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Geopolitical Risk and U.S. Market Cap Indices

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ABSTRACT:
Geopolitical risk has gained popularity in financial research in recent years. Prior research has shown geopolitical risk to potentially have explanatory power over stock returns. However, the form and the extent of this relationship remain disputed among scholars. One unexplored aspect of this relationship is whether geopolitical risk influences stock returns asymmetrically based on the market capitalisation of the company. This thesis aims to contribute to this discussion by examining geopolitical risk as an explanatory variable of stock returns between different company size classes, while also providing additional evidence on the shape of the relationship between geopolitical risk and individual stock indices.

In its main tests, this thesis examined daily data, covering the period from the beginning of the year 1999 until the end of October 2023. To approximate geopolitical risk, the paper utilised the newspaper-based GPR indices and tested their explanatory power over the daily returns of large-, mid-, small-, and micro-cap stock indices, composed of U.S.-based companies. The methodology of the paper is divided into two segments. In the first segment, the explanatory power of the GPR indices on individual stock indices was tested through a quantile autoregression model. In the second phase of testing, several size-based portfolios were constructed to mimic the return differences of varying company size classes. The significance of geopolitical risk on these portfolios' returns was tested using a GARCH(1,1) model while being controlled for crude oil prices.

The results obtained from the empirical testing of individual stock indices did show that geopolitical risk has influence over stock returns and the relationship is negative, regardless of company size. For the size-based portfolios, the results indicated that geopolitical risk has explanatory power over the return differences between micro-cap companies and larger companies. The same relationship among large-, mid-, and small-cap companies was deemed statistically insignificant. Further testing also revealed that the explanatory power of geopolitical risk over the size-based return differences is time-variant.

The main conclusions drawn from these results are twofold. Firstly, the findings of this thesis support the notion that geopolitical risk has a negative relationship with daily stock returns. Secondly, geopolitical risk does have an asymmetric relationship to the stock returns of companies with different market capitalisations. However, this relationship is not stable across time and could only be found in the return difference of micro-caps versus their larger counterparts. Furthermore, contrary to earlier literature, this thesis does find that geopolitical acts have more explanatory power over stock returns than geopolitical threats.

KEYWORDS: GARCH models, geopolitics, indexes, market value, risks, stock prices

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TIIVISTELMÄ:

Geopoliittinen riski on viime vuosina saavuttanut suosiota rahoitusalan akateemisessa tutkimuksessa. Aiemmat tutkimukset ovat osoittaneet, että geopoliittisella riskillä on todennäköisesti selitysvoimaa osaketuottojen suhteen. Tämän suhteen laajuus ja yleistettävyys ovat kuitenkin edelleen kiistanalaisia tutkijoiden keskuudessa. Yksi tämän riippuvuussuhteen tutkimaton osa-alue on yrityksen markkina-arvon vaikutus geopoliittisen riskin ja osaketuottojen välisessä vuorovaikutuksessa. Tämän pro gradu-työn tarkoituksena on tarkastella ja analysoida geopoliittista riskiä erikokoisten yritysten osaketuottoja selittävänä tekijänä ja tutkia geopoliittisen riskin ja yksittäisten osakeindeksien välisen riippuvuussuhteen muotoa.

Työn keskeisin tutkimusaineisto muodostui yhdysvaltalaisten yritysten pörssidatasta ajanjaksolta 1.1.1999 – 31.10.2023. Geopoliittisen riskin arvioimiseksi tässä työssä käytettiin sanomalehtipohjaisia GPR-indeksejä ja niiden selitysvoimaa testattiin suurten, keskisuurten, pienten ja mikroyhtiöiden osakeindeksien päiväkohtaisiin tuottoihin. Työn menetelmälliset valinnat jakautuvat kahteen osaan. Ensimmäisessä osassa GPR-indeksien selitysvoimaa testattiin yksittäisten osakeindeksien tuottoihin autoregressiivisen kvantiiliregressiomallin avulla. Testauksen toisessa vaiheessa rakennettiin useita yritysten markkina-arvoon perustuvia osakeportfolioita, joilla pyrittiin approksimoimaan erikokoisten yritysten tuottoeroja. Geopoliittisen riskin merkitystä näiden portfolioiden tuottoihin testattiin GARCH(1,1)-mallilla, samalla kun tuloksia kontrolloitiin raakaöljyn hinnanvaihtelun suhteen.

Yksittäisten osakeindeksien empiirisellä testauksella saadut tulokset osoittivat, että geopoliittinen riski vaikuttaa osaketuottoon ja suhde on negatiivinen yrityksen koosta riippumatta. Kokoon perustuvien osakeportfolioiden osalta tulokset osoittivat, että geopoliittisella riskillä oli selitysvoimaa mikroyhtiöiden ja niitä suurempien yritysten tuottoeroon. Samaa suhdetta suurten, keskisuurten ja pienten yhtiöiden välillä ei havaittu. Tutkimuksen päätulosten ja reliabiliteetin testien tuloksien avulla havaittiin myös, että geopoliittisen riskin ja yrityksen kokoon perustuvien tuottoerojen suhteen voimakkuus vaihteli tutkitun aikajakson mukaan.

Tämän tutkimuksen tuloksista on tehtävissä kaksi johtopäätöstä. Työn tulokset tukevat käsitystä, että geopoliittisella riskillä on negatiivinen suhde osaketuottoihin. Lisäksi tutkimuksen tulokset tukevat näkemystä, että geopoliittisella riskillä on epäsymmetrinen suhde eri kokoisten yritysten osakkeiden tuottoon. Tämä epäsymmetrinen suhde on havaittavissa vain mikroyhtiöiden ja tätä isompien yhtiöiden osakkeiden välillä. Lisäksi suhde ei vaikuta olevan vakaa, koska sen selitysvoima vaihtelee eri ajanjaksoina. Työn päätulosten ohelle, tämän työn tulokset poikkeavat aikaisemmissa tutkimuksissa tehdyistä havainnoista viittaamalla, että geopoliittisilla teoilla on enemmän selitysvoimaa osaketuottoihin kuin geopoliittisilla uhilla.

AVAINSANAT: GARCH-mallit, geopolitiikka, indeksit, markkina-arvo, pörssikurssit, riskit

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Abbreviations

GPR Geopolitical risk
GPA Geopolitical acts
GPT Geopolitical threats

1 Introduction

Geopolitical risk, as defined by Caldara and Iacoviello (2022, p. 1197), refers to a risk associated with tensions between states, terrorism, or war. In addition to concrete acts, they also include threats to their definition. During the 21st century, geopolitical risk (abbreviated as GPR) has become an interest of research within the academic finance community. In addition to the apparent systematic risk that geopolitical risk possesses, different sectors and commodities have notable differences in their exposure to it (Baur & Smales, 2020; Caldara & Iacoviello, 2022). However, the idiosyncratic elements of GPR have not been extensively explored and further research needs to be conducted.

Among other possibly influential variables, one lacking area of research has been GPR and its relation to market capitalisation. Given the absence of literature on the topic, it is unclear whether a company's size has an impact on its exposure to GPR. Therefore, this paper examines whether geopolitical risk affects the stock returns asymmetrically based on the market capitalisation of the company. To investigate this relationship, this thesis aims to find if the market responses are generalizable among different company size classes. Furthermore, the research methodology employed in this paper grants insight into the other unknowns of the relationship between stock returns and GPR, contributing to the wider discussion.

To approximate stock returns of different-sized companies, this thesis uses index returns. As opposed to individual stocks, the importance of this relationship on an index level is highlighted by the rise of index investing. Indices form a considerable portion of the whole market ecosystem. As an example, S&P Dow Jones Indices (2023a) estimate the indexed asset value linked to the S&P 500 to be 5.7 trillion USD, whereas the whole U.S. equity market was estimated to be 45.5 trillion by the Securities Industry and Financial Markets Association (2023).

1.1 Purpose of the study

Despite prior literature having examined the relationship between GPR and stock returns, the research has not extensively explored whether other variables influence this relationship. Company size is an unexamined subsegment of this relationship that has theoretical and practical implications. The author of this thesis is only aware of a handful of published papers considering this relationship, while it has not been the main research objective of these studies (see Ahmed et al., 2023; Ren et al., 2023). From these papers in question, this master's thesis differs by examining the relationship directly, utilising indices from a different market, applying a different methodology and aiming to generalize the relationship.

Given the above-mentioned research gap, this thesis approaches the relationship through the comparison of returns of large-, mid-, small-, and micro-cap indices and investigates whether they are influenced asymmetrically by geopolitical risk. Further defining the scope of this research, this paper examines the relationships on a daily timeframe and within the U.S. stock market.

1.2 Hypothesis development

The purpose of this thesis is to examine whether geopolitical risk affects stock returns differently based on the market capitalisation of the company. Therefore, the main question this thesis aims to answer is defined as:

Research question: Does the market capitalisation of a company influence how its stock returns are impacted by geopolitical risk?

Based on the literature examining geopolitical risk as an explanatory factor in financial markets, which is further discussed in the literature review chapter, the relationship and its extent are unclear. Whereas the majority of the prior literature does find a negative relationship between geopolitical risk and stock returns, the strength and stability of the relationship are called into question. Therefore, answering the research question requires further assumptions to be made. In order to test these assumptions and provide additional evidence for the discussion surrounding the relationship between geopolitical risk and stock returns, this paper approaches the research question first through testing of individual stock indices. Therefore, based on the findings of prior studies, the first hypothesis is derived to be:

Hypothesis 1: Geopolitical risk has a negative relationship with stock returns.

The second hypothesis examined in this paper considers whether the relationship between geopolitical risk and stock returns is dependable on the market capitalisation of the company. The second hypothesis is founded upon prior literature on geopolitical risk within the financial markets, on the size effect and flight-to-safety phenomenon, further explored in later parts of this paper.

Hypothesis 2: Geopolitical risk has a stronger effect on the stock returns of smaller companies than on larger companies.

1.3 Contribution

To summarise the intended contribution of the research, a core aspect of financial research has been the search for factors that can explain stock returns. Given the existing literature on the topic, geopolitical risk is a potential factor. Therefore, this thesis aims to contribute to the growing amount of literature on the topic and among other papers, aid scholars in their quest to understand the market and its risks. Furthermore, it also aims to provide further information on how stock returns of companies with different market capitalisations react to external risk. The research also has utility for practitioners by identifying whether the selection of certain market cap indices can potentially protect their investment from different types of geopolitical risk.

Additionally, this thesis provides further information about the relationship between stock returns and geopolitical risk. As the majority of the existing literature is skewed towards mean-based regression approaches or event studies focusing on major geopolitical events, they potentially overlook asymmetricities in this relationship and thus, present challenges to interpreting the effects geopolitical risk may have. Therefore, the first quantitative test of this paper uses a quantile regression approach, enabling the examination of the relationship between the two variables in different return quantiles. Consequently, this thesis contributes to the wider scientific discussions regarding GPR and stock returns by providing additional evidence about the form of the relationship. Furthermore, as a considerable portion of the literature has used monthly variants of the GPR indices, their results reflect the long-term impacts of geopolitical risk. By approximating geopolitical risk with the daily GPR indices, this paper provides additional information on the short-term market reactions.

1.4 Structure of the thesis

In addition to answering the research question, this thesis aims to familiarize the reader with the key concepts and relevant prior research surrounding the topic. In the second chapter, geopolitical risk and the GPR indices used to approximate it in this paper are presented. The third chapter discusses and summarises the relevant previous studies and their results regarding stock returns and geopolitical risk, in addition to studies concerning size effect and its implications. The fourth chapter introduces the theoretical framework upon which the assumptions and hypotheses made in this paper are founded. The fifth chapter displays the data and methodology used in this paper with the reasoning behind their selection. The sixth chapter shows the obtained results and evaluates their significance. The last main chapter summarises the research while also considering its limitations and gives recommendations for future research.

2 Geopolitical risk

The purpose of this chapter is to give an overview of geopolitical risk. Later subchapters introduce the GPR indices, developed by Caldara and Iacoviello (2022), that are used to approximate geopolitical risk in this paper. Furthermore, it highlights a potential timing issue within the indices.

As for the meaning of geopolitical risk, this thesis uses the definition of Caldara and Iacoviello (2020, p.1197). In addition to events related to wars and terrorism, their definition includes the threats, escalations, and realization of risks related to them. Measuring the total economic impact of geopolitical risk is difficult due to the challenges related to determining what costs are related to geopolitical risk. However, when taking a relatively broad definition, the direct costs of global military expenditure, conflict deaths, and terrorism collectively reached 2.89 trillion USD in 2017 (Igbal et al., 2021, p. 417). Despite the uncertainty related to these estimations, the economic implications of geopolitical risk are considerable, highlighting the importance of the topic.

2.1 GPR index

The GPR index of Caldara and Iacoviello (2022) is a corpus-based index, derived by analysing and classifying articles published in major newspapers. The GPR index has two variants: the historical index (1900-) relies on three newspapers and the recent index (1985-) measures ten papers. Six of these newspapers are from the U.S. (USA Today and the Wall Street Journal among others), three are from the U.K. (the Daily Telegraph, the Financial Times, and the Guardian), and one is from Canada (the Globe and Mail). By choosing major newspapers from different countries, the creators of the index hoped to be able to identify geopolitical events with global ramifications.

To form their index, Caldara and Iacoviello (2022) first selected words that were deemed to be closely related to geopolitical risk and created themes around word pairs and phrases that were seen to be associated with GPR, based on geopolitical textbooks and a dictionary. To avoid misspecifications of non-geopolitical events, articles including words such as movies or war anniversaries were excluded. By comparing their list of words to their occurrence in news articles around major geopolitical events, they were able to create a scoring system. After pooling the scores of the individual articles together, the daily GPR values were able to be computed.

The robustness of the GPR index was also tested by Caldara and Iacoviello (2022). Testing of the index was conducted by comparing the timings of its peaks against major geopolitical events from 1900 to 2019, to which the monthly GPR index reacted accordingly (see Figure 1 below). The index was also compared against an index constructed from the front pages of the New York Times. As the two illustrated a high degree of correlation, the GPR index was seen to be able to capture the most important geopolitical headlines. Furthermore, the index was also tested against different economic variables, the results of which are discussed in-depth in chapter three of this thesis.

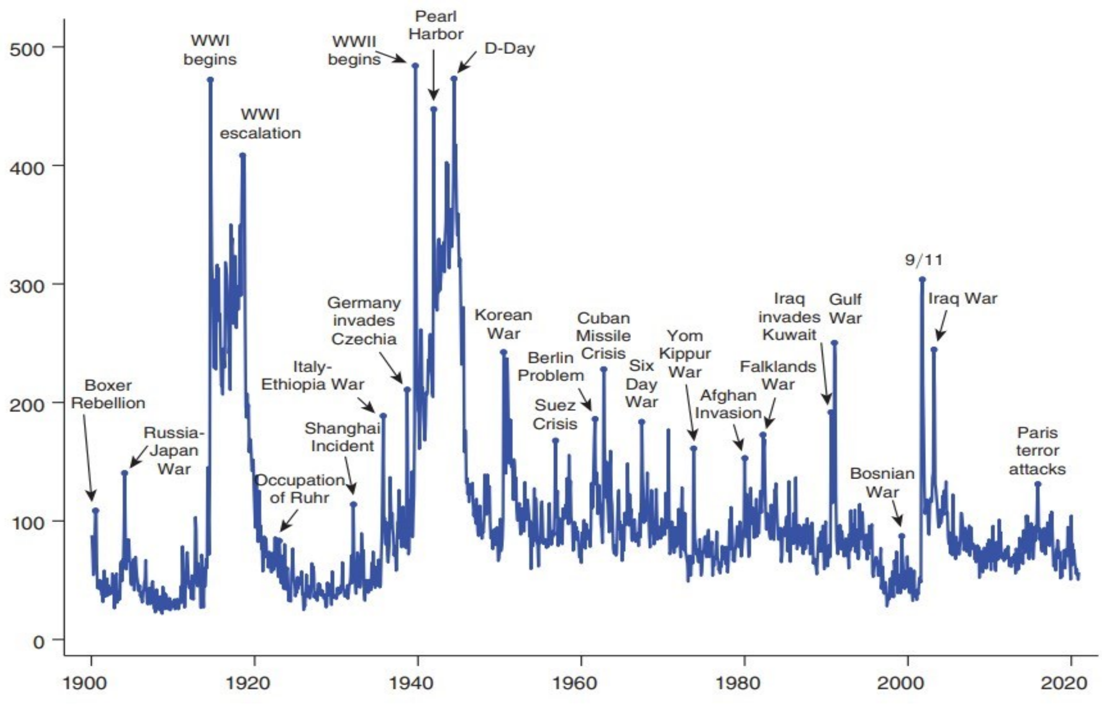


Figure 1. Historical GPR index from 1900 (Caldara and Iacoviello, 2022, p. 1203).

2.2 GP acts and threats indices

The main GPR index presented above was built from two separate indices, the GP Acts (abbreviated as GPA) and GP Threats (abbreviated as GPT) indices. While also created by Caldara and Iacoviello (2022), the GP Acts index represents words and themes associated with the occurrence or escalation of geopolitical events. The terms associated with the GP Acts index include themes surrounding the beginning and escalation of a war, in addition to terrorist attacks. GP Threats index includes themes associated with the threat of war, threats of terrorist attacks, or nuclear weapons, while also accounting for articles covering threats to peace and military buildups. The differences between the indices can be observed below in Figure 2, where the GPA index reacts strongly to the September 11th 2001 terrorist attacks, while the GPT index has a relatively minute reaction. The other major spike in the indices, according to Caldara and Iacoviello (2022, p. 1205), represents the beginning of the Iraq War in 2003. It should be noted that the reaction to the war is more homogeneous among the indices when compared to the 9/11 attacks.

