

Financial Market Reactions under the Russia-Ukraine Conflict

—An Empirical Study Based on a Multi-factor Model

Lefei Hong¹, Yonghao Li², Ran Tao^{3,a,*}

¹*Fuzhou University of International Studies and Trade, Fuzhou, China*

²*Guangdong University of Technology, Guangzhou, China*

³*SKEMA Business School, Finance*

a. ranl.tao@skema.edu

**corresponding author*

Abstract: This paper takes advantage of the turbulent situation in eastern Ukraine to study and examine the correlation between war conflicts and stock yields, and to study the impact on the stock returns of A-share listed companies in China. The background of this article is that with the Russian Ministry of Defense announcing the withdrawal of troops stationed on the border between Russia and Ukraine, the crisis situation in eastern Ukraine has been cooling since October 2021, until February 2022, when Ukraine announced in civilian forces that it would evacuate the local population to Russia on the same day, while the situation in eastern Ukraine deteriorated, the local government banned foreign aircraft from entering the country, and declared Ukraine a state of war. This article constructs an index factor that measures the degree of war through the cryptocurrency market price fluctuation index and the cryptocurrency market price fluctuation index. In addition, a new war impact index factor is added to the basic three-factor model, and the explanatory performance of the new multi-factor model for the stock yield of listed companies is more in-depth and whether it is more explanatory than the three-factor model. The study will test whether the Russian-Ukrainian conflict will significantly affect equity returns in China's A-share market. Helps investors better describe the expected returns of a cross-sectional stock portfolio.

Keywords: Russia-Ukraine conflict, war intensity factor, four-factor model

1. Background

Existing research on the impact of the Russian-Ukrainian conflict on financial markets has found that the impact of the Russian-Ukrainian conflict on financial markets is multidimensional [1] and that this impact includes influencing investor sentiment and beliefs as well as causing price volatility in important crude oil futures [2]. Although existing research tends to suggest that financial markets can respond to unpredictable war shocks, there is no answer in the literature to the question of how individual markets react to shocks and, in particular, whether the impact of war on financial markets, futures markets and cryptocurrency markets can be quantified. In [3]. This paper examines the impact

of the war between Russia and Ukraine on the major stock markets, but not from the perspective of the basic three-factor model.

Firstly, the war differs from previous catastrophic events such as earthquakes and air crashes, and its impact on financial markets is worth studying in depth. Secondly, the impact of this event is widespread. Whether the most basic securities market, the more complex cryptocurrency market, or the futures market, this paper explores how to construct a new four-factor model to quantify the impact of the Russia-Ukraine conflict on the world financial markets.

This paper has used literature, comparative, quantitative, and other research methods. The literature analysis method [5] provides more insight into the basic three-factor model's development, application, and extension. The FAMA-FRENCH three-factor model divides the portfolio into different portfolios in the comparative analysis method. Then this paper compares and analyses the portfolio returns in different situations. The war intensity factor is selected and analyzed using principal component analysis in the quantitative analysis. The principal components are an index of crude oil market prices and Cryptocurrency market prices.

The final result of this paper is that, through the final factor construction and model composition and the GRS test, this paper has confirmed that this paper's newly constructed four-factor model has more substantial explanatory power for the cross-sectional returns of this paper's chosen time window of 2021.9-2022.8 compared to the original underlying three-factor model and that this paper also has considerable research implications for other anomalous applicable factor models or the establishment of new four-factor models.

2. Data

All A-share data from September 2021 to August 2022 is used to calculate daily returns as a weighted average of the market capitalization of all A-shares, all from the WIND database. In this paper, the market price data of crude oil and digital currencies from September 2021 to August 2022 are selected as the sample for the study. The price index of the digital currency, the price index of crude oil is obtained based on two aspects: the partial crude oil price return and the panic index, and finally the degree of war factor is constructed by grouping the daily log returns of the digital currency market and the log-returns of the crude oil market price in a bivariate ranking.

