Lisbon School of Economics & Management
Universidade de Lisboa

MASTER

FINANCE

MASTER´S FINAL WORK

DISSERTATION

THE EFFECTS OF GEOPOLITICAL RISK ON STOCK PRICE CRASH RISK AND THE MODERATING ROLE OF FOREIGN OWNERSHIP

TIAGO FRANCISCO FERREIRA DA CRUZ DUPONT TEIXEIRA

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SUPERVISION:
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OCTOBER - 2024

Em homenagem ao meu Pai, Tiago Dupont, à minha Avó, Anabela Dupont, e à minha Princessa, Duby Dupont.

Tal como as Pirâmides de Gizé, uma das Sete Maravilhas do Mundo Antigo, erguidas entre 2580 e 2510 a.C., meticulosamente alinhadas com as três estrelas mais luminosas da constelação de Órion, associada ao deus Osíris - guardião da vida eterna - dedico esta tese às minhas três estrelas que vivem através de mim, servindo como o meu compasso moral e que jamais se apagam, nem nas noites mais escuras. Aos três, um beijo do tamanho do Universo e um até já...

Disclaimer regarding the use of Artificial Intelligence

This master thesis was developed with strict adherence to the academic integrity policies and guidelines set forth by ISEG, Universidade de Lisboa. The work presented herein is the result of my own research, analysis and writing, unless otherwise cited. In the interest of transparency, I provide the following disclosure regarding the use of artificial intelligence (AI) tools in the creation of this project.

I disclose that AI tools were utilized during the development of this thesis in the following ways: AI-assisted research tools were employed to support coding in Stata (the statistical software used), facilitating more efficient data analysis, model construction and ensuring robust results; AI was also used for English language and grammar checking across sections of the written text; and AI tools provided support in the literature review process.

Nevertheless, I have ensured that the use of AI tools did not compromise the originality and integrity of my work. All sources of information have been appropriately cited in accordance with academic standards.

Abstract

This thesis explores the intricate relationship between geopolitical risk (GPR) and stock price crash risk, with a particular emphasis on the role of foreign ownership. Drawing on a dataset of 463 non-financial companies from the STOXX Europe 600 index over a seventeen-year period (2004-2020 inclusive), this research strengthens the existing literature and introduces novel insights into the combined influence of these variables. Several key conclusions are reached: heightened GPR significantly increases the frequency of stock price crashes. This finding is robust across various crash risk measures and withstands multiple robustness checks, including addressing potential endogeneity concerns using an Instrumental Variables (IV) approach; GPR's impact is predominantly driven by geopolitical threats (GPT) - anticipated risks - rather than realized geopolitical acts (GPA); foreign ownership amplifies the effect of GPR on stock price crash risk; and terrorism and military conflicts are identified as two primary channels through which GPR manifests in financial markets. These findings provide a comprehensive understanding of how geopolitical dynamics and foreign ownership interact to influence stock price stability.

KEYWORDS: Geopolitical Risk; Stock Price Crash Risk; Foreign Ownership; STOXX Europe 600.

JEL CODES: D53; F30; F51; G12; G15; G34.

Resumo

Esta tese explora a relação complexa entre o risco geopolítico (GPR) e o risco de queda abrupta de preços das ações, com especial ênfase no papel do capital estrangeiro. Com base num conjunto de dados de 463 empresas não financeiras do índice STOXX Europe 600 ao longo de um período de dezassete anos (2004-2020 inclusive), esta investigação reforça a literatura existente e introduz novas perceções sobre a influência combinada destas variáveis. Diversas conclusões essenciais são alcançadas: o aumento do GPR incrementa significativamente a frequência de quedas abruptas nos preços das ações. Este resultado revela-se robusto em várias medidas de risco de queda e resiste a múltiplos testes de robustez, incluindo a resolução de potenciais preocupações de endogeneidade através de uma abordagem de variáveis instrumentais (IV); o impacto do GPR é predominantemente impulsionado por ameaças geopolíticas (GPT) - riscos antecipados - em vez de atos geopolíticos realizados (GPA); o capital estrangeiro amplifica o efeito do GPR sobre o risco de queda abrupta de preços das ações; por fim, o terrorismo e os conflitos militares são identificados como dois dos principais canais através dos quais o GPR se manifesta nos mercados financeiros. Estes resultados proporcionam uma compreensão abrangente de como as dinâmicas geopolíticas e o capital estrangeiro interagem para influenciar a estabilidade dos preços das ações.

PALAVRAS-CHAVE: Risco Geopolítico; Risco de Queda Abrupta de Preços das Ações; Capital Estrangeiro; STOXX Europe 600.