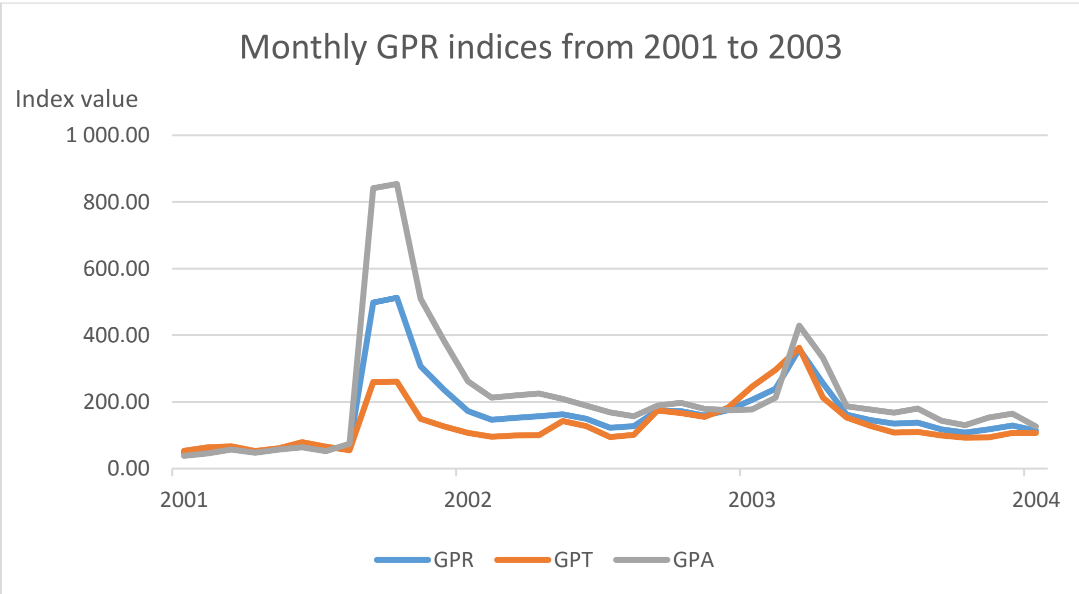


Figure 2. Monthly GPR indices from 2001 to 2003.

Similarly to the main GPR index, the GPA and GPT indices were also subjected to robustness testing. By comparing the spikes within the monthly indices to major historical events, Caldara and Iacoviello (2022) determine the indices to be able to capture significant geopolitical events. When comparing the GPR indices against global war-related deaths, they find a high degree of correlation during the world wars for the GPR index, but the relationship becomes weaker afterwards. GPA was found to have the highest correlation to war deaths, while GPT had the weakest correlation.

2.3 GPR indices and time error

As pointed out by Baur and Smales (2020, p.2), the GPR indices have an inherent issue with their timing. The monthly version of the index suffers from being a monthly average of daily values. Where they might be able to capture slowly developing changes in the geopolitical environment, they are likely to underestimate fast and unexpected events. Notably for the purposes of this thesis, the daily GPR indices suffer from another issue. Due to the way the daily indices are compiled, they do tend to lag a day behind the actual events. As the news articles reporting on specific events are published in the next day's issue relative to the event, the publications are constantly at least one day behind. Moreover, depending on the time of the day when an event occurs, how fast journalists write about it, and when the paper is published, the lag between the indices and the event can be even longer.

To examine the time error further, Table 1 presents the daily values of the GPR indices against major geopolitical events. From the fluctuations of the index values, it can be determined that the GPR indices do lag a day behind actual events. Furthermore, in the case of the Paris terrorist attacks, the indices reach their peak only on the third day after the attacks. The author of this thesis suspects that the lag is due to the attacks occurring late on the 13th of November 2015 and continued till the first hour of the 14th. Thus, the papers for the 14th of November did not have enough time to be able to cover the attacks.

Table 1. The daily values of the geopolitical risk indices compared to the timing of major geopolitical events.

	Days from the event					
	t_{-2}	t_{-1}	t_0	t_1	t_2	t_3
Event (event date)						
9/11 (11.9.2001)						
GPR	20.6	38.2	154.1	725.5	633.5	667.8
GPA	13.7	41.6	218.6	1 319.5	1 178.9	1 231.8
GPT	22.8	28.9	98.6	294.3	206.3	210.4
London bombings (7.7.2005)						
GPR	126.4	83.5	46.7	469.2	241.4	152.8
GPA	160.3	115.3	64.0	879.4	399.2	220.9
GPT	114.6	42.7	24.2	249.7	146.9	101.7
Paris terrorist attacks (13.11.2015)						
GPR	52.0	44.1	61.6	121.1	129.1	292.0
GPA	75.4	44.0	73.7	181.2	220.6	401.5
GPT	31.4	42.8	41.0	94.4	51.1	251.2
Beginning of the large-scale invasion, the Russo-Ukrainian War (24.2.2022)						
GPR	286.7	436.0	381.8	515.8	398.6	202.1
GPA	127.0	189.8	197.7	160.4	362.6	157.7
GPT	450.3	700.1	560.8	794.9	489.1	277.6

Note: GPR, GPA, and GPT refer to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices.

3 Literature review

The following portion of the thesis aims to present the key findings of prior research related to the research objectives of this thesis. It also intends to evaluate their trustworthiness as individual studies and their relation to the wider academic field of research. The following studies were selected due to their relevance to the examined topic, trustworthiness and standing within the academic literature.

The studies regarding GPR and stock returns were divided into subchapters based on the countries they were examining. As a considerable portion of the papers examined multiple markets, studies that discussed U.S. stocks or indices separately from others were grouped into the U.S. category, and if not, into the other countries category. A summary of these papers can be found in Appendix 1. Furthermore, the literature surrounding the size effect is discussed in the third subchapter. In the last subchapter, the key pieces of the existing literature are summarised to present the reader with a comprehensive picture of the state of the research as it stands during the writing of this thesis.

3.1 Geopolitical risk and stock returns in the U.S.

After developing the GPR indices and testing them against other approximators of geopolitical risk, Caldara and Iacoviello (2022) aimed to validate their indices in an economic context. By utilising a Granger causality test, they find that their main index provides novel information when compared to common macroeconomic, financial, and uncertainty metrics, such as oil prices, the VIX-index, and the Economic Policy Uncertainty index (commonly abbreviated as EPU). Through their analysis of U.S. data via VAR and quantile regression models, they find that GPR has explanatory power over GDP growth and business investments, where higher levels of GPR tend to lower them. Furthermore, historically high GPR levels seem to have an impact on the VIX-index, while having a negative impact on lagged S&P 500 returns. By extending their research to different sectors via industry portfolios and using daily returns from 1985 to 2019, they discovered that certain industries have more exposure to geopolitical risk. Industrial metal mining and defence relatively benefitting the most from higher GPR, while aircraft and apparel are negatively impacted.

Ali et al. (2023) extended the research by examining the impact of geopolitical threats on different asset classes between the years 1985 and 2021, by using the GPT index. In their research, they use daily and monthly data and control for various macroeconomic factors. By comparing the responses of different markets to changes in the geopolitical threat index, they find that the S&P 500 has a statistically significant positive response to higher geopolitical threat levels, while the responses of other major country indices and assets do not reach statistical significance. However, the results of their linear regression model indicate that while the relationship was significant in 2005-2021 and 2015-2021, it was insignificant between the years 1995-2021. The researchers also examined the daily returns of sector ETFs between 2015 and 2021, finding that financial and information technology sectors experience significant positive returns in a high geopolitical threat environment. Overall, different sectors were deemed to have heterogenous responses to changes in GPT. It should also be noted that these results were not robust when accounting for conditional volatility and using monthly data.

Baur and Smales (2020) examine the relationship between precious metals and geopolitical risk, with the research objective of determining whether contracts on these assets can be used to hedge GPR. In their research, they use monthly and daily data from 1985 to 2018. By approximating geopolitical risk by using the GPR index in their regression analysis, they find that futures contracts on precious metals have a positive correlation with geopolitical risk. The S&P 500, Treasury notes, and the dollar index react adversely to increases in the GPR index, but the relationship does not reach statistical significance. Moreover, Baur and Smales theorize that the found difference in sensitivity might be related to the production chains, as the mining of precious metals might be interfered with by local terrorist attacks abroad, while the same attacks have a much more limited impact on other asset classes. However, when they emphasize extreme geopolitical events through the use of the GPR shocks index, S&P 500 returns become statistically significant at a 1% level while the relationship is negative. T-bonds and the dollar index remain statistically insignificant also when testing for other forms of GPR, hinting that a possible flight-for-safety response from the market is on average limited, inconsistent or non-existent. Furthermore, through the testing of different GPR indices, they find that the precious metals reaction to geopolitical risks is mainly driven by threats, rather than geopolitical acts. The S&P 500 does seem to display a similar pattern, although being statistically weaker.

Salisu et al. (2022) investigated the impact of geopolitical risk in developed economies. Their dataset consists of over 100 years of monthly stock data from the G7 countries and Switzerland, being adjusted for conditional heteroskedasticity. To approximate geopolitical risk, Salisu et al. use the GPR, GPA, and GPT indices. Through a bias-adjusted OLS regression and while controlling for crude oil prices, they find GPR to have predictive power over the index returns within the examined nations, with the exception of Italy. When examining the S&P 500 returns of the U.S. market, they find that all the GPR indices are statistically significant at a 1% level and that higher levels of geopolitical risk cause lower returns. Among the three indices, the GPT has the strongest impact on returns, while the GPA has the weakest. Moreover, to robust their findings, they test their model in an out-of-sample environment against a historical average model via a Clark and West test. Through their test, they find that the inclusion of geopolitical risk indices does reduce forecasting errors, although not significantly for all indices and forecasting horizons.

In addition to the relationship between asset returns and GPR indices, past studies have also examined the relationship between the GPR indices and market sentiment. He (2023) found that the monthly GPR indices have explanatory power over investor sentiment when the sentiment is estimated by using the BW sentiment index developed by Baker and Wurgler (2006), compiled from different market metrics, such as the volume of initial public offerings and equity share in new issues. Through a Granger causality test, the relationship is observed to be unidirectional as increases in geopolitical risk were observed to lead to lower investor sentiment but not vice versa. Sentiment response to geopolitical shocks was also shown to vary over time as the response weakened during the 2010s compared to data points from two decades prior. In addition, the sentiment response to geopolitical shocks was observed to slowly diminish, influencing the investors' outlook for up to a year into the future. When comparing the sentiment responses to the GPR, GPA, and GPT indices, no notable differences between the geopolitical indices were discovered.

Whereas the GPR indices have been popular approximators of geopolitical risk among scholars, prior research has also utilised alternative proxies. Chesney et al. (2011) examined how terrorist attacks influence the daily returns of different financial indices. The examined indices include stock, commodity, and bond indices, while the examined stock indices can be further divided according to the country and industry. In their research examining attacks from 1990 till 2003, they employ several research methodologies including a non-parametric polynomial regression, an event study, and a GARCH model. Through their research, Chesney et al. find that most terrorist attacks lead to negative index returns at least in one of the examined indices and that there are differences in how susceptible different stock markets are to terrorist attacks. When comparing American to European stock indices, they deem the former to be the least impacted by the examined acts of terror. Moreover, the authors discover that the stocks of airliners and insurance providers are more vulnerable to terrorist attacks, while the banking sector shows the most resistance. In addition to these results, the authors also conclude that when examining market reactions to terrorism, non-parametric approaches seem to be the most well-suited choice out of the tested methodologies due to the inherent limitations of event studies and GARCH models.

Goel et al. (2017) provide contrary evidence on the relationship between terrorism and financial markets. Using data starting from the year 1991 and ending in 2010, they approximate terrorist attacks by employing the Global Terrorism Database, operated by the

University of Maryland. The researcher refined the data further by excluding events with economic estimated damage deemed less than one million USD and continued their selection process by only including dates during which a considerable number of these types of attacks occurred. After identifying the 49 most impactful days, Goel et al. conducted an event study. Concluding from the numbers of positive and negative trading days, and from the cumulative abnormal returns following attacks, the authors state that the S&P 500 and the bond market do not seem to have a strong or systematic response to terrorist attacks. Furthermore, these findings hold even when only considering events that occurred in the United States. Furthermore, the researcher did not find terrorist attacks to facilitate a significant flight-to-safety response in gold or treasury bond markets.

3.2 Geopolitical risk and stock returns in other countries

The geopolitical risk can have an asymmetric effect on stock returns based on the country or region that is being observed. As discovered by Balcilar et al. (2018), the market response to geopolitical risk can vary between countries, while Boubaker et al. (2022) find that factors such as proximity to a geopolitical event can cause heterogeneous market responses. Due to these limitations, patterns observed in other markets have limited applicability to the U.S. market. Despite the differences in the market dynamics, the author of this thesis argues that research on other markets does provide relevant information regarding the research question, as they supply evidence on the relationship between GPR and stock returns, further strengthening the observations made in the U.S. markets. In addition, they provide information on how variances in policies, industry structures and the level of economic development influence market reactions to GPR.

Balcilar et al. (2018) investigate geopolitical risk as a factor contributing to stock returns and volatility in BRICS countries. Their main statistical research method consists of examining Granger causalities between index returns and volatility against the GPR index and eight of its variants in different return and volatility quantiles. While the extent of their examined stock data varies by country, the majority of the data is dated between the years 1990 and 2016. The authors summarise their findings by stating that GPR does seem to have a more consistent effect on volatility than on index returns. Furthermore, increases in GPR are observed to facilitate the outflow of capital from the respective markets. When comparing country-specific reactions, Balcilar et al. find BRICS markets to have heterogeneous responses to GPR. The authors conclude Russia to have the highest exposure to geopolitical risk, whereas they find India to have the lowest. However, as Balcilar et al. do not extensively explore the reasons behind these differences, the author of this thesis would like to point out the findings of Abdel-Latif and El-Gamal (2020), who discovered geopolitical risk and oil prices having a connection, possibly explaining the Russian sensitivity to geopolitical risk through their energy sector.

Kannadhasan and Das (2020) examine the index-level responses to economic policy uncertainty and geopolitical risk within Asian markets. While using monthly data from 1997 till 2018 in their quantile autoregression model, they find that higher economic policy uncertainty has a pronounced negative impact on returns across the distribution of returns. Geopolitical risk on the other hand does not reach statistical significance in most return quantiles and countries. Furthermore, Kannadhasan and Das discovered that the Asian markets are more sensitive to EPU and GPR in bearish markets when compared to bullish ones. In addition to varying susceptibility according to market modes, they also discover increasing GPR to be connected to negative returns in bear markets, while being associated with higher returns in neutral and bullish markets. However, the author of this thesis would like to criticize these findings, as the observed impact of GPR does not reach statistically significant in most instances, partially invalidating their interpretation of the shape of the relationship across the return quantiles. Furthermore, their use of global EPU and GPR indices instead of local ones could introduce undesirable noise into the regression, diminishing the observed impact of more consequential local events.

Continuing the research on the impact of geopolitical risk on financial markets, Zaremba et al. (2022) examine the relationship between the GPR index and stock market returns in emerging markets. In their research, the researchers assess the impact that the country-specific GPR indices have on the value of the country's stock market, represented by the most notable locally listed companies on a monthly basis. By first ranking the countries based on the changes in their volatility-adjusted GPR indices within consecutive months, they divided the markets into high and low GPR countries. Through a Fama-MacBeth nested regression, Zaremba et al. discovered that the high GPR markets do generate abnormal returns in the following month when compared to low GPR markets. The researchers attribute the found anomaly to investors initially overreacting to heightening geopolitical tensions while displaying a reversal pattern in the subsequent month. Moreover, their findings support the notion that the observed return differences are mainly driven by local idiosyncratic geopolitical risk rather than the global systematic geopolitical risk.

Feng et al. (2023) approach geopolitical risk from the perspective of international capital flows. In their paper, international capital flows from 45 advanced and emerging markets are considered from 2005 to 2019 with a quarterly sequence. To approximate geopolitical risk, they use the main GPR index, supplemented with the GPA and GPT index variants. By conducting a regression analysis, they find that increases in geopolitical risk tend to lower the inflow and outflow of capital in advanced and emerging markets. Also, Feng et al. discovered that capital flows are heterogeneous between the two groups under geopolitical stress. Direct investment from advanced to developing economies indicates a flight-to-safety type of behaviour, while other investments displayed signs of a flight-to-home effect. Furthermore, they find that the GPA index only has a statistically significant impact on the inflows, while the GPT index has a significant impact on inflows and outflows.

Similarly to the U.S. market, studies regarding other markets have also used alternative proxies of geopolitical risk. Nikkinen and Vähämaa (2010) study how terrorist attacks influence investor sentiment regarding the future performance of FTSE100, containing large-caps listed on the London Stock Exchange. For their dependent variable, they use a density function derived from options on FTSE100, deriving the respective values for each trading day from the beginning of the year 2000 until the end of 2005. While examining the effects of the September 11th 2001 attacks, the Madrid 2004 train bombings, and the London 2005 bombings, they discover that the option-implied future market performance expectations decrease significantly after each attack. Furthermore, they discover the implied volatility to have a pronounced reaction, considerably increasing after the acts. Nikkinen and Vähämaa also examine the following trading days after the incidents, discovering that the sentiment took over two weeks to rebound, while negative skewness of the associated distribution took over 80 days to recover from the 9/11, implying a long-lasting decrease on the expected future returns for some investors. Lastly, to investigate the recovery of the market, they construct a GARCH model, confirming that the market sentiment density function is statistically significantly negatively impacted by the studied terror attacks on the day of the attacks. On the following day, expectations tend to drift towards their preattack state. However, the skewness of the distribution remains significant on the second day. To robust their findings, the authors also test their model on other indices, such as VIX-derived S&P 500 options, discovering similar patterns to the FTSE100 options.

Ahmed et al. (2023) examined the impact of the Russo-Ukrainian conflict, focusing on the European stock markets. The researchers selected to study the daily stock returns of the STOXX Europe 600 component companies and conducted an event study centred around the Russian recognition of the so-called People's Republics of Donetsk and Luhansk on the 21st of February 2022. Ahmed et al. found negative abnormal returns occurring two days before the event and on the event day, statistically insignificant and slightly positive returns on the following day, and negative abnormal returns two and three days after. Ahmed et al. suspect that the negative stock performance could be a result of the market participants accounting for intelligent information prior to the recognition and following attack. Continuing their research, they tested different event horizons and discovered that the most substantial negative average cumulative returns of -4.02% were experienced when considering ten days before and after the event, while other horizons also displayed statistically significant negative returns. Furthermore, they also compare the impact on different industries. The researchers found that on the event day, consumer staples were the most adversely affected, while the financial sector suffered the most when considering a three-day event window before and after the recognition. The energy sector experienced the highest positive returns on the event day and the days after it and despite being statistically insignificant in most event windows, the researchers believe the sector to have benefitted indirectly from the increasing geopolitical tensions.

Ahmed et al. (2023) also tested the companies based on their size, discovering that large-caps collectively were the least affected, experiencing statistically significant negative returns only on the event day, while mid- and small-caps were negatively impacted also on the other days and displayed statistically significant dependencies on more days. Finishing their research by comparing individual countries, the researchers found that geographical distance to Ukraine was not the best determinant of its impact on a given stock market, while factors such as sectoral distribution and military alliances could be concurrent contributors. However, the author of this thesis would like to remark that the start of the large-scale fighting in the Russo-Ukrainian war began on the 24th of February 2022, coinciding with some of the examined event windows and thus, possibly influencing the results of the returns observed in the latter parts of the examined event window.

