting the adjusted GARCH model with a dummy variable could approximately delineate the effects of Defense Industry Development Act. However, it is intuitively to employ an endogenous deciding model, the ST-GARCH model, to straightly catch the real date of volatility structural changes of Defense Industry Development Act.

It is necessary to examine the parameter constancy by the LM test built by [10] before estimating the ST-GARCH model. Firstly, we assume that the null model is the conventional GARCH $(1, 1)$ model. Then, we calculate the LM statistics for $k = 1, 2$, and 3. Lastly, we make a list of the estimation results in Table 3. We show that the parameter constancy is violated for all defense stocks. To put it another way, the regime changes in the dynamic volatility pattern practically exist against the corresponding GARCH $(1, 1)$ model. In addition, we discover that the parameter, $k = 2$, reveals the smallest p-value for AIDC, MTC, CSBC, LE, and TK, but the parameter, $k = 1$, discloses the smallest p-value for NAFCO.

Table 4 expresses the estimated results of the ST-GARCH $(1, 1)$ model. The parameter estimates of the GARCH $(1, 1)$ model are also reported in Table 5 for the object of contradistinction at the same time. According to the parameter estimates in Tables 4 and 5, we observe that the existence of serial correlation up to the 10^{th} order in the standardized residuals and residuals squared for both models exhibit almost negligible for all defense stocks. The estimation of volatility persistence of state 1 is stronger than that of state 2 for all defense stock returns in Table 3. It shows that the event of the Defense Industry Development Act diminishes the persistence of shocks in the

Table 2 The estimation of adjusted GARCH $(1,1)$ model with exogenous variables

$$R_t = \varepsilon_t$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + D_t(\theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 h_{t-1})$$

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\theta}_0$	$\hat{\theta}_1$	$\hat{\theta}_2$	$Q(10)$	$Q^2(10)$	LogL
AIDC	0.031*	0.006*	0.915*	0.004	0.091*	-0.062*	7.174	17.500	-3480.85
	[< 0.001]	[< 0.001]	[< 0.001]	[0.619]	[< 0.001]	[< 0.001]	[0.709]	[0.064]	
MTC	0.268*	0.097*	0.834*	0.123*	0.209*	-0.181*	11.026	3.185	-4217.474
	[< 0.001]	[< 0.001]	[< 0.001]	[0.010]	[< 0.001]	[< 0.001]	[0.356]	[0.955]	
NAFCO	0.020*	0.027*	0.969*	0.182*	0.048*	-0.082*	17.579	11.080	-4490.145
	[< 0.001]	[< 0.001]	[< 0.001]	[0.010]	[< 0.001]	[< 0.001]	[0.062]	[0.351]	
CSBC	0.026*	0.095*	0.913*	0.090*	0.022	-0.042*	20.400	24.812	-4190.505
	[< 0.001]	[< 0.001]	[< 0.001]	[0.010]	[0.077]	[< 0.001]	[0.026]	[0.006]	
LE	0.122*	0.082*	0.887*	0.075*	-0.006	0.003	18.551	5.472	-4387.808
	[< 0.001]	[< 0.001]	¡< 0.001]	[0.015]	[0.710]	[0.881]	[0.046]	[0.858]	
TK	0.125*	0.099*	0.847*	0.243*	-0.025	0.016	9.235	9.969	-4148.342
	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[0.193]	[0.471]	[0.510]	[0.443]	

Notes:

[1]The number in brackets is p-value. * denotes significance at the 5% level. Normality tests are based on the Bera-Jarque statistics. The Ljung-Box [18] test for serial correlation up to the 10^{th} order in the standardized residuals represents as $Q(10)$, and the Ljung-Box [18] test for serial correlation up to 10^{th} order in the squared standardized residuals shows as $Q^2(10)$.

[2]Before May 30, 2019, the dummy variable D_t is 0. After May 31, 2019, the dummy 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
AIDC	14.074	24.642	25.926
	[0.003]	[< 0.001]	[0.003]
MTC	1.658	9.838	11.522
	[0.046]	[0.132]	[0.364]
NAFCO	1.528	3126	3.380
	[0.676]	[0.793]	[0.959]
CSBC	1.658	9.838	11.522
	[0.646]	[0.132]	[0.364]
LE	4.708	8.908	9.348
	[0.195]	[0.179]	[0.449]
TK	17.531	22.858	24.450
	[0.001]	[0.001]	[0.007]

Note: The number in brackets is p-value.

dynamic volatility process. In addition, we find that the estimated volatility persistent rates for the GARCH model and the ST-GARCH model are distinct from each other.