CÓDIGOS JEL: D53; F30; F51; G12; G15; G34.

Acknowledgements

This thesis has undoubtedly been the most challenging academic endeavor of my life, and possibly will remain so in the future. As we are often reminded, the path to success is rarely straightforward. In fact, it is full of ups and downs, much like the distribution of a company's stock returns. What differentiates those who succeed, in my view, is one crucial quality: the ability to endure. It is about continuing to move forward, no matter how many setbacks are encountered; rising as many times as we fall; persevering through every obstacle.

That said, perseverance is never achieved alone, and I am deeply grateful to those who supported me along this demanding journey.

First and foremost, I want to thank Professor Tiago Gonçalves, who guided me from the very beginning, helping me shape my ideas into a coherent research question and supporting me through the entire process. With his ever-present smile, concise yet insightful feedback, and a sense of humor, he consistently asked me the most important question: "What is the economic rationale?" For all of this, I extend my heartfelt gratitude.

Secondly, I am deeply grateful to my family, especially my Mother, Carla Cruz, who constantly reminded me - not that I needed it - that December would be *the* month, since it would be my thesis defense, even a year before it was due. She endured my less-than-brilliant moods and offered me unwavering support throughout this past year.

Finally, I want to give special thanks to two brilliant colleagues and one special friend who were instrumental during this journey: Tiago Pereira, Bruno Mendes and Diogo Pereira.

To all the others pursuing a Master's thesis and who may find yourselves, by accident or not, reading this paper, I wish you the best of luck. Don't hesitate to seek help when needed, and most importantly, never, ever give up. Onward and upward!

Glossary

DUVOL – Down-to-Up Volatility

EBIT – Earnings Before Interests Taxes and Depreciation

ESG – Environmental, Social and Governance

FDI – Foreign Direct Investment

FE – Fixed Effects

FIO – Foreign Investor's Ownership

GPA – Geopolitical Acts

GPR – Geopolitical Risk

GPRD – Geopolitical Risk Daily

GPT – Geopolitical Threats

H1 – Hypothesis 1

H2 – Hypothesis 2

H3 – Hypothesis 3

IFRS – International Financial Reporting Standards

IMF – International Monetary Fund

ISIN – International Securities Identification Numbering system

IV – Instrumental Variables

LEV – Leverage

LN – Natural Logarithm

N_CRASH – Binary Crash Risk Indicator

NCSKEW – Negative Coefficient of Skewness

OECD – Organisation for Economic and Cooperation Development

OLS – Ordinary Least Squares

R&D – Research & Development

ROA – Return on Assets

STDEV – Yearly Standard Deviation of Stock Returns

US – United States

VIF – Variance Inflation Factor

WEF – World Economic Forum

WGI – World Governance Indicators

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1. Introduction

The Global Future Council on the Future of Geopolitics, hosted by the World Economic Forum (WEF), has aptly observed in its mission statement, *"A new, more contentious geopolitical era appears to be unfolding, with the possibility that a once stable and cooperative order is being replaced by a more turbulent and fragmented global landscape"* (World Economic Forum, n.d., para. X). This shift from global cooperation to increasing contention and fragmentation underscores the changing nature of international relations.

Several landmark events have characterized this transformation. The United Kingdom's official departure from the European Union, or Brexit, on January 31st, 2020, marked a significant political and economic shift within Europe. The collapse of the Islamic Republic of Afghanistan on August 15th, 2021, led to the return of the Taliban and the withdrawal of U.S. Armed Forces after two decades of conflict. Russia's full-scale invasion of Ukraine on February 24th, 2022, further escalated geopolitical tensions, as did Hamas's surprise attack within Israel on October 7th, 2024. These events, while disparate in their specifics, are all geopolitical shocks that reverberated through global markets.

What ties these events together is their geopolitical significance and their broader impact on global financial stability. Traditionally, geopolitics has focused on state control and territorial competition. However, in recent decades, it has expanded to include power struggles over trade, political influence and competition involving non-state actors such as corporations, rebel groups and political parties. These evolving forces operate within an increasingly interconnected global framework, contributing to heightened uncertainty in financial markets.

According to the Global Risks Report 2024, developed by the WEF in collaboration with Marsh McLennan and Zurich Insurance Group, geopolitical risk (GPR) ranks fifth among the top ten global risks in the short term and fifteenth out of thirty-four in the long term. This category encompasses a wide array of risks, including interstate conflicts, terrorist attacks and geoeconomic confrontations. As Chris Hyzy, Chief Investment Officer for Merrill and Bank of America Private Bank, properly noted, *"Geopolitics used to be considered a lower-level financial risk. Now, it may be the top risk"* (CIO, 2023, para. X).