Boubaker et al. (2022) also investigate the impact of the Russo-Ukrainian conflict on major stock indices, altogether representing 47 separate markets. Through an event study, they compare the respective index returns around the beginning of the full-scale invasion on February 24th 2022. By analysing the average abnormal returns and cumulative abnormal returns five days before and after the event, they find that most indices experienced statistically significant negative returns on the beginning day of the invasion and positive returns on the following day. The examined American Dow Jones Industrial Average index experienced statistically significant positive returns on the event day and insignificant negative cumulative abnormal returns on the following three days.

Moreover, they also identified other heterogeneous reactions among the countries and examined possible contributing factors to these differences. Economies that were comparatively more entangled with global trade experienced more severe negative returns, while membership in NATO provided comparatively higher returns. Also, geographical proximity to the conflict was associated with stronger negative returns on average. Despite not being discussed by Boubaker et al., their results show significant negative abnormal returns three days before the invasion among European stocks, while the pooled stock indices for developed and developing markets are also negative and statistically significant. These results are similar to Ahmed et al. (2023), whose findings were discussed before.

3.3 Market capitalisation and size effect

The discovery of the size effect is commonly attributed to Banz (1981), who discovered that small-cap stocks listed on the New York Stock Exchange had higher risk-adjusted returns compared to mid- and large-cap stocks. Since then, the market anomaly has become a key part of academic literature. Most notably, the size effect was included in the landmark three-factor model of Fama and French (1993). Due to its position within the literature, the size effect has been extensively tested. However, the extent of its explanatory power over stock returns and why it exists have remained a common topic among scholars. This subchapter of the literature review aims to discuss papers regarding these questions.

The explanatory power of the size effect and its origins are discussed by van Dijk (2011), in his analysis of the scientific literature. By examining prior research on U.S. and international markets with varying samples, he finds that most research does support the existence of the size effect. Within the U.S. market, he finds that the size premium has varied from 0.4% to 2.52% per month. Van Dijk attributes this variance in the results to the differences in the tested time periods, chosen samples, and methodologies. From the literature, he also identifies four possible explanations for the existence of the size effect. The first explanation describes the size premium arising from risks that the investors have to carry when investing in smaller companies, such as the higher bankruptcy risk. The second explanation considers the size effect as a consequence of higher liquidity risk associated with smaller firms, while the third explanation suggests that behavioural finance-related factors might be the culprit, as investors prefer large-caps due to the availability of information and better historical growth rates. The fourth explanation considers the size effect as a statistical error, arising from time-period biases, extreme returns from only a handful of companies, and survivorship biases due to delistings. The fourth explanation also includes the hypothesis that the size effect originates from the January effect, which was found to be a notable contributor to the return difference between small and large stocks. The author of this thesis notes that whereas van Dijk's review article does provide valuable information by pooling multiple journal articles, its conclusions are drawn from studies using data from the 20th century. Given that market participants adapt their behaviour to new research findings and therefore considerably reduce the associated abnormal returns (McLean & Pontiff, 2016), the conclusions drawn by van Dijk must be extrapolated with caution to newer data.

Related to the behavioural explanation given by van Dijk (2011), further evidence on market capitalisation influencing the degree of informational efficiency is provided by Jiang and Zhu (2017). In their study of short-term market reactions to information shocks, the U.S. stock market does seem to have an underreaction to information shocks on average. When differentiating companies based on their size, they found that small-cap and micro-cap stocks had a more pronounced underreaction when compared to large-caps.

Asness et al. (2018) contribute to the discussion surrounding the size effect by examining a longer time period and controlling for quality. By examining U.S. stock returns between 1926 and 2012 and placing them in different portfolios annually according to their market capitalisations, they find significant abnormal returns in January for the small-caps and insignificant returns for the rest of the year. Furthermore, they identified a twentyyear period following Banz's (1981) publication, when the size effect seemed to disappear, but reappeared afterwards. Apart from the January returns, the results are statistically insignificant or marginally significant, indicating the size effect to be weaker than initially thought and displaying considerable variation across time. However, when controlling for the quality of the company, which is approximated by factors such as profitability and growth rate, they find the size effect to become stronger and statistically significant even during the 1980-1999 period following Banz's publication. Moreover, accounting for quality also diminishes the explanatory power of the January effect and places statistically significant returns for the rest of the year. When examining the relationship between company size and liquidity risk, they find a limited relationship but suspect it not to be strong enough to explain the size effect solely.

Rompotis (2019) extends the study of the size effect into exchange-traded funds (commonly abbreviated as ETFs) by comparing the daily returns of one hundred U.S.-based funds. After analysing the returns of large-cap and small-cap funds from 2012 to 2016, he finds small-caps to yield higher average returns and market-adjusted returns. However, when accounting for risk factors such as volatility and funds' exposure to market risk, Rompotis discovers that small-cap ETFs offer smaller risk-adjusted returns compared to large-cap funds. Moreover, the size effect does not seem to be consistent as the quarter-over-quarter analysis of the returns shows great fluctuations, sometimes preferring small-caps and other times large-caps. When assessing the result of Rompotis, it should be noted that the examined data is limited in its length. Given that the strength of the size effect fluctuates over time, his findings should be interpreted with caution.

3.4 Summary of previous studies

When assessing the impact of geopolitical risk on stock returns, the literature provides conflicting results. Whereas most studies do find a statistically significant relationship, no relationship or an insignificant one was found by Goel et al. (2017) between the S&P 500 returns and terrorist attacks, and by Baur and Smales (2020) among the standard

GPR indices and the S&P 500 returns. Supplementing their findings, Kannadhasan and Das (2020) did not find a significant relationship between the composite GPR index and most of the Asian stock indices. Although their findings form the minority within the academic research, a possible publication bias cannot be ruled out. However, given that multiple event studies of major geopolitical events and papers utilising regression models where the GPR indices were restricted to their highest values, did find a significant relationship, it can be concluded that at least the most extreme events are likely to cause a market response.

Within prior literature, another common finding is that the sector in which a company operates does influence the exposure that investors have to geopolitical risk. However, these findings differ based on which approximation of geopolitical risk is used and on the time period examined. To further highlight this disparity, Caldara and Iacoviello (2022) find industrial metal mining and defence sectors to benefit the most from higher GPR, Ali et al. (2023) discovered financial and information technology sectors to have the highest positive returns in high GPT environments, while Ahmed et al. (2023) found that the energy sector had the best performance in the wake of the rising Russo-Ukrainian tensions, while consumer staples and finance had the worst.

From the observed variance within the country-level and sector-level responses, we can conclude that the global market is likely to vary its response based on the type of geopolitical risk and the location of its occurrence. This notion is supported by the likes of Balcilar et al. (2018) who found heterogeneous responses between different countries. Investigating further, Boubaker et al. (2022) do name factors such as proximity to the event, level of participation in international trade and membership in military alliances to be contributing factors to the strength of the market reaction.

Most research does find a negative correlation between stock returns and geopolitical risk. Furthermore, event studies have found the market to rebound in the following days after a major geopolitical event (Ahmed et al., 2023; Boubaker et al., 2022; Nikkinen &

Vähämaa, 2010) but the bounce-back effect is not statistically significant in all cases. Overall, papers examining the impact of geopolitical risk on stock returns do provide a reason to believe that the relationship does exist. However, the prior literature does not provide a compatible view of the nuances of the relationship. Whereas different research methods, time period biases, examined assets, and markets might explain the variance of the results, in the opinion of the author of this thesis, no conclusive evidence to accurately characterise this relationship has been presented. Furthermore, a considerable portion of the literature utilising the GPR indices does not seem to take into account the time error discussed in chapter two of this paper. As such, more research on the relationship is needed.

The prior literature on the size effect does seem to agree that the effect has existed. Its existence in newer data is debated but does seem to conditionally be observable, although having become weaker since its popularisation. Moreover, the effect does seem to be time-variant, disappearing and reappearing across time. The origin of the effect remains to be debated but is likely a combination of differing levels of information efficiency among large and small-caps, the January effect, and compensation for small-cap investors for carrying a higher level of risk.

4 Theoretical framework

This chapter presents and discusses the theoretical framework of the thesis. It aims to highlight and comment on the key theories from which the research question, hypotheses and methodology of this paper were derived. The following subchapters address the above-mentioned aims by first discussing theories on how the market reacts to new information on a general level. After establishing how the economic consequences of geopolitical risks can facilitate a market response through the efficient market hypothesis, its psychological factors are assessed through behavioural finance. Lastly, the final subchapter introduces a theory regarding the flow of capital from one asset to another during market distress.

4.1 Market efficiency

War and terrorism bring imaginable suffering. In addition to psychological distress, wars can have significant and quantifiable economic effects. Arising from factors such as the loss of trade, destroyed production capabilities, and infrastructure, the effects of major wars are not only noticeable among the belligerents but also in the economies of neutral nations (Glick & Taylor, 2010). Similarly to conflicts between nations, terrorism has direct economic implications through damaged or destroyed private and public property, but also indirect consequences through causing disruptions in supply chains and decreasing availability of foreign capital (Czinkota et al., 2010).

Based on the academic literature, there are competing theories on how external and internal factors influence stock prices. Market efficiency is the degree to which the market is able to effectively and correctly incorporate available information into the prices. Market efficiency, according to Fama (1970), has three different sub-sets. The weak form states that markets efficiently incorporate information from past prices, the semi-strong form suggests that the market also prices in relevant publicly available information, and the strong form states that the market prices further include non-public information. As

Fama initially found the most support for the semi-strong form, the consequent efficient market hypothesis does imply that systematically exceeding the average market return without insider information is impossible.

In its current state, the financial literature has found multiple arguments against the efficient market hypothesis. However, the exact cause of the found violations remains debated among researchers (Engelberg et al., 2018, p.1971). Further study of these market anomalies has yielded possible explanations for the origin of the found anomalies. Whereas the violations could be explained by misspecifications in the used pricing models or time period biases, the strongest evidence on market reactions to information shocks points to the presence of biases among investors (Engelberg et al., 2018; Jiang & Zhu, 2017). As such, psychological factors become relevant and obligatory in explaining how the market works. This orientation deviating from the efficient market hypothesis is commonly known as behavioural finance.

Despite the evidence against the efficient market hypothesis, it does provide a theoretical framework for how economic damages originating from GPR are translated into stock prices. Given that the market has incorporated all available relevant information into the market prices, new relevant information should be the only source of fluctuation (Malkiel, 2003, p.59). Therefore, the mere news of elevating or lowering of risk-levels should prompt a market response. Consequently, the economic impact of the different types of geopolitical risk could be directly observable in market prices under the efficient market hypothesis. However, behavioural finance states that there are biases in the market. These irrationalities can lead the market prices to over- or under-react to certain news, separating the true value of an asset from its market price.

4.2 Behavioural finance and risk

Studies on the impact of war on mental health have found several negative consequences. Among the affected populations, common findings include a considerably elevated incidence of depression, anxiety, and post-traumatic stress disorder (Murthy & Lakshminarayana, 2006). Terrorist attacks have also been linked to short-term and long-lasting mental health issues, in the form of depression and post-traumatic stress disorder (Fisher & Ai, 2008). However, the psychological reaction that a given population has to terrorism seems to be affected by different factors, such as the recurrence of terrorism and the population's level of adaptation to it (Romanov et al., 2012).

While the impact of the psychological aspects of geopolitical turmoil on financial markets is difficult to directly measure, the field of psychology has studied the effects of emotions in decision-making processes. Terrorism has a strong emotional response in the form of fear (Makkonen et al., 2020), while armed conflicts have also been observed to increase the fear of violence among the affected population (Williams et al., 2018). When experiencing feelings of fear, a person has a heightened perception of risk, altering their behaviour to be more risk-averse (Lerner et al., 2015). Through the same decision-making processes of individuals, strong emotions can also influence organizational decisions (Dorison et al. 2020). Considering the long-lasting effects of geopolitical risk in the U.S., depression has been found to be associated with a shorter financial planning horizon (Choung et al., 2022). Furthermore, the difficulty of depression was surveyed to be negatively correlated with the ownership of risky assets (Bogan & Fertig, 2013).

Given that geopolitical risk causes widespread psychological distress, it has the potential to influence market prices and geopolitical risk can be hypothesized to be a behavioural factor within the stock market. Thus, geopolitical risk has two theoretical pathways through which it can influence the market: its economic implications dictated by the efficient market hypothesis and its psychological ramifications. The notion that GPR has an impact on investors’ outlook is supported in the literature by Nikkinen and Vähämaa (2010) who found a connection between stock market sentiment and terrorist attacks and by He (2023), who found a relationship between investor sentiment and the GPR indices.

4.3 Flight-to-safety effect

The second hypothesis of this thesis is: "*Geopolitical risk has a stronger effect on the stock returns of smaller companies than on larger companies*". This hypothesis is partly based on a limited amount of prior research presented earlier, as the event study of Ahmed et al. (2023) on the Russo-Ukrainian War in European stock markets found evidence that companies with larger market capitalisation fared better during the event. Whereas this observation could be explained by using the efficient market hypothesis or behavioural finance, the literature does provide additional theoretical frameworks. To further explain how geopolitical risk might alter investor preferences, this subchapter presents the theory behind the flight-to-safety phenomenon.

Flight-to-safety refers to market behaviour in which the risk-return preference of market participants changes, allocating capital from riskier assets to safer ones. During a flight, the sought-after assets usually have lower volatility, downside risk and default risk, while also having a liquid market (Boucher & Tokpavi, 2019, pp.27–28). On average, the duration of flight-to-safety events is under five days, during which capital from equity markets is reallocated to bond markets, safe haven currencies appreciate in relation to other currencies, and occur when investor sentiment becomes more bearish and implied volatility increases in the stock market (Baela et al., 2020).

The research on flight-to-safety events has mainly focused on the capital flows from one asset class to another. Nevertheless, some discoveries within the equity market have been made. Kaul and Kayacetin (2017) discovered that investors prefer larger stocks compared to smaller stocks when expecting an economic slowdown while displaying contrary behaviour during expected economic growth. Furthermore, Galvani (2021) finds that investors prefer value stocks over growth stocks among small- and medium-sized companies during flights, while shunning companies with higher financial leverage during the market turmoil.

Following a flight-to-safety event, a reversal pattern in which capital flows back into the stock market has been observed in different timescales within the U.S. market. On a daily scale, a reversal of capital flows from bonds to stocks has been found by Brocato and Smith (2012). Similarly, Lehnert (2022) discovered the stock market to produce significant market excess returns after a flight, identifying a similar reversal pattern on monthly data.

Building upon the literature surrounding the flights-to-safety and size effects, investors should prefer larger stocks over smaller stocks during flights. In terms of price movement, the stock returns of companies with smaller market capitalisations should be smaller than the returns of companies with larger market capitalisations. However, whether geopolitical risk can facilitate a comparable market movement from one company size class to another is unknown. Nevertheless, previous studies have found that smaller companies have a more pronounced negative reaction to other types of uncertainty. These studies include the likes of Chung and Chuwonganant (2014), who found that in the U.S., market uncertainty affects the liquidity of smaller stocks comparatively more negatively than the liquidity of larger companies. Furthermore, in the Australian stock market companies with smaller market capitalisation were more strongly affected by the beginning of the COVID-19 pandemic (Naidu & Ranjeeni, 2021). Thus, the prior studies grant a reason to hypothesize the existence of the phenomenon, but the existing literature does not provide sufficient evidence to confirm or deny the hypothesis. The examination of this discrepancy is the central scientific contribution of this paper.

5 Data and methodology

This chapter introduces the data and methodology of the study. Its purpose is to ensure the integrity of the paper by boosting the replicability and transparency of the paper. Moreover, it provides insight into the reasoning of the author and thus, explains why certain approaches were chosen over others to answer the research question. The first and second subchapters present the data and its preparation process. The third subchapter discusses the chosen methodology.

5.1 Data

In this research, geopolitical risk is approximated by using the daily GPR, GPT, and GPA indices created by Caldara and Iacoviello (2022). Their selection is supported by their wide use in prior research, easing the comparison of results. The geopolitical risk indices are derived from a database overseen by Iacoviello (https://www.matteoiacoviello.com/gpr.htm). When examining the prior research, many studies did find the GPT index to have the most explanatory power over the stock returns (Baur & Smales, 2020; Salisu et al., 2022), while He (2023) did not find significant differences among the indices. To avoid overlooking potentially influential types of geopolitical risk, this thesis tests all three GPR indices to provide further insight into the discussion.

Stock index data from the U.S., as opposed to the rest of the world, was chosen as the American market represents a sizable portion of the global market capitalisation. As such, a considerable portion of prior research has focused on it, aiding in the assessment of possible findings in a wider context. Furthermore, as the most commonly used GPR indices mainly follow North American newspapers, it was concluded that they are likely to contain news reports from events that are most relevant for companies and investors based in the United States. In order to capture the impact of market capitalisation, indices that choose their components mainly based on their size were selected. Furthermore, these indices also aim to represent the industry distribution of the respective size classes.

The S&P 500 is a well-known benchmark and is tracked by many different derivatives and funds, highlighting its importance for the market as a whole. Its mid-cap (S&P 400) and small-cap (S&P 600) variations were also chosen for this study due to their similar selection processes of component companies. However, inclusion in these indices does present requirements to potential companies, such as requirements on their profitability, that are not filled by all the companies. Therefore, the Wilshire index family was also included in the study as it was seen to have comparably relaxed inclusion criteria for potential component companies, allowing the examination of the wider market compared to S&P indices. The examined Wilshire indices included the U.S. large-, mid-, small-, and micro-cap indices. The time frame for the examined data is restricted by the availability of the Wilshire Micro-Cap Index, starting from the beginning of 1999 to the end of October 2023. The daily price data for the S&P indices is derived from Yahoo.com utilising a Python script and Wilshire's from a databank operated by the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/). All of the chosen stock indices are float-adjusted market capitalisation-weighted indices and their performance was measured through their daily adjusted closing values. The key aspects of the indices are listed below.

Table 2. General information on the examined stock indices (based on S&P Dow Jones Indices 2023b; 2023c; 2023d & Wilshire Indexes 2023a;2023b; 2023c; 2023d).

