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油價波動度對台股報酬影響

Impact of Oil Price Volatility on Taiwanese Stock Return

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摘要

從歷史上看，原油市場的波動一直影響股市走勢的重要因素。本文研究了油價波動風險與台灣股市報酬之間的關係。本文使用了原油波動率指數 (OVX) 作為石油價格變動程度的代表，因為它可以估計原油價格在跨越 30 天時間段的兩個時期價格波動的預計變化。本文旨在探討 OVX 是否對台灣的加權股票報酬有影響，若有則這種影響是否分別對正和負 OVX 變動有不同的衝擊。此外，本文將談討原油波動風險高和低的股票之平均報酬率之間是否存在顯著差異。第三，我們將透過在 CAPM 模型中加入 OVX 因子來測試原油波動度是否具有顯著的風險溢酬。最後，本篇將透過細分在台灣證券交易所交易的公司來分析跨行業的油價波動風險。

Abstract

Volatility in the oil market has historically been a strong predictor for the movement of the stock market. This paper investigates the relationship between oil price volatility risk and the performance of the Taiwanese stock market. As a proxy for oil price uncertainty, the crude oil volatility index (OVX) is used, as it can estimate the projected variation of crude oil prices up to two option expiry dates that span a 30-day period of time. The purpose of this paper is to determine if the OVX has an impact on Taiwan's aggregate stock return and, if so, whether or not this effect is different for positive and negative OVX movements, respectively. Following that, it will be determined whether there is a statistically significant difference between the average return of stocks with little and high exposure to oil volatility. Third, we will test if oil volatility carries a significant risk premium by adding OVX factor into CAPM model. Finally, this paper will also analyze exposure to oil price volatility across sectors by segmenting companies trading on the Taiwan Stock Exchange.

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I. Introduction

Global oil prices have responded to geopolitical and other events in the past. Examples include the Gulf War in 1990, the Asian economic crisis in 1997, the global financial crisis in 2007-2008, and the COVID-19 pandemic in 2020. Oil prices have also become more volatile since the establishment of the Organization of Petroleum Exporting Countries (OPEC) in the 1960s, as OPEC has demonstrated its ability to manipulate prices for political reasons. Following up on this observation, we intend to look into the relationship between oil price volatility and the stock market. And if the stock market is indeed affected by oil price volatility, how much has this uncertainty been priced into the stock market.

The study of oil price change has been a popular topic, and both upward and downward movements appear to both get considerable mention. The majority of the studies focus on what drives oil price, and how oil price shock affects stock market as well as the real economy. While the results of these studies vary, most of them imply that there is some relationship between the oil price shock and the stock market return. When attempting to explain this effect, some believe that the movement of the oil price will have an effect on the cost of doing business, whilst others may claim that the modern economy is too complex to be forecast by a single component. In this paper, however, we focus on the linkage between oil price uncertainty and stock market movement rather than how oil price will affect stock price. That is to say, we look into the risk of oil price itself.

To investigate oil price volatility, it requires the use of a proxy for oil price volatility in order to carry out the analysis. The use of historical data and realized price uncertainty is used in some studies. The fact remains that these measures are based on historical price data, which cannot be relied upon to accurately reflect current information and market sentiment regarding future oil price movement. In order to accurately reflect current market information, option prices and implied volatility are the best approaches to take. Hence, the Chicago Board Options Exchange (CBOE) compiled the crude oil volatility index (OVX), and according to CBOE website:

> The Cboe Crude Oil ETF Volatility Index (OVX) is an estimate of the expected 30-day volatility of crude oil as priced by the United States Oil Fund (USO). Like the Cboe VIX Index, OVX is calculated by interpolating between two time-weighted sums of option mid-quote values - in this case, options on the USO ETF. The two sums essentially represent the expected variance of the price of crude oil up to two option expiration dates that bracket a 30-day period of time. OVX is obtained by annualizing the interpolated value, taking its square root and expressing the result in percentage points.[1]

As we can see, CBOE apply the volatility index methodology to options on the United States oil fund in order to measure the risk of oil price movement. Therefore, we utilize this direct measure of the oil price uncertainty rather than calculating volatility based on historical data.