The estimation of the smooth transition function, $F(t)$, is graphed in Fig. 3. It is obvious that the graphs of $F(t)$ display U-shaped designs for AIDC, MTC, CSBC, LE, and TK, but Z-shaped patterns for NAFCO. In the line of the model specification, the upper state could be expressed as $F(t) = 1$, and the lower state as $F(t)$ reaches its minimum value. The minimum values of the estimated smooth transition function are zero for all defense stocks. This article also takes the estimated location parameters, ν_1 and ν_2, to measure the relatively objective structure change date for the volatility pattern, which is shown in Table 6. The responses of volatility structure break for AIDC, NAFCO, CSBC, LE, and TK occurred before the episode of the Defense Industry Development Act. However, the responses of volatility structure break for MTC arose after the episode of the Defense Industry Development Act. The empirical findings indicate that adopting a given and biased judgment in structure change time in fitting the dynamic volatility pattern might receive inconsistent estimation results.

By the diagram of the time-varying unconditional volatility for all defense stocks in Figure 4, we could definitely exhibit the shifting shape of the dynamic volatility process. The dynamic unconditional volatilities for most defense stocks, including AIDC, MTC, SCBC, LE, and TK change from a lower phase to a higher one, and then it returns to a lower case. On the other hand, the unconditional volatilities for defense stocks of NAFCO merely change from a lower state to a higher case. We infer that the scenario of the Defense Industry Development Act raises the dynamic unconditional volatility pattern during the sample period for all defense stocks.

In this section, the estimation of the ST-GARCH model also consists of some beneficial meaning. First, the adjusted GARCH model with a dummy variable seems reasonable for estimating the dynamic volatility process. However, hiring the ST-GARCH model to fit dynamic volatility patterns can receive more actual estimates of

Table 4 Estimation results of ST-GARCH model

$$R_t = \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + F(t)(\overline{\alpha_0} + \overline{\alpha_1} \varepsilon_{t-1}^2 + \overline{\beta_1} h_{t-1})$$
$$F(\tau_t; \gamma, \boldsymbol{\nu}) = (1 + \exp(-\gamma \prod_{i=1}^{k} (\tau_t - v_i)))^{-1}$$

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{k}$	$\hat{\gamma}$	$\hat{v}_1$	$\hat{v}_2$	$\hat{\overline{\alpha_0}}$	$\hat{\overline{\alpha_1}}$	$\widehat{\overline{\beta_1}}$	$Q(10)$	$Q^2(10)$	LogL	State 1	State 2
AIDC	0.245*	0.146*	0.581*	2	390282.6	0.173*	0.605*	0.679*	0.296*	-0.251*	7.829	17.623	-3449.871	0.727	0.045
	[< 0.001]	[< 0.001]	[< 0.001]		[0.987]	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[0.646]	[0.062]			
MTC	0.004	-0.036*	1.022*	2	2378.49*	0.506*	0.616*	0.389*	0.223*	-0.279*	13.003	2.670	-4197.844	0.986	-0.056
	[0.643]	[< 0.001]	[< 0.001]		[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[0.024]	[0.988]			
NAFCO	0.215*	0.086*	0.870*	1	-64143.2	0.175		3.905*	0.004	-0.580*	17.002	5.650	-4480.101	0.956	-0.576
	[< 0.001]	[< 0.001]	[< 0.001]		[0.999]	[0.999]		[0.006]	[0.926]	[0.111]	[0.074]	[0.844]			
CSBC	0.132*	0.088*	0.903*	2	162091.3	0.347*	0.653	-0.034	0.166*	-0.135*	18.555*	14.177	-4171.742	0.991	0.031
	[< 0.001]	[< 0.001]	[< 0.001]		[0.664]	[< 0.001]	[0.442]	[0.136]	[< 0.001]	[< 0.001]	[0.046]	[0.165]			
LE	0.281*	0.103*	0.824*	2	91.980*	0.011	0.900*	0.205*	-0.174*	0.215*	14.833	2.587	-4358.487	0.927	0.041
	[< 0.001]	[< 0.001]	¡< 0.001]		[< 0.001]	[0.065]	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]	[0.138]	[0.990]			
TK	0.229	0.039*	0.754*	2	2148.04	0.171*	0.435*	0.003	0.045*	0.117	12.404	12.141	-4124.803	0.793	0.162
	[0.072]	[0.022]	[< 0.001]		[0.478]	[< 0.001]	[< 0.001]	[0.981]	[0.031]	[0.357]	[0.259]	[0.276]			

