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The Short-Term Fear Effects for Taiwan's Equity Market from Bad News Concerning Sino-U.S. Trade Friction

Shu Ya YANG[1], Hsiu Hsu LIN[2], Ying Sing LIU[3]

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Abstract

Mainland China area has been a long-term, major trade rival and partner of Taiwan, accounting for more than 40% of Taiwan's total annual trade exports, and so Sino-US trade friction is expected to have a significant impact on Taiwan's economy in the future. This study focuses on major bad news of Sino-US trade frictions and how it generates short-term shocks for Taiwan's equity market and fear sentiment. It further explores the mutual interpretation relationship between price changes such as VIX, Taiwan's stock market index, and the VIX ETF to identify which factors have information leadership as leading indicators. The study period covers 750 trading days from 2017/1/3 to 2020/1/31. This study finds that, when a policy news is announced, the stock market index falls significantly, the change in the trading price (net value) of the VIX ETF rises significantly, and the overprice rate significantly drops, but VIX does not, showing that fear sentiment exists in the Taiwan's market. The net value of the VIX ETF shows an information advantage as a leading indicator. This study suggests that, when the world's two largest economies clash over trade, the impact on Taiwan's equity market is inevitable, and that short-term fear effects will arise.

Keywords: Sino-US Trade Friction, Fear Sentiments, Shocks of the Bad News, VIX, ETF

JEL Classification Code: G41, G14, C32

1. Introduction

As the US long-term trade deficit with China continues to expand, the US began a series of trade announcements and policy adjustments in mid-2018 to impose tariffs on Chinese imports. The topic of Sino-US trade frictions has received widespread attention by many scholars who have put forward some concrete views on the future economic and political evolution of the world. Tu, Du, Lu, and Lou (2020) investigate the direct impact of the Sino-US trade friction on their economy, and argue that the friction will not only endanger bilateral welfare, but also undermine the global value chains and the multilateral trading system. Tang (2020) proposes that copyright trade is the sector that sparks the conflict between China and the US, suggesting that China spearhead its law-making and enforcement in copyright trade, strives for market cultivation, and revolutionizes corporate globalization so that a sound development in copyright trade can be fostered. Ng (2020) discovers that the Sino-US trade friction harms both, though; it does more harm to the US than to China.

The actual trade deficit of the US to China is far lower than expected; the deficit gap is the result of an insufficiency in domestic savings by the US. Zhang (2018) articulates that South Korea relies on the US militarily, on the one hand, and cooperates, politically and economically, with China, on the other hand. South Korea, thus, is faced with the tension brought about by the worsening tug-of-war between the US and China. It is advised that in the midst of a growing fierce Sino-US competition, South Korea should work out a strategy not to be trapped by such a dilemma and devise a mechanism to facilitate quick efficient foreign policy making and response. To weather such a situation,

[1]First Author. College of Humanities and Social Sciences, Chaoyang University of Technology, Taiwan. Email: angela58x@gmail.com
[2]Department of Applied English, College of Humanities and Social Sciences, Chaoyang University of Technology, Taiwan
[3]Corresponding Author. Researcher, College of Humanities and Social Sciences, Chaoyang University of Technology, Taiwan [Postal Address: 168, Jifeng E. Road, Wufeng District, Taichung, 413330, Taiwan] Email: liuyingsing@yahoo.com.tw; t5200294@cyut.edu.tw

South Korea has to discern not only the geopolitical, but also the geo-economic climate signals of East Asia and forecast the path to avoid the devastation of any storms stirred up in the Pacific by the US and China. Li, Zhuang, Wang, and Zhang (2020) analyze the impact of the Sino-US trade friction on the stock market of China. It is found that the stability of the market is weak and vulnerable when the weighted stocks suffer unexpected fluctuations or targeted shocks. It is also found that the stronger the trade friction events are, the stronger the impact and repercussions will be.

There exists an array of indices for the evaluation of investor sentiment and its impact on the equity market, among which CBOE Volatility Index (VIX) is a major index frequently employed. Smales (2017a) maintains that VIX is a top tool index to account for sentiment, and confirms that VIX will boost the return of a company's equity. In Taiwan, Huang and Wang (2017) uses VIX to gauge the impact of fear on the investors and their behavior on the stock market in Taiwan. It is found that herding behavior increases with the rise of VIX, i.e., investor fear fuels herding behavior, and that investors react faster to bad news than they do to good news, which manifests an asymmetric reaction to news. On the other hand, it is held that VIX is a leading index on the equity market. Copeland and Copeland (1999) corroborate that VIX of the Chicago Board Options Exchange is a significant leading index of daily market returns. When VIX hikes on a trading day, large-value stock portfolios will outperform small-value stock portfolios; the opposite happens when VIX dips. Kozyra and Lento (2011) use VIX as a trading rule, and finds that using VIX as a trading signal will yield significant profits. Badshah (2018) disentangles the cross-market volatility correlations between VIX and VXEFA in the developed-market, and VXEEM in the emerging market. It is discovered that VIX plays a leading role at the onset of a fluctuation and exhibits information content effects on VXEFA and VXEEM.

