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The Impact of Non-war Geopolitical Risk on Return and Implied Volatility on Stock

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Abstract: The impact of non-war geopolitical risks on stocks has not been adequately studied in the academic literature. This paper intends to explore whether disputes between countries or related political news have some impact on stocks prior to the occurrence of war. This paper focused on examining the impact of non-war geopolitical risks on the returns and implied volatility of the call option related to Taiwan Semiconductor Manufacturing Company's stock. In this paper, different models are used to predict the stock returns and the implied volatility of some call options related to this stock and then compares the estimation with the real data in order to perform hypothesis testing to determine whether the difference is significant. This paper found that non-war geopolitical controversies do not affect the stock returns, but that investors' reaction to risk can be affected differently depending on the nature of the event.

Keywords: geopolitical risk, stock return, implied volatility

1. Introduction

This paper examines the impact of geopolitical events on a stock's return and its related call option's implied volatility. Geopolitical risk is one of the threats to global and regional security, peace, and prosperity. How to detect, evaluate, anticipate, and manage geopolitical risks has become a prevalent topic of discussion domestically and overseas. The event of the Russian-Ukrainian war launched on 24 February were of great concern to investors worldwide. As a result of the Russian-Ukrainian conflict, major global indexes such as the S&P 500 and the Russian MOEX have experienced varying degrees of price declined. However, the average value of the indexes' changes over time indicates that most indexes have moved from down to up in the seven trading days following the conflict.

Throughout history, geopolitical conflicts, such as the wars in Afghanistan and Libya, have impacted international capital markets, mainly in the form of "volatile sentiment, rapid reflection and short duration of impact". The impact is mainly reflected in the "V" shape of asset movements, with generally steep patterns. At the same time, the magnitude of the price fluctuations depends on the strength of the geopolitical impact. The start of war will severely impact the economies of the countries in dispute. However, it is a question worth examining whether the negotiations and news between countries prior to the start of the war have already affected national economic development.

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Recently, the Speaker of the US House of Representatives, Nancy Pelosi, led a House delegation to Taiwan on August 2, 2022, as part of her trip to Asia. While China has always claimed the autonomous democratic island of Taiwan as its territory, the Taiwan issue is a matter of China's national sovereignty and territorial integrity, involves China's core interests, and is the most important and sensitive core issue in US-China relations. At one point, China stated that it would use military forces to recover Taiwan. The US has intensified its efforts to "use Taiwan to control China", pushing the situation in the Taiwan Strait to further tension. Hence, this paper wants to examine whether the news of uncertain geopolitical conflicts between China, the United States and Taiwan and inter-state bargaining will impact the stock in the same way as the occurrence of war. This event study has been carried out in order to draw appropriate statistical inferences.

2. Industry and Stock Selection

Semiconductors are a vital area of national research and development that substantially influences the economic growth of nations worldwide. As globalization of the economy continues, semiconductors fuel advancements in communications, computers, healthcare, military systems, transportation, renewable energy, and numerous other uses. In addition to affecting the actual economy, variations in semiconductor prices can affect financial markets. Research on the return and volatility of the semiconductor market has significant ramifications for investment portfolios, asset pricing, risk management, and other areas. Understanding the return and volatility may facilitate a more sensible allocation of resources. However, excessive volatility and negative return can compromise the interests of all stakeholders and result in financial crises. Accurate modelling and forecasting of the return and volatility of the semiconductor market are essential for the nation's future and for improving people's lives. In order to investigate the influence of geopolitical risk. Hence, this paper chose to examine the impact of Pelosi's visit to Taiwan on the return and volatility of Taiwan Semiconductor Manufacturing Company (TSMC). TSMC is the world's largest professional Interstitial cystitis manufacturing company, offering the industry's most advanced process technology and specialized wafer fabrication services. TSMC is a Taiwanese manufacturer listed on the NYSE in the USA. In contrast to the emerging economic systems of China and the United States, Taiwan's economic system will be more severely affected by the US-China geopolitical conflict. The US and Taiwan are the forces on one side of this event, and China is the force on the other, so TSMC's Taiwanese origin but US-owned corporate background fits well with the theme of this study.

3. Objectives and Scope

This study examines the linear relationship between individual stocks and the market and then compares the difference between actual returns and predicted returns based on this linear relationship before and after the event. This paper set the null hypothesis as "abnormal returns on and around the day of the event are less than or equal to zero". If the null hypothesis is rejected, the study would conclude that geopolitical bargaining between countries can affect the price of individual stocks even without the occurrence of war and vice versa. The implied volatility analysis, similar to the return analysis, focuses on identifying the difference between actual and predicted implied volatility. By indicating the change of direction of the implied volatility allows the paper to conclude the impact of the geopolitical risk on investors' risk preferences.

