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Geopolitical Risk and the U.S. Stock Returns

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ABSTRACT:
The conspicuousness of the geopolitical risk has grown considerably in recent years among experts from various fields. Especially late in the 21st century, the topic has been approached in the academic literature, for example, through oil, tourism, national defense, and financial markets. However, studies that specifically has been dealt with the connection of different sectors of the United States stock market to the geopolitical risk are rare when writing this thesis. This study examines the impact of the Ukraine War 2022, the Iraq War 2003, and September 11, 2001, terrorist attacks between stock returns from Information Technology, Consumer Staples, and Energy sectors of the U.S. S&P 500 index, as well as the effect of the geopolitical risk on the stock returns of various industries in the United States.

The theoretical framework of the research has been built from the development of geopolitics, geopolitical risk, and its relationship to various industries in the United States and other risk indicators such as the VIX and the EPU indices, as well as the efficient market hypothesis with focusing on event study. The data for the study consists of returns from the U.S. S&P 500 index, returns of various industries in the years 1985–2023, and geopolitical information from the same period. In the empirical part of the research, the event study methodology is implemented in the review period of the 21st century and the ordinary least squares estimation method in the timespan from 1985 to 2023.

The research results of this thesis show that geopolitical risk affects stock market returns in the United States with both empirical methods. The results obtained through the OLS estimation method indicate that the U.S. value-weighted stock returns of different industries react more significantly than the equally weighted returns. The companies in the Consumer Staples and Information Technology sector lose relative to the market in the event of a geopolitical incident. In addition, the results show that the GPA index is statistically the most significant in terms of stock returns.

The results obtained through the event study, in turn, indicate that companies in the Energy sector gain from the geopolitical risk in longer event windows at the start of the war in Ukraine. Moreover, the results show that stock returns in the Consumer Staples sector are increasing in connection with the Iraq War and the Information Technology sector in shorter event windows around September 11, 2001. In other event windows and events, all three sectors perform negatively during geopolitical tension as measured by the stock returns. As a side note, in the empirics of the study, it is found that investors can utilize a hedging strategy with the put options of the Information Technology sector firms during a geopolitical threat. The variation of the research results between different geopolitical incidents and event windows of the event study indicates the possibility of further future research on the subject area.

KEYWORDS: geopolitical risk, stock returns, the United States, sectors, S&P 500 index, event study, OLS methodology

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TIIVISTELMÄ:
Geopoliittisen riskin tunnettuus on kasvanut huomattavasti viime vuosien aikana eri alojen asiantuntijoiden keskuudessa. Varsinkin lähimenneisyydessä 2000-luvulla akateemisessa kirjallisuudessa aihealuetta on lähestytty esimerkiksi öljyn, matkailualan, maanpuolustuksen, sekä rahoitusmarkkinoiden kautta. Kuitenkin tutkimukset, joissa on käsitelty erityisesti Yhdysvaltojen osakemarkkinan eri sektoreiden yhteyttä geopoliittiseen riskiin ovat harvinaisia tämän opinnäytteen tekohetkellä. Tässä tutkimuksessa tarkastellaan Ukrainan sodan 2022, Irakin sodan 2003, sekä vuoden 2001 syyskuun 11. päivän terroristi-iskujen vaikutusta Yhdysvaltojen S&P 500 indeksin informaatioteknologia-, päivittäistavara-, ja energiasektoreiden osaketuottoihin, sekä myös geopoliittisen riskin vaikutusta eri teollisuudenalojen osaketuottoihin Yhdysvalloissa.

Tutkimuksen teoreettinen viitekehys on rakennettu geopolitiikan kehityksestä, geopoliittisesta riskistä ja sen indekseistä, geopoliittisen riskin suhteesta Yhdysvaltojen eri teollisuudenaloihin ja muihin riski-indikaattoreihin kuten VIX- ja EPU-indekseihin, sekä tehokkaiden markkinoiden hypoteesista keskittyen tapahtumatutkimukseen. Tutkimuksen aineisto koostuu Yhdysvaltojen S&P 500 indeksin yritysten ja kokonaisindeksin, sekä eri teollisuudenalojen tuotoista vuosina 1985–2023 sekä myös geopoliittisesta informaatiosta samalta aikajaksolta. Tutkimuksen empiirisessä osassa toteutetaan tapahtumatutkimuksen metodologiaa 2000-luvun tarkastelujaksolla sekä pienimmän neliösumman estimointimenetelmää aikavälillä 1985–2023.

Tämän opinnäytetyön tutkimustulokset esittävät, että geopoliittinen riski vaikuttaa osakemarkkinoiden tuottoon Yhdysvalloissa kummallakin empiirisellä menetelmällä. Pienimmän neliösumman estimointimenetelmän kautta saadut tulokset osoittavat, että Yhdysvaltojen eri teollisuudenalojen arvopainotetut osaketuotot reagoivat merkittävämmin kuin tasapainotetut tuotot, ja että yritykset päivittäistavara- ja informaatioteknologiasektorissa häviävät suhteessa markkinoihin geopoliittisen tapauksen sattuessa. Lisäksi tulosten kautta havaitaan, että GPA-indeksi on tilastollisesti merkittävin osaketuottojen kannalta.

Tapahtumatutkimuksen kautta saadut tulokset puolestaan osoittavat, että yritykset energiasektorissa reagoivat positiivisesti geopoliittiseen riskiin pidemmissä aikaikkunoissa Ukrainan sodan alkaessa, päivittäistavarasektorissa Irakin sodan yhteydessä, sekä informaatioteknologiasektorissa lyhemmissä aikaikkunoissa syyskuun 11. päivän ympärillä vuonna 2001. Muissa aikaikkunoissa ja tapahtumissa kaikki kolme sektoria suoriutuvat negatiivisesti geopoliittisen jännitteen aikana osaketuotoilla mitattuna. Sivuhuomiona tutkimuksen empiriassa löydetään, että sijoittajat voivat hyödyntää suojausstrategiaa informaatioteknologiasektorin yritysten myyntioptioilla geopoliittisen uhan aikana. Tutkimuksen tulosten vaihtelu eri geopoliittisten tapahtumien sekä tapahtumatutkimuksen eri aikaikkunoiden välillä kertoo aihepiirin lisätutkimuksen mahdollisuudesta tulevaisuudessa.

AVAINSANAT: geopoliittinen riski, osaketuotot, Yhdysvallat, sektorit, S&P 500 indeksi, tapahtumatutkimus, pienimmän neliösumman estimointimenetelmä

Contents

Figures

Tables

Abbreviations

AAR	=	Average abnormal returns
Aero	=	Aircraft

Agric	=	Agriculture
APT	=	Arbitrage pricing theory
AR	=	Abnormal returns
Autos	=	Automobiles and Trucks
Banks	=	Banking
Beer	=	Alcoholic Beverages
BldMt	=	Construction Materials
Books	=	Printing and Publishing
Boxes	=	Shipping Containers
Bps	=	Basis point(s)
BRICS	=	Brazil, Russia, India, China, and South-Africa
BusSv	=	Business Services
CAAR	=	Cumulative average abnormal returns
CAPM	=	The capital asset pricing model
CAR	=	Cumulative abnormal returns
Chems	=	Chemicals
Chips	=	Electronic Equipment
Clths	=	Apparel
Cnstr	=	Construction
Coal	=	Coal
CRSP	=	The Center for Research in Security Prices
DCC	=	The dynamic conditional correlation model
DCC-MVGARCH	=	Dynamic conditional correlation multivariate GARCH
Drugs	=	Pharmaceutical Products
EconUnc	=	Economic uncertainty
ElcEq	=	Electrical Equipment
EMH	=	Efficient market hypothesis
ENSO	=	El Niño-Southern Oscillation
EPU	=	Economic policy uncertainty
FabPr	=	Fabricated Products
Fin	=	Trading
FMOLS	=	Fully modified ordinary least square model
Food	=	Food Products
FS	=	Financial stress indicator
Fun	=	Entertainment
GARCH	=	Generalized autoregressive conditional heteroskedasticity
GDP	=	Gross domestic product
Gold	=	Precious Metals
GPR	=	Geopolitical risk
GPRA (GPA)	=	Geopolitical acts
GPRT (GPT)	=	Geopolitical threats
Guns	=	Defense

Hardw	=	Computers
Hlth	=	Healthcare
Hshld	=	Consumer Goods
Insur	=	Insurance
IT	=	Information Technology
LabEq	=	Measuring and Control Equipment
Mach	=	Machinery
MacroUnc	=	Macroeconomic uncertainty
Meals	=	Restaurants, Hotel, and Motel
MedEq	=	Medical Equipment
MENA	=	Middle East and North African
MGARCH	=	Multivariate GARCH
MIDAS	=	Mixed data sampling
Mines	=	Nonmetallic Mining
Misc	=	Miscellaneous
NARDL	=	A nonlinear autoregressive distributed lag
OIL	=	Brent crude oil prices
Oil	=	Petroleum and Natural Gas
OLS	=	Ordinary least squares regression
Paper	=	Business Supplies
PerSv	=	Personal Services
RlEst	=	Real Estate
Rtail	=	Retail
Rubbr	=	Rubber and Plastic Products
Ships	=	Shipbuilding and Railroad Equipment
Smoke	=	Tobacco Products
Soda	=	Candy and Soda
Softw	=	Computer Software
Steel	=	Steel Works, Etc.
Telcm	=	Telecommunications
Toys	=	Recreational Products
Trans	=	Transportation
TVP-VAR	=	Time-varying parameter vector autoregression model
Txtls	=	Textiles
U.S.	=	The United States
UK	=	The United Kingdom
USD index	=	US dollar index
Util	=	Utilities
VAR	=	Variance
VAR-BEKKGARCH	=	Vector autoregressive Baba, Engle, Kraft, & Kroner GARCH
VIX	=	Cboe Volatility Index®
Whlsl	=	Wholesale

1 Introduction

Caldara and Iacoviello (2019) present the geopolitical risk index in their first paper, describing a new concept of geopolitical risk using the news-based method. European Central Bank, World Bank, and International Monetary Fund are among the institutions that use the geopolitical risk index (Caldara & Iacoviello, 2022). The Bank of England notes geopolitical risk as a massive threat to business economics that can be kept in the uncertainty circle together with political and economic uncertainty (Carney, 2016). Additionally, Wells Fargo's (2017) survey states that 75% of the investors (from more than 1,000) fear possible diplomatic and military tensions worldwide. These issues demonstrate awakened consciousness of the geopolitical risks among the market participants.

Concerning geopolitical risk, the latest and maybe the best-known episode in the past few years escalated from the spring of 2022 onwards in Ukraine when Russia attacked the country. World Population Review (2023), ACLED (2023), and Wikipedia (2023) webpages show that besides the Russo-Ukrainian War, there are two other ongoing large wars in the world located in Ethiopia and Myanmar. Approximately one-third of the world's surface area witnesses current terrorist acts or wars. Since trade relations and political placements are nowadays global, the countries' internal tensions can affect the peaceful course of international relations or its permanence. Examples are the Burma Act which U.S. President Joe Biden signed for Myanmar's democracy and humanitarian aid, and his comment on the defense support for Taiwan in case of China's invasion (Eleven Myanmar, 2022; Brunnstrom & Hunnicutt, 2022). Additionally and according to Enuma (2021), the Epiphany 2021 events in the United States dramatically shaped the nation's internal order and the political field of the U.S.

In their paper, Caldara and Iacoviello (2019) argue that there is a lack of measures that count for geopolitical risk because the measurements are inconsistent over time. The lack of empirical research on geopolitical risk also arises from the too-broad estimate of the geopolitical risk components or the definition of geopolitical risk. The previous measures are tough to replicate since the determination and data are not publicly provided and consist of subjective analysis without mentioning the methodology. However, the geopolitical risk index by Caldara and Iacoviello (2019; 2022) fills that gap in the macroeconomic field. They use real-time newspaper measure, which catches press and public discussion by the policymakers and the investors. Their index systematically captures the latest crisis in Ukraine and all other geopolitically big and risky events (e.g., 9/11). The following sub-chapter shows the purpose of the thesis regarding geopolitical risk (GPR from this onwards).

1.1 Research problem and purpose of the thesis

The thesis examines the relationship between the GPR and stock market returns in the United States. Specifically, this thesis looks at the Information Technology, Consumer Staples, and Energy sectors of the S&P 500 index in the US. Fossung et al. (2021) conducted that sort of study earlier, and the thesis follows their approach in the empirics. Consequently, a researcher divides the firms into sectors using the sectors by the GICS® (Global Industry Classification Standard) procedure and standards that MSCI (2020) presents. This thesis also follows the event study methodology with four event windows described by Fossung et al. (2021).

Delimitation of the thesis goes as follows; first, the geopolitical risk index by Caldara and Iacoviello (2019) provides data from 1900 onwards, while their recent index provides data from 1985. However, to keep the thesis manageable, this thesis focuses on the 21st century of geopolitical events. Second, Fossung et al. (2021) focus on 58 geopolitical events in the GPR index from 1962 to 2020. With that number of occasions, they perform more than 17,000 regressions. However, that number of estimations goes beyond the purpose of the thesis. In detail, this thesis focuses on the three (3) most significant geopolitical events (spikes in the GPR-index) in the 21st century, titled 9/11 in 2001, Iraq War in 2003, and Ukraine War in 2022.

Third, the delimitation means that a researcher calculates the regressions in the Information Technology sector with event studies as follows: 3 (number of events) *4 (number of event windows) *75 (number of firms in the IT sector) = 900. The total number of regressions needed with the event studies is 1,572. In addition, to calculate the industry exposure of the GPR with the OLS methodology, a researcher follows the first equation by Caldara and Iacoviello (2019). That approach allows a broader empirical part in the thesis while simultaneously, a researcher seeks to compare the results between different methodologies.

Research problems for the thesis are the following:

1. Does the geopolitical risk affect the stock market returns in the U.S.,
2. Does the effect of the geopolitical risk differ between the Information Technology, Consumer Staples, and Energy sectors of the S&P 500 index,
3. Do the results differ between methodologies,
4. Do the results differ between geopolitical events?

In addition, a researcher compares the results between different event windows in this thesis and the papers by Caldara and Iacoviello (2019; 2022) and Fossung et al. (2021) to the final results.

1.2 Research gap and intended contribution

Even though geopolitical risk is quite a new concept in academic research, studies are increasing. However, research on the relationship between geopolitical risk and stock market returns is rare, especially with U.S. data. Another gap in the literature is a lack of studies with an event study approach, sector incorporation, and the S&P 500 index. Additionally, there is a lack of studies that use daily data on the stock returns and the GPR, therefore, not allowing to consider the impact of the GPR at a higher frequency.

Figure 1 shows that geopolitical risk reaches wide dimensions in everyday business and life. For example, a few terms regarding geopolitical risk are the U.S.-China trade, the London 2005 bombings, the Paris 2015 attacks, the Iraq invasion, national political affairs, uncertainties with the future, the threat of wars and terrorism, global tensions and tensions within states, and cyber-attacks. Specifically, this thesis aims to focus on the market dynamics part of Figure 1 regarding geopolitical risk.

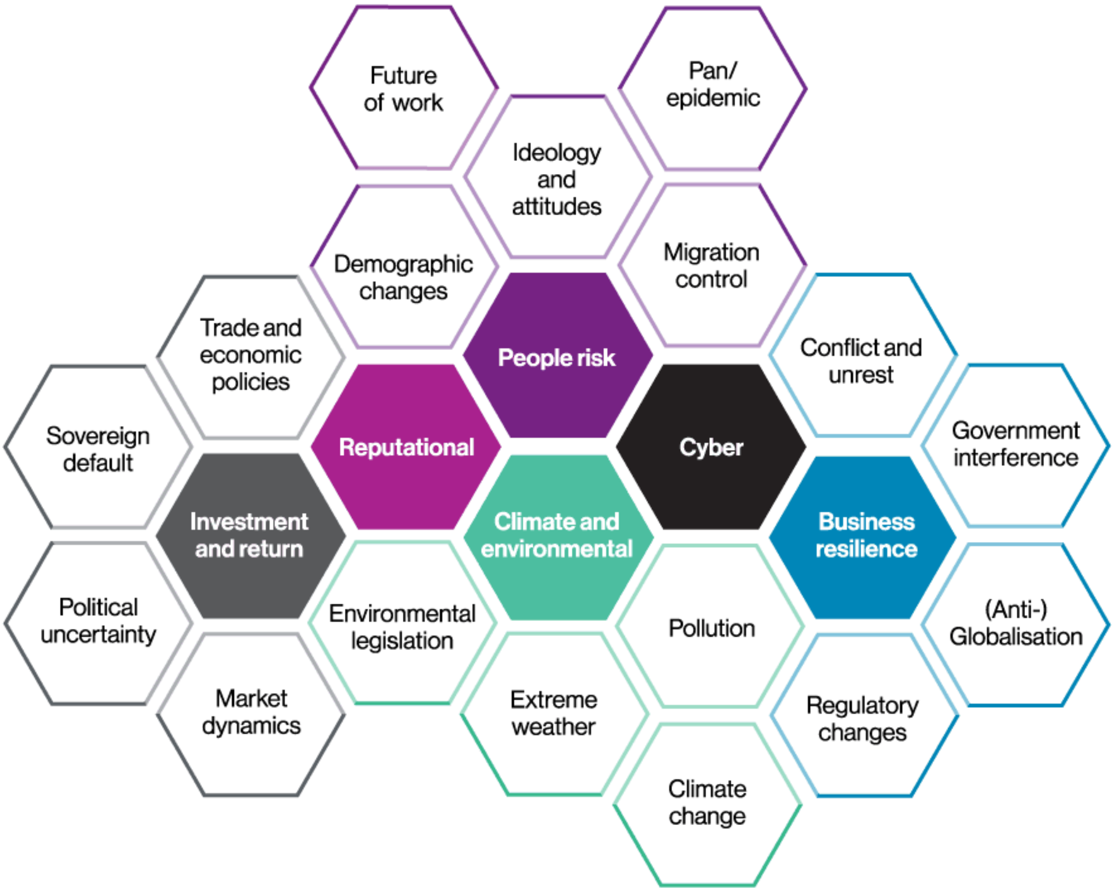


Figure 1. Geopolitical threats and its involved aspects (Brown, 2022).

The primarily intended contribution comes from the concept of geopolitical risk itself. The index by Caldara and Iacoviello (2019; 2022) offers an opportunity to focus on some specific areas of the financial markets together with the GPR because there is room for more studies with this novel concept. In this study, the contribution comes by focusing on the U.S. data of the S&P 500 index, investigating how geopolitical events affect the stock market returns, and examining the effect between different sectors of the index. When Fossung et al. (2021) use only event study methodology, a thesis researcher also uses the OLS methodology from Caldara and Iacoviello (2019). Therefore, this study connects data from the Fama and French (1997) website, titled 49 industry portfolios (monthly), for the thesis to compare the results of the OLS regressions to the event study method.

Furthermore, when Fossung et al. (2021) focus on the Information Technology, Communication Services, and Consumer Staples sectors of the S&P 500 index, in this thesis, a new industry, the Energy sector, is brought along to the research which replaces the Communication Services sector. Because of that, it is possible to compare part of the results of the thesis to their previous study but simultaneously permits producing a piece of new information from the Energy sector of the S&P 500 index. Lastly, this study concentrates on the 21st century's geopolitical events while taking well-known 9/11 from 2001 and Iraq War from 2003 to the study, but also the latest geopolitical event of the world, the Ukraine War from 2022. The extension to the timeline of the events makes it possible to compare the newest event to the other ones the GPR index is capturing.

1.3 Structure of the thesis

This thesis contains six different chapters covering the project. First, a brief introduction starts the thesis with the purpose of the research and research questions, research gap, and intended contribution. The second chapter moves into the literature review of geopolitical risk and defines the hypotheses. The third chapter presents a detailed theoretical framework of geopolitical risk and the efficient market theory. In chapter four, the study moves to the empirical part of the project showing data and methodology, along with the reliability and robustness of the research. Chapter five delivers the empirical results of the thesis, and Chapter six concludes with practical implications and contributions, as well as restrictions and future research directions.

2 Literature review and hypothesis development

This chapter takes a more detailed look at the previous studies related specifically to geopolitical risk, financial markets, and stock returns. This chapter aims to make a basis for formulating a theoretical framework later in Chapter 3, increase knowledge of the relevant research, and critically analyze the previous literature. Lastly, the hypothesis development takes place at the end of the chapter.

2.1 Studies related to the U.S. market

The first study shows how specific events can cause uncertainties regarding the Consumer Staples sector in the U.S. Seo et al. (2013) analyze the impact of food safety events on the market value of food-related firms in the U.S. between 1993–2012. They calculate abnormal and cumulative abnormal returns and find that firm-specific factors and media attention affect the significance of the impact of food safety events. Furthermore, the results show that abnormal returns are significantly negative during t_1 and t_2. Cumulative abnormal returns stay significantly negative 57 days after the event, staying negative 254 days as a whole, meaning that negative returns are related to the event's appearance and that it takes approximately one year to recover from the event entirely.

The article from Antonakakis et al. (2017) examines the relationship between geopolitical risk and the oil-stock nexus from 1899–2016. The monthly data for their paper comes from the S&P 500 index, WTI oil index, and historical GPR index. They use VAR-BEKK-GARCH and multivariate GARCH models to capture the results. The findings show that the GPR significantly affects the oil returns and its volatility, and the impact is not positive. Also, the covariance between oil and stock markets decreases considerably when the time lag of the GPR index is in the regressions. Regarding stock returns, the impact of the GPR is statistically insignificant. The lack of a newfound connection between the GPR and stock returns may be because Antonakakis et al. (2017) use monthly data.