3. Introduction to the Model Construction

This paper first constructs a three-factor model based on the market factor R_{mt} - R_{ft} , the size factor SMB_t and the book-to-market ratio factor HML_t . For the market factor, where the market capitalization factor is calculated by the total market capitalization of listed companies, the risk-free yield is selected by using the 1-year treasury yield as the data, and the book-to-market ratio is calculated based on the net assets and total market capitalization in the balance sheet. As the financial reports are disclosed quarterly, this paper processes the OIT data based on the disclosure date. In this paper, this paper will use the calculation method of logarithmic return:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}} - 1\right) \quad (1)$$

to obtain the daily excess return of the stock market portfolio, then by splitting the stocks of the exchange into two categories, small scale S and large scale B (the first 50% are group B and the last 50% are group S in descending order of market capitalization), followed by three groups based on the book-to-market ratio of the sample stocks in descending order (the first 30% are The second group was divided into three groups (the first 30% is high, the middle 40% is the medium (M) and the bottom 30% is the low (L)) based on the book-to-market ratio of the stocks in the sample, and the

previous two size groups to form six portfolios (SH, SM, SL, BH, BM, BL) to observe the return of the three small size portfolios (SH, SM, SL) compared to the return of the three large size portfolios (BH, SL).

$$SMB_t = \frac{SH_t + SM_t + SL_t - BH_t - BM_t - BL_t}{3} \quad (2)$$

The difference between the returns of the two high book-to-market portfolios (SH, BH) and the two low book-to-market portfolios (SL, BL) (to investigate the different return behavior of large and small-cap stocks) is observed by grouping the high and low book-to-market and size portfolios into four portfolios:

$$HML_t = \frac{SH_t + BH_t - SL_t - BL_t}{2} \quad (3)$$

This paper uses the above approach to construct the underlying three-factor model (Table 1).

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + S_i SMB_t + h_i HML_t + e_{it} \quad (4)$$

Table 1: One-year daily returns for the basic three factors.

	Date	Mkt.daily.ret	SMB	HML
0	2021-08-02	0.000000	0.000000	0.000000
1	2021-08-03	-0.004146	0.002663	0.003631
2	2021-08-04	0.013514	-0.003690	-0.018729
.....	
261	2022-08-29	0.002031	0.008213	-0.000452
262	2022-08-30	-0.003450	0.001732	0.005082
263	2022-08-31	-0.011608	-0.016885	0.007337

3.1. Construction of Indicators

The study in this paper selects a crude oil price market volatility index combined with a cryptocurrency market change index as the battle intensity index. It constructs a multi-factor model based on the original three-factor model. For crude oil market prices, data from September 2021 to August 2022 were selected to analyze the liquidity impact of crude oil through the following financial attributes of crude oil: USD-based - risk appetite - liquidity. Panic Index (VIX) (Volatility Index) for risk appetite analysis: Oil prices are significantly more risky assets and less stable than equity indices and copper prices. This article uses 20 as the VIX cut-off point to measure investor panic about the overall market. **Figure 1** below shows the weekly closing price of the Chicago Board Options Exchange Volatility Index from September 2021 to August 2022 as a log-return benchmark analysis of the daily settlement price of INE crude oil.

Fig.1: It can be seen that the VIX index was highly volatile during this period, when investors lacked confidence in the crude oil market for most of the Russian-Ukrainian war, and can also side-step the fact that the volatility of crude oil prices during this war can significantly affect equity returns in the Chinese A-share market.

Secondly, for the construction of the crude oil model, a new regression equation with a β term associated with the crude oil price market volatility index and individual stock returns was finally derived by first performing a log-return calculation on the crude oil market price volatility index:

$$E(R) = R_f + \beta_1 * WNIT \quad (5)$$

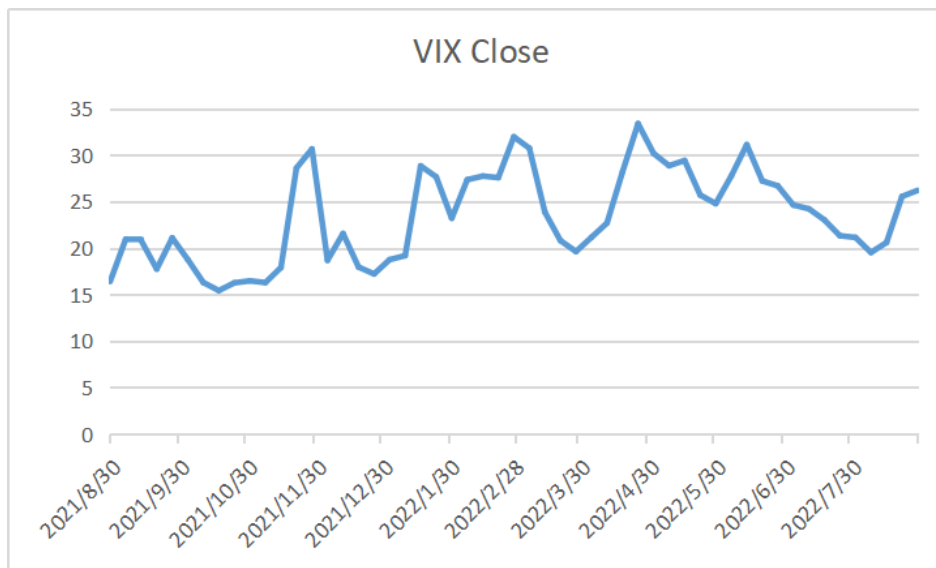


Figure 1: Panic Index VIX Line chart by period change over a year.

Fig. 2.: The daily return is obtained from the oil price and subtracted from the risk-free return to obtain the excess return. The daily excess return for each stock is used as the LHS, and a rolling 20-day regression is performed to obtain the factor exposure of the stock to the oil market.

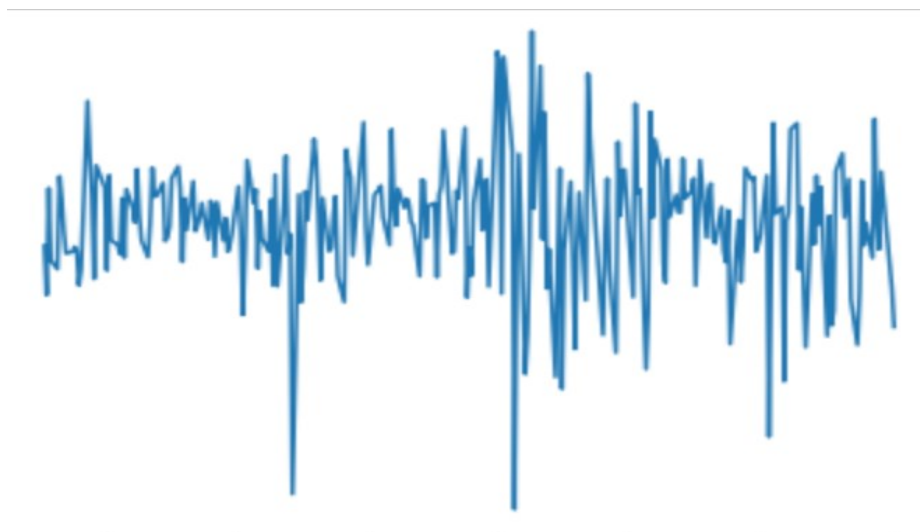


Figure 2: A chart of the daily rate of return of each stock in the factor exposure of the oil price.

For the construction of the Cryptocurrency market price volatility index, this paper still selects the window from September 2021 to August 2022, through the three mainstream currencies (BTC, ETH, XRP), from market capitalization, turnover, and liquidity to observe the data, to obtain a sufficient number of continuous data series, this paper chooses the daily return index and carries out the calculation of logarithmic return, and finally arrives at the new regression equation with β term related to the digital currency market price volatility index and individual stock returns:

$$E(R) = R_f + \beta_2 * CRYPTO \quad (6)$$

The Cryptocurrency index is weighted by averaging the daily returns of the three currencies to obtain the daily monthly returns of the money market. Regression is performed in the same way to obtain the factor exposure of each stock in the digital currency market.