Size classification	Name of the index	Bloomberg ticker	Approx. number of components	Market cap of components (billion USD)
S&P Dow Jones Indices				
Large-cap	S&P 500	SPX	500	≥ 14.5
Mid-cap	S&P MidCap 400	MID	400	≥ 5.4 & ≤ 14.5
Small-cap	S&P Small Cap 600	SML	600	≥ 0.85 & ≤ 5.2
Wilshire Indices				
Large-cap	Wilshire Large-Cap US	W5KLC	750	≥ 1.1 & ≤ 2676.7
Mid-cap	Wilshire US Mid-Cap	W5KMC	500	≥ 1.7 & ≤ 17.5
Small-cap	Wilshire US Small-Cap	W5KSC	1750	≥ 0.03 & ≤ 13.37
Micro-cap	Wilshire US Micro-Cap	W5KMICRO	900	≤ 6.35

As can be observed from Table 2, the market capitalisation of component companies overlaps among the Wilshire indices due to their selection method. Furthermore, due to the differing inclusion criteria used by S&P Dow Jones Indices and Willshire Indexes and the varying market capitalisations of the companies, it was deemed likely that the sector weights deviated between the indices. Based on previous findings showing different industries having heterogeneous reactions to GPR (Ahmed et al., 2023; Chesney, 2012), the sector weightings of the indices were seen as a potential differentiating factor. Based on the GICS-based sector classifications found in the fact sheets of the examined stock indices, Table 3 below displays the respective sector weights.

Table 3. Sector weights of the examined stock indices (based on S&P Dow Jones Indices 2023b; 2023c; 2023d & Willshire Indexes 2023a;2023b; 2023c; 2023d).

	S&P 500 Large-Cap	**S&P 400 Mid-Cap**	**S&P 600 Small-Cap**	**Wilshire Large-Cap**	**Wilshire Mid-Cap**	**Wilshire Small-Cap**	**Wilshire Micro-Cap**
Information technology	28.1 %	10.0 %	12.0 %	27.0 %	14.0 %	14.0 %	9.0 %
Health care	13.1 %	8.2 %	10.2 %	13.0 %	11.0 %	15.0 %	26.0 %
Financials	12.8 %	15.1 %	18.3 %	13.0 %	15.0 %	15.0 %	25.0 %
Consumer discretionary	10.6 %	15.1 %	14.0 %	10.0 %	13.0 %	12.0 %	9.0 %
Communication services	8.7 %	1.7 %	2.9 %	9.0 %	4.0 %	3.0 %	3.0 %
Industrials	8.3 %	21.4 %	17.3 %	9.0 %	17.0 %	19.0 %	11.0 %
Consumer staples	6.6 %	4.4 %	5.2 %	6.0 %	4.0 %	3.0 %	2.0 %
Energy	4.5 %	6.2 %	5.4 %	5.0 %	4.0 %	5.0 %	6.0 %
Utilities	2.5 %	3.5 %	1.9 %	2.0 %	3.0 %	3.0 %	1.0 %
Materials	2.4 %	7.0 %	5.1 %	3.0 %	8.0 %	5.0 %	4.0 %
Real estate	2.4 %	7.4 %	7.7 %	3.0 %	7.0 %	6.0 %	4.0 %

Among the same size classes, the sector weights of S&P and Wilshire indices do not substantially deviate from their counterparts. However, the market capitalisation of the component companies does seem to influence the sector weightings of the indices. Notably, the Wilshire U.S. Micro-Cap Index does contain relatively fewer companies operating in the information technology sector, while the health care and financial sectors make over half of its weight.

The selection of control variables for the testing of the market capitalisation-dependent effects follows Salisu et al. (2022), who used the West Texas Intermediate prices to approximate the impact of oil prices. The selection to control for oil prices is based on prior literature finding a connection between oil prices and geopolitical risk (Abdel-Latif & El-Gamal, 2020; Brandt & Gao, 2019) and oil prices having explanatory power over stock returns (see Smyth & Narayan, 2018). Therefore, there is a substantial reason to believe that not controlling for oil prices could result in an omitted-variable bias. The daily spot price data for the WTI crude oil was derived from the Federal Reserve Bank of St. Louis' economic database (*https://fred.stlouisfed.org/series/DCOILWTICO)*.

5.2 Data preparation and descriptive statistics

The data preparation included several steps. First, the GPA index contained 69 days and the GPT six days when the indices reached the value of zero. Due to the following data preparation steps requiring non-zero numbers, these values were replaced with the next lowest non-zero value that each index respectively contained. Furthermore, as the GPR indices have a daily interval and trading days differ from them, dates when the stock market was not open were excluded from the GPR indices. This was done to ensure that the given changes within the GPR indices reflect the changes in the geopolitical environment that two consecutive trading days were subjected to. Furthermore, excluding non-trading days also reduces potential issues regarding the weekends and the variance that they might induce when compared to weekdays. Similarly, the WTI spot prices were matched to the trading days by excluding non-trading days and if no price data was available for a trading day, it was given the previous day's value. In addition, on the 20th of

April 2020, the spot price fell to negative. The price of 0.01$ was assigned to this date, as later steps require positive numbers.

As this study investigates the impact of GPR on stock returns on a daily scale and assumes that the daily changes within the GPR indices are the main driver of the relationship, instead of absolute GPR index levels, the data was further prepared by taking the first log difference of two values, representing a pair of consecutive trading days. Following Mensi et al. (2014) and Kannadhasan and Das (2020), the transformation was applied to all GPR and stock indices, as well as to the crude oil price data. By using the natural logarithm as a base, Formula 1 below shows the calculation process, resulting in the daily deltas for the given day. The derived daily deltas represent daily returns for the stock and oil indices, while they represent the daily changes within the GPR indices.

$$\Delta\, Index_t = \log_e(Index_t) - \log_e(Index_{t-1})\ . \tag{1}$$

Lastly, due to the time error inherently present in the GPR indices, as discussed in the second chapter, a lead of one day was applied to the GPR indices in relation to the stock and oil indices. Therefore, the resulting daily deltas of the GPR indices are not aligned with the original data presented by Caldara and Iacoviello (2022) but are a day ahead of them. As a result, the actual timing of geopolitical events is more closely aligned with the daily GPR deltas.

To investigate whether market capitalisation influences the reaction that the market has to geopolitical risk, several size-based portfolios were constructed. Formula 2 below describes this method, in which the daily natural log returns of a larger market capitalisation index are deducted from the natural log returns of a smaller one. The result is the daily return R for a portfolio A-Minus-B. The computation was carried out for each day and each index pair from the same index provider.

$$R_{\,Portfolio\ A-B,t} = \log_e(Index\ A_t) - \log_e(Index\ B_t)\ . \tag{2}$$

After these preparation steps, the indices were ready to be tested. Table 4 presents the descriptive statistics of the prepared data.

Table 4. Descriptive statistics.

	Mean	Min.	Max.	STD	Skewness	Kurtosis	Jarque-Bera p-value
GPR indices							
GPR	0.0002	-2.9959	2.9693	0.3820	0.1370	5.4232	0.00
GPA	0.0001	-3.0040	3.5086	0.6162	0.0652	5.4291	0.00
GPT	0.0002	-3.4526	2.6550	0.4900	-0.0019	4.2447	0.00
***Individual* indices**							
S&P 500	0.0002	-0.1277	0.1096	0.0124	-0.3618	12.9522	0.00
S&P 400	0.0003	-0.1479	0.1017	0.0138	-0.5622	12.0443	0.00
S&P 600	0.0003	-0.1421	0.0862	0.0147	-0.4604	9.8884	0.00
Wil. Large-cap	0.0003	-0.1293	0.1101	0.0124	-0.3831	12.8217	0.00
Wil. Mid-cap	0.0003	-0.1531	0.1005	0.0137	-0.6464	12.4848	0.00
Wil. Small-cap	0.0003	-0.1530	0.0931	0.0148	-0.5616	10.6845	0.00
Wil. Micro-cap	0.0003	-0.1409	0.0860	0.0131	-0.9081	12.9968	0.00
Size-based portfolios							
S&P S-M-L	0.0001	-0.0558	0.0510	0.0070	0.0648	7.1155	0.00
S&P S-M-Mid	0.0000	-0.0302	0.0370	0.0041	0.1403	7.3093	0.00
S&P Mid-M-L	0.0001	-0.0559	0.0414	0.0052	-0.1919	9.7622	0.00
Wil. S-M-L	0.0000	-0.0571	0.0536	0.0062	-0.1112	7.9740	0.00
Wil. S-M-Mid	0.0000	-0.0152	0.0242	0.0029	0.2587	6.3242	0.00
Wil. Mid-M-L	0.0001	-0.0424	0.0329	0.0047	-0.3284	8.6320	0.00
Wil. Micro-M-L	0.0000	-0.0856	0.0788	0.0080	-0.4299	10.8389	0.00
Wil. Micro-M-Mid	0.0000	-0.0500	0.0528	0.0062	-0.0189	8.7345	0.00
Wil. Micro-M-S	0.0000	-0.0425	0.0442	0.0055	-0.1089	8.1220	0.00
Control variable							
WTI	0.0003	-7.5126	6.7923	0.1311	-7.8686	2883.041	0.00

Note: The values presented in the table are calculated from the daily log differences. GPR, GPA, and GPT refer to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. STD is the abbreviated form of standard deviation. For the size-based portfolios, the S-M-L indicates a Small-Minus-Large portfolio, the Micro-M-L indicates a Micro-Minus-Large portfolio, and so forth. The abbreviation Wil. indicates that the index or size-based portfolio is based on the Wilshire indices. WTI is the control variable for crude oil prices. Sample period: 4th of January 1999 – 31st of October 2023.

Based on the statistics presented in Table 4, the indices display a high degree of kurtosis, indicating fat-tailedness. The GPR indices are observed to be the closest to a normal distribution but also fail the Jarque-Bera test. Thus, we cannot assume the indices to follow a normal distribution. The extreme minimum and maximum values of the WTI returns are explained by the price fluctuation seen on the 20th of April 2020. However, even when excluding these dates, the WTI returns were not normally distributed according to the Jarque-Bera test.

Supplementing the descriptive statistics, the correlation matrices can be found in Appendix 2. When comparing the correlations of individual GPR indices, crude oil prices, and stock indices or size-based portfolios, the correlations are low. For individual stock indices, the correlations with the GPR indices are consistently weak and negative. For the size-based portfolios, the correlations with the GPR indices are mixed with positive and negative relationships.

5.3 Methodology

The testing of the data is divided into two different parts. In the first test of the paper, the general shape of the relationship between the GPR indices and the individual stock indices is examined, while also aiming to identify potentially influential asymmetries within the relationships. The purpose of the first test is to add to the existing literature by further examining the nature of the relationship by utilising a regression method that has not been commonly applied to this relationship and investigating whether the relationship between GPR and stock returns is symmetrical across the return distribution. In the second phase, the influence of geopolitical risk on the size-based portfolios is directly examined by using a GARCH(1,1) model. Furthermore, the second portion of the methodology also introduces an alternative model used to test whether exceptionally high jumps within the GPR indices have market capitalisation-dependent asymmetrical effects. Due to the lack of studies directly examining the relationship between GPR and market capitalisation, the second phase of the testing was conducted by using an exploratory approach. Therefore, it aims to identify and generalize the nature of the relationship between geopolitical risk and market capitalisation, rather than explore it in detail.

5.3.1 Quantile autoregression model

A considerable portion of the existing literature on the impact of GPR uses a mean-based approach, such as ordinary least square regression. However, as shown by Kannadhasan and Das (2020) in Asian markets, GPR has been observed to have an asymmetric relationship to stock returns. Due to this limitation, mean-based regression only grants us information that might not reflect the relationship correctly. Similarly, event studies are widely utilised in the study of geopolitical risk, but only focus on major events and dismiss environments of low levels of geopolitical risk. Therefore, this paper opted for quantile regression that is able to capture the direction and the extent of the relationship in different return quantiles. Additionally, the nonparametric nature of the test does combat the non-normality observed within the data.

In order to accept or reject the first hypothesis, the first test of this paper follows the methodology used by Guo et al. (2018) and Kannadhasan and Das (2020). In their studies, they introduce an autoregressive component to their quantile regression models. First introduced by Koenker and Xiao (2006), this type of quantile autoregression (QAR) model is able to account for dependency structures in which the explained variable is dependent on its past values. The constructed QAR model is presented below.

$$Q_\tau(R_t | F_{t-1}, GPR_{t+1}) = \alpha_i(\tau) + \sum_{j=1}^{p} \beta_i(\tau) R_{t-j} + \gamma_i(\tau) R_{t-1}\, I\,(R_{t-1}| > R^q) + \theta_i(\tau)\Delta GPR_{t+1} + e^t \,. \tag{3}$$

In Formula 3, R_t represents the daily index returns on day t. The past index returns are marked by F_{t-1} and the tested GPR index deltas are denoted by GPR_{t+1}, indicating that the used values are advanced by one day relative to their original dates. On the right-hand side of the equation, the autoregressive elements are captured and represented by the parameter $\beta_i(\tau)$. The optimal lag order p is determined by using the Schwartz information criterion, computed for each index separately. For extreme values, an indicator function $I\ (R_{t-1}| > R^q)$ is used, returning the value of one if the previous day's return exceeds a predetermined threshold. If the threshold is not exceeded, the indicator function returns the value of zero. The influence of these extreme values is captured by the parameter $\gamma_i(\tau)$. The $\theta_i(\tau)$ indicates the conditional degree of dependency between index returns and the GPR indices within a given quantile. For each of the selected stock and GPR indices, the quantile autoregression is carried out separately. Examining the estimated θ_i and the associated test statistic enables us to determine whether GPR has explanatory power over the returns within a given return quantile, allowing us to answer our first hypothesis. Furthermore, regarding the second hypothesis, the comparison of these results between the explained stock indices enables the preliminary identification of symmetrical or asymmetrical responses.

Following Guo et al. (2018) and Kannadhasan and Das (2020), the R^q threshold to control extreme previous returns was set to the 95th percentile of the return distribution. To further specify the computation process, the Huber Sandwich Estimator was used as the covariance estimator. As for the kernel function, Epanechnikov's function was chosen. Compared to other commonly used kernel functions, Epanechnikov's function was seen as the theoretically optimal function when minimizing the mean integrated standard error (see Epanechnikov, 1969).

5.3.2 GARCH(1,1) model

Through the quantile autoregression, the most prominent return quantiles for the relationship can be identified for individual indices. However, in order to quantify whether the geopolitical risk and stock returns have market capitalisation-dependent asymmetric qualities, a second model is needed. The initial model aiming to examine this relationship was a modified version of the equation used by Caldara and Iacoviello (2022, p.

1219), who utilised their version of the model in a linear regression, examining the relationship between the GPR indices and industry-based portfolio returns. The modified version of the model is shown below in Formula 4.

$$R_{Portfolio\ A-B,t} = \alpha_i + \beta_1(\Delta GPR_{t+1}) + \varepsilon_t\ . \tag{4}$$

The model shown above deviates from Caldara and Iacoviello (2022) by replacing the industry returns with the returns of the size-based portfolios. In this model, the dependent variable $R_{Portfolio\ A-B,t}$ is the returns of the portfolio constructed by deducting the returns of index B from the returns of index A on the day t. The α_i is the intercept term, ΔGPR_{t+1} represents the daily deltas of a GPR index, while the ε_t is the error term.

To further enhance the model, a control variable capturing the influence of crude oil prices was added. As discussed earlier, this was done to ensure the robustness of the results by potentially avoiding an omitted-variable bias. However, during the preliminary testing of the model, the resulting residuals displayed signs of considerable conditional heteroskedasticity. Specifically, White's, Glejser's, Engel's ARCH, and Ljung-Box tests were used to determine that the observed heteroskedasticity was time-dependent and not related to the explanatory variables. Therefore, a GARCH(1,1)-model was chosen to improve the reliability of the estimates. After these modifications, the final model was defined as:

$$R_{Portfolio\ A-B,t} = \alpha_i + \beta_1(\Delta GPR_{t+1}) + \beta_2 \Delta Oil_t + \varepsilon_t\ . \tag{5A}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta_3\sigma_{t-1}^2\ . \tag{5B}$$

For the main portion of the model seen in Formula 5A, the daily returns $R_{Portfolio\ A-B,t}$ of a size-based portfolio are explained by a given GPR index and a control variable. ΔGPR_{t+1} is the daily change within the studied GPR index, expressed as a log difference. The model also includes a control variable ΔOil_t, represented by the daily natural log difference of WTI prices. As seen in Formula 5B, the GARCH portion of the model is noted following the work of Bollerslev (2023, p. 26) with slight modifications to fit the (1,1) framework. The σ_t^2 represents the conditional variance. The term ω is the unconditional variance and α is the ARCH-component, estimated from the lagged residuals. The GARCH-coefficient β_3 represents the persistence of the conditional variance in time.

When specifying the GARCH(1,1) model in preliminary testing, it was observed that the resulting standard errors did not follow a normal distribution. In order to find the best fitting assumed error distribution for the model, normal distribution, Student's t-distribution, and generalized error distribution were considered. The comparison was carried out by comparing the resulting penalized log-likelihoods in the form of the Akaike criterion. Through this process, the Student's t-distribution was deemed as the best alternative.

To further investigate the market capitalisation-related dependencies in the explanatory power of geopolitical risk, an alternative GARCH(1,1) model was constructed. In this model, the GPR indices are limited to their highest values, separating the most potentially impactful geopolitical developments from the rest of the data. For this purpose, this thesis followed Ali et al. (2023, p.5) and adopted a dummy variable into the model. Formula 6 shows the resulting model.

$$R_t = \alpha_i + \beta_1(\Delta GPR_{t+1}\, Dum.GPR_t) + \beta_2 \Delta Oil_t + \varepsilon_t \,. \tag{6A}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta_3\sigma_{t-1}^2 \,. \tag{6B}$$

While the alternative model is otherwise identical to Formula 5, the highest levels of geopolitical risk are controlled by using the $Dum.GPR_t$ dummy variable. The variable returns one if the value is within the desired range and zero if not. Following Ali et al. (2023), the cutoff value for the dummy variable was determined to be the lower bound of the highest decile for the respective GPR index.

6 Results

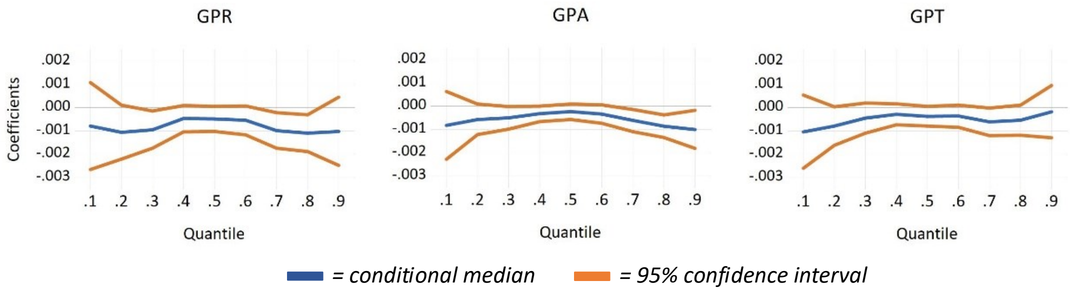
This chapter presents the obtained results from the empirical testing. In addition to displaying the results, each test is followed by a discussion of the obtained results as they were interpreted by the author of this thesis. The first subchapter contains the results and discussion regarding the quantile autoregression test of individual indices, while the second subchapter presents and discusses the results of the GARCH(1,1) model, used to test the returns of the market capitalisation-based portfolios. The results from the GARCH(1,1) model are further tested by using alternative samples in the third subchapter. The fourth subchapter describes and discusses the results of the robustness tests. When discussing the statistical significance of the results, this thesis accepts the associated p-values to be statistically significant if they are below the 5% threshold.