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4. Data

4.1. Event Window Selection

The event study method requires the identification of the event date, event window, estimation window, and isolation window [1]. This event is divided into two primary periods. The first crucial time point is the US press announcement of Pelosi's planned travel to Taiwan on July 19, 2022, followed by the date of Pelosi's official visit to Taiwan on August 2, 2022. Based on this information, the estimation window spans from January 3, 2022, to June 25, 2022. The estimated window is utilized to determine the linear relationship between TSMC and the market, providing the data necessary to define the normal return. The isolation window spans from June 26, 2022, to July 1, 2022. This isolation window is intended to prevent the affected period from being included in the model calculations. In cases where information is leaked or known before an event, using a period that has already been affected for subsequent empirical testing can lead to inaccuracies in the model. The event window spans from July 2, 2022, and August 10, 2022. The event window is used to quantify the difference between the actual TSMC's return after the event and the forecasted return, which is used to determine the event's impact.

4.2. Return

To calculate the return, this paper used the Bloomberg database to obtain the stock prices of TSMC and the index prices of the S&P 500 for each trading day between January 3, 2022, and August 10, 2022. A benchmark index is required to predict a stock's return in an event study. This paper selected the S&P 500 index as the benchmark since it is an index of 500 publicly traded U.S. firms with large sample size, high representativeness, precision, and consistency. Although TSMC's manufacturer is situated in Taiwan, it is a US-owned corporation; thus, the S&P 500 index is the best suitable indicator for predicting the future share price of TSMC.

4.3. Implied Volatility

This paper used the Bloomberg database to obtain a single call option with the highest trading volumes of TSMC for the period of May 19, 2022, to August 9, 2022, to calculate the market implied volatility. This paper has applied the criterion that the option must have at least 40 days to expire since De Jong et al. (1992) observe a modest decrease in volatility near expiration dates. To minimize this effect, this paper excludes calls with extremely short maturities. The data is also used to calculate the model implied volatility on the Heston model in the part of the event study on implied volatility.

5. Estimation Procedure

5.1. Return

5.1.1. OLS Model

Above all, the procedure first needs to estimate the daily returns of the estimation window. This paper selected the OLS (ordinary linear regression) model for calculating the normal returns as the model has higher accuracy and potential of returning better results [2]. The normal return, R_t, is calculated as:

$$R_t = \alpha + \beta R_{mt} + \varepsilon_t,\ var(\varepsilon_t) = \sigma^2 \tag{1}$$

Where

α and β are the intercepts and slope coefficients of this model.

R_{mt} is the rate of return on the benchmark index (S&P 500) on day t.

ε_t is the standard deviation of the abnormal returns (absolute value of result by the predicted R_t by regression abstracting actual R_t during the event window).

The alpha and beta coefficients are calculated with the stock data available for the 130 trading days from January 3, 2022, to June 25, 2022.

5.1.2. Calculating the Abnormal Returns

For conducting the event study, the daily abnormal returns should be calculated [1]. Since the actual returns for the TMSC and S&P 500 index have already computed, the return data are then used with the OLS model to obtain the α and β in terms of the daily indices of TMSC's returns and the benchmark returns:

$$\alpha + \beta R_{mt}, t \in \varepsilon \tag{2}$$

After this, the calculation used the coefficients got from the estimation window to estimate the predicted TSMC's returns in the event window in terms of the S&P 500's returns, and defined abnormal returns by means of the following formula:

$$AR_t = R_t - ER_t \tag{3}$$

$$AR_t = R_t(\beta + R_{mt}), t = 1, \ldots, E \; for \; t \in \varepsilon \tag{4}$$

Where

AR_t is the abnormal return on index i on day t.

R_t is the actual return on index i on day t.

ER_t is the expected or normal return on the index i on day t.

Moreover, for the event study to be successfully carried out, the abnormal returns should satisfy a normal distribution with mean of 0 and standard deviation of σ^2.

$$AR_t = \varepsilon_t \sim N(0, \sigma^2), t = 1, \ldots, E \tag{5}$$

5.1.3. Calculating the Cumulative Abnormal Returns (CAR)

To test the null hypothesis, the cumulative abnormal returns is needed. The CAR adding up all of the abnormal returns from all of the indices and divided by number of days in the event window, and the formula for each t is shown as below:

$$CAR(t) = \sum_{s=1}^{t} AR_s = \sum_{s=1}^{t} \varepsilon_s \sim N(0, t\sigma^2) \tag{6}$$

And calculated the ultimate value of CAR with:

$$CAR(t) = \frac{1}{n} \sum_{i=1}^{n} CAR(t) \tag{7}$$

Where

ε is the standard deviation of the abnormal returns.

n is the number of indices.