Evidence shows that the daily data works better to find the connection between the GPR and stock returns or volatility (e.g., Caldara & Iacoviello, 2019; Balcilar et al., 2018; Yang et al., 2021; Apergis et al., 2018). Another issue may be that discounting and incorporating the exogenous GPR news into the U.S. market is more efficient. However, the frequency of the data better explains the unfound connection between variables in this case since other studies prove that the connection exists in the U.S. market between the GPR and the stock returns (e.g., Caldara & Iacoviello 2019; Fossung et al., 2021; Yang & Yang, 2021, Smales, 2021; Salisu et al., 2021).

Caldara and Iacoviello (2019) find that geopolitical risk negatively affects the U.S. stock market returns, but the result depends on the industry. They show that when the GPR changes and spikes, the stock market returns decline, and economic activity decreases. They collect the industry data from Fama and French's (1997) website, titled 49 industry portfolios (daily). They find that exposure to the GPR differs between industries when positive exposure means declining stock returns and negative exposure means growing stock returns. Among positive exposure are, for instance, fabricated products, medical equipment, and tobacco products. Negative exposure includes petroleum and natural gas, precious metals, and alcohol products.

Moreover, they indicate that fixed investments in the U.S. market decline when the GPR spikes. Indeed, Caldara and Iacoviello (2019) demonstrate that the possible threat affects the markets more than the realized act. They comment that GPR can act as a support for previous theories predicting economic uncertainty. Thus the variations in GPR and other macroeconomic factors can push the economic and business cycles.

Atems et al. (2020) concentrate on a specific industry, the U.S. food and agricultural industry, and its stock returns in terms of El Niño-Southern Oscillation (ENSO) shocks between 1980–2018. They use monthly data of 12 companies with a vector autoregression model and find that ENSO shocks affect significantly and positively seven of the twelve companies. All twelve companies belong to the S&P 500 index, and ten are in the

Consumer Staples sector. However, the results significantly decrease close to zero after three to six months, meaning that the effect of the shock is short to the stock returns. They also find that the predictive explanatory power of the ENSO shocks is small and that historically other shocks impact the U.S. food and agricultural stock returns.

Baur and Smales (2020) investigate the relationship between geopolitical risk and asset prices. They find that geopolitical risk is a new and exogenous risk that cannot be straightly compared to the other possible risks, such as financial or political (cf. Das et al., 2019). Their study shows that the precious metals industry serves as a hedge against geopolitical risk, and gold and silver demonstrated the best cover for the crisis during geopolitical threats. Vice versa, stocks and bonds negatively correlate with geopolitical risk. The data used for stock prices is from the S&P 500 index. Additionally, they find that stock prices respond more to GPR threats than GPR acts and that after 9/11 and the market reopening, the S&P 500 index was 5.31% lower than before the terrorist attacks. The results which Bauer and Smales (2020) find indicate that investors can reduce the risk involved in geopolitical risk when hedging it with precious metals. This risk is not in economic, financial, or other political indexes.

Triki and Maatoug (2021) examine the relationship between gold and the S&P 500 index under geopolitical risk from 1985 to 2018. Specifically, they use monthly data for GPR, gold, and the stock market. The model they utilize in their paper is a multivariate GARCH model to capture moving variances and covariances over time. The results of their work show that the average geopolitical risk is lastingly higher after the 9/11 terrorist attacks. In addition, gold correlates highly with the S&P 500 index during high-ranking geopolitical tensions and lowly during small GPR, and gold hedges significantly against S&P 500 index volatility, particularly during geopolitical tensions. Moreover, they find that S&P 500 index monthly returns are negatively skewed, meaning expected future losses (and small gains). Gold and GPR show positive asymmetry representing an improved probability of positive returns. Their results indicate that the gold and materials industry can differ from the other industries of the S&P 500 index during geopolitical threats and that GPR affects the stock market returns in the U.S.

Yang and Yang (2021) examine in their article the relationship between mixed-frequency geopolitical risk and stock market returns with OLS and MIDAS regression models during the sample period of 2000–2019. They find that the S&P 500 and Dow Jones index stock returns decline significantly during higher GPR spikes when using quarterly, monthly, and weekly frequency. They also calculate the economic significance of the results with weight coefficients finding that if the GPR increases by 1% in one month, the quarterly stock market returns will fall by 3.74%. Similarly, if the weekly GPR increases by 1% in one week, the quarterly stock market returns will decrease by 3.22%. Additionally, they find that the MIDAS model with mixed frequency generates better β and R^2 compared to the traditional OLS regression meaning that the MIDAS model explains better the variation of the stock returns.

Lee et al. (2021) investigate the association between oil prices, geopolitical risk, and the green bond index with monthly U.S. data. Their methodology is the Granger-causality in quantile analysis within 2013–2019. The results tell that the GPR and the oil prices have positive skewness. Lee et al. (2021) state unidirectional relationships exist between the GPR and oil prices at the extreme quantiles. The relationship between the GPR and the green bond index exists at the lower quantiles. Specifically, at the quantiles 0.80 and 0.90, a p-value is 0.029 with a 5% significance level and one lag between the GPR and the oil prices. The results remain approximately the same, with two or three lags.

In his paper, Smales (2021) studies the role and effect of geopolitical risk in oil and stock markets from 1986 to 2018. The author uses OLS, univariate and multivariate GARCH models to calculate the results and the daily data of the S&P 500 index, the WTI index, and the GPR. The results uncover that the growth in the GPR correlates positively with oil returns and negatively with stock market returns. In detail, the OLS regressions reveal that the change in the GPR predicts 20 (0.2%) basis points higher oil returns and –7 (–

0.07%) basis points lower stock returns. The results are significant at the 1% level. Economic significance follows when, for instance, four standard-deviation changes in the GPR relate to –15.6 (55.8*4*–0.07) percent change in stock returns when all else is equal. Since the mean daily stock price return is 3.1%, the four standard-deviation change in the GPR has a multiple of 5.03 towards it.

Additionally, the GPR predicts higher variations in oil price volatility than in stock price volatility. The local environment of some geopolitical events may explain this issue when some circumstances – such as disruptions in oil supply from terrorist attacks to oil fields – immediately change oil production. Finally, the author finds a positive connection between the GPR and VIX index and a negative correlation with the GPR and EPU index.

2.2 Studies related to the emerging markets

Balcilar et al. (2018) analyze the connection between geopolitical risk, stock market return, and volatility in the BRICS countries. They use monthly GPR and stock return data with a nonparametric causality-in-quantiles test. However, the stock returns have daily data to calculate realized volatility. The sample period under study varies from 1985 to 2016. The results reveal that the impact of the GPR is heterogeneous regarding stock returns in BRICS countries, but the volatility reacts more than the returns. Additionally, the GPR affects the stock return quantiles below the median. The results show that using daily data is justifiable when researching this area of the GPR to get more accurate results.

The second study regarding geopolitical risk and emerging markets comes from Bouras et al. (2019). Specifically, they study the relationship between GPR, stock returns, and volatility with the panel GARCH model under the sample period of 1998–2017. They use monthly data and find that neither the country-specific GPR nor global GPR index has significant touch on stock returns and that the effect of global GPR is more substantial on the volatility of the returns than the impact of domestic GPR factor. In detail, the coefficient for the country-specific GPR is 0.691, and for the global GPR, 0.650 with a 5% significance level, but the country-specific GPR variable is insignificant.

Hoque and Zaidi (2020) find in their 2003–2017 sample that the effect of the GPR is nonlinear with emerging economies, named by Brazil, India, Indonesia, South Africa, and Turkey, yielding negative and positive stock market returns when the crucial factor was volatility. However, political uncertainty generates negative stock market performance, except in India, where the performance is positive (cf. Hoque et al., 2019). However, none of their study's countries are big-running economies worldwide. With a more extended period, Apergis et al. (2018) demonstrate similarly to Hoque and Zaidi (2020) that volatility is the primary explanatory factor relating to stock returns. Still, regarding the prediction of stock returns, there is no evidence that the GPR would explain future returns. Similar results come from Rawat and Arif (2018).

Hedström et al. (2020) research the emerging market contagion under geopolitical insecurity. They use monthly data between 1995–2016 with variance autoregression and the GARCH model to capture spillovers between markets. They find that the possibility of contagion with ten emerging markets is high and that the GPR does not affect the stock market returns and has a weak or no spillover effect on the emerging markets. The GPR spillover varies from 0.03% to 1.15% between the markets, having a value of 0.51% in the U.S. The results uncover that the GPR correlates positively with the VIX index, the standard risk measure for stock market risk in financial markets. They also find that when comparing the GPR to the EPU index, the results show a more significant spillover influence revealing the importance of policy and economic choices.

Hasan et al. (2020) scrutinize the relationship between geopolitical risk and tourism stock returns in emerging markets. They use non-parametric causality-in-quantiles and cross-quantilogram models with monthly data from 13 emerging markets. Their findings tell that the global and country-specific GPR has significant predictive power to explain the average stock returns in the tourism sector of emerging markets under normal market circumstances. Still, exceptions include South Korea and Columbia, where the tourism stock trade is limited or is in the emerging phase. Additionally, the global GPR has more potent power than the country-specific GPR when discussing future stock returns. The results indicate that the sector under study can matter when finding the connection between stock returns and the GPR. Furthermore, the stock returns of the tourism stocks are more negatively than positively skewed.

Yang et al. (2021) take the geopolitical component with China's stock market volatility and returns. They use the GARCH-MIDAS model and CSI 300 index for China's daily stock returns to calculate and discover that global and country-specific GPR significantly influences China's stock market volatility. In detail, they study the impact of the global GPR index, GPR action and threat indexes, GPR broad and narrow indexes, and country-specific indexes on China's stock market returns. Yang et al. (2021) find that the GPR actions have a most noticeable predictive effect on stock returns between 2011–2020, but otherwise, the GPR threat is more significant than other indexes.

Another study that examines the effect of political uncertainty and the GPR on the Chinese financial markets comes from Chiang (2021). He uses the DCC model with monthly stock data between 2000–2020. He finds that stock-bond return correlations are adversely associated with changes in the EPU, and stock-gold return correlations correlate positively with changes in the GPR in the Chinese market. Specifically, Chiang (2021) finds that changes in the EPU and the GPR create negative stock returns. This divergence with the GPR's effect from Yang et al. (2021) can be from different methodologies, data, and sample periods, and Chiang (2021) uses change (Δ) in indexes.

In their article, Saadli et al. (2021) explore the relationship between Turkish stock returns, geopolitical risk, and investor sentiment between 2004 and 2017. They use monthly data for stock returns and the GPR index with MGARCH methodology to calculate the results. The results show that the GPR and the investor sentiment adversely affect the Turkish stock market returns of the BIST 100 index and its volatility. Furthermore, results tell that the GPR index is more volatile than the Turkish stock market or the investor sentiment captured by the Consumer Confidence Index.

A related study by Erdoğan et al. (2022) examines the Turkish stock markets and the effect of economic policy uncertainty, geopolitical risk, and oil prices on the returns. They employ the arbitrage pricing theory model with NARDL methodology between 1997 and 2020. They find that the country-specific GPR positively affects the Turkish stock market results, that the EPU negatively affects the stock returns, and that the oil prices affect stock returns positively if the real oil price change is not positive. The results of these last two studies differ regarding the GPR and the Turkish stock market returns. Still, the difference can be because Saadli et al. (2021) use a recent monthly GPR index. In contrast, Erdoğan et al. (2022) use a country-specific GPR index for Turkey because of a different methodology and sample period. Finally, these results indicate that the global GPR factor affects the stock returns more than the domestic factor.

A paper from Zaremba et al. (2022) studies the impact of geopolitical risk on emerging stock market returns under a sample period of 1990 to 2020 with asset pricing models. The results show that the change in GPR is associated with positive forecasts of future stock market returns and that the countries with the greatest exposure to geopolitical risk surpass their equivalents with the lowest exposure by up to 1% in a month. Moreover, the results indicate that the GPR does not massively correlate with the other regression variables. The country-specific idiosyncratic risk pushes the change in GPR more than the global systematic geopolitical risk. They also find that abnormal returns tend to have relative asymmetry depicted from the long and short strategies. That means the alphas are larger in high GPR countries than in the low GPR countries, unveiling evidence that the GPR rises matter more than the GPR reductions.

2.3 Studies related to the advanced economies, MENA-, and OPEC-countries

In their article, Nikkinen and Vähämaa (2010) find that terrorism negatively correlates with stock market sentiment and that the expected outcome of the FTSE 100 index decline during the damaging episode. The FTSE 100 index locate in London, so two of the three terrorist attacks that took place outside of the United Kingdom (in the U.S. and Madrid) within the study prove that the impact of the geopolitical events is intercontinental. In general, it makes sense that shocking events increase people's uncertainty. In their paper, Nikkinen and Vähämaa (2010) find that implied kurtosis is higher after the adverse events, meaning that investors expect a more extreme positive or negative impact for the FTSE 100 index options after the attacks.

The research from Apergis et al. (2018) investigates the association between GPR and stock returns of top defense companies with a nonparametric causality test. Their sample period runs from 1985 to 2016, and the data is at monthly frequency. Under consideration are 24 global defense companies whose results show no proof that the GPR would forecast stock returns. Caldara and Iacoviello (2019) find the opposite in their paper that the defense industry is negatively exposed to the GPR, meaning in their article that defense companies gain more than the market when the GPR spikes. Apergis et al. (2018) find that the GPR predicts 50% of the realized volatility of leading defense companies by using the daily stock price data, which can prove that results within stock returns may differ because of the frequency of the data. Contradictory results with stock returns may also be due to different data samples, periods, and methodology. Especially the frequency in the data by Caldara and Iacoviello (2019) is quarterly, while Apergis et al. (2018) have a monthly frequency. In addition, Yang and Yang (2021) show in their article that setting the data to a minor frequency may provide more accurate results.

A paper from Bouoiyour et al. (2019) examines the link between geopolitical risk and oil prices. In detail, they research whether the GPR threats or acts would be the main driver behind the higher oil prices. The authors use monthly GPR and oil price data with dynamic conditional correlation, copula, and multifractal detrended fluctuation analysis models. Their findings show that the realization of the GPR acts has a powerful and positive effect on oil prices, while the impact of the GPR threats remains small or non-significant. Specifically, the result of the GPR acts on the oil price is positive and greater during high-level quandary times. In addition, the level of oil prices does not affect the relationship when the association between the changes in the GPR and the oil price returns remains significant and positive under a larger probability of a crisis period. The correlation is forceful and positive within the countries which are large suppliers or consumers of oil. Similar results with oil return performance come in studies from Alqahtani et al. (2020) and Liu et al. (2019); in oil-dependent countries, there is some delicate evidence that the GPR predicts crude oil returns. Finally, Bouoiyour et al. (2019) find that in specific events, the oil price and the GPR correlate positively, for instance, after 9/11, during the Iraq Invasion in 2003, and the 2014 Russia-Ukraine crisis.

Alqahtani and Taillard (2020) chart in their article the changes in geopolitical risk regarding the returns of oil prices. They use monthly data with vector autoregression, GARCH, and OLS models within the sample period of 2004 to 2018 and find that the shock in the GPR is not in connection with the oil prices and that the GPR does not produce the oil returns. However, the authors conclude that the GPR can be beneficial when decreasing the uncertainty of the regressions from the oil price predictions when incorporating the change in the GPR with a two-month lag into the models, which will develop the returns of oil indexes.

An article from Salisu et al. (2021) explores the relationship between historical geopolitical risk and stock returns in advanced economies, specifically G7 countries and Switzerland. They use monthly data for stock indexes, GPR between 1899 and 2020, and the historical average (constant return) model. Their results show that an increase in the GPR index produces smaller stock returns in all countries and that a 10% increase in geopolitical threat (GPRT) produces lower stock returns, but when the GPRT decreases by 10%, then stock returns increase. Furthermore, they find that the GPR predicts stock returns in all countries except Italy, and the GPRT predicts more minor returns. For instance, the GPR predicts with controls –6.87% lower stock returns in the U.S. and its S&P 500 index, while the GPRT predicts –7.77% lower stock returns in the U.S. during the latest month.

In their article, Elsayed and Helmi (2021) map the association between geopolitical risk and stock return volatility in MENA (Middle East and North African) countries. They use daily stock price data between 2005 and 2018 with ADCC-GARCH and vector autoregression models for spillover effects. The results show that the GPR does not promote the spillovers of returns in the MENA's financial markets. Still, the dynamic analysis reveals that the total spillover index responds to large political events. They also find that correlation coefficients between countries' stock returns and the GPR are roughly zero, meaning that the returns are independent of the GPR index. Moreover, the results tell that the GPR explains fewer than 0.5% of the forecast-error variance in the MENA countries, meaning that stock returns of the MENA countries may already reflect historically shaky events and tensions.

Related research from Abdel-Latif and El-Gamal (2021) investigates the relationship between geopolitical risk, economic growth, and investment in MENA countries. They use quarterly data from 1979 to 2017 with the global vector autoregression model and find that increased GPR has adverse effects on GDP and investment and that the influence of investment declines during geopolitical tension. They also discover that the negative impact of the GPR on the GDP is greater in countries that are exporting oil. The effect of increased GPR on investments lasts around 5 to 10 quarters in nearly all countries.

Aloui and Hamida (2021) examine the association between the oil-stock nexus and geopolitical risk in Saudi Arabia, an oil-rich territory. The authors utilize the bivariate, partial, and multivariate wavelet coherency model with monthly data and a sample period from 1989 to 2019. The findings disclose that the GPR spikes produce a higher relationship to the stock prices at high-frequency with stock price as a lagging variable meaning that the GPR spikes impact Saudi Arabia's stock market over the short-term time-scale. The longer the time scale produces an elevated impact of the GPR on oil prices. Moreover, the higher GPR reduces the oil-stock connectedness in a short time horizon and decreases the volatility correlation of the oil-stock nexus, which is in line, for instance, with Smales (2021).

The article from Singh and Roca (2022) studies the connection between China's geopolitical risk and Canada's equity markets. They use GARCH, a cointegration-based fully modified ordinary least square model (FMOLS), and monthly data from 2000 to 2018 for the GPR to calculate the results. The results show that China's GPR continuously affects Canada's stock market returns and volatility. The effect is most profound on Canada's stock market's Energy and Resources sectors, which depend on the trade relationship with China. Additionally, the impact of China's GPR is more significant than that of the global GPR on Canada's national stock index. Jarque-Bera test reveals that all the sectors (not including Consumer Staples) of Canada's national index desert the normality conditions. The results tell that Canada is open to the GPR because of its international connections meaning that its national markets are vulnerable to geopolitical tensions and that the GPR affects globally due to the linkages between economies of the world's countries.

2.4 Summary of the previous studies

Previous U.S. studies' findings have yielded similar results in geopolitical risk, financial markets, and stock returns. Antonakakis et al. (2017) find that the impact of the GPR is insignificant to the S&P 500 index stock returns, whereas Caldara and Iacoviello (2019) show that higher GPR risk lowers the stock returns. However, Caldara and Iacoviello (2019) do not show the significance of their values related to Figure number six. Nevertheless, Baur and Smales (2020) find that stock returns decline due to the GPR, but gold is a hedge during geopolitical tensions. Similarly, Triki and Maatoug (2021) discover the same results as Baur and Smales (2020). Yang and Yang (2021) report that stock returns fall significantly in the U.S. during the elevated geopolitical tensions. Smales (2021) also finds a negative correlation between the GPR and stock market returns. Therefore and based on the literature review, in the U.S., the GPR effects with negative and mainly significant touch on the stock market returns.

In emerging markets, Hoque and Zaidi (2020) find that the GPR alone cannot predict future stock prices, and Hedström et al. (2020) report that the GPR does not impact the stock returns in emerging countries. On the contrary, Hasan et al. (2020) reveal that the GPR predicts both positive and negative stock returns in emerging countries when the stock market sector is specified. Chiang (2021) presents that the change in the GPR creates negative stock returns in China, and Saadli et al. (2021) show the negative impact of the GPR on Turkish stock returns. However, Erdoğan et al. (2022) reveal GPR’s positive impact on the Turkish stock market. Zaremba et al. (2022) find that the positive future returns in emerging markets are associated with the change in the GPR. To conclude, the results are non-linear in emerging markets regarding the impact of the GPR.

Previous studies on advanced economies, MENA, and OPEC countries have also yielded varied results. First, Apergis et al. (2018) indicate that the GPR does not predict the future stock returns of top global defense companies. Second, Bouoiyour et al. (2019) find that the GPR positively affects oil prices, while Alqahtani and Taillard (2020) show that the GPR does not correlate with the oil price returns. Third, Salisu et al. (2021) report decreased stock returns in G7 countries and Switzerland due to increased GPR. Singh and Roca (2022) indicate that China’s GPR adversely affects Canada’s national stock market returns because of Canada’s dependence on China due to trade linkages. Thus, the impact of the GPR varies from non-significant to positive and negative, subject to the methodology, country, time, and sector, for instance.

2.5 Hypothesis development

With the development of the hypotheses, the expectation is that geopolitical risk influences the stock market returns. For instance, Caldara and Iacoviello (2019; 2022) prove in their paper that a higher GPR adversely affects the stock market returns in the United States. In his article, Lee (2018) discover that the GPR affects the world’s stock market returns statistically significantly. Caldara and Iacoviello (2019; 2022) also reveal that positive exposure to the GPR leads at the industry level to greater and more consistent declines in stock prices. Vice versa, the industries with negative exposure to the GPR tend to outperform the market in terms of stock returns during the GPR spikes. Trade openness, the business's cyclicity, and the company's leverage level affect the exposure level. In addition, the firm's location, the nature of the industries and business, and the logistic network can raise imbalance with the magnitude effect of the exposure for the GPR (Caldara & Iacoviello, 2019). Thus there are variations in the stock prices.

