Erasmus University Rotterdam
Erasmus School of Economics
Bachelor Thesis Economics and Business
Spcialization: Financial Economics

The Effect of the Russia-Ukraine war on the Chinese Stock Market: An Event Study

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Date final version:	30th June 2024

Abstract

This study investigates the impact of the Russia-Ukraine conflict on the Chinese stock market, focusing on abnormal returns and industry-specific effects. The event study reveals significant abnormal returns during the 11-day event window. The highest average abnormal return (AAR) is recorded 3 days before the event and lowest AAR took place on the event day itself. Results from the cumulative of average abnormal returns (CAAR) show varying returns depending on the purchase date and the holding period. The CAAR of interest has a significant return of 2.20% over the whole event window. Lastly, the regression analysis, which controls for four company fundamentals, shows that industries were each affected differently. The energy industry outperformed the other industries with a significant average cumulative abnormal returns (CAR) of 4.46% and the communication services industry recorded the lowest significant CAR of -7.50% compared to the reference variable being the energy industry.

1 Introduction

The 24th of February 2022 can be regarded as the beginning of the Russia-Ukraine military conflict, despite Russian authorities never officially declaring war on Ukraine. However, this conflict has deep historical roots, mostly shaped by their roots within the Soviet Union until its fall in 1991 in which shortly after Ukraine declares independence from Moscow (Reuters, 2022). Following, Ukraine developed a sovereign national identity and intends towards joining NATO. In 2014, tensions arose after Pro-Russian separatists in the eastern region of Donbas declared independence and Russia annexed Crimea. Ukraine's goal to integrate with the EU combined with Pro-Russian separatists' declaration of independence from Ukraine has led to strained relations between Russia and Ukraine. In the fall of 2021, satellite images showed a buildup of Russian troops near the border with Ukraine, followed by a period of high tensions between Russia, Ukraine and NATO. Finally, on the 24th of February 2022, Putin announces "special military operations" in Ukraine (Reuters, 2022). Consistent with the characterizations of a 'black swan' event, the Russia-Ukraine military conflict has been a pivotal geopolitical event with significant implications for global financial markets (Yousaf et al., 2022), which reacted promptly to the uncertainty and potential trade disruptions that arose.

Multiple event studies regarding the effects of the Russia-Ukraine conflict have found that the conflict has had negative impacts on the global financial market overall (Ahmed et al., 2023; Assaf et al., 2023; Yousaf et al., 2022). Yousaf et al. (2022) delved into the immediate effects of the conflict on the stock markets of the G20+ countries using daily stock market data and benchmarking them to MSCI's ACWI index using the OLS Market Model. Using the OLS Market Model as a framework, Yousaf et al. (2022) calculated the abnormal returns, cumulative returns, aggregate of abnormal returns and cumulative aggregate of abnormal returns. Their country-wise analysis shows that the countries close to Russia responded the quickest in anticipation of the conflict, whereas stock markets in the western regions of Europe showed adverse effects in the days that followed the day of the event. Further research by Assaf et al. (2023) shows that developed countries experienced more negative effects immediately after the conflict broke out compared to emerging markets. Furthermore, different sectors in aggregate European stock markets had a varying degree in which they were affected soon after the Russia-Ukraine conflict began (Ahmed et al., 2023), some sectors experiencing larger positive or negative changes in their normal returns while others having minor changes. These event studies and other numerous papers regarding the Russia-Ukraine conflict align with other academic papers that have examined market reactions to geopolitical events, proving robustness of event study approaches in immediate market reactions to conflicts. Furthermore, event studies surrounding the Russia-Ukraine conflict were, and still are, important as they provide early empirical evidence of the conflicts' implications which is critical for investors and policymakers.

While most studies focus on the implications of the Russia-Ukraine conflict for financial markets on a global or continental scale. There is a scarcity in event studies of this conflict's sector-specific effect on a country's stock market. Furthermore, to this date China has not yet been studied through this lens. China is an interesting context to study the effects of the

Russia-Ukraine war on its stock market given that China has a significant economic relationship with Russia involving energy import and technology exchanges (Observatory of Economic Complexity, n.d.). In the short term, the geopolitical issues following the conflict might have influenced China's economic relationship with Russia and by extension also the Chinese companies and sectors related to these markets. Furthermore, the implications of the conflict on the global supply chain might also pose a significant factor in analyzing the Chinese market's reaction given China's role in the global trade. Therefore, examining the sector-specific impacts within the Chinese stock market provides new and broader insights into the implications of the Russia-Ukraine war. Hence, the research question this thesis aims to answer is: How did the Russia-Ukraine conflict affect the Chinese stock market on an industry-specific level?

Similar to the methodology of Yousaf et al. (2022), I will focus on daily stock prices of companies listed in the Shanghai and Shenzen stock exchanges. The event window spans from t-5 to t+5 days, whereas the estimation window spans from t_{-126} to t_{-6} days as MacKinlay (1997) and Sayed and Eledum (2021) suggested that a 120-day window is sufficient in forming an efficient benchmark for normal returns. Daily stock prices starting from t_{-126} until t_{+5} will be gathered from the China Stock Market & Accounting Research (CSMAR) database provided by Wharton Research Data Services (WRDS). Moreover, the dataset provided contains the sector and industry classification of each stock which opens up the possibilities in examining the effects of the Russia-Ukraine conflict on an industry-specific level. Furthermore, the daily data of the Shanghai Composite Index will be used as a benchmark. According to Dyckman et al. (1984), the OLS Market Model forms the better results for event study analysis among all the models, thus I will use this model in my thesis. Hence, to test how the Russia-Ukraine conflict has affected different sectors within the Chinese Stock market, I will calculate for the industries within each sector the abnormal returns (AR) and cumulative abnormal returns (CAR). And for each industry the average of abnormal returns (AAR) and cumulative average of abnormal returns (CAAR).

Similar to the results of the paper by Yousaf et al. (2022) who studied the effect of the Russia-Ukraine conflict on G20+ countries, I hypothesize to also find a significant negative (cumulative) aggregate of abnormal returns on the day of the event. Implying that the conflict had a negative impact on the Chinese stock market overall. Moreover, this anticipated result is further supported by the findings of Assaf et al. (2023) that countries in the Asia-Pacific region experienced negative effects of the conflict that arose. Furthermore, Ahmed et al. (2023) observe a varying level of sector-specific AAR and CAR surrounding the event day for European stocks. Based on this finding, I also expect that the Russia-Ukraine conflict has varying effects on different sectors within the Chinese stock market, with the degree in which each sector is affected is partially dependent on the interconnectedness of the trade volume between Russia and China with regards to these sectors and several other factors.

The remainder of this paper is structured as follows. Section 2 discusses relevant literature and previous research. Section 3 presents the data used in this paper. The methodologies used in this paper are described in Section 4. Section 5 presents the findings and results. Section 6 discusses the main findings but also the limitations of this paper. Section 7 summarizes and concludes the paper. Lastly, supportive materials referenced in the main text can be found in the Appendix.

2 Theoretical Framework

This section provides context regarding the scope of the paper. Furthermore, it will look into the current academic literature surrounding event study methodologies and the impact of the Russia-Ukraine conflict on the global financial market.

2.1 Financial market impact: terrorism, wars and black swan events

Taleb (2007) describes an event as being a black swan if it simultaneously has the following three features: (1) the event is an outlier as its probability of happening is not in line with regular expectations, hence no data in the past can convincingly signal the possibility of the event happening; (2) the event has a significant impact; (3) despite the event being an outlier, our human nature inclines us to create explanations for why such an outlier happens and try to make it predictable.

In the current academic literature, there are numerous studies regarding the effects of black swan events on financial markets. Phadnis et al. (2021) lists some of the major black swan events in recent history based on their uniqueness and their siginificant impact on equity markets: (1) Asian Market Real Estate crisis (1997); (2) The Dot Com Bust (2000); (3) Stock Market Crash following the 9/11 attacks (2001); (4); Global Financial Crisis (2008); (5) European Crisis (2011); (6) Brexit (2016).

A bibliometric analysis by Pandey et al. (2023) showcases the current literature on how border disputes, conflicts and war impact returns, volatility and stability on global financial market returns. As described, geopolitical risks associated with conflicts have significant multidimensional effects on the global stock market. Chortane and Pandey (2022) and Lyócsa and Plíhal (2022) show how the Russian Ruble and currencies of neighbouring European countries depreciated in value and experienced an increase in volatility due to the escalation of the Russia-Ukraine conflict.

In another context, studies show how armed conflicts affect the global supply chain of oil and several other commodities resulting in an increase of asset prices as seen in Iran, US, Russia and the Philippines (Adekoya et al., 2022; Agaton, 2022; Ruiz Estrada et al., 2020). These papers provide evidence for how armed conflicts affect global financial markets of non-related countries.

Behavioural finance relates to the spillover effects of conflicts on stock markets and consequently provides possible explanations as it highlights the role of psychological factors and rationales in decision-making in times of increased uncertainty (Costa et al., 2019; Kumar et al., 2022; Pandey et al., 2023).

