Utrecht University

Master Thesis U.S.E.

The effect of geopolitical risks on stock returns and volatility of European companies[1]

Marina Logroño Calvo (9648267)

m.logronocalvo@students.uu.nl

First supervisor: Dr. Thomas Walther

Second supervisor: Dr. Yilong Xu

Abstract

This thesis explores the effect of global geopolitical risks (GPRs) on the stock returns and volatility of returns of 1,378 European companies, which have been listed in the STOXX Europe 600 during this century. Using the daily geopolitical risk index constructed by Caldara and Iacoviello (2018), I calculate the individual exposure of each company to the percentage change in the index and, by means of a panel data model with an annual frequency, I find that exposure to geopolitical events affects firm-level stock returns positively, at a ten percent significance level. Volatility also appears to be positively and significantly affected by geopolitical threats, even after controlling for company characteristics and year and country fixed effects. This demonstrates that a specific measure for GPRs should be included in asset pricing and risk management models, as they are an important factor when it comes both to stock returns and volatility.

JEL classification: C33, G12, G14.

Keywords: Geopolitical risks, firm-level, Europe, returns, volatility, panel data.

---

[1] I would like to thank my supervisor, Dr. Thomas Walther, for providing me with support, guidance, and many helpful comments throughout the thesis. I also thank the University for giving me access to different data sets to conduct the empirical analysis. A big thank you to my family, friends, and classmates for their support and motivation.

Table of Contents

1. Introduction 1

2. Literature Review 3

3. Theoretical Framework and Hypotheses 5

4. Data and Methodology 7

4.1. Data 7

4.1.1. Dependent variables 8

4.1.2. Independent variables 9

4.1.3. Control variables 10

4.2. Methodology 13

5. Results 15

5.1. Descriptive statistics 15

5.2. Empirical results 17

5.2.1. Time series regression 17

5.2.2. Fixed-effects regression on returns 18

5.2.3. Fixed-effects regression on volatility 20

6. Robustness 21

6.1. Diagnostic tests 21

6.2. Robustness checks 23

7. Conclusion and discussion 28

8. References 30

9. Appendix 34

1. Introduction

The fact that national crises affect national economies and financial markets is well known. So is the fact that, in a context of relentless globalization, crises that seem to be far away geographically can still have international repercussions. A shock can now be quickly transmitted through different equity markets, due to the growing interconnectedness between them (Omar et al., 2017). Some of these shocks might stem from geopolitical tensions and conflicts, commonly named as geopolitical risks (hereafter GPRs).

The Oxford English Dictionary defines the adjective 'geopolitical' as something "connected with the political relations between countries and groups of countries in the world, as influenced by their geography". This can undoubtedly have a much broader meaning. For this reason, different authors have proposed diverse definitions for what they have considered geopolitical risks in their studies. For instance, Caldara & Iacoviello (2018), with the purpose of constructing their GPR index, consider geopolitical events those "in which power struggles over territories cannot be resolved peacefully", namely wars, terrorist attacks, and other tensions between states. Engle & Campos-Martins (2020) use a broader definition and include other events such as strictly political events (for example, the Brexit referendum and other similar ones), natural disasters, or cyber-attacks, among others.

The number of studies regarding geopolitical risks has increased in recent years, as academia has been able to demonstrate their importance. Different authors, financial institutions, and governments now consider GPRs one of the key determinants of investment decisions, since they can significantly affect the stability of financial markets and, subsequently, economic growth (Elsayed & Helmi, 2021). This is partly because the magnitude of the effects is not circumscribed to stocks. As previous studies have shown, such as the one conducted by Berkman et al. (2011), GPRs can also disrupt supply chains and company's operations, hinder consumer's confidence and, consequently, consumption, as well as greatly affect commodity markets (Ramiah et al., 2019).

As this paper is being written, we are witnessing the global impact that a single event can have, with the Russian invasion of Ukraine. Markets are being affected in many ways: there are problems in production processes, shortages in many exported products, and numerous companies have abandoned their operations in Russia in response to the sanctions imposed, among other consequences. This event may shed some light on the different channels through which GPRs can affect both stock returns and volatility. For instance, the uncertainty caused by GPRs may shape consumers and companies' expectations, thus influencing their economic decisions. Studies have demonstrated empirically that, when this happens, agents in the economy decide to postpone investment decisions (Favara et al., 2020), or even hiring processes (Bloom, 2009), as well as to withdraw capital from countries with a higher geopolitical risk to those with a lower risk (Caldara & Iacoviello, 2018). These channels are discussed in more detail in Section 3.

To analyze GPRs, researchers have focused on studying three aspects using different empirical methods. First, and the most common, how GPRs affect stock returns, especially in US stock markets and emerging countries. Second, how GPRs affect volatility and if there are any volatility spillovers or volatility jumps. Third, a growing body of literature is extending this study to other assets, such as commodities. Many studies have also studied the predictive power of geopolitical risks to anticipate movements in financial markets, whether in equity, oil, or commodity prices.

However, the effect of GPRs on European markets has been rarely studied. Most geopolitical events that have taken place during this century have not occurred in European territory, which may imply that their financial markets have been more resilient against global geopolitics. On the other hand, the growing globalization, and the strong interlinkage between countries, makes global geopolitics one of the main risks for countries and companies worldwide. This study therefore aims to explore to what extent are European companies, and therefore financial markets, affected by GPRs.

The objective of this thesis is to use the GPR index developed by Caldara & Iacoviello (2018) to answer two main research questions. First, if geopolitical risks affect stock returns of listed companies in the STOXX Europe 600 throughout this century, and the magnitude of this impact. Second, how GPRs affect volatility of returns of these companies. These questions are answered empirically by using panel data models.

Most of the recent literature regarding geopolitical risks suggests that they do have a negative effect on stock returns (Bloom, 2009; Caldara & Iacoviello, 2018; Smales, 2021), whereas volatility of returns increases after a shock of this nature (Bouras et al., 2019; Elsayed & Helmi, 2021). Differently from extant studies, I find that there is a positive association between returns and geopolitical events, while there is no significant relationship when geopolitical threats are considered. This may be because certain companies in the sample may benefit from geopolitical acts (e.g., defense companies or oil companies). On the contrary, volatility does respond positively and significantly to geopolitical threats, but not to the realization of these threats, precisely because, once the threat stops and materializes, the instability in the financial environment ceases.

This study differentiates itself from prior research, and aims to fill a gap in the literature, by studying the effect of geopolitical risks on European financial markets, something that has not been done before. Another interesting addition to the literature is the fact that the empirical study is conducted at firm-level, unlike previous ones, which have usually studied the impact at country-level.

The remainder of this proposal is organized as follows: Section 2 goes through prior research regarding the effects of geopolitical risks on stock returns and volatility. Section 3 provides the theoretical background and develops the research hypotheses. Section 4 describes the data set used to perform the empirical analysis and the models used to test the hypotheses. In Section 5, I present the results. Section 6 reports the robustness checks that were conducted to ensure the reliability of the analysis. Finally, Section 7 summarizes the findings and concludes this paper.

2. Literature Review

Since the publication of the paper by Caldara & Iacoviello (2018), where they construct the novel GPR index, there has been an increasing interest of researchers to explore and quantify the effects caused by geopolitical risks. Among the existing literature, most papers focus on the effect of GPRs on stock returns. However, there is a growing strand of literature that extends this analysis to other assets, such as oil (Bouoiyour et al., 2019), commodities (Ramiah et al., 2019) or precious metals (Baur & Smales, 2020). Some authors have also studied the effect of GPRs and other forms of uncertainty on corporate policies (Favara et al., 2020). Furthermore, other lines of research have focused on the predictive power GPRs may have to anticipate changes in stock prices, bitcoin returns (Bouri & Gupta, 2021) or volatility, among others.

In this regard, the study conducted by Caldara & Iacoviello (2018), where they develop a daily and monthly GPR index based on textual analysis, is at the center of this paper. These authors define geopolitical risk as the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations, to then count the occurrences of keywords related to GPRs in articles published on eleven English-language newspapers, starting in 1985[2]. The authors

[2] The daily GPR index is still being updated every day and can be retrieved from the author's website: www.matteoiacoviello.com/gpr.htm.

use this index, together with vector autoregressive (VAR) models and find that stock returns significantly decrease in an environment of heightened geopolitical risks (shown by a spike on the GPR index). However, this effect is found to be different among different industries. This index has been used by many authors for two reasons. First, it covers a wide range of geopolitical risks, so it is not only restricted to terrorist attacks, for instance (*see* Drakos, 2010; Kollias et al., 2011). Second, it captures both the risk that these events materialize, and the new risk associated with the escalation of new events. These reasons make the GPR index an appropriate way of capturing the effect of GPRs. Therefore, the present paper also utilizes it to measure the impact of GPRs on stock returns and volatility of returns.

One of the recent papers which uses the daily GPR index to measure the effect of GPRs on US stock returns and volatility is the one written by Smales (2021). This author finds evidence to support the negative relationship that exists between GPRs and stock returns. He also combines the use of univariate and multivariate GARCH models, providing evidence that shows a statistically significant positive impact of changes in geopolitical risk on oil price volatility and stock price volatility. This paper is thus related to Smales' (2021) work by adopting a similar approach. However, the author overlooks the fact that using the daily GPR index may create some noise in the regression results, although it may also provide more insight in some short-lived effects. Nevertheless, and to avoid this potential problem, the present study uses the monthly GPR index.

The third paper which is taken into consideration is the one written by Elsayed & Helmi (2021). These authors conduct a very similar study to determine the returns and volatility spillovers in MENA countries, using the GPR index. They use conditional correlation GARCH models and find evidence to support that there is a very weak correlation between stock returns and volatility, and the GPR index in MENA financial markets, except for major events such as the Arab Spring or the Yemen Civil War. Similarly, Balcilar et al. (2018) find that terrorist attacks do not trigger a significant effect on volatility (except for Japan and the UK), whereas the effect on stock market returns is significant, apart from France.