The impact of oil price volatility on the Taiwanese stock market is the main focus of this paper. There are currently few research that analyze the relationships between oil

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[1] Source: https://www.cboe.com/us/indices/dashboard/ovx/

price uncertainty and the stock market through the lens of the implied volatility index, and little study that focus on the influence of oil price volatility on the Taiwanese stock market. Nonetheless, because the Taiwanese stock market possesses characteristics of both developing and developed countries, the outcome may differ significantly from previous research that have primarily focused on the US stock market or the Chinese stock market. As a result, it is crucial to expand research on the oil and Taiwanese stock linkages from the standpoint of price movement uncertainty.

II. Literature Review

An earlier body of work concentrated on the link between crude oil prices and macroeconomic factors, and the association between crude oil prices and macroeconomic variables has been well documented (e.g., Akram, 2009; Arora and Tanner, 2013; Berument et al., 2014). Later, a huge number of literatures looked into the links between the oil market and the stock market. The research focused on the impact of oil prices on stock markets in a wide variety of developed and emerging countries. Nevertheless, the findings of these investigations, are inconsistent. A large number of papers give evidence that fluctuations in oil prices can have a detrimental impact on stock returns (e.g., Nandha and Faff, 2008; Chen, 2010). Some research, on the other hand, finds a positive association between oil stocks and the price of oil (e.g., El-Sharif et al., 2005). Despite the fact that the findings of these studies appear to be contradictory, the majority of them found that the association between oil prices and stock markets is positive in net oil exporting nations and negative in net oil importing nations.

In recent years, various papers have begun to study the relationship between oil price shock and stock market movement. The conclusions of these investigations, however, are also equivocal. Park and Ratti (2008) discovered that an increase in the volatility of oil prices greatly depresses real stock returns contemporaneously or within one month for numerous European countries but not for the United States. Similarly, Alsalman (2016) shown, using a bivariate GARCH-in-mean VAR model, that uncertainty about the real price of oil had a positive but small effect on aggregate stock returns in the United States. Christoffersen and Pan (2018), on the other hand, discovered a different conclusion when concentrating on the US stock market. They discovered that oil volatility risk is inversely related to future expected stock returns, and that stocks with a high exposure to oil volatility risk earn a poor average future return. Some studies also investigated the relationship between oil price volatility risk and emerging market stock performance. Xiao et al. (2018), for example, apply quantile regression to analyze the relationship between China stock return and OVX. They discovered that OVX shocks had a considerably negative influence on the returns of all stock indices at low quantiles, and that positive OVX shocks have a greater impact on the Chinese stock market during the bearish phase than negative OVX shocks.

Recently published literature has not only looked at the relationship between oil price volatility and aggregate market return, but it has also investigated the impact of oil price movement on stock returns in several industry sectors. Most of the research finds that different industries react differently to oil price shock. Caporale et al. (2015), for example, used bivariate VAR-GARCH-in-mean models to study the links between oil price uncertainty and Chinese stock returns at the sectoral level, and they discovered that oil price volatility influences stock returns differently across sectors. Hamdi et al. (2019)

investigated the effect of oil price volatility on 12 stock sector returns in the Gulf Cooperation Council (GCC) countries using QRA, wavelet denoising based quantile regression and frequency domain Granger-causality analyses. They discovered that, depending on the market conditions, different industries react in different ways to fluctuations in oil prices. When oil price volatility is strong, the researchers' findings may potentially give useful hedging strategies for traders and business owners alike.

III. Econometric Framework

This paper examines if OVX has an effect on Taiwan's aggregate stock return and, if so, whether there is a difference between positive and negative OVX movement. To do so, we first assume that the impact of OVX on Taiwan stock returns is symmetric, as stated by the following equation (1):

$$R^{m}_{prem,t} = \beta_0 + \beta_1 FX_t + \beta_2 R^{m}_{prem,t-1} + \beta_3 \Delta OVX_t + \varepsilon_t \quad (1)$$