Another rationale under the statement that a relationship between GPR and stock prices should exist is the empirical evidence that terrorism affects stock market returns. Memdani and Shenoy (2019) find in their article that terrorist attack impacts the stock market indices either positively or negatively in Japan, the UK, China, and Germany. Additionally, the article from Aslam and Kang (2015) shows that terrorism strikes decrease the stock returns in the Pakistani market and that the effect is short-breathed, lasting only one day. This finding justifies using the event study as a methodology with different event windows to capture the impact of the GPR on stock returns. However, Aslam and Kang (2015) reveal that the attack's magnitude correlates with negative KSE-100 stock market returns. This finding shows that the thesis's decision to focus on big GPR spikes is reasonable. Moreover, Aslam and Kang (2015) find that the threat of terrorism can affect through rumors and warnings to the stock market when one day before the attack, the stock market returns decrease –0.24% (–0.32% on the attack day), which is in line with Caldara and Iacoviello (2019). The word terrorism is a subclass for geopolitical risk. In their papers, Caldara and Iacoviello (2019; 2022) show how they construct the GPR index using the word terrorism in search queries. Hence terrorism news is part of the risks that their indexes capture.

Previous research also expresses the fact that there is an association between geopolitical risk and stock returns in the U.S. market (e.g., Fossung et al., 2021; Yang & Yang, 2021; Smales, 2021; Salisu et al., 2021). Therefore, it is a logical prediction that the GPR affects the stock prices in the U.S. However, the direction of the stock returns in the GPR index is hard to predict, although the previous studies find an existing link between the stock returns and the GPR in the U.S. The studies, for example, from Baur and Smales (2020), Hoque and Zaidi (2020), Zaremba et al. (2022), Saadli et al. (2021), and Erdoğan et al. (2022) show that the GPR may affect either positively or negatively to the stock prices. Other studies present that the effect on stock returns does not exist (Bouras et al., 2019; Balcilar et al., 2018; Elsayed & Helmi, 2021; Apergis et al., 2018; Alqahtani & Taillard, 2020). Consequently, in a hypothesis setting, the direction of the relationship between the GPR and the stock market returns is not specified.

H_1: The geopolitical risk affects the stock market returns in the U.S.

The outcome and impact of the geopolitical risk can also vary between industries and sectors, similar to what Caldara and Iacoviello (2019; 2022) find. Ntatis et al. (2021) find that geopolitical risk negatively affects the Information Technology sector, which aligns with Fossung et al. (2021). Comparably, Khan et al. (2022) result in their article that there is a two-way connectedness between the GPR and the IT sector; in detail, they find that there are both positive and negative influences from the GPR on the Technology sector. Baur and Smales (2020) show in their paper that precious metals respond positively to geopolitical tension, which is the same as what Caldara and Iacoviello (2019) results in their research.

Demiralay and Kilincarslan (2019) reveal that when the industry performs weakly, the impact of the GPR is higher on the travel and leisure stock returns (not including Asia and Pacific index). Additionally, the actual GPR spikes correlate with the decreasing travel and leisure stock returns, and the GPR threat affects only during times of decreasing travel and leisure stock returns. Collaterally, Hailemariam and Ivanovski (2021) discover that the GPR negatively impacts the demand for tourism service export. One standard deviation surprise in the GPR explains approximately 12.6% of the fluctuation in tourism net service exports. Moreover, Atems et al. (2020) result that ENSO shocks bring food and agricultural stock prices higher in the U.S., while Seo et al. (2013) uncover that food safety events lead to negative stock returns of food-related firms. Results also vary with defense companies in studies by Caldara and Iacoviello (2019) and Apergis et al. (2018). These articles reveal a variation between different sectors regarding stock market returns during various shocks. Hence, the direction of the GPR's influence is not straightforward.

In addition to what Caldara and Iacoviello (2019; 2022) find relating to the variation between industries regarding GPR effectiveness, studies present that the crisis period can distinctly affect different sectors. For example, in his article, Thorbecke (2020) studies how COVID-19 impacts 125 industries and their stock returns in the U.S. The author finds that the COVID-19 virus negatively affects the industries such as oil, funerals, aerospace, airlines, brewers, retail apparel, tourism, real estate, and airlines. Under the positive impact of the virus are industries such as electronic entertainment, biotechnology, computer hardware and software, diversified retailers, and nondurable household goods. These findings form a rationale under the second hypothesis, that the impact of the crisis period, which in this study is the GPR, results in a variation between different sector's stock returns of the S&P 500 index.

H_2: The effect of the geopolitical risk differs between Information Technology, Consumer Staples, and Energy sectors

Empirical findings from the past also show that results can differ between methodologies regarding the effectiveness of the GPR. For instance, Caldara and Iacoviello (2019) reached different results with their OLS regression compared to Fossung et al. (2021) with the event study methodology. In detail and as an example, Caldara and Iacoviello (2019) get the results where the GPR negatively affects the communication industry. In contrast, Fossung et al. (2021) find that the GPR affects the Communication Services sector mainly positively. The period under study and the different datasets also affect the results. However, a foreconceived assumption can still be that different methodologies might give variation to the results, and therefore the basis for the third hypothesis is established.

Another example is that Zaremba et al. (2022) find with asset pricing models that the GPR positively predicts the stock market returns in emerging markets. However, Bouras et al. (2019) do not find any effect of the panel GARCH model in emerging countries. The same difference exists between Saadli et al. (2021) with MGARCH and Erdoğan et al. (2022) with NARDL in Turkish stock market returns, but the sample period and frequency of the data are again distinct. In China's market, the outcomes are also prone to variation. Yang et al. (2021) find with the GARCH-MIDAS model that the GPR predicts positive stock market returns, but Chiang (2021), with the DCC model, presents that the GPR creates negative stock prices. Apergis et al. (2018), with a nonparametric causality test, and Caldara and Iacoviello (2019), with OLS regressions, also compose contrary conclusions when considering defense companies. The results also differ under the oil concept; for instance study from Alqahtani and Taillard (2020) with OLS, GARCH, and vector autoregression models versus a study from Antonakakis et al. (2017) with VAR-BEKK-GARCH and multivariate GARCH models. The latter finds that the GPR significantly affects oil prices, and the former does not.

H_3: The results differ between methodologies

Finally, the results can vary between different geopolitical events. Fossung et al. (2021) study 58 different geopolitical events in their article and show that the impact of the geopolitical risk varies between different geopolitical events and event windows (–3,3; 0,5; 0,1; –10,10). Specifically, they reveal that historical average CAARs per sector are separate and that the percentage of events with statistically significant CAARs varies between sectors and different event windows. The finding also aligns with the level of risk from the GPR index by Caldara and Iacoviello (2019). For instance, their monthly GPR index gave a value of 498.65 for September 2001, 358.71 for Iraq Invasion in March 2003, and 330.78 for Ukraine War in March 2022. The value differs according to the percentage of the real-time news relating to the GPR their search query captures. Moreover, the literature review shows that the results can vary even within the same country if the sample period differs. One example is the Turkish stock market returns (Saadli et al., 2021; Erdoğan et al., 2022), where the former find that the GPR affects the stock market returns adversely, and the latter finds that the GPR affects positively to the stock market returns. The commonsense support this since the more extended period under study also means more geopolitical events to the sample period and thus more variation in the results because the level of the GPR varies in the index.

H_4: The results differ between geopolitical events

3 Theoretical framework

This chapter aims to provide a theoretical framework for the thesis, increase knowledge of the core finance theories relevant to this study, and link the theoretical framework to the research problem. The framework starts with handling the progress of geopolitics, then moving to different parts of the geopolitical risk index, GPR by industries, and its capability to capture a novel exogenous risk. The efficient market theory concludes the chapter.

3.1 Development of the geopolitics

Geopolitics is better known and longer than geopolitical risk. They mean different things; however, geopolitics and its history form the foundation of the new concept, which in this study is geopolitical risk. Chapter 3.2 provides a review in more detail of the GPR-concept. According to Hagan (1942), geopolitical situations did not begin any further than those of the Greeks and Romans when people tried to find their place in a geographical environment. In his article, there is already a connection between economic, social, and political dimensions within geographical locations. Hagan gives the honor of formulation of modern geopolitics to Ratzel (1898), which combines the state with different surroundings and things.

In more recent literature, Woodley (2015) describes terms uncertainty, globalism, and the U.S. as today’s shaky international leader together with geopolitics. Cohen (2014) says that geopolitics aims not to offer specific information about future events, threats, or crises but to concentrate on the policymakers and how they can influence them. In addition, Dodds (2004) and Agnew et al. (2003) regard geopolitics as a common international and global issue. Caldara and Iacoviello (2019; 2022) describe geopolitics as the exercise of states and organizations to monitor and race for region and state that media often refer to geopolitics when talking about global disasters and brutality. Finally, Dodds (2004, pp. 1) defines geopolitics as a ’’study of the state, its borders, and its relations with other states.’’

3.2 Geopolitical risk and index

Caldara and Iacoviello (2019) define the term geopolitical risk as ''the risk associated with wars, terrorism, and tensions among states that affect the normal course of international relations.'' Their latest paper defines the following: ''the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations'' (Caldara & Iacoviello, 2022). They describe the geopolitical risk also through ''immaterial tensions'' as power battles, such as Cuban Missile Crisis, or pressures between countries, for instance, between the U.S. and Iran or North Korea. Their constructed index captures the risks from the acts and the new risks that could escalate from the threat of current actions. However, their index covers only the events that are usually considered geopolitical. Hence, events such as Brexit, the global financial crisis, or climate change are not included in their index since they are not always considered geopolitical. This approach allows them to exclude the tiny weight from what those events are creating to the index based on the algorithm's results and to exclude the events separate from the words war and terrorism.

The authors (Caldara & Iacoviello, 2019) created the geopolitical risk index from 11 newspapers' data with an algorithm that captures the percentage of articles associated with geopolitical risk. In detail, the authors ran an automated text-search query in ProQuest Newsstream starting from 1985 to find the number of articles using geopolitical terms conversing risks and events related to the GPR. Then they split it with the total number of articles per month. They use a dictionary-based methodology to capture the existence of words relating to geopolitical risk in the newspapers. That method allows capturing the preliminary information about exact words such as military or terror concerning the final sample. Their sample covers about 25 million news articles resulting in approximately 30,000 articles per month in a recent sample and 10,000 articles per month in a historical sample. The newspapers included in the index are *The Boston Globe, The Chicago Tribune, The Daily Telegraph, The Financial Times, The Globe and Mail, The Guardian, The Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and*

The Washington Post. The index includes one Canadian newspaper, four UK newspapers, and six U.S. newspapers. Therefore, the GPR index captures the risk from the U.S. and simultaneously catches the global threat but concentrates on these three countries.

Figure 2 plots the recent monthly geopolitical risk index from 1985 built on ten newspapers, also named the benchmark GPR index (Caldara & Iacoviello, 2019). When concentrating on the 21st century, the three most giant spikes in the index are 9/11, Iraq Invasion, and Ukraine War. These three spikes are also the events under examination in this thesis. The index spikes for the first time during the U.S.'s bombing of Libya in April 1986 after the terrorist happenings. Subsequent spikes happen during the U.S. Invasion of Panama, the Iraq Invasion of Kuwait, and the Gulf War. In 1994, the summer Bosnian War and tensions in Iraq from airstrikes executed by the Turkish air force spiked up the GPR index, following the 1999 spike from the Iraq Disarmament Crisis. Then the index spikes from the well-known 9/11 in the U.S., and other spikes during the 21st century are, for instance, the London bombings, Russia's annexation of Crimea, and the Paris attacks. After 9/11, the mean of the index is higher than before, indicating heightened news reporting of geopolitical concerns and terror realizations.

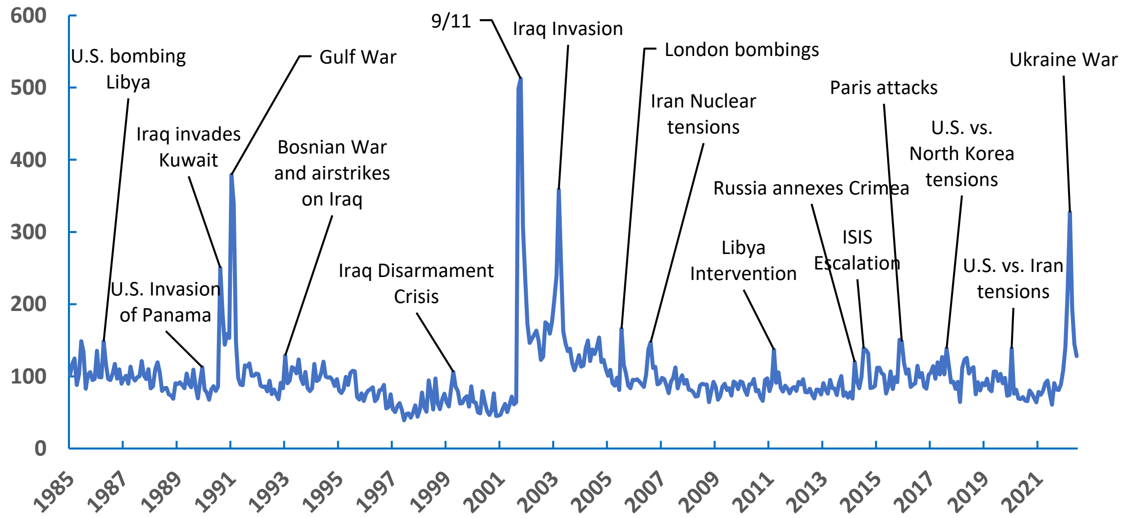


Figure 2. Recent GPR index from January 1985 through June 2022.

Figure 3 plots the GPR index at a daily frequency, which is understandably noisier than the monthly equivalent index. Caldara and Iacoviello (2019) show that the green dots depict the daily observations, whereas the solid blue line represents the monthly GPR index. The red dots display spikes in the index together with descriptions. According to the authors, the daily index captures some events which are not apparent in the monthly GPR index because the reported news relating to the specific events are short-lived. For

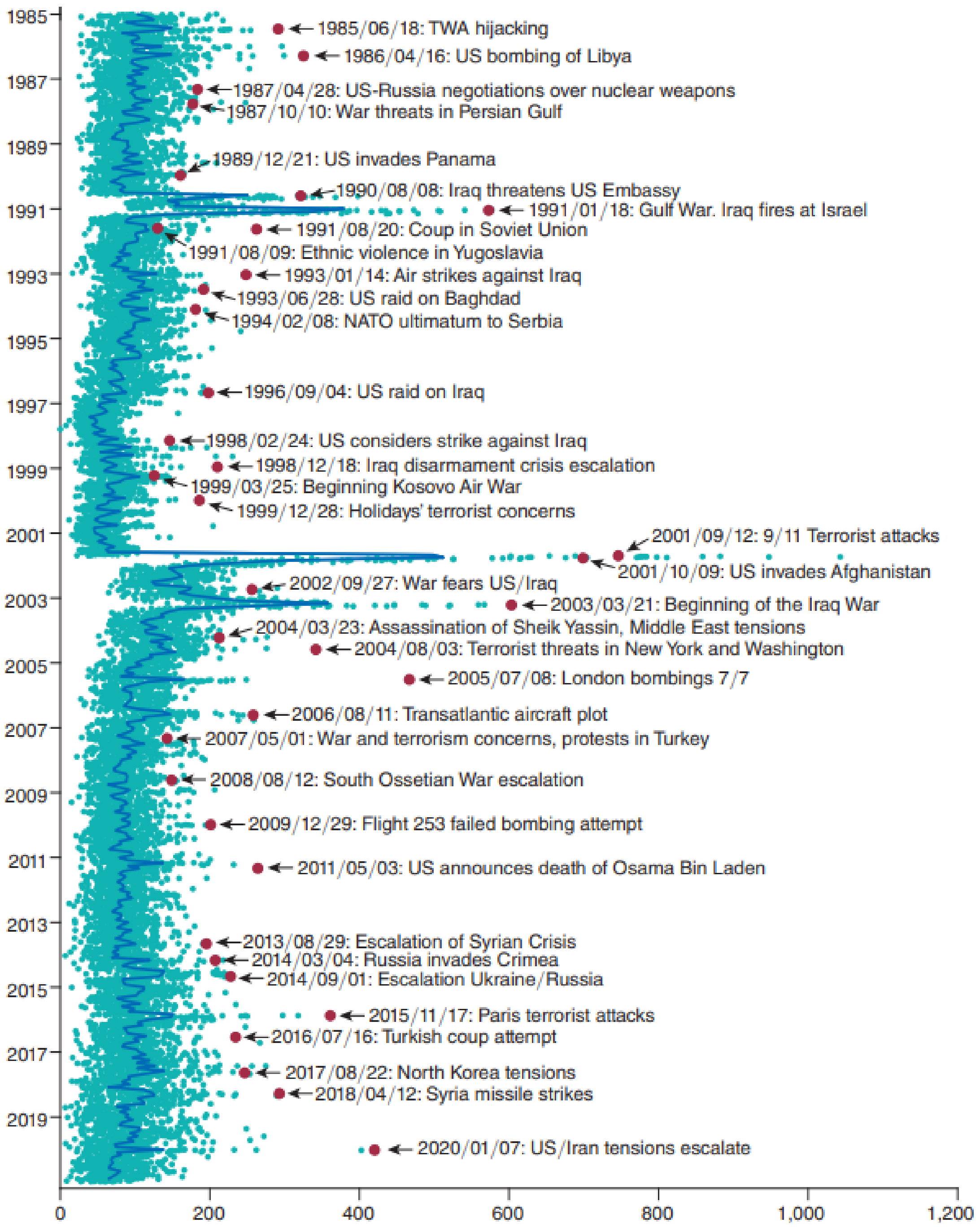


Figure 3. Daily GPR index from 1985 through end-2020 (Caldara & Iacoviello, 2022).

example, the index plots escalated tensions in former Yugoslavia in August 1991 and the tried attack on the Soviet Union. The index also captures NATO’s air strikes in Kosovo in March 1999. Moreover, Caldara and Iacoviello (2019) say that the daily index can show how prolonged tensions in the daily index can lead to big spikes in the monthly GPR index, as in the case of the Gulf War. Another finding is that one climax event can produce increased plots in the daily GPR index following higher average spikes in the after-effects, as after 9/11. Additionally, in the daily GPR index, the slow-moving geopolitical conflicts in news coverage can create improved spikes in the monthly GPR index, as in the 2017–2018 North Korea crisis (Caldara and Iacoviello, 2019). The daily GPR index correctly captures the risk – revealing the valuable capability of the index in high frequencies, such as days and weeks – leading to increased efficacy and practicality in short-time effects, such as the reaction of the stock prices during geopolitical spikes.

Figure 4 shows the historical monthly GPR index starting from 1900. In this index, Caldara and Iacoviello (2019) use three newspapers to construct the monthly historical index: The Chicago Tribune, The Washington Post, and The New York Times. The authors state that the correlation with the benchmark index is 0.95 from 1985 onwards. The index's spikes depict growing geopolitical pressures around the increased conflict events, similar to the benchmark index. At the beginning of the sample, the index spikes during World War I and II staying high during the time of both wars. From the 1950s to 1980s index shows high-ranking stages, indicating different wars and crises, but also a threat of nuclear weapons and rising geopolitical pressures between countries. In the 21st century, terrorism occurs in the index with increased two-sided conflicts between nations, most recently in Ukraine. The most significant spikes in the index are the beginning of WWI and WWII, the Pearl Harbor attacks and D-Day, and the well-known 9/11.

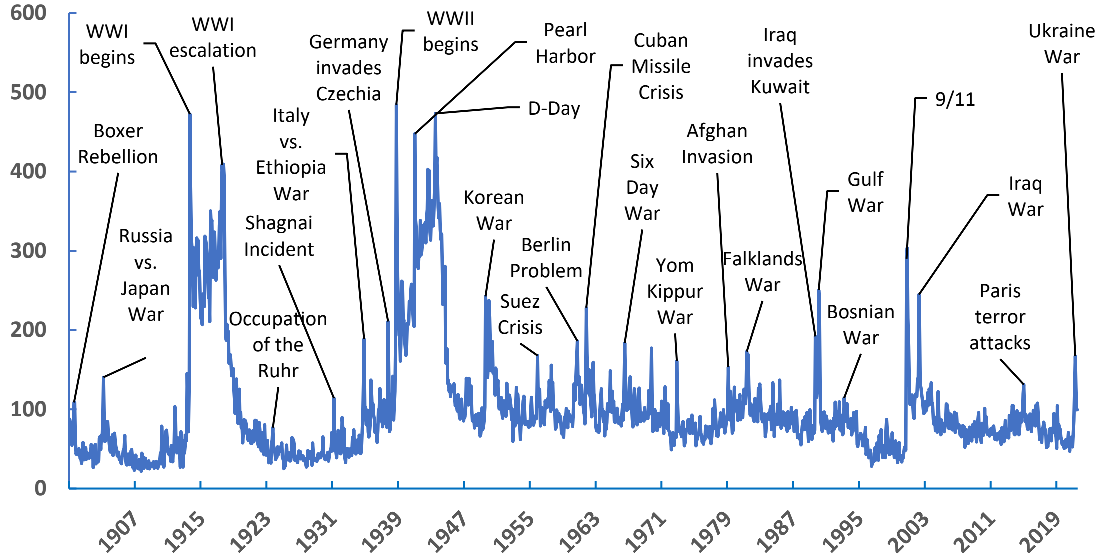


Figure 4. Historical GPR index from January 1900 through June 2022.

3.3 Geopolitical threats and acts

Table 1 presents examples of the words used to build the GPR indexes, divided into six categories. According to Caldara and Iacoviello (2019), the phrase selection is based on a pilot audit of newspapers most likely discussing the geopolitical risk. Chapter 4.3 discuss the pilot audit in more detail. The authors state that another selection criterion for the words is the most general uni-grams and bi-grams from the geopolitical textbooks. For example, a book from Dalby et al. (2003) – named as *The Geopolitics Reader* – totals 91,210 bigrams. It covers docker of 39 essays from geopolitics, and the most frequent of those bigrams are “world war,” “gulf war,” “unit(ed) states,” “nation secur(ity),” “war II,” “world order,” “cold war,” “nation(al) state,” “nuclear weapon,” and “foreign polic(y).” Similarly, with uni-grams, Flint’s (2016) textbook *Introduction to Geopolitics* includes the most usual word roots, such as “terror,” “geopolit,” “polit,” “nation,” “war,” “global,’’ and “countri.” In their recent paper, Caldara and Iacoviello (2022) report that the goal is to make an index that can catch different features of the GPR and share geographically and conceptually, which serves their part as a reason for selecting the words. They have also increased the number of words in search phrases and excluded words in the search query in their latest (2022) paper.