6.1 Results for individual stock indices

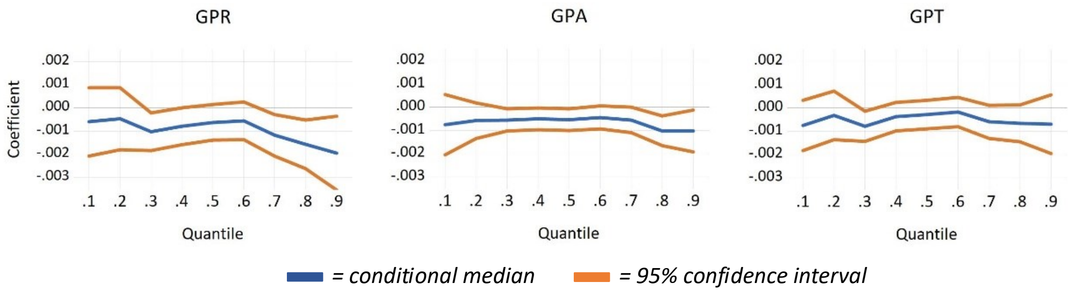
Prior to running the quantile autoregression, the optimal lag order for each stock index had to be determined. As described earlier, the optimal length was decided based on the Schwartz information criterion. In addition, the explanatory power of the previous returns was also examined through a VAR model, confirming the optimal lag order through an alternative method. The lag of order of one was determined to be optimal for all of the S&P indices and the large-cap and small-cap Wilshire indices. For the Wilshire micro-cap, a lag order of two was chosen, while for the Wilshire mid-cap index, it was zero. Following Kannadhasan and Das (2020), the number of estimated quantiles was set to ten.

The results obtained through the quantile autoregression model are shown in graphical and tabular form. The graphs aim to visualize the relationship across different stock return quantiles, while the table presents the statistical significance of the relationship in the respective quantiles. Figures 3 and 4 show the estimated conditional median coefficients alongside the 95% confidence bounds for each of the tested stock and GPR indices.

S&P 500 (large-cap)



S&P 400 (mid-cap)



S&P 600 (small-cap)

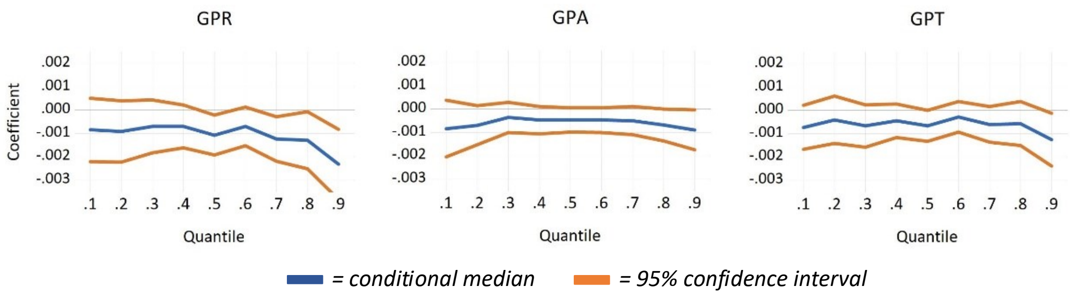
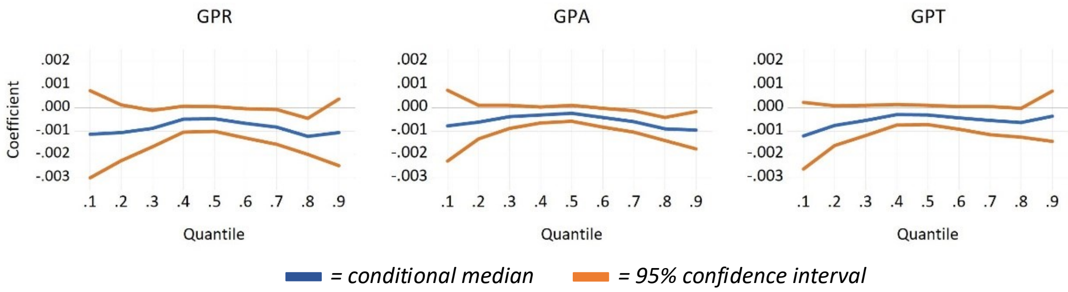
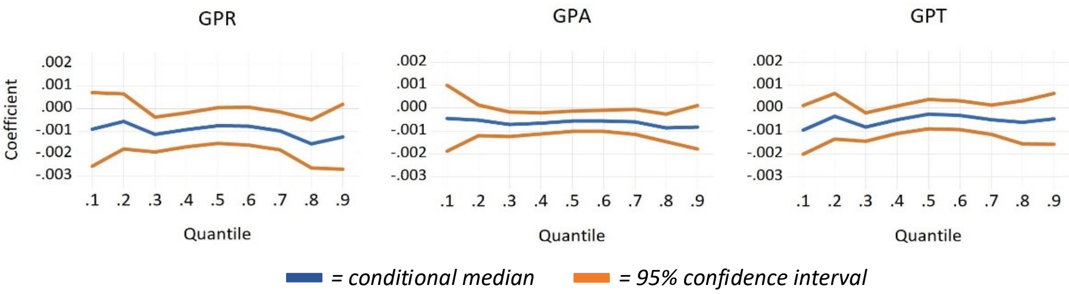


Figure 3. Estimated conditional median coefficients for the geopolitical risk indices from the quantile autoregression model explaining the returns of S&P stock indices.

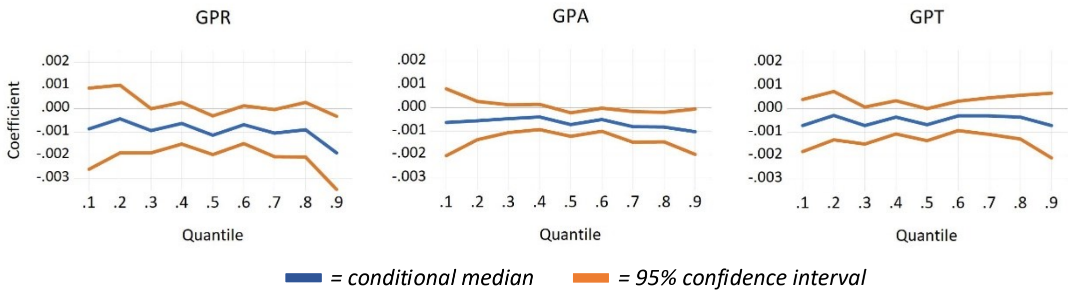
Wilshire US Large-Cap



Wilshire US Mid-Cap



Wilshire US Small-Cap



Wilshire US Micro-Cap

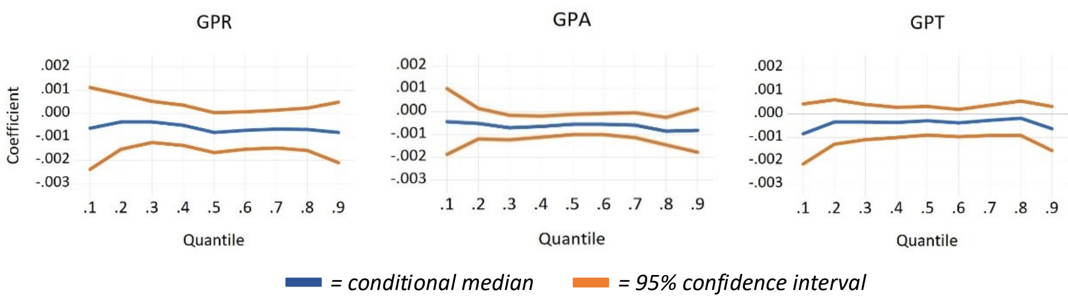


Figure 4. Estimated conditional median coefficients for the geopolitical risk indices from the quantile autoregression model explaining the returns of Wilshire stock indices.

Figure 3 displays the results for the S&P indices. Based on the estimated median coefficients, the relationship between the GPR indices and stock indices seems to be slightly negative and quite stable across the return distributions. When observing the 95% confidence boundaries, the area between them grows when approaching both extremes of the return distribution. Similarly to the S&P indices, the Wilshire indices seem to display equivalent relationships to the GPR indices. As shown in Figure 4, the estimated conditional medians seem to be negative and close to zero, while the confidence intervals separate from each other when approaching the extremities of the return quantiles. When comparing the results for both the examined small-cap indices to their large-cap counterparts, they seem to share a common characteristic: their estimated median coefficients for GPR become increasingly negative when approaching the highest quantile of returns, whereas the large-caps do not show this tendency.

To further examine the obtained results, Table 5 displays the regression estimates with their test statistics. Overall, the GPR indices show variation in their statistical significance across the return quantiles. The GPR indices are more often statistically significant around the high and median quantiles than in the lower return quantiles. When comparing the statistical significances of the GPR indices amongst each other, the GPT index seems to reach statistical significance less often than its counterparts. Furthermore, when comparing the stock indices to each other in the 0.9 quantile, the small-cap indices do seem to react more strongly to changes in the GPR index than the other indices. The strength of the relationship can be viewed as relatively weak. To ease the interpretation of the results, the coefficient of -0.001 would indicate that on average, the sample maximum for the GPR index would lead to approximately -0.3% index returns, all else being equal.

Table 5. Estimated median coefficients and test statistics for the geopolitical risk indices from the QAR model explaining the returns of the individual stock indices.

	Quantile								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
S&P 500									
GPR	-0.0008	-0.0011*	-0.0009**	-0.0005*	-0.0005*	-0.0005*	-0.0010**	-0.0011***	-0.0010
	(-0.819)	(-1.780)	(-2.326)	(-1.646)	(-1.766)	(-1.696)	(-2.526)	(-2.708)	(-1.363)
GPA	-0.0008	-0.0006*	-0.0005**	-0.0003*	-0.0002	-0.0003*	-0.0006**	-0.0009***	-0.0010**
	(-1.097)	(-1.694)	(-2.038)	(-1.914)	(-1.420)	(-1.677)	(-2.512)	(-3.448)	(-2.382)
GPT	-0.0010	-0.0008*	-0.0004	-0.0003	-0.0004*	-0.0004	-0.0006**	-0.0005	-0.0002
	(-1.285)	(-1.857)	(-1.354)	(-1.242)	(-1.727)	(-1.484)	(-2.011)	(-1.629)	(-0.294)
S&P 400									
GPR	-0.0006	-0.0005	-0.0010**	-0.0008*	-0.0006	-0.0005	-0.0012**	-0.0016***	-0.0020**
	(-0.795)	(-0.676)	(-2.440)	(-1.920)	(-1.572)	(-1.313)	(-2.566)	(-2.935)	(-2.403)
GPA	-0.0008	-0.0006	-0.0005**	-0.0005**	-0.0005**	-0.0004*	-0.0005*	-0.0010***	-0.0010**
	(-1.135)	(-1.472)	(-2.263)	(-2.071)	(-2.223)	(-1.746)	(-1.938)	(-3.131)	(-2.233)
GPT	-0.0008	-0.0003	-0.0008**	-0.0004	-0.0003	-0.0002	-0.0006*	-0.0007	-0.0007
	(-1.369)	(-0.587)	(-2.377)	(-1.199)	(-0.935)	(-0.549)	(-1.651)	(-1.640)	(-1.087)
S&P 600									
GPR	-0.0008	-0.0009	-0.0007	-0.0007	-0.0011**	-0.0007*	-0.0012**	-0.0013**	-0.0023***
	(-1.218)	(-1.356)	(-1.201)	(-1.476)	(-2.468)	(-1.658)	(-2.536)	(-2.055)	(-3.019)
GPA	-0.0008	-0.0007	-0.0004	-0.0005	-0.0005*	-0.0005*	-0.0005	-0.0007*	-0.0009**
	(-1.347)	(-1.627)	(-1.072)	(-1.563)	(-1.722)	(-1.729)	(-1.618)	(-1.957)	(-2.022)
GPT	-0.0007	-0.0004	-0.0007	-0.0004	-0.0007*	-0.0003	-0.0006	-0.0006	-0.0013**
	(-1.500)	(-0.781)	(-1.430)	(-1.211)	(-1.947)	(-0.833)	(-1.539)	(-1.178)	(-2.168)
Wilshire Large-cap									
GPR	-0.0011	-0.0011*	-0.0009**	-0.0005*	-0.0005*	-0.0007**	-0.0008**	-0.0012***	-0.0011
	(-1.176)	(-1.746)	(-2.212)	(-1.674)	(-1.712)	(-2.043)	(-2.160)	(-3.077)	(-1.440)
GPA	-0.0008	-0.0006*	-0.0004	-0.0003*	-0.0002	-0.0004**	-0.0006**	-0.0009***	-0.0010**
	(-0.987)	(-1.668)	(-1.492)	(-1.728)	(-1.354)	(-2.031)	(-2.508)	(-3.531)	(-2.333)
GPT	-0.0012	-0.0008*	-0.0005	-0.0003	-0.0003	-0.0004*	-0.0005*	-0.0006**	-0.0003
	(-1.628)	(-1.732)	(-1.601)	(-1.309)	(-1.457)	(-1.693)	(-1.754)	(-1.983)	(-0.631)
Wilshire Mid-cap									
GPR	-0.0009	-0.0006	-0.0011***	-0.0009**	-0.0007*	-0.0008*	-0.0010**	-0.0016***	-0.0012*
	(-1.107)	(-0.914)	(-2.894)	(-2.436)	(-1.846)	(-1.796)	(-2.296)	(-2.868)	(-1.703)
GPA	-0.0004	-0.0005	-0.0007**	-0.0007***	-0.0006**	-0.0006**	-0.0006**	-0.0009***	-0.0008*
	(-0.592)	(-1.552)	(-2.547)	(-2.796)	(-2.488)	(-2.326)	(-2.110)	(-2.776)	(-1.718)
GPT	-0.0009*	-0.0004	-0.0008***	-0.0005	-0.0003	-0.0003	-0.0005	-0.0006	-0.0005
	(-1.725)	(-0.696)	(-2.605)	(-1.629)	(-0.806)	(-0.955)	(-1.544)	(-1.281)	(-0.821)
Wilshire Small-cap									
GPR	-0.0009	-0.0004	-0.0009*	-0.0006	-0.0011***	-0.0007	-0.0010**	-0.0009	-0.0019**
	(-0.966)	(-0.585)	(-1.944)	(-1.356)	(-2.685)	(-1.635)	(-2.012)	(-1.486)	(-2.347)
GPA	-0.0006	-0.0006	-0.0005	-0.0004	-0.0007***	-0.0005**	-0.0008**	-0.0008**	-0.0010**
	(-0.851)	(-1.320)	(-1.530)	(-1.413)	(-2.750)	(-2.011)	(-2.449)	(-2.550)	(-2.076)
GPT	-0.0007	-0.0003	-0.0007*	-0.0004	-0.0007*	-0.0003	-0.0003	-0.0004	-0.0007
	(-1.251)	(-0.551)	(-1.788)	(-0.989)	(-1.925)	(-0.956)	(-0.763)	(-0.744)	(-1.010)
Wilshire Micro-cap									
GPR	-0.0006	-0.0003	-0.0003	-0.0005	-0.0008*	-0.0007*	-0.0007	-0.0007	-0.0008
	(-0.707)	(-0.582)	(-0.775)	(-1.142)	(-1.858)	(-1.754)	(-1.583)	(-1.451)	(-1.219)
GPA	-0.0006	-0.0002	-0.0003	-0.0003	-0.0005**	-0.0006**	-0.0007***	-0.0006**	-0.0006
	(-1.396)	(-0.625)	(-1.064)	(-0.883)	(-2.090)	(-2.422)	(-2.887)	(-1.967)	(-1.442)
GPT	-0.0008	-0.0003	-0.0003	-0.0004	-0.0003	-0.0004	-0.0003	-0.0002	-0.0006
	(-1.288)	(-0.690)	(-0.873)	(-1.082)	(-0.906)	(-1.270)	(-0.814)	(-0.464)	(-1.291)

Note: The reported coefficients are the median estimated conditional coefficients from the quantile autoregression of daily index log differences (Sample period: 1999 - October 2023). The values in parenthesis show the corresponding test statistics. GPR, GPA, and GPT refer to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. The * sign denotes significance at 10%, ** at 5%, and *** at 1%.

When evaluating regression results shown in Table 5, the GPR indices are conditionally statistically significant explanatory variables. Furthermore, this relationship does seem to be negative for each stock index. Therefore, it can be concluded that they have explanatory power over stock return and the first hypothesis of this thesis can be confirmed. However, the relationship is not statistically significant in all return quantiles. When comparing these results to prior literature, especially the lack of observed statistical significance in the lower return quantiles is noteworthy. For example, Nikkinen and Vähämaa (2010, p. 270) found that major terrorist attacks were associated with extreme implied volatility within the FTSE100 stock index, and their timing coincided with some of the highest implied volatility seen in their sample. In the opinion of the author of this thesis, major geopolitical events are likely so rare that their impact on the generalised relationship is limited. Additionally, the author hypothesises that other drivers of the market are more dominant explanatory variables in the lowest return quantiles. A third possible explanation for this variation across the quantiles is the computation methodology used to weigh the observations. As this paper uses a quantile regression model, the influence of outliers on both sides of the return distribution is reduced when compared to linear regression methods. This is due to the lesser weighting assigned to these types of observations in the estimation process. Thus, the influence of major geopolitical events could have been underweighted to their actual market response. Furthermore, the indicator variable included in the autoregression model could hide a possible bounce back effect. Given that GPR indices trend downwards after substantial geopolitical events and the stock market recovers over the following days, the indicator function could absorb a part of these returns.

When comparing the regression results to other previous literature, the relative weakness of the explanatory power of the GPT is also surprising. Contradicting the results of the likes of Salisu et al. (2022) along Baur and Smales (2020), geopolitical threats do not seem to have more explanatory power over the returns than geopolitical acts or the base index. In fact, GPT does not seem to reach statistical significance as often as the GPR and

GPT indices across the return distribution, while the estimated coefficients do not show considerable deviation among the GPR indices.