The most recent major black swan event that comes to mind is the outbreak of Covid-19. Multiple studies show that the pandemic has had mainly negative global impacts. Naseer et al. (2023) state that capital markets, labor markets, foreign trades, consumer spending and production have experienced negative effects of lockdowns due to the temporal burden of measures put in place to avoid spreading the virus. These findings are in line with the results of the study of Ozili and Arun (2023) in which they give two key causes for why the pandemic turned into a global financial crisis: (1) social isolation measures to avoid spreading the virus led to financial markets, businesses and offices being closed down; (2) as time went by, unpredictability in the increase of spreading rate and how long it will continue has caused a certain distrust and indecision amongst international investors and consumers. Further supporting this thought, Ashraf (2020) used daily data from January 22 to April 17, 2020 from 77 countries and states that social distancing measures issued by governments have a direct negative effect on stock market returns due to their adverse effect on economic activity, but public awareness programs have an indirect positive effect on stock market returns.

However, an early study by Sansa (2020) applied a simple regression model to test the relationship of Covid-19 cases as an independent variable and the Shanghai Stock Exchange and the New York Dow Jones as dependent variables, concluding that there is a positive significant relationship between the Covid-19 cases and the returns in the mentioned financial markets from the 1st until the 25th of March 2020. In addition, new infection cases amplify the realized volatility of the S&P 500 and the fatality ratio has a significant positive impact on the volatility of the US financial market (Albulescu, 2021).

2.2 The Russia-Ukraine Conflict

Russia's invasion of Ukraine in February 2022 has significantly intensified the conflict that started eight years earlier with Russia's annexation of Crimea, signifying a pivotal moment for European security. This conflict has deep historical origins, mostly shaped by their roots within the Soviet Union until its fall in 1991 in which shortly after Ukraine declared independence from Moscow (Reuters, 2022). Following, Ukraine developed a sovereign national identity while striving to align itself with Western institutions such as the EU and NATO. However, Kyiv faced challenges in balancing its international relations and overcoming significant internal disparities. In the country's western regions, a predominantly nationalist and Ukrainian-speaking demographic generally advocated for greater integration with the West, whereas the mostly Russian-speaking demographic in the eastern part of Ukraine tended to prefer closer ties with Russia. In 2014, tensions arose after Pro-Russian separatists in the eastern region of Donbas declared independence and Russia annexed Crimea. In the fall of 2021, satellite images showed a buildup of Russian troops near the border with Ukraine, followed by a period of high tensions between Russia, Ukraine and NATO. Finally, on the 24th of February 2022, Putin announces "special military operations" in Ukraine (Reuters, 2022). Consistent with the characterizations of a 'black swan' event, the Russia-Ukraine military conflict has been a pivotal geopolitical event with significant implications for the global economy.

Multiple event studies regarding the effects of the Russia-Ukraine conflict have found that the conflict has had negative impacts on the global financial market overall (Ahmed et al., 2023; Assaf et al., 2023; Yousaf et al., 2022). A study by Izzeldin et al. (2022) compares the reactions of global financial markets on the Covid-19 outbreak and the Russo-Ukrainian war and concludes that investors interpreted the conflict as significant news given that there was an instantaneous reaction of global stock markets, whereas financial markets' reactions to the 2008 global financial crisis and the Covid-19 outbreak were registered at a lag. Further reinforcing this finding, an analysis on the aggregate of global financial markets' reactions indicates a significant negative effect on abnormal returns on the day and the following days the conflict broke out (Yousaf et al., 2022). Looking at the literature on the effects of the war, multiple countries and their industries show different reactions. For example, the 100 largest European listed banks experienced significant negative effects of the conflict on their stock prices on the day of the event and the days after (Martins et al., 2023). However, Russian banks and banks that have more exposure to Russia experienced an amplified effect. This is in line with findings of multiple academic literature stating that countries that are geographically and economically close to Russia experienced a higher negative abnormal returns compared to farther situated countries and countries with less economic ties with Russia (Boungou & Yatié, 2022; Federle et al., 2022; Sun & Zhang, 2022; Yousaf et al., 2022). Specifically, Federle et al. (2022) identified on average 1.1 percent higher stock market returns for every 1000km distance from the conflict zone, further reinforcing the case of "proximity penalty" in numerous financial markets' response to the conflict.

In the case of Australia, the stock market reacted negatively on the event-day, but the negative reaction is negated in the post-event days (Kamal et al., 2023). Another study focusing on the conflict's effects on stocks trading in the Borsa Istanbul Stock Exchange (BIST) finds that the negative effects of the war began before the announcement of the invasion and that the effects differed for each industry (Keleş, 2023). Adding to that, leverage and debt appear to be significant factors in amplifying the conflict's effects on stock market return. Kumari et al. (2023) find that developed nations and NATO countries experienced significant positive effects on their stock indices during the event. Implying that the economic state and international relations of a country are an important factor.

Contradictory to the previous literature, an event study consisting of 23 developed and 24 emerging markets finds that developed markets are - in general - more negatively impacted by the conflict compared to emerging markets (Boubaker et al., 2022). Another notable finding in this paper is that the US has experienced positive abnormal returns during the event day, which coincides with the findings of Kumari et al. (2023). Lastly, Assaf et al. (2023) and Boubaker et al. (2022) argue that the Trade-to-GDP of a country is negatively associated with the abnormal returns during the event.

In another event study using a sample of 1630 firms from 75 countries, results show that energy firms collectively outperform the stock market during the conflict (Nerlinger & Utz, 2022). This suggests that sanctions regarding oil and gas exports imposed against Russia may be the cause of the adverse effect on the stock prices of energy firms during the event. In line with other literature, abnormal returns varies per sub-industry and regions.

Mohamad (2022) exhibits the flight from ruble to safer assets. After the conflict started, purchase of energy commodities, cryptocurrencies and foreign currencies are seen as a hedging method against the devaluation of the Russian ruble. In this analysis, Brent and Bitcoin appear to perform better compared to other assets with regards to price discovery.

A study by Mottaleb et al. (2022) using data from 163 countries reveals the potential spillover effects of the decrease in wheat production by Russia and Ukraine[1] as a result of the conflict: (1) a hypothetical 50% reduction of wheat export by both Russia and Ukraine will lead to an increase of wheat price by 15% and a global decrease in wheat intake and dietary energy intake by at least 8%; (2) a decrease of 1% in global wheat trade results in the increase of price of

[1]For your reference, Russia and Ukraine account for 17% and 12% of the world's wheat export, respectively (Lin et al., 2023).

wheat by 1.1% on average and consequently decreasing daily calorie and protein intake in the sampled countries.

Lastly, a study by Ahmed et al. (2023) focuses on the conflict's effect on European stock markets. It finds that the European stock market reacted negatively during the whole event_window aside from an average abnormal return of 0.06% on the day after the event. Furthermore, in line with the findings current literature (Keleş, 2023; Mohamad, 2022; Nerlinger & Utz, 2022), Ahmed et al. (2023) finds that industries reacted differently to the event. In particular, the energy industry outperformed other industries by a huge margin. For reference, the cumulative abnormal returns of the energy industry during an event window of t_{-3} to t_{+3} recorded 3.86% whereas the second highest CAR corresponding to the real estate industry only had 0.51%.

2.3 Spillover effects: the case of China

The first securities traded in China were conducted in Hong Kong and Shanghai in the middle of the 19th century right after the Opium Wars ended. Initially, both stock exchanges in Hong Kong and Shanghai were mostly used by foreign companies. This changed in 1872 when the first Chinese public company was established and subsequently listed on the Shanghai Stock Exchange, paving the way for other (newly established) public companies to follow suit (Marszk, 2014). The first development phase of the Chinese stock market ends with the official opening of the stock exchanges in Hong Kong in 1914 (Hong Kong Exchanges and Clearing Limited, 2013) and in Beijing and Shanghai, in 1918 and 1920 respectively (Ji & Thomas, 2003). Shanghai's stock market developed into the nation's largest stock exchange in terms of market capitalization and value of transactions up until right before the Japanese invasion in 1931, which led to trades of shares being almost completely halted (Marszk, 2014). In the beginning of 1990, the Chinese government permitted the establishment of 24 stock exchanges to satisfy the needs for the increase of trading shares and the expanding number of shares. Following in the late 1990s and onwards, China officially reinstated two major national stock exchanges, one in Shanghai and another in Shenzhen where all trading of Chinese shares was gradually centralized to (Ji & Thomas, 2003). Furthermore, regulatory bodies were established and the scope of securities trading regulations were gradually expanded the following years (Marszk, 2014; Wong, 2006).
Currently, there are two stock exchanges in the mainland of China: (1) the Shanghai Stock Exchange (SHSE) which is a non-profit membership institution and uses a computerized trading system that follows the principles of time priority and price priority; and (2) the Shenzhen Stock Exchange (SZSE) which is a non-profit self-disciplined membership institution and a legal person, just like the SHSE, the SZSE also uses a computerized trading system that uses the principles of time priority and price priority (Seddighi & Nian, 2004). The equities traded on these exchanges are mostly A shares and B shares: A shares are denominated in RMB and B shares are measured in foreign currencies, either USD or HKD. Furthermore, there are certain restrictions held in place by the Chinese government to maintain the stability of the financial markets and to prevent over-speculation: (1) Mainly traders from the mainland are allowed to trade A shares, whereas B shares are traded by foreign investors and mainland investors with foreign exchange deposits; (2) A shares have a "T+1" trading rule and B shares "T+3", which implies that A shares can only be sold the next trading day of purchase and for B shares three

trading days after purchase; (3) there is a 10% limit on daily stock price spread which means that stocks cannot increase or decrease in price by 10% compared to the closing price of the previous trading day (Pan & Mishra, 2018).