The dependent variable $R^{m}_{prem,t} = R_{m,t} - R_{f,t}$ represents the daily Taiwan aggregate stock market excess return, $\mathrm{FX_t}$ represents the foreign exchange rate between the New Taiwan Dollar and the U.S. Dollar, and $\Delta\mathrm{OVX_t}$ represents the OVX index movement between time t-1 and time t. To reflect earlier market condition and momentum, the lagged market premium is added. Moreover, because international investments have a big influence on Taiwan's stock market, the foreign exchange rate between the New Taiwan Dollar and the US Dollar is also included. After assessing the symmetrical impact of OVX on Taiwan stock market, we perform an analysis of the asymmetric influence of OVX movement on the Taiwan stock market by first splitting the relevant data regarding OVX movement into two distinct groups. We then perform regression using the following equation (2) to see if changes in OVX have a different impact on Taiwan stock returns:

$$R^{m}_{prem,t} = \beta_0 + \beta_1 FX_t + \beta_2 R^{m}_{prem,t-1} + \beta_{31}\Delta OVX^{+}_{t} + \beta_{32}\Delta OVX^{-}_{t} + \varepsilon_t \tag{2}$$

where $\Delta \mathrm{OVX}^{+}_{t} = \max(\Delta \mathrm{OVX}_t, 0)$ and $\Delta \mathrm{OVX}^{-}_{t} = \min(\Delta \mathrm{OVX}_t, 0)$ denote positive and negative OVX shock, respectively. The setting in the above regression model is similar to Xiao et al. (2018), which compared the asymmetric impacts of oil price uncertainty on Chinese stock returns.

It will next be determined whether there is a statistically significant difference between the average return and volatility of stocks with little and high exposure to oil volatility. As a model for sorting each stock, we utilize the following equation (3) as a starting point. At the end of each quarter, we run regression for each stock daily excess return on market excess return and OVX during the quarter:

$$R^{i}_{prem,t} = \beta^{i}_{0} + \beta^{i}_{m} R^{m}_{prem,t} + \beta^{i}_{ovx} OVX_t + \varepsilon_t \tag{3}$$

where $\mathrm{R}^{\mathrm{i}}_{\mathrm{prem,t}}$ is the daily excess return on each stock *i*. Our regression model makes use of returns on the 105 highest-valued stocks traded on the Taiwan Stock Exchange (TWSE). Following the completion of the time series regressions shown above on each stock, we divide the stocks into terciles depending on the value of $\beta^{\mathrm{i}}_{\mathrm{ovx}}$, with the bottom tercile having the lowest beta and the top tercile having the highest beta. This technique is repeated by moving the beta estimation window forward one quarter at a time, starting at the beginning of the procedure. Among other things, this configuration is comparable to that used by Ang et al. (2006) and Christoffersen and Pan (2018), which employ daily returns within a one-month window to capture changes in the factor exposures.

At the end of each quarter, we will utilize the sorted terciles of stocks to build three equally weighted portfolios. Then we will look at the difference in average return between the top and bottom tercile of the portfolio. After that, we can run the following capital asset pricing model (4) using the daily returns on the three post-ranking portfolios.

$$R^{p}_{prem,t} = \alpha^{p} + \beta^{p}_{m} R^{m}_{prem,t} + \varepsilon_{t} \tag{4}$$

The outcome of the above equation (4) yields post-ranking quarterly Jensen's alpha, which is daily alpha multiplied by 63. We may test the null hypothesis of $\alpha = 0$ against $\alpha \neq 0$ using estimated quarterly Jensen's alpha in the sample period.

After testing excess return for each stock, we will find the price of oil price volatility using Fama-Macbeth regression procedure from Fama and MacBeth (1973). In the previous stage, we derive the estimation of the market beta coefficient and OVX beta coefficient using equation (3) to run regression on a quarterly basis. In this stage, however, we would run the regression for each stock on the entire period to get $\{\widehat{\beta^{1}_{m}}, \widehat{\beta^{2}_{m}}, \dots, \widehat{\beta^{105}_{m}}\}$ and $\{\widehat{\beta^{1}_{\mathrm{ovx}}}, \widehat{\beta^{2}_{\mathrm{ovx}}}, \dots, \widehat{\beta^{105}_{\mathrm{ovx}}}\}$. After calculating the estimate betas from the adjusted time-series regression model (3), we will then move on to determine the price of oil price volatility. In stage two, we run the following regression (5):

$$R_{prem} = \lambda_0 + \lambda_m \widehat{\beta_m} + \lambda_{\mathrm{ovx}} \widehat{\beta_{\mathrm{ovx}}} + \varepsilon$$

(5)

where R_{prem} is the excess return for each individual stock during the entire sample period. If the risk premium associated with oil price volatility (OVX) is significant, then the risk factor connected with oil price volatility (OVX) is priced in the Taiwan stock market. This methodology used test the significance of oil price volatility is comparable to the method used in Christoffersen and Pan (2018).