In an attempt to uncover the relationship between VIX and the statistics of the stock market and/or economy, Sarwar (2012) discovers that there exists strong negative contemporaneous relationship between the daily fluctuation and the returns of S&P 100, 500 and 600. The strength of the relationship is determined by the mean VIX and its volatility, i.e. the higher the VIX and its fluctuation is, the stronger the relationship exhibits. Smales (2017b) studies the fear degrees (using ASX 200 implied volatility index as a proxy variable) and the returns of the Australian financial market and finds that the returns in the stock market decrease with the increase of investors' fear degree. The high sensitivity of investment returns to the fear degrees during the 2008–2009 global financial crisis supports the conclusion of a close relationship between the returns in the Australian stock market and the fear degrees of its investors. Baba and Sakurai (2011) employ the regime-switching model and takes the US macroeconomic variables as leading factors in the regime change of VIX index. It is found that the macroeconomic variables will yield to the low, high and extremely high volatility of the VIX.

Smales (2016) discusses the relationship between aggregate news sentiment, S&P 500 index returns, and changes of the VIX through the vector autoregressive model (VAR). A significant negative contemporaneous and asymmetrical relationship is observed between VIX changes and news sentiment (or stock returns). VIX changes dramatically after the release of bad news (hence, the drop of the market). It is suggested that VIX serves better than news sentiment in predicting investment returns. Nikkinen and Peltomäki (2020) analyze journals reports/articles and web searches that reflect investors' worries about the market to investigate their influence on the stock market and VIX. It is evidenced that web searches exemplify an instant and significant influence on stock market returns and the VIX implied volatility; the influence of journal reports/articles, on the other hand, can last up to 11 weeks. Furthermore, in investigating emerging stock markets, Hacihasanoglu, Simga-Mugan, and Soytas (2012) use VIX (among others) as global risk perceptions to test emerging market return volatilities, and suggest that VIX be considered in analyzing emerging markets. Sarwar (2019) explores the transfer between VIX and VIX-like measures of the Chinese, Brazilian, and overall emerging stock markets (EM) and supports that VIX and EM fluctuations are capable of predicting each other. Sarwar and Khan (2017) examine the American VIX impact on the Latino stock market returns. It is discovered that the increase of VIX (change) will lead to an immediate and lagged drop of returns in the emerging markets. Bouri, Lien, Roubaud, and Shahzad (2018), meanwhile, find that the change of VIX in the US will form a leading indicator in the individual implied volatility indexes of the BRIC, viz. Brazil, Russia, India, China.

Ben-David, Franzoni, and Moussawi (2018) suggest that exchange-traded funds (ETFs) have the advantage of low cost in trading, and serve as a potential catalyst for short-term liquidity traders to engage in arbitrage operations and increase non-fundamental volatility of target stocks. Tee and Ting (2017) prove the idea of volatility indexes constructed to overestimate the risk-neutral variance, and consequently the magnitude of variance risk. Li, Yu, and Luo (2019) research the Shanghai Stock Exchange's the revised Chinese implied volatility index (iVX) and discover iVX to be an effective barometer for ETF, i.e., the anxiety of a plunge of the market can serve as an effective 'fear index.' Broman and Shum (2018) suggest the importance of fluidity to ETF. It is uncovered that stocks of higher fluidity tend to attract investors. The relativity fluidity positively and significantly predicts the net fund flows, inflows and outflows. Diaw (2019) explores that the performance of Saudi Arabian ETFs and find that of the three ETFs investigated, two of them exhibit over-pricing in trading and one with price discount.

China, including its two special administrative regions Hong Kong and Macau, has been Taiwan's biggest opponent in trading. Sino-US trade friction, therefore, is expected to have a tremendous impact on the economic growth of Taiwan. The present study, thus, aims to examine the impact of Sino-US trade friction on Taiwan's stock market, the window of a country's economic performance from a market sentiment perspective. It will focus on the releases of major bad news and their immediate short-term impact on the fluctuations of the US VIX to see what changes fear sentiment will induce on Taiwan's equity market, e.g., the stock market index, and the net value and trading price of the listed VIX ETF on the stock market of Taiwan. VAR-cum-dummy model will be employed to capture the dynamics of VIX, the net and market values of Taiwan's VIX ETF, and the stock market index to sort out the relationship between them and work out which sequence is information leading, and can serve as a leading indicator. Finally, the validity of the impact of news breaking of the Sino-US Trade Friction regarding American VIX and Taiwan's equity market fluctuation caused by fear sentiment will be tested under the VAR model. It is hoped that the present study will shed light on the understanding of the information content of VIX and its ETF trading on the Taiwan Stock Exchange and TSEI on the one hand, and the exposure bad news concerning Sino-US trade friction and its temporal effect(s) on investors of Taiwan's equity market.