Fig. 3.: is a line graph of the logarithmic return on the price of the digital currency market. (The data is still for September 2021 Road September 2022)

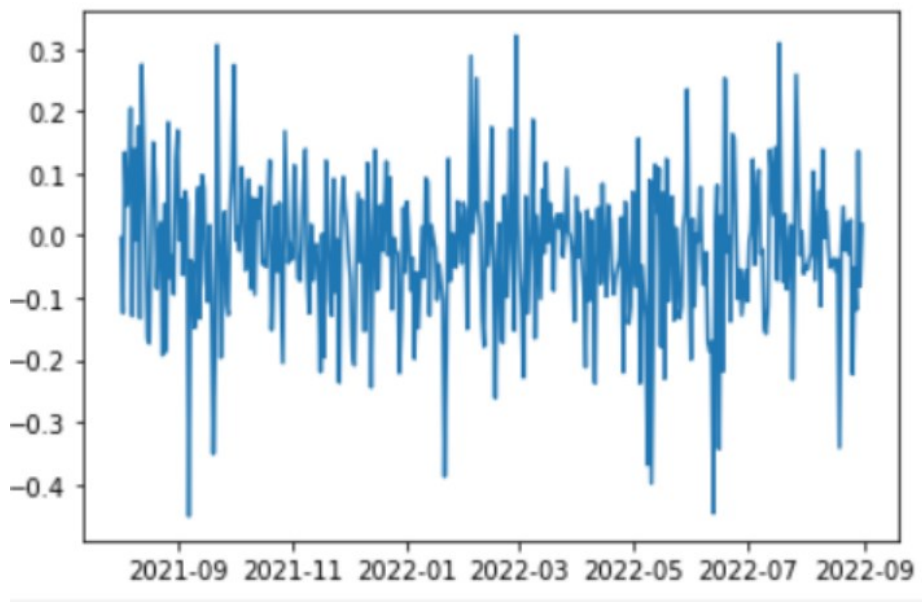


Figure 3: A chart of the daily rate of return of each stock in the factor exposure of the Cryptocurrency market.

3.2. Combination of Indicators - Four-Factor Model

In this paper, it is hypothesized that the war factor consisting of the beta of the crude oil market price volatility index and the beta of the digital currency market price volatility index will directly affect the movement of stock market returns.

This paragraph describes how the indicators are combined to form the final four-factor model, starting with a first regression using the previous time series approach to obtain two sets of β s for two different financial markets. The two groups of β in two markets were grouped into four groups: " β_{11} (high)", " β_{12} (low)", " β_{21} (high)," and " β_{22} " (low), which were then combined to obtain: " $\beta_{11} \beta_{21}$ " (the group with higher sensitivity in both markets), " $\beta_{11} \beta_{22}$ " and " $\beta_{12} \beta_{21}$ ", " $\beta_{12} \beta_{22}$ ", and then applying " $\beta_{11} \beta_{21}$ " (the group where the sensitivity of both β is in this group is more significant in equities) minus " $\beta_{12} \beta_{22}$ " (the group with both β sensitivities being relatively low in the stock) to obtain the war extent factor (WARt) for this study, and then adding the war impact factor (WARt) to the original three-factor model to obtain the new four-factor model:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + S_i SMB_t + h_i HMI_t + c_i WAR_t + e_{it} \quad (7)$$

Following the above approach, this paper further corroborates that the WAR factor is a suitable factor.

Fig. 4, Daily returns of the War factor were obtained and this paper compared them with the market returns:

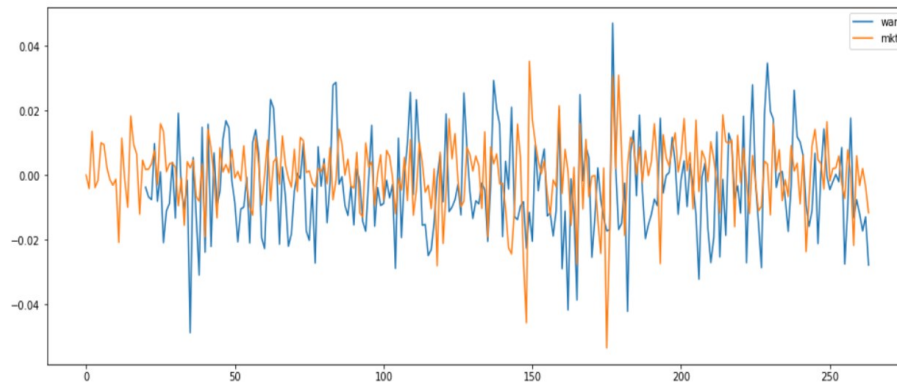


Figure 4: War Factor Daily Returns vs Market Returns.