These papers evidence that results are still inconclusive. However, this could also be due to geopolitical events affecting to a greater extent those countries in which they occur, in comparison to those that are far away. This idea is worth proving, and this is precisely one of the reasons for choosing European markets. Most of the geopolitical risks documented during this century have not occurred in European territory, so one could hypothesize that European markets will be less affected and show greater resilience. On the contrary, it may also be the case that, having a stronger connection to markets outside Europe's borders, perhaps compared to other less developed countries, European companies will end up suffering more from this type of risk.

Surprisingly, this line of research has not been applied to European markets since they are considered by many to be less exposed to geopolitical risks than emerging countries (Salisu et al., 2021). Most of the literature analyzes the effect of GPRs on U.S. stock markets, while other extant studies focus on the impact on emerging countries (Bouras et al., 2019), G7 countries (Balcilar et al., 2018; Salisu et al., 2021), BRICS countries (Balcilar et al., 2018), and MENA countries (Elsayed & Helmi, 2021). This provides additional motivation for this research since carrying out a similar analysis for European countries would be an interesting addition to the existing literature.

The second contribution this paper aims to make to the literature is shedding some light on the effect of GPRs at firm-level. To the best of my knowledge, the effect of geopolitical risks on stock returns and volatility has been rarely studied at firm-level. Except for a few studies, such as the one conducted by Apergis et al. (2017), where they researched whether GPRs had a predictive effect on stock returns and volatility of 24 global defense companies, most papers have analyzed the impact on general indices, without decomposing them to discover the effect on individual stock returns. Therefore, this study aims to provide a more in-depth analysis of the impact of GPRs on returns and volatility of European companies.

Lastly, the third contribution refers to a different way of incorporating the GPR index into the regression model. Instead of using the GPR index as the main independent variable in the model, this paper uses it to calculate the individual exposure of the stock returns and volatility of each firm in the sample to changes in the GPR index. This means the model does not strictly measure the effect of GPRs on both dependent variables, but the effect of firm-level sensitivity to the percentage change in those geopolitical risks. I believe this is a novel contribution and a different way of approaching the study of the effects of geopolitical risks, both on returns and on volatility.

3. Theoretical Framework and Hypotheses

Aside from exploring the effect of GPRs on stock returns, it is equally important to discover the transmission channels through which this is happening. The literature has put forward several channels. First, it has been widely documented through previous studies that, during periods of economic uncertainty, companies tend to postpone their investment decisions (Favara et al., 2020). This is also true for consumers, who may decide to delay their purchases of non-durable goods. For instance, Berkman et al. (2011) found in their study that changes in disaster risk negatively affect expected future consumption growth, due to a decline in consumer confidence, which in turn triggers changes in returns and volatility.

Bloom (2009) simulated a macro uncertainty shock and found empirical evidence to demonstrate that, in an environment of higher uncertainty, firms also defer temporarily their hiring processes. This, together with the fall in investment rates, puts stress on financial markets and may cause stock prices to decrease, at least in the short run.

Another channel through which geopolitical risk might be transmitted to stock returns is the disruption of supply chains (as is happening now with the Ukraine-Russia war). If the supply side is affected by higher geopolitical risk, and the demand for a specific product is not being satisfied, then prices of products may rise. If, on the other hand, the risk has an impact on the demand side, prices would fall (Smales, 2021). If prices are modified in either direction, then it is almost certain that this will trigger changes in stock returns. This effect has been analyzed in previous studies, such as the one conducted by Hendricks & Singhal (2003). The evidence from this study suggests that announcements regarding production or shipment delays triggered an abnormal decrease in shareholder value of 10.28 percent, although the effect depended on the size of the firm and their growth prospects. Other authors, such as Baghersad & Zobel (2021) also documented the same effect.

Lastly, there may also be a link between geopolitical risk and outflows of capital. Recent research has suggested that there is a flight of capital away from countries with high geopolitical risk to those with lower, which are considered safer and less exposed to this risk (Caldara & Iacoviello, 2018). Companies might even decide to cease operations in these countries. This has been seen in the case of the Russian invasion of Ukraine where, since February 24th, over 450 companies have withdrawn from Russia (Sonnenfeld and Tian, 2022), provoking a crash in Russian markets.

Based on the above-mentioned previous research, the aim of this paper is to specifically explore the effect of geopolitical risks on the stock returns and volatility of European companies. To do this, this study tests the following hypotheses against the data:

Hypothesis 1. Geopolitical risks influence stock returns in Europe.

As mentioned, geopolitical risks may be transmitted to stock returns via diverse channels. Since the GPR index is used to measure geopolitical risk, and this risk only considers terrorism, war, or threats of war (therefore, only negative news), the relationship between GPRs and stock returns is predicted to be negative. Berkman et al. (2011) point out that the more severe a crisis is, the stronger the effect on stock returns.

Hypothesis 2. Geopolitical risks influence volatility in European financial markets.

Berkman et al. (2011), among other authors, find empirical proof that geopolitical risks tend to affect volatility more than stock returns. They state that, during an international crisis, the volatility of world market returns increases, to decrease back again once it finishes. Similar results were reported by Gkillas et al. (2018), who went one step further and were also able to find evidence to demonstrate that geopolitical risk drives changes in volatility by affecting volatility jumps.

Hypothesis 3. Geopolitical threats have a greater effect on stock returns than geopolitical events.

Hypothesis 4. Geopolitical threats have a greater effect on volatility than geopolitical events.

The expected result is that geopolitical threats will have a greater effect both on stock returns and on volatility. According to the Efficient Market Hypothesis (EMH), which states that stock prices fully reflect all the available information about the stock (Fama, 1970), all the financial uncertainty should be already absorbed by the market before the uncertainty is resolved. It could also be that the event solves the uncertainty that is driving the movements in the market, as Caldara & Iacoviello (2018) point out in their study. This is also what most of the research shows, regarding stock returns (Baker et al., 2016; Salisu et al., 2021), and volatility (Gkillas et al., 2018).

4. Data and Methodology

4.1. Data

To investigate the impact of geopolitical risks on stock returns and volatility of European companies listed in the STOXX Europe 600, a sample period which ranges from January 1st, 2000, to December 31st, 2021, is used. This period is selected to cover the geopolitical risks documented during the 21st century. Since the models have an annual frequency, the end date is driven by the availability of the variables which are part of the model, at the time of starting the empirical analysis.

The companies in the sample are limited to those that were part of the STOXX Europe 600 index at some point during the sample period. This is due to two reasons. First, the STOXX Europe 600 gathers European companies from seventeen different countries[3], accounting for approximately 96 percent of the overall market capitalization. Therefore, this index and the companies listed there, provide a representative sample of financial markets in the European region. Second, to avoid survivorship bias, I include all the companies that were part of the index at some point, without applying additional selection criteria. The list of the index constituents during the sample period has been retrieved from the Compustat database. After removing duplicates and those companies that did not have at least two consecutive observations for every variable used in the models, the data set comprises 1,378 companies and covers a time span of 21 years. Nevertheless, it should be noted that this study deals with an unbalanced panel data set, meaning not all the companies have observations for all time periods due to corporate reasons, such as the disappearance of a company as a result of being acquired by another, mergers, or extinction of a specific company.

4.1.1. Dependent variables

The first dependent variable in this study is the annual returns for each company during the sample period. The returns of the index itself are also collected to explore the difference between firm returns and index returns. However, these are collected with a monthly frequency, with the intention of increasing the number of observations, in order to have a representative sample. Both are collected from Factset since they are readily available.

The dependent variable for the third model is the annual volatility of returns. Daily stock returns are used to calculate the realized volatility estimates for each year. Annual realized volatility is thus equal to the square root of the sum of the daily squared returns over a year (assuming 252 business days per year). This is a common assumption when annualizing daily volatility (*see* Engle, 2002; Fleming et al., 2003). The equation below shows the formula used for calculating the annual volatility.

[3] Companies in the following countries are eligible to be included in the STOXX Europe 600: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK.

$$\sigma_{i,t} = \sqrt{\sum_{i=1}^{N=252} r_{i,t}^2}$$

The annual realized volatility estimates are used to examine the effects of geopolitical risk on the volatility of returns, as previous studies have done before (Pástor & Veronesi, 2013; Balcilar et al., 2018).

4.1.2. Independent variables

To test the four hypotheses, the main variable of interest is constructed based on the monthly GPR index, which represents geopolitical risks. This index has been created by Caldara & Iacoviello (2018) and is available on their website. Instead of directly using the GPR index in the model, as existing studies have done before, this paper calculates the individual exposure of each firm in the sample to the percentage change in the GPR index. To do this, the past 36 monthly returns of each company are regressed on the past 36 percentage changes of the monthly GPR index. For instance, taking year 2021 as an example, the monthly percentage change of the GPR index from 2018 to 2020 is used to measure the exposure of the company's returns on this same period. This is done by using the following equation:

$$return_{i,t} = \alpha_0 + \alpha_1 \Delta GPR_t + \varepsilon_{i,t}, \quad (1)$$

where $return_{i,t}$ denotes the monthly returns of firm *i* over the most recent three years and ΔGPR_t represents the percentage changes in the GPR index over the past 36 months, calculated as $[(GPR_t - GPR_{t-1})/GPR_{t-1}]*100$. α_1 therefore, gauges the annual, firm-specific exposure of returns to changes in GPRs. Since the same time frame as for the stock returns is used, the exposure is considered with an annual frequency from 2000 to 2021.

This method of calculating the exposure of returns to different variables is not uncommon in the literature. For instance, Favara et al. (2020) calculate industry's exposure to GPRs by estimating the beta of the industry's monthly returns to the change in GPR index, using a 60-month rolling regression. Hong & Kacperczyk (2009) calculate the firm's time-varying, industry beta by using monthly returns in the past 36 months. Similarly, Montone et al. (2021) calculate sentiment betas by regressing five-year monthly excess stock returns on an investor sentiment index. Therefore, taking these papers as reference, this study mimics this method to make a novel contribution to the existing literature on geopolitical risks, by focusing on the sensitivity of returns to the changes in the GPR index, rather than only utilizing the index.

The same method is used when calculating the exposure of the volatility of returns to geopolitical risks. Therefore, the past 36 monthly volatility estimates of each individual firm are regressed on the past 36 percentage changes of the monthly GPR index.