2. Data and Empirical Methodologies

2.1. Data

Volatility Index (VIX) is a popular market index used to measure the market's expectation of 30-day forward-looking volatility on the Chicago Board Options Exchange (CBOE). When investors expect a major fluctuation of the stock market index to happen, VIX will rise. VIX is, thus, a frequent measure used to gauge investors' panic sentiment (Smales, 2016; Huang & Wang, 2017). This research studies the short-term fear effects for Taiwan's equity market in the bad news of the Sino-US trade friction and focuses on the listed VIX's ETF launched by Fubon Securities in Taiwan (Codename: TW–00677U) by observing its daily net value and closing price (trading price) and their changes to determine the international influence on the anticipatory sentiment of the investors on Taiwan's stock market, and market index returns (%) for the Taiwan Capitalization Weighted Stock Index (TAIEX; Codename" TW–Y9999). A total of 750 trading days ranging from January 3, 2017, through to January 31, 2020, forms the backbone of this study. The data are drawn from Taiwan Economic Journal Database (TEJ) [URL: https://www.spglobal.com/spdji/en/indices/strategy/sp-500-vix-short-term-index-mcap/#overview]. The bad news exposure is determined following the China-United States trade war entry on Wikipedia [URL: https://en.wikipedia.org/wiki/China%E2%80%93United_States_trade_war]. The exposure dates (UTC + 8) of bad news is summarized as follows:

1) 2018/3/22: The US government announced to raise tariffs on up to $60 billion in imports from China.
2) 2018/6/16: The list of Chinese imports worth $50 billion subject to tariffs raising from 10% to 25% is announced by the US (in response to China's alleged pressure on U.S. firms).
3) 2019/5/5: The previous tariffs of 10% levied in $200 billion worth of Chinese goods will be raised to 25% on 20195/10; the total of Chinese exports affected by the 25% tariff amounts to $250 billion.
4) 2019/5/13: In retaliation, China will raise tariffs, ranging from 5% to 25% pending on the products), on $60 billion US imports.
5) 2019/6/1: China and the United States have announced tariffs on each other's imports.
6) 2019/8/1: "The U.S. will start, on September 1st, putting a small additional Tariff of 10% on the remaining 300 Billion Dollars of goods and products coming from China into our Country," said Trump in a tweet.
7) 2019/8/5: RMB sunk to a 11-year low at 7 against the US dollar, the US Treasury declares China to be a currency manipulator; in response, China announces not to import agricultural products from the US.
8) 2019/8/24: China announces to raise 5%–10% tariffs on $75 billion US goods; President Trump threatens tariff increases on Chinese imports.

In addition to the above summary of news exposure, the important dates of related measures taking effect are in order:

1) 2018/7/16: The first round of tariffs takes effect; the US Customs and Border Protection (CBP) begins collecting a 25-percent tariff on 818 imported Chinese products (worth $34 billion).
2) 2018/8/23: The US implements a second round of tariff on China, giving 25% tariffs on $16 billion goods originated from China.
3) 2019/6/1: The tariffs on $60 billion worth of US goods announced on 2019/5/13 begins.
4) 2020/1/16: The phase one US-China trade deal is signed.

According to the above summaries of eight bad news exposure and four dates of implementation, this research will examine the VIX, the net values and trading prices of the ETF, and TAIEX of a total six days (the day prior to the events in question through to five days after them) to see the significance of how the market changes are being affected by the trade war events.

2.2. Empirical Methodologies

The 750 days studied in this research will be divided into two sample groups: the shock period of bad news (i.e., police announcement and policy implementation) and the non-shock period of bad news. Levene test is conducted first for the equality of variances to see if the variables are equal or not. *t*-test is run on the result variable to check the significance of the means of the two groups. The normal distribution of the variable undergoes Jarque-Bera test. For unit root tests, Augmented Dickey-Fuller (ADF) test proposed by Said and Dickey (1984) is employed to test if the sequence is stationary so as to conform to the statistical hypothesis requirement of Granger Causality Tests and VAR. The AR for the ADF is given Eq. (1) below:

$$\Delta y_t = \alpha_0 + \gamma_0 \cdot y_{t-1} + \sum_{i=1}^{p-1} \gamma_i \cdot \Delta y_{t-i} + \varepsilon_t \quad (1)$$

Where: $\Delta y_t = y_t - y_{t-1}$ is the first order difference of the trading day t, $\{y_t\}$ sequence; $\{y_{t-1}\}$ lag one-order sequence; γ_0 intercept; γ_i lag i-order of estimated parameter; p lag order; ε_t error term. The null hypothesis $H_0 : \gamma_0 = 0$ is rejected when the sequence is stationary.

Pairwise Granger Causality Tests are tests for the mutual explanatory relationship between two sequences. The simultaneous equations of Pairwise Granger Causality Tests of $\{y_t\}$ sequence and $\{x_t\}$ sequence conforming to the VAR model are Eq. (2) and Eq. (3):

$$y_t = c_1 + \sum_{i=1}^{p} a_{1,i} \cdot y_{1,t-i} + \sum_{j=1}^{p} b_{1,j} \cdot x_{1,t-j} + \varepsilon_{1,t} \quad (2)$$

$$x_t = c_2 + \sum_{i=1}^{p} a_{2,i} \cdot y_{2,t-i} + \sum_{j=1}^{p} b_{2,j} \cdot x_{2,t-j} + \varepsilon_{2,t} \quad (3)$$