5.1.4. Test the Null Hypothesis with the CAR Value by T-test

Finally, the value of CAR is used to test the hypothesis by t-test [3] (confidence interval):

$$\frac{CAR}{\sqrt{T * \sigma^2}} \sim N(0,1) \tag{8}$$

$$-Z_{\frac{\alpha}{2}} \times \sqrt{T \times \sigma^2} < CAR < Z_{\frac{\alpha}{2}} \times \sqrt{T \times \sigma^2} \tag{9}$$

Where

T is the number of days during the event window.

$\boldsymbol{\sigma^2}$ is the sum of total daily variance.

$Z_{\frac{\alpha}{2}}$ is the $\frac{\alpha}{2}$ quantile of the normal distribution of the confidence level α.

After obtaining this value, this paper can determine if the null hypothesis can be rejected or not by observing if this value is within the range. This paper cannot reject the null hypothesis if this value lies between this range. On the contrary, rejecting the hypothesis means that the event indeed has an impact on the company's returns by means of the regression with the S&P 500 market returns.

5.2. Implied Volatility

The stock's implied volatility in the event window is predicted using the Heston model [4]. This model is a type of stochastic volatility model used to price European options. The Heston model has five independent parameters, all of which may be obtained by calibrating the different strike prices and/or the observed market prices of European options at expiration.

Denote $C(S_i, K_i, T_i, r_i)$ to be the market price of a call option with stock price $S_0 = S_i$, strike price $K = K_i$, time to maturity $T = T_i$, and risk free rate $r = r_i$. Calibration to historical data intends to find $\boldsymbol{\Theta}^* = (\boldsymbol{v_0^*}, \boldsymbol{k}^*, \boldsymbol{\theta}^*, \boldsymbol{\sigma}^*, \boldsymbol{\beta}^*)$ which satisfies:

$$\Theta^* = argmin\Theta \sum_{i=1}^{N} (C(S_i, K_i, T_i, r_i) - C^{\Theta}(S_i, K_i, T_i, r_i))^2 \tag{10}$$

where $C^{\Theta}(S_i, K_i, T_i, r_i)$ is the model price of a call option with parameter Θ under the Heston model. After determining the five independent parameters, they can be used to predict the implied volatility of the event window and compare them with the actual market implied volatility, from which indicating whether the event has an impact on the implied volatility of TSMC.

5.2.1. Heston Model

The price of the underlying asset follows a typical lognormal distribution, whereas the variance V follows a mean-reverting square root distribution [4].

$$dS_t = \mu S_t dt + \sqrt{v_t} S dW_t^{(1)} \tag{11}$$

$$dv_t = k(\theta - v_t)dt + \sigma\sqrt{v_t} dW_t^{(2)} \tag{12}$$

$$dW_t^{(1)} W_t^{(2)} = \rho dt \tag{13}$$

$$v_t \; is \; strictly \; positive \; if:$$

$$2k\theta > \delta^2 \tag{14}$$

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where the five independent parameters are:

v_0, the initial variance.

θ, the long-run average variance of the price, the expected value of v_t tends to θ as t tends to infinity.

ρ, the correlation of the two Brownian motions.

k, the rate at which v_t reverts to θ.

σ, the volatility of the implied volatility, which determines the variance of v_t.

Based on these assumptions, the European call option's price is hence:

$$C(S,t) = S_t e^{-q(T-t)} P1 - K e^{-t(T-t)} P2 \tag{15}$$

The price of the European put option using the put-call parity attribute is [5]:

$$P(S,t) = C(S,t) + K e^{-rT} - S_0 e^{-qT} \tag{16}$$

Where r is the interest rate, q is the dividend yield, the p_1 and p_2 are risk neutral probabilities obtained by characteristic function f_j.

$$\mathrm{P}_j = \frac{1}{2} + \frac{1}{\pi}\int_0^{\infty} Re\left[\frac{e^{-i\phi ln(K)f_j}}{i\phi}\right] d\phi \tag{17}$$

Where

$$f_j = exp(C_j + D_j v_t + i\phi ln S_t)$$

$$C_j = (r-q)\phi i(T-t) + \frac{k\phi}{\sigma^2}\left[(b_j - \rho\sigma\phi i + d_j)(T-t) - 2ln(\frac{1-g_j e^{d_j(T-t)}}{1-g_j})\right]$$

$$D_j = \frac{b_j - \rho\sigma\phi i + d_j}{\sigma^2}(\frac{1-e^{dj(T-t)}}{1-g_j e^{d_j(T-t)}})$$

$$g_j = \frac{b_j - \rho\sigma\phi i + d_j}{b_j - \rho\sigma\phi i - d_j}$$

$$d_j = \sqrt{(\rho\sigma\phi i)^2 - \sigma^2(2u_j\phi_i - \phi^2)}$$

The parameter i is the imaginary unit and $u_1 = \frac{1}{2}, u_2 = -\frac{1}{2}, b_1 = k + \lambda - \rho\sigma, b_2 = k + \lambda$. The parameter λ refers to the market value of the risk of volatility. In a risk neutral world, the value of $\lambda = 0$.