Given the increasing frequency of such incidents, it is essential to understand how geopolitical tensions influence decision-making processes and financial stability. Early studies, using the Caldara and Iacoviello GPR index, have demonstrated that geopolitical risk significantly influences macroeconomic conditions. GPR has been found to affect gold price volatility (Gkillas, Gupta, & Pierdzioch, 2020) and increase the possibility of recessions (Clance, Gupta, & Wohar, 2019; Francis, Owyang, & Soques, 2022). At the firm level, GPR has been linked to decreased bank stability and profitability (Alsagr & Almazor, 2020; Phan, Tran, & Iyke, 2022). More recent studies, such as those by Agoraki, Kouretas and Laopodis (2022), highlight the significantly negative impact of GPR on stock returns, while others (Yang, Zhang, Yi, & Peng, 2021) highlight a positive relationship between GPR and stock market volatility.

When these findings are combined with agency cost theory (Jin & Myers, 2006), which posits that managers may conceal negative information due to performance-sensitive compensation schemes (Kim, Li, & Zhang, 2011; Kothari, Shu, & Wysocki, 2009), GPR emerges as a critical driver of stock price crashes. Managers, under pressure to meet performance targets, may delay disclosing negative news in the face of geopolitical uncertainty, increasing the likelihood of a sudden, sharp decline in stock prices when the bad news eventually emerges. This thesis aims to explore whether geopolitical risk elevates stock price crash risk.

Although research on the relationship between GPR and stock price crashes is still in its early stages, initial studies offer compelling evidence of a positive correlation. For instance, Xu, He, Zhou, Ding, and Chen (2023) explore this relationship in China, while Fiorillo, Meles, Pellegrino, and Verdoliva (2024) take a broader, global approach, incorporating the mitigating role of environmental, social, and governance (ESG) factors in their analysis.

Foreign ownership is another key factor frequently studied in relation to stock price crash risk. This refers to the equity stakes held by international investors in domestic companies. Some studies (Kim et al., 2011a, 2011b, 2014, 2019; Callen & Fang, 2015) suggest that foreign ownership reduces crash risk by introducing more effective governance and monitoring, which in turn minimizes agency costs and information asymmetry (Shleifer & Vishny, 1986). However, other research suggests that foreign ownership may actually increase crash risk, as foreign investors seeking short-term profits may destabilize corporate governance by demanding excessive dividends or rapidly divesting in response to geopolitical shocks (Huang, Tang, & Huang, 2020; Vo, 2020).

The potential interaction between GPR and foreign ownership adds complexity to this dynamic. Foreign ownership may serve as a transmission mechanism, amplifying the effects of geopolitical risk and exacerbating market instability. This is particularly relevant in regions like

Europe, where geopolitical tensions are prevalent and foreign investments play a substantial role in domestic markets. Foreign investors, often more sensitive to global risks, may react more swiftly to geopolitical shocks, which could intensify the likelihood of stock price crashes.

This thesis makes a significant contribution to the field by addressing several key gaps in the literature. Firstly, it is the only study, to the best of my knowledge, that simultaneously examines the impact of GPR on stock price crash risk and the role of foreign ownership in this relationship. Secondly, it provides an European focus, using non-financial firms from the STOXX Europe 600 index as a benchmark, thereby strengthening the limited research on the positive relationship between GPR and stock price crash risk. Thirdly, this thesis differentiates between geopolitical threats (GPT) and geopolitical acts (GPA), demonstrating that threats play a more substantial role in driving crash risk. Fourthly, it aims to enhance the understanding of how foreign ownership influences stock price crash risk, clarifying whether foreign investors exacerbate or mitigate this risk. Lastly, the analysis of two key channels of geopolitical risk - terrorism and military conflicts - is based on case studies of three major events: the 2005 London Bombings, the 2014 Annexation of Crimea and the 2015 Terrorist Attacks in Great Britain. These case studies highlight the heightened likelihood of stock price crashes for firms based in Great Britain during periods of geopolitical instability, reinforcing the results presented.

The empirical analysis employs ordinary least squares (OLS) and fixed effects (FE) regressions, with winsorization applied to all variables except those expressed in logarithmic form. The crash risk measures include NCSKEW, DUVOL and N_CRASH, while the key independent variables are LN(GPR) and FIO (Foreign Investor's Ownership). The control variables include LN(TotalAssets), representing firm size, as larger firms may have different risk profiles; LEV, accounting for a firm's level of indebtedness; Profitability, measuring operational efficiency and performance; STDEV, reflecting stock price volatility; and T_Analyst, representing the level of market attention through analyst coverage. In the analysis involving foreign ownership, T_Analyst is excluded and Profitability is replaced by ROA (Return on Assets), a common measure in related literature for capturing firm efficiency. To address potential endogeneity, a two-step instrumental variables (IV) approach is utilized, alongside multiple robustness checks, to ensure the validity of the results.