Finally, this paper will also analyze exposure to oil price volatility across sectors by segmenting companies trading on the Taiwan Stock Exchange. We do so by regressing Taiwan sectoral stock index excess return on changes in OVX using the following equation (6):

$$R^s_{prem,t} = \beta^s_0 + \beta_1 FX_t + \beta^s_2 R^s_{prem,t-1} + \beta^s_3 \Delta OVX_t + \varepsilon_t$$

(6)

where $R^s_{prem,t} = R_{s,t} - R_{f,t}$ is the daily excess return in sectoral index. In a manner analogous to that which is utilized in the analysis of the aggregate stock market, the foreign exchange rate between the New Taiwan Dollar and the United States Dollar is incorporated. Because we want to capture the momentum of the market, we have also factored in the lagging excess return of the sectors stock. After examining the symmetrical impact of OVX on Taiwan's sectoral stock market, it's necessary to analyze the asymmetric influence by dividing the relevant data into two groups. Similar to the methodology used in the first part, we use the following equation (7) to capture asymmetric impact of OVX on sectoral stock:

$$R^s_{prem,t} = \beta^s_0 + \beta_1 FX_t + \beta^s_2 R^s_{prem,t-1} + \beta^s_{31}\Delta OVX^+_t + \beta^s_{32}\Delta OVX^-_t + \varepsilon_t \quad (7)$$

where similar to equation (2),$\Delta OVX^+_t = max(\Delta OVX_t, 0)$ denote positive OVX shock and $\Delta OVX^-_t = min(\Delta OVX_t, 0)$ denote negative OVX shock.

IV. Data Source and Variables

This paper investigates the influence of oil price volatility on Taiwan aggregate and individual stock returns from January 1, 2010, to December 31, 2021, because the Taiwan stock market's market structure has become more stable since the 2008 financial crisis. In the empirical analysis, the daily data are used because the OVX index is a way to measure how volatile oil prices are in the short term. All the return data are denoted as daily return percentage.

As shown in Table 1, for oil price volatility, we use CBOE Crude Oil Volatility Index (OVX) as a proxy for oil volatility, and the data collected from the Chicago Board Options Exchange's website. The graph of OVX data during January 1, 2010, to December 31, 2021 is shown in Figure 1. OVX is an estimate of the expected 30-day volatility of crude oil as priced by the United States Oil Fund (USO). The market portfolio is represented by TSEC weighted index.

For individual stock, we use individual stock data traded on Taiwan Stock exchange (TWSE). We chose 105 stocks depending on their market value on May 7, 2022. The 105 stocks we chose represented 78% of the total market value of all stocks trading on the TWSE, which is more than enough to reflect the broader market. Furthermore, because smaller market value stocks have lower trade value, their prices can be easily manipulated. As a result, selecting stocks with a low market value may not be relevant for our study. For the sake of simplicity, the stocks we select do not change over time; that is, even if market value has changed in the past, we did not record the change. Nonetheless, as of January 1, 2010, the 105 stocks we chose accounted for 68 percent of total market value, indicating that the TWSE structure has not evolved significantly over the preceding decade.

Finally, we utilize the daily percentage change in the TAIEX Sub-Index to reflect each sector's daily return. Iron and steel, building materials and construction, finance and insurance, trading and consumer goods, semiconductors, and electronic parts/components are among the industries we have chosen. Because the indices' launch dates varied, so do their base values. To correct for this inaccuracy, we re-scale the indices, starting at 100 and setting the base date to January 4, 2010.

V. Empirical Result

5.1 Impact of OVX movement on aggregate stock return

The empirical investigation starts with the use of regression to evaluate the impacts of the OVX changes on the aggregate return of the Taiwan stock market. The outcome of the regression model without the inclusion of OVX is displayed in the first column of the Table 2. When we use the exchange rate between TWD and USD as well as the lagged market premium as independent variables, we can see that the coefficient for the exchange rate is significant at a confidence interval of 99%, while the coefficient for the lagged market premium is significant at a confidence interval of 90%. Because the foreign exchange rate is computed by converting 1 USD to TWD, the result shows that the value of the New Taiwan Dollar has a positive impact on the aggregate stock return. Furthermore, the lagged dependent variable has a positive effect on market excess return, indicating that the Taiwan stock market retains momentum beyond trading days. These findings are consistent across three models. The introduction of the OVX index into the model simply changes the magnitude of the effect.