In addition to the regression results, the equality of the slopes was also tested. In order to determine whether the market response to geopolitical risk is similar across the return distribution, a slope-equality test following Koenker and Basset (1982) was conducted. The test was carried out by selecting two quantiles and comparing their estimated conditional coefficients for the GPR indices. The results of the test are reported in Table 6, in which the null hypothesis for the Wald test was homoscedasticity across the return quantiles. When observing the results, most of the quantile pairs do not provide sufficient evidence to reject the null hypothesis. However, as two quantile pairs for the mid-cap indices and one for the micro-cap index are statistically significant, we have a reason to suspect that the relationship between the returns of these indices and GPR and GPA might be asymmetric. Furthermore, as only a part of the quantiles were tested, the test might miss violations of symmetry in other quantiles. Therefore, the relationship between the GPR and GPA indices and mid-caps and micro-cap returns is likely not perfectly linear across the return distribution. For the GPT index, the test does not give a reason to reject the null hypothesis.

Table 6. Equality of the slopes test results on the estimates of the quantile autoregression model.

	Tested quantiles					
	0.05 - 0.95		**0.25 - 0.75**		**0.5 - 0.95**	
	t-stat	**p-value**	**t-stat**	**p-value**	**t-stat**	**p-value**
S&P indices						
S&P 500 (Large-cap)						
GPR	0.265	0.606	0.023	0.879	0.952	0.329
GPA	2.345	0.126	0.679	0.410	1.017	0.313
GPT	0.020	0.889	0.031	0.861	1.335	0.248
S&P 400 (Mid-cap)						
GPR	1.136	0.287	2.192	0.139	3.714*	0.054
GPA	0.240	0.624	1.941	0.164	4.478**	0.034
GPT	0.003	0.958	0.463	0.496	1.127	0.289
S&P 600 (Small-cap)						
GPR	1.104	0.293	0.134	0.714	1.574	0.210
GPA	0.003	0.957	0.000	0.983	0.526	0.468
GPT	0.034	0.854	0.143	0.705	0.033	0.857
Wilshire US indices						
Large-cap						
GPR	0.032	0.857	0.160	0.689	1.141	0.285
GPA	1.796	0.180	0.332	0.564	0.891	0.345
GPT	0.013	0.908	0.018	0.893	1.696	0.193
Mid-cap						
GPR	0.766	0.381	3.931**	0.047	2.145	0.143
GPA	0.118	0.731	1.208	0.272	0.571	0.450
GPT	0.012	0.914	0.689	0.407	0.603	0.437
Small-cap						
GPR	0.059	0.809	0.699	0.403	0.887	0.346
GPA	0.034	0.854	0.239	0.625	1.764	0.184
GPT	0.476	0.490	0.040	0.842	0.084	0.772
Micro-cap						
GPR	2.163	0.141	1.067	0.302	2.431	0.119
GPA	1.458	0.227	1.783	0.182	4.753**	0.029
GPT	0.256	0.613	0.036	0.849	0.860	0.354

Note: GPR, GPA, and GPT refer to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. Sample period: 4th of January 1999 – 31st of October 2023.

To summarise the main findings from the quantile autoregression, it can be confirmed that geopolitical risk has explanatory power over the index returns but the relationship is not statistically significant across all return quantiles. The relationship is negative and on average, the composite GPR and GPA indices are more significant explanatory factors than the GPT index. For the returns of the mid-cap indices and micro-cap index, there is reason to believe that their relationship to geopolitical risk is asymmetric across their return distribution.

When evaluating the results of the quantile regression from the perspective of the second hypothesis, the indices do not have identical reactions to changes within the GPR indices. Although the general shape of the relationship and the estimated coefficients do not vary considerably, market capitalisation-based differences in exposure to geopolitical risk cannot be ruled out. To further examine this hypothesis, the following subchapter investigates it directly.

6.2 Results for size-based portfolios

In the first iteration of the GARCH(1,1) model, the explanatory power of the GPR indices on the returns of the market capitalisation-based portfolios was tested using the model shown in Formula 5. The results from the model are presented in Tables 7, 8, and 9 in which the returns of each size-based portfolio were explained by the different GPR indices separately. Table 7 shows the results for the size-based portfolios constructed from the S&P indices and Tables 8 and 9 for the Wilshire indices. Due to space constraints, results for the Wilshire indices are split in two. Table 8 shows the results for the Micro-Minus portfolios and the rest of the Wilshire size-based portfolios are shown in Table 9.

When observing the estimated coefficients and their corresponding test statistics in Table 7, it can be observed that none of the GPR indices had statistically significant explanatory power over the return differences of the S&P indices. However, when observing the data in Table 8, the GPA index is a statistically significant explanatory variable for all of the Wilshire Micro-Minus portfolios. This finding does indicate that geopolitical acts have explanatory power over the return difference between the micro-cap index and the other Wilshire indices. It should also be noted that the 5% significance level is breached by the GPR index in the Micro-Minus-Mid portfolio, but not in explaining the returns of other Micro-Minus portfolios.

Table 7. Estimated coefficients and test statistics from the GARCH(1,1) model explaining the returns of the S&P-based portfolios**.**

Small-Minus-Large

Constant	0.000128*	(1.81)		0.000128**	(1.81)		0.000128**	(1.81)
GPR	-0.000051	(-0.27)	GPA	0.000013	(0.11)	GPT	0.000044	(0.29)
WTI	0.009458***	(9.34)		0.009427***	(9.32)		0.009411***	(9.31)
Var. Con.	0.000001***	(4.80)		0.000001***	(4.80)		0.000001***	(4.80)
ARCH	0.060428***	(10.57)		0.060422***	(10.57)		0.060380***	(10.58)
GARCH	0.927319***	(137.88)		0.927335***	(137.99)		0.927381***	(138.14)
Adj. R^2	-0.01959			-0.01951			-0.01942	
S.E. reg	0.00711			0.00711			0.00711	
Log like.	22865.96			22865.93			22865.97	
DW	2.08170			2.08170			2.08165	

Small-Minus-Mid

Constant	-0.000010	(-0.239)		-0.000010	(-0.24)		-0.000010	(-0.24)
GPR	-0.000056	(0.000)	GPA	0.000019	(0.29)	GPT	-0.000056	(-0.64)
WTI	0.000793	(0.001)		0.000787	(0.77)		0.000794	(0.78)
Var. Con.	0.000001***	(0.000)		0.000001***	(4.04)		0.000001***	(4.04)
ARCH	0.040510***	(0.004)		0.040558***	(9.21)		0.040603***	(9.21)
GARCH	0.951734***	(182.03)		0.005232***	(181.89)		0.951614***	(181.67)
Adj. R^2	-0.00023			-0.00022			-0.00031	
S.E. reg	0.00414			0.00414			0.00414	
Log like.	26093.60			26093.52			26093.68	
DW	2.21310			2.21309			2.21304	

Mid-Minus-Large

Constant	0.000113**	(2.28)		0.000113**	(2.28)		0.000113**	(2.28)
GPR	-0.000003	(-0.03)	GPA	0.000003	(0.04)	GPT	0.000061	(0.60)
WTI	0.011620***	(11.12)		0.011614***	(11.12)		0.011546***	(11.11)
Var. Con.	0.000001***	(4.75)		0.000001***	(4.75)		0.000001***	(4.75)
ARCH	0.062193***	(10.70)		0.062189***	(10.71)		0.062024***	(10.70)
GARCH	0.928205***	(145.04)		0.928211***	(145.06)		0.928406***	(145.51)
Adj. R^2	-0.06587			-0.06580			-0.06503	
S.E. reg	0.00540			0.00540			0.00540	
Log like.	24953.84			24953.84			24954.01	
DW	2.10582			2.10578			2.10518	

Note: The estimates are calculated from the daily log differences and the values in parenthesis show the corresponding z-statistics. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. GPR, GPA, and GPT are the variables of interest, referring to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. WTI is the control variable for crude oil prices. Coefficients ω, α, and β from Formula 5 are represented by the terms Var.Con (Variance Constant), ARCH, and GARCH for ease of interpretation. S.E. reg stands for standard error of regression and DW for Durbin-Watson statistic. Sample period: 4th of January 1999 – 31st of October 2023.

Table 8. Estimated coefficients and test statistics from the GARCH(1,1) model explaining the returns of the Wilshire Micro-Minus portfolios**.**

Micro-Minus-Large

Constant	0.000091	(1.25)		0.000092	(1.25)		0.000090	(1.23)
GPR	0.000309*	(1.65)	GPA	0.000278**	(2.31)	GPT	0.000025	(0.17)
WTI	0.004727***	(3.83)		0.004741***	(3.83)		0.004775***	(3.89)
Var. Con.	0.000001***	(4.52)		0.000001***	(4.52)		0.000001***	(4.52)
ARCH	0.077320***	(11.77)		0.077836***	(11.79)		0.077200***	(11.77)
GARCH	0.915362***	(131.17)		0.914851***	(130.48)		0.915461***	(131.25)
Adj. R^2	-0.00121			-0.00173			-0.00149	
S.E. reg	0.00797			0.00797			0.00797	
Log like.	22437.60			22438.78			22436.39	
DW	1.90719			1.90754			1.90710	

Micro-Minus-Mid

Constant	-0.000062	(-1.07)		-0.000062	(-1.07)		-0.000063	(-1.09)
GPR	0.000313**	(2.01)	GPA	0.000238**	(2.41)	GPT	0.000011	(0.09)
WTI	0.000761	(0.59)		0.000771	(0.59)		0.000787	(0.62)
Var. Con.	0.000001***	(4.28)		0.000001***	(4.28)		0.000001***	(4.27)
ARCH	0.077008***	(11.41)		0.077306***	(11.42)		0.076568***	(11.40)
GARCH	0.916582***	(134.03)		0.916310***	(133.63)		0.917105***	(134.84)
Adj. R^2	0.00077			0.00006			-0.00001	
S.E. reg	0.00624			0.00624			0.00624	
Log like.	23852.05			23852.84			23850.14	
DW	1.86627			1.86625			1.86656	

Micro-Minus-Small

Constant	-0.000045	(-0.89)		-0.000045	(-0.89)		-0.000046	(-0.90)
GPR	0.000225*	(1.68)	GPA	0.000188**	(2.20)	GPT	-0.000061	(-0.58)
WTI	-0.000639	(-0.60)		-0.000638	(-0.60)		-0.000611	(-0.57)
Var. Con.	0.000001***	(4.05)		0.000001***	(4.04)		0.000001***	(4.03)
ARCH	0.067148***	(11.24)		0.067155***	(11.23)		0.066784***	(11.22)
GARCH	0.927366***	(152.51)		0.927414***	(152.62)		0.927788***	(153.30)
Adj. R^2	-0.00016			-0.00061			-0.00097	
S.E. reg	0.00552			0.00552			0.00552	
Log like.	24676.22			24677.25			24675.06	
DW	1.98714			1.98716			1.98729	

Note: The estimates are calculated from the daily log differences and the values in parenthesis show the corresponding z-statistics. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. GPR, GPA, and GPT are the variables of interest, referring to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. WTI is the control variable for crude oil prices. Coefficients ω, α, and β from Formula 5 are represented by terms Var.Con (Variance Constant), ARCH, and GARCH for ease of interpretation. S.E. reg stands for standard error of regression and DW for Durbin-Watson statistic. Sample period: 4th of January 1999 – 31st of October 2023.

Table 9. Estimated coefficients and test statistics from the GARCH(1,1) model explaining the returns of the Wilshire Small-Minus and Mid-Minus-Large portfolios**.**

Small-Minus-Large

Constant	0.000094	(1.55)		0.000094	(1.55)		0.000094	(1.55)
GPR	0.000044	(0.28)	GPA	0.000050	(0.50)	GPT	0.000073	(0.59)
WTI	0.010693***	(11.12)		0.010690***	(11.12)		0.010666***	(11.12)
Var. Con.	0.000001***	(4.92)		0.000001***	(4.92)		0.000001***	(4.92)
ARCH	0.071925***	(11.25)		0.071972***	(11.25)		0.071818***	(11.25)
GARCH	0.916036***	(124.12)		0.915994***	(124.09)		0.916159***	(124.36)
Adj. R^2	-0.03608			-0.03609			-0.03583	
S.E. reg	0.00631			0.00631			0.00631	
Log like.	23777.54			23777.62			23777.67	
DW	2.01095			2.01098			2.01076	

Small-Minus-Mid

Constant	-0.000026	(-0.84)		-0.000026	(-0.84)		-0.000026	(-0.84)
GPR	0.000031	(0.37)	GPA	0.000037	(0.72)	GPT	0.000002	(0.03)
WTI	0.001109***	(3.06)		0.001109***	(3.06)		0.001113***	(3.08)
Var. Con.	0.000001***	(4.07)		0.000001***	(4.07)		0.000001***	(4.07)
ARCH	0.039547***	(9.03)		0.039687***	(9.04)		0.039539***	(9.03)
GARCH	0.950596***	(169.90)		0.950435***	(169.51)		0.950615***	(169.94)
Adj. R^2	-0.00069			-0.00082			-0.00078	
S.E. reg	0.00290			0.00290			0.00290	
Log like.	28106.60			28106.79			28106.53	
DW	2.16492			2.16479			2.16498	

Mid-Minus-Large

Constant	0.000095**	(2.19)		0.000096**	(2.20)		0.000095**	(2.19)
GPR	0.000012	(0.11)	GPA	0.000037	(0.52)	GPT	0.000058	(0.66)
WTI	0.008261***	(10.56)		0.008242***	(10.54)		0.008224***	(10.53)
Var. Con.	0.000001***	(4.83)		0.000001***	(4.83)		0.000001***	(4.83)
ARCH	0.080514***	(11.62)		0.080547***	(11.62)		0.080286***	(11.62)
GARCH	0.910380***	(124.63)		0.910359***	(124.61)		0.910648***	(124.9)
Adj. R^2	-0.03799			-0.03790			-0.03767	
S.E. reg	0.00483			0.00483			0.00483	
Log like.	25714.08			25710.53			25714.29	
DW	1.94508			1.94553			1.94472	

Note: The estimates are calculated from the daily log differences and the values in parenthesis show the corresponding z-statistics. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. GPR, GPA, and GPT are the variables of interest, referring to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. WTI is the control variable for crude oil prices. Coefficients ω, α, and β from Formula 5 are represented by the terms Var.Con (Variance Constant), ARCH, and GARCH for ease of interpretation. S.E. reg stands for standard error of regression and DW for Durbin-Watson statistic. Sample period: 4th of January 1999 – 31st of October 2023.

When comparing the results for the Wilshire- and S&P-based market cap portfolios (see Tables 7 and 9), they do seem to produce similar coefficients and test statistics to their counterparts. For both index families, none of the GPR indices are statistically significant independent variables in explaining the returns of the Small-Minus-Large, Small-Minus-Mid, and Mid-Minus-Large portfolios. Overall, the variation within the component companies between these two index families does not seem to considerably influence the explanatory power of the GPR indices.

When assessing the role of the control variable in both index families, the crude oil prices (WTI) showed high statistical significance in all variations of the GARCH model containing the large-cap indices, while also being significant for the returns of the Wilshire-based Small-Minus-Mid portfolio. However, other portfolios constructed using the micro-, small-, and mid-cap indices showed insignificant sensitivity to fluctuations in crude oil prices. Despite crude oil prices not being the main interest of this research, these findings do confirm that the observed explanatory power of the GPA over the Micro-Minus portfolios is not only indirectly driven by crude oil prices.

Summarising the results from the GARCH(1,1) model presented in Tables 7, 8, and 9, the GPR indices do not have statistically significant explanatory power over the return differences among the small-, mid-, and large-cap indices. For the Micro-Minus portfolios, GPA is the only geopolitical risk index variant that can be deemed to have statistically significant explanatory power over all of the examined return differences. The only other statistically significant geopolitical risk index is the GPR index in the case of the Micro-Minus-Mid portfolio.

Overall, the results do not support the second hypothesis of this paper. Whereas changes in the GPA index do have explanatory power over the return differences of the micro-cap index against its larger counterparts, the coefficients are positive. These results indicate that increasing (decreasing) GPA would relatively benefit (negatively affect) the returns of micro-caps in relation to larger market-caps, contradicting the second hypothesis where the stock returns of smaller companies were assumed to be more sensitive to geopolitical risk. Based on the p-values of the GPT index in the different iterations of the model, we cannot reject the null hypothesis. The composite GPR index was found to have a statistically significant positive relationship over the returns of the Micro-Minus-Mid portfolio, but not in explaining the returns of any other portfolio. As the main GPR index is a combination of the GPA and GPT indices, it is intuitively logical that its explanatory power is situated between the GPA and GPT indices.

As discussed in the literature review and methodology portions of this thesis, previous papers have obtained significant results by restricting the GPR indices to their highest decile (see Ali et al., 2023). Following the process shown in the methodology section of this thesis (see Formula 6), the relationship between the portfolios and the GPR indices was further examined through the use of a dummy variable. Tables 10 and 11 show the result of this variation of the GARCH(1,1) model, where the former shows the results for the S&P-based portfolios and the latter for the Wilshire-based Micro-Minus portfolios. To ease the reading process, portfolios considering the return differences among the Wilshire large-, mid-, and small-caps are not reported. However, these portfolios were also regressed through the same model and their results do follow their S&P-based counterparts.

When observing the results shown in Table 10 for the S&P-based portfolios, they do not considerably differ from the results obtained without the restrictions imposed on the GPR indices (see Table 7). None of the variables of interest reaches statistical significance in any variation of the model when explaining the daily returns of the S&P-based portfolios. Similarly, the results presented in Table 11 show that none of the GPR indices reach statistical significance in explaining the returns of the Micro-Minus portfolios. When comparing these results to the results from the regression of Wilshire's Micro-Minus portfolios (see Table 8), the previously statistically significant Geopolitical Acts index is not a significant variable for any portfolio when restricted to its highest decile. Overall, restricting of the GPR indices to their highest deciles does not seem to improve their explanatory power over the return differences of the market cap indices.

Table 10. Estimated coefficients and test statistics from the dummy variable GARCH(1,1) model explaining the returns of the S&P-based portfolios.