Notes: The number in brackets is p-value. * denotes significance at the 5% level. Normality tests are based on the Bera-Jarque statistics. The Ljung-Box [18] test for serial correlation up to the 10^{th} order in the standardized residuals is expressed as $Q(10)$, and the Ljung-Box [18] test for serial correlation up to 10^{th} order in the squared standardized residuals is represented as $Q^2(10)$. The state 1 and 2 shows the upper and lower state, separately.

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

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

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_0$	$Q(10)$	$Q^2(10)$	LogL	Persistence
AIDC	0.042*	0.118*	0.873*	6.344	13.856	-3492.925	0.991
	[< 0.001]	[< 0.001]	[< 0.001]	[0.786]	[0.180]		
MTC	0.321*	0.177*	0.761*	11.811	3.244	-4238.744	0.938
	[< 0.001]	[< 0.001]	[< 0.001]	[0.298]	[0.975]		
NAFCO	0.179*	0.068*	0.898*	16.199	6.818	-4508.129	0.966
	[< 0.001]	[< 0.001]	[< 0.001]	[0.094]	[0.799]		
CSBC	0.070*	0.125*	0.875*	19.518	17.426	-4206.021	0.999
	[< 0.001]	[< 0.001]	[< 0.001]	[0.034]	[0.864]		
LE	0.149*	0.075*	0.893*	19.494	5.381	-4397.743	0.968
	[< 0.001]	[< 0.001]	¡< 0.001]	[0.034]	[0.864]		
TK	0.082*	0.087*	0.894*	10.476	9.582	-4175.838	0.981
	[< 0.001]	[< 0.001]	[< 0.001]	[¡0.400]	[0.478]		

Notes: The number in brackets is p-value. * denotes significance at the 5% level. Normality tests are based on the Bera-Jarque statistics. The Ljung-Box [18] test for serial correlation up to the 10^{th} order in the standardized residuals is expressed as $Q(10)$, and the Ljung-Box [18] test for serial correlation up to 10^{th} order in the squared standardized residuals is represented as $Q^2(10)$. The persistence rate is computed by the sum of short- and long-term effects.

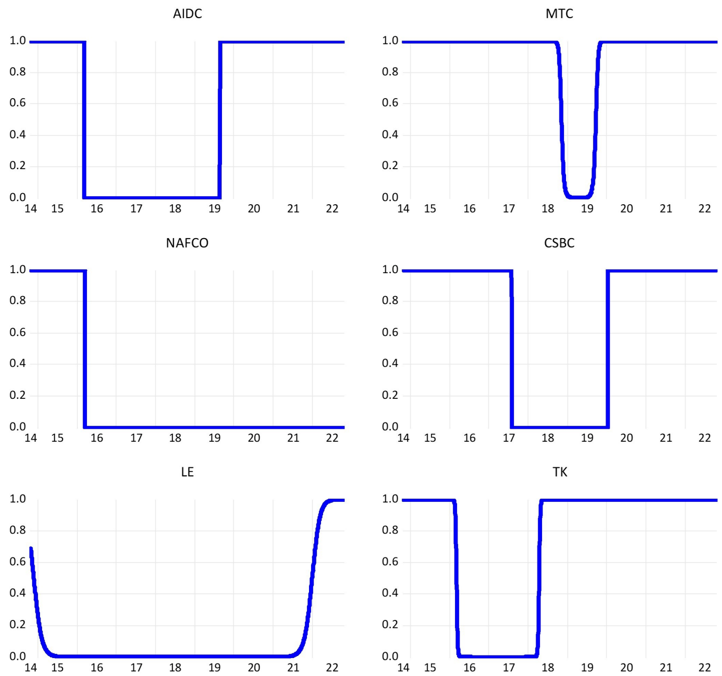

Fig. 3 Estimated smooth transition functions for defense stocks

Table 6 Estimated location parameters and corresponding calendar dates

Defense stock	c_1	Date	c_2	Date
AIDC	0.173	March 11, 2016	0.605	August 23, 2019
MTC	0.506	November 7, 2018	0.616	September 23, 2019
NAFCO	0.175	March 16, 2016		
CSBC	0.347	August 1, 2017	0.653	January 10, 2020
LE	0.011	November 26, 2014	0.900	December 29, 2021
TK	0.171	March 4, 2016	0.435	April 13, 2018