The null hypotheses are $H_{01} : b_{1,j} = 0$ and $H_{02} : a_{2,i} = 0$, which are tested by joint hypotheses test (F-statistics) to examine if the estimated parameter $b_{1,j}$ or $a_{2,i}$ is significant not zero. The null hypothesis $H_{01} : b_{1,j} = 0$ ($H_{02} : a_{2,i} = 0$) is rejected when the value of the F-statistic is larger than the critical value. Therefore, $b_{1,j} \neq 0$ ($a_{2,i} \neq 0$) means the $\{x_t\}$ sequence ($\{y_t\}$ sequence) does Granger Cause the $\{y_t\}$ sequence ($\{x_t\}$ sequence). When null hypotheses $H_{01} : b_{1,j} = 0$ and $H_{02} : a_{2,i} = 0$ are rejected simultaneously, there exists a feedback relationship between the two sequences, and they are mutually explanatory. Finally, the two sequences $\{x_t\}$ and $\{y_t\}$ do not account for each other when H_{01} and H_{02} are not simultaneously rejected.

The VAR model is frequently used and proven to be useful in describing the dynamic behavior of economic time series (Dinh, 2020; Ortiz, Xia, & Wang, 2015) and in accounting for financial market changes such as the prices of stocks and currency rates (Parsva, & Lean, 2017), especially in exhibiting whether the variables are mutually explanatory or not. Modeling in VAR, this research explores changes of time series of VIX, the net value and trading price of ETF, and stock exchange index, and aims to account for their lead-leg relationship. Thus, let Change (%) of VIX be C_{VIX}; Change (%) of ETF's net value, C_{ETF_NV}; Change (%) of ETF's trading price, C_{ETF_TP}; Return (%) of stock market index, R_{SMP}, the matix for the changes of the four sequences on the trading day t will be, Eq. (4):

$$CR_t = c_0 + \alpha_1 \cdot CR_{t-1} + \cdots + \alpha_p \cdot CR_{t-p} + \theta_1 \cdot D_1 + \theta_2 \cdot D_2 + \varepsilon_t \quad (4)$$

In the Eq. (4), c_0 is the 4 × 1 constant matrix; CR_{t-i}, lag i-order of price changes in the four-sequence matrix, where the dimension of the matrix below is 4 × 1; α_i, 4 × 4 matrix of estimation parameter of lag i-order period; ε_i is a 4 × 1 error matrix. In Eq. (4), the parameters of all regression equations are estimated by Ordinary Least Square (OLS), and further tested to check if they are significantly not zero so as to decide the sequence is significantly influenced by its own lag-order or that/those of other sequence(s). Such processes will help uncover and account for which sequence(s) contributes to the changes in the VIX, ETF's net value, ETF's trading price and the stock market index. p represents optimum lag-order and is adopted according to the Schwarz's Information Criterion (Schwarz, 1978). Finally, θ_1 and θ_2 indicate inferred effect of (bad news) announcement and inferred implementation respectively; bad news will manifest a positive (negative) effect on the sequence(s), if the estimated parameter is significantly larger (smaller) than zero.

3. Empirical Results

Figure 1 shows the statistical charts of VIX and Taiwan's equity market, which describe the daily net value and trading price in Taiwan of the VIX ETF, the chart of the trend and changes (%) in the stock market index, as well as the tracking difference (%) and overprice/underprice rate (%) on the VIX ETF. In Figure 1, the daily net value and market trading price of VIX and the VIX ETF in Taiwan are in a long-term decline, with two significant rebounds and price changes between the first and fourth quarters of 2018 and a smaller rebound in the third quarter of 2019. The timing of these phenomena is broadly in line with the significant bad news exposure that occurred from Sino-US trade frictions.

Table 1 shows the descriptive statistics and unit root tests of the VIX and Taiwan's equity market. The change (%) of VIX, change (%) of net value in the VIX ETF, change (%) of trading price in the VIX ETF, and the mean return rate (%) of the stock market index are –0.144%, –0.146%, –0.193%, and 0.032%, respectively. The VIX ETF has a mean of 2.931%, showing that it is popular with Taiwanese investors as a safe haven over the long term, and so the market has long been overpriced.