Table 1. Examples of phrases sought to build the GPR indexes (Caldara & Iacoviello, 2019).

Search Category	*Examples of Search Terms*
1. Geopolitical Threats	geopolitical AND (risk* OR concern* OR tension* OR uncertaint*) AND "United States'' AND (coup OR guerrilla OR warfare) AND ("Latin America'' OR "Central America'' OR "South America'' OR Europe OR Africa OR "Middle East'' OR "Far East'' OR Asia)
2. Nuclear Threats	("nuclear war'' OR "atomic war'' OR "nuclear conflict'') AND (fear* OR threat* OR risk* OR peril* OR menace*)
3. War Threats	"war risk*'' OR "war fear*'' OR "military threat*''
4. Terrorist Threats	"terrorist threat*'' OR "terrorism menace*''
5. War Acts	((beginning OR outbreak OR start OR escalation) "of the war'')
6. Terrorist Acts	"terrorist act'' OR "terrorist acts''

NOTE: This table shows a subclass of phrases explored in building the GPR indexes, arranged by categories. The precise search query is in the appendix. The asterisk (*) symbol indicates a wildcard character.

In Table 1, Caldara and Iacoviello (2019) define different geopolitical threats and concerns covering categories from 1 to 4, and the last two categories include different geopolitical actions and happenings. The words' division allows the construction of two separate subindexes under the GPR index, GPR acts (GPRA/GPA) and GPR threats (GPRT/GPT). The authors state that category number one divides the areas where geopolitical risks are happening in the United States and extensive territories. The articles discussing GPR contain either immediate United States participation (e.g., the 2003 Invasion of Iraq) or district conflicts between the group of countries with the political involvement of the United States. Additionally, category number one defines the search terms from the articles that distinctly refer to GPR and military-related words regarding conflicts of the U.S. and other parts of America, Europe, Africa, Asia, and the Middle as well as the Far East.

Caldara and Iacoviello (2019) show in category number two of Table 1 the nuclear tenseness-related words searched from the articles. Category number three contains terms which are portraying war tensions. Similarly, category number four represents words relating to terrorism tensions. Category five turns to search the words from the articles containing war actions – the real happenings – contrasted to only risks. Ultimately, category number six involves phrases describing terrorist acts. According to the authors, the words represent the negative GPR affairs instead of positive ones, increasing the accuracy of the index. For example, the search query terms include the war's beginning rather than the war's closing.

Moreover, Caldara and Iacoviello (2022) show an updated search query for the construction of the GPR index, which contains eight search categories in their recent paper. The threat part of the index is now divided into five categories and acts as part of the index into three categories. The difference with the 2019 search query is that the “Geopolitical Threats’’ search category consists of “Peace threats’’ and “Military buildup’’ search categories, and the “War Acts’’ search category includes “Beginning of war’’ and “Escalation of war’’ search categories. That allows allocating the parts of the index more accurately.

In their article, Caldara and Iacoviello (2019) split the GPR index into two subindexes, GPR threats (GPRT) and GPR acts (GPRA). They show the GPR index as a measure of the threat of possible future risks and tensions in sight of happenings or actual materialized risks related to geopolitical events. According to the authors, the articles containing the search terms in categories 1 to 4 in Table 1 create the GPRT index. Similarly, the search terms in the categories from 5 to 6 in Table 1 produce the GPRA index. Thus, the two subindexes split the search terms; in the GPRA, the actual realized events define the index, whereas in the GPRT, the possible future risks and tensions are more prevalent. One example of how the two subindexes can provide separate information is that the actualized GPR can serve as a launch of elevated GPR. For instance, during Ukraine War in 2022 spring, the threat of war may increase in other parts of Europe, or after the terrorist assault, the threat of future terrorist assaults may be higher. The authors state that the division of the GPR index performs an essential part of the analysis as the accuracy of the timing of the GPRA events can be distinct from the benchmark GPR index.

Figure 5 draws the GPRT and the GPRA indexes. Caldara and Iacoviello (2019) have found a correlation between these indexes is 0.51. Figure 5 shows that almost all spikes in the

GPRA index overlap with the GPRT index's spikes. However, there is still a massive volume of individual discrepancies between the indexes. Authors state that, in some cases, the GPRT index rises sometime before the actual geopolitical event, such as before Gulf War, Arab Spring, Iraq Invasion, and Ukraine War. This feature may catch information and associated news from future geopolitical risks and happenings. At some point, the GPRT index rises without existing incidents, such as across 2017–2018 U.S. vs. North Korea tensions when the two subindexes move in different directions. In some cases, the GPRT spikes, but the GPRA does not, such as during the Kuwait Invasion in August 1990. Caldara and Iacoviello (2019) profess this feature is due to the media coverage and its reporting, the associated news about the possibilities versus the actual realized geopolitical events.

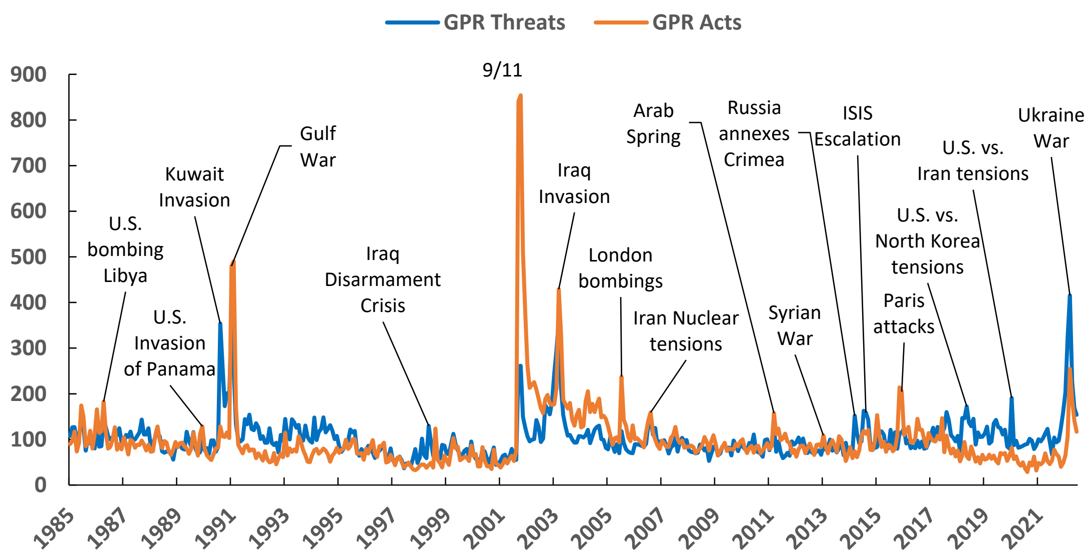


Figure 5. GPRT and GPRA subindexes of the Geopolitical Risk Index.

3.4 Geopolitical risk by industries

In their article, Caldara and Iacoviello (2019) study the role of industry exposure to geopolitical risk and find that positively exposed industries to aggregate GPR tend to have smaller investments than firms with negative exposure. In this thesis, the primary interest is whether the effect of the geopolitical risk differs between the Information Technology, Consumer Staples, and Energy sectors of the S&P 500 index and whether the exposure to the GPR varies between industries in the United States. Caldara and

Iacoviello (2019) find that industries such as petroleum and natural gas, beer and liquor, and electronic equipment are under negative exposure to the GPR, meaning that the stock returns of these industries outperform the market during the GPR pressures. Under positive exposure to the GPR are industries such as tobacco products, coal, and computer software, meaning that their stock returns underperform the market stock returns for the period of higher geopolitical conflicts.

Daily data is essential when measuring the industry's exposure to the GPR. In their article, Caldara and Iacoviello (2019) study that after 9/11, the first trading day on September 17th in the United States revealed –13% loss in the transportation industry, opposite to the precious metals industry, which gained +7.4%. Thus, daily data is justified since stock market returns fluctuate rapidly due to responding to the news. The authors state that the daily geopolitical risk data also aims to find a more accurate connection between variables since some GPR events last only some days, as with the stock return fluctuations. Chapter 4.2 shows the equation for the industry exposure measure by Caldara and Iacoviello (2019). The meaning of the method is that throughout elevated geopolitical pressures – the industries which expose positively to the GPR are losing concerning stock returns when compared to the cumulative returns of the market – therefore denoting the connection between rising GPR and negative stock returns (of the positively exposed industries). Vice versa, the industries which are negatively exposed to the GPR are gaining in terms of stock market returns relative to the market, consequently uncovering the correlation between the GPR spikes and positive stock price returns (of the negatively exposed industries).

According to Caldara and Iacoviello (2019), raised exposure to GPR follows industries where commerce is higher, business is more cyclically-unprotected, and leveraging numbers are higher. The authors read 100 transcripts of earning calls between firms and investors from the conversations of the GPR and its effect on a firm's business and find, for instance, that the transportation industry may be more exposed to the GPR because of terrorism, natural disasters, and high fuel prices. The same conclusion happened on the first trading day on September 17th after 9/11 (Caldara & Iacoviello, 2019), when the transportation industry lost –13 %. Another finding from the literature is that the sectors and industries more dependent on the international markets and demand can be more exposed to the GPR because the GPR can lower oversea demand for the firms operating internationally (Boutchkova et al., 2012). For example, agricultural manufacturing companies can suffer from geopolitical situations because of Russia's annexation of Crimea and the Ukraine War since Ukraine is one of the biggest corn and wheat producers in the world (World Population Review, 2022; Index Mundi, 2022), and therefore a great user of the agricultural products.

Indeed, Caldara and Iacoviello (2019) show that weakening trade, lack of credit availableness, and injunction of financial penalties to Russia impact apparatus sales of international companies. Finally, according to Caldara and Iacoviello (2019), one example of high leverage is that geopolitical risk can increase the effectiveness of more forceful disaster shocks due to financial tightness. Thus, the effect of the reinforced credit can strengthen the impact of the disaster with high GPR companies (Gourio, 2013).

Caldara and Iacoviello (2022) say that other factors influencing the exposure include geographical locality, the logistics network of the industries, diplomatic relationships, and risk-controlling procedures. Examples provided by the authors contain the general location of the significant oil sources, which could impact petroleum (and defense) companies during suspensions in the Middle East, and terrorism assaults could have more impact on industries such as entertainment, airlines, and transportation. More fresh evidence comes from the geopolitical situation in Ukraine, which has raised the price of food and energy together with increased inflation and the risk of stagflation since Ukraine is a giant player in the agriculture industry, and Russia is one of the biggest oil exporters (World Bank, 2022; World Population Review, 2022; Index Mundi, 2022; Worldometer, 2022).

3.5 Geopolitical risk vs. other risk indicators

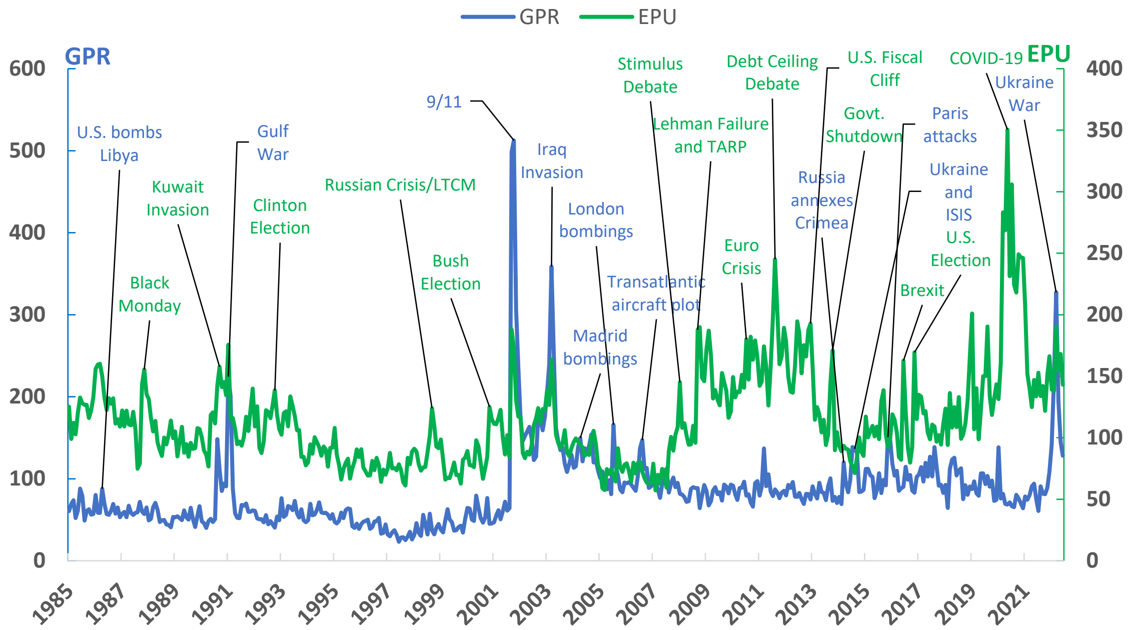
Caldara and Iacoviello (2019) argue in their paper that the GPR is a novel and exogenous risk for the U.S. economic changes, which differs from the Cboe Volatility Index® (VIX) and Economic Policy Uncertainty (EPU) indicators. They find, for instance, that the GPR is not Granger-caused by the economic advancements in financial, economic uncertainty, or macroeconomic factors. Economic uncertainty involves the log of the VIX and the EPU indexes, and the macroeconomic variable consists of the log differences of private employment, U.S. industrial production, and the log of the WTI value deflated by the U.S. consumer price index. Financial factor includes the gains of the two-year Treasury Yield and S&P 500 index. Hence, the authors state that the GPR can depict and segregate risks from geopolitical tensions, for example, terrorism and escalation of wars, which are not measured and fully understood by the other risk indicators or the economic developments in the U.S. economy at the frequency of the commercial cycle.

Even so, the GPR index by Caldara and Iacoviello (2019) still correlates at some amount with the EPU index by Baker et al. (2016). For instance, a two-standard deviation shock in the GPR index produces a brief decline in the median impulse response of the EPU index from approximately 15% to 3% after one year. It vanishes close to zero after eight quarters (cf. –20 basis point drop in the yield of the U.S. two-year treasuries from the same shock). By contrast, the identical effect with the S&P 500 index lasts more than 12 quarters, bottoming at –2.5% after two quarters, together with statistical and economic magnitude. Authors continue that, on the other hand, the division of the GPR index to the GPRT and the GPRA indexes shows that the two-standard-deviation growth in the GPRA index creates a negative response to the EPU index from quarters one to eight. The same effect from the GPRT index indicates the positive reaction of the EPU index from quarters zero to eight. This finding means that the increased threats in the GPRT index can also raise the EPU index when actual materialized events can move the EPU index the other way, revealing the exogenous property of the GPR index.

Additionally, the authors show that a remarkable quantity of separate and supernumerary fluctuation follows from what the GPR index exhibit and produces, leading to a forecast of diminished economic operations. Moreover, the GPR index is uncorrelated with well-known episodes such as the global financial crisis or recessions. This finding reveals an uncorrelation with the VIX and EPU indexes, which capture the global financial crisis. Thus, the GPR index highlights episodes not captured in the VIX and EPU indexes, which are mostly self-standing of the economy in terms of the U.S. enterprise cycle frequency.

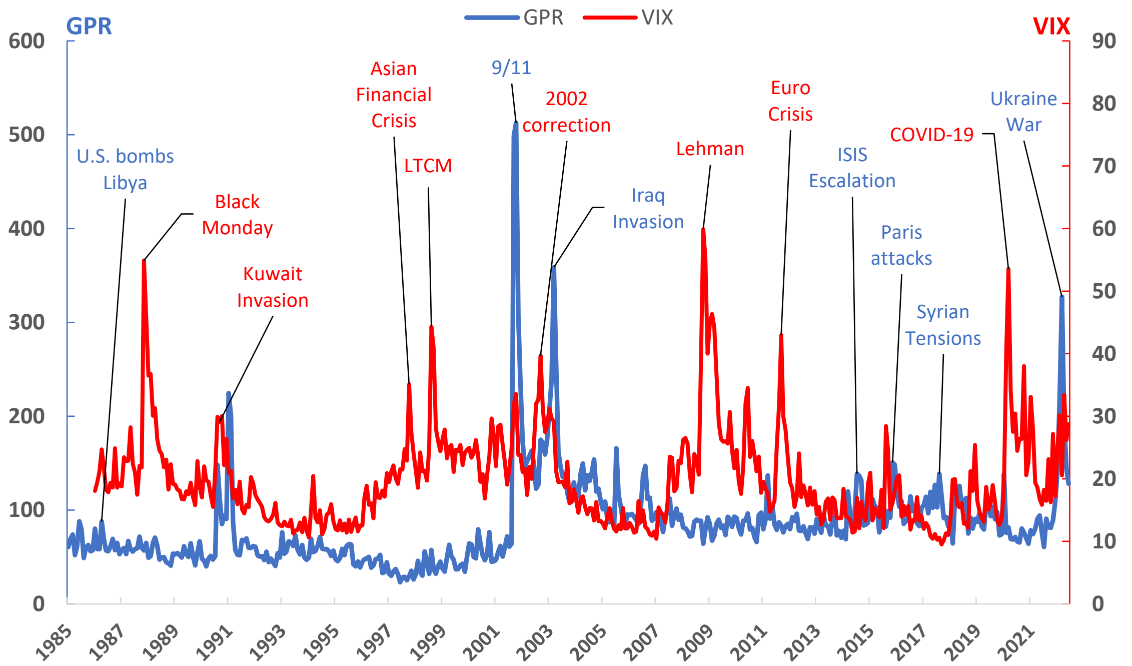
Figure 6 plots the relationship between the benchmark GPR index and the EPU index by Baker et al. (2016). Figure 7 depicts the association between the benchmark GPR and VIX indexes, where the latter denotes financial volatility. In both figures, the indexes spiked during Gulf War in 1991 and over the 9/11 terrorist strikes in the U.S. The correlation in Figure 6 is 12.68%, and the correlation between GPR and VIX indexes is 7.17%. Taken together, Caldara and Iacoviello (2019) claim in their paper that it is reasonable that the correlation between indexes rushes from the GPR to the other indexes in examples of the Gulf War and 9/11. Correspondingly, Iraq Invasion by the U.S. in 2003 spiked the EPU index even though the impact on the VIX index is more moderate or practically nonexistent.

Caldara and Iacoviello (2019) state that the indexes' figures show a considerable extent of independent alteration. For instance, the Asian financial crisis at the end of the 1990s or the euro crisis beginning of the 2010s does not follow the GPR index, opposite what the VIX and EPU indexes capture. Similarly, the bankruptcy of Lehman Brothers, the dot-com bubble in the late 1990s, political elections, or Black Monday does not induce spikes in the GPR index. Also, COVID-19 is independent of the GPR index. The figures support the authors finding that the GPR is not Granger-caused by financial, economic uncertainty, or macroeconomic factors. Vice versa, the spikes in the GPR index, such as Syrian tensions, the Paris attacks, the rise of ISIS, or the geopolitical situation in Ukraine in 2014, do not cause spikes in the VIX or the EPU indexes. These findings are similar which Baur



Note: This figure compares the benchmark GPR index from Caldara and Iacoviello (2019) and the economic policy uncertainty index from Baker et al. (2016). The EPU index in this figure is the three-component index. The GPR index is normalized to 100 from January 1985-June 2022.

Figure 6. Comparison between benchmark GPR index and EPU index.



Note: This figure plots the comparison between the benchmark GPR index from Caldara and Iacoviello (2019) and option-implied volatility from Cboe Volatility Index® according to S&P 500 firms. The data of 1986–1990 within the VIX index is matched to the old VXO index. The GPR index is normalized to 100 from January 1985-June 2022.

Figure 7. Comparison between benchmark GPR index and VIX index.

and Smales (2020) results in their article that the GPR is separate from other risk measures related to financial volatility (VIX), economic policy uncertainty (EPU), economic uncertainty (EconUnc) by Bekaert et al. (2022), and macroeconomic uncertainty (MacroUnc) by Jurado et al. (2015). The GPR index also uncorrelates with the USD index and U.S. 10-year treasury notes. Additionally, Das et al. (2019) show that the effect of EPU, GPR, and financial stress (FS) by Püttmann (2018) is heterogenous in emerging markets regarding causation and intensity. Lastly, Sharif et al. (2020) show that the GPR moves in a different direction during COVID-19 than the EPU index, which is a similar finding in Figure 6 above.

The authors (Caldara & Iacoviello, 2019) conclude that the GPR index has two independent features compared to the other risk indexes. First, it can portray the cases which might upsurge accumulated financial instability and political insecurity. Second, it can catch events that are probably exogenous from the primary business and financial frequency. In their recent paper, Caldara and Iacoviello (2022) state that the GPR positively correlates with U.S. military spending (Ramey, 2011) and the human cost of conflict factors such as war deaths. But like in the case of risk indicators, the GPR still captures much evidence not revealed by other indicators handled at this point. Authors research that war deaths are associated with the GPRA by 83%; in contrast, the correlation with the GPRT is 46%. The GPR index and war death indicator are close to each other during World Wars. However, only GPR remains relatively high to its mean after the World Wars, revealing the increased awakening to the geopolitical issues by news coverage and audience after the brutal World Wars.

3.6 Efficient market theory in the light of event studies

A theoretical framework continues with an efficient market theory and presents the core finance theories relevant to this study around the event study methodology. The start of the event studies can be stretched to 1969 in a paper by Fama et al. (1969). In their paper, the authors research the adaptation of standard stock prices to the new information, measured as stock splits and its inherent data. The authors discuss the extensive research on the continuous price changes in common stocks, revealing that the changes are maverick and logical. However, according to the authors, the stock price changes are maverick and logical only in “efficient’’ markets – a market that quickly conforms to the latest data. Fama et al. (1969) argue that before their paper, there was a lack of studies concentrating on detailed data and its pace of adapting to the new information. Instead, studies have used detected maverick and logical, continuous stock price changes and deduced market efficiency from that. Therefore, the authors are turning the research focus to the data testing of stock price modification pace regarding market efficiency.