According to current academic literature, it is evident that black swan events has had many global spillover effects in (relatively) recent times. Given the scope of this paper, it is also interesting to look at the spillover effects of major events on Chinese financial markets. The interdependence theory of global financial markets hypothesizes that stock markets transcends geological borders and are rather closely linked to other factors such as politics and economics (Pandey et al., 2023).

A study by Fang et al. (2021) investigates the financial spillovers between China and the G7 economies, it appears that international spillover effects between these countries are an important driver in asset prices. Furthermore, it is evident that Chinese financial markets have a growing impact on the global financial market, especially during turbulent times. Although, the same paper finds that the spillover effects from the G7 countries to Chinese financial markets still outweigh the spillback effects of China to the G7 countries, implying that China is more influenced by G7 countries rather than the other way around.

In the case of the global financial crisis, it appears that China was hit significantly as it experienced a huge drop in its exports caused by the recession (Li et al., 2012). However, China's economic growth exceeded the average of other countries during the post-event, but it is evident the global financial crisis affected the growth of China's economy with the same order of magnitude as for the United States (Li et al., 2012). Furthermore, Singhania and Anchalia (2013) found that the sub-prime crisis in led to significantly higher volatility in the Chinese stock market returns.

An event study by Yousaf et al. (2022) on the impacts of the Russia-Ukraine war on the global financial market finds that Chinese stock markets experienced significant negative abnormal returns (-1.548%) on the day the conflict broke out. This further reinforces the existence of "proximity penalties" according to the findings of Federle et al. (2022) given the geographical proximity of Russia and China. In line with this idea, Carmignani and Kler (2018) explores the spillover effects of conflicts on neighbouring countries and finds that wars significantly raises uncertainty in neighbouring countries and consequently decreases economic developments. One might expect that the increased uncertainty associated with Russia-Ukraine war can externalize in the Chinese stock market in the form of increased volatility.

3 Data

Despite Russian authorities never officially declaring war on Ukraine, the 24th of February 2022 will be regarded in this paper as the event date (t). The event window spans 11 trading days $[t_{-5}, t_{+5}]$ which consists of the 5 trading days preceding the event day, the day of the event and the following 5 trading days. Therefore, only trading days are considered in this analysis. MacKinlay (1997) and Sayed and Eledum (2021) suggest that a 120-day window is sufficient in estimating an efficient benchmark for normal returns, hence the estimation window spans from t_{-125} to t_{-6}, that is from August 16 2021 up until March 6 2022.

Given the scope of this analysis, I will be using panel data of Chinese firms listed on the SHSE and SZSE during the estimation window and event window. Data for the daily stock prices are retrieved from the TRD database provided by China Stock Market & Accounting Research (CSMAR), obtained through Wharton Research and Data Services (WRDS). The TRD database contains trading data of all Chinese listed companies since the establishment of the SHSE and SZSE. Given the unique characteristics of the Chinese stock market and the occurrences of activities such as cash dividends, share splits and rights offerings, which might affect closing prices, the TRD database strictly employs adjusting techniques of reputable databases such as Centre for Research in Security Prices (CRSP) and Compustat (Shenzhen CSMAR Data Technology Co., Ltd., 2023). For this analysis, only the adjusted closing prices are considered. Moreover, stocks with missing stock price data during the event and estimation window were omitted. Daily closing prices of the CSI 300[2] will be used as a benchmark for normal returns and is also retrieved from CSMAR's TRD database which is gathered from WRDS.
The TRD database has three levels of classifications. The classification of interest is the mid-level classification (variable: *Nindnme*) which consists of 41 different industries. Appendix 1 shows the list of the industries found in *Nindnme*. Note that some industries only consist of a small N of firms, which is undesirable for our analysis. Hence, it might be good to group industries found in *Nindnme* according to more universal industries classifications. Thus, for the sake of generalization and less clutter of data, the 41 industries will be grouped into 11 different sectors according to the Global Industry Classification Standard (GICS). The GICS, developed in 1999 by Morgan Stanley Capital International (MSCI) and S&P Dow Jones Indices, is designed to be a universal framework in the equity investment universe globally (MSCI, 2020). The industries stored in the variable *Nindnme* are ultimately assigned to the most appropriate GICS sector based on the descriptions stated in the MSCI's GICS methodology guide book. Given the structure of the dataset, no firm can be assigned to multiple sectors. How the variable *Nindnme* is grouped can be found in Appendix 2. The number of observations for each of the 11 GICS sectors are shown in Table 1 and Table 2 shows the number of companies in each sector.

To conduct our regressions on the CARs, certain firm factors are needed to control for the level of abnormal returns experienced during the estimation window. Our control variables will be based on the findings of Martani and Khairurizka (2009) which states that (1) Net Profit Margin; (2) Return on Equity; (3) Total Asset Turnover and (4) Price to Book Ratio have significant impacts to stock returns. Company fundamentals that are needed to calculate these

[2]The CSI 300 is a market capitalization-weighted stock market index that aims to replicate the performance of the top 300 stocks listed on the Shanghai Stock Exchange and Shenzen Stock Exchange.

Table 1: Frequency distribution of GICS categories

GICS	N Firms	Percent (%)	Cumulative (%)
Communication Services	8,908	1.57	1.57
Consumer Discretionary	66,810	11.79	13.36
Consumer Staples	27,772	4.90	18.26
Energy	20,960	3.70	21.96
Financials	4,192	0.74	22.70
Health Care	37,990	6.71	29.41
Industrials	176,195	31.10	60.51
Information Technology	103,228	18.24	78.75
Materials	91,831	16.20	94.95
Real Estate	15,982	2.82	97.77
Utilities	12,052	2.13	100.00
Total	**565,920**	**100.00**	

Table 2: Number of Unique Companies by GICS

GICS	N Firms	Percent (%)	Cumulative (%)
Communication Services	68	1.57	1.57
Consumer Discretionary	510	11.81	13.38
Consumer Staples	212	4.91	18.29
Energy	160	3.70	21.99
Financials	32	0.74	22.73
Health Care	290	6.71	29.44
Industrials	1345	31.13	60.57
Information Technology	788	18.24	78.81
Materials	701	16.21	95.02
Real Estate	122	2.82	97.84
Utilities	92	2.13	100.00
Total	**4,320**	**100.00**	

control variables are retrieved from CSMAR's Financial Data database provided by WRDS. The net profit margin is calculated by dividing the net profit (*B002000000*) by the total operating revenue (*B001100000*). Return on equity is then calculated by dividing the net profit (*B002000000*) with the outcome of the total assets minus the total liabilities (*a001000000* - *a002000000*). Next, the total asset turnover is calculated by dividing the operating revenue (*B001101000*) with the total assets (*a001000000*). Lastly, the Price to Book ratio is then calculated by dividing the closing price (*Clsprc*) with the book value per share which is generated by subtracting the total assets with the total liabilities (*a001000000* - *a002000000*) and then dividing it with the total shares outstanding (*Nshripo_Abs*).

The descriptive statistics of the the regression variables are shown in table 3.

Table 3: Descriptive statistics for regression variables

Variable	Obs	Mean	Std. dev.	Min	Max
CAR	4,320	2.197266	8.239839	-43.50053	84.79134
NPM	4,320	-0.1448813	8.654694	-533.58	16.74123
ROE	4,320	0.052412	2.871157	-40.47358	174.6478
TATO	4,320	0.6201771	0.5837941	0.0000168	13.91353
PB	4,320	0.4120763	1.193636	-53.93805	22.83992

4 Methodology

4.1 Event Study

According to Dyckman et al. (1984), the OLS Market Model performs better for event studies among all the models, thus I will use it for my analysis. Normal returns of stock i will be calculated during the estimation window of t_{-125} to t_{-6} using the following formula:

$$E(R_{i,t}) = \alpha + \beta_i R_{m,t} \tag{1}$$

Where $R_{m,t}$ is the return of the CSI 300 on day t. Furthermore, the actual daily returns of each firm will be calculated using the following formula:

$$R_{i,t} = ln[\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}] \cdot 100 \tag{2}$$

Where $R_{i,t}$ is the daily return of stock i on day t, $P_{i,t}$ is the adjusted closing price of stock i on day t and $P_{i,t-1}$ is the adjusted closing price of the same stock on the previous day. Actual daily returns are then compared to expected returns resulting in the abnormal returns. The abnormal returns (AR) are calculated as follows:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{3}$$