Under many circumstances, Monte-Carlo simulation is used to calculate the price of European options under a dynamic model. However, Monte-Carlo simulation has the disadvantage of high error and slow speed. Hence, this paper wants to use a closed form formula to calculate the threotical options price. However, the integral in the formula P_j is an anomalous integral because its upper limit is positive infinity. Hence, there will always be errors for any chosen bounds when using the numerical method to calculate the output. Therefore, this paper will need to identify a bound such that the error of the solution is within the 95% confidence interval of Monte-Carlo, ensuring the accuracy of the following calculation.

5.2.2. Monte-Carlo Simulation

The Monte-Carlo simulation assigns a random value to the variable whose value is uncertain. The model is then executed, and the outcome is delivered. This procedure is done several times while numerous values are assigned to the variable involved. Upon completion of the simulation, the results are averaged to get an estimate. Then, the Monte-Carlo's price is used to compute the option prices under event windows.

Steps to simulate two correlated Brownian motions of $W_1,\ W_2$[6]:

1.Produce a set of $2 \times k$ matrix of independent normal random numbers called N^i.

2.Use Cholesky decomposition to covariance matrix Σ to get matrix L. Note, the matrix Σ is $\begin{pmatrix} 1 & p \\ p & 1 \end{pmatrix}$ without t.

3. $E^i = L \times N^i$.${W_1}^k{}_{(i+1)\delta t} = {W_1}^k{}_{i\delta t} + \sqrt{\delta_t}\ {E^i}_{1k}$, ${W_2}^k{}_{(i+1)\delta t}$=${W_2}^k{}_{i\delta t}$+$\sqrt{\delta_t}{E^i}_{2k}$.

The ${W_1}^k{}_{(i+1)\delta t}$ means the value of W_1 at time point $(i\ +1)\delta t$ in the kth ${E^i}_{1k}$. ${E^i}_{1k}$ represents the element in the first row, the kth column of the matrix E^i.

After simulating two correlated Brownian motions, the Euler method is used to simulate stock routes according to the Heston model [7].

$$v_{(i+1)\delta t} = v_{i\delta t} + k(\theta - v_{i\delta t})\delta_t + \sigma\sqrt{v_{i\delta t}}({W_2}^Q(i+1)\delta_t - {W_2}^Q{}_{i\delta t}) \tag{18}$$

$$S_{(i+1)\delta t} = S_{i\delta t} + (rS_{i\delta t})\delta_t + \sqrt{v_{i\delta t}}S_{i\delta t}({W_1}^Q(i+1)\delta_t - {W_1}^Q{}_{i\delta t}) \tag{19}$$

Hence, the Monte-Carlo price is:

$$V(S_0, 0) = {E_t}^Q(e^{-rT}f(S_T)) \tag{20}$$

The Heston model is a dynamic model and utilizing a dynamic model to anticipate a lengthy time will certainly present an erroneous result, and this error cannot be determined whether it is due to the event or the model itself. Hence, this paper calibrates the whole period but only use estimated window data to calculate the error between the model implied volatility and market implied volatility. Assuming this error follows a Gaussian distribution, computing its standard deviation, as this paper did in the section on return analysis.

5.2.3. Black-Scholes Model

Monte-Carlo simulation is used to calculate the theoretical call option price and this price is compared to the price calculated by Heston's closed formula. Once we have checked the accuracy of this formula, it is used to calibrate parameter Θ^* . We then are able to use Black-Scholes formula to inverse solve the model implied volatility under the event window and compare it with the market implied volatility to identify the impact of the event [8].

The model implied volatility is the root of the following equations:

$$C(S_i, K_i, T_i, r_i, \sigma_{K,T}) = C^{\Theta^*}(S_i, K_i, T_i, r_i) \tag{21}$$

where $C^{\Theta^*}(S_i, K_i, T_i, r_i)$ is the option price with strike K_i and maturity T_i under Heston model, and $C(S, K, T, r, \sigma_{K,T})$ is the Black-Scholes formula for the European option. Under the black-scholes model, it defines $C(S, K, T, r, \sigma)$ to be the price of the European call option. So, by definition:

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$$C(S\,,K\,,T\,,r\,,\sigma) = SN(d1) + e^{-rT}KN(d2) \tag{22}$$

where

$$d1 = \frac{1}{\sigma\sqrt{T}}(log(S/k) + (k + \frac{1}{2}\sigma^2)T) \tag{23}$$

and

$$d2 = \frac{1}{\sigma\sqrt{T}}(log(S/k) + (k + \frac{1}{2}\sigma^2)T) \tag{24}$$