That is the perspective also adopted in this thesis. When Fama et al. (1969) researched the extraordinary (abnormal) performance of stock price returns around stock splits, the research conducted in this thesis studies the performance of the stock price returns of three different sectors from the S&P 500 index in the U.S. around three unique geopolitical events in the 21st century. Fama et al. (1969) manifest that the average stock price returns increase three or four months before the stock split, but after the stock split, the increase of average stock prices stops, and cumulative abnormal returns stay stable and end their growth. The authors conclude that the market uses the stock split publication to forecast future predicted stock dividends and that the stock prices contain all the information available regarding the stock split without delay right after the stock split’s declaration moment or instantly after the split month.

In his article, Fama (1970) continues the work from the 1969 article and presents the efficient market hypothesis. According to Fama (1970), the efficient market hypothesis means that all openly available new stacked information is reflected in the price of a given security at a particular time. Therefore, for example, the efficient market hypothesis is applicable within a stock market. In addition, the author claims that the level of the stock price measures the corporation's value. Thus the capitalization of the company contains all publicly available information in its stock prices defined by the market. Fama (1970) continues that the optimal market would be where investors can pick the firm's stock, which always contains all publicly available information. Firms can make choices relating to investments and output because the market communicates through securities that already hold all the information accessible. Therefore the communication provided by the market is precise and correct. He concludes that among three different subgroups regarding accessibility and timing of the information, the market model performs the best (based on weak form tests, i.e., on historical prices and returns). It can provide results when stock price changes or returns go through one day or more (e.g., during geopolitical events under uncertainty). However, the semi-strong tests also endorse the EMH, such as stock splits, where the security price contains all publicly offered information by the time of the stock split (Fama et al., 1969; Fama, 1970).

Bowman (1983) goes on with the event studies and argues in his article that outside decisions affect the event study method, not only the decisions made within the corporation. For instance, the stock split or the announcement of the annual accounting earnings would be examples made within the firm. Accounting standards set by the financial accounting standard board or other usual actions, such as the oil embargo, can be examples of outside decisions or declarations affecting the event study modification. The author focuses intensely on event studies by segregating them to separate subclasses by type and sets up the parameters for shaping event studies with five steps.

The five steps in numerical order include identifying the event of interest, modeling the security price reaction, estimating the excess returns (including the market model), organizing and grouping the excess returns (e.g., CARs), and analyzing the results. In addition, he provides a comprehensive discourse about optional procedures for event studies to manage and apprehend the topic. Finally, the author notes that the information content of the event studies published by Ball and Brown (1968) focuses on the time before and concurrent with the specific event regarding the stock price. In contrast, Fama et al. (1969) concentrate mainly on time after the event in EMH (but also on time before and concurrent with the stock split, as discussed above).

Brown and Warner (1985) prolong the research on the event studies by taking along the daily frequency data relating to the stock price returns under investigation and examining features of that data and its influence on the event study method. The result of the article is that the event study methods built upon the OLS market model and t-tests are determined and justified well in different circumstances. The authors find a high correlation between the empirical and theoretical strengths of the event study practices. The authors also disclose that under excess daily returns, the dependency in the cross-section of the gains, the autocorrelation, and the variance changes can impact the outcome of the results. In addition, Brown and Warner (1985) conclude that the impact of the event study methodology is much more substantial when using daily instead of monthly data and that the nonnormality of the daily stock returns does not affect the results. Additionally, the variance changes in daily returns are tiny and not often repeated, the dependence's effect in the excess returns' cross-section is rare, and the autocorrelation has limited influence with methods.

Klein and Rosenfeld (1987) investigate the event study methods under different market conditions, in detail, under the bull and bear markets. They utilize four various event study methodologies and assess their soundness with the help of modeling practices and events to find potential biases concerning abnormal returns and their definition. Their study's outcomes reveal that the CARs are considered positive during the bull market. During the bear market, the CARs are considerably not positive before and after the event windows in models that do not conform with the market movements, for instance, in raw-market and mean-adjusted return models. Thus, these two models generate upward and downward biases regarding the results of abnormal returns. However, the distinctions are small and insignificant through the 2-day announcement period (especially during normal market conditions). Single-index and market-adjusted models significantly produce a smaller amount of extraordinary return movement during the pre- and post-event periods.

Fama (1991) presents an updated version of the efficient market hypothesis and suggests that event studies assess the EMH in a particular subclass of the stock market. The author professes that the event study is a methodology that is beneficial when estimating the impact of a specific event on companies of some segment of the economy. He continues that the event study methodology works best with daily returns; generally, the best evidence demands two factors. First, the researcher must date the event's start accurately (according to Fama 1991, on average, it takes no longer than one day for the stock to adapt to the new information coming from the event). Second, it is beneficial for the results if the event significantly influences stock price returns.

In addition, when scrutinizing specific events deeply, the result of the research can provide a strong understanding of the pace of modification of prices to the new data. Fama (1991) also researches that prices adapt effectively to the information closely related to the firm, such as dividend changes, company-control transactions, financing choices, and capital structure changes. He concludes with the existing evidence that the fluctuation in the expected returns of the securities is caused either by shocks in consumption between the differences of current and future consumption or by technology surprises connected to investments and savings.

MacKinlay (1997) releases an encompassing report of the event studies in his article. In detail, he recapitulates and traverses different event study methodologies and presents potential processes to perform an event study and analyze the abnormal returns (e.g., ARs, CARs) and their variances. The author introduces the market model, the constant mean return model, and the factor model under models, which simulate numerical data for normal returns. In his article, the arbitrage pricing theory (APT) and the capital asset pricing models are also under research to capture more restricted standard returns with the help of some best-known economic models. He reports that when conducting the event studies, it is crucial to capture any likely biases from the sample construction, for instance, by providing descriptive statistics of the sample and its qualities. Finally, the author stresses the importance of defining an event date as accurately as possible since the studies have been less triumphant otherwise.

Binder (1998) extend the research of the event studies with its developments starting from 1969 (Fama et al., 1969). These developments involve various fixed points for the normal rate of return (CAPM, APT, market model, and market and mean-adjusted returns) and the simulation of multivariate equations when the abnormal returns are regression coefficients (beta estimation). Other developments are the theoretical and empirical power of the event study methods under a variety of circumstances (under specific or uncertain event dates), resolutions of the statistical problems (heteroscedasticity and dependence), and hypothesis testing (AARs, CAARs). In addition, the author uses event periods as a dummy variable in a multivariate equation to conclude the specific event's outcomes.

However, Binder (1998) notes that under statistical problems, the solutions are straight-forward and answerable since they are commonly slight in practice. For example, he states that the cross–sectional dependency does not affect the results remarkably if the event periods are distributed randomly over the calendar time (non-clustered). The results remain non-affected if the stocks are selected randomly from different industries (even with the same event and calendar time), and the market model applies to the abnormal return calculations. In addition, he concludes that the time series dependency (of the AARs) is irrelevant when the estimation period is longer than the event period in relative terms and that the larger sample reduces the likelihood of biases.

Campbell et al. (2012) conclude the efficient market hypothesis based on the event study methodology presented here. He states that the market is efficient if the stock prices do not change when all market participants have the new information. He finalizes that ever since the 1970s, the market model has been the most commonly used in the field of event studies and that, presumably, the returns from the market and expected returns from the particular stock are linearly associated when the security and market are from the same source, for instance from the S&P 500 index. He concludes that the market model can diminish the variance of abnormal returns by eliminating part of the returns connected to the market's fluctuation. Therefore the better R^2 explains a higher variance decrease and a better possibility to capture event reactions regarding abnormal returns.

4 Data and methodology

The empirical part of the thesis starts from this chapter. The fourth chapter presents data gathering and description. Additionally, the chapter presents the data's suitableness and sufficiency relating to the research problem. The chapter aims to increase the repeatability of the research by providing a detailed data collection process and presenting the research methods of the thesis with justifications. The connection between the theoretical framework and the empirical part of the thesis occurs by providing appropriate research methods for the research needs. Lastly, the reliability of the research and robustness of the results concludes the chapter.

4.1 Data gathering and description

The data for the geopolitical part of the thesis comes from the website of the geopolitical risk index. The website comes from https://www.matteoiacoviello.com/gpr.htm and is publicly available to all interested. A researcher downloaded the monthly data from the website on May 8, 2023. Caldara and Iacoviello (2022) – the creators of the GPR index – update data by the beginning of every month regarding monthly data and at the start of every new week concerning the daily data.

The monthly GPR data can be used and downloaded as an excel-file. The monthly GPR file includes 17 separate header rows from which the first four are relevant to this study; month (Date, year/month), GPR (Recent GPR Index, 1985:2019=100), GPRT (Recent GPR Threats Index, 1985:2019=100), and GPRA (Recent GPR Acts Index, 1985:2019=100) to spot the three most significant geopolitical events in the 21st century and to calculate the OLS regressions. In addition, the file includes a share of articles divided by the search categories from 1 to 8 presented in Caldara and Iacoviello (2022), the countries' GPR as a percent of articles, and the countries' historical GPR as a percent of articles from 39 countries. The monthly GPR, GPRA, and GPRT indexes are used in OLS regressions in the thesis as independent variables.

The data for the monthly portfolio returns in the 49 different industry groups used as a dependent variable in OLS regressions in the thesis comes from Fama and French's (1997) website. The website comes from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, and it is also publicly available for all interested participants. The data was downloaded last time from the website on May 8, 2023, and the excel-file contains the average value- and equal-weighted monthly portfolio returns from the 49 different industries. The data in the file starts from 1926 onwards with the help of the CRSP database.

A researcher downloaded the historical S&P 500 index closing values data from two databases. The data for the recent five years comes from the Nasdaq database (Nasdaq, 2022) on August 1, 2022, and for years before that from the Kaggle-database (Han, 2022) on June 22, 2022. The two excel-files were combined into one file and arranged according to the index's date and closing values in consecutive order. The S&P 500 index closing values are used in the event study calculations to calculate market model returns. In addition, Fama and French's (1997) website provides the market factor used as market excess returns (independent variable) to calculate OLS regressions in the thesis.

The risk-free rate used in the thesis is the U.S. 1-Month Treasury Bill Rate. The values between January 1985, and March 2023, are retrieved from the Fama and French (1997) website on May 8, 2023. OLS regressions use the risk-free monthly rates in the thesis.

The last part of the data was gathered from the Thomson Reuters (Datastream/Worldscope) database through the University of Vaasa resources on June 21, 2022. The excel-file incorporates daily closing stock prices for the S&P 500 index companies from December 31, 1984, to June 20, 2022, and time series data of the listed companies in the S&P 500 index from the year 1984 to 2021. The general descriptive information of the companies includes sector and industry classification variables used as help when creating a compacted excel-file that contains the companies that belong to the Information Technology, Consumer Staples, and Energy sector of the S&P 500 index. This data is used in the event study calculations to calculate all abnormal returns.

The thesis follows the theory presented by Fossung et al. (2021). It divides the S&P 500 index firms into three sectors by conducting MSCI (2020) standards and the GICS® (Global Industry Classification Standard) procedure. Therefore, the primary business activity description divides the firms into sectors. For instance, the food and staples retailing, beverage, and household products stocks belong to the Consumer Staples sector. The Energy sector includes stock from the oil, gas, and energy equipment industries. The Information Technology sector belongs to stocks from the software and services and technology hardware and equipment. In addition, industry and sector variables from the S&P 500 data mentioned in the previous paragraph divide the firms into the corresponding sectors. Finally, the visual picture from (Ross, 2020) sharpens the extensive view of the S&P 500 firms according to their sectors and industries below them.

Table 2 shows the descriptive statistics of the whole sample (except the risk-free rates) to calculate the study results. The data is quite large but focuses on the four different event windows. However, the period from 1985 to March 2023 runs in the OLS regressions. In the S&P 500 section, the mean is 3% which is similar to that Fossung et al. (2021) examine and close to Fama and French's (1997) sample mean with the 49 industries (0.050). It is also close to the average of the three sectors' means (0.054). Another interesting finding is that in all sections, the mean of the 0,1 event window is always positive concerning all three events' averaged together.

Nevertheless, the mean is not positive in all three geopolitical events since the results vary. Additionally, the second best event window in terms of most positive returns (but still primarily negative) is –10,10, indicating that the effect of the GPR changes its sign when more time passes and the event window is longer. In number order, the worst event windows regarding most negative returns are 0,5 and –3,3. In the GPR section, the heightened GPR causes spikes in the index which appears in the 0,1 event window's mean, and the spikes slowly weaken when the event window is extended (e.g., in the –10,10 event window).

When looking at the standard deviation, the GPR section has the highest risk, and the risk's effect remains low in the 0,1 event window relative to the others. This finding means that according to the GPR index, the impact of the geopolitical event stays high in immediate relation to the time after the event date (since there is a high variation in the standard deviation). When examining between sectors, the Information Technology has the highest risk, whereas the Consumer Staples sector has the lowest risk. The S&P 500 index and the 49 industries from Fama and French (1997) are close to each other with a degree of risk. The most risk-free event window is –10,10, and the riskiest event window is 0,5, according to the averaged results of all three geopolitical events between sectors. The most extended period incorporates the lowest risk, a reasonable result because the time and higher number of observations reduce the risk. For instance, the sectors' full sample standard deviations are always more minor than in the event windows.

Between the sectors, the highest maximum numbers within the event windows are from the Information Technology sector. The lowest maximum observations are from the Consumer Staples sector, which correlates with the observed risk measured by the standard deviation. The values within the sectors are higher than the market, lower than the GPR, and close to the 49 industry values meaning that the sector and event window separation pinpoints abnormal returns and that the abnormal performance is at least partly caused by the GPR (e.g., maximum amounts are smallest in the 0,1 event window, similarly with the GPR). The most extended event window –10,10- captures all sections' highest maximum return. Vice versa, the longest event window –10,10 captures the highest (and shared in the IT and the GPR) minimum return in all sections. The IT sector has the highest minimum returns, whereas the Energy sector has the best minimum and mean returns.

Table 2. Descriptive statistics focused on the event windows' averages.

	Period	Obs.	Mean	Std. Dev.	Max.	Min.	Skewness	Kurtosis
S&P500	Full Sample	9444	0.030	1.161	10.957	–22.899	–1.227	26.057
	–3,3	7x3	–0.363	1.870	1.900	–3.497	–0.453	1.091
	0,5	6x3	–0.542	1.780	1.495	–3.398	–0.688	0.005
	0,1	2x3	0.185	1.852	1.495	–1.124	–0.600	1.175
	–10,10	21x3	–0.214	1.753	3.281	–3.877	0.105	0.192
Energy	Full Sample	224,802	0.046	2.198	87.731	–61.047	0.484	50.373
	–3,3	7x3	–0.115	2.602	10.367	–6.306	0.667	4.523
	0,5	6x3	–0.042	2.736	10.464	–7.228	0.609	4.101
	0,1	2x3	0.202	2.568	7.923	–5.346	0.224	4.365
	–10,10	21x3	0.054	2.559	14.283	–8.441	0.791	5.773
Cons. Staples	Full Sample	322,542	0.049	1.752	83.156	–68.535	1.132	88.688
	–3,3	7x3	–0.118	2.186	7.225	–8.681	–0.350	2.573
	0,5	6x3	–0.342	2.305	8.706	–8.681	–0.180	2.157
	0,1	2x3	0.244	2.436	6.320	–6.912	–0.488	2.433
	–10,10	21x3	–0.045	2.121	11.095	–10.250	–0.131	3.742
IT	Full Sample	733,050	0.066	2.388	70.533	–59.525	0.589	23.699
	–3,3	7x3	–0.403	3.364	14.872	–28.197	–1.983	28.288
	0,5	6x3	–0.516	3.495	15.100	–31.184	–2.130	23.191
	0,1	2x3	0.342	3.167	13.482	–15.647	–1.303	13.434
	–10,10	21x3	–0.384	3.312	17.507	–31.184	–0.611	12.770
GPR	Full Sample	13,683	–10.774	61.025	1442.763	–95.001	5.521	76.437
	–3,3	7x3	42.575	88.932	173.875	–47.512	0.390	–1.362
	0,5	6x3	41.546	97.554	194.756	–45.318	1.051	1.280
	0,1	2x3	118.085	34.898	142.762	93.409	0.329	–0.492
	–10,10	21x3	18.718	65.411	196.403	–47.512	1.331	1.583
49 ind.	Full Sample	462,756	0.050	1.540	25.590	–24.120	–0.200	12.968
	–3,3	7x3	–0.364	2.390	9.947	–10.603	–0.334	3.834
	0,5	6x3	–0.481	2.444	9.937	–10.320	–0.235	2.553
	0,1	2x3	0.220	2.755	9.173	–9.970	–0.576	2.425
	–10,10	21x3	–0.145	2.233	11.280	–10.860	0.044	2.742

Note: This table represents descriptive statistics for the sample's daily values (multiplied by 100). Each of the four event windows contains average values of all three geopolitical events under examination in this study, named 9/11 2001, Iraq War 2003, and Ukraine War 2022. For instance, event window –3,3 and its mean column in the S&P 500 section includes the average daily stock returns from 9/11 2001, the Iraq War 2003, and the Ukraine War 2022, and all summed together in the event window in question. The period for the full sample calculations is 2.1.1985–20.6.2022. The GPR here denotes the daily benchmark geopolitical risk index. The figures are with three decimals. The 49 industries are from Fama and French (1997) website and with the value-weighted data. The U.S. national holidays and market closure days are ignored in the sample so that the event windows contain only the days when the market is open. The winsorizing applies to the Consumer Staples maximum values by cutting off the top three maximum values from the entire sample.

The skewness depicts the degree of asymmetry of the distribution around its mean, and kurtosis shows how regularly outliers occur from the distribution by measuring the ''tailedness.'' The IT sector has the worst skewness in event windows. In contrast, the Energy sector has the best. The attention goes to the 0,1 event window since all the mean returns are positive. Still, the skewness is negative (except in the GPR and the Energy section), meaning that the average returns are positive, but the outlier daily returns are negative. These negative outlier daily returns are at least partly associated with the GPR because they have negative skewness, and the GPR has a positive overall performance but also positive skewness.

Table 2 also shows some situations when the skewness is positive, but the mean returns are negative, such as with the Energy sector (in –3,3 & 0,5) and S&P 500 index (in –10,10). This finding reveals positive outlier daily returns but overall negative performance. Table 2 also shows situations when the skewness and mean returns are negative, which is not good since extreme negative observations exist with the overall negative performance. Finally, the kurtosis column shows that the outliers are found most often in the IT sector and the least often in the Consumer Staples sector regarding event windows, and outliers occur more often when the sample period is longer.

4.2 Research methods of the thesis

A researcher uses the quantitative methodology with two different methods in the thesis. First, the ordinary least square (OLS) regression takes place to run the regressions relating to the industry exposure measure for the geopolitical risk, as Caldara and Iacoviello (2019) show. This method gives an overview regarding how the effect of the GPR differs between industries relative to the market, and the comparison to the event study results is also possible. Second, the event study calculations follow Fossung et al. (2021) methodology, which allows for calculating the abnormal returns during different event windows in times of heightened geopolitical risk. The event study method pinpoints the abnormal performance of the stocks and makes possible the comparison between different sectors' returns.

The industry exposure to the geopolitical risk by Caldara and Iacoviello (2019) is regressed as follows:

$$R_{k,t} = \alpha_k + \beta_k \Delta GPT_t + \gamma_{\mathrm{k}} RM_t + \varepsilon_{k,t,} \quad (1)$$

where $R_{k,t}$ is the monthly excess return of the 49 industries by Fama and French (1997) in industry k at time t minus the U.S. 1-Month Treasury Bill Rate, ΔGPT_t is the shift in the monthly geopolitical threat index, RM_t is the monthly market excess return minus the U.S. 1-Month Treasury Bill Rate, and $\varepsilon_{k,t}$ is the error term. The data for the equation runs from January 1985 to March 2023. The industry exposure is $\Lambda_{k,t}$ and it incorporates the β_k coefficients with the signs altered. Thus, positive values denote high exposure, and negative values low exposure for the GPR. In addition and before the sign change, the demeaning applies to the beta coefficients.

Equation 1 is modified according to Caldara and Iacoviello (2022) to the following format and compared to the other OLS regressions:

$$R_{k,t} = \alpha_k + \beta_k \Delta GPR_t + \gamma_{\mathrm{k}} RM_t + \varepsilon_{k,t,} \quad (2)$$

where ΔGPR_t is the change in the monthly geopolitical risk index (monthly benchmark GPR index). Other coefficients in the equation remain the same.

The last of the three OLS regressions come from the first two with a tiny difference:

$$R_{k,t} = \alpha_k + \beta_k \Delta GPA_t + \gamma_{\mathrm{k}} RM_t + \varepsilon_{k,t,} \quad (3)$$

where ΔGPA_t is the change in the monthly geopolitical acts index. Other coefficients in the equation remain the same as in the previous equations. Thus, a researcher regresses the monthly portfolio returns from Fama and French (1997) to the changes in the monthly geopolitical index, geopolitical threats index, and geopolitical acts index producing 147 separate regressions.

The second methodology is the event study method. First, it is helpful to present the timeline for the event study, which Figure 8 depicts (Fossung et al., 2021; Campbell et al., 2012).