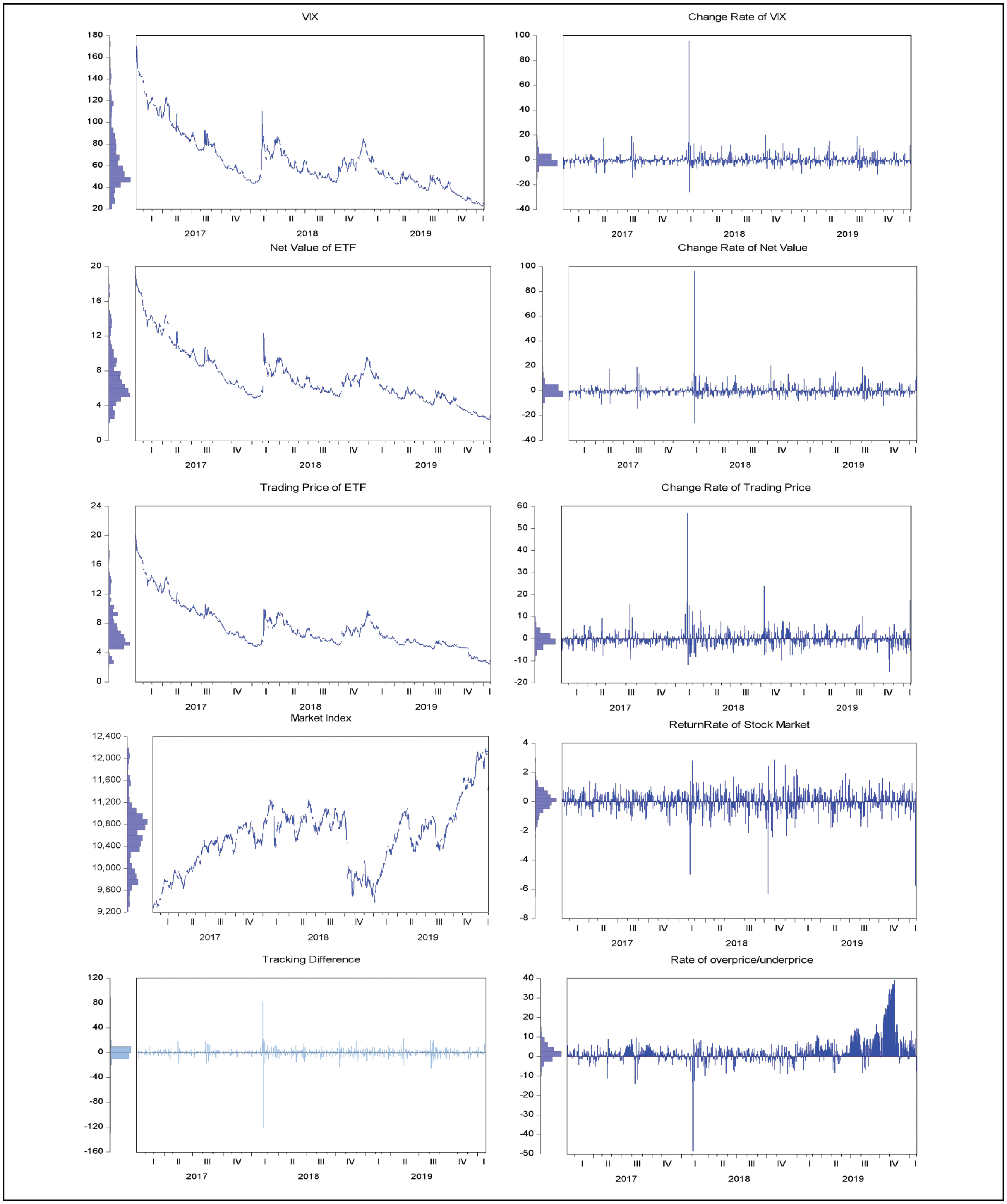

Figure 1: Statistical Charts on the VIX and Taiwan's Equity Market (Obs. = 750)

At a significant level of 1%, the change (%) can be found for VIX, the change (%) in net value of the VIX ETF, the change (%) of trading price in the VIX ETF, and return rate (%). The Augmented Dickey-Fuller test statistics of the stock market index all show significant results, thus rejecting the null hypothesis and accepting the four time series being stationary. At a significant level of 1%, found change (%) of VIX, change (%) of net value in the VIX's ETF, change (%) of trading price in the VIX's ETF and return rate (%) of stock market index in Augmented Dickey-Fuller test statistics all show that significant results, so reject the null hypothesis and accept the four time series being stationary.

Table 2 shows the *t*-tests of the mean difference between the bad news period and the non-bad news period. In part I, the *t*-test results of the average difference between the bad news period and non-bad news period are based on announcements of new policies. At a significant level of 5%, the average difference in change (%) of the ETF's net value is 2.367% and the t statistic is 2.293 (the Levene test accepts that the variance in both groups is not equal). The change (%) in the ETF's trading price is 1.605%, and the *t* statistic is 2.060 (the Levene test accepts that the variance in both groups is not equal). The return (%) of the stock market index is –0.475%, and the *t* statistic is 2.213 (the Levene test accepts that the variance in both groups is equal). The average difference in overprice rate (%) is –2.419%, and the *t* statistic is 2.213 (the Levene test accepts that the variance in both groups is equal). These results all support that the average difference is significantly not equal to zero.

The study notes that when a new trade policy was announced that was bad news, it would significantly increase panic among investors in Taiwan's securities market, and the stock market's return rate would drop significantly to negative values. The overprice rate (3.113%) of the VIX ETF has a significant reduction (0.694%) that brings its trading prices to be in line with its net value in the market, showing that ETF investors are making reverse selling moves in the short term as VIX rises. Finally, at a significant level of 5%, the average difference in change (%) of VIX is 1.686%, and the *t* statistic equal to 1.740 (the Levene test accepts that the variance in both groups is not equal). This is not significant and accepted equal to zero, indicating that no significant change (%) of VIX has been found.