Caldara & Iacoviello (2018) decompose the GPR index into two additional subindices, one which covers geopolitical threats and tensions, while the other refers to geopolitical events and acts. They do so by grouping different types of keywords into groups numbered from one to six. Those related to geopolitical threats are part of groups one to four, while those that refer to geopolitical events are included in groups five and six. For instance, groups three and four only include words that describe war threats and terrorist threats. This helps in differentiating perceived from realized geopolitical risk (Phan et al., 2021). Therefore, the method illustrated above is applied considering both indices, the one that refers to threats, and the one that refers to events. This gives rise to two different independent variables in the regression equation, GPR^{Threat} and GPR^{Act}, as a way of distinguishing the impact of geopolitical tensions from the impact of materialized events.

4.1.3. Control variables

Several control variables are included in the regression model. The first one is the oil price of the European Brent crude (in euros), which is retrieved from Factset. Previous literature highlights its connection with stock returns of advanced economies (Wei, 2003; Bouoiyour et al., 2019). Furthermore, Smales (2021) finds evidence to show that geopolitical risk is positively correlated with oil prices. As GPRs increase, oil prices rise.

Oil price has also been found to influence stock returns volatility. For instance, Schwert (1989) finds that oil shocks, such as the OPEC shock, trigger a rise in the volatility of stocks and bond returns. Similarly, Bastianin et al. (2016) found evidence to suggest that, even though oil supply shocks do not affect market volatility of the G7 stock markets, demand shocks do affect it.

The VSTOXX50 index (‘the European VIX’) is also used as a control variable. Previous literature recommends this to differentiate the effects caused by market risk from those that arise solely from geopolitical risks (Caldara & Iacoviello, 2018), which is what this study is interested in. Moreover, as Baker et al. (2016) mention in their paper, indices such as the VIX, measure or refer to uncertainty about equity returns. Thus, it is important to consider it as a control variable. The values of the VSTOXX50 index are also retrieved from Factset. Since these two control variables will only be part of the first model (measuring the relationship between index returns and GPRs), they will be considered with a monthly frequency, extending from January 2000 to December 2021.

Lastly, I introduce other control variables related to company characteristics, which have been widely used in asset pricing models. These variables are retrieved either from Factset or Eikon. To be consistent throughout the empirical analysis, all the variables in the model are considered with an annual frequency and extend from January 1st, 2000, to December 31st, 2021. The first of the control variables is the natural logarithm of the market capitalization of each company contained in the index (named as *logSize),* calculated by multiplying the common shares outstanding at the end of each year by the price per share, and measured in millions of euros. This variable accounts for the size of the company (Hong & Kacperczyk, 2009). As a proxy for firm performance, the return on equity at the end of each of the years covered in the sample period (*ROE)* is also included in the specification of the model. Some authors have previously used ROE as a control variable for the firm's profitability (Hong & Kacperczyk, 2009; Phan et al., 2021).

Following the well-known model proposed by Fama & French (1993), and as many other later studies have also done, the natural logarithm of the yearly book-to-market ratio (*logBMR)* is incorporated into the regression equation. These authors found evidence to prove that stocks with high book-to-market ratios generate higher returns than the market average. Therefore, this variable is introduced to control for this circumstance. Nevertheless, it is introduced as its natural logarithm, to avoid having negative values and to correct for the presence of outliers (Hong & Kacperczyk, 2009).

The natural logarithm of the price-to-earnings ratio (*logPE)* of each individual company is included as a measure of the valuation of a firm. Previous literature tends to include a valuation ratio when analyzing the effect of different variables on stock returns (Hong & Kacperczyk, 2009). For instance, Berkman et al. (2011) find that both the PE ratio and the dividend yield for the S&P500 index are significantly positively correlated with crisis risk.

The annual volatility of returns for each individual firm also serves as a control variable. Previous studies such as the one conducted by Duffee (1995) document a strong contemporaneous relationship between volatility and firm stock returns. For this reason, it is included in the regression model as the last control variable. Moreover, I include a dummy variable for years and another one for the countries where the companies are based in.

To estimate the regression for volatility of returns, different control variables are used. The size of the company remains in this third model, since it has been documented by different authors that large firms tend to experience lower volatility of returns (Bae et al., 2004). Moreover, leverage is another firm characteristic that has been extensively used as a control variable in studies regarding the volatility of returns at firm-level. Leverage appears to be positively correlated with volatility. This could be because investors perceive stocks from highly leveraged companies as riskier, due to a greater bankruptcy risk (Bae et al., 2004). Even though many different leverage ratios have been used in the literature, this study uses the ratio of total debt to total assets. Annual share turnover (*Turnover*), calculated as the average daily number of shares traded during a year divided by the number of shares outstanding at the end of the year, is also part of the model, based on existing studies (Chen et al., 2013; Li et al., 2011). It is a widely held view that firms with a high trading turnover are more volatile, therefore it is worth controlling for this possible effect. Finally, I include the lagged volatility as the last control variable in the regression model, to control for autocorrelation (Chen et al., 2013). As in the previous model, dummy variables for years and countries are also included. Table 1 summarizes the variables that are used in the study.

Table 1. Definitions of variables

Variable	Definition	Data source
Dependent variables		
Returns	Annual stock returns for each company in the sample	Factset and Compustat
Volatility	Annual volatility of firm stock returns calculated from daily returns	Calculated with Factset's data
Independent variables (Geopolitical risk measures)		
GPR^{Threat}	Annual firm exposure to changes in the Geopolitical Risk Threat Index	Calculated based on Caldara & Iacovello (2018)
GPR^{Act}	Annual firm exposure to changes in the Geopolitical Risk Acts Index	Calculated based on Caldara & Iacovello (2018)
Control variables		
OilPrice	Monthly prices of the European Brent crude	Factset
VSTOXX50	Monthly estimates for the VSTOXX 50 index, as a measure of implied volatility	Factset
logSize	Natural logarithm of the year-end market capitalization computed by multiplying common shares outstanding times the share price	Calculated with Factset's data
ROE	Return on equity	Factset
logBMR	Natural logarithm of the book-to-market ratio	Factset
logPE	Natural logarithm of the price-to-earnings ratio	Factset
FirmVolatility	Annual volatility of stock returns	Calculated with Factset's data
Leverage	Total debt to total assets ratio	Factset
Turnover	Average number of shares traded in a year divided by the number of shares outstanding at the end of the year	Calculated with Eikon and Factset's data
LagVolatility	Lagged volatility of stock returns	Generated in Stata

4.2. Methodology

The first regression model consists of a time series model, where the dependent variable is the monthly returns of the STOXX Europe 600 index during the mentioned sample period. This serves as a preliminary regression to compare the effect of geopolitical risks on the index, to the individualized effect on the listed European companies. It should be noted that when analyzing the impact on the STOXX Europe 600 (therefore, not at firm-level), control variables related to the firm's characteristics are not included in the regression equation. Therefore, to investigate the relationship between geopolitical risks and index returns, Equation 2 is estimated:

$$Returns_t = \beta_1 \Delta GPR_t^{Threat} + \beta_2 \Delta GPR_t^{Act} + \beta_3 VSTOXX50_t + \beta_4 OilPrice_t + u_t \quad (2)$$

where $Returns_t$ denotes the index's monthly returns, ΔGPR_t refers to the monthly percentage change in the geopolitical risk index, as constructed by Caldara & Iacovello (2018), disaggregated into threats and acts, $VSTOXX50_t$ represents the index to measure implied volatility, $OilPrice_t$ captures the price of the Brent crude, and u_t is the Newey-West standard error.

To measure the causality between the independent variables and the annual returns at firm-level, a panel data model is used. The regression is first done without control variables (including only the independent variables related to the GPR index), to check if the effect changes when introducing these variables, and how it changes. Therefore, to test Hypothesis 1 and 3, the following panel data econometric model is employed:

$$Returns_{i,t} = \alpha_i + \beta_1 GPR_{i,t}^{Threat} + \beta_2 GPR_{i,t}^{Act} + \beta_3 logSize_{i,t} + \beta_4 ROE_{i,t} + \beta_5 logBMR_{i,t} + \beta_6 logPE_{i,t} + \beta_7 FirmVolatility_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where $Returns_{i,t}$ denotes the stock returns of firm i and year t, α_i are firm-fixed effects, $GPR_{i,t}$ measures the exposure of returns to changes in the GPR threat or act index of firm i and year t, $logSize_{i,t}$ refers to the natural logarithm of the market capitalization of company i at the end of year t, $ROE_{i,t}$ is the return on equity, $logBMR_{i,t}$ represents the natural logarithm of the book-to-market ratio, $logPE_{i,t}$ denotes the natural logarithm of the price-to-earnings ratio of company i at the end of year t, whereas $FirmVolatility_{i,t}$ measures the volatility of returns of firm i and year t.

The last regression equation shown below (Equation 4) is used to measure the relationship between the annual volatility of returns at firm-level and GPRs, and therefore to test Hypothesis 2 and 4.

$$Volatility_{i,t} = \alpha_i + \beta_1 GPR_{i,t}^{Threat} + \beta_2 GPR_{i,t}^{Act} + \beta_3 logSize_{i,t} + \beta_4 Leverage_{i,t} + \beta_5 Turnover_{i,t} + \beta_6 LagVolatility_{i,t-1} + \varepsilon_{i,t}, \quad (4)$$

where $Volatility_{i,t}$ denotes the volatility of returns of firm i and year t, $GPR_{i,t}$ measures the exposure of volatility to changes in the GPR threat or act index of firm i and year t,

$Leverage_{i,t}$ measures firm's i leverage ratio at the end of year t, $Turnover_{i,t}$ refers to firm's i share turnover and year t, and $LagVolatility_{i,t}$ represents the one-year lagged volatility.

Authors have measured the effect of geopolitical risks on different variables (i.e., stock returns, oil prices or volatility, among others) in a variety of ways. Event study methodology has been applied by some authors when studying the effects of specific geopolitical events (Omar et al., 2017). For instance, Kollias et al. (2011) studied the effect on stock returns of the Madrid and London terrorist attacks. Quantile analysis has also been used by several authors to investigate this (Balcilar et al., 2018; Gkillas et al., 2018). On the other hand, others perform a panel data regression, usually with a fixed-effects model (Baker et al., 2016; Bouras et al., 2019; Phan et al., 2021).

