Impact of Oil Price Volatility on Taiwanese Stock Return

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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.

1. 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. (source: https://www.cboe.com/us/indices/dashboard/ovx/)

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 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.

2. Research Data

2.1 Download and clean price data

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.

Function to Scrape data

```
def clean_price_data(ticker, start_date, end_date, download=False):
    """
    Clean and process price data for a given ticker and date range.

    Args:
```

```
        ticker (str): Ticker symbol.
        start_date (str): Start date in "YYYY-MM-DD" format.
        end_date (str): End date in "YYYY-MM-DD" format.
        download (bool, optional): Whether to download and save the data to CSV.

    Returns:
        pd.DataFrame: Processed price data.
    """
    data_df = yf.download(ticker, start=start_date, end=end_date)

    # save the data to csv
    if download == True:
        cleaned_ticker = ''.join([char for char in ticker if char.isalnum()])
        csv_filename = f"data/{cleaned_ticker.lower()}_data.csv"
        data_df.to_csv(csv_filename)
    else: None

    # The difference betwen consecutive 'Close' data
    data_df['diff']  = data_df['Close'].diff()
    data_df['pct_return'] = data_df['Close'].pct_change() * 100

    # Drop Open, High, Low, Adj Close, Volume
    columns_to_drop = ['Open', 'High', 'Low', 'Adj Close', 'Volume']
    data_df = data_df.drop(columns_to_drop, axis=1)

    return(data_df)
```

Clean OVX data

```
                Close      diff  pct_return  diff_pos  diff_neg
Date
2010-01-04  35.439999       NaN         NaN  0.000000  0.000000
2010-01-05  34.270000 -1.169998   -3.301349  0.000000 -1.169998
2010-01-06  34.400002  0.130001    0.379344  0.130001  0.000000
2010-01-07  33.610001 -0.790001   -2.296514  0.000000 -0.790001
2010-01-08  31.340000 -2.270000   -6.753944  0.000000 -2.270000
```

Clean ^TWII ,USDTWD=X and ^TNX data

```
                  Close        diff  pct_return   mktprem
Date
2010-01-04  8207.849609         NaN         NaN       NaN
2010-01-05  8211.400391    3.550781    0.043261  0.043117
2010-01-06  8327.620117  116.219727    1.415346  1.415200
2010-01-07  8237.419922  -90.200195   -1.083145 -1.083291
2010-01-08  8280.900391   43.480469    0.527841  0.527695
                Close      diff  pct_return
Date
2010-01-04  31.660000       NaN         NaN
2010-01-05  31.860001  0.200001    0.631714
2010-01-06  31.780001 -0.080000   -0.251098
2010-01-07  31.809999  0.029999    0.094395
2010-01-08  31.790001 -0.019999   -0.062869
```

Find top 105 market cap symbols

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.

```
['2330', '2317', '2454', '2382', '2412', '2308', '2881', '6505', '2882']
```

Get top 105 stock returns

```
                2330      2317      2454      2382      2412      2308  \
Date
2010-01-04       NaN       NaN       NaN       NaN       NaN       NaN
2010-01-05 -0.616335  0.660067  0.176370 -0.725689  0.168630 -0.696519
2010-01-06  0.620157 -0.655739  1.232392  1.461988  0.336702 -0.400801
2010-01-07 -1.078589 -0.990101 -2.434778 -0.864551 -2.013425 -1.810868
2010-01-08 -0.311522  0.333334 -1.960782 -0.436051 -0.513697 -0.102457

                2881      6505      2882      2303  ...      2352  8464  \
Date                                                ...
2010-01-04       NaN       NaN       NaN       NaN  ...       NaN   NaN
2010-01-05  0.637756  0.728153 -0.168075  1.176475  ... -3.605770   0.0
2010-01-06  3.168571  2.168678  1.683503  6.976737  ...  0.498755   0.0
2010-01-07 -1.597052  0.825468 -0.993378  0.000000  ... -2.481390   0.0
2010-01-08  0.499372  0.233915  1.003345 -1.086950  ...  1.781173   0.0

                2059      3035      9904      1477      2354      2385  2633  \
Date
2010-01-04       NaN       NaN       NaN       NaN       NaN       NaN   NaN
2010-01-05 -1.977398 -2.463769  3.162061  0.166110  0.000000 -1.948055   0.0
2010-01-06  0.864555  2.080240 -0.574719  0.829189  0.000000  0.000000   0.0
2010-01-07 -0.857144 -3.202328 -0.770709 -1.644741 -1.639348  0.264900   0.0
2010-01-08 -0.288188  1.203004  1.165046  0.000000  0.000000  2.245709   0.0

                1519
Date
2010-01-04       NaN
2010-01-05 -1.826483
2010-01-06  0.155038
2010-01-07  0.000000
2010-01-08 -0.773991

[5 rows x 105 columns]
```