In Table 2's Part II, the *t*-test results of the average difference between a bad news period and non-bad news period are based on the implementation of a new policy. At a significant level of 5%, the average difference in return (%) of the stock market index is 0.336%, and the *t* statistic is 2.192 (the Levene test accepts that the variance in both groups is equal). The ETF's overprice rate (%) is −1.468%, and the *t* statistic is –3.436 (the Levene test accepts that the variance in both groups is not equal). These results all support that the average difference is significantly not equal to zero.

Table 1: Descriptive Statistics and the Unit Root Tests (Obs. = 750)

Variable Estimator	VIX		VIX ETF Net Value		VIX ETF Trading Price		Overprice/ Underprice		Stock Market	
	Index	Change (%)	Price (NT)	Change (%)	Price (NT)	Change (%)	Price (NT)	Rate (%)	Index	Return (%)
Mean	63.657	−0.144	7.233	−0.146	7.372	−0.193	0.139	2.931	10566.71	0.032
Median	56.835	−0.414	6.435	−0.401	6.475	−0.402	0.120	1.870	10609.75	0.075
Maximum	170.060	96.109	18.960	96.491	20.040	56.940	1.270	39.077	12179.81	2.898
Minimum	22.860	−25.949	2.430	−25.893	2.450	−15.122	−5.980	−48.539	9272.880	−6.313
Std. Dev.	25.868	5.201	3.091	5.243	3.045	3.970	0.396	6.793	584.069	0.781
Skewness	1.149	8.760	1.189	8.677	1.297	4.694	−4.885	1.525	0.152	−1.605
Kurtosis	4.274	159.761	4.367	157.287	4.712	62.505	79.389	14.751	3.081	14.743
Jarque-Bera	215.909**	777525.7**	235.271**	753299.1**	301.722**	113405.2**	185336.6**	4606.07**	3.101	4631.38**
A.D.F. test	−3.260*	−29.232**	−3.356**	−28.841**	−4.239**	−26.533**	−6.894**	−4.6234**	−2.264	−28.685**

Note: *$p < 0.05$; **$p < 0.01$; Overprice/Underprice = Trading Price – Net Value (in the VIX ETF); Rate (%) of Overprice/Underprice = (Trading Price – Net Value) / Net Value × 100%.

Table 2: The *t*-tests of the Mean Difference between on the Bad News Period and Non-Bad News Period (Obs. = 750)

Variable Statistic	The Shock Period of Bad News	Descriptive Statistics		The Difference Analysis			
				Levene's test for Equality of Variances		*t*-test for Equality of Mean	
		Mean ± Std. Dev.	Average Difference	Null Hypothesis: Equality of Variances	*F* statistic (*p*-value)	*t* statistic	*p*-value (2-tailed)
Part I. The disclosure of announce policy in bad news period v.s.non-bad news period							
Change(%) of VIX	YES	1.480 ± 6.148	1.686	Equal	10.859 (0.001)	2.020	0.044
	NO	−0.206 ± 5.192		Not #		1.740	0.089
Change (%) of ETF's net value	YES	2.107 ± 6.564	2.367*	Equal	14.646 (0.000)	2.820	0.005
	NO	−0.260 ± 5.193		Not #		2.293	0.027
Change (%) of ETF's trading price	YES	1.352 ± 4.953	1.605*	Equal	8.931 (0.003)	2.528	0.012
	NO	−0.253 ± 3.929		Not #		2.060	0.045
Rate of overprice (%)	YES	0.694 ± 5.258	−2.419*	Equal #	0.029 (0.865)	−2.213	0.027
	NO	3.113 ± 6.961		Not		−2.833	0.007
Return (%) of stock market index	YES	−0.427 ± 1.208	−0.475*	Equal	14.112 (0.000)	−3.858	0.000
	NO	0.048 ± 0.740		Not #		−2.517	0.016
Part II. The disclosure of implement policy in bad news period v.s.non-bad news period							
Change(%) of VIX	YES	−1.196 ± 2.631	−0.990	Equal#	0.265 (0.607)	−0.929	0.353
	NO	−0.206 ± 5.192		Not		−1.729	0.094
Change (%) of ETF's net value	YES	−0.859 ± 2.706	−0.600	Equal#	0.365 (0.546)	−0.563	0.574
	NO	−0.260 ± 5.193		Not		−1.022	0.315
Change (%) of ETF's trading price	YES	−1.213 ± 2.386	−0.961	Equal#	0.647 (0.421)	−1.190	0.235
	NO	−0.253 ± 3.929		Not		−1.885	0.070
Rate of overprice (%)	YES	1.646 ± 1.637	−1.468**	Equal	7.773 (0.005)	−1.031	0.303
	NO	3.113 ± 6.961		Not #		−3.436	0.001
Return (%) of stock market index	YES	0.384 ± 0.701	0.336*	Equal#	0.158 (0.691)	2.192	0.029
	NO	0.048 ± 0.740		Not		2.304	0.030

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; # represent the accepted assumption.