Hence, the estimated implied volatilities $\sigma_{K,T}$ can be computed through the following equation:

$$C(S, K, T, r, \sigma_{K,T}) - C^{\Theta}(S_i\,, K_i\,, T_i\,, r_i) = 0 \tag{25}$$

5.2.4. Calculating Cumulative Abnormal Implied Volatility (CAIV) and Test

This paper then use the predicted implied volatilities to compare with the market implied volatilities to compute the abnormal implied volatilities which is calculated as:

$$AIV_t = IV_t \; - \; EIV_t \tag{26}$$

Where
AIV_t is the abnormal implied volatility on index i on day t.
IV_t is the market implied volatility on index i on day t.
EIV_t is the predicted implied volatility on the index i on day t.
Moreover, for the event study to be successfully carried out, the abnormal implied volatility should satisfy a normal distribution with mean 0.

$$AIV_t = \varepsilon_t \sim N(0, \sigma^2), t = 1, \ldots, E \tag{27}$$

To test the null hypothesis, the cumulative abnormal implied volatilities (CAIV) need to calculate out by adding up all the abnormal implied volatilities from all the indices and divided by number of days in the event window, and the formula for each t is shown as below:

$$CAIV(t) = \sum_{s=1}^{t} AIV_s = \sum_{s=1}^{t} \varepsilon_s \sim N(0, t\sigma^2) \tag{28}$$

And calculated the ultimate value of CAIV with:

$$CAIV(t) = \frac{1}{n}\sum_{i=1}^{n} CAIV_i(t) \tag{29}$$

Where
ε is the standard deviation of the abnormal implied volatilities.
n is the number of indices.
Finally, the CAIV value is used to test the hypothesis by t-test (confidence interval):

$$\frac{CAIV}{\sqrt{T * \sigma^2}} \sim N(0,1) \tag{30}$$

$$-Z_{\frac{\alpha}{2}} \times \sqrt{T \times \sigma^2} < CAIV < Z_{\frac{\alpha}{2}} \times \sqrt{T \times \sigma^2} \tag{31}$$

Where
T is the number of days during the event window.
σ^2 is the sum of total daily variance.

$Z_{\frac{\alpha}{2}}$ is the $\frac{\alpha}{2}$ quantile of the normal distribution of the confidence level α.

After obtaining this value, this paper can determine if the null hypothesis can be rejected or not. If the hypothesis can be rejected which means that the event indeed has an impact on the TSMC's implied volatility.

6. Test and Interpretation of Results

6.1. Return

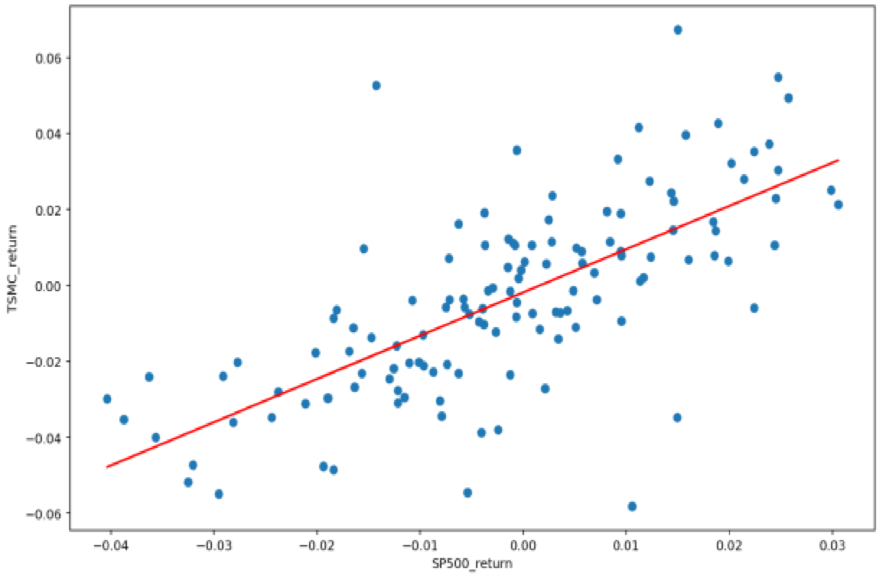

Figure 1: Return regression on TSMC and S&P 500. [Owner-draw]

First, the relationship between the market's and TSMC's return rates is tested. This paper used the OLS (ordinary least squares) model and linear regression model to test the stock data from the estimation window (1.3.2022~6.24.2022). Figure 1 shows that there is a positive correlation. The slope is approximately 1.138, and the r-square is approximately 0.50, indicating that the return rates have a strong positive correlation (shown in the graph above). Most of the TSMC's return rates can be predicted in terms of S&P 500 data. Moreover, the calculation has the p-value that is less than 0.0001 (<0.01), with which the null hypothesis can be rejected that there is no relationship between the return rates of TSMC and the S&P 500 market.