2.2 Data Visualization

```
def plot_and_save(df, label, filename):
    plt.figure().gca().tick_params(axis='both', which='both', length=0.02)
    plt.plot(df.index, df['Close'], 'k', lw=1.25, label=label)
    plt.xticks(rotation=45, fontsize=8)  # Changed fontsize to 8
    plt.yticks(fontsize=8)  # Changed fontsize to 8
    plt.legend(loc='upper right', prop={'size': 10})
    plt.tight_layout()
```

```
plt.savefig(filename)
plt.close()
```

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. 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.

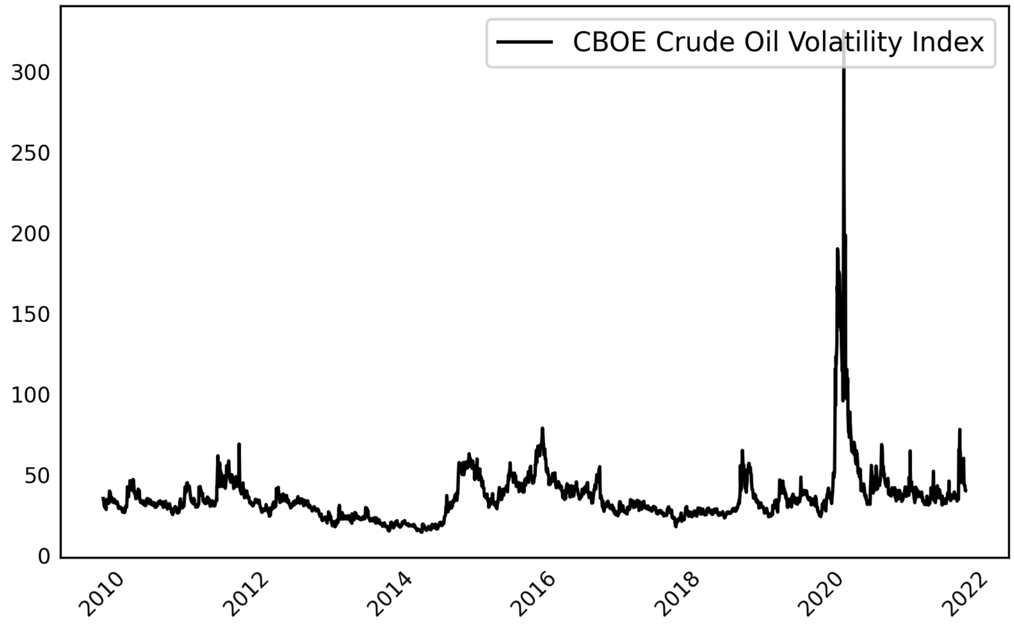

Figure 1: "CBOE Crude Oil Volatility Index"

Plot TSEC weighted index

Plot Interest Rate

3. Model OVX movement on aggregate stock return

3.1 Base Model

Set up the Base model without incorporating OVX:

$R^m_{prem,t} = \beta_0 + \beta_1 FX_t + \beta_2 R^m_{prem,t-1} + \varepsilon_t$

The dependent variable $R^m_{prem,t} = R_{m,t} - R_{f,t}$ represents the daily Taiwan aggregate stock market excess return (pending), FX_t represents the foreign exchange rate between the New Taiwan Dollar and the U.S. Dollar, and ΔOVX_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.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 mkt_rt   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                  0.000
Method:                 Least Squares   F-statistic:                     1.585
```

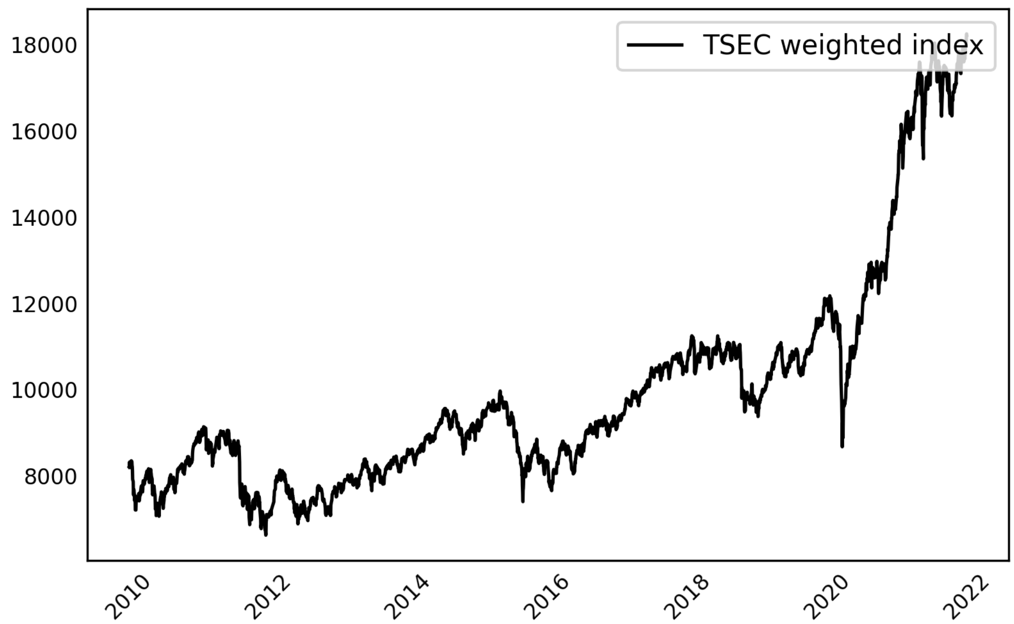

Figure 2: “TSEC weighted index”

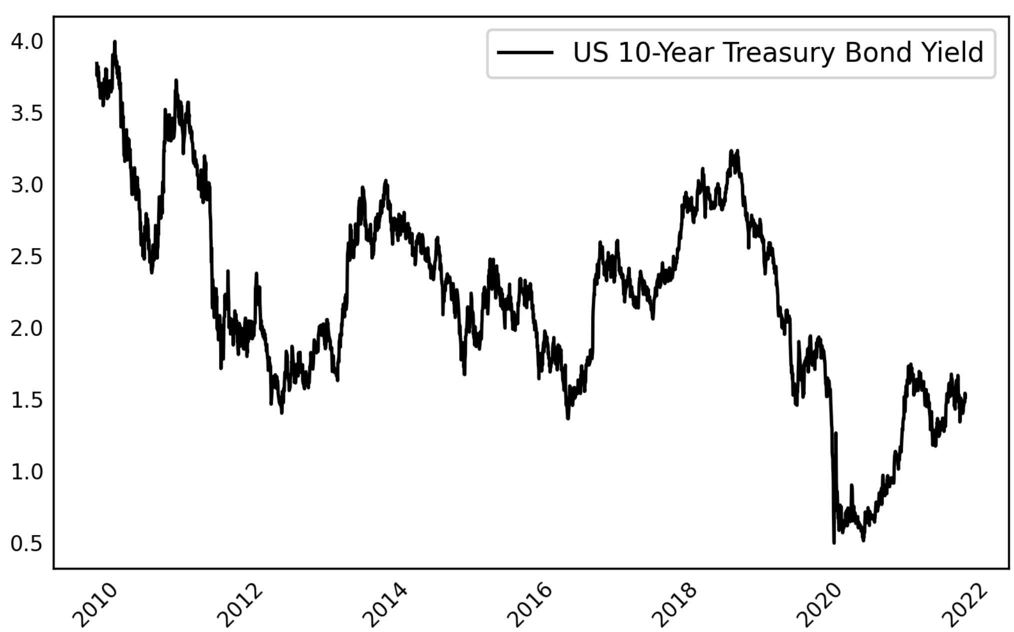

Figure 3: “US 10-Year Treasury Bond Yield”