Table 3: Pairwise Granger Causality tests

Null Hypothesis	**Obs.**	***F*-Statistic**	***p*-value**
Change (%) of ETF's net value does not Granger Cause Change (%) of VIX	747	9560.15**	0.000
Change (%) of VIX does not Granger Cause Change (%) of ETF's net value		0.756	0.519
Change (%) of ETF's trading price does not Granger Cause Change (%) of VIX	747	29.929**	0.000
Change (%) of VIX does not Granger Cause Change (%) of ETF's trading price		0.978	0.402
Return (%) of stock market index does not Granger Cause Change (%) of VIX	747	10.687**	0.000
Change (%) of VIX does not Granger Cause Return (%) of stock market index		0.968	0.407
Change (%) of ETF's trading price does not Granger Cause Change (%) of ETF's net value	747	0.764	0.514
Change (%) of ETF's net value does not Granger Cause Change (%) of ETF's trading price		477.30**	0.000
Return (%) of stock market index does not Granger Cause Change (%) of ETF's net value	747	1.097	0.350
Change (%) of ETF's net value does not Granger Cause Return (%) of stock market index		49.496**	0.000
Return (%) of stock market index does not Granger Cause Change (%) of ETF's trading price	747	3.174*	0.024
Change (%) of ETF's trading price does not Granger Cause Return (%) of stock market index		1.824	0.141

Note: *$p < 0.05$; **$p < 0.01$.

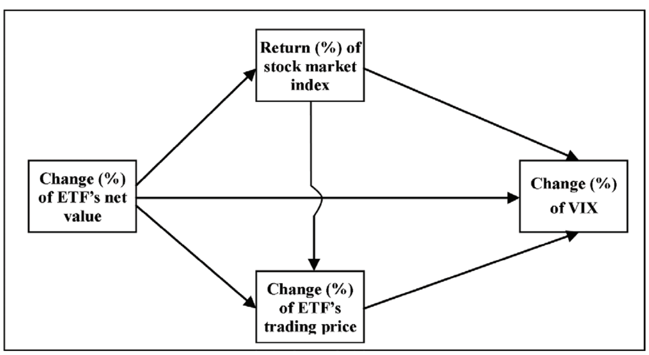

Figure 2: The Chart of Grander Causality on Change(%) of VIX, Change (%) of ETF's Net Value, Change (%) of ETF's Trading Price, and Stock Market Return (Obs. = 750)

This study finds that, when the news of implementation of a new trade policy came to light, the panic of market investors did not increase significantly. The bad news has been fully reflected into the prices of the stock market and no longer affected price changes. The overprice rate (3.113%) of the VIX ETF shows that a significant reduction due to the implementation of the new policy brings its trading prices in the market to be in agreement with the net value. Finally, at a significant level of 5%, the average difference in change (%) of VIX is −0.990%, and the t statistic equal to −0.929 is not significant and accepted equal to zero.

Table 3 lists the results for the Pairwise Granger Causality Tests of the change (%) of VIX, change (%) of the ETF's net value and trading price, and the return (%) of the stock market index. This study collates the results obtained from Table 3 into Figure 2, and from Figure 2 it finds that the change (%) of the ETF's net value does Grander-cause the change (%) of VIX, the change (%) of the ETF's trading price, and the return (%) of the stock market index. These results show that the change (%) of the ETF's net value is an information leader and can be used as a reference indicator (explanatory variable) for changes in (%) of VIX, ETF's trading price, and stock market index. In addition, this study finds that the return (%) of Taiwan's stock market index does Granger-cause the change (%) of VIX (change (%) of ETF's trading price), and that the change (%) of the ETF's trading price does Granger-cause the change (%) of VIX.

Table 4 shows the results of vector autoregression estimates based on the change (%) of VIX, change (%) of ETF's net value, change (%) of ETF's trading price, and return (%) of the stock market index. The VAR model finds the optimum lag-order through the Schwarz information criterion where $p = 3$ (Schwarz Criterion value is 14.95676). In the VAR(3) model, after adding dummy variables and , the result of the equation system (4) of the structure is obtained by OLS estimation. In Table 4's VAR model, the equations in dependent variable are the change of VIX, change of the ETF's net value and trading price, and return (%) of the stock market index, respectively.

Table 4: The Results of Vector Autoregression Estimates (Obs. = 750)