The results are shown in Table 2. The constant term alpha is tested to see if it is significant and if it is significant, it means that the WAR factor has a cross-sectional return difference that is not explained by the FF three factors. The t-value of the constant term is found to be 4.636 and greater than 2. The constant term is then said to be significant, proving that the factor is valid and suitable as an additional pricing factor to form a multi-factor pricing model.

Table 2: Regression models for constant term tests.

OLS Regression Results			
Dep. variable:	Ret-war	R-squared:	0.088
Model:	OLS	Adj.R-squared:	0.077
Method:	Least Squares	F-statistic:	7.729
Date	Tue,04 Oct2022	Prob(F-statistic)	5.99e-05
Time:	21:40:45	Log-Likelihood	691.72
No.Obser.:	244	AIC:	-1375.
Df Residuals:	240	BIC:	-1361
Df Model:	3		
Covariance Type:	nonrobust		
	coef	stderr	t
const	0.0043	0.001	4.636
Mtk.daily.ret	-0.2172	0.086	-2.511
smb	0.0243	0.101	-0.240
hml	0.3097	0.095	3.277
Omnibus:	1.308	Durbin-Watson	1.782
Skew:	-0.153	Prob (JB):	0.586
Kurtosis	3.1-5	Cond.No.	119

4. Test Methodology

If the model can fully explain the portfolio, then the asset pricing model developed in this study can be considered valid if the hypothesis that the intercept is simultaneously equal to zero cannot be rejected in a joint test of the total intercept.

The reason for using the GRS test in this paper, as in FF1996, is precisely because it allows us to test whether the intercept term of multiple linear regressions is 0 at the same time, i.e. the original hypothesis: $H_0: \alpha_1 = \alpha_2 = \dots = \alpha_n$ and ultimately equal to 0. The GRS statistic is expressed as follows.

$$GRS\ statistic = \frac{T}{N} \times \frac{T - N - L}{T - L - 1} \times \frac{\alpha' \epsilon^{-1} \alpha}{1 + \mu' \Omega^{-1} \mu} \quad (8)$$

However, at that time, Fama & French looked at the p-values, comparing them to the significance level. FF (1996) conclude that there is a significant difference and thus they reject the original hypothesis. This implies that there are other factors that have a significant impact on the return on assets. In their 2015 paper, Fama & French added two other new factors. However, the GRS test of the new model still shows that the five-factor model does not perfectly explain the variation in asset returns.

The GRS methodology used in this paper is as follows: the WAR factor and the market capitalization factor/BM are divided into five groups of 25, and two GRS tests are conducted to test whether the alpha of all intercept terms is jointly equal to 0. Suppose the model can fully explain the cross-sectional excess returns. In that case, the joint test will reject the original hypothesis that it is simultaneously equal to 0, and thus the model is considered valid.

Furthermore, by this paper's calculation of the GRS statistic, this paper gets (Fig.5): the statistic of the first GRS test (WAR factor vs. market capitalization factor) is 682.67 with a p-value of $1.1e-16$, and the limit is close to 0. It can be found that the p-value limit is close to 0. The statistic of the second GRS test (WAR factor vs. BM factor) is 635.59 with a p-value of $1.11e-16$ (Fig.6), thus proving through the two GRS tests that the cross-sectional return differences are primarily explained by the four factors, proving the validity of this factor pricing model and thus also fulfilling the expectations of this paper, proving that the explanatory strength performance of this paper new multi-factor model for listed company stock returns is relatively strong. By examining the war impact factors constructed and the four-factor model completed, compared to the original, The new model is more explanatory in the presence and absence of war than the original three-factor model.