The outcome of the regression model that was used in equation (1) may be found in column (1) of Table 2. We can observe that changes in OVX have a negative impact on the aggregate stock return by looking at the value of β_3 in column (1) of the Table. According to the empirical result, increased levels of uncertainty in the oil market are associated with decreased levels of average stock returns in Taiwan. One of the possible explanations for this phenomenon is that, given that oil is a crucial component in the manufacture of a wide variety of goods, an increase in the volatility of oil prices has a deleterious effect on the investments that corporations make in the real economy, which, in turn, has a negative impact on the stock returns.

The column (2) of Table 2 contains the results of the regression model employed in equation (2). In contrast to equation (1), which only looks at the symmetrical impact of OVX on aggregate stock returns, equation (2) looks at the asymmetrical impact. We can observe from the sign of the value of β_{31} and β_{32} that both positive and negative movement of the OVX have a negative impact on aggregate stock return. This means that any change in the degree of oil price uncertainty will always have a negative impact on the stock market. In other words, whether the price of oil rises or falls in a short amount of time, the stock market will suffer. Using the scale of the coefficients β_{31} and β_{32}, we can observe that a positive change in oil price uncertainty has a greater negative impact on aggregate stock return than a negative change. This conclusion is consistent with the proposed explanation in the first model, in which we say that the volatility of oil prices has a negative influence on corporate investments in the real economy.

5.2 Impact of OVX movement on individual stock return

For the influence of OVX movement on individual stock return, we first sort the stocks depending on the scale of OVX impact using the equation (3) presented in Table 3. The stocks are classified into terciles in each quarter, with the top tercile having higher β_{ovx} and the bottom tercile having lower β_{ovx}. Following that, we build three equally weighted portfolios and run the regression using equation (4). This regression's descriptive statistic result is shown in Table 3. Because our sample period lasted 12 years, or 2840 trading days (excluding missing data), and each quarter has about 63 trading days, we can divide 2840 by 63 to get 45 sub-periods. According to the findings, the maximum level of alpha is achieved by the top tercile, while the lowest level of alpha is achieved by the middle tercile. If an investor builds the portfolio on a quarterly basis by buying stocks that fall within the top tercile and shorting stocks that fall within the lowest tercile, then there would be a premium of 0.025% every day, which would be equivalent to around 6.45% per year. As a result, our finding demonstrates that stocks with a greater risk of being adversely affected by changes in the price of oil do, in fact, carry a positive premium.

As for the price of oil volatility risk using beta, which is measured by beta derived from the total sample of daily returns, we analyze the effect using equation (5). The estimated coefficients are relatively high because they are based on the return on the stock over the entire sample period. Although oil price volatility carries a significant risk premium, which is approximately 6.45% per year, this premium is not significantly priced during the sample period, as we can see from the estimated value and standard error of λ_{ovx} in Table 4. However, even though the result may not be statistically significant, the result in Table 4 does indeed show that OVX carries a negative price effect to individual stock return. This is consistent with the results obtained from the earlier models.

5.3 Impact of OVX movement on sectoral stock return

Similar to the result presented in Table 2, the conclusion that an increase in the value of the New Taiwan Dollar has a positive influence on the aggregate stock return is supported by the finding that the exchange rate between TWD and USD is statistically significant at a level of 99% across all industries. When it comes to the lagging dependent variable, the results are similar across different businesses. It is clear from looking at each lagging sectoral excess return that the lagged dependents all have a positive effect on the sectoral excess return; this indicates that the stock return for each sector maintains momentum beyond the trading day. However, only the lagging variable of the Electronic Components industry and the Building Materials sector are significant. Next, we are able to observe the effect of the OVX asymmetry influence on sectoral stock return by looking at the value of β_3^s in each sector. In terms of symmetrical impact, we can see that the volatility in the price of oil has a negative effect on all industries, with the coefficient for electronic components having the lowest impact and the coefficient for trading and consumer having the biggest impact. Despite this, there is little statistical or economic significance to be found in the differences between the various industries. This result will change after asymmetric impact is investigated.