Variable Estimator	Change of VIX	Change of ETF's net value	Change of ETF's trading price	Return of stock market index
Change of VIX (−1)	−0.7258**	−0.0389	−0.0884	0.0176
	(−19.5521)	(−0.1652)	(−0.8733)	(0.5512)
Change of VIX (−2)	−0.3494**	0.1659	0.2283*	−0.0436
	(−8.4605)	(0.6329)	(2.0273)	(−1.2250)
Change of VIX (−3)	0.0179	0.1622*	0.1385**	−0.0257**
	(1.6348)	(2.3375)	(4.6440)	(−2.7324)
Change of ETF's net value (−1)	0.9921**	−0.0572	0.6667**	−0.0653**
	(158.895)	(−1.4423)	(39.1567)	(−12.1437)
Change of ETF's net value (−2)	0.7237**	0.0120	0.4209**	−0.0526
	(19.9301)	(0.0520)	(4.2508)	(−1.6835)
Change of ETF's net value (−3)	0.3543**	−0.1345	−0.0889	0.0175
	(8.8037)	(−0.5265)	(−0.8101)	(0.5050)
Change of ETF's trading price (−1)	−0.0096	−0.1606	−0.3557**	0.0291
	(−0.5549)	(−1.4676)	(−7.5645)	(1.9632)
Change of ETF's trading price (−2)	−0.0198	−0.0293	−0.1631**	0.0298
	(−1.1102)	(−0.2588)	(−3.3585)	(1.9454)
Change of ETF's trading price (−3)	−0.0253	−0.2474*	−0.1141**	0.0290**
	(−1.5689)	(−2.4208)	(−2.5987)	(2.0920)
Return of stock market index (−1)	0.1375**	−0.4866	0.7619**	−0.1410**
	(2.6536)	(−1.4792)	(5.3910)	(−3.1618)
Return of stock market index (−2)	0.0196	−0.1747	0.1870	0.0048
	(0.3646)	(−0.5123)	(1.2761)	(0.1030)
Return of stock market index (−3)	0.0353	−0.3585	−0.1314	0.0059
	(0.6558)	(−1.0501)	(−0.8962)	(0.1268)
	0.0144	−0.2716	−0.1608	0.0413
	(0.4563)	(−1.3515)	(−1.8620)	(1.5175)
	0.1807	2.3303**	0.7089*	−0.3934**
	(1.3528)	(2.7480)	(1.9658)	(−3.4211)
	0.1040	−0.7084	−0.3784	0.2902*
	(0.6101)	(−0.6547)	(−0.8140)	(1.9778)
R-squared	0.9757	0.0383	0.6904	0.2049
Adj. *R*-squared	0.9753	0.0199	0.6845	0.1900
F-statistic	2103.327**	2.0814	116.5865**	13.4730**
Log likelihood	−902.1636	−2282.607	−1651.508	−790.0649
Schwarz SC	2.5483	6.2442	4.5546	2.2482

Note: *t*-statistics in parentheses; *$p < 0.05$; **$p < 0.01$.

These equations exhibit independent variables of the lagged values of themselves or other sequences (lagged 1st–3rd order), and the estimated parameters of the independent variables are significantly not zero.

The results indicate that the sequences such as the change of VIX, change of the ETF's net value and trading price, and the return of the stock market index are affected and explained by the lagged values of themselves or other variables. At a significant level of 1%, in the equation with the change of the ETF's net value as the independent variable, the estimated parameter of the dummy variable is 2.3303 (*t*-statistics = 2.7480), which is significantly positive. In the equation of the return of the stock market index as the independent variable, the estimated parameter of is −0.3934 (*t*-statistics = −3.4211), which is significantly negative. At a significant level of 5%, in the equation with the change of the ETF's trading price as the independent variable, the estimated parameter of the dummy variable is 0.7089 (*t*-statistics = 1.9658), which is significantly positive.

This study presents that when a new trade policy was announced with significant bad news exposure, the change (%) of the ETF's net value (trading price) has a short-term positive shock (fear sentiments increase), and the return (%) of the Taiwan stock market index has a negative shock. At a significant level of 5%, in the equation with the return (%) of the stock market index as the independent variable, the estimated parameter of the dummy variable is 0.2902 (*t*-statistics = 1.9778), which is significantly positive. This result shows that, when the new trade policy is exposed with specific implementation of bad news, that there is a positive shock on the stock market index. Bad news of the implementation of a new trade policy does not have a negative shock to the Taiwan's securities market, and short-term fear effects are not found at this time.

4. Conclusions

This study focuses, not only on the fear sentiment (VIX) and the cross-market returns explored in the bulk of literature, but more important on all extends of concerns to the daily net value and trading price of the oversea VIX's ETF traded in Taiwan. By analyzing VIX, the net value and trading price of VIX's ETF, and stock market index regarding the lead/lag relationship between them, it is found that the net value of VIX's ETF constitutes information content in terms of information-based trading, and thus can serve as a leading indicator. In addition, in wake of the announcement of tariff raising in the Sino-US trade friction, Taiwan stock exchange would plunge drastically in response. Both the net value and trading price of the VIX's ETF would rise and the overprice rate shrink. Such a price hike, however, is not attested in the US market. Such phenomena suggest that Taiwan's equity market would suffer a short-term panic attack in response to the bad news exposure of tariff measures in the trade war; such a sentiment response, however, was not observed when the tariff policy was being put to effect. The shrinkage of VIX's EFT overprice rate may be that the holders of VIX take the soaring to be temporary and thus sell ETF accordingly, which accounts for the asymmetry in the trading prices and net values of the ETF during the shock period. Furthermore, the positive rate of overprice of VIX's ETF, which leads to the higher market value of the ETF than its net value, suggests that a high degree of negative sentiment persists among the investors. Changes in the net value of VIX's ETF constitute an advantage in information leading to the market's adjustment of prices, which can thus serve as a leading indicator.

It is concluded that if bad news exposures of Sino-US trade friction persist intensively over a long period of time, the short-term panic strike of Taiwan's equity market can affect its long-term performance. For the clash of Titans will spare no one; not to mention the one such as Taiwan, of which the economy relies heavily on the two Titans across the Pacific. The authorities of Taiwan, and those in similar situations around the world, should always be ready for the shockwaves and prepare counter measures for the strike.

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