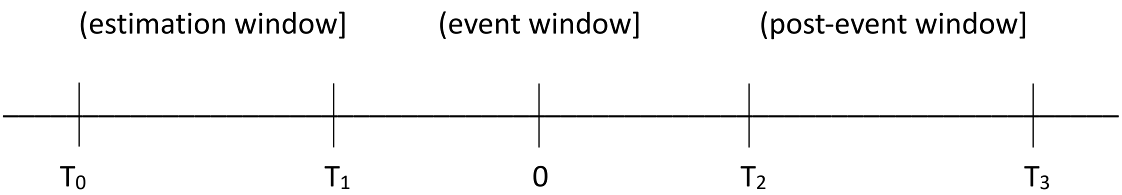


Figure 8. The timeline for the event study.

In the event study calculations, T_0 depicts the start of the estimation window, and T_1 describes the end of the estimation window and the beginning of the event window. Therefore the timespan of the estimation window corresponds to $T_0 – T_1$. The T_2 signifies the event window's end and the post-event window's start. Thus the $T_1 – T_2$ indicates the period for the event window. The T_3 implies the end of the post-event window; hence, T_2 - T_3 represents the period for the post-event window. The 0 describes the geopolitical event. Finally, the following notations prevail in the summation equations; $\tau = T_1$ to $\tau = T_2$ is the event window, $\tau = T_0$ to $\tau = T_1$ means the estimation window, and L_1 describes the duration of the estimation window, $T_1 – T_0$.

This thesis follows the definition of the four event windows presented by Fossung et al. (2021), producing (–3,3), (0,5), (0,1), and (–10,10) event windows. For example, in the –10,10 event window, T_1 is set ten days before the realized geopolitical event and T_2 ten days after. The different event windows allow capturing short-time, post-event, and immediate impacts and prior information leak effects on the stock prices around the event date. In addition, the estimation window is set to 253 trading days to catch a full calendar year before the realized geopolitical event.

The idea of the event study methodology in the thesis is that a particular geopolitical event affects stock prices. Therefore if the event influences the securities – the expectation is that the return of the security diverges from its regular return during the heightened geopolitical tension. The event study method here is derived based on the market model for the reason (for instance) that according to Campbell et al. (2012), the market model has better validity than other models. The market model is the following (Fossung et al., 2021; MacKinlay, 1997):

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}, \tag{4}$$

where $R_{i,t}$ depicts the return of the company *i* at time t, $E(\varepsilon_{i,t}) = 0$ and $Var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon i}$, $R_{m,t}$ indicates the return of the market *m* at time *t*, and α_i, β_i, and $\sigma^2_{\varepsilon i}$ are the parameters of the model. Finally, $\varepsilon_{i,t}$ is the error term. Therefore, the expected value of the (4) is (Fossung et al., 2021):

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t}, \tag{5}$$

which predicts the normal return for the security *i*. The abnormal return is the difference between actual and normal returns. Deriving from equation (5), a researcher calculates the daily expected returns corresponding to the market model for firm *i* as follows (Fossung et al., 2021; MacKinlay, 1997; Campbell et al., 2012):

$$AR_{i,\tau} = R_{i,\tau} - \hat{\alpha}_i + \hat{\beta}_i R_{m,\tau}, \tag{6}$$

where $AR_{i,\tau}$ is the abnormal return for the firm *i* at the event window τ, and the τ is the event window or an out-of-sample data ($T_1 - T_2$). The condition for the null hypothesis $AR_{i\tau} \sim (0, \sigma^2(AR_{i\tau}))$ and the event window is denoted as follows (Fossung et al., 2021; MacKinlay, 1997):

$$\sigma^2(AR_{i\tau}) = \sigma^2_{ei} + \frac{1}{L_1}\left[1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}^2_m}\right], \tag{7}$$

where,

$$L_1 \text{ is the duration of the estimation}, Var(R_{mt}) = \sigma_m^2, and\ \hat{\mu}_m = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1} R_{m\tau}.$$

When L_1 grows, the second portion from the right-hand side of the formula (7) approaches zero. The perception of the abnormal return below the null hypothesis in the event window is the following (MacKinlay, 1997; Fossung et al., 2021):

$$AR_{i\tau} \sim N\left(0, \sigma^2(AR_{i\tau})\right). \tag{8}$$

The abnormal returns can be cumulated to form cumulative abnormal returns (CARs). The sample CAR_i (τ_1, τ_2) is represented over time in the following way (Fossung et al., 2021; MacKinlay, 1997):

$$CAR_i\ (\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau.} \tag{9}$$

The variance of the CAR_i (τ_1, τ_2) is asymptotically (Fossung et al., 2021; MacKinlay, 1997):

$$\sigma_i^2(\tau_1, \tau_2)\ = (\tau_2 - \tau_1 + 1)\sigma_{ei}^2, \tag{10}$$

where a researcher should correct small sample variance estimations of the CARs for the estimation error, and large sample variance estimations can be used for rational values of the L_1. The distribution of the CARs beneath the null hypothesis is (Fossung et al., 2021; MacKinlay, 1997):

$$CAR_i(\tau_1, \tau_2) \sim N\left(0, \sigma_i^2(\tau_1, \tau_2)\right). \tag{11}$$

The sample average abnormal return (AAR) for the company *i* at event window τ with *N* events is (Fossung et al., 2021; MacKinlay, 1997):

$$AAR_t = \overline{AR}_\tau = \frac{1}{N}\sum_{i=1}^{N} AR_{i\tau}. \tag{12}$$

Moreover, with big $L_1$the variance of the AAR is (Fossung et al., 2021; MacKinlay, 1997):

$$VAR(\overline{AR}_\tau) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_{ei}^2. \tag{13}$$

The CAAR (cumulative average abnormal return) for the event window τ can be computed similarly to the CARs for the stock *i* (MacKinlay, 1997; Fossung et al., 2021):

$$CAAR(\tau_1, \tau_2) = \overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_{\tau.} \tag{14}$$

The variance for the CAAR goes as follows (MacKinlay, 1997; Fossung et al., 2021):

$$VAR\left(\overline{CAR}(\tau_1, \tau_2)\right) = \sum_{\tau=\tau_1}^{\tau_2} VAR(\overline{AR}_\tau). \tag{15}$$

Finally, the findings must be statistically significant to find the connection between the event and the security price returns (Ghauri & Grønhaug, 2010). The t-test by Müller (2020) is derived as follows for the AAR (Fossung et al., 2021):

$$t_{AAR_e} = \sqrt{N}\,\frac{AAR_e}{S_{AAR}}, \tag{16}$$

where t_{AAR_t} is a t-test for the AAR in the event *e*, N is the number of averaged ARs across companies, and S_{AAR_t} is the standard deviation of the AARs through companies during the estimation window. The value of the t-test more than 1.96 in absolute value denotes the significance at the 5% level ($(|t_{AAR_t}| > 1.96)$). The t-test by Müller (2020) is derived as follows for the CAAR (Fossung et al., 2021):

$$t_{CAAR_e} = \frac{CAAR_e}{\sqrt{T_2 - T_1} S_{AAR}}, \tag{17}$$

where $CAAR_e$ is a t-test for the CAAR for the event e, $T_2 - T_1$ denotes the number of days in the event window, and S_{AAR} describes the standard deviation of the AARs across the companies.

4.3 Reliability of the research and robustness of the results

Reliability of the data and research increases by providing a detailed data collection process and description (Carroll, 2022). The description of the data gathering and sector division (by MSCI, 2020; Fossung et al., 2021; Ross, 2020) raises the research's repeatability and the study's objectiveness. Therefore, they can reduce the randomness of the results. For instance, the thesis can give reliable results to the extent that the thesis is repeatable through new geopolitical events by acquiring the data from the same sources described earlier in Chapter 4.1. Additionally, the precise definition of geopolitical events raises the repeatability of new research in event studies. Data were verified multiple times during the data gathering to minimize mistakes. Also, with the help of used formulas, a researcher checked and estimated the calculated results several different times. Thus two other evaluators would arrive at the same results with the help of the same data and equation formulas used from the same stock price and geopolitical material.

The following data is publicly available for all interested participants; the data for the geopolitical risk (Caldara & Iacoviello, 2019; 2022), monthly portfolio returns in 49 different industry groups by Fama and French (1997), S&P 500 index closing values from the databases (Nasdaq, 2022; Han, 2022), and risk-free rates denoted as U.S. 1-Month Treasury Bill Rates (Fama & French, 1997). Only the daily closing stock prices for the S&P

500 index companies come from the Thomson Reuters (Datastream/Worldscope) database through the University of Vaasa resources. However, the well-known database represents over 95% of the global market value (University of Vaasa, 2022). Thus, the presumption is that the database is well-accessible within most of the world's universities. However, websites such as Yahoo Finance contain extensive daily closing stock price information.

Therefore, all data for the thesis is publicly available to anyone interested, increasing the ethicality and soundness of the results (Fossung et al., 2021). In addition, the data quality was compared, for instance, between different sources for the S&P 500 index values and stock price closing values, and it was exact. Regarding the quantity of the data, the descriptive statistics in Table 2 show almost 1.8 million observations concentrating on the 648 observations (plus estimation window) within four different event windows focusing on three different sectors. Consequently, the data is more than sufficient and suitable for the master's thesis level.

The validity of the research, on the other hand, means that the metrics used in it precisely measure things initially intended to be measured (Carroll, 2022). The choice of a quantitative research method was one reason the thesis could precisely calculate the planned values. The metrics used in the thesis are valid because the metrics are well-established and commonly used equations in event study analysis on finance since the 1960s event study beginning (cf. Fama et al., 1969). The formulas used to obtain the empirical results are also publicly available. Finally and in general, the basis of the event study analysis and research is the correctness of the data used, as they form the basis for the accuracy of the research results.

According to Fossung et al. (2021), the robustness of the results improves by including an estimation window for 253 trading days, indicating one full calendar year before the geopolitical event to ensure that the market model has a sufficient amount of data to generate precise results of the expected returns. They continue that the estimation window and event window does not overlap together, which can prevent the rise of possible errors included in the estimation window period. The authors also state that by executing the research with identical parameters and repeating similar methods with three different sectors (131 companies in this thesis) of the S&P 500 index, the research outcomes are more robust and trustworthy, together with reduced biases.

In their paper, Caldara and Iacoviello (2019) present the pilot audit to find GPR-related words when building the GPR indexes. The U (which includes approximately 70 000 articles each month) depicts the sample of newspaper articles applied to build up the indexes. The ε indicates the subclass for the U, and it comprises articles including any of the subsequent phrases: *geopolitics*, *war*, *military*, *terrorism/t*. The words are selected based on the assessment of the most frequent unigrams discovered from the books in the field of geopolitics. The ε includes 15% of the articles in the U each month. The authors continue that they conducted a pilot audit by randomly choosing 50 months from 1985 to 2016, together with the choice of 50 articles from ε at a random base. After that, they read the 2,500 articles allocated to the group ε^1 which includes articles mentioning elevated geopolitical tensions and the group ε^0 which is not underscoring any recent geopolitical happenings or tensions. The ε^0 therefore contains articles such as the anniversary of World War I, movie and book announcements, and the dormition of historical characters.

Caldara and Iacoviello (2019) reveal that shy 50% of the articles in ε mention high-level or elevated GPR, and the error rate $\varepsilon^0/\varepsilon$ shows a volatility of 17% in terms of monthly standard deviation meaning that an extensive search would cause an index with a high noise-to-signal ratio. They state that text-analyzing techniques from ε^1 and ε^0 find most often occurred bi-grams. Next, Caldara and Iacoviello (2019) calculate the odds ratio using Bayes' rule to find a percentage of articles count in ε^1 instead of ε^0 considering every bi-gram. Table 1 consists of the group of search phrases based on the input of a bi-gram record with the greatest odds-ratio. The authors continue that similarly, the bi-grams with the greatest odds-ratio included to the ε^0 were used to capture the words not incorporated into the search phrases to build up the GPR index. These words include *art*, *museum*, *movie*, *film*, *air force*, *memorial*, *anniversary*, *human rights*, *civil war*, and *war* in closeness to the word *end* (end N/2 war).

Caldara and Iacoviello (2019) also present in their paper the full-scale audit, which includes a human-created GPR index and a computer-created GPR index together with a detailed audit guide. The correlation between these two indexes from 1899 to 2018 is 86% quarterly and 98% monthly. The narrative index confirms that the indexes are not probably affected by the language changes over time since the human-created index was created by reading the front pages of the New York Times and then dividing the headlines into groups from 0 to 5 according to the relevance to the geopolitical risk. In addition, the authors unveil that their results are also robust when using 9/11 dummy variables and different vector autoregression analyses from Cholesky ordering, placebo variables in the regressions, and using a censored GPR index.

According to Caldara and Iacoviello (2019), the geopolitical data is also robust to broad and narrow search criteria with a high correlation to the benchmark GPR index. The change in media interest to political slant, sports events, or natural disasters does not account for the fluctuations in the GPR index. The authors finalize that the benchmark GPR index and the index which ignores finance and associated economic phrases are heavily correlated. Additionally, they complete the audit process conditions set by other research and state that the GPR is a secure and robust instrument of geopolitical risk compared to other risk proxies.

In their recent paper, Caldara and Iacoviello (2022) exhibit some updated robustness and validity of their methodology and results. For instance, they show that in the last 120 years, the index is catching all of the most significant geopolitical risks lagged with three lags to reflect the shock to the contemporaries. Additionally, they display that country-specific indexes capture the most significant spikes than in the benchmark GPR index. The GPR index correlates highly with a worldwide war deaths variable from conflicts and terrorism (82%) and news about U.S. military spending (29%). Additionally, the authors state that the benchmark and historical GPR indexes correlate by 95%. However, the latter consists of only three newspapers, and the former includes ten, meaning that the indexes are not affected by the amount or type of newspapers. Moreover, the authors show that the association in the GPR index between U.S. and non-U.S. newspapers is 88% revealing the universal nature of many geopolitical tensions. Lastly, the Cronbach alpha is 96% in the benchmark GPR index.

5 Empirical results

The purpose of the fifth chapter of the study is to report and interpret the empirical results of the thesis. The methodologies divide the chapter into two parts for better reading fluency. The first section presents the outcomes of the OLS regressions, and the second section shows the numbers of the event study calculations. A researcher compares the results to the theoretical framework of the thesis and the papers from Fossung et al. (2021) and Caldara and Iacoviello (2019; 2022). Finally, the empirical results answer the research questions of the thesis.

5.1 Results of the OLS regressions

Contrary to previous GPR-related studies (e.g., Caldara & Iacoviello, 2019; Baur & Smales, 2020; Salisu et al., 2021; Bouoiyour et al., 2019), the results argue that the geopolitical acts index is the most influential index from among other GPR indexes (geopolitical risk and -threat indexes). Table 3 presents the findings of the OLS regressions with the equal-weighted stock returns. The industry exposure measure created by Caldara and Iacoviello (2019; 2022) describes the exposure to geopolitical risk when using Fama and French (1997) 49 industries as a dependent variable. For instance, if the geopolitical threat increases by one unit, then the monthly stock returns in the Defense industry (Guns) rise by 3.38 percent relative to the aggregate market in Table 3. Similarly, if the geopolitical acts increase by one unit, the monthly stock returns in the Alcoholic Beverages industry (Beer) decrease by –0.667 percent.

Caldara and Iacoviello (2019) do not reveal the significance of the industry exposure results. This thesis finds that only two of the betas are statistically significant in the geopolitical threat column, indicating that the geopolitical threats impact the Fama and French (1997) equally weighted stock returns through Defense (3.38%) and Personal Services (–0.971%) industries. However, the quarterly rolling for the estimated betas is not used during the regressions because it goes far beyond the purpose of the thesis. Additionally, the utilized data in the thesis is approximately four years longer, also capturing the Ukrai-

Table 3. Industry exposure to GPT, GPR, and GPA with the monthly average equal-weighted stock returns.

Industry	***GPT***			***GPR***			***GPA***		
	α_k	β_k	γ_k	α_k	β_k	γ_k	α_k	β_k	γ_k
Agric	−0.00308	0.00714	0.860***	−0.00300	0.00561	0.860***	−0.00296	0.00285	0.858***
Food	0.00185	−0.00542	0.698***	0.00171	−0.00254	0.700***	0.00166	−0.000770	0.702***
Soda	0.00440	−0.00833	0.809***	0.00419	−0.00385	0.812***	0.00420	−0.00254	0.813***
Beer	0.00438**	−0.00449	0.670***	0.00443**	−0.00587	0.667***	0.00464**	−0.00667**	0.664***
Smoke	0.0108***	−0.00729	0.683***	0.0105***	−0.000343	0.689***	0.0104***	0.00136	0.692***
Toys	−0.00270	0.00141	1.105***	−0.00259	−0.00122	1.103***	−0.00250	−0.00200	1.101***
Fun	−0.00206	−0.00487	1.225***	−0.00213	−0.00331	1.226***	−0.00209	−0.00267	1.225***
Books	−0.00173	0.00225	1.181***	−0.00169	0.00139	1.180***	−0.00165	0.000350	1.179***
Hshld	−0.00158	−0.00338	1.072***	−0.00153	−0.00488	1.070***	−0.00143	−0.00448	1.069***
Clths	−0.000790	−0.00407	1.078***	−0.000641	−0.00783	1.073***	−0.000518	−0.00659*	1.072***
Hlth	0.000322	0.00789	1.068***	0.000469	0.00483	1.066***	0.000607	0.000951	1.062***
MedEQ	0.000759	0.00424	1.051***	0.000787	0.00379	1.052***	0.000817	0.00190	1.050***
Drugs	0.00239	−0.000676	1.303***	0.00239	−0.000603	1.302***	0.00242	−0.000764	1.302***
Chems	0.0000884	0.000478	1.142***	0.000119	−0.000221	1.141***	0.000134	−0.000352	1.141***
Rubbr	0.00123	−0.00294	1.063***	0.00131	−0.00497	1.060***	0.00144	−0.00484	1.059***
Txtls	−0.00360	0.00967	1.163***	−0.00336	0.00449	1.159***	−0.00327	0.00148	1.156***
BldMt	0.00122	−0.00127	1.070***	0.00123	−0.00179	1.069***	0.00128	−0.00181	1.069***
Cnstr	−0.00239	−0.00801	1.218***	−0.00249	−0.00602	1.219***	−0.00259	−0.00235	1.222***
Steel	−0.00145	0.00148	1.312***	−0.00133	−0.00125	1.310***	−0.00128	−0.00147	1.309***
FabPr	−0.00387	−0.00149	1.051***	−0.00382	−0.00265	1.050***	−0.00373	−0.00299	1.048***
Mach	0.000531	0.0000197	1.229***	0.000555	−0.000539	1.229***	0.000569	−0.000544	1.228***
ElcEq	−0.00175	−0.00537	1.203***	−0.00175	−0.00573	1.202***	−0.00171	−0.00410	1.202***
Autos	−0.00295	−0.00624	1.343***	−0.00294	−0.00678	1.341***	−0.00296	−0.00383	1.343***
Aero	0.00366	−0.00528	1.027***	0.00389*	−0.0109*	1.019***	0.00410**	−0.00982**	1.017***
Ships	−0.00192	0.00865	1.239***	−0.00193	0.00930	1.242***	−0.00203	0.00712	1.241***
Guns	0.00550**	0.0338***	0.808***	0.00549**	0.0360***	0.819***	0.00552**	0.0216***	0.809***
Gold	0.0000126	0.0158	0.840***	0.000160	0.0131	0.840***	0.000287	0.00621	0.835***
Mines	−0.000212	0.0142	1.125***	0.000186	0.00555	1.118***	0.000240	0.00262	1.115***
Coal	−0.00427	0.00281	0.988***	−0.00429	0.00353	0.989***	−0.00443	0.00424	0.992***
Oil	−0.00133	0.00789	1.195***	−0.00107	0.00235	1.190***	−0.000918	−0.000843	1.186***
Util	0.00496***	−0.00322	0.477***	0.00489***	−0.00173	0.478***	0.00483***	−0.000211	0.479***
Telcm	−0.00145	−0.00485	1.314***	−0.00135	−0.00756	1.310***	−0.00125	−0.00614	1.310***
PerSv	−0.00235	−0.00971*	1.069***	−0.00247	−0.00739	1.069***	−0.00255	−0.00326	1.073***
BusSv	0.000515	−0.00309	1.143***	0.000558	−0.00429	1.141***	0.000597	−0.00321	1.141***

Table 3. Industry exposure to GPT, GPR, and GPA with the monthly average equal-weighted stock returns (contd.).

Industry	***GPT***			***GPR***			***GPA***		
	α_k	β_k	γ_k	α_k	β_k	γ_k	α_k	β_k	γ_k
Hardw	−0.000696	−0.00245	1.475***	−0.000638	−0.00396	1.472***	−0.000616	−0.00274	1.473***
Softw	0.000422	−0.00684	1.373***	0.000537	−0.00992	1.368***	0.000651	−0.00776*	1.368***
Chips	0.00139	−0.00385	1.444***	0.00147	−0.00594	1.440***	0.00159	−0.00539	1.439***
LabEq	0.00267	−0.00619	1.179***	0.00264	−0.00589	1.177***	0.00265	−0.00374	1.179***
Paper	−0.00221	−0.000731	1.101***	−0.00224	−0.000112	1.102***	−0.00224	−0.0000814	1.102***
Boxes	0.00180	0.00000221	1.001***	0.00191	−0.00254	0.998***	0.00189	−0.00133	0.999***
Trans	−0.000402	−0.00844	1.083***	−0.000364	−0.00980**	1.080***	−0.000369	−0.00595*	1.082***
Whlsl	0.000277	0.00120	1.087***	0.000272	0.00138	1.088***	0.000305	0.000367	1.087***
Rtail	−0.00171	−0.00222	1.182***	−0.00164	−0.00401	1.179***	−0.00157	−0.00356	1.178***
Meals	−0.00113	−0.00159	1.014***	−0.00100	−0.00466	1.010***	−0.000917	−0.00414	1.009***
Banks	0.00259	0.00104	0.738***	0.00252	0.00256	0.740***	0.00251	0.00176	0.740***
Insur	0.00290**	0.00181	0.818***	0.00289**	0.00208	0.819***	0.00290**	0.00125	0.818***
RlEst	−0.00182	−0.00198	0.970***	−0.00192	0.000329	0.972***	−0.00192	0.000288	0.972***
Fin	0.00194	0.00122	0.992***	0.00197	0.000627	0.992***	0.00203	−0.000577	0.990***
Other	−0.000948	−0.00804	1.009***	−0.000920	−0.00914*	1.006***	−0.000867	−0.00638*	1.007***

Note: This table presents the estimated coefficients from the industry exposure measure stated in Caldara and Iacoviello (2019; 2022), and the equation (3, GPA) is derived based on their earlier work. The results are not standardized, demeaned, and signs shifted in this table. The timeline for the regressions runs from February 1985 to March 2023. The stars ***, **, * denote statistical significance at 1%, 5%, and 10% level measured by t-statistics. The abbreviations for the industries are in the list of abbreviations. The U.S. 1-Month Treasury Bill Rate is used as a risk-free rate to construct this table.

ne War in the spring of 2022. Therefore, the betas of the GPT column are not directly comparable to those Caldara and Iacoviello (2019) report in the working paper through Figure 6. Moreover, a researcher does not annualize the stock returns and utilizes the monthly data because these adjustments give more realistic results.