Where $AR_{i,t}$ is the abnormal return of stock i on day t. $R_{i,t}$ is the return of stock i on day t and $E(R_{i,t})$ is the expected normal return of the same stock on the same day. Furthermore, the cumulative abnormal returns (CAR) for each stock over the event window from days Γ_1 to Γ_2 will be calculated using the following formula:

$$CAR_i(\Gamma_1, \Gamma_2) = \sum_{t=\Gamma_1}^{\Gamma_2} AR_{i,t} \tag{4}$$

Where $CAR_i(\Gamma_1, \Gamma_2)$ is the cumulative of abnormal returns of stock i from day Γ_1 to Γ_2. To capture the conflict's effect on stocks listed on the SHSE and SZSE, the aggregate daily reactions of all stocks will be examined with the following formula:

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \tag{5}$$

Where AAR_t is the average of the abnormal returns on day t and N is the number of stocks. Consequently, the cumulative average abnormal returns (CAAR) will give us a view on the aggregated effect of the conflict on Chinese stocks during the event window. The CAAR is calculated with the following formula:

$$CAAR(\Gamma_1, \Gamma_2) = \sum_{t=\Gamma_1}^{\Gamma_2} AAR_t \tag{6}$$

Where $CAAR(\Gamma_1, \Gamma_2)$ shows the cumulative average abnormal returns of all stocks during the event window from the days Γ_1 to Γ_2.

4.2 Significance Tests

In order to check whether the conflict had significant effects on stock market returns, we will have to test the significance of the average abnormal returns and the cumulative average abnormal returns across all stocks.

A cross-sectional t-test will be used in order to examine whether the conflict had significant effects on the stock market's average abnormal returns. The null hypothesis of interest is $H_0 : E(AAR_t) = 0$ and the test statistic is calculated as follows:

$$t_{AAR_t} = \sqrt{N} \cdot \frac{AAR_t}{\sigma_{AAR_t}} \tag{7}$$

Where N is the total number of stocks and σ_{AAR_t} is the standard deviation of AAR_t which will be calculated using the following formula:

$$\sigma_{AAR_t} = \sqrt{\frac{1}{N-1} \cdot \sum_{i=1}^{N} (AR_{i,t} - AAR_t)^2} \tag{8}$$

Too see the whether the conflict had significant effects on the cumulative average abnormal returns during certain days within the event window, a cross-sectional t-test will also be used with the following formula for the t-statistic, under the null of $H_0 : E(CAAR(\Gamma_1, \Gamma_2)) = 0$:

$$t_{CAAR(\Gamma_1,\Gamma_2)} = \sqrt{N} \cdot \frac{CAAR(\Gamma_1, \Gamma_2)}{\sigma_{CAAR(\Gamma_1,\Gamma_2)}} \tag{9}$$

Where $\sigma_{CAAR(\Gamma_1,\Gamma_2)}$ is the standard deviation of the cumulative average abnormal returns in the period Γ_1 to Γ_2. $\sigma_{CAAR(\Gamma_1,\Gamma_2)}$ will be calculated as follows:

$$\sigma_{CAAR} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (CAR_i(\Gamma_1, \Gamma_2) - CAAR(\Gamma_1, \Gamma_2))^2} \tag{10}$$

4.3 Regression Analysis

As found in current academic literature, it is evident that industries were affected differently by the conflict (Keleş, 2023; Nerlinger & Utz, 2022). At the time of writing however, there is little to no studies known on how Chinese industries were affected by the Russia-Ukraine conflict. Thus, besides looking at the AAR and the CAAR of Chinese stocks during the event window, it is also interesting to check for any industry specific effects. This is done by conducting a cross-sectional regression on the CARs[3] of all stocks as the dependent variable and the independent variables being dummies for industries and company fundamentals. A study by Martani and Khairurizka (2009) found that (1) Net Profit Margin; (2) Return on Equity; (3) Total Asset Turnover and (4) Price to Book Ratio have significant impacts to stock returns, thus these variables will be used in the regression as control variables.

In summary, the OLS regression will have the following model:

$$CAR_i = \beta_0 + \beta_1 NPM_i + \beta_2 ROE_i + \beta_3 TATO_i + \beta_4 P/B_i + \sum_{k=2}^{11} \beta_{k+3} GICS_{k,i} \tag{11}$$

Where CAR_i is the CAR of stock i over the whole event window of 11 trading days. In order to avoid collinearity, the industry "Energy" will be used as the reference industry. Consequently, the industry effect of "Energy" will be captured by β_0. Industry effects are ultimately examined by looking at the coefficient and significance of the dummy variable assigned to each industry ($\beta_5 ... \beta_{13}$). The term $\sum_{k=2}^{11} \beta_{k+3} GICS_{k,i}$ is the sum of the dummy variables of the different industries (excluding the reference industry). Here, k stands for the index for the different industries. $GICS_{k,i}$ gets a value of 1 if stock i belongs to industry k and 0 otherwise.

Lastly, it is important to determine the appropriate type of standard errors for this regression as it impacts the reliability of the results. Cross-sectional data involves collecting observations of different subjects over a given period which makes the observations independent of each other in time, thus making it challenging to detect any potential correlations between the residuals of different observations. Hence, the assumption on errors being uncorrelated has to be made since it is difficult to verify whether residuals of different observations are correlated.

Furthermore, the White-test and Breusch-Pagan test will be conducted to check for any heteroskedasticity in the residuals. Under the null hypothesis of both tests, it states that the variance of the residuals of a regression model is constant (homoskedastic). Therefore, if the p-value associated to the White-test or Breusch-Pagan test falls below the 5% significance level threshold, the null hypothesis has to be rejected and it has to be concluded that the data is significantly heteroskedastic, resulting in the estimators being biased.

[3] For this regression, we will assume the CAR during the whole event window ($CAR_i(t_{-5}, t_{+5})$).

5 Results

This section provides the results following the methodologies presented in the previous section.

5.1 Event Study

Table 4 shows the average abnormal returns of all stocks for each day during the event window. Furthermore, the AARs are tested of their significance using a cross-sectional t-test.

First, we find that the standard deviations corresponding to the days leading up to the event rose until the day of the event where it peaked ($\sigma_{AAR_{t=0}} = 3.0293$), implying that the Chinese stock market experienced an increase in volatility of stock prices leading up to the day of the event, such as Chortane and Pandey (2022) and Lyócsa and Plíhal (2022) regarding the currencies of neighbouring countries. This might suggest speculative and anticipatory trading. This could be partially explained by the information surrounding the event signalling the increasing probability of any conflict outbreaks (Reuters, 2022) and which impacts investors' sentiments (Izzeldin et al., 2022). The peak on the event day can be attributed to the uncertainty regarding the implications of the Russia-Ukraine conflict on the global supply chain as discussed by Ahmed et al. (2023).

The highest AAR recorded during the event window corresponds to the 21st of February which has a significant positive AAR of 1.54%. In contrast, the lowest AAR (-1.09%) is recorded during the event day. This is in line with the findings of (Yousaf et al., 2022) where they recorded a significant negative abnormal return (-1.55%) of the CSI300 bench-marked against the MSCI's All Country World Index.

The next trading day concludes with a significant AAR of 0.28%, which is in turn partially negated by next day's AAR of -0.19%. Lastly, the final three trading days had significant AARs of 0.21%, 0.96% and 0.08%, respectively. This pattern is in line with the case of Australia where the country experienced negative returns on the event day, but was shortly negated in the post-event days (Kamal et al., 2023).

Of the 11 trading days during the event windows, only 4 days had negative AARs of which only the last day's AAR is insignificant on a 1% significance level. Considering the magnitude of the AARs and the portion of negative AARs, our findings suggests that the conflict has not negatively impacted the Chinese stock market overall during the event window, but rather only on the day the conflict broke out similar to the findings of Kamal et al. (2023) and Yousaf et al. (2022) To examine the conflict's aggregated impact during the event window, it is more fitting to look at the CAAR during the event window. To provide robustness to our findings, we will also look check for different CAARs.

Figure 1 and Table 13 in appendix 6 shows the outcome of our CAAR analysis. The CAAR of interest corresponds to the window of 5 days before and 5 days after the event. For this window, we find that the cumulative of the average abnormal returns across our sample totals to 2.20% with a corresponding t-statistic of 17.5066 which is significant at a 1% level. This implies that the Chinese stock market had, on average, positive stock market returns around the days the Russia-Ukraine war broke out. Thus, our findings are in line with the findings of Boubaker et al. (2022) and Fang et al. (2021) which states that emerging markets were less, if not positively

Table 4: AAR, σ_{AAR}, and t_{AAR} values during the event window

Variable	Average Abnormal Returns	Std. Deviation	t_{AAR}
t_{-5}	-0.49	2.48152	-12.84878***
t_{-4}	0.37	2.21324	10.93899***
t_{-3}	1.54	2.50989	40.20495***
t_{-2}	-0.31	2.434409	-8.309139***
t_{-1}	0.85	2.7198	20.52165***
t_{0}	-1.09	3.0293	-23.71341***
t_{+1}	0.28	2.359102	7.688018***
t_{+2}	-0.19	2.457075	-5.02515***
t_{+3}	0.21	2.18174	6.312591***
t_{+4}	0.96	2.101426	29.89993***
t_{+5}	0.08	2.588068	1.946035*

Note: t_{AAR} stands for the cross-sectional t-statistic. ***, **, * show the significance level at a 1%, 5% and 10%, respectively.

affected by the conflict outbreak. Furthermore, it is interesting to see that our window of interest is coincidentally positioned in the green area found in the heat map. This indicates a certain trend of CAARs with slightly different event windows. In this same area, we find the highest CAARs of 2.68% and 2.61% for CAAR(-4,5) and CAAR(-4,4), respectively. Both are significant on a 1% level. Furthermore, there also seems to be a trend of higher CAARs corresponding to a Γ_1 of 4. This might signal a possible optimistic sentiment among investors surrounding the possibility of any de-escalation, as a result of potential sanctions imposed against Russia by the West (Reuters, 2022).