This paper adopts the latter methodological approach, where a panel regression is employed to estimate the effect of GPRs. To select the most suitable type of model and decide between a random effect or a fixed-effects model, the so-called Hausman test (Hausman, 1978), is performed. The Hausman test assesses the suitability of both models, by determining if the individual-specific effects (represented by the constant α_i) are correlated with the independent variables. If they are, then the fixed-effects model is chosen over the random effect model (Wooldridge, 2016). The constant will be firm-specific and will allow to control for potential heterogeneities across companies.

5. Results

5.1. Descriptive statistics

Table 2 below shows the mean, standard deviation, maximum and minimum values for the variables used in the time series regression, over the sample period January 2000 to December 2021, with a total of 264 monthly observations. The index's average monthly return during the sample period is of 0.19 percent.

Table 2. Descriptive statistics for time series regression

Variable	Obs.	Mean	Std. Dev.	Min	Max
Returns	264	0.1924	4.3815	-14.7992	13.7279
GPR^{Threat}	264	3.3521	32.6170	-46.1598	371.0481
GPR^{Act}	264	6.4773	68.8629	-54.3280	1,023.184
VSTOXX50	264	23.6453	8.9081	11.9864	61.34
OilPrice	264	51.8196	19.0492	21.2186	92.2730

As Table 2 documents there is a major difference between the minimum and maximum values of both GPR variables. The spike for the variable GPR^{Act} takes a value of 1023.18 and coincides with the 9/11 terrorist attacks, whereas the maximum value for the GPR^{Threat} variables increases up to 371.05 and is associated to the outbreak of the war in Iraq in March 2003. The minimum values for both variables are associated with periods of international geopolitical stability.

Secondly, we present the summary statistics for the firm-level variables used in the returns model (Equation 3). As can be seen in Table 3, stock returns for all companies in the sample have an annual average of 11.1 percent. Based on the minimum and maximum values, returns appear to be quite volatile. The average firm-level exposure to changes in geopolitical risks, decomposed into threats and acts, is found to be -0.006 and 0.014, respectively. This shows the exposure to geopolitical threats is negative on average, causing a decline in stock returns, while it appears to be positive for geopolitical acts. In the empirical analysis that follows in the next section, I dive deeper into these values to shed light on the relationship between returns and GPRs. Regarding the variables corresponding to company characteristics, they show similar values to those reported in other studies (i.e., Hong & Kacperczyk, 2009).

Table 3. Descriptive statistics for firm-level variables in returns model

Variable	Obs.	Mean	Std. Dev.	Min	Max
Returns	21,266	11.1020	49.6008	-99.7975	1,598.276
GPR^{Threat}	22,612	-0.0056	0.1392	-6.6252	6.2089
GPR^{Act}	22,612	0.0138	0.2037	-24.7339	4.7173
logSize	21,712	8.1960	1.7984	-6.956	14.0801
logBMR	21,067	-0.9780	1.2310	-7.6743	6.9476
ROE	22,182	12.1856	165.5618	-17098.8	5,676.923
logPE	18,386	2.8922	0.8285	-3.3673	12.0668
FirmVolatility	22,013	35.5515	22.5719	0.2841	1234.39

Lastly, Table 4 illustrates the descriptive analysis of companies' volatility of returns. The annual average volatility for companies in the sample is equal to 35.89 percent. As expected, volatility values are quite dispersed, something that is also confirmed by the high standard deviation. At first glance, given the higher average value of the exposure to GPRs of returns and volatility, it seems that returns are more sensitive to GPRs than volatility (-0.003 as the exposure of volatility to changes in geopolitical threats versus -0.006 as the exposure of returns). Nevertheless, the causal relationship between these variables is analyzed in the following section.

Table 4. Descriptive statistics for firm-level volatility model.

Variable	Obs	Mean	Std. Dev.	Min	Max
Volatility	22,523	35.8871	22.9376	0.2841	1,234.391
GPR^{Threat}	23,361	-0.0028	0.1237	-13.7318	3.5712
GPR^{Act}	23,361	-0.0023	0.1254	-7.0279	8.8728
logSize	22,174	8.1721	1.8111	-6.956	14.0801
Leverage	23,541	0.2706	0.4475	0	27.8922
Turnover	21,164	0.0085	0.2720	0	27.9990
LagVolatility	21,575	36.1114	23.1719	0.2841	1,234.391

5.2. Empirical results

The empirical analysis is performed in three stages. First, I study if there is a causal relationship between geopolitical risks and index returns by performing a monthly time series regression. Second, I use a fixed-effects panel data model to explore how GPRs influence firm-level returns of companies in the sample. Finally, a similar regression is conducted to analyze if GPRs affect the volatility of returns of individual firms.

5.2.1. Time series regression

As a preliminary test, I study the relationship between monthly returns of the STOXX Europe 600 index between 2000 and 2021, and the GPR independent variables, namely GPR^{Threat} and GPR^{Act}. This is done by using a time series regression, following Eq. (2). Table 5 reports the results of this regression.

After controlling for the implied volatility, using as a proxy the VSTOXX50 index, and for the price of the Brent crude oil, column (4) indicates that GPR^{Threat} has a negative, statistically significant (at a ten percent significance level) association with the index returns. As GPR^{Threat} increases by one percent (meaning geopolitical risks are heightened), index returns decrease by 0.02 percent. This result was expected and has economic significance, indicating that stock returns can be negatively affected by an increase in geopolitical risks. On the contrary, the relationship between stock returns and the percentage change in the index for geopolitical acts is not statistically significant. Furthermore, the coefficient for GPR^{Act} is positive, reflecting the opposite relationship: as the GPR index for acts increases, the returns of the STOXX Europe 600 index increase too. This is true even when taking the natural logarithm of both independent variables, to correct for potential outliers.

For comparative purposes, as well as to avoid potential problems due to multicollinearity, the same regression was carried out with both independent variables separately, as can be seen in columns 2 and 3. The results change. While GPR^{Threat} still maintains a negative coefficient, it becomes significant even at the one percent level. The coefficient for GPR^{Act} also becomes statistically significant, representing a negative relationship with the index returns. It can also be seen how this coefficient is lower than in the case of the GPR^{Threat} variable, which suggests that geopolitical threats have a greater effect on returns than geopolitical acts.

On the other hand, both control variables do have a significant relationship with the index returns, when introduced in the model. Implied volatility is negatively and significantly associated with index returns, showing that as volatility in the market increases, returns decrease. The relationship between oil prices and returns is positive.

Table 5. Baseline results for time series regression

Variables	(1) Returns	(2) Returns	(3) Returns	(4) Returns
GPR^{Threat}	-0.0206	-0.0159***		-0.0204*
	(0.0141)	(0.0056)		(0.0114)
GPR^{Act}	-0.0005		-0.0048**	0.0028
	(0.0058)		(0.0021)	(0.0046)
VSTOXX50		-0.184***	-0.187***	-0.185***
		(0.0333)	(0.0330)	(0.0332)
D.OilPrice		0.244***	0.243***	0.246***
		(0.0556)	(0.0554)	(0.0558)
Constant	0.265	4.581***	4.608***	4.587***
	(0.287)	(0.683)	(0.682)	(0.682)
Observations	264	263	263	263
F-Stat	5.345	36.21	32.64	26.74
Prob > F	0.0053	0	0	0

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts on STOXX Europe 600 index returns based on the following regression model: $Returns_t = \beta_1 \Delta GPR_t^{Threat} + \beta_2 \Delta GPR_t^{Act} + \beta_3 VSTOXX50_t + \beta_4 OilPrice_t + u_t$. Newey-West standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

5.2.2. Fixed-effects regression on returns

There is evidence in the literature (Fama & French, 1993; Hong & Kacperczyk, 2009) that several company characteristics, such as size, book-to-market ratio or firm-specific volatility affect the evolution of firm returns. To further understand the relationship between GPRs and stock returns, I now conduct the same analysis at firm-level by including some of these company-specific characteristics and a large set of 1,313 companies that were listed at some point in the STOXX Europe 600, to test Hypothesis 1 and 3. Estimated coefficients for the model in Eq. (3) are reported in Table 6.

Table 6. Panel A: Stock returns and GPRs.

Variables	(1) Fixed-effects: Returns	(1) Fixed-effects: Returns	(2) Fixed-effects: Returns	(3) Fixed-effects: Returns
GPR^{Threat}	-24.62***	-0.184		-0.885
	(6.353)	(2.729)		(2.720)
GPR^{Act}	1.999		3.262*	3.330*
	(1.719)		(1.773)	(1.797)
logSize		0.211	0.209	0.216
		(1.071)	(1.067)	(1.069)
logBMR		-19.65***	-19.64***	-19.64***
		(1.365)	(1.362)	(1.363)
ROE		-0.0117	-0.0117	-0.0117
		(0.0079)	(0.0079)	(0.0079)
logPE		0.0882	0.0917	0.0897
		(0.638)	(0.638)	(0.638)
FirmVolatility		0.263***	0.262***	0.263***
		(0.0902)	(0.0901)	(0.0901)
Constant	10.91***	-27.29***	-27.14***	-27.18***
	(0.0470)	(9.401)	(9.371)	(9.389)
Observations	21,169	17,648	17,648	17,648
R-squared	0.004	0.284	0.284	0.284
Number of Firms	1,315	1,313	1,313	1,313
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts on firm-level returns based on the following regression model: $Returns_{i,t} = \alpha_i + \beta_1 GPR_{i,t}^{Threat} + \beta_2 GPR_{i,t}^{Act} + +\beta_3 logSize_{i,t} + \beta_4 ROE_{i,t} + \beta_5 logBMR_{i,t} + \beta_6 PE_{i,t} + \beta_7 FirmVolatility_{i,t} + \varepsilon_{i,t}$. Clustered standard errors at firm-level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

As the first column shows, without control variables, only the coefficient for the variable GPR^{Threat} has statistical significance, implying that returns respond negatively to an increase in geopolitical threats. However, when the control variables are introduced in the model, including year and country fixed effects to control for the variation in factors each year, only GPR^{Act} is statistically significant at a ten percent significance level. Unlike most of previous studies, there seems to be a positive association between stock returns and geopolitical acts, whereby one percent increase in the exposure to the geopolitical act index causes returns to increase by 3.33 percent. This relationship departs from the results obtained in previous studies, such as the one by Smales (2021), who finds a negative association between S&P500 stock returns and both GPR magnitudes. Even if this is not the expected sign for this coefficient, there are some other studies that have also found the relationship between the geopolitical act index and returns to be positive.