Based on this strong positive correlation between the company's and the market's returns, the error term is then analysed. This paper obtained the error terms by subtracting the actual values of the TSMC returns from the predicted ones from the S&P 500 returns in the estimation window. Nonetheless, to put the error terms in use, they need to be tested if they fit a normal distribution. This paper adopted a normal test and got the statistic of approximately 13.810 and a P-value of 0.001, which is less than 0.01, indicating that the null hypothesis can be rejected that there is normality in the distribution of the error terms. However, by looking at the test graphically and simplifying the pattern, the normality test diagram reflects an approximate normal distribution shape which is shown below:

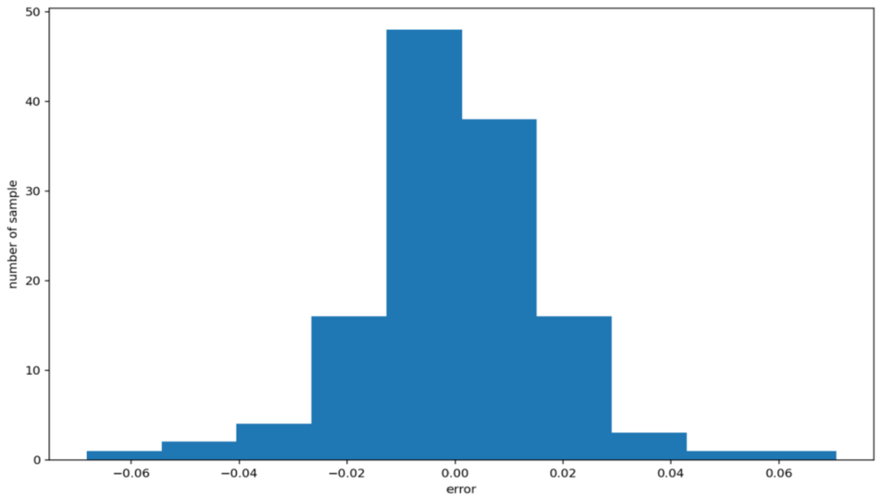

Figure 2: Error normality test diagram. [Owner-draw]

Hence, the error term can be used as it fits an approximate normal distribution as shown in figure 2. With the values of abnormal returns, the values of their standard deviation (sigma) are obtained. Furthermore, the CAR's value is obtained by summing up the abnormal returns and dividing them by N (number of event days). This paper applied a t-test to test the hypothesis. This paper set an upper- and lower bond employing a 95% confidence interval. If the CAR curve goes beyond these two bonds, the null hypothesis can be rejected. By running out the results, the following graph is generated:

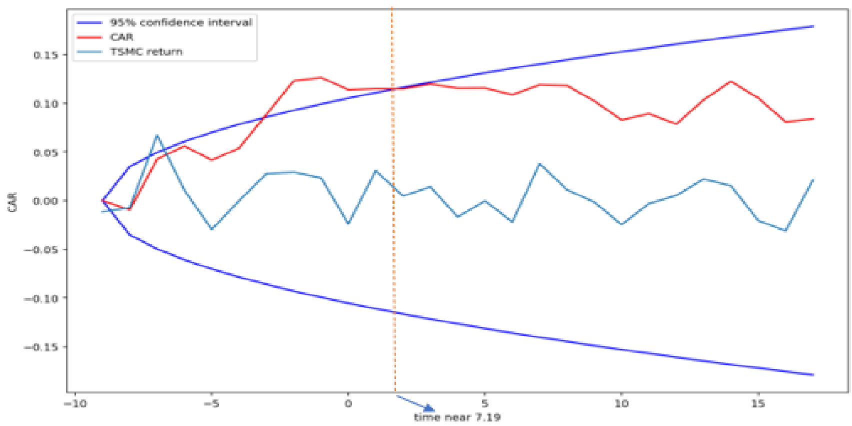

Figure 3: CAR confidence interval test. [Owner-draw]

However, the CAR value goes beyond the confidence interval before the date when the message of Pelosi’s visit was officially released (2022.07.19) as shown in figure 3. This is interesting because this paper assumed that the CAR curve would go beyond the confidence intervals after July 19, 2022, which indicates that this event poses an insignificant impact on TSMC’s returns or no changes occur before and after July 19, 2022.However, the actual result indicate that the event poses some impacts on TSMC’s returns before the event begins (2022.07.19).

One way to explain this phenomenon is that the market is not an efficient market, which means that the majority of the investors had already known that this event would happen later through other channels (not officially or publicly), so they reacted to this event much earlier than this event happened publicly. As a result, this can explain why the null hypothesis can be rejected (the event does not have influences on the returns of TSMC) before the date 7.19 but not after that.