In contrast, we find that stark difference between CAARs with Γ_1 of -2 or lower and CAARs with a Γ_1 of 3 and higher. This was to be expected looking at the daily AARs from Table 5.1, here we find that the sum of AAR_{-2} until AAR_{t3} were mostly negative. Next, the cumulative effects of the conflict seem to be negated on the fourth day after the event. Here we find that CAARs corresponding to a Γ_2 of 4 and 5 contrasts that of the CAARs of the preceding values of Γ_2. This finding signals a cool-down and recovery cut-off similar to the findings of Kamal et al. (2023) where the negative AR on the event day was eventually reversed in the post days. Taking the 'T+3' rule into account, the CAARs corresponding to the following days after $t = 3$ provide counter-intuitive results as one might expect a 3-day lagged increase in selling pressure due to the maturing of the 'T+3' rule relative to the event day.

Lastly, it is notable how the CAARs corresponding to a Γ_2 of -10 seem to show negative returns, even after a positive CAAR during the event window. In particular, the window corresponding to (0,-10) has a significant CAAR of -1.80%, the lowest of the recorded CAARs found in the matrix. This signals the longer horizon implications of the conflict on Chinese stock returns, implying that there might have been a lagged response of the market on the conflict. Furthermore, a Γ_2 of 10 encompasses the temporal restriction of the 'T+3' rule, meaning that this most probably not have been a factor in the negative returns following our event window.

Overall, we find that the outcome of the CAARs are dependent on the purchase date surrounding the event and the holding period.

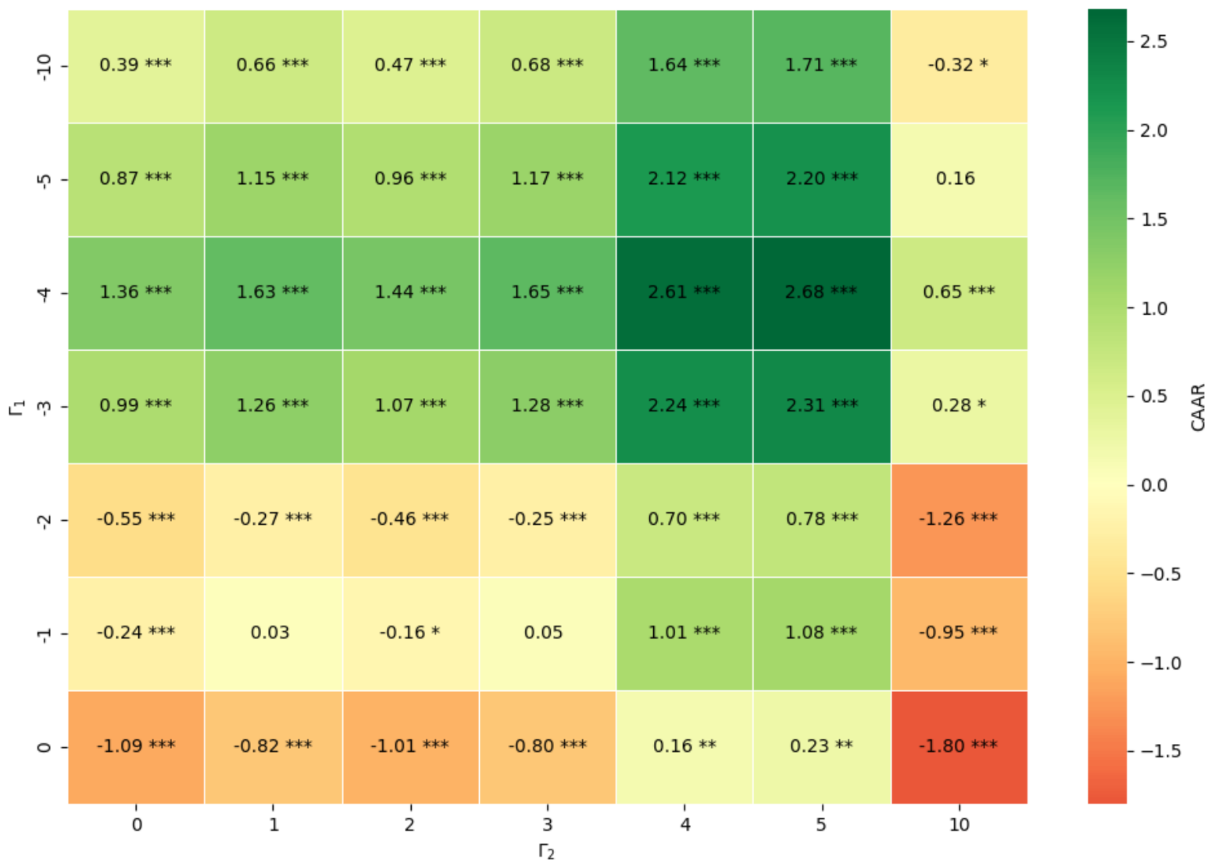

Figure 1: CAAR and t-statistics from Event Study (Heat Map)

Note: The values in the cells represent the CAAR of each corresponding Γ_1 and Γ_2. The colours of the cells depend on the level of the CAARs as given on the colour-bar on the right hand side of the figure. The asterisks denote the significance of the corresponding cross-sectional t-statistic. ***, **, * show the significance level at a 1%, 5% and 10%, respectively.

5.2 Regression Analysis

This subsection will discuss the results of our regression analysis. First, it is important to check our variables for any anomalies that may distort our interpretation of the model.

When two or more independent variables are highly correlated, the relationship between the independent and dependent variables may become misrepresented resulting into a possible misinterpretation of our regression variables (Daoud, 2017). Therefore, it is necessary to check our regression model for any possible multicollinearity. The first indicator we will use is the correlation matrix to check for any pairwise correlations. The matrix can be found in Table 9 in Appendix 3. A pairwise correlation of 0.8 or 0.9 is usually considered as a cutoff to indicate a significant correlation (Mason & Perreault, 1991). Looking at the results of our correlation matrix, it might be safe to assume that our independent variables are free from multicollinearity. However, Chan et al. (2022) argue that this method is not sufficient for testing for multicollinearity as the pairwise correlations do not necessarily imply multicollinearity. Therefore, a Variance Inflation Factor (VIF) test is performed to further check for multicollinearity. The results are shown in Table 10 in appendix 4. There is no definitive VIF value to indicate presence of multicollinearity, but Weisberg (2005) argues that a VIF value of 10 or greater is often indicative for the presence of multicollinearity. Looking at our independent variables, the highest VIF value (6.48, corresponding to *Industrials*) does not exceed our cut-off value of 10. The results, together with the correlation matrix, suggest that multicollinearity should not be an issue within our regression model.

Next, the White-test is performed to check for any variance in the residuals of our regression model. The null of the White-test states that the residual variance is non-constant. The result of the White-test is a Chi-square of 52.9306 with a corresponding p-value of 0.8368, which implies that we do not have sufficient significant statistical evidence to reject the null hypothesis. Furthermore, a Breusch-Pagan Test is performed to further examine the heteroskedasticity in the residuals. The results of this test is a Chi-square of 1.21 and a corresponding p-value of 0.2713 further reinforcing the conclusion that the residuals are homoskedastic. Therefore, standard errors should be sufficient to use in our regression analysis.

Table 5 shows the results of our regressions on the CAR during the whole event window with and without the control variables, respectively. The second model, the regression without the control variables, has also been tested for multicollinearity and residual variance. The tests conclude that multicollinearity and residual variance should not be an issue in this regression model. The results can be found in appendix 5.

As mentioned in the data section, observations for which values for our regression variables were missing, were eventually ommited from the dataset. This results in our regression model having a total observation consisting of 4,320 unique firms. Furthermore, model 1 and 2 have a R-squared of 0.0357 and 0.0328, respectively. This means that in model 1 and 2, 3.57% and 3.28% of the variance in the cumulative abnormal returns can be explained by the independent variables, respectively.