Such is the case of the study conducted by Caldara & Iacoviello (2018), where they conclude that, while world stock returns react negatively to GPT shocks, they react positively to GPA shocks. This conclusion is in line with my results. Therefore, it seems that, depending on the type of geopolitical risk considered, the subsequent response of returns varies. When considering returns at firm-level and the individual exposure of each firm to changes in GPR, the positive coefficient could mean that there are companies in the sample that are benefiting from geopolitical events.

Regarding the variable GPR^{Threat}, its coefficient shows a negative relationship between stock returns and geopolitical threats, in line with that previous studies report (Caldara & Iacovello, 2018; Salisu et al., 2021; Smales, 2021); nevertheless, this is not statistically significant at any significance level. Therefore, according to these results, the relationship between firm-level stock returns and geopolitical risks appears to be driven by GPR acts rather than GPR threats. The same signs for both coefficients maintain when each GPR variable is included separately in the regression models, as can be seen in columns (2) and (3), and only GPR^{Act} remains significant.

5.2.3. Fixed-effects regression on volatility

Estimated regression coefficients for the second baseline panel data model (Eq. 4) are documented in Table 7. The first column shows the regression, where volatility acts as the dependent variable, and GPR^{Threat} and GPR^{Act} as the independent variables. The remaining columns also include firm-specific control variables and year and country fixed effects.

Regarding the relationship between geopolitical risks and volatility of returns, I find that GPR^{Threat} is positively associated with volatility, indicating that firm volatility increases (declines) as geopolitical threats increase (decrease). The coefficient of GPR^{Threat} is equal to 29.68, and statistically significant at the five percent level. Hence, a percentage increase in the exposure to the geopolitical threat index, increases firm volatility by almost thirty percent. This supports Hypothesis 2 and is consistent with geopolitical threats creating an extremely uncertain environment, which in turn increases volatility in the markets.

On the other hand, the coefficient of GPR^{Act} is found to be statistically insignificant. The relationship with volatility of returns appears to be negative. This could be due to the fact that, once the threat materializes and the geopolitical event takes place, the certainty in the financial environment is restored, forcing volatility to decrease (Caldara &

Iacoviello, 2018). The statistical insignificance of this second independent variable proves Hypothesis 4, meaning that volatility of returns is driven by geopolitical threats, rather than by geopolitical events. The size of the coefficients also reveals that geopolitical risks affect volatility to a greater extent than they do affect stock returns, meaning volatility is more sensitive than returns to changes in the global geopolitical situation. This is in line with the findings and conclusions of extant studies (Apergis et al., 2017; Balcilar et al., 2018). Nevertheless, coefficients for both independent variables seem to be quite high. This could imply that they may be affected by outliers in the sample, something that will be checked in the next section through a robustness test.

Table 7. Panel B: Volatility of returns and GPRs.

Variables	(1) Fixed-effects: Volatility	(2) Fixed-effects: Volatility	(3) Fixed-effects: Volatility	(4) Fixed-effects: Volatility
GPR^{Threat}	11.99	15.04		29.69**
	(12.76)	(11.02)		(15.11)
GPR^{Act}	-61.58***		-143.5	-205.9
	(6.944)		(130.6)	(126.4)
logSize		-4.460***	-4.559***	-4.302***
		(0.405)	(0.421)	(0.291)
Leverage		5.691*	6.593*	6.230*
		(3.427)	(3.574)	(3.666)
Turnover		-0.0006***	-0.0010**	-0.0013**
		(0.0002)	(0.0005)	(0.0005)
LagVolatility		0.449***	0.431***	0.459***
		(0.0198)	(0.0292)	(0.0194)
Constant	35.89***	76.07***	76.43***	72.85***
	(0.0185)	(4.516)	(4.494)	(3.033)
Observations	22,047	19,162	19,162	19,162
R-squared	0.036	0.430	0.448	0.476
Number of Firms	1,378	1,371	1,371	1,371
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts on firm-level volatility of returns based on the following regression model: $Volatility_{i,t} = \alpha_i + \beta_1 GPR_{i,t}^{Threat} + \beta_2 GPR_{i,t}^{Act} + +\beta_3 logSize_{i,t} + \beta_4 Leverage_{i,t} + \beta_5 Turnover_{i,t} + \beta_6 LagVolatility_{i,t-1} + \varepsilon_{i,t}$. Clustered standard errors at firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

6. Robustness

6.1. Diagnostic tests

A battery of diagnostic tests is performed before carrying out the regressions described in the previous section, to ensure reliable results. The results of these preliminary analyses can be found in the Appendix. Firstly, the presence of unit roots in the time series regression is checked using the Augmented Dickey Fuller (ADF) test (Dickey & Fuller, 1981). Most financial time series such as the ones involving stock prices are highly persistent, therefore it is imperative to check their stationarity to obtain reliable results. Section A1 reports the results of both time series and panel data unit root tests. Exhibit A shows that the ADF test rejects the null hypothesis of unit roots at the one percent significance level, except for the oil price series. The variable 'OilPrice' is found to be first-difference stationary, therefore it is included as such in the model. In the case of both panel data models, the Fisher test (Fisher, 1932) is used to check for unit roots. This test is chosen because it allows for unbalanced panels (Maddala & Wu, 1999), as is the case with the data sets used in this study. As Exhibit B and C report, no unit roots were found in the firm-specific variables part of these models, at all levels of statistical significance.

Another potential source of concern is the presence of multicollinearity between the variables in the model. To account for the problems derived from multicollinearity, the correlation between the independent and control variables is checked by constructing a correlation coefficient matrix and calculating the Variance Inflation Factor (VIF). Collinearity might be especially relevant when it comes to the GPR subindices, GPR^{Threat} and GPR^{Act}, since both variables may be correlated to some extent. As Table A2.2 shows, correlation between both independent variables is 0.77. Even though the correlation seems high, the calculated VIF factor (not reported) is lower than 5, suggesting multicollinearity is not a concern in this model. In any case, to avoid this potential problem, the three regressions were conducted with both independent variables separately, as already reported and explained in the previous section. For the rest of the variables, no multicollinearity is detected with these tests.

Thirdly, to select the appropriate model between fixed-effects or random effects for the panel data models, the Hausman test is performed (Hausman, 1978). As shown both in Table A3.5 and A3.6 in the appendix, the results of the Hausman test show evidence to reject the null hypothesis statement, where the random effect model is preferred to the fixed-effects one. Therefore, this is the rationale to choose the fixed-effects specification, as it will yield more consistent estimates.

An important potential problem is heteroskedasticity, which is tested using the Breusch-Pagan test. The squared residuals (calculated from the residuals of the regressions for the three models used in this paper) are regressed on the explanatory variables. For each of them, the F-statistic is checked. There is evidence to reject the null hypothesis (F-statistic is smaller than 0.05), meaning the model is not homoscedastic (see tables in Section A4 in the Appendix).

Lastly, I test for the presence of serial correlation in the residuals of the models using the Breusch-Godfrey test. The residuals of the regressions are used as the dependent variable, while the lagged values of these residuals, together with the regressors, serve as the independent variables (Wooldridge, 2016). Tables in Section A5 show the lagged residuals are statistically significant, meaning there is no support of the null hypothesis of no autocorrelation for the first lag (the others are not reported). Since both heteroskedasticity and autocorrelation are present in the models, I therefore use robust standard errors to perform the time series regression, and clustered standard errors at firm level for both panel data models, which control for both issues, ensuring robustness of the estimated models.

6.2. Robustness checks

I conduct two robustness tests for both panel data models to validate my findings, and an additional one for the volatility model. Firstly, I determine the robustness of my results by considering an alternative time frame when calculating firm-level exposure to changes in geopolitical risks. Instead of regressing the past 36 monthly returns (and then the estimates for volatility of returns) on the past 36 changes in the GPR index, I now do the same considering only the past 24 points of data. Results are shown in Table 8 and 9, for returns and volatility, respectively.

Table 8 shows that when only the last 24 months of returns and changes in the GPR index are considered to build the GPR variables, the results change completely. Although the signs of the coefficients remain the same, the statistical significance changes. In my main model, GPR^{Act} seemed to lead the influence on returns. In contrast, in this model it appears to be driven by the GPR^{Threat} variable, as it is the only significant variable in the three different reported specifications. These results are more in line with the findings of previous studies, who have often concluded that geopolitical threats are more important than events in predicting and affecting returns, as already discussed in the results section. Furthermore, most of previous studies have also found that the relationship between GPRs and returns is negative (Smales, 2021), as is the case with this alternative specification. Overall, the robustness estimation results of the model do not support my main findings when *Returns* acts as the dependent variable, but they do support my initial hypotheses (Hypothesis 1 and 3).

Table 8. Panel A: Robustness check

Variables	(1) Fixed-effects: Returns	(2) Fixed-effects: Returns	(3) Fixed-effects: Returns	(4) Fixed-effects: Returns
GPR^{Threat}	4.285*	-4.308*		-5.137**
	(2.527)	(2.450)		(2.470)
GPR^{Act}	-0.667		1.526	2.417
	(2.773)		(1.417)	(1.492)
logSize		0.242	0.209	0.248
		(1.070)	(1.068)	(1.069)
logBMR		-19.64***	-19.65***	-19.63***
		(1.366)	(1.363)	(1.365)
ROE		-0.0117	-0.0117	-0.0117
		(0.0078)	(0.0079)	(0.0078)
logPE		0.0719	0.0907	0.0720
		(0.638)	(0.638)	(0.638)
FirmVolatility		0.262***	0.263***	0.261***
		(0.0901)	(0.0901)	(0.0901)
Constant	11.10***	-27.16***	-27.34***	-27.23***
	(0.0618)	(9.388)	(9.387)	(9.388)
Observations	21,169	17,648	17,648	17,648
R-squared	0.000	0.284	0.284	0.284
Number of Firms	1,315	1,313	1,313	1,313
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts (calculated using the past 24 points of data) on firm-level returns.
Clustered standard errors at firm-level are reported in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

On the other hand, the results for volatility are generally robust to whether the 3-year or the 1-year past points of data are used to calculate the exposure to GPRs. As can be seen in Table 9, the signs of the coefficients remain the same for the four specifications. When considered separately, the independent variables are still not statistically significant, but both become significant when they are together in the regression equation, with and without control variables. Therefore, the same relationship between volatility of returns and GPRs is maintained, although the coefficients greatly decrease in size. I now find that as the exposure to geopolitical threats increase by one percent, firm volatility increases by almost seven percent. This could be due to the presence of outliers in the sample, something that will be checked by means of another robustness test.