5. Conclusion

In the context of the Russia-Ukraine conflict and with reference to other literature, this paper chooses the time window of 2021.9~2011.8 and adds the war factor to the original three-factor model based on A-share data.

this paper's methodology is to obtain the daily return on oil prices and subtract the risk-free return to obtain the excess return, and the daily excess return on each stock as LHS, and perform a rolling 20-day regression to obtain the factor exposure of the stock in the oil market.

The daily returns of the three currencies are weighted and averaged to obtain the daily returns of the money market. The factor exposure of each stock in the digital currency market is obtained by regressing in the same way.

The two-factor exposures of each stock are divided into two groups of size separately to obtain a total of four groups of stocks. The WAR factor is obtained using $1s2s-1b2b$ as the factor return.

This article was doing the ALPH test for the multi-factor model yield test, using the WAR factor return as the LHS and the FF triple factor as the RHS. Ultimately, this paper concludes that the test

constant term α is significant, which implies that the WAR factor has a cross-sectional return difference that cannot be explained by the basic three factors compared to the FF three factors, and by constructing the GRS, and finally obtaining the test result that the new factor War, constructed based on the crude oil market price volatility index and the digital currency market price volatility index, is added to the crude oil three factor model, indicating that for this anomaly, this paper's model has more substantial explanatory power than the basic three factor model.

Translated with www.DeepL.com/Translator (free version) The time window in this paper is small, and the data is not sufficient, as this article can only use data for all A-share stocks within one year due to the period of the war. In the future, this article can analyze more previous wars, take a long period of data, or conduct an Event study in stages. This article can then construct more accurate war factors and build a more accurate four-factor model according to the outbreak of war in the outbreak of war. The results of the different Event studies can be used to build a multi-factor model that is more appropriate for each Event study.

References

- [1] AROURI., AYED.: *War and Cryptocurrency markets: An Empirical Investigation. et al.* (2022).
- [2] Jiang.,Tao.: *research on the Sector Effect and Scale Effect of the Impact of International Crude Oil Price Fluctuations on the Stock Market.* (2022).
- [3] Yousaf.,Patel. *The reaction of G20+ stock markets to the Russia –Ukraine conflict “black-swan” event: Evidence from event study approach. et al.* (2022).
- [4] Han, L.Y.,Cai, L.X.:Yin, L.B.: *Green incentives in the Chinese securities market:A four-factor model.* (2017).
- [5] Zhaodong Wang.: *Analysis of multi-factor stock selection model in Chinese stock market.* (2014).
- [6] NOVY-MARX.: *Factor Momentum Everywhere**Tarun Gupta and Bryan Kelly. (2015).
- [7] Jungshik Hur., Vivek Singh.: *Reexamining momentum profits : Underreaction or overreaction to firm-specific information?* (2016)
- [8] Patton., Weller.: *What you see is not what you get: the costs of trading market anomalies.* (2020)
- [9] Liu., Yeh.: *Investor Psychological and Behavioral Bias : Do high sentiment and momentum exist in China stock Market?* (2011)
- [10] Yin ann Wei.: *Market momentum in China driven by overall earnings instability* (2020)
- [11] Chui.: *Momentum performance in markets with different cultural backgrounds. et al.* (2010).
- [12] Rabeh Khalfaoui., Giray Gozgor.: John W. Goodell.: *Impact of Russia-Ukraine war attention on cryptocurrency: Evidence from quantile dependence analysis* (2022).
- [13] Eugene F. Fama., Kenneth R. French.: *A five-factor asset pricing model* (2014)
- [14] Imran Yousaf., Ritesh Patel.: Larisa Yarovaya.: *The reaction of G20+ stock markets to the Russia–Ukraine conflict “black-swan” event: Evidence from event study approach* (2022).
- [15] Meihong Sun., Chao Zhang., Huasheng Song.: *The determinants of global stock market reactions to the Russia-Ukraine war* (2022).
- [16] Liang Wang., Bi xiao Li., Xutao Ma ., Wei Zheng.: *Price Volatility Spillover Effect between China Crude Oil Futures and International Crude Oil Futures and its Persistence--A Study Based on BEKK-MGARCH Model* (2021).
- [17] Xiaoli Si.: *A Study of Shanghai Crude Oil Futures Price Volatility Based on EGARCH-SGED Model.* (2021).