```
Date:                Sat, 16 Sep 2023   Prob (F-statistic):                0.205
Time:                        01:53:07   Log-Likelihood:                  -3964.3
No. Observations:                2837   AIC:                               7935.
Df Residuals:                    2834   BIC:                               7952.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.2164      0.377      0.574      0.566      -0.523       0.956
fx            -0.0063      0.012     -0.503      0.615      -0.031       0.018
lag_mkt_rt     0.0317      0.019      1.687      0.092      -0.005       0.069
==============================================================================
Omnibus:                      386.916   Durbin-Watson:                   2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2650.372
Skew:                          -0.445   Prob(JB):                         0.00
Kurtosis:                       7.651   Cond. No.                         620.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

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 ??%, while the coefficient for the lagged market premium is significant at a confidence interval of ??%. 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.

3.2 Symmetric Impact

We first assume that the impact of OVX on Taiwan stock returns is symmetric:

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

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 mkt_rt   R-squared:                       0.017
Model:                            OLS   Adj. R-squared:                  0.016
Method:                 Least Squares   F-statistic:                     15.88
Date:                Sat, 16 Sep 2023   Prob (F-statistic):           3.05e-10
Time:                        01:53:07   Log-Likelihood:                -3942.2
No. Observations:                2837   AIC:                             7892.
Df Residuals:                    2833   BIC:                             7916.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.2243      0.374      0.599      0.549      -0.509       0.958
fx            -0.0065      0.012     -0.528      0.597      -0.031       0.018
lag_mkt_rt     0.0318      0.019      1.704      0.088      -0.005       0.068
ovx_diff      -0.0246      0.004     -6.666      0.000      -0.032      -0.017
==============================================================================
```

```
Omnibus:                      383.871   Durbin-Watson:                   2.032
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2935.642
Skew:                          -0.396   Prob(JB):                         0.00
Kurtosis:                       7.920   Cond. No.                         620.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

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.

3.3 Asymmetric Impact

After assessing the symmetrical impact of OVX on Taiwan stock market, it is sufficient to execute an analysis of the asymmetric influence of OVX movement on the Taiwan stock market by splitting the relevant data regarding OVX movement into two distinct groups.

$$R^m_{prem,t} = \beta_0 + \beta_1 FX_t + \beta_2 R^m_{prem,t-1} + \beta_{31}\Delta OVX^+_t + \beta_{32}\Delta OVX^-_t + \varepsilon_t$$

$\Delta OVX^+_t = max(\Delta OVX_t, 0)$ and $\Delta OVX^-_t = min(\Delta OVX_t, 0)$ denote positive and negative OVX shock, respectively. The setting in the regression model (2) is similar to Xiao et. al. (2018), who compare the asymmetric impacts of oil price uncertainty on Chinese stock returns.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 mkt_rt   R-squared:                       0.017
Model:                            OLS   Adj. R-squared:                  0.015
Method:                 Least Squares   F-statistic:                     11.91
Date:                Sat, 16 Sep 2023   Prob (F-statistic):           1.34e-09
Time:                        01:53:07   Log-Likelihood:                -3942.2
No. Observations:                2837   AIC:                             7894.
Df Residuals:                    2832   BIC:                             7924.
Df Model:                           4
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.2258      0.374      0.603      0.547      -0.509       0.960
fx              -0.0066      0.012     -0.530      0.596      -0.031       0.018
lag_mkt_rt       0.0317      0.019      1.701      0.089      -0.005       0.068
ovx_pos_diff    -0.0249      0.005     -5.114      0.000      -0.034      -0.015
ovx_neg_diff    -0.0241      0.006     -3.948      0.000      -0.036      -0.012
==============================================================================
Omnibus:                      383.617   Durbin-Watson:                   2.032
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2941.945
Skew:                          -0.394   Prob(JB):                         0.00
Kurtosis:                       7.926   Cond. No.                         621.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

We can observe 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. We can also 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.