Comparing both models, all industries' significance are unaffected by the (non-)presence of the control variables as the significance of the dummy variables stay significant at the same significance threshold. However, the beta-coefficients slightly differ across both models. The biggest coefficient difference (0.1075) belongs to β_0 which corresponds to the reference industry 'Energy'. This suggests that the Energy industry has on average 0.1% lower CAR in model 2, all else equal to zero. Given that the first model has a marginally higher R-squared and having control variables incorporated, further discussion will only take the first model into account.

Looking at the constant, we find a statistically significant coefficient of 4.4641 on a 1% level. This suggests that all else equal to zero, the expected value of CAR is 4.46% meaning that the reference industry (*Energy*) has a positive impact on the CAR during the event window. Furthermore, when comparing the coefficient of β_0, it is notable that other industries that have a significant coefficient are all negative. This suggests that we have sufficient statistical evidence that the *Energy* industry outperformed other industries during the event window, further supporting the findings of Ahmed et al. (2023), Mohamad (2022) and Nerlinger and Utz (2022). A reason for this out-performance could be due to the sanctions that were imposed against Russian oil and gas exports, which resulted to higher prices and demand for other countries' energy export markets (Ahmed et al., 2023; Nerlinger & Utz, 2022). Moreover, different coefficients of other industries' dummies provide evidence to further reinforce the thought that the conflict had different effects across industries (Ahmed et al., 2023; Keleş, 2023; Mohamad, 2022; Mottaleb et al., 2022; Nerlinger & Utz, 2022).

Contradictingly to the findings of Martani and Khairurizka (2009), of the four control variables that they deemed to have significant effects on abnormal returns, only the *Net Profit Margin* seems to be the only one that has. The regression results in Table 5 states a beta-coefficient for *NPM* of -0.0473 that is significant on a 1% level. This suggests that on average and all else being equal, an increase of *NPM* by 1 unit leads to a -0.05% lower CAR during the event window. Paradoxically, this means that companies that generate a high net income compared to their revenues were generally worse off during the event window. Other control variables in our regression model being insignificant might suggest that *ROE*, *TATO* and *PB* might be less meaningful in explaining abnormal returns during major events.

The industry *Communication Services* has a significant coefficient of -7.4972 on a 1% significance level. This means that other variables being zero, this industry has a -7.50% lower CAR compared to our reference industry. In other words, the *Communication Services* industry recorded a CAR of -3.03%. With regards to other industries, this industry experienced the lowest abnormal returns during the whole event window. Consequently, it was also the only industry that had a negative CAR.

Consumer Discretionary recorded a coefficient of -3.4042 which is significant on a 1% level. This implies that, on average and other variables equal to zero, this industry experienced -3.40% cumulative abnormal returns compared to our baseline returns during the event. However, this still means that the industry had a positive CAR during the event. This might be due to China's major global role in the production of consumer products, hence this industry might be more robust to economic shocks on a national scale given that it relies on the global aggregate demand.

Next, the industry *Consumer Staples* also had a coefficient of -2.6931, significant on a 1% level, meaning that this industry had -2.69% CAR compared to the *Energy* industry. However, this industry recorded a positive CAR overall. Further supporting the findings of Landier and Thesmar (2020) which states that consumer staples is generally less sensitive to any major economic downturns.

Financials has a coefficient of -3.3024 which is significant on a 1% significance level. All else equal to zero, this industry experienced -3.30% lower CAR during the event compared to the reference industry. Overall, the *Financials* industry has still a positive CAR of 1.16%. This can be attributed to the fall of the Russian rouble and the sanctions imposed against Russian banks as Chortane and Pandey (2022) concludes that the Chinese yuan had a positive CAR during the event window.

The industry *Industrials* experienced a beta of -2.2377 that is significant on a 1% level, meaning that this industry had on average -2.24% lower CAR compared to our reference industry. Still, *Industrials* had a positive CAR during the event window, which can be attributed to China's export volume of products that corresponds to this industry. For reference, electrical and general machinery accounted for 43% of China's export product share (World Integrated Trade Solution, n.d.), of which they mainly exported to the United States, East-Asia and the Pacific, regions that were not negatively impacted by the conflict (Boubaker et al., 2022; Kumari et al., 2023; Yousaf et al., 2022).

Firms corresponding to the industry *Information Technology* recorded an aggregated coefficient of -3.6075, significant on a 1% level. This implies that this industry performed -3.61% worse than our reference industry by pair-wise comparison of the CARs. However, it still had a positive CAR of 0.86% during the event, although it had the lowest positive CAR of all significant industries, consequently supporting the findings of Ahmed et al. (2023).

The industry *Real Estate* has a significant of -2.0848, significant on a 1% level. This implies that, compared to our reference industry, the *Real Estate* industry has on average -2.08% lower CAR during the event window. However, this industry recorded a positive CAR of 2,38% overall, which can be attributed to China's growing real estate markets (Glaeser et al., 2017).

Lastly, for we find insignificant coefficients for the following industries: (1) *Health Care*; (2) *Materials* and (3) *Utilities*. This suggests that these industries had no significant effect on the CAR during the whole event window.

Overall, our industry-wise regression results suggest that the Ukraine-Russia war had varying level of effects per industry which provides further support and globalizes the findings of Ahmed et al. (2023), Boubaker et al. (2022), Keleş (2023), Kumari et al. (2023), Mohamad (2022), Mottaleb et al. (2022), Nerlinger and Utz (2022) and Yousaf et al. (2022).

Table 5: Regression Results

	CAR (Model 1)	**CAR (Model 2)**
NPM	-0.0473***	
	(0.0143)	
ROE	0.0371	
	(0.0627)	
TATO	-0.2492	
	(0.2186)	
PB	0.1472	
	(0.1511)	
Communication Services	-7.4972***	-7.4470***
	(1.1746)	(1.1745)
Consumer Discretionary	-3.4042***	-3.4577***
	(0.7361)	(0.7352)
Consumer Staples	-2.6931***	-2.6797***
	(0.8492)	(0.8496)
Financials	-3.3024***	-3.1866***
	(1.5733)	(1.5711)
Health Care	1.0687	1.1088
	(0.7987)	(0.7990)
Industrials	-2.2377***	-2.2052***
	(0.6780)	(0.6785)
Information Technology	-3.6075***	-3.5223***
	(0.7035)	(0.7035)
Materials	-1.0631	-1.0923
	(0.7109)	(0.7108)
Real Estate	-2.0848***	-2.0249***
	(0.9789)	(0.9752)
Utilities	0.4301	0.4806
	(1.0631)	(1.0615)
_cons	4.4641***	4.3566***
	(0.6575)	(0.6414)
Observations	4,320	4,320
R-squared	0.0357	0.0328
Adj R-squared	0.0326	0.0305

Note: Regression results corresponding to Models 1 and 2. Standard errors are given in parentheses. ***, **, * show the significance level at a 1%, 5% and 10%, respectively.

6 Discussion

This paper provides several insights in how the conflict affected the Chinese stock market over time and across industries. Furthermore, its findings aligns with the findings of Ahmed et al. (2023), Boubaker et al. (2022), Keleş (2023), Kumari et al. (2023), Mohamad (2022), Mottaleb et al. (2022), Nerlinger and Utz (2022) and Yousaf et al. (2022). It is evident that the Russia-Ukraine conflict has global and complex implications. This study shows the resilience of investors in price discovery even in times of uncertainty. The extensive dataset provides evidence for how the Chinese stock market reacted to the conflict the escalated in Eastern-Europe. However, there are still some limitations in the methodologies used in this paper which can provide possible directions for further research.

The regression model used in this paper included control variables, however it is uncertain whether this model contains sufficient control variables to minimize the probability of misinterpreting the regression results. Furthermore, it is fair to assume that Chinese stocks were not solely affected by the conflict during the event window, but also by other factors. Although, taking these factors into account would exceed the scope of this study.

Additionally, given the uniqueness of the 'T+1' and 'T+3' trading rules, it might be interesting to study how it factors into the short term effects of the conflict on the Chinese stock market. As seen in our results from Table 4, 13 and Figure 1 we find counter-intuitive results from the abnormal returns of each day. Taking the trading rules into account, one would expect a lagged reaction on the conflict due to the temporal restrictions of newly purchased stocks.

At the time of writing, the war is still ongoing. Besides, this paper only investigated the short term effects of the conflict. As seen by the CAAR analysis, the CAAR corresponding to (0,10) had contrasting values compared to the values found in the CAAR matrix in Table 1 and 13. Hence, it might be interesting to expand the event window and and investigate the underlying cause of this significantly negative CAAR. Furthermore, a study on the long term effects of the conflict or the effects of any major events during the war could be studied.

7 Conclusion

The goal of this paper is to study the impact of the Russia-Ukraine war on the Chinese stock market using an event study method and a regression analysis. This paper provides several insights in how the conflict affected the Chinese stock market over time and across industries.