Table 9. Panel B: Robustness check

Variables	(1) Fixed-effects: Volatility	(2) Fixed-effects: Volatility	(3) Fixed-effects: Volatility	(4) Fixed-effects: Volatility
GPR^{Threat}	3.403**	3.961		6.985***
	(1.723)	(2.803)		(2.703)
GPR^{Act}	-13.89***		-5.894	-11.51**
	(5.136)		(5.845)	(5.070)
logSize		-4.181***	-4.193***	-4.134***
		(0.281)	(0.285)	(0.280)
Leverage		5.698	5.841	5.725
		(3.820)	(3.789)	(3.795)
Turnover		-0.0005**	-0.0005**	-0.0005***
		(0.0002)	(0.0002)	(0.0002)
LagVolatility		0.450***	0.450***	0.459***
		(0.0199)	(0.0220)	(0.0196)
Constant	36.02***	72.87***	73.10***	72.36***
	(0.0177)	(3.040)	(3.106)	(3.031)
Observations	22,024	19,157	19,157	19,157
R-squared	0.005	0.487	0.487	0.489
Number of Firms	1,377	1,371	1,371	1,371
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts (calculated using the past 24 points of data) on firm-level volatility of returns.
Clustered standard errors at firm-level are reported in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

Regarding the second model (Eq. (4)), as an additional check, I also measure volatility in an alternative way. Instead of using daily squared returns, I now calculate the volatility by annualizing the daily standard deviation of returns. My main conclusion remains unaffected. Coefficients for both independent variables increase, but GPR^{Threat} remains significant at the five percent significance level, while GPR^{Act} now becomes significant at the ten percent level, as shown in Table 10 below. The same results maintain when only the past 24 points of data are considered, instead of 36, although in this case coefficients become more significant, in the same way as what is documented in the previous table (Table 9). Therefore, the robustness estimation results of this model support my main findings, meaning that the positive (negative) impact of geopolitical threats (acts) on firm-level volatility of returns is statistically robust.

Table 10. Panel B: Robustness check using volatility, calculated from daily standard deviation of returns, as dependent variable.

Variables	(1) Fixed-effects: Volatility	(2) Fixed-effects: Volatility	(3) Fixed-effects: Volatility	(4) Fixed-effects: Volatility
GPR^{Threat}	14.44	19.93		35.79**
	(15.91)	(16.44)		(16.13)
GPR^{Act}	-50.26***		-189.4	-251.1*
	(5.832)		(154.7)	(133.5)
logSize		-4.491***	-4.601***	-4.259***
		(0.478)	(0.473)	(0.294)
Leverage		5.420	6.624*	6.215*
		(3.438)	(3.586)	(3.710)
Turnover		-0.0006***	-0.00115**	-0.00149***
		(0.0002)	(0.0005)	(0.0006)
LagVolatility		0.451***	0.426***	0.459***
		(0.0202)	(0.0298)	(0.0200)
Constant	35.74***	76.45***	76.71***	72.14***
	(0.0336)	(5.203)	(4.944)	(3.045)
Observations	22,105	19,139	19,139	19,139
R-squared	0.025	0.403	0.436	0.476
Number of Firms	1,378	1,371	1,371	1,371
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts on firm-level volatility of returns (calculated from the daily standard deviation of returns).
Clustered standard errors at firm-level are reported in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

The second test for robustness consists in calculating the exposure to geopolitical risks in a different way. Still focusing on the specific exposure of each company to GPRs, instead of considering the percentage change in the index, I now decide to consider the value of the index as such, to calculate this exposure. Results are reported in Section A6 of the Appendix, with the intention of saving space in the main text. Regardless of whether the regression is done considering the last 36 values of the index, or the last 24 values, to calculate both independent variables, the results for the returns model are not statistically significant (see Table A6.13). The same can be said for the volatility model. Overall, the results of this last set of robustness tests do not support my main findings. Nevertheless, this does not necessarily mean that the results obtained are not valid, but rather that one way of measuring geopolitical risks is more appropriate than the other, when it comes to analyzing the effects of GPRs on firm-level returns and volatility. From these results we could conclude that, while the individual exposure of each company to changes in the GPR index is relevant in affecting returns and, to a greater extent, volatility, exposure to the values recorded by the index is not. The changes in the global geopolitical situation are, therefore, what triggers the response of financial markets, affecting returns and volatility.

As a final robustness check, and in order to test whether my results are prone to the presence of outliers, I re-run my two panel data models, after removing outliers from the data. In particular, I remove those points of data that are below the one percent percentile, and those that are above the 99 percent percentile, for all the variables in the model, including the control variables. Results for both the returns and the volatility models are documented in Tables 15 and 16 in the Appendix, respectively. Results for the returns model remain unaffected. Even though the coefficient of GPR^{Act} drops to 1.901, it remains statistically significant (now at all significance levels) and continues to retain the positive sign for its coefficient, suggesting a positive relationship between returns and geopolitical events at firm-level. The variable GPR^{Threat} shows a negative relationship with firm returns, however, it continues to be statistically insignificant. Therefore, even though coefficients are slightly lower than those reported in Table 6 for my main test, the same conclusion is maintained. The influence of geopolitical risks on firm-level returns is lead mainly by geopolitical events, rather than by geopolitical threats, being this influence positive.

Regarding the volatility model, my main conclusions also remain unaffected. Only GPR^{Threat} continues to drive the effect of geopolitical risks on volatility, indicating a positive association between both. GPR^{Act} remains to be not statistically significant. Nevertheless, the value of the coefficients decreases greatly for both variables, and these coefficients seem to make more economic sense. A one percentage increase in the exposure to changes in the GPR^{Threat} index, would trigger an increase in volatility of 5.82 percent, as my results show. Therefore, even if the same relationship between volatility and the independent variables is maintained, the coefficients previously obtained could have been biased due to the presence of outliers. Furthermore, all the control variables show the right coefficients, based on the findings of previous literature. For instance, the negative sign accompanying the variable *logSize* signals a negative relationship between firm size and volatility. This is in accordance with previous studies, which show that large firms tend to experience lower volatility of returns (Bae et al., 2004). I can thus conclude that my previous conclusions are generally robust to the presence of outliers.

7. Conclusion and discussion

This thesis studies the effect of geopolitical risks on firm-level stock returns and volatility of returns of companies listed in the STOXX Europe 600, between 2000 and 2021. The purpose of this study is two-fold. Firstly, I explore the relationship between stock returns and volatility of European companies and global GPRs. Secondly, I analyze whether geopolitical threats have a greater effect on returns and volatility, or whether, on the contrary, it is the events that provoke a more pronounced response. This has been done by using fixed effect panel data models. Additional sensitivity tests have also been conducted to check the robustness of the obtained results.

My results indicate that stock returns appear to be driven by geopolitical acts rather than threats, and that the relationship between returns and geopolitical events is positive. It should be noted that this finding is contrary to what I had hypothesized in the beginning, and to what most of previous studies have found before. Nevertheless, and because this paper, unlike others, has carried out the analysis at firm-level, this positive relationship between both magnitudes may be due to the fact that, during the sample period, certain companies benefited from the increase in global geopolitical instability. This is the case of oil companies right now, which have seen their returns increase since the start of the war in Ukraine, due to the surge in oil prices. At the same time, this result can also shed light about something that has already been discussed by some authors before (*see* Berkman et al., 2011). Crisis risk is priced, therefore those companies that are more sensitive to changes in GPRs, could yield higher returns to compensate for this increased risk, explaining the positive coefficient.

When it comes to volatility, I find strong and consistent evidence that geopolitical threats are positively associated with volatility. However, the statistical significance of this positive effect disappears once realized geopolitical risk is considered. This therefore means that volatility seems to be more affected by threats, rather than by the materialization of those threats, which is line to my baseline hypothesis and with prior studies. Threats increase uncertainty, which in turn increases volatility in the markets. On the other hand, it could be argued that geopolitical events resolve this uncertainty to a certain extent, and consequently, reduce volatility, leading to a negative relationship.

Overall, my findings indicate that geopolitical risks can indeed influence both stock returns and volatility at firm-level. This highlights the importance of incorporating GPRs both in asset pricing models and in models designed for risk management purposes, both for investors and companies themselves. It is important for companies so that they can become aware of their potential exposure to geopolitical risks and how this exposure can affect their daily operations and returns. Secondly, it is crucial for investors, when constructing their optimal portfolios, to assess whether the returns offered by a specific company are compensating for their exposure to GPRs, and to what extent (Bouri et al., 2018), as well as to know how to diversify their portfolios in periods of heightened geopolitical instability.

This research has some limitations that should be discussed and that could form the basis of futures studies. First, even though this paper has not used the values of the GPR index as the main independent variable, but the firm exposure to changes in this index, it should be noted that, as Caldara & Iacoviello (2018) acknowledge, the GPR index is 'mostly relevant from a North-American and British perspective'. This is because the newspapers used to construct the GPR index come from English-speaking countries. This could mean that there are events that have had a strong impact in other non-English speaking European countries, which have not been recorded with the correct importance in the index, introducing bias in the result. The construction of a 'European GPR index' would be a great addition to the research, to explore how global GPRs affect European financial markets, regardless of, in this case, the language.