Under the geopolitical risk column in Table 3 are four significant values. The Aircraft (–1.09%), Transportation (–0.980%), and Other (–0.914%) industries tend to lose from the one-unit increase of the GPR, and the Defense (3.60%) industry gain. The finding of the Aircraft, Transportation, and Defense industries leans on the published version from Caldara and Iacoviello (2022), but opposite to their results; the Other industry loses by

0.914 percent relative to the aggregate market at the 10 percent significance level from the intensified GPR. Partially, the difference within the Other industry can be because, during the GPR regressions, the applied sample is approximately three years longer than in Caldara and Iacoviello (2022). For that duration, the Other industry loses 0.1% more than earlier in the sample measured by the monthly equally weighted excess returns.

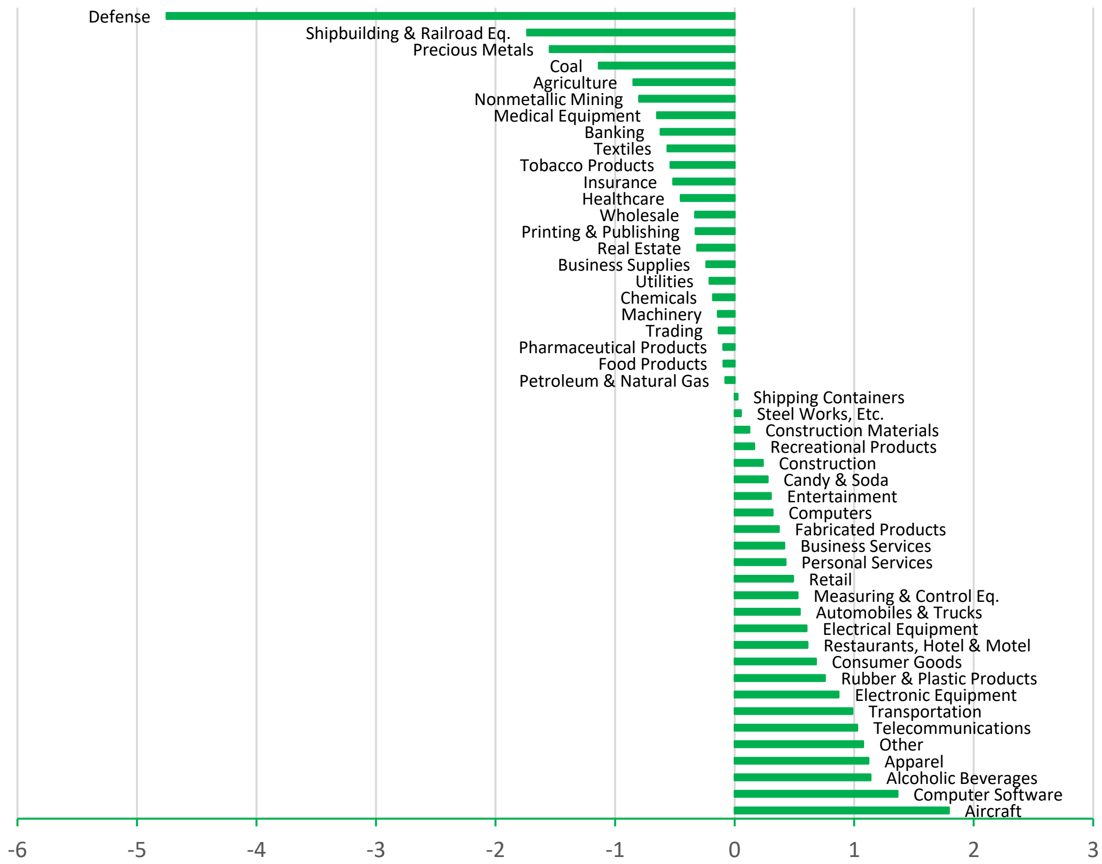
The third column of Table 3 reveals the outcomes of the regressions when using the geopolitical acts index as a central independent variable. This approach does not occur in Caldara and Iacoviello (2019) or Caldara and Iacoviello (2022). Unexpectedly, the regressions show that the GPA impacts the Fama and French (1997) equally weighted stock returns more than the GPT or the GPR. The impact of the GPA on the stock returns is statistically significant in seven industries; Alcoholic Beverages (–0.667** %), Apparel (–0.659* %), Aircraft (–0.982** %), Defense (2.16*** %), Computer Software (–0.776* %), Transportation (–0.595* %), and Other (–0.638* %). The average R-squared (R^2) value for these seven industries is 48.4%. Therefore, the Defense industry is gaining during actualized geopolitical happenings, and the other six industries are losing relative to the market.

Finally, in Table 3, all of the market coefficients included in the model are positive and significant at the one percent level. This finding signals that when the market increases by one unit and geopolitical risk remain the same, stock returns of the 49 equally weighted industries from Fama and French (1997) increase upwards. The average of the market coefficients from the GPA column is 1.065, which is close to the market (1). According to the gamma values, the riskiest industry is Computers and risk-free Utilities. The alphas are statistically significant and always positive in six industries (Alcoholic Beverages, Tobacco, Aircraft, Defense, Utilities, and Insurance), pointing to the average values of the omitted independent variables. Therefore, the equally weighted stock returns are statistically significant and increasing in these industries if the geopolitical and market factors are zero in the model (no independent variables).

The results claim that the equal-weighted stock returns of the industries which can be supposed to have a high level of consumer demand in every circumstance are positive and increasing, without geopolitical risk, and when the average market return is zero in the model. For instance, it can be supposed that people use water products daily because they need water; therefore, the Utilities industry's stock prices push upwards.

Appendix two report also the estimated coefficients from the industry exposure measure when using Fama and French's (1997) value-weighted stock returns as a dependent variable. The impact of the GPA on stock returns is statistically significant in nine industries. The most relevant findings for the thesis are the betas of the Computers (Hardw) and Electronic Equipment (Chips) industries. The former loses –0.702* and the latter –0.734** under the GPA column, indicating a decrease in stock returns relative to the market when the GPA spikes. All of the market coefficients are statistically significant at the one percent level. With the value-weighted stock returns, the findings also show industries with statistically significant and both positive and negative alphas. Therefore, the value-weighted stock returns can even decrease according to their proportional weight of the total market capitalization when the independent variables are zero in the model.

Figure 9 plots the industry exposure to the geopolitical acts with the Fama and French (1997) equally weighted stock returns. The figure consists of the estimated beta coefficients from the third column of Table 3. The Defense industry is under negative exposure when considering only the significant beta values. Under positive exposure are Alcoholic Beverages, Apparel, Aircraft, Computer Software, Transportation, and Other industries. Therefore, geopolitical risk significantly affects the stock market returns of these industries in the U.S., where the former industry gain and the latter lose from the geopolitical actualization relative to the market. Thus, the Consumer Staples and Information Technology sectors lose from the geopolitical actions based on the OLS regressions. The article from Fossung et al. (2021) supports the Consumer Staples and IT sector result.



Note: This figure shows industry exposure to the monthly geopolitical acts index derived from Caldara and Iacoviello (2019; 2022). The figure shows observations from February 1985 to March 2023. The values are betas from equation (3), demeaned to have zero mean, signs shifted, and unit standard deviation. Positive (negative) values indicate a higher (a smaller) exposure to geopolitical acts meaning a greater decrease (increase) in industry monthly stock returns and vice versa.

Figure 9. Exposure to the geopolitical acts by industries with the monthly stock returns.

When considering the non-significant beta values of Table 3 and Figure 9, there are several other connections to the theoretical framework of the thesis. For example, Baur and Smales (2020) find that Precious Metals gain from geopolitical risk, and Triki and Maatoug (2021) show that gold succeeds as a hedge against S&P 500 index volatility. Atems et al. (2020) report that the U.S. Food and Agriculture industries are affected positively by the ENSO shocks. These articles have the same result and positive effect from the geopolitical risk as Figure 9 with the named industries. Moreover, Bouoiyour et al. (2019) reveal that geopolitical actions positively affect oil returns supported by the Coal and Petroleum and Natural Gas industries from Figure 9.

Finally, in Figure 9, Defense, Precious Metals, Agriculture, Textiles, Wholesale, Utilities, Food Products, and Petroleum and Natural Gas industries are gaining from the geopolitical acts similar to those in Caldara and Iacoviello (2019) with the GPT and Caldara and Iacoviello (2022) with the GPR. On the contrary, Construction Materials, Construction, Entertainment, Fabricated Products, Business Services, Personal Services, Retail, Automobiles and Truck, Restaurants, Hotel and Motel, Transportation, Telecommunications, Apparel, Computer Software, and Aircraft industries lose from geopolitical acts, risks, and threats.

5.2 Results of the event study calculations

Table 4 presents the results of the event study calculations. The first observation is that geopolitical risk significantly impacts the stock market returns in the United States, but the significance varies between sectors, geopolitical events, and event windows. For example, around 9/11 in the Energy sector, the cumulative abnormal returns were –11.14 percent within the –3,3 event window at the 1 percent significance level.

In the Energy sector and around 9/11, the returns are negative in all event windows. When looking at the significance of the results, the –3,3 and the 0,5 event windows contain the most significant results. For instance, in the 0,5 event window, the CARs are –12.42 percent at the 1 percent significance level, which is also the highest negative number in that line. The findings reveal that the stock market returns tend to react shortly before and after 9/11, and the event windows also capture the post-event variations in the stock values. On average, the AARs are –0.12 percent and CAARs –0.73 percent across the 9/11 with 0,5 event window in the Energy sector.

During the Invasion of Iraq in 2003, the results were less significant than around 9/11 in the Energy sector. Some of the reasons for that are the U.S. data utilized in the thesis and that 9/11 was a more surprising event than the Iraq Invasion 2003, which was, to some extent, a consequence of the terrorist attacks towards the U.S. on September 11th, 2001. In addition, some of the large oil producers operate in the Middle East (Oil & Gas, 2023). However, the Energy sector also suffers from the Invasion of Iraq, showing instant –0.069 percent AARs, and –6.87 percent CARs in the –10,10 event window, supporting the theory of the early info outflows and longer post-event instabilities relating to the stock prices.

The Energy sector provides engaging and sustaining findings through the war started in 2022 in Ukraine. The results support a seen price increase in energy and inflation by only the negative immediate stock returns with –1.17* CARs. All the other events windows include statistically significant positive returns. The biggest returns belong to the longest event window –10,10, with 17.29 percent CARs, 0.036 percent AARs, and 0.75 percent CAARs, all significant at the 5 percent level. The finding suggests that the war in Ukraine has raised the energy price, and the effect is more pronounced in a more extended period measured by the event windows.

Similarly to the Energy sector, the Consumer Staples sector also produced negative returns in all event windows around 9/11. The effect of the geopolitical event on the stock prices is most profound in the 0,5 event window resulting in short-time post-event variations in the stock prices together with –7.40 percent CARs, –0.043 percent AARs, and –0.26 percent CAARs at the 1 percent significance level. The stock returns of the Consumer Staples sector also decreased shortly before 9/11 in the –3,3 event window, directly after the event in the 0,1 event window with the AARs, and also in the longest –10,10 event window measured by the CARs.

Across the Invasion of Iraq in 2003, the stock returns were not equally significant in the Consumer Staples sector as around 9/11. Still, the returns are more significant than in the Energy sector. The stock returns are also positive, while the –3,3 event window is the best time for positive returns, having 1.89 percent CARs and 0.0093 percent AARs at the 5 percent significance level.

The observations made at the time of the start of the Ukraine War are not endorsing the short-time pre- and post-event variations of the stock returns in the Consumer Staples sector. Thus, the ongoing price increase of the consumer staple products does not support the findings from the shorter event windows; additionally, the results are not statistically significant. However, the most extended event window –10,10 offers weak evidence of the price decrease of the consumer staple products with –1.96* percent CARs. Based on the four event windows and the comparison to the Energy sector, the price increase and inflation originate more from the higher energy stock prices than lower consumer staple stock returns. Even so, the longest event window regarding changes in the macro factors is still short. However, Seo et al. (2013) find that the surprises in food industries lead to negative abnormal returns lasting a maximum year, and undoubtedly Ukraine's power as one of the biggest corn and wheat producers in the world (World Population Review, 2022; Index Mundi, 2022) can partly explain the negative returns in the –10,10 event window in Table 4 within the Consumer Staples sector.

The IT sector had both positive and negative abnormal returns around 9/11. The 0,5 event window is the best positive event window carrying 5.83 percent CARs and 0.018 percent AARs at the 1 percent significance level, and when the –10,10 event window contains the negative values with –8.18 percent CARs and –0.0073 percent AARs. Therefore, the results show positive short-lived pre- and post-event changes in the stock prices and negative differences within the stock returns when the period is lengthy, contributing some weak evidence of the hedging possibilities with the put options in the IT sector.

At the time of the Iraq Invasion in 2003, the IT sector's abnormal stock returns were significant in two event windows. In the 0,1 event window, the AARs are –0.013*** percent implying immediate adverse effects of the event on the stock prices, and in the –10,10 event window, the CARs are –1.93** percent, indicating early info outflows, which are adjusting to the stock prices before the actualized geopolitical event, and post-event uncertainties.

Table 4. Results of the event study calculations (values in the percentage form).

Panel A Energy												
Event window	(–3,3)			(0,5)			(0,1)			(–10,10)		
Method	CAR	AAR	CAAR	CAR	AAR	CAAR	CAR	AAR	CAAR	CAR	AAR	CAAR
9/11 (17)	–11.14***	–0.094***	–0.66**	–12.42***	–0.12***	–0.73***	–2.07	–0.061**	–0.12	–12.29***	–0.034	–0.72
Iraq 2003 (17)	–2.29	–0.019	–0.13	1.13	0.011	0.066	–2.34	–0.069***	–0.14	–6.87***	–0.019	–0.40
Ukraine 2022 (23)	5.95***	0.037**	0.26	4.71**	0.034**	0.20	–1.17*	–0.025	–0.051	17.29**	0.036**	0.75**
Panel B Cons. Staples												
Event window	(–3,3)			(0,5)			(0,1)			(–10,10)		
Method	CAR	AAR	CAAR	CAR	AAR	CAAR	CAR	AAR	CAAR	CAR	AAR	CAAR
9/11 (29)	–4.83***	–0.024***	–0.17**	–7.40***	–0.043***	–0.26***	–1.67	–0.029***	–0.058	–3.23***	–0.0053	–0.11
Iraq 2003 (29)	1.89**	0.0093**	0.065	–0.07	–0.00041	–0.0024	1.00	0.017***	0.03	1.66***	0.0027	0.057
Ukraine 2022 (33)	–0.44	–0.0019	–0.013	0.72	0.0036	0.022	0.08	0.0013	0.0026	–1.96*	–0.0028	–0.059
Panel C IT												
Event window	(–3,3)			(0,5)			(0,1)			(–10,10)		
Method	CAR	AAR	CAAR	CAR	AAR	CAAR	CAR	AAR	CAAR	CAR	AAR	CAAR
9/11 (53)	5.67***	0.015***	0.11	5.83***	0.018***	0.11	3.43	0.032***	0.065	–8.18***	–0.0073*	–0.15
Iraq 2003 (54)	–1.46	–0.0039	–0.027	0.59	0.0018	0.011	–1.41	–0.013***	–0.026	–1.93**	–0.0017	–0.036
Ukraine 2022 (75)	–0.40	–0.00076	–0.0053	–1.63*	–0.0036***	–0.022	–0.22	–0.0015**	–0.0030	–0.25	–0.00016	–0.0033

Note: The CARs are average values per sector, and CAARs represent each firm's average portion of the index. The AAR value is the average value from the event window in question. The U.S. national holidays and market closure days are ignored in the sample so that the event windows contain only the days when the market is open (except in the case of 9/11, the daily returns are zero=0). The stars ***, **, * indicate statistical significance at 1%, 5%, and 10% levels measured by t-statistics. The number of firms within the sector related to each geopolitical event is in the brackets after the event name.

In the case of Ukraine 2022, the IT sector abnormal returns are significantly negative after the event in the 0,5 event window with –1.63* percent CARs and –0.0036*** percent AARs signaling post-event variations of the stock prices, and directly after the event in the 0,1 event window with –0.0015** percent AARs. The results suggest that some of the large IT companies in the U.S. suffered within a short time after Ukraine's War start date and that the actual returns in the IT sector are smaller than the predicted returns.

The 0,5 event window contains the most significance with 32 stars, the –3,3 event window has 31 stars, the –10,10 event window has 25 stars, and the 0,1 event window produces 20 stars. When measuring which event window contains the most significant values, the 0,5 and the –3,3 event windows split first, while the –10,10 is third and the 0,1 is fourth. Therefore, geopolitical events have the largest impact on the stock prices in the U.S. through the 0,5 event window when the 0,1 event window is the least-transitional event window. The descriptive statistics in Table 2 partially support the outcome and the article from Aloui and Hamida (2021), who find that the GPR impacts stock returns over a short-term time scale.

Baur and Smales (2020) found that after the market reopening, the S&P 500 index was 5.31% lower than before the 9/11 terrorist attacks, supported by Table 4 with the Energy and the Consumer Staples sectors, where all of the values are negative around 9/11 (also with the IT sector in the –10,10 event window). A similar link with the U.S. data comes in the study by Yang and Yang (2021), where S&P 500 returns decline after geopolitical events, and in the article by Salisu et al. (2021). Zaremba et al. (2022) find that the GPR can lead to positive future returns in emerging markets. In Table 4, the situation is the opposite when the stock returns are positive within the Energy sector in the U.S. In contrast, the geopolitical risk is happening in Europe through Ukraine's situation.

In their article, Singh and Roca (2022) present that the geopolitical tensions in other countries can affect the North American national stock market returns, a finding supported by the Iraq 2003 and Ukraine 2022 numbers in Table 4. Smales (2021) finds that the GPR negatively impacts the stock market returns in the U.S. but positively to the oil market returns. This variation can partially explain the differences between panel A's negative and positive results in Table 4. In addition, Bouoiyour et al. (2019) find that in specific events, the oil price and the GPR correlate positively, for instance, after 9/11 in 2001, during the Invasion of Iraq in 2003, and the 2014 Russia-Ukraine crisis, resulting increase in oil prices after enlarged geopolitical risk and meaning that the GPR influences to the oil prices.

Atems et al. (2020) find that the ENSO shocks positively affect the U.S. consumer staple stocks of the S&P 500 index similarly to the GPR effects in Iraq’s situation in panel B of Table 4. However, the authors find that the effect is short-lived and historically affected by shocks other than the ENSO shocks. Lee et al. (2021) show that a unidirectional relationship exists between the GPR and oil prices at the extreme quantiles. The Energy sector from Table 4 endorses this finding, where it has the most significant values among the sectors.

Caldara and Iacoviello's (2019) findings with the industry exposure measure support the Energy sector’s positive results in Table 4 by the Petroleum and Natural Gas industries and negative returns by the Coal and Transportation industries. The Alcoholic, Agriculture, Food, and Soda industries support the Consumer Staples sector's positive results. The Consumer Goods and Tobacco industries support the negative results of consumer staple products. Finally, the IT sector's positive returns in the thesis align with Caldara and Iacoviello (2019) by the Electronic Equipment, Computers, and Electrical Equipment industries and the negative returns with the Computer Software industry.

Caldara and Iacoviello's (2022) results align with the Petroleum, Natural Gas, and Coal industries regarding positive Energy sector returns of Table 4, and the Transportation industry supports the negative energy returns. The Food, Tobacco, Agriculture, Alcoholic, and Consumer Goods industries endorse the positive Consumer Staples sector returns and negative returns by the Soda industry. Lastly, the IT sector's negative returns obtained from the thesis are similar to that Caldara and Iacoviello (2022) discover with the

Electronic Equipment, Computers, Electrical Equipment, and Computer Software industries.

The results are similar between the OLS and the event study methodologies if looking at the most extended –10,10 event window of Table 4, which is the closest window compared to the lengthy OLS regressions run over 35 sample years. The Energy sector results indicate positive and negative abnormal returns in Table 4. The same finding comes through the OLS regressions with the Coal, Transportation, and Petroleum and Natural Gas industries in Figure 9. Also, with the Consumer Staples sector, the results are mixed in Table 4 and Figure 9 with the Agriculture, Food Products, Candy and Soda, Alcoholic Beverages, Consumer Goods, and Tobacco Products industries. However, with the IT sector, both methodologies provide the same outcome; the Information Technology sector loses relative to the market from the increased geopolitical tensions. The industries which support this finding in Figure 9 are Computers, Electronic Equipment, Electrical Equipment, and Computer Software. Nevertheless, only part of the industries' betas are statistically significant with the OLS regressions, and thus, when considering the significance, the results vary between methods.