4. Model OVX movement on individual stock return

4.1 Post-ranking quartly Jensen's alpha

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 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

$$R^i_{prem,t} = \beta^i_0 + \beta^i_m R^m_{prem,t} + \beta^i_{ovx} OVX_t + \varepsilon_t$$

where $R^i_{prem,t}$ 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 in the above equation on each stock, we divide the stocks into terciles depending on the value of β^i_{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.

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 in the equation below using the daily returns on the three post-ranking portfolios.

$$R^p_{prem,t} = \alpha^p + \beta^p_m R^m_{prem,t} + \varepsilon_t$$

The outcome of this equation yields post-ranking quartly 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 quartly Jensen's alpha in the sample period.

	Statistics	N	Mean	Std.Dev	Min	Max
0	Top Tercile Alpha	45	0.048368	0.059141	-0.052876	0.239429
1	Middle Tercile Alpha	45	0.004880	0.037014	-0.080000	0.072016
2	Bottom Tercile Alpha	45	0.031753	0.049277	-0.085701	0.121825

For the influence of OVX movement on individual stock return, we first sort the stocks depending on the scale of OVX impact. 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:

Because our sample period lasted 11 years, or 2840 trading days, 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 0.016 % every day, which would be equivalent to around 4.18 % 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.

4.2 Impact on individual stock return

After testing excess return for each stock, we will find the price of oil price volatility using Fama-Macbeth regression procedure. In the previous stage, we derive the estimation of the market beta coefficient and OVX beta coefficient using equation $R^i_{prem,t} = \beta^i_0 + \beta^i_m R^m_{prem,t} + \beta^i_{ovx} OVX_t + \varepsilon_t$ 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 $\{\hat{\beta}^1_m, \hat{\beta}^2_m, ..., \hat{\beta}^{105}_m\}$ and $\{\hat{\beta}^1_{\text{ovx}}, \hat{\beta}^2_{\text{ovx}}, ..., \hat{\beta}^{105}_{\text{ovx}}\}$. After calculating the estimate betas from the adjusted time-series regression model, we will then move on to determine the price of oil price volatility. In stage two, we run the following regression:

$$R_{prem} = \lambda_0 + \lambda_m \hat{\beta}_m + \lambda_{\text{ovx}} \hat{\beta}_{\text{ovx}} + \varepsilon$$

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.

OLS Regression Results

Dep. Variable:	Stock_Return	R-squared:	0.033
Model:	OLS	Adj. R-squared:	0.014
Method:	Least Squares	F-statistic:	1.747
Date:	Sat, 16 Sep 2023	Prob (F-statistic):	0.179
Time:	01:53:07	Log-Likelihood:	-819.74
No. Observations:	105	AIC:	1645.
Df Residuals:	102	BIC:	1653.
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	606.0962	209.426	2.894	0.005	190.700	1021.492
Beta_MKT	-138.7660	214.127	-0.648	0.518	-563.486	285.954
Beta_OVX	-1.524e+04	9048.792	-1.684	0.095	-3.32e+04	2706.451

Omnibus:	90.613	Durbin-Watson:	2.021
Prob(Omnibus):	0.000	Jarque-Bera (JB):	669.361
Skew:	2.962	Prob(JB):	4.47e-146
Kurtosis:	13.858	Cond. No.	213.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

As we can see, 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 4.18% 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}. However, despite the fact that the result may not be statistically significant, the result 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. Summary

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 project 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.