Secondly, an important limitation has been data unavailability for some of the companies in the sample. Although companies with a high number of missing observations were discarded from the sample, there were other companies that were acquired, merged with others, or simply disappeared, and therefore also had many missing observations for some of the years. In future studies it would be interesting to expand the sample period, and classify these companies into different groups, according to their status, in order to investigate the effects of GPRs on each group separately as well. Furthermore, another line of research that would also be of great value in understanding the impact of geopolitical risks would be to study what exactly it is that makes a company less or more exposed to these risks.

8. References

Apergis, N., Bonato, M., Gupta, R., & Kyei, C. (2017). Does Geopolitical Risks Predict Stock Returns and Volatility of Leading Defense Companies? Evidence from a Nonparametric Approach. *Defence and Peace Economics, 29*(6), 684–696. https://doi.org/10.1080/10242694.2017.1292097

Bae, K. H., Chan, K., & Ng, A. (2004). Investibility and return volatility. *Journal of Financial Economics*, *71*(2), 239–263. https://doi.org/10.1016/S0304-405X(03)00166-1

Baghersad, M., & Zobel, C. W. (2021). Assessing the extended impacts of supply chain disruptions on firms: An empirical study. *International Journal of Production Economics*, *231*. https://doi.org/10.1016/j.ijpe.2020.107862

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2018). Geopolitical risks and stock market dynamics of the BRICS. *Economic Systems*, *42*(2), 295–306. https://doi.org/10.1016/j.ecosys.2017.05.008

Balcilar, M., Wohar, M. E., Gupta, R., & Pierdzioch, C. (2018). Terror Attacks and Stock-Market Fluctuations: Evidence Based on a Nonparametric Causality-in-Quantiles Test for the G7 Countries. *The European Journal of Finance*, *24*(4), 333–346. http://dx.doi.org/10.1080/1351847X.2016.1239586

Bastianin, A., Conti, F., & Manera, M. (2016). The impacts of oil price shocks on stock market volatility: Evidence from the G7 countries. *Energy Policy*, *98*, 160–169. https://doi.org/10.1016/j.enpol.2016.08.020

Baur, D. G., & Smales, L. A. (2020). Hedging geopolitical risk with precious metals. *Journal of Banking and Finance*, *117*. https://doi.org/10.1016/j.jbankfin.2020.105823

Berkman, H., Jacobsen, B., & Lee, J. B. (2011). Time-varying rare disaster risk and stock returns. *Journal of Financial Economics*, *101*(2), 313–332. https://doi.org/10.1016/j.jfineco.2011.02.019

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, *77*(3), 623–685. https://doi.org/10.3982/ecta6248

Bouoiyour, J., Selmi, R., Hammoudeh, S., & Wohar, M. E. (2019). What are the categories of geopolitical risks that could drive oil prices higher? Acts or threats? *Energy Economics*, *84*. https://doi.org/10.1016/j.eneco.2019.104523

Bouras, C., Christou, C., Gupta, R., & Suleman, T. (2019). Geopolitical Risks, Returns, and Volatility in Emerging Stock Markets: Evidence from a Panel GARCH Model. *Emerging Markets Finance and Trade*, *55*(8), 1841–1856.

Bouri, E., Demirer, R., Gupta, R., & Marfatia, H. A. (2018). Geopolitical Risks and Movements in Islamic Bond and Equity Markets. *Defence and Peace Economics*, *30*(3), 367–379. https://doi.org/10.1080/10242694.2018.1424613

Bouri, E., & Gupta, R. (2021). Predicting Bitcoin returns: Comparing the roles of newspaper- and internet search-based measures of uncertainty. *Finance Research Letters*, *38*. https://doi.org/10.1016/j.frl.2019.101398

Caldara, D., & Iacoviello, M. (2018). Measuring Geopolitical Risk. *International Finance Discussion Paper*, *2018*(1222), 1–66. https://doi.org/10.17016/IFDP.2018.1222

Chen, Z., Du, J., Li, D., & Ouyang, R. (2013). Does foreign institutional ownership increase return volatility? Evidence from China. *Journal of Banking and Finance*, *37*(2), 660–669. https://doi.org/10.1016/j.jbankfin.2012.10.006

Drakos, K. (2010). Terrorism activity, investor sentiment, and stock returns. *Review of Financial Economics*, *19*(3), 128–135. https://doi.org/10.1016/j.rfe.2010.01.001

Duffee, G. R. (1995). Stock returns and volatility A firm-level analysis. *Journal of Financial Economics*, *37*, 399–420.

Elsayed, A. H., & Helmi, M. H. (2021). Volatility transmission and spillover dynamics across financial markets: the role of geopolitical risk. *Annals of Operations Research*, *305*, 1–22. https://doi.org/10.1007/s10479-021-04081-5

Engle, R. (2002). New frontiers for ARCH models. *Journal of Applied Econometrics*, *17*(5), 425–446. https://doi.org/10.1002/jae.683

Engle, R. F., & Campos-Martins, S. (2020). *"Measuring and Hedging Geopolitical Risk" Measuring and Hedging Geopolitical Risk*. https://ssrn.com/abstract=3685213

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *Source: The Journal of Finance*, *25*(2), 383–417.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds*. *Journal of Financial Economics*, *33*, 3–56.

Favara, G., Gao, J., & Giannetti, M. (2020). Uncertainty, Access to Debt, and Firm Precautionary Behavior. *Journal of Financial Economics (Forthcoming)*. http://dx.doi.org/10.2139/ssrn.3026939.

Fisher, R. A. (1932). *Statistical Methods for Research Workers* (4th edition). Oliver & Boyd.

Fleming, J., Kirby, C., & Ostdiek, B. (2003). The economic value of volatility timing using "realized" volatility. *Journal of Financial Economics*, *67*, 473–509.

Gkillas, K., Gupta, R., & Wohar, M. E. (2018). Volatility jumps: The role of geopolitical risks. *Finance Research Letters*, *27*, 247–258. https://doi.org/10.1016/j.frl.2018.03.014

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica*, *46*(6), 1251–1271.

Hendricks, K. B., & Singhal, V. R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, *21*(5), 501–522. https://doi.org/10.1016/j.jom.2003.02.003

Hong, H., & Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, *93*(1), 15–36. https://doi.org/10.1016/j.jfineco.2008.09.001

Kollias, C., Papadamou, S., & Stagiannis, A. (2011). Terrorism and capital markets: The effects of the Madrid and London bomb attacks. *International Review of Economics and Finance*, *20*(4), 532–541. https://doi.org/10.1016/j.iref.2010.09.004

Li, D., Nguyen, Q. N., Pham, P. K., & Wei, S. X. (2011). Large Foreign Ownership and Firm-Level Stock Return Volatility in Emerging Markets. *Journal of Financial and Quantitative Analysis*, *46*(4), 1127–1155. https://doi.org/10.1017/S0022109011000202

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*, 631–652.

Montone, M., van den Assem, M. J., & Zwinkels, R. C. J. (2021). *Company Name Fluency and Stock Returns*. http://dx.doi.org/10.2139/ssrn.3123201

Omar, A. M. A., Wisniewski, T. P., & Nolte, S. (2017). Diversifying away the risk of war and cross-border political crisis. *Energy Economics*, *64*, 494–510. https://doi.org/10.1016/j.eneco.2016.02.015

Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, *110*(3), 520–545. https://doi.org/10.1016/j.jfineco.2013.08.007

Phan, D. H. B., Tran, V. T., & Iyke, B. N. (2021). Geopolitical risk and bank stability. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2021.102453

Ramiah, V., Wallace, D., Veron, J. F., Reddy, K., & Elliott, R. (2019). The effects of recent terrorist attacks on risk and return in commodity markets. *Energy Economics*, *77*, 13–22. https://doi.org/10.1016/j.eneco.2018.10.025

Salisu, A. A., Lasisi, L., & Tchankam, J. P. (2021). Historical geopolitical risk and the behaviour of stock returns in advanced economies. *European Journal of Finance*. https://doi.org/10.1080/1351847X.2021.1968467

Schwert, G. W. (1989). Why Does Stock Market Volatility Change Over Time? *The Journal of Finance*, *44*(5), 1115–1153. https://doi.org/10.1111/j.1540-6261.1989.tb02647.x

Smales, L. A. (2021). Geopolitical risk and volatility spillovers in oil and stock markets. *Quarterly Review of Economics and Finance*, *80*, 358–366. https://doi.org/10.1016/j.qref.2021.03.008

Wooldridge, J. M. (2016). *Introductory econometrics* (6th ed.). CENGAGE Learning.

9. Appendix

A1. Unit root tests

Table 1. Unit roots tests for time series and panel regressions

Exhibit A: Time series unit root tests (ADF)		
Variables	ADF Test statistic	p-value
Returns	-10.997	0.000 (***)
GPR^{Threat}	-14.315	0.000 (***)
GPR^{Act}	-12.476	0.000 (***)
VSTOXX50	-4.785	-0.005(***)
OilPrice	-2.664	0.2515
Exhibit B: Panel A Fisher unit root tests		
Variables	Inverse chi-squared	p-value
Returns	0.0002	0.000 (***)
GPR^{Threat}	8714.1268	0.000 (***)
GPR^{Act}	9373.2507	0.000 (***)
logSize	3990.157	0.000 (***)
logBMR	6299.508	0.000 (***)
ROE	0.0001	0.000 (***)
logPE	0.0001	0.000 (***)
FirmVolatility	8468.6789	0.000 (***)
Exhibit C: Panel B Fisher unit root tests		
Variables	Inverse chi-squared	p-value
Volatility	8714.329	0.000 (***)
GPR^{Threat}	8834.7527	0.000 (***)
GPR^{Act}	0.0002	0.000 (***)
logSize	4112.0906	0.000 (***)
Leverage	5611.8409	0.000 (***)
Turnover	8496.4921	0.000 (***)
LagVolatility	6305.3191	0.000 (***)

A2. Correlation matrices

Table 2. Correlation matrix for time-series regression

e(V)	GPR^{Threat}	GPR^{Act}	VSTOXX50	D.OilPrice
GPR^{Threat}	1			
GPR^{Act}	-0.7763	1		
VSTOXX50	-0.0372	-0.0262	1	
D.OilPrice	-0.0297	0.0512	0.2393	1