The OLS Market Model is used for the event study methodology as it performed the best among all models (Dyckman et al., 1984; MacKinlay, 1997). The day that the Russians commenced their offence, February 24 2022, is considered the event day for this paper. The estimation window consists of 120 trading days preceding the event window which spans from t_{-5} up until t_{+5}. Given the broad categories of the dataset, the industries were grouped into 11 different industries as per the classifications of the GICS. The event study analysis finds significant abnormal returns during the event window. At the same time, the volatility in the Chinese stock market steadily increased in the days leading up to the event day, which signals the heightened uncertainty among investors preceding the conflict outbreak. The highest AAR (1.54%) is significant on a 1% level and corresponds to t_{-3}, which might suggest speculative and anticipatory trading. In contrast, the lowest AAR recorded (-1.09%) which is also significant on a 1% level belongs to the event day, signalling the immediate negative sentiment among investors.

The CAAR of interest indicates an overall positive significant return of 2.20%. This suggests that the immediate negative returns were eventually negated in the post event days, in line with the findings of Kamal et al. (2023). However, it is important to take purchase date and holding period into account as it can have significant impacts on the CAAR. As seen with the CAAR of (0,-10), we find a significant cumulative average return of -1.80%. This might be indicative of a lagged response of the Chinese stock market, in which the impact of the 'T+3' rule can be ruled out.

A regression analysis is performed to further investigate any industry specific effects on the cumulative abnormal return during the whole event window. Furthermore, four control variables were added to further increase the explanatory power of our regression model. Martani and Khairurizka (2009) suggests that *NPM*, *ROE*, *TATO* and *PB* are all significant in predicting abnormal returns of stocks. However, our regression results indicate that of the four, only the *Net Profit Margin* had significant coefficients. To provide robustness, tests for multicollinearity and homoskedasticity of the residuals were performed. The tests conclude that both obstacles should not be an issue for our regression model. The findings of the OLS regression states that the *Energy* industry outperformed all the other industries, further supporting the findings of Ahmed et al. (2023), Mohamad (2022) and Nerlinger and Utz (2022). Notably, *Communication Services* was the only industry that recorded a significant negative CAR, taking the coefficient of the reference industry in consideration. *Communication Services* had on average a significant net CAR of -3.03%. Of all 11 industries, only three industries had insignificant coefficients: (1) *Health Care*; (2) *Materials* and (3) *Utilities*.

Overall, the industry-wise regression results suggest that the Ukraine-Russia war had varying level of effects per industry, such as Ahmed et al. (2023), Boubaker et al. (2022), Keleş (2023), Kumari et al. (2023), Mohamad (2022), Mottaleb et al. (2022), Nerlinger and Utz (2022) and Yousaf et al. (2022).

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8 Appendix 1: Industry Distribution

Table 6: Industry Distribution in the Sample

Industry Name B	**Observations**	**N Firms**	**Percent**	**Cum.**
Agriculture	2,227	17	0.39	0.39
Air Transportation	1,703	13	0.30	0.69
Arts	1,048	8	0.18	0.88
Banking	131	1	0.02	0.90
Beverages	6,550	50	1.16	2.06
Chemical Fibre Manufacturing	3,406	26	0.60	2.66
Civil Engineering Construction	8,646	66	1.53	4.18
Coal Mining and Quarrying	3,013	23	0.53	4.72
Communication Service	2,227	17	0.39	5.11
Computer Application Service	45,064	344	7.95	13.06
Conglomerates	1,703	13	0.30	13.36
Culture and Education Goods, Sporting	2,489	19	0.44	13.80
Decoration	3,930	30	0.69	14.50
Electric Power,Steam and Hot Water Generation	9,956	76	1.76	16.25
Electrical Machinery and Equipment Manufacturing	36,680	280	6.47	22.73
Ferrous Metal Mining	655	5	0.12	22.84
Ferrous Metal Smelting and Extruding	4,192	32	0.74	23.58
Fishing and Hunting	917	7	0.16	23.75
Food Manufacturing	8,253	63	1.46	25.20
Food Processing	7,205	55	1.27	26.47
Food and Beverage	393	3	0.07	26.54
Forestry	524	4	0.09	26.64
Furniture Manufacturing	3,013	23	0.53	27.17
Furs, Leather, Feather and Related Products	1,572	12	0.28	27.45
Garment and Other Fabric Products Manufacturing	5,109	39	0.90	28.35
Gas Production and Supply	3,537	27	0.62	28.97
General Machinery Manufacturing	20,043	153	3.54	32.51
Graziery	2,227	17	0.39	32.90
Health Care,Nursing Care Services	1,572	12	0.28	33.18
Highway Transportation	4,978	38	0.88	34.06
Hotels	917	7	0.16	34.22
Information Technology	131	1	0.02	34.24
Information technology	58,164	444	10.27	44.51
Instruments and Appearances, Culture	8,908	68	1.57	46.08
Manufacture of petroleum, chemical, rubber products	13,231	101	2.34	48.42
Medicine Manufacturing	36,418	278	6.43	54.84

Continued on next page

Table 6 – continued from previous page

Industry Name B	Observations	N Firms	Percent	Cum.
Metal Products	11,135	85	1.97	56.81
Miscellaneous media and cultural services	262	2	0.05	56.86
Non-Ferrous Metal Smelting, Rolling, Processing	10,087	77	1.78	58.64
Non-metallic Mineral Products	12,838	98	2.27	60.90
Nonferrous Metal Mining	4,192	32	0.74	61.64
Nonmetallic Mineral Mining and Quarrying	262	2	0.05	61.69
Oil and Gas Extraction	917	7	0.16	61.85
Other Finance	2,096	16	0.37	62.22
Other Manufacturing	2,227	17	0.39	62.61
Other Public Services	18,340	140	3.24	65.85
Paper and Allied Products	4,716	36	0.83	66.68
Petroleum Processing	2,096	16	0.37	67.05
Petroleum,Chemical, Plastics and Rubber Products	262	2	0.05	67.10
Postal services	524	4	0.09	67.19
Printing	1,834	14	0.32	67.51
Professional and scientific research services	9,825	75	1.73	69.25
Public Facilities Services	2,620	20	0.46	69.71
Publishing Industries	3,275	25	0.58	70.29
Radio, Film and Television	3,144	24	0.55	70.84
Railroad Transportation	655	5	0.12	70.96
Raw Chemical Materials and Chemical Products	36,680	280	6.47	77.43
Real Estate	16,113	84	2.85	80.28
Rental and Leasing Services	393	3	0.07	80.35
Retail Trade	12,445	95	2.20	82.54
Securities and Futures	1,572	12	0.28	82.82
Special Equipment Manufacturing	38,645	295	6.82	89.64
Support Service for Transportation	1,048	8	0.18	89.83
Support Services for Mining	1,965	15	0.35	90.17
Textile	6,550	50	1.16	91.33
Timber Processing and Bamboo, Rattan Products	1,048	8	0.18	91.51
Transportation Equipment Manufacturing	29,868	228	5.27	96.79
Warehousing	1,179	9	0.21	96.99
Water Generation and Supply	2,096	16	0.37	97.36
Water Transportation	3,930	30	0.69	98.06
Wholesale and Retail Trade	11,004	84	1.94	100.00
Total	565,920	4,320	100.00	

Appendix 2: Industry Classification According to GICS

GICS	Nindnme
Energy	Coal Mining and Quarrying Manufacture of petroleum, chemical, rubber products Oil and Gas Extraction Gas Production and Supply
Materials	Chemical Fibre Manufacturing Ferrous Metal Smelting and Extruding Forestry Metal Products Non-Ferrous Metal Smelting, Rolling, Processing Non-metallic Mineral Products Nonferrous Metal Mining Nonmetallic Mineral Mining and Quarrying Ferrous Metal Mining Paper and Allied Products Petroleum, Chemical, Plastics and Rubber Products Petroleum Processing Raw Chemical Materials and Chemical Products Timber Processing and Bamboo, Rattan Products
Industrials	Air Transportation Conglomerates Electrical Machinery and Equipment Manufacturing General Machinery Manufacturing Highway Transportation Civil Engineering Construction Other Manufacturing Other Public Services Postal services Public Facilities Services Railroad Transportation Special Equipment Manufacturing Support Service for Transportation Support Services for Mining Transportation Equipment Manufacturing Warehousing Printing Water Transportation

Consumer Discretionary	Arts Furniture Manufacturing Decoration Furs, Leather, Feather and Related Products Garment and Other Fabric Products Manufacturing Hotels Instruments and Appearances, Culture Culture and Education Goods, Sporting Professional and scientific research services Retail Trade Textile Wholesale and Retail Trade
Consumer Staples	Agriculture Food Manufacturing Food Processing Food and Beverage Graziery Fishing and Hunting Beverages
Health Care	Health Care, Nursing Care Services Medicine Manufacturing
Financials	Banking Insurance Other Finance Rental and Leasing Services Securities and Futures
Information Technology	Computer Application Service Information Technology Information technology
Communication Services	Communication Service Miscellaneous media and cultural services Publishing Industries Radio, Film and Television
Utilities	Electric Power, Steam and Hot Water Generation Water Generation and Supply
Real Estate	Real Estate