The regression result of equation (7) for asymmetric effect is provided in Table 6. The outcome for the foreign exchange rate and the lag dependent variable is the same as in Table 5. However, when it comes to OVX impact, there is a big difference between positive and negative OVX movement. Across all industries, negative OVX movement has a smaller impact on stock returns than positive OVX movement. This means that an increase in oil price uncertainty lowers stock returns more than a decrease in oil price uncertainty across all sectors. Positive OVX movement has a statistically significant impact on stock performance across all industries. The Finance and Insurance industry is the most influenced by changes in oil prices among the six sectors studied. At first glance, this result may appear to be surprising, because we have assumed that volatility in oil prices has a negative impact on corporate investments in the real economy; however, the Finance and Insurance sector has no greater connection to the real economy than other sectors such as the Iron and Steel sector or the Building Materials sector. Nonetheless, there could be another explanation for this behavior. The oil market has become an integral aspect of the financial system due to the maturity of the oil futures market and the enrichment of oil derivatives. Investors in the finance and insurance sectors may be more active in both the oil and stock markets at the same time. As a result of the increased uncertainty in the oil market, this effect may be passed to investors in the Finance and Insurance sector via two pathways, affecting its stock return. Hence, we can see that the asymmetric effect of OVX movement on sectoral stock return is more significant than the symmetric effect.

VI. Conclusion

Volatility in the oil market has historically been a strong predictor of stock market movement. In this paper, we look at the relationship between oil volatility risk and Taiwanese stock market performance, and we use the crude oil volatility index (OVX) as a proxy for oil price uncertainty. The goal of this paper is to see if the OVX has an effect on Taiwan's stock return and, if the stock market is affected by oil price volatility, how much of that uncertainty has been priced into the stock market.

First, this paper investigates whether the OVX has an effect on Taiwan's aggregate stock return and, if so, whether this effect is different for positive and negative OVX movements. We discovered in the symmetric model that higher levels of uncertainty in the oil market are associated with lower levels of average stock returns in Taiwan. On the other hand, the asymmetric model shows that both positive and negative OVX movement have a negative impact on aggregate stock return. However, a positive change in oil price uncertainty has a greater negative impact on aggregate stock return than a negative change, which is likely because oil price volatility has a negative impact on corporate investments in the real economy.

Second, we investigate whether there is a statistically significant difference between the average return of individual stocks with little and high exposure to oil volatility. By dividing the stocks into terciles depending on the scale of OVX impact, we found that stocks with a greater risk of being adversely affected by changes in the price of oil do, in fact, carry a positive premium. Nevertheless, using Fama-Macbeth regression technique, we found that the premium for OVX is not significantly priced during the sample period.

Finally, we use the daily percentage change in the TAIEX Sub-Index to reflect the daily return of each sector. In terms of symmetrical impact, we discovered that oil price volatility has a negative impact on all industries. The differences between industries, nevertheless, have little statistical or economic significance. As for asymmetric impact, we discovered that positive OVX movement has a more significant impact on stock performance across all industries than negative OVX movement. Furthermore, among the six sectors studied, the Finance and Insurance industry is most affected by changes in oil prices. This is likely due to the fact that investors in the finance and insurance sectors are more active in both the oil and stock markets, hence an increased uncertainty in the oil market may be transmitted to investors in the finance and insurance sectors via two channels.

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Table 1: Data Source and Description (Daily Percentage)

Variables	Description	Source
$R_{m,t}$	Taiwan Stock market aggregate return	Yahoo Finance
$R_{f,t}$	Taiwan 10-year treasury rate	TEJ Data Base
FX_t	TWD to USD Spot Exchange Rate	FRED Website
OVX_t	OVX change rate	CBOE Website
$R_{i,t}$	Taiwan individual stock return	TEJ Data Base
$R_{s,t}$	Taiwan sectoral index return	Taiwan Index Plus Website