Small-Minus-Large

Constant	0.000158**	(2.12)		0.000125*	(1.69)		0.000139*	(1.86)
GPR	-0.000449	(-1.40)	GPA	0.000037	(0.18)	GPT	-0.000117	(-0.45)
WTI	0.009578***	(9.41)		0.009418***	(9.32)		0.009461***	(9.34)
Var. Con.	0.000001***	(4.81)		0.000001***	(4.80)		0.000001***	(4.81)
ARCH	0.060436***	(10.57)		0.060417***	(10.57)		0.060434***	(10.57)
GARCH	0.927276***	(137.80)		0.927345***	(138.04)		0.927314***	(137.95
Adj. R^2	-0.01991			-0.01946			-0.01963	
S.E. reg	0.00711			0.00711			0.00711	
Log like.	22866.86			22865.94			22866.03	
DW	2.08180			2.08172			2.08174	

Small-Minus-Mid

Constant	-0.000003	(-0.08)		-0.000003	(-0.07)		0.000000	(0.01)
GPR	-0.000102	(-0.54)	GPA	-0.000066	(-0.58)	GPT	-0.000114	(-0.74)
WTI	0.000793	(0.79)		0.000791	(0.79)		0.000796	(0.78)
Var. Con.	0.000001***	(4.04)		0.000001***	(4.05)		0.000001***	(4.04)
ARCH	0.040545***	(9.21)		0.040657***	(9.21)		0.040561***	(9.21)
GARCH	0.951686***	(181.88)		0.951546***	(181.44)		0.951665***	(181.8)
Adj. R^2	-0.00017			-0.00015			-0.00021	
S.E. reg	0.00414			0.00414			0.00414	
Log like.	26093.62			26093.63			26093.76	
DW	2.21306			2.21287			2.21281	

Mid-Minus-Large

Constant	0.000136***	(2.62)		0.000103**	(2.01)		0.000115**	(2.20)
GPR	-0.000354	(-1.60)	GPA	0.000094	(0.66)	GPT	-0.000025	(-0.14)
WTI	0.011805***	(11.14)		0.011541***	(11.11)		0.011628***	(11.12)
Var. Con.	0.000001***	(4.77)		0.000001***	(4.74)		0.000001***	(4.76)
ARCH	0.062408***	(10.70)		0.062136***	(10.71)		0.062203***	(10.70)
GARCH	0.927908***	(144.48)		0.928353***	(145.18)		0.928193***	(144.9)
Adj. R^2	-0.06782			-0.06496			-0.06595	
S.E. reg	0.00541			0.00540			0.00540	
Log like.	24955.03			24950.88			24953.85	
DW	2.10712			2.10639			2.10591	

Note: The estimates are calculated from the daily log differences and the values in parenthesis show the corresponding z-statistics. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. GPR, GPA, and GPT are the variables of interest, referring to the geopolitical risk indices developed by Caldara and Iacoviello (2022) and are restricted to have a value of zero if they are not in the highest decile of the sample. GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. WTI is the control variable for crude oil prices. Coefficients ω, α, and β from Formula 6 are represented by the terms Var.Con (Variance Constant), ARCH, and GARCH for ease of interpretation. S.E. reg stands for standard error of regression and DW for Durbin-Watson statistic. Sample period: 4th of January 1999 – 31st of October 2023.

Table 11. Estimated coefficients and test statistics from the dummy variable GARCH(1,1) model explaining the returns of the Wilshire Micro-Minus portfolios.

Micro-Minus-Large

Constant	0.000068	(0.89)		0.000065	(0.86)		0.000075	(0.96)
GPR	0.000348	(1.07)	GPA	0.000264	(1.25)	GPT	0.000170	(0.64)
WTI	0.004746***	(3.86)		0.004754***	(3.85)		0.004757***	(3.88)
Var. Con.	0.000001***	(4.52)		0.000001***	(4.52)		0.000001***	(4.52)
ARCH	0.077319***	(11.78)		0.077372***	(11.78)		0.077224***	(11.77)
GARCH	0.915371***	(131.22)		0.915289***	(131.11)		0.915430***	(131.2)
Adj. R^2	-0.00152			-0.00173			-0.00133	
S.E. reg	0.00797			0.00797			0.00797	
Log like.	22436.89			22437.11			22436.59	
DW	1.90709			1.90725			1.90699	

Micro-Minus-Mid

Constant	-0.000088	(-1.44)		-0.000075	(-1.24)		-0.000069	(-1.12)
GPR	0.000410	(1.56)	GPA	0.000129	(0.77)	GPT	0.000060	(0.29)
WTI	0.000773	(0.60)		0.000786	(0.61)		0.000783	(0.62)
Var. Con.	0.000001***	(4.27)		0.000001***	(4.27)		0.000001***	(4.29)
ARCH	0.076787***	(11.42)		0.076716***	(11.41)		0.076966***	(11.41)
GARCH	0.916849***	(134.55)		0.916927***	(134.56)		0.916589***	(134.1)
Adj. R^2	0.00047			-0.00015			0.00009	
S.E. reg	0.00624			0.00624			0.00624	
Log like.	23851.21			23850.40			23846.11	
DW	1.86633			1.86654			1.86656	

Micro-Minus-Small

Constant	-0.000075	(-1.41)		-0.000062	(-1.17)		-0.000061	(-1.14)
GPR	0.000453	(1.90)	GPA	0.000166	(1.12)	GPT	0.000165	(0.90)
WTI	-0.000634	(-0.59)		-0.000623	(-0.58)		-0.000624	(-0.59)
Var. Con.	0.000001***	(4.04)		0.000001***	(4.04)		0.000001***	(4.03)
ARCH	0.067219***	(11.25)		0.066998***	(11.23)		0.066884***	(11.24)
GARCH	0.927289***	(152.60)		0.927539***	(152.89)		0.927642***	(153.2)
Adj. R^2	-0.00021			-0.00096			-0.00046	
S.E. reg	0.00552			0.00552			0.00552	
Log like.	24676.66			24675.52			24675.30	
DW	1.98684			1.98705			1.98714	

Note: The estimates are calculated from the daily log differences and the values in parenthesis show the corresponding z-statistics. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. GPR, GPA, and GPT are the variables of interest, referring to the geopolitical risk indices developed by Caldara and Iacoviello (2022) and are restricted to have a value of zero if they are not in the highest decile of the sample. GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. WTI is the control variable for crude oil prices. Coefficients ω, α, and β from Formula 6 are represented by the terms Var.Con (Variance Constant), ARCH, and GARCH for ease of interpretation. S.E. reg stands for standard error of regression and DW for Durbin-Watson statistic. Sample period: 4th of January 1999 – 31st of October 2023.

When discussing the results obtained from the GARCH(1,1) model with the dummy variable, the results do not support the notion that only major geopolitical events have explanatory power over the return differences of companies with different market capitalisations. Overall, geopolitical risk only had statistically significant explanatory power when it was estimated using the unrestricted GPA index and while explaining the returns of portfolios containing the Wilshire micro-cap index, in addition to the unrestricted GPR index in explaining the Micro-Minus-Mid returns. Compared to the findings of the event study of Ahmed et al. (2023), who found that European large-caps outperformed mid- and small-caps in a high geopolitical risk environment, the results of this thesis do not support the existence of such a relationship. However, as the chosen methodology aims to generalise the relationship, the existence of such a relationship in special circumstances cannot be ruled out.

The root cause for why geopolitical acts were only significant when the micro-cap index was involved is unclear. The author of this thesis hypothesises that the observed variations among the size-based portfolios could be due to the lesser sensitivity of the micro-cap stocks to external shocks compared to larger companies. As the micro-caps are considerably smaller, their presumably lower intraday liquidity could prevent stock owners from selling their holdings during GPA events. This notion is supported by the findings of Chung and Chuwonganant (2014), who found that uncertainty in financial markets has a greater negative impact on the liquidity of stocks that have a smaller market capitalisation than in companies with higher market capitalisation. Alternatively, long-term owners could be relatively more heavily represented among the micro-cap shareholders. Consequently, these explanations could explain why the daily returns of micro-caps would be less sensitive to geopolitical risk in relation to the returns of larger firms.

6.3 Out-of-sample and sub-sample testing

The reasoning behind sub-sample and out-of-sample testing is twofold. Foremost, the high kurtosis present in the return distributions of the examined stock indices does raise the possibility of the results of this paper only being sample-specific and not reflective of the underlying population of index returns. Secondly, the findings of He (2023) indicate that the sentiment response to geopolitical risk is time-sensitive. This introduces the possibility that the earlier findings of this paper suffer from a time-period bias, given that the market sentiment does have explanatory power over stock returns.

The data used to carry out the testing for the S&P-based portfolios extends from the beginning of 1990 till the end of October 2023. The sample was divided into three sections which each cover approximately 11 years. The first sample covers the years from 1990 to 2000 and due to data availability, this sample only includes the S&P-based portfolios. The Wilshire-based Micro-Minus portfolios are also included in the latter sample periods, covering the years 2001-2011 and 2012-2023. Additionally, the Wilshire Micro-Minus portfolios were tested using the 1999-2004 subsample. The model used to test these samples is the GARCH(1,1) model seen in Formula 5. The results from the out-of-sample and sub-sample testing can be seen in Table 12.

The results from the combined out-of-sample and sub-sample tests show that none of the GPR indices reached statistical significance in explaining the returns of the S&P-based portfolios in any of the tested samples. For the Wilshire-based portfolios, GPA reaches statistical significance for all portfolios but only in one of the sample periods per portfolio. The composite GPR index is a statistically significant explanatory variable for the Micro-Minus-Mid portfolio in the 1999-2004 subsample but not in other subsamples. GPT is not statistically significant in any sample or portfolio combination.

When considering these results in the context of the earlier results of this paper, it seems that the market response to geopolitical risk does vary over time. Therefore, the explanatory power of the GPA index over the Micro-Minus-Large, Micro-Minus-Mid, and Micro-Minus-Small portfolios cannot be extrapolated outside of the examined data. Similarly, the results do indicate that the explanatory power of the GPR index over the Micro-Minus-Mid portfolio is time-variant. Moreover, it should be noted that the observed time-variance could be caused by different types of geopolitical events present in the samples or by the changing investor response.

Table 12. Estimated coefficients and test statistics for the geopolitical risk indices in explaining the returns of the size-based portfolios, GARCH(1,1) model with alternative samples.

	Years covered by the samples					
	1990-2000		**2001-2011**		**2012-2023**	
	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat
S&P-based portfolios						
Small-Minus-Large						
GPR	-0.000234	(-0.79)	-0.000253	(-0.79)	0.000063	(0.27)
GPA	0.000069	(0.40)	-0.000323	(-1.41)	0.000141	(1.02)
GPT	-0.000269	(-1.13)	0.000030	(0.13)	0.000068	(0.35)
Small-Minus-Mid						
GPR	-0.000040	(-0.23)	-0.000119	(-0.58)	-0.000050	(-0.39)
GPA	0.000034	(0.35)	-0.000198	(-1.36)	0.000079	(1.03)
GPT	-0.000043	(-0.30)	0.000010	(0.07)	-0.000116	(-1.09)
Mid-Minus-Large						
GPR	-0.000144	(-0.60)	-0.000163	(-0.74)	0.000118	(0.73)
GPA	0.000029	(0.20)	-0.000113	(-0.70)	0.000063	(0.66)
GPT	-0.000192	(-0.99)	-0.000045	(-0.27)	0.000157	(1.19)
	1999-2004		**2001-2011**		**2012-2023**	
Wilshire-based portfolios						
Micro-Minus-Large						
GPR	0.000074	(0.13)	-0.000052	(-0.18)	0.000439*	(1.75)
GPA	0.000083	(0.22)	-0.000029	(-0.13)	0.000380**	(2.51)
GPT	0.000240	(0.54)	-0.000070	(-0.31)	0.000036	(0.18)
Micro-Minus-Mid						
GPR	0.000803**	(2.02)	0.000155	(0.65)	0.000328	(1.52)
GPA	0.000592**	(2.19)	0.000146	(0.87)	0.000246*	(1.92)
GPT	0.000355	(1.13)	-0.000004	(-0.03)	-0.000069	(-0.40)
Micro-Minus-Small						
GPR	0.000483	(1.06)	0.000168	(0.72)	0.000205	(1.21)
GPA	0.000588**	(1.96)	0.000242	(1.45)	0.000140	(1.36)
GPT	0.000014	(0.04)	-0.000068	(-0.40)	-0.000104	(-0.76)

Note: The estimates are calculated from the daily log differences and the values in parenthesis show the corresponding z-statistics. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. GPR, GPA, and GPT refer to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices.

6.4 Robustness tests

The purpose of this subchapter is to increase the validity of the findings by testing the assumptions made in this paper. The robustness testing is divided into two segments. The first segment tests the assumptions made about the length of the news cycle. The second segment examines if the explanatory power of the GPR indices is related to the January effect. As the size-based portfolios constructed out of the S&P and Wilshire indices did show similar results, the robustness testing among the small-, mid-, and large-cap indices was carried out using the S&P indices. For the Micro-Minus portfolios, the Wilshire indices were used.

6.4.1 Testing of alternative news cycle lengths

In this thesis, the length of the news cycle for a newspaper was assumed to be approximately one day. However, as the result of this paper deviates from earlier research which did not impose a lead to the GPR indices relative to the stock returns, this assumption may not be correct. As an example, if on average the newspapers used to compute the GPR indices take more than a day to publish articles about a given geopolitical event, the GPR and stock data would be misaligned. Furthermore, the stock market could also react to complex geopolitical developments non-instantaneously. Therefore, the direction of the potential timing error cannot be assumed when approximating geopolitical risk with the GPR indices.

In order to confirm the assumption that the news cycle has a one-day lag, alternative lag and lead lengths were tested. Relative to the timing method used earlier in this thesis, two- and one-day lags were introduced for the GPR indices. Furthermore, a lead of one day was also tested, relative to the timing used earlier in this paper. In addition to the results of these alternative lags and lead, Table 13 also shows the estimated coefficients from earlier testing in the column named *0 days* for reference. Due to space constraints, Table 13 only shows the estimated coefficients for the GPR indices alongside the associated z-statistics. These news cycle lengths were tested by using the GARCH(1,1) model seen in Formula 5 by altering the timing of the GPR component while keeping the other variables the same.

Table 13. Estimated coefficients and test statistics for the geopolitical risk indices with alternative news cycle lengths, GARCH(1,1) model explaining the returns of the size-based portfolios.

	Lag lengths							
	-2 days		**-1 day**		**0 days**		**+1 day**	
	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat
S&P-based portfolios								
Small-Minus-Large								
GPR	-0.000174	(-0.92)	-0.000017	(-0.09)	-0.000051	(-0.27)	0.000082	(0.43)
GPA	-0.000110	(-0.94)	0.000064	(0.55)	0.000013	(0.11)	-0.000060	(-0.51)
GPT	-0.000051	(-0.34)	-0.000150	(-1.02)	0.000044	(0.29)	0.000091	(0.62)
Small-Minus-Mid								
GPR	-0.000023	(-0.21)	0.000086	(0.77)	-0.000056	(0.00)	-0.000100	(-0.90)
GPA	0.000041	(0.59)	0.000002	(0.02)	0.000019	(0.29)	-0.000059	(-0.86)
GPT	-0.000019	(-0.21)	0.000041	(0.48)	-0.000056	(-0.64)	0.000016	(0.18)
Mid-Minus-Large								
GPR	-0.000187	(-1.41)	-0.000148	(-1.12)	-0.000003	(-0.03)	0.000238*	(1.82)
GPA	-0.000137	(-1.64)	0.000016	(0.19)	0.000003	(0.04)	0.000047	(0.58)
GPT	-0.000049	(-0.48)	-0.000183*	(-1.78)	0.000061	(0.60)	0.000139	(1.39)
Wilshire-based portfolios								
Micro-Minus-Large								
GPR	-0.000045	(-0.23)	-0.000433**	(-2.23)	0.000309*	(1.65)	0.000158	(0.85)
GPA	0.000065	(0.54)	-0.000210*	(-1.69)	0.000278**	(2.31)	-0.000017	(-0.14)
GPT	-0.000038	(-0.26)	-0.000282*	(-1.88)	0.000025	(0.17)	0.000179	(1.24)
Micro-Minus-Mid								
GPR	0.000029	(0.19)	-0.000209	(-1.36)	0.000313**	(2.01)	0.000005	(0.03)
GPA	0.000176*	(1.79)	-0.000217**	(-2.17)	0.000238**	(2.41)	-0.000012	(-0.12)
GPT	-0.000071	(-0.60)	-0.000033	(-0.28)	0.000011	(0.09)	0.000053	(0.45)
Micro-Minus-Small								
GPR	0.000012	(0.09)	-0.000125	(-0.94)	0.000225*	(1.68)	0.000108	(0.81)
GPA	0.000094	(1.12)	-0.000139	(-1.64)	0.000188**	(2.20)	0.000071	(0.83)
GPT	-0.000041	(-0.40)	-0.000030	(-0.30)	-0.000061	(-0.58)	0.000105	(1.01)

Note: The estimates are calculated from the daily log differences and the values in parenthesis show the corresponding z-statistics. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. GPR, GPA, and GPT refer to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. The length of the imposed lag on the GPR indices is calculated from the timing used earlier in this paper. Sample period: 4th of January 1999 – 31st of October 2023.

When observing Table 13, it can be noted that none of the GPR indices reached statistical significance when they were lagged by two days or advanced by one day in relation to earlier testing presented in this thesis. However, the models with one-day GPR lag did produce statistically significant results. While using this lag, the GPR index reaches statistical significance in explaining the Micro-Minus-Large returns and the GPA index in explaining the returns of the Micro-Minus-Mid portfolio. Furthermore, these estimated coefficients with the one-day lag are negative.

Overall, the results from the testing of alternative news cycle lengths do not give a reason to suspect that the chosen news length would be suboptimal in explaining the relationship between geopolitical risk and the returns of the size-based portfolios. Altogether, the tested alternative lengths did not produce results in which the GPR indices reached statistical significance more often. However, lagging the GPR indices by one day did produce statistically significant and contradictory results to the earlier findings of this paper, as the GPR in explaining the Micro-Minus-Large and the GPA in explaining Micro-Minus-Mid did have negative estimated coefficients. This would indicate that increasing (decreasing) GPR levels would benefit (adversely affect) the larger capitalisation indices in relation to the micro-index.

In the opinion of the author of this thesis, the significant relationships found in the one-day lag model are likely a bounce-back reaction, as a similar market reaction has been observed in prior studies (Ahmed et al., 2023; Boubaker et al., 2022; Nikkinen & Vähämaa, 2010). As the absolute values of the estimated coefficients are comparable with the one-day and zero-day lags, on average the large-cap and mid-cap indices are likely to first have a comparably stronger reaction to changes within the geopolitical risk environment and then revert to their initial states on the following day, compared to the micro-caps. Alternatively, the timing of the market reaction could also be incorrectly specified. However, the author of this thesis does find this possibility unlikely as the relationship was observed to be more often statistically significant while using the zero-day lag than the one-day lag. Moreover, the findings of Jiang and Zhu (2017) indicate that a smaller market capitalisation is associated with having a more pronounced underreaction to information shocks, coinciding with this theory.