6.2. Volatility

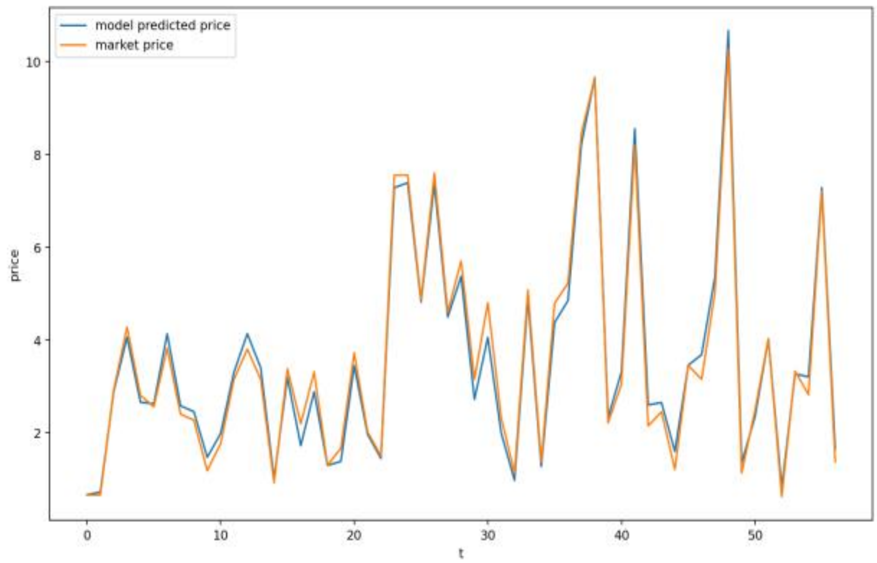

Figure 4: Comparing model predicted price and actual market price. [Owner-draw]

After applying the Heston model and performing the calibration, we determined the fixed parameters of its five independent variables and by plugging these numbers into Heston's formula, we can obtain the theoretical prices of this option. Figure 4 shows, under the calibrated parameters, the model prices fit well with the actual market price. Hence, the model can be used to compute the model implied volatility.

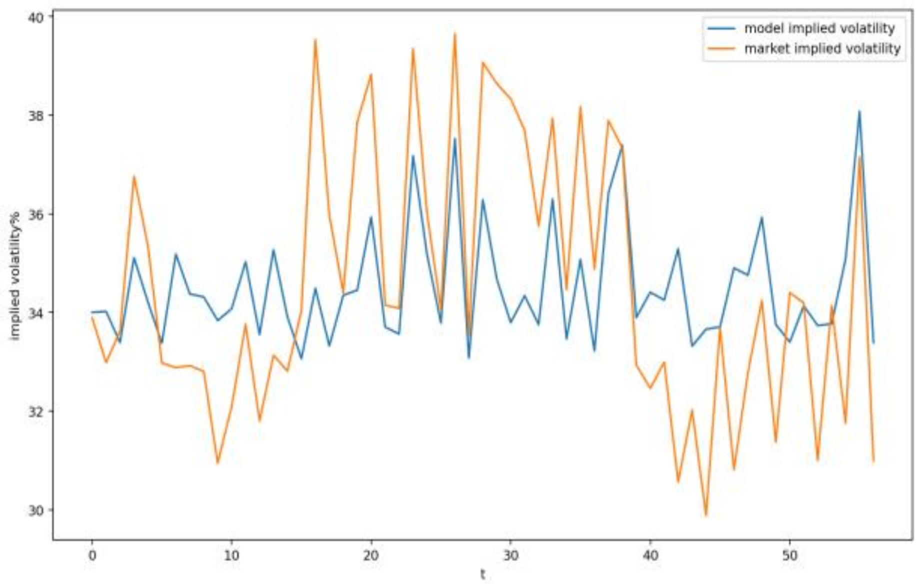

Figure 5: Comparing model implied volatility and market implied volatility. [Owner-draw]

Figure 5 indicates that the model implied volatility in comparison to the market implied volatility. There are differences between the predicted and the actual implied volatility. Therefore, the cumulative abnormal implied volatilities are then calculated and test whether the abnormal is significant.

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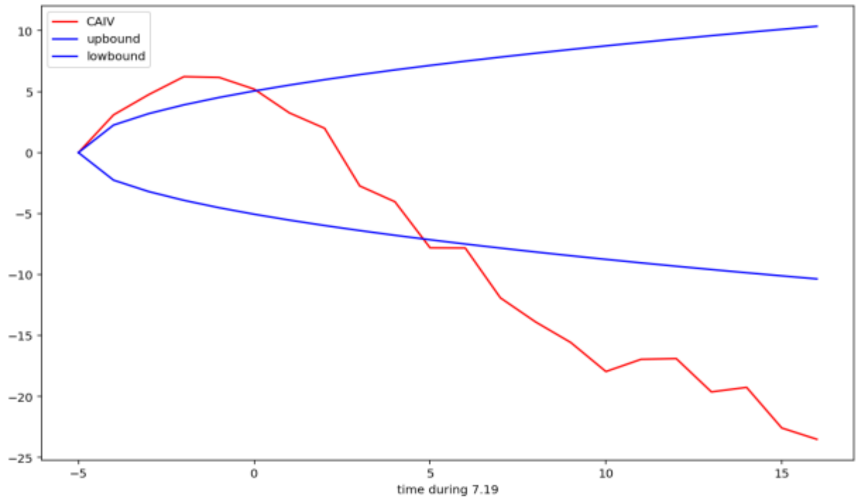