Figure 1: CBOE Crude Oil Volatility Index

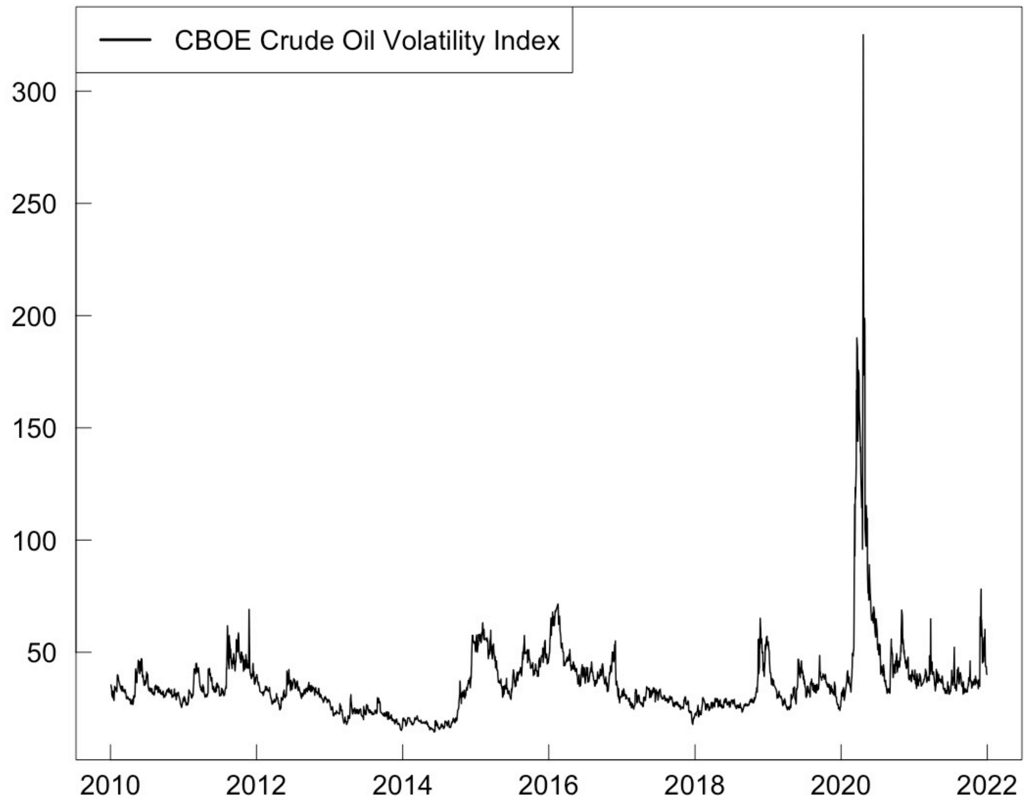

Table 2: OVX on aggregate stock return

		Dependent variable		
		(0)	(1)	(2)
		Market Premium		
(Intercept)	(β_0)	0.023	0.024	0.039^{**}
		(0.018)	(0.018)	(0.019)
FX Rate	(β_1)	-1.064^{***}	-1.057^{***}	-1.058^{***}
		(0.061)	(0.060)	(0.060)
Lag Mkt. Prem	(β_2)	0.030^{*}	0.013	0.013
		(0.018)	(0.018)	(0.018)
ΔOVX	(β_3)		-0.026^{***}	
			(0.004)	
ΔOVX^{+}	(β_{31})			-0.034^{***}
				(0.005)
ΔOVX^{-}	(β_{32})			-0.015^{***}
				(0.006)
Observations				
Adjusted R^2				
Note:		$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

Eq. (0): $R^m_{prem,t} = \beta_0 + \beta_1 FX_t + \beta_2 R^m_{prem,t-1} + \varepsilon_t$

Eq. (1): $R^m_{prem,t} = \beta_0 + \beta_1 FX_t + \beta_2 R^m_{prem,t-1} + \beta_3 \Delta OVX_t + \varepsilon_t$

Eq. (2): $R^m_{prem,t} = \beta_0 + \beta_1 FX_t + \beta_2 R^m_{prem,t-1} + \beta_{31} \Delta OVX_t^{+} + \beta_{32} \Delta OVX_t^{-} + \varepsilon_t$

Table 3: Post-ranking quarterly Jensen's alpha

Statistics	N	Mean	Std. Dev	Min	Max
Top Tercile Alpha	45	0.064	0.071	-0.035	0.346
Middle Tercile Alpha	45	0.021	0.044	-0.063	0.111
Bottom Tercile Alpha	45	0.039	0.062	-0.098	0.156