6.4.2 January effect

The final robustness test examines whether the relationship between geopolitical risk and market capitalisation is dependent on the January effect. As multiple researchers have remarked, the size effect is likely to be at least partially explained by the January effect (see Asness et al., 2018; van Dijk, 2011). To investigate whether the findings of this thesis are also associated with the January effect, the GARCH(1,1) model seen in Formula 5 was employed and run by using two separate datasets. The first dataset only includes observations dating to the month of January and the second dataset consists of data from other months. The two datasets were created from the data used in the main tests of this paper, covering the period from the beginning of 1999 to the end of October 2023.

The results of the testing can be seen in Table 14. When examining the results for the S&P-based portfolios, it can be observed that in the January sample, GPT reaches statistical significance in explaining the Mid-Minus-Large portfolio returns, while there is no other instance of statistical significance. For all of the Wilshire Micro-Minus portfolios, GPA is statistically significant in the sample consisting of non-January observations but not in the January sample. Similarly, the composite GPR index is statistically significant in the non-January sample when explaining the Micro-Minus-Mid returns. It should also be noted that the GPT index is significant in the January sample explaining the returns of the Micro-Minus-Small portfolio but not in the sample containing other months.

Table 14. Estimated coefficients and test statistics for the geopolitical risk indices in month-based samples, GARCH(1,1) model explaining the returns of the size-based portfolios.

	Months included in the samples			
	Januarys		**Other months**	
	Coef.	z-stat	Coef.	z-stat
S&P-based portfolios				
Small-Minus-Large				
GPR	0.000820	(1.40)	-0.000165	(-0.83)
GPA	0.000304	(0.71)	-0.000012	(-0.09)
GPT	0.000791	(1.62)	-0.000056	(-0.36)
Small-Minus-Mid				
GPR	-0.000091	(-0.27)	-0.000072	(-0.63)
GPA	-0.000072	(-0.28)	0.000020	(0.29)
GPT	-0.000027	(-0.10)	-0.000078	(-0.87)
Mid-Minus-Large				
GPR	0.000799*	(1.93)	-0.000085	(-0.61)
GPA	0.000364	(1.24)	-0.000023	(-0.27)
GPT	0.000731**	(2.07)	-0.000016	(-0.15)
Wilshire-based portfolios				
Micro-Minus-Large				
GPR	0.000472	(0.80)	0.000298	(1.50)
GPA	0.000447	(1.00)	0.000275**	(2.20)
GPT	-0.000092	(-0.19)	0.000032	(0.21)
Micro-Minus-Mid				
GPR	-0.000079	(-0.15)	0.000338**	(2.07)
GPA	0.000245	(0.65)	0.000238**	(2.33)
GPT	-0.000629	(-1.49)	0.000056	(0.44)
Micro-Minus-Small				
GPR	-0.000504	(-1.16)	0.000289**	(2.03)
GPA	0.000039	(0.12)	0.000205**	(2.30)
GPT	-0.000933***	(-2.77)	0.000012	(0.11)

Note: The estimates are calculated from the daily log differences and the values in parenthesis show the corresponding z-statistics. The * sign denotes significance at 10%, ** significance at 5%, and *** significance at 1%. GPR, GPA, and GPT refer to the geopolitical risk indices developed by Caldara and Iacoviello (2022). GPR is the composite index composed of the Geopolitical Act (GPA) and Geopolitical Threats (GPT) indices. Sample period: 4th of January 1999 – 31st of October 2023.

In the previous tests, the strongest relationship was found when the GPA index was employed to explain the returns of the Micro-Minus portfolios. As these relationships were statistically significant also outside of the January sample, we can conclude that the explanatory power of the GPA is not only limited to the January effect. Similarly, the previously found statistically significant relationship between the GPR index and the Micro-Minus-Mid portfolio was determined to be significant outside of the month of January. Furthermore, these results also highlight the time-varying nature of the relationship between geopolitical risk and size-based portfolio returns. As the January samples were the first instances when the GPT index had statistically significant explanatory power over the S&P Mid-Minus-Large and Wilshire Micro-Minus-Small portfolios, we cannot be sure if the explanatory power of the GPT is related to the January effect. However, as this relationship was not observed to be significant in the larger samples, these observations were not considered to be crucial for the validity of the key findings of this thesis.

7 Conclusions

The main research objective of this thesis was to examine whether geopolitical risk affects the stock returns of companies asymmetrically based on their market capitalisation. Additionally, this paper also aimed to provide further evidence on the relationship between geopolitical risk and stock returns. Based on the previous literature investigating GPR and stock returns, it was hypothesized that geopolitical risk has a negative relationship with stock returns. Building upon these prior studies and the flight-to-safety phenomenon, it was also hypothesized that the stock returns of smaller companies are more sensitive to geopolitical risk than the returns of larger companies.

To answer the first hypothesis of this paper, the explanatory power of the GPR indices was tested on the returns of individual stock indices through a quantile autoregression. By testing large-, mid-, small-, and micro-cap indices, it was concluded that geopolitical risk does have explanatory power over stock returns and that the relation is generally negative. However, the obtained results do indicate that geopolitical risk is not a statistically significant explanatory variable across the whole return distribution.

The relationship between geopolitical risk and market capitalisation was examined by utilising a GARCH(1,1) model. The resulting estimates show that geopolitical risk cannot be generalized to be a significant explanatory factor for the return differences among large-, mid-, and small-cap indices, although it is a significant factor in explaining the return differences of the micro-cap index against its three larger counterparts. Contrary to the second hypothesis, the daily returns of the micro-cap index showed lesser sensitivity to geopolitical risk than the larger indices. However, the results from the robustness tests do indicate that the explanatory power of the geopolitical risk over the return differences is not constant across time and thus, cannot be extrapolated outside of the examined data set without further research.

When evaluating the results of this paper in relation to the existing literature, this paper provides new information about the role of geopolitical risk within the stock market.

Firstly, it does provide further evidence supporting the notion that geopolitical risk does have explanatory power over stock returns. Secondly, it grants new insight into the relationship between geopolitical risk and market capitalisation. Contrary to the findings of Baur and Smales (2020) and Salisu et al. (2022), this thesis did find geopolitical acts to be a stronger explanatory variable of stock returns than geopolitical threats. Furthermore, conflicting with the findings of the event study by Ahmed et al. (2023) on the European markets, this thesis did not find evidence of large-caps outperforming mid- and small-caps during high geopolitical tension.

Overall, the relationship between geopolitical risk and market capitalisation does seem to be complex. As the findings of this paper show, there is evidence of a relationship existing, but it is dependent on the market capitalisation of the examined companies, the type of geopolitical risk, and the time period examined. Due to these observed conditions, more research on the nature of this relationship is needed to understand the nuances of this relationship.

7.1 Limitations of the study

One of the key limitations of this thesis is its dependency on the GPR indices. While claimed by its creators (Caldara & Iacoviello, 2022) to be a good approximation for the type of risk, there is a possibility that the actual geopolitical climate does differ from the measured one. A possible source for a measurement error could stem from the fact that the geopolitical risk is in its true essence a subjective variable. Therefore, the newspapers used to construct the indices could have biases towards publishing certain types of news, whereas the stock market could be collectively concerned with different types of geopolitical news.

As the research did include a limited number of indices, there is a possibility that other indices respond to GPR differently. These differences might arise from factors such as varying inclusion criteria used to create the index or through the weighting rules used to calculate the index values. Furthermore, given the results of the robustness tests and the findings of He (2023), the obtained results could be suffering from a time period bias, weakening their explanatory power outside of the examined sample. Also due to the inclusion criteria used by the S&P and Wilshire, the obtained result might not be applicable to individual companies, as their component companies may differ from the market average. Furthermore, as the examined indices are market cap-weighted collections of stocks, the collective returns of the component companies can hide the true extent of geopolitical risk an individual stock can be subject to.

The methodology of this thesis chose to approximate geopolitical risk through the daily deltas of the GPR indices. Given that the markets do adjust their expectations and positions prior to major geopolitical events, as indicated by the findings of Ahmed et al. (2023), it is important to recognize that this study might not be able to recognize the full extent of geopolitical risk. Although the GPT index is at least partially capable of capturing impending geopolitical events before they transpire, their true significance might not be fully captured by the daily deltas of the GPR indices. Especially, the implications of slow buildups of geopolitical tensions could be identified more accurately by utilising the index levels of the GPR indices rather than their daily log differences. This concern is further highlighted by the time error associated with the GPR indices, as discussed in subchapter 2.3 of this paper.

7.2 Future research

As the relationship between geopolitical risk and market capitalisation has not been extensively examined within the literature, conclusions drawn in this paper do need to be investigated further. A possible direction for future research could be to investigate why the market reaction to geopolitical risk seems to be time-variant. In addition to He's (2023) observation on the sentiment response weakening, differing types of geopolitical risks and changing sector weights could be explored as a potential explanation. Furthermore, also other findings of this thesis should be investigated more thoroughly. Why the returns of micro-caps were found to be less sensitive to geopolitical acts than the returns of larger companies remains to be unknown. Whereas this phenomenon could be attributed to a time period bias, as hinted by the results of the robustness testing, the confirmation of this relationship could be valuable for risk hedging purposes. Moreover, if the relationship can be generalised, its root cause should be investigated. If the effect is caused by low liquidity within the micro-segment, its feasibility for trading purposes could be hindered.

This thesis examined the impact of geopolitical risk on index returns by first restricting the estimates according to return quantiles and then investigated the relationship between geopolitical risk and size-based portfolio returns by restricting the associated deltas of the GPR indices through the use of a dummy variable. Thus, it provided information on two possibly connected but separate open questions in academic research. As such, future research could try to combine these two methods by simultaneously restricting the left-hand and right-hand sides of the equation. Through methods such as quantile-on-quantile regression, future researchers could be able to gain a more comprehensive understanding of the underlying dependency structures.

Another path future research could take relates to the nature of the market reaction. As pointed out by Zaremba et al. (2022, p.2), factors such as news coverage, emotions, and proximity can influence how market participants perceive a given risk. Given that this thesis utilised a news-based approach to estimate geopolitical risk, it did not distinguish between the actual economic consequences of geopolitical risk and the perceived ones. Therefore, future research could try to examine whether the observed market responses can be explained by behavioural factors or if they reflect the changes in the fundamental value of the asset.

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Appendices

Appendix 1. Summary of past studies: GPR and stock returns

Panel A: Studies regarding the U.S. market

Author & publication year	Variable of interest (examined time frame)	GPR approximated by	Methodology	Key findings
Caldara and Iacoviello (2022)	Quarterly lagged S&P 500 returns and daily industry portfolio returns. (1900-2019, 1985-2019)	GPR, GPT & GPA	Granger causality test, VAR & quantile regression	GRP contains novel information. High GPR has an impact on VIX and lowers stock and oil returns, among other macroeconomic and firm-level effects. Different industries have heterogeneous reactions to GPR.
Ali et al. (2023)	Monthly and daily S&P 500 returns, among other stock indices and financial assets. (1985-2021)	GPT	OLS & EGARCH(1,1)	Daily returns of the S&P 500 show safe haven properties against high GPT, while other markets show weaker responses. Sectors have heterogenous responses.
Baur and Smales (2020)	Daily and Monthly S&P 500 returns in addition to precious metals. (1985-2019)	GPR, GPT, GPA, & GPR Shocks	OLS & EGARCH(1,1)	Precious metals have positive relationship to GRP, while S&P 500 and t-bonds generally have a negative and non-statistically significant response. Markets react to GP Threats, but not to Acts.
Salisu et al. (2022)	Monthly returns of major broad stock indices of G7 countries + Switzerland. (~1900-2020)	GPR, GPT, GPA	Bias-adjusted OLS & Clark and West test	GPR indices have explanatory power over index returns. GPT has a stronger negative impact than GPA. S&P 500 reacts negatively and statistically significantly to all GPR indices.
He (2023)	Monthly BW sentiment index. (1985-2018)	GPR, GPT & GPA	Granger causality test & TVP-VAR	GPR has an impact on market sentiment. Effects of GPR shocks visible in sentiment after 4,8, and 12 months. No observed difference between the GPR indices.
Chesney (2012)	Daily returns of various USA and European financial asset indices. (1990-2003)	Terror attacks	Event study, polynomial regression & GARCH-EVT	Most terror attacks have a negative impact on stock index returns, there are differences in how indices in different countries reacts. There are also sectoral differences.

Panel A (continued)				
Goel et al. (2017)	Daily returns of various major US (S&P 500) and global indices. (1990-2010)	Global Terrorism Database (days with multiple attacks with 1 million USD in damage)	Event study	Terror attacks did not produce a significant or systematic response in the SP500. Neither one was seen in gold or treasury bonds.

Panel B: Studies regarding the other markets

Author(s) & publication year	**Variable of interest (examined time frame)**	**GPR approximated by**	**Methodology**	**Key findings**
Balcilar et al. (2018)	Monthly average returns and volatility of BRICS country indices. (~1990-2016)	GPR and its 8 subsegments (terror; arms control; war)	Granger causality-in-quantiles	GPR and index returns/volatility have a connection. BRICS have heterogeneous responses to it.
Kannadhasan and Das (2020)	Monthly Asian stock index data. (1997-2018)	EPU and GPR	Quantile auto regression	GPR is not a significant factor in most return quantiles. The examined markets are more sensitive to GPR in bear markets.
Zaremba et al. (2022)	Monthly compiled stock returns of emerging markets. (1990-2020)	Volatility-adjusted country-specific GPR index	Fama-MacBeth regression	High GPR countries outperform low GPR countries in the following month, indicating a market overreaction. The effect is driven by local GPR, not global GPR.
Feng et al. (2023)	Quarterly capital inflow and outflows from 45 different countries. (2005-2019)	GPR, GPA & GPT	OLS & Generalized method of moments	Countries have heterogeneous responses to GPR. Both in advanced and emerging markets GPR decreases capital in- and outflows.
Nikkinen and Vähämaa (2010)	Daily FTSE100 (UK) sentiment derived from options. (2000-2005)	Three Terrorist attacks (9/11, Madrid 2004 train bombings, London 2005 bombings)	GARCH(1,1)	Market sentiment is significantly impacted by major terrorist attacks. The average sentiment recovers quickly (the next day), while some investors remain cautious for longer.
Ahmed et al. (2023)	Daily stock returns of individual STOXX Europe 600 companies. (February 2021- March 2022)	Russian recognition of Donetsk and Luhansk People's Republics. (Feb 21st 2022)	Event study	The event caused negative stock performance before, on, and after the event day. Energy performed the best, consumer staples and finance the worst. Large-caps fare better than mid- and small-caps. Many factors contributed to the differing country-level responses.

Panel B (continued)

Boubaker et al. (2022)	Daily returns of 23 developed markets and 24 emerging markets. (2021-2022)	Start of the large-scale invasion in the Russo-Ukrainian war (Feb. 24th 2022)	Event study	Main stock indices of different countries had heterogeneous responses to the event. Identified contributing factors were proximity, participation in global trade, and NATO membership.

Appendix 2. Correlation matrices

Panel A: Correlation matrix for individual indices

	GPR	GPA	GPT	S&P 500	S&P 400	S&P 600	Wil. Large	Wil. Mid	Wil. Small	Wil. Micro
GPR	1.000	0.631	0.798	-0.037	-0.039	-0.036	-0.038	-0.039	-0.034	-0.026
GPA	0.631	1.000	0.183	-0.040	-0.041	-0.038	-0.041	-0.041	-0.038	-0.036
GPT	0.798	0.183	1.000	-0.031	-0.029	-0.026	-0.032	-0.030	-0.025	-0.022
S&P 500	-0.037	-0.040	-0.031	1.000	0.926	0.879	0.998	0.928	0.900	0.794
S&P 400	-0.039	-0.041	-0.029	0.926	1.000	0.960	0.935	0.987	0.975	0.875
S&P 600	-0.036	-0.038	-0.026	0.879	0.960	1.000	0.887	0.956	0.985	0.907
Wil. Large-cap	-0.038	-0.041	-0.032	0.998	0.935	0.887	1.000	0.939	0.910	0.807
Wil. Mid-cap	-0.039	-0.041	-0.030	0.928	0.987	0.956	0.939	1.000	0.982	0.892
Wil. Small-cap	-0.034	-0.038	-0.025	0.900	0.975	0.985	0.910	0.982	1.000	0.929
Wil. Micro-cap	-0.026	-0.036	-0.022	0.794	0.875	0.907	0.807	0.892	0.929	1.000

Panel B: Correlation matrix for size-based portfolios

	GPR indices			*S&P-based portfolios*			*Wilshire-based portfolios*						
	GPR	**GPA**	**GPT**	**S-L**	**S-Mid**	**Mid-L**	**Micro -L**	**Micro - Mid**	**Micro -S**	**S- L**	**S-Mid**	**Mid-L**	**WTI**
GPR	1.000	0.631	0.798	-0.011	0.000	-0.015	0.016	0.031	0.029	-0.005	0.012	-0.013	0.007
GPA	0.631	1.000	0.183	-0.010	-0.001	-0.013	0.004	0.014	0.015	-0.008	0.001	-0.011	-0.006
GPT	0.798	0.183	1.000	-0.001	0.004	-0.005	0.014	0.020	0.015	0.004	0.014	-0.004	0.009
S&P. S-L	-0.011	-0.010	-0.001	1.000	0.674	0.811	0.666	0.239	-0.093	0.938	0.691	0.805	0.033
S&P. S-Mid	0.000	-0.001	0.004	0.674	1.000	0.115	0.447	0.403	0.057	0.522	0.758	0.219	0.015
S&P. Mid-L	-0.015	-0.013	-0.005	0.811	0.115	1.000	0.543	0.002	-0.171	0.849	0.329	0.909	0.033
Wil. Micro-L	0.016	0.004	0.014	0.666	0.447	0.543	1.000	0.804	0.630	0.723	0.531	0.621	0.032
Wil. Micro-Mid	0.031	0.014	0.020	0.239	0.403	0.002	0.804	1.000	0.885	0.244	0.468	0.033	0.017
Wil. Micro-S	0.029	0.015	0.015	-0.093	0.057	-0.171	0.630	0.885	1.000	-0.080	0.004	-0.107	0.008
Wil. S-L	-0.005	-0.008	0.004	0.938	0.522	0.849	0.723	0.244	-0.080	1.000	0.678	0.893	0.034
Wil. S-Mid	0.012	0.001	0.014	0.691	0.758	0.329	0.531	0.468	0.004	0.678	1.000	0.275	0.021
Wil. Mid-L	-0.013	-0.011	-0.004	0.805	0.219	0.909	0.621	0.033	-0.107	0.893	0.275	1.000	0.032
WTI	0.007	-0.006	0.009	0.033	0.015	0.033	0.032	0.017	0.008	0.034	0.021	0.032	1.000