Figure 6: CAIV confidence interval test for time period around 19 July, 2022. [Owner-draw]

The CAIV surpassed the confidence interval at the time of the news release of this event (2022.7.19) as shown in figure 6. It means that the geopolitical news release influences TSMC's implied volatility. Moreover, the implied volatilities exceed the upper bound of the confidence interval, suggesting that individuals will have more significant risk assessments for the future prior to the occurrence of an uncertain event and that the implied volatility will expand.

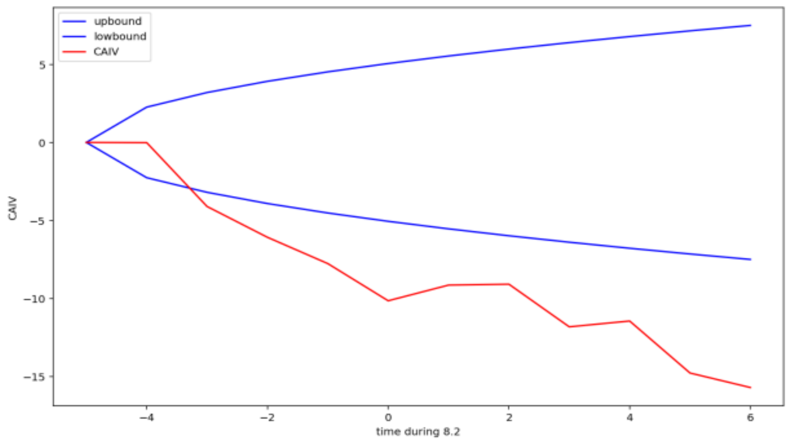

Figure 7: CAIV confidence interval test for time period around 2 August 2022. [Owner-draw]

On the other hand, figure 7 reveals that the CAIV is also outside the confidence interval around the time of Pelosi's formal appearance (2022.08.02), suggesting that real event activity has impacted on TSMC's implied volatilities. However, the fact that the occurrence of an actual event is what causes IV to go below the lower bond of the confidence interval implies that individuals will lower their risk estimations for a particular occurrence, resulting in a decline in implied volatilities.

7. Conclusion

Based on our findings, this paper concluded that news of uncertain geopolitical conflicts between China, the United States and Taiwan and inter-state bargaining does not have the same impact on the stock market as the occurrence of war. The return of TSMC has shown to be abnormal before the two important dates which means this geopolitical event does not affect the TSMC’s return. However, in

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terms of the implied volatility, this paper found that the abnormal implied volatilities on both important dates are significant. It indicates that investors will have greater risk assessments for an uncertain event and vice versa. However, this paper only focuses on the impact of the one specific geopolitical event on a single selected stock. Although TSMC can be a representative for the semiconductor manufacturing industry, this paper can only suggest that such geopolitical conflicts will only affect TSMC's implied volatilities but not the other companies. In order to identify whether the non-war geopolitical event has an impact on the countries' economy or a specific industry, more research are needed to be carried out.

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Hao Lin and Ziwei Zhang contributed equally to this work and should be considered co-first authors.

References

- [1] *S. P Khotari , Jerold B. (Ch. 1, 2006) Warner. Econometrics of Event Studies.*
- [2] *Alexander L. Burton. (2021) OLS(Linear) Regression. Print ISBN: 9781119110729.*
- [3] *Adam Massey, Steven J. Miller. (2021) Tests of Hypotheses Using Statistics. Providence, RI 02912.*
- [4] *Steven L. Heston. A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options. The Review of Financial Studies Vol. 6, No. 2 (1993), pp. 327-343 Published By: Oxford University Press.*
- [5] *John C. Hull. (2009) Options, Futures, And Other Derivatives (NINTH EDITION). Printer/Binder: Courier Kendallville.*
- [6] *Burgess, Nicholas, Correlated Monte Carlo Simulation using Cholesky Decomposition (March 25, 2022). Available at SSRN: https://ssrn.com/abstract=4066115.*
- [7] *Kloeden, P.E. & Platen, E. (1992). Numerical Solution of Stochastic Differential Equations. Springer, Berlin. ISBN 3-540-54062-8.*
- [8] *Black, F. and Scholes, M. (1973) The Pricing of Options and Corporate Liabilities.*