Table 5 compares the historical sector average CAAR values from Fossung et al. (2021) to the sectors' average CAAR values from Table 4. The attention belongs to the point that Fossung et al. (2021) have more geopolitical events in the study and, therefore, more significant CAARs included within the geopolitical events. The tables by Fossung et al. (2021) make only this modest comparison between the numbers possible. The authors do not report more detailed numbers since their study has many geopolitical events. The first values are from Fossung et al. (2021), and the latter are from Table 4.

Table 6 presents the S&P 500 index daily stock market returns around the three geopolitical events. In the case of 9/11, the stock prices started to modify from the initial information escapes before the actualized geopolitical event. The cumulative returns before the terrorist attacks were –8.04 percent, and when the market was re-opened from

Table 5. Comparison with the CAAR values to Fossung et al. (2021).

Cumulative average abnormal returns		
	The sector of the S&P 500 index	
Event window	Information Technology	Consumer Staples
(–3,3)	–7.75% / 1.27%	–1.16% / –1.13%
(0,5)	–5.14% / 1.60%	0.90% / –2.25%
(0,1)	–1.30% / 0.60%	–0.71% / –0.20%
(–10,10)	4.31% / –3.45%	–1.30% / –1.18%

Note: The latter values from Table 4 are the total sum of firms' CAARs. For instance, for the –3,3 event window in the IT sector, the value 1.27 is calculated from the CAR column: (5.67–1.46–0.40)/3 = 1.27.

the day 17th of September, 2001 onwards, the cumulative returns were –4.52 percent. Therefore the numbers indicate short-term pre- and post-event fluctuations in the stock prices and the leaks before the event.

Before the Invasion of Iraq in 2003, the market waited ''good'' in the U.S., resulting in positive 5.36 combined returns at the doorstep of the invasion. After the Invasion, the market was open every day, and the cumulative returns were positive but tiny at 0.25 percent during ten days. The result implies that the market participants have been highly anticipating the Invasion of Iraq since 9/11, and most of the information is adjusting to the market prices before the event.

Before Ukraine's War start date on the 24th of February, 2022, the cumulative returns were –6.67 percent over ten days, and after the beginning of the war, the aggregated returns were –0.54 percent. The values show the possibility of planned attacks by interested parties before the war and that the long-term tensions since 2014 were adjusting to the market prices before the event. The S&P 500 index return was positive 1.50 percent on the 24th of February, 2022.

Table 6. Market daily returns around geopolitical events.

Standard & Poor's 500 index daily stock market returns			
	Geopolitical event		
Day	9/11	Iraq 2003	Ukraine 2022
–10	–0.48	–0.93	1.45
–9	–1.50	0.83	–1.81
–8	–1.11	–2.58	–1.90
–7	–1.70	–0.84	–0.38
–6	0.40	0.43	1.58
–5	–0.06	3.45	0.09
–4	–0.11	0.16	–2.12
–3	–2.24	3.54	–0.72
–2	–1.86	0.42	–1.01
–1	0.62	0.87	–1.84
0	0.00	0.19	1.50
1	–4.92	2.30	2.24
2	–0.58	–3.52	–0.24
3	–1.61	1.22	–1.55
4	–3.11	–0.55	1.86
5	–1.90	–0.16	–0.53
6	3.90	–0.58	–0.79
7	0.88	–1.77	–2.95
8	–0.52	1.21	–0.72
9	1.15	2.61	2.57
10	2.19	–0.51	–0.43

Note: The values are in the percentage format and rounded with two decimals. Day zero (0) indicates the event date. The U.S. national holidays and market closure days are ignored in the sample so that the event windows contain only the days when the market is open (except in the case of 9/11, the daily return is zero=0).

6 Conclusions

The purpose of the thesis was to investigate how geopolitical risk impacts to the stock market returns in the U.S from 1985 to 2023 with the OLS regressions and during the 21st century with the event study methodology focusing on the three biggest geopolitical events; 9/11 in 2001, Invasion of Iraq in 2003, and Ukraine War in 2022. The thesis also aimed to research whether the effect of geopolitical risk differs between the Information Technology, Consumer Staples, and Energy sectors of the S&P 500 index. In addition, two subproblems derived from the research question were whether the results differ between methodologies and geopolitical events. Previous studies show that the GPR impacts the stock market returns in the U.S. market (e.g., Fossung et al., 2021; Yang & Yang, 2021; Smales, 2021; Salisu et al., 2021). The result of the thesis confirms that the GPR influences the stock market returns in the U.S. Still, the impact varies between sectors of the S&P 500 index, geopolitical events, and different event windows.

The first hypothesis of the thesis expected that geopolitical risk affects the stock market returns in the U.S. (e.g., Caldara & Iacoviello, 2019). The empirics show statistically significant results with both OLS and event study methodologies. Regarding the OLS regressions, the value-weighted stock returns from Fama and French (1997) respond more significantly than the equally weighted returns. Furthermore, the GPA impacts more to the stock prices than the GPT or the GPR. The results also show through the S&P 500 index data that ten days before and after 9/11 in 2001 and Ukraine War in 2022, the aggregated S&P 500 index returns were negative, but in the case of the Iraq War 2003, the returns were positive. Consequently, the first non-directional hypothesis of the thesis is accepted.

Given the second hypothesis of the thesis, a researcher expected that the effect of the geopolitical risk differs between the Information Technology, Consumer Staples, and Energy sectors of the S&P 500 index (e.g., Fossung et al., 2021; Caldara & Iacoviello, 2022; Khan et al., 2022; Apergis et al., 2018). The OLS regressions state that the geopolitical acts positively affect Defense and negatively affect Alcoholic Beverages, Apparel, Aircraft, Computer Software, Transportation, and Other industries. Therefore, the OLS regressions report that the Consumer Staples and the Information Technology sector lose statistically significantly from the GPA relative to the market. With the event study method, the results indicate a mixed influence of the geopolitical risk on the stock market returns between sectors. However, all sectors have positive and negative stock price responses, but the effect of the geopolitical risk differs between event windows (and geopolitical events). In fact, none of the event windows contains similar responses to the geopolitical risk between sectors; thus, the thesis's results accept the second two-sided hypothesis.

For the third hypothesis with the thesis, a preconceived assumption was that the results differ between methodologies (e.g., Caldara & Iacoviello, 2019; Fossung et al., 2021; Zaremba et al., 2022; Bouras et al., 2019; Saadli et al., 2021; Erdoğan et al., 2022; Apergis et al., 2018; Yang et al., 2021; Chiang, 2021). The empirical part of the thesis shows that the results differ between methodologies when considering the significance of the OLS regressions (if the results ignore the significance of the OLS regressions, then the results are in line between methods within the –10,10 event window). Each of the methodologies shows a positive and negative correlation to the heightened geopolitical tensions in the Energy and Consumer Staples sectors; however, with the OLS regressions, only the Alcoholic Beverages industry’s beta is statistically significant. Both methodologies exhibit negative responses in the Information Technology sector during increased geopolitical conflicts, and the significance also remains in the OLS regressions. To conclude, the third alternative hypothesis of the thesis is also accepted.

The last and fourth hypothesis of the thesis expected that the results of the empirics differ between geopolitical events. Previous literature from Fossung et al. (2021) and Caldara and Iacoviello (2022) have provided evidence that the effectiveness of the GPR varies between events in the former study and between months (and days) in the latter research measured by the value of the GPR index. The thesis results present that around the Ukraine War in 2022, the Energy sector responded positively to the GPR. In contrast, the response is negative in the IT and the Consumer Staples sector and more minor in magnitude. During 9/11, the Energy and the Consumer Staples sectors are in negative and similar correlations to the GPR. Still, the IT sector shows positive and negative responses to the GPR depending on the event window. Finally, with the Invasion of Iraq in 2003, the Energy and the IT sector reacted similarly with negative stock returns to the GPR. However, in the Consumer Staples sector, the reaction was only positive. The S&P 500 index data also confirm that the effect of the GPR varies between geopolitical events. Therefore, the fourth hypothesis is accepted.

6.1 Practical Implications and contributions

The theoretical framework of the thesis showed that the GPR index illustrates a considerable number of spikes and variations not captured in the VIX or the EPU indexes (cf. Caldara & Iacoviello, 2019; 2022). Theory shows that the GPR index could spot the events most likely exogenous from the basic business and financial frequency cycle in the U.S. The GPR index can also describe incidents that might add to the accumulated economic instability and political uncertainty and thus measure a new, exogenous risk not caught in the financial, economic, or other political indexes.

The U.S. business and policy organizations can use this information in their decision-making. For instance, the firms can start reporting GPR-related data for their stakeholders to stay ahead of the mainstream in the U.S., establish teams working on GPR-linked issues, and track GPR indexes to stay up-to-date about possible future crises. Current topics include strategic hot spots like Taiwan, national political affairs, trade policy, and technology with other countries and governments. Based on the research of the GPR, proactive decision-making could have prevented the U.S. banks' massive losses on their Russian loans, retail operations, and trade counterparties due to the Ukraine War 2022, for example.

In addition, the U.S. Energy, Consumer Staples, and IT sectors can utilize the thesis results and the GPR data to define how their stock prices respond when increased tensions push up new unstable happenings. For instance, weak evidence remains that investors can use IT stocks as a hedge through the put options when geopolitical events happen since the stock prices of the IT companies change to negative when the period is extended, compared to the positive initial prices. Furthermore, the Energy sector's positive response to the Ukraine War verifies that investors can benefit from the GPR-related research and data when considering how specific events affect stock prices differently, confirming the thesis's assumed second and fourth hypotheses.

The investors can employ the results of the OLS regressions when deciding how to allocate the resources for the portfolios between equal- and value-weighted strategies. For example, the equally-weighted industries have positive alphas when the industry belongs to a merchandise group for which there is always enough demand. Still, the value-weighted alphas are positive and negative according to the demand and industries' proportional weight from the total market capitalization. The industries also respond differently to the GPA between equal- and value-weighted stock returns (the significance of the results varies). In addition, the Computer Software industry has a negative beta with the equally weighted model, confirming the IT sector's hedging opportunity, similar to the event study method.

As far as a researcher is concerned, there is only one study before this thesis investigating the relationship between the GPR and the stock market returns in the U.S. with the event study methodology at a sector level (Fossung et al., 2021). After more than 1,500 regressions with the daily data, the empirics show that the impact of the GPR varies between sectors of the S&P 500 index, confirming the Ukraine-Russia situation through the Energy sector result. The thesis results also reveal that the event window and the geopolitical event should be respected when considering the impact of the GPR.

Finally, opposite what other studies suggest (e.g., Caldara & Iacoviello, 2019; Baur & Smales, 2020; Salisu et al., 2021; Bouoiyour et al., 2019), the results of the thesis display through the OLS regressions that the GPA is more influential index than the GPT or the GPR in terms of stock returns.

6.2 Restrictions and future research directions

The data sample, period, and methodologies limit the empirical results of the thesis. The event study methodology is relatively slow to calculate the empirical numerical results. Therefore, future research can employ the industry exposure measure for a more profound analysis (cf. Caldara & Iacoviello, 2019; 2022). For instance, researchers can utilize firm data such as investments to analyze how the GPR impacts the companies' values. Statistical programs could help run a more comprehensive empirical part of the research.

One possibility is to use a quantile regression model, which can provide additional information regarding the relationship between stock market returns and the GPR. With the quantile regression model, the bearish and bullish market situations measured by the quantiles can be linked (or unlinked) to the GPR, and because the geopolitical situations themselves contain a lot of uncertainty, the results of that approach can be beneficial and novel to the several companies' stakeholder groups. In addition, unlike Fossung et al. (2021) mention, the CAPM model is not easily applicable to the event study or geopolitical setting if using a specific event date in the empirics because the daily data makes it hard to get accurate and robust results when having a too few observations in the variables when using tiny event windows. However, the researchers can estimate the rolling betas for the event windows if they use the CAPM.

Avenues for future research can also include different sectors of the S&P 500 index or from other similar markets which resemble the U.S. (e.g., the UK index data), different securities in a dependent variable such as bonds, and various event windows if using the event study methodology. It is also possible to obtain data from small and medium-sized enterprises and compare the results to the S&P 500 index companies. Furthermore, the finding of the thesis that the GPA index is the most influential in terms of stock returns proposes the avenue to scrutinize the relationship between the GPR, GPT, and GPA indexes by using the spikes of the indexes as a benchmark for the dates in the empirics with the event study method. Therefore, this approach can provide additional information about how the effect of these indexes differs from each other regarding stock returns. Ultimately, Caldara and Iacoviello (2019; 2022) offer country-related data on the GPR on their website, which would extend the analysis across the countries if using the country data as a variable in the model a researcher selects.

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Appendices

Appendix 1. The search query for the benchmark GPR index

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pub.Exact("Boston Globe" OR "Chicago Tribune" OR "The Daily Telegraph" OR "Financial
Times" OR "The Globe and Mail" OR "The Guardian" OR "Los Angeles Times" OR "New York
Times" OR "The Times" OR "Wall Street Journal" OR "The Washington Post") AND
DTYPE(article OR commentary OR editorial OR feature OR front page article OR front
page/cover story OR news OR report OR review) AND (("United States" AND tensions AND
(military OR war OR geopolitical OR coup OR guerrilla OR warfare) AND ("Latin America"
OR "Central America" OR "South America" OR Europe OR (Africa NOT "South Africa") OR
"Middle East" OR "Far East" OR Asia)) OR (geopolitical AND (risk* OR concern* OR
tension* OR uncertaint*)) OR (("nuclear war" OR "atomic war" OR "nuclear conflict" OR
"atomic conflict" OR "nuclear missile*") AND (fear* OR threat* OR risk* OR peril* OR
menace*)) OR ("war risk*" OR "risk* of war" OR "fear of war" OR "war fear*" OR
"military threat*" OR "war threat*" OR "threat of war" OR (("military action" OR
"military operation" OR "military force") AND (risk* OR threat*))) OR ("terrorist
threat" OR "terrorist threats" OR "menace of terrorism" OR "terrorism menace" OR
"threat of terrorism" OR "terrorist risk" OR "terror risk" OR "risk of terrorism" OR
"terror threat" OR "terror threats") OR ("beginning of the war" OR "outbreak of the
war" OR "onset of the war" OR "escalation of the war" OR "start of the war" OR ((war
OR military) AND "air strike") OR (war AND "heavy casualties") OR (battle AND "heavy
casualties")) OR ("terrorist act" OR "terrorist acts") NOT ("civil war" OR "human
rights" OR (end N/2 war) OR "air force" OR movie OR film OR museum OR anniversary OR
memorial OR art))
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Note: This figure presents the precise search query for the benchmark GPR index to calculate the articles debating geopolitical risk with a running search from the ProQuest Newsstream (Caldara & Iacoviello, 2019).

Appendix 2. Industry exposure to GPT, GPR, and GPA with the monthly average value-weighted stock returns

Industry	***GPT***			***GPR***			***GPA***		
	α_k	β_k	γ_k	α_k	β_k	γ_k	α_k	β_k	γ_k
Agric	0.00203	0.00490	0.788***	0.00205	0.00472	0.789***	0.00200	0.00359	0.789***
Food	0.00412**	0.00277	0.585***	0.00408**	0.00381	0.587***	0.00412**	0.00182	0.585***
Soda	0.00380	0.00377	0.768***	0.00375	0.00511	0.770***	0.00381	0.00237	0.768***
Beer	0.00563***	–0.000713	0.622***	0.00556***	0.00104	0.624***	0.00554***	0.000854	0.624***
Smoke	0.00646**	0.00255	0.618***	0.00639**	0.00445	0.621***	0.00629**	0.00416	0.622***
Toys	–0.00292	–0.00171	1.100***	–0.00285	–0.00343	1.098***	–0.00283	–0.00237	1.098***
Fun	0.000854	–0.00185	1.333***	0.000894	–0.00289	1.331***	0.00102	–0.00367	1.329***
Books	–0.00278*	0.00543	1.075***	–0.00274	0.00473	1.075***	–0.00277*	0.00343	1.075***
Hshld	0.00208	0.00147	0.688***	0.00208	0.00166	0.688***	0.00208	0.00103	0.688***
Clths	0.00104	–0.00535	1.093***	0.00111	–0.00732	1.090***	0.00114	–0.00486	1.091***
Hlth	–0.00183	0.0176**	0.920***	–0.00159	0.0128**	0.919***	–0.00147	0.00615	0.913***
MedEQ	0.00296*	0.00660	0.875***	0.00292*	0.00787**	0.878***	0.00287*	0.00557**	0.877***
Drugs	0.00417**	–0.00250	0.722***	0.00398**	0.00194	0.727***	0.00386**	0.00292	0.729***
Chems	0.000330	–0.000145	1.065***	0.000201	0.00292	1.068***	0.0000817	0.00353	1.070***
Rubbr	0.000902	0.00309	1.057***	0.000905	0.00318	1.058***	0.000927	0.00164	1.056***
Txtls	–0.00214	–0.00187	1.205***	–0.00209	–0.00300	1.203***	–0.00206	–0.00228	1.203***
BldMt	–0.0000563	–0.000105	1.181***	–0.0000812	0.000479	1.181***	–0.0000958	0.000508	1.182***
Cnstr	–0.000327	–0.00488	1.201***	–0.000327	–0.00512	1.199***	–0.000369	–0.00254	1.202***
Steel	–0.00403	0.00375	1.463***	–0.00384	–0.000538	1.459***	–0.00377	–0.00134	1.457***
FabPr	–0.00218	–0.00307	1.074***	–0.00210	–0.00529	1.071***	–0.00209	–0.00333	1.072***
Mach	–0.0000550	–0.00393	1.250***	–0.00000763	–0.00526	1.248***	0.0000141	–0.00355	1.249***
ElcEq	0.000155	0.000384	1.258***	0.000157	0.000362	1.258***	0.000112	0.000872	1.259***
Autos	–0.00159	0.00602	1.394***	–0.00136	0.000960	1.389***	–0.00123	–0.00132	1.386***
Aero	0.00204	–0.0194***	1.030***	0.00214	–0.0227***	1.022***	0.00217	–0.0144***	1.027***
Ships	–0.00191	0.0222***	1.102***	–0.00192	0.0237***	1.109***	–0.00197	0.0152***	1.104***
Guns	0.00393	0.0255***	0.633***	0.00413	0.0219***	0.635***	0.00426*	0.0117***	0.627***
Gold	0.00205	0.00628	0.394***	0.00188	0.0105	0.400***	0.00203	0.00437	0.394***
Mines	0.000736	0.00729	1.136***	0.000860	0.00474	1.135***	0.000900	0.00232	1.133***
Coal	0.000620	–0.00240	1.086***	0.000623	–0.00260	1.085***	0.000590	–0.00111	1.086***
Oil	0.00169	0.00466	0.841***	0.00170	0.00462	0.842***	0.00169	0.00301	0.841***
Util	0.00368**	–0.00724	0.432***	0.00354**	–0.00434	0.434***	0.00343**	–0.00105	0.437***
Telcm	–0.000645	0.00192	0.906***	–0.000676	0.00277	0.908***	–0.000692	0.00193	0.907***
PerSv	–0.00265	0.00234	0.991***	–0.00268	0.00318	0.993***	–0.00270	0.00211	0.992***
BusSv	–0.000786	0.00168	1.080***	–0.000726	0.000356	1.079***	–0.000759	0.000699	1.080***

Appendix 2. Industry exposure to GPT, GPR, and GPA with the monthly average value-weighted stock returns (contd.)

Industry	***GPT***			***GPR***			***GPA***		
	α_k	β_k	γ_k	α_k	β_k	γ_k	α_k	β_k	γ_k
Hardw	−0.00130	−0.00690	1.290***	−0.00114	−0.0112*	1.283***	−0.00112	−0.00702*	1.285***
Softw	0.00162	0.00673	1.307***	0.00173	0.00430	1.306***	0.00166	0.00372	1.306***
Chips	0.000989	−0.0113*	1.392***	0.00101	−0.0123**	1.388***	0.000992	−0.00734**	1.391***
LabEq	0.000197	−0.00308	1.189***	0.000241	−0.00427	1.186***	0.000236	−0.00256	1.188***
Paper	−0.000553	−0.00338	0.912***	−0.000681	−0.000524	0.915***	−0.000776	0.00107	0.917***
Boxes	0.000692	0.00573	0.966***	0.000861	0.00203	0.963***	0.000917	0.000421	0.961***
Trans	0.000146	−0.00210	0.987***	0.000139	−0.00206	0.987***	0.0000333	0.000278	0.990***
Whlsl	−0.000341	0.000738	0.953***	−0.000309	0.0000265	0.952***	−0.000256	−0.000755	0.951***
Rtail	0.00168	0.00160	0.980***	0.00174	0.000192	0.979***	0.00177	−0.000227	0.979***
Meals	0.00252	−0.00574	0.871***	0.00256	−0.00700*	0.868***	0.00263*	−0.00535**	0.868***
Banks	−0.000284	−0.00289	1.089***	−0.000425	0.000302	1.092***	−0.000455	0.000628	1.093***
Insur	0.00149	0.00454	0.907***	0.00139	0.00713*	0.911***	0.00132	0.00537**	0.910***
RlEst	−0.00503**	0.00241	1.149***	−0.00508**	0.00370	1.151***	−0.00508**	0.00223	1.150***
Fin	0.0000760	−0.00235	1.279***	0.000153	−0.00429	1.277***	0.000263	−0.00424*	1.275***
Other	−0.00337*	−0.00426	1.053***	−0.00351*	−0.00107	1.055***	−0.00373*	0.00252	1.061***

Note: This table presents the estimated coefficients from the industry exposure measure stated in Caldara and Iacoviello (2019; 2022), and the equation (3, GPA) is derived based on their earlier work. The results are not standardized, demeaned, and signs shifted in this table. The timeline for the regressions runs from February 1985 to March 2023. The stars ***, **, * denote statistical significance at 1%, 5%, and 10% level measured by t-statistics. The abbreviations for the industries are in the list of abbreviations. The U.S. 1-Month Treasury Bill Rate is used as a risk-free rate to construct this table.