Eq. (3): $R^i_{prem,t} = \beta^i_0 + \beta^i_m R^m_{prem,t} + \beta^i_{ovx} OVX_t + \varepsilon_t$

Eq. (4): $R^p_{prem,t} = \alpha^p + \beta^p_m R^m_{prem,t} + \varepsilon_t$

Table 4: The price of oil volatility risk using beta from the full sample of daily returns

		Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	(λ_0)	258.48	320.88	0.81	0.42
Market Beta $\widehat{\beta_m}$	(λ_m)	262.10	310.95	0.84	0.40
OVX Beta $\widehat{\beta_{OVX}}$	(λ_{OVX})	-14,523	10,754	-1.35	0.18

Eq. (5): $R_{prem} = \lambda_0 + \lambda_m \widehat{\beta_m} + \lambda_{\text{ovx}} \widehat{\beta_{\text{ovx}}} + \varepsilon$

Table 5: OVX on sectoral stock return

	Dependent variable:					
	Iron & Steel	Building Materials	Finance & Insurance	Trading & Consumer	Semi-Conductor	Electronic Component
(Intercept)	0.012	0.004	0.019	0.033	0.057^{**}	0.029
	(0.022)	(0.021)	(0.020)	(0.022)	(0.024)	(0.025)
FX Rate	-0.913^{***}	-0.845^{***}	-1.035^{***}	-0.854^{***}	-1.233^{***}	-1.197^{***}
	(0.075)	(0.071)	(0.068)	(0.076)	(0.083)	(0.086)
Lag IS.	0.019					
	(0.018)					
Lag BC.		0.081^{***}				
		(0.018)				
Lag FI.			0.009			
			(0.018)			
Lag TC.				0.012		
				(0.018)		
Lag SC.					0.003	
					(0.018)	
Lag EC.						0.041^{***}
						(0.018)
ΔOVX	-0.023^{***}	-0.021^{***}	-0.027^{***}	-0.013^{***}	-0.027^{***}	-0.028^{***}
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
N	2,840	2,840	2,840	2,840	2,840	2,840
Adj. R^2	0.058	0.061	0.088	0.044	0.081	0.075

Eq. (6): $R^s_{prem,t} = \beta^s_0 + \beta_1 FX_t + \beta^s_2 R^s_{prem,t-1} + \beta^s_3 \Delta OVX_t + \varepsilon_t$

Table 6: OVX on sectoral stock return with asymmetric effect

	Dependent variable:					
	Iron & Steel	Building Materials	Finance & Insurance	Trading & Consumer	Semi-Conductor	Electronic Component
(Intercept)	0.032	0.016	0.043^{**}	0.040^{**}	0.073^{**}	0.038
	(0.023)	(0.022)	(0.021)	(0.024)	(0.026)	(0.027)
FX Rate	-0.913^{***}	-0.845^{***}	-1.035^{***}	-0.854^{***}	-1.234^{***}	-1.197^{***}
	(0.075)	(0.071)	(0.068)	(0.076)	(0.083)	(0.086)
Lag IS.	0.019					
	(0.018)					
Lag BC.		0.082^{***}				
		(0.018)				
Lag FI.			0.009			
			(0.018)			
Lag TC.				0.012		
				(0.018)		
Lag SC.					0.003	
					(0.018)	
Lag EC.						0.041^{***}
						(0.018)
ΔOVX^{+}	-0.032^{***}	-0.027^{***}	-0.038^{***}	-0.016^{***}	-0.035^{***}	-0.032^{***}
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)
ΔOVX^{-}	-0.008	-0.013^{*}	-0.010	-0.008	-0.016^{**}	-0.022^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
N	2,840	2,840	2,840	2,840	2,840	2,840
Adj. R^2	0.059	0.062	0.091	0.044	0.082	0.075

Eq. (7): $R_{prem,t}^{s} = \beta_0^s + \beta_1 FX_t + \beta_2^s R_{prem,t-1}^{s} + \beta_{31}^{s} \Delta OVX_t^{+} + \beta_{32}^{s} \Delta OVX_t^{-} + \varepsilon_t$