Table 3. Correlation matrix for Panel A

e(V)	GPR^{Threat}	GPR^{Act}	logSize	logBMR	ROE	logPE
GPR^{Threat}	1					
GPR^{Act}	0.0869	1				
logSize	-0.0892	-0.0383	1			
logBMR	0.0842	-0.2789	0.2335	1		
ROE	-0.0255	-0.0243	0.0916	0.1972	1	
logPE	0.0566	-0.1016	-0.3244	0.2353	0.0346	1
FirmVolatility	-0.0729	0.143	0.2631	-0.3869	-0.1129	-0.2369

Table 4. Correlation matrix for Panel B

e(V)	GPR^{Threat}	GPR^{Act}	logSize	Leverage	Turnover	LagVolatility
GPR^{Threat}	1					
GPR^{Act}	-0.3596	1				
logSize	0.0942	-0.0868	1			
Leverage	-0.018	-0.0158	0.0868	1		
Turnover	-0.0186	0.0396	0.016	-0.0788	1	
LagVolatility	0.1513	-0.076	0.2871	-0.0352	0.0195	1

A3. Hausman test

Table 5. Hausman test for Panel A

	Coefficients			
	(b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
GPR^{Threat}	-0.8854	-0.0251	-0.8604	0.7765
GPR^{Act}	3.3299	2.3642	0.9657	0.6276
logSize	0.2163	-1.4447	1.6610	0.5293
logBMR	-19.642	-10.9029	-8.7393	0.6238
ROE	-0.0117	-0.0064	0.0053	0.0026
logPE	0.0897	0.8056	0.7159	0.1648
FirmVolatility	0.2626	0.2444	0.0183	0.0140

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(28) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 400.54

Prob>chi2 = 0.0000

Table 6. Hausman test for Panel B

	Coefficients			
	(b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
GPR^{Threat}	38.5847	38.5847	-8.8958	0.26759
GPR^{Act}	-205.9134	-271.6599	65.7466	2.3982
logSize	-4.3017	-2.1949	-2.1068	0.1229
Leverage	6.2298	5.4314	0.7983	0.4950
Turnover	-0.0013	-0.0010	0.0003	.
LagVolatility	0.4588	0.5667	0.1080	0.0032

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(24) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 1757.42

Prob>chi2 = 0.0000

A4. Heteroskedasticity tests (Breusch-Pagan)

Table 7. Heteroskedasticity test for time-series regression

Variables	(1) Squared residuals
GPR^{Threat}	-0.0930
	(0.0795)
GPR^{Act}	0.0099
	(0.0376)
VSTOXX50	1.014***
	(0.189)
D.Oilprice	0.320
	(0.377)
Constant	-9.866**
	(4.752)
Observations	263
R-squared	0.105
F-Stat	7.548
Prob > F	0.000

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8. Heteroskedasticity test for Panel A

Variables	(1) Squared residuals
GPR^{Threat}	-0.885
	(2.549)
GPR^{Act}	3.330**
	(1.539)
logSize	0.216
	(0.613)
logBMR	-19.64***
	(0.746)
ROE	-0.0117**
	(0.0051)
logPE	0.0897
	(0.426)
FirmVolatility	0.263***
	(0.0310)
Constant	-27.19***
	(4.969)
Observations	17,649
Number of Firms	1,314
R-squared	0.284
F-Stat	231.3
Prob > F	0

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 9. Heteroskedasticity test for Panel B

Variables	(1) Squared residuals
GPR^{Threat}	12,391***
	(277.9)
GPR^{Act}	-99,827***
	(1,341)
logSize	-9.135
	(18.27)
Leverage	662.8***
	(151.0)
Turnover	-0.327**
	(0.150)
LagVolatility	11.72***
	(1.745)
Constant	-808.2***
	(186.4)
Observations	19,162
R-squared	0.247
F-Stat	1046
Prob > F	0

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

A5. Autocorrelation tests

Table 10. Breusch-Godfrey test for time-series regression

lags(p)	chi2	df	Prob > chi2
1	3.583	1	0.0584
2	3.863	1	0.1149

Table 11. Autocorrelation test for Panel A

Variables	(1) Residuals
L.Residuals	0.107***
	(0.0069)
GPR^{Threat}	-4.431
	(3.258)
GPR^{Act}	4.866
	(3.542)
logSize	-1.612***
	(0.187)
logBMR	11.07***
	(0.281)
ROE	0.0046
	(0.0075)
logPE	0.605*
	(0.363)
FirmVolatility	-0.164***
	(0.0210)
Constant	27.37***
	(2.099)
Observations	15,087
R-squared	0.205

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 12. Autocorrelation test for Panel B

Variables	(1) Residuals
L.Residuals	0.172***
	(0.0128)
GPR^{Threat}	24.62***
	(2.116)
GPR^{Act}	-23.28***
	(2.060)
logSize	2.256***
	(0.0767)
Leverage	-2.042***
	(0.464)
Turnover	1.072**
	(0.433)
LagVolatility	0.0844***
	(0.0086)
Constant	-21.17***
	(0.871)
Observations	17,768
R-squared	0.159

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

A6. Additional robustness tests

Table 13. Panel A: Robustness test, where independent variables measure the firm-level exposure of returns to the GPR index

Variables	(1) Fixed-effects: Returns	(2) Fixed-effects: Returns	(3) Fixed-effects: Returns	(4) Fixed-effects: Returns
GPR^{Threat}	-1.501	-0.0057		0.0133
	(1.273)	(1.260)		(1.265)
GPR^{Act}	3.882		3.813	3.813
	(3.148)		(3.913)	(3.909)
logSize		0.210	0.225	0.224
		(1.070)	(1.070)	(1.071)
logBMR		-19.65***	-19.64***	-19.64***
		(1.363)	(1.366)	(1.365)
ROE		-0.0117	-0.0118	-0.0118
		(0.0079)	(0.0079)	(0.0079)
logPE		0.0886	0.0803	0.0804
		(0.640)	(0.641)	(0.642)
FirmVolatility		0.263***	0.263***	0.263***
		(0.0901)	(0.0900)	(0.0900)
Constant	11.10***	-27.28***	-27.12***	-27.11***
	(0.0163)	(9.396)	(9.354)	(9.363)
Observations	21,169	17,648	17,648	17,648
R-squared	0.000	0.284	0.284	0.284
Number of Firms	1,315	1,313	1,313	1,313
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts on firm-level returns. Clustered standard errors at firm-level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

Table 14. Panel B: Robustness test, where independent variables measure the firm-level exposure of volatility to the GPR index

Variables	(1) Fixed-effects: Volatility	(2) Fixed-effects: Volatility	(3) Fixed-effects: Volatility	(4) Fixed-effects: Volatility
GPR^{Threat}	2.228	3.310		4.708
	(7.798)	(8.798)		(7.593)
GPR^{Act}	19.26**		39.06	39.55
	(9.626)		(27.42)	(26.72)
logSize		-4.586***	-4.517***	-4.519***
		(0.480)	(0.360)	(0.358)
Leverage		5.993*	6.732**	6.724**
		(3.407)	(3.380)	(3.393)
Turnover		-0.0005***	-8.27e-05	-5.23e-05
		(0.0002)	(0.0003)	(0.0003)
LagVolatility		0.433***	0.463***	0.463***
		(0.0257)	(0.0238)	(0.0238)
Constant	36.30***	77.64***	76.43***	76.44***
	(0.274)	(5.472)	(3.826)	(3.818)
Observations	22,047	19,162	19,162	19,162
R-squared	0.030	0.423	0.466	0.468
Number of Firms	1,378	1,371	1,371	1,371
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts on firm-level volatility of returns. Clustered standard errors at firm-level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

Table 15. Panel A: Stock returns and GPRs, without outliers.

Variables	(1) Fixed-effects: Returns	(2) Fixed-effects: Returns	(3) Fixed-effects: Returns	(4) Fixed-effects: Returns
GPR^{Threat}	-23.42***	-2.707		-3.100
	(5.539)	(2.245)		(2.255)
GPR^{Act}	0.762		1.668***	1.901***
	(2.068)		(0.617)	(0.659)
logSize		-0.168	-0.191	-0.167
		(0.761)	(0.759)	(0.761)
logBMR		-17.35***	-17.38***	-17.36***
		(1.193)	(1.192)	(1.192)
ROE		0.0212	0.0196	0.0204
		(0.0466)	(0.0466)	(0.0466)
logPE		0.289	0.285	0.283
		(0.553)	(0.553)	(0.553)
FirmVolatility		-0.0767*	-0.0781*	-0.0774*
		(0.0409)	(0.0408)	(0.0408)
Constant	9.187***	-9.246	-8.978	-9.148
	(0.0474)	(5.816)	(5.801)	(5.816)
Observations	20,741	17,331	17,331	17,331
R-squared	0.006	0.366	0.366	0.366
Number of Firms	1,308	1,305	1,305	1,305
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts on firm-level returns, when outliers are removed from the sample. Clustered standard errors at firm-level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

Table 16. Panel B: Volatility of returns and GPRs, without outliers.

Variables	(1) Fixed-effects: Volatility	(2) Fixed-effects: Volatility	(3) Fixed-effects: Volatility	(4) Fixed-effects: Volatility
GPR^{Threat}	-2.092	5.165***		5.824***
	(3.492)	(1.580)		(1.843)
GPR^{Act}	-3.803**		12.12	-7.540
	(1.769)		(18.16)	(9.117)
logSize		-3.049***	-3.080***	-3.048***
		(0.206)	(0.208)	(0.205)
Leverage		8.254***	8.280***	8.287***
		(1.140)	(1.151)	(1.143)
Turnover		7.769	7.603	7.878
		(6.866)	(6.919)	(6.822)
LagVolatility		0.398***	0.393***	0.398***
		(0.0159)	(0.0170)	(0.0157)
Constant	35.09***	62.41***	62.91***	62.34***
	(0.0101)	(2.108)	(2.163)	(2.089)
Observations	21,674	18,916	18,916	18,916
R-squared	0.001	0.589	0.588	0.589
Number of Firms	1,376	1,367	1,367	1,367
Year FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes

Note: This table reports the results for the effect of geopolitical threats and geopolitical acts on firm-level volatility of returns, when outliers are removed from the sample. Clustered standard errors at firm-level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.