the break time dating. Lastly, the impacts of the release of Defense Industry Development Act really being and can alter the volatility structure of defense stocks. It also means that this policy brings a variation on the volatility of defense industry corporate performance.

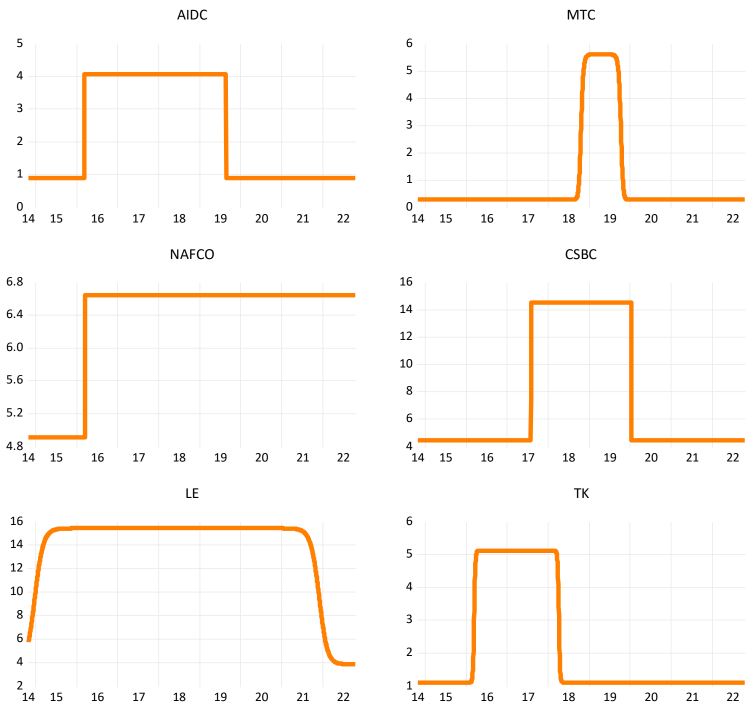

Fig. 4 Estimated unconditional variance under ST-GARCH model for defense stocks

4 Conclusions

In this article, we investigate how the shocks of the launch of Defense Industry Development Act triggered structure change in the volatility process for all defense stocks.

We employ the conventional GARCH model, the adjusted GARCH model with exogenous threshold variable, and the ST-GARCH model to delineate the dynamic volatility process, separately. The empirical results display statistically considerable volatility regime break in defense corporations by the estimation of both adjusted GARCH and ST-GARCH models. We further find that the volatility persistent rate computed from the conventional GARCH $(1,1)$ model could involve a single and fixed value, as the dynamic volatility conceals state changes. The case of Defense Industry Development Act cuts down the volatility persistent rate for all defense stock returns. In addition, the estimation of the adjusted GARCH model with an exogenous threshold variable might simultaneously provide a biased state break date. Our investigation also illustrates that the dynamic volatility structure for most defense stocks embedded two state change points through the LM test suggested by [10].

Furthermore, we apply the estimation of the ST-GARCH model to graph the time-varying unconditional volatilities and to calculate the calendar day of switching time for all defense stocks. The patterns of unconditional volatility for most defense stocks (AIDC, MTC, SCBC, LE, and TK) show a similar inverted U-shaped. On the other hand, the patterns of unconditional volatility for NAFCO display the inverted Z-shaped. The empirical estimation shows that the dynamic volatility shifting dates are earlier than the event of Defense Industry Development Act for most defense stocks except MTC.

Declarations

Conflict of interest. The authors have no further competing interests to declare that are relevant to the content of this article. The datasets analyzed during the current study are available from the corresponding author on reasonable request

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