Appendix 3: Correlation Matrix for Model 1

Table 9: Correlation Matrix

	NPM	ROE	TATO	PB
NPM	1.0000			
ROE	0.0019	1.0000		
TATO	0.0240	0.0017	1.0000	
PB	0.0125	-0.7249	0.0039	1.0000

Appendix 4: Variance Inflation Factor for all independent variables of Model 1

Table 10: Variance Inflation Factor (VIF) for each variable

Variable	VIF	1/VIF
NPM	1.00	0.997
ROE	2.13	0.470
TATO	1.07	0.934
PB	2.14	0.467
Communication Services	1.41	0.711
Consumer Discretionary	3.71	0.269
Consumer Staples	2.21	0.452
Financials	1.20	0.835
Health Care	2.63	0.381
Industrials	6.48	0.154
Information Technology	4.85	0.206
Materials	4.52	0.221
Real Estate	1.73	0.578
Utilities	1.55	0.645
Mean VIF	2.62	

Appendix 5: Variance Inflation Factor for all independent variables of Model 2

Table 11: Variance Inflation Factor (VIF) for each variable

Variable	VIF	1/VIF
Communication Services	1.40	0.713
Consumer Discretionary	3.69	0.271
Consumer Staples	2.21	0.452
Financials	1.19	0.840
Health Care	2.62	0.381
Industrials	6.48	0.154
Information Technology	4.84	0.206
Materials	4.51	0.222
Real Estate	1.71	0.584
Utilities	1.54	0.649
Mean VIF	3.02	

Table 12: Test Statistics

Test	Test Statistic	P-value
White's General	6.16059	0.8016
Breusch-Pagan	0.34	0.5590

Appendix 7: ANOVA and Tukey's HSD Test Results

Table 14: Summary of CAR by GICS

GICS	Mean	Std. dev.	Freq.
Communication Services	-3.0903495	8.458975	68
Consumer Discretionary	0.8988877	7.5057393	510
Consumer Staples	1.6769567	7.3880428	212
Energy	4.3566184	8.509555	160
Financials	1.1699949	6.2995981	32
Health Care	5.4653966	8.1359045	290
Industrials	2.1514338	8.2182679	1,345
Information Technology	0.83435367	8.4223794	788
Materials	3.2643012	8.6006464	701
Real Estate	2.3317154	5.5656273	122
Utilities	4.8372628	7.1454193	92
Total	2.1972661	8.2398391	4,320

Table 15: CAR Contrasts with Tukey's HSD Test Results

Comparison	Contrast	Std. Err.	p
Consumer Discretionary vs Communication Services	3.989237***	1.047408	0.007
Consumer Staples vs Communication Services	4.767306***	1.130702	0.001
Energy vs Communication Services	7.446968***	1.174477	0.000
Financials vs Communication Services	4.260344	1.73925	0.335
Health Care vs Communication Services	8.555746***	1.093149	0.000
Industrials vs Communication Services	5.241783***	1.008433	0.000
Information Technology vs Communication Services	3.924703***	1.025441	0.006
Materials vs Communication Services	6.354651***	1.030484	0.000
Real Estate vs Communication Services	5.422065***	1.227817	0.001
Utilities vs Communication Services	7.927612***	1.297487	0.000
Consumer Staples vs Consumer Discretionary	0.778069	0.66299	0.985
Energy vs Consumer Discretionary	3.457731***	0.7351631	0.000
Financials vs Consumer Discretionary	0.2711072	1.478533	1.000
Health Care vs Consumer Discretionary	4.566509***	0.5966948	0.000
Industrials vs Consumer Discretionary	1.252546	0.4219074	0.103
Information Technology vs Consumer Discretionary	-0.064534	0.4610845	1.000
Materials vs Consumer Discretionary	2.365413***	0.4721928	0.000
Real Estate vs Consumer Discretionary	1.432828	0.8176829	0.808

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Table 15: CAR Contrasts with Tukey's HSD Test Results (Continued)

Comparison	Contrast	Std. Err.	p
Utilities vs Consumer Discretionary	3.938375***	0.9189896	0.001
Energy vs Consumer Staples	2.679662*	0.8496399	0.061
Financials vs Consumer Staples	-0.5069618	1.538662	1.000
Health Care vs Consumer Staples	3.78844***	0.7331221	0.000
Industrials vs Consumer Staples	0.4744771	0.599524	0.999
Information Technology vs Consumer Staples	-0.842603	0.6277119	0.961
Materials vs Consumer Staples	1.587344	0.6359161	0.307
Real Estate vs Consumer Staples	0.6547587	0.9219699	1.000
Utilities vs Consumer Staples	3.160306*	1.012899	0.067
Financials vs Energy	-3.186623	1.571111	0.629
Health Care vs Energy	1.108778	0.798985	0.952
Industrials vs Energy	-2.205185**	0.6784822	0.046
Information Technology vs Energy	-3.522265***	0.7035135	0.000
Materials vs Energy	-1.092317	0.7108434	0.908
Real Estate vs Energy	-2.024903	0.9751603	0.594
Utilities vs Energy	0.4806444	1.061543	1.000
Health Care vs Financials	4.295402	1.511281	0.143
Industrials vs Financials	0.9814389	1.451183	1.000
Information Technology vs Financials	-0.3356413	1.463053	1.000
Materials vs Financials	2.094306	1.466592	0.942
Real Estate vs Financials	1.16172	1.611376	1.000
Utilities vs Financials	3.667268	1.665073	0.503
Industrials vs Health Care	-3.313963***	0.5252791	0.000
Information Technology vs Health Care	-4.631043***	0.5572353	0.000
Materials vs Health Care	-2.201095**	0.5664612	0.005
Real Estate vs Health Care	-3.133681**	0.8755099	0.015
Utilities vs Health Care	-0.6281338	0.9708008	1.000
Information Technology vs Industrials	-1.31708**	0.3639675	0.013
Materials vs Industrials	1.112867	0.377941	0.110
Real Estate vs Industrials	0.1802815	0.7671236	1.000
Utilities vs Industrials	2.685829*	0.8743085	0.077
Materials vs Information Technology	2.429948***	0.4212274	0.000
Real Estate vs Information Technology	1.497362	0.789349	0.720
Utilities vs Information Technology	4.002909***	0.8938727	0.000
Real Estate vs Materials	-0.9325858	0.7958887	0.985
Utilities vs Materials	1.572962	0.899653	0.810
Utilities vs Real Estate	2.505547	1.120274	0.479

Note: ***, **, * show the significance level of the contrasts at a 1%, 5% and 10% level, respectively.

Results from the pairwise comparisons for the Tukey post hoc test are shown in table 15. This analysis checks whether the industries are significantly different from each other. By comparing the results from this analysis with the regression results, we find that the coefficients and the contrasts are the same (as they should be). However, it is notable that the significance of some industries are different between the Tukey post hoc test and the regression results. The significance of the following industries are consistent between the two analyses: communication services, consumer discretionary, health care, information technology, materials and utilities. We find strong evidence of difference between groups, mostly for health care, energy and industrials with regards to other industries. In contrast, the financials industry records no significant difference with other industries which suggests that this sector's CAR has similar performance to the other industries.

Appendix 6: CAAR and t-statistics

Table 13: CAAR and t-statistics from Event Study

	Γ_2						
Γ_1	0	1	2	3	4	5	10
-10	0.38578	0.66003	0.47119	0.68023	1.63621	1.70995	-0.32234
	(3.1921)***	(5.5597)***	(3.7983)***	(5.3934)***	(12.4094)***	(12.0797)***	(-1.8070)*
-5	0.87291	1.14716	0.95831	1.16736	2.12334	**2.19708**	0.16478
	(8.5774)***	(11.2665)***	(8.7854)***	(10.5957)***	(18.2480)***	**(17.5066)*** **	(1.0273)
-4	1.35693	1.63117	1.44233	1.65138	2.60735	2.6811	0.6488
	(14.9105)***	(17.8864)***	(14.7156)***	(16.4298)***	(24.1428)***	(22.4199)***	(4.1593)***
-3	0.98939	1.26364	1.07480	1.28384	2.23982	2.31356	0.28127
	(11.7064)***	(14.7390)***	(11.5102)***	(13.5060)***	(22.0379)***	(20.6600)***	(1.8859)*
-2	-0.54780	-0.27355	-0.46239	-0.25335	0.70263	0.77637	-1.25592
	(-7.0912)***	(-3.3852)***	(-5.1373)***	(-2.7889)***	(7.3024)***	(7.2643)***	(-8.7354)***
-1	-0.24158	0.03267	-0.15617	0.05287	1.00885	1.08259	-0.94970
	(-3.8064)***	(0.4582)	(-1.9092)*	(0.6363)	(11.4900)***	(10.9817)***	(-6.9427)***
0	-1.09125	-0.81700	-1.00584	-0.79680	0.15918	0.23292	-1.79937
	(-23.6536)***	(-14.8417)***	(-14.8309)***	(-11.3269)***	(2.0267)**	(2.4565)**	(-13.4559)***

Note: CAARs from their corresponding Γ_1 and Γ_2. T-statistics are given in parentheses. The CAAR of interest (-5,5) is stated in bold. ***, **, * show the significance level at a 1%, 5% and 10% level, respectively.