The thesis is structured as follows: Chapter 2 reviews the relevant literature; Chapter 3 outlines the methodology, variables and sample; Chapter 4 presents the baseline results and robustness checks; finally, Chapter 5 concludes with a discussion of limitations and suggestions for future research.

2. Literature Review

Stock price crash risk, or simply crash risk, refers to an extreme and significant decline in stock prices, characterized by negative skewness in the distribution of returns for individual stocks (Chen et al., 2001; Kim et al., 2014; Callen & Fang, 2015a). This concept holds significant implications for portfolio theories, as well as asset and option pricing models (Kim & Zhang, 2015). The presence of pronounced negative skewness compels investors to demand higher returns, underscoring skewness as a priced risk factor (Harvey & Siddique, 2000; Conrad et al., 2013). Recent global financial crises have heightened the imperative to scrutinize the determinants of stock price crash risk, garnering increased attention from investors, regulators and policymakers (Xu et al., 2013).

Understanding this risk is particularly relevant in the current economic climate due to the increased volatility and uncertainty in global markets. Stock price crash risk is extensively discussed in contemporary literature (Habib, Hasan & Jiang, 2018). Several determinants of crash risk have been deeply explored.

Firstly, corporate governance and managerial behaviour are pivotal. Recent empirical research, which partially explains the price crash risk (Xu et al., 2023), predominantly adheres to the agency theoretical framework advocated by Jin & Myers (2006). This framework posits that information asymmetries between corporate insiders and external stakeholders intensify crash risk. Such asymmetries allow managers to conceal adverse news for extended periods, aiming to maximize compensation, safeguard employment and reduce litigation risks associated with the disclosure of such news (Kothari et al., 2009). The eventual dissemination of this accumulated negative information typically results in severe stock price declines, culminating in a crash.

Secondly, financial reporting and transparency play a crucial role. Firms that maintain high-quality disclosure practices provide timely and accurate information to the market, reducing uncertainty and the risk of sudden negative surprises (Lang & Lundholm, 1996). Companies that engage in voluntary disclosures tend to have lower crash risk because they pre-emptively address potential issues that might otherwise lead to negative shocks (Healy & Palepu, 2001).

Thirdly, market conditions and investor behaviour significantly influence crash risk. Stocks with higher trading volumes are generally less prone to crashes because high liquidity allows for smoother adjustment of stock prices to new information (Chordia, Roll & Subrahmanyam, 2008). During times of high uncertainty, investors tend to follow the crowd, which can lead to abrupt and severe price declines if a negative event triggers widespread selling (Bikhchandani, Hirshleifer & Welch, 1992).

Fourthly, corporate policies and financial health are critical factors. Firms with high leverage are more vulnerable to stock price crashes because financial distress or bankruptcy risk increases when adverse information is revealed (Graham, Harvey, and Rajgopal, 2005). While high capital expenditures and R&D investments are generally positive for long-term growth, they can also increase crash risk if they are not aligned with market conditions or fail to generate expected returns (Chen, Harford & Kamara, 2019).

Numerous studies provide strong and robust evidence that better corporate governance is associated with lower stock price crash risk (Kim et al., 2011a, 2011b, 2014; Kim & Zhang, 2014; Callen & Fang, 2015).

For instance, studies by Kim, J.B., Li, Y., and Zhang, L. (2011a, 2014) investigate the relationship between corporate tax avoidance and stock price crash risk. Their research demonstrates that robust corporate governance mechanisms can mitigate the likelihood of stock price crashes. Utilizing a substantial sample of U.S. firms from 1995 to 2008, the studies reveal that tax avoidance, which enables managerial opportunistic behaviour, is positively correlated with crash risk. However, this relationship is attenuated by strong external monitoring mechanisms.

Additionally, research by Jebran, K., Chen, S., and Zhu, D. H. (2019) underscores the critical role of effective corporate governance structures, particularly as balanced board hierarchies, in reducing stock price crash risk. Their study, based on 13,159 firm-year observations from 2,411 firms between 2004 and 2014, highlights the critical role of corporate governance in safeguarding against stock price crashes. These studies collectively suggest that corporate governance acts as a significant moderating factor in the relationship between various risk factors and stock price crashes.

The extant literature delineates three primary measures of firm-specific crash risk, derived from weekly returns calculated as residuals from the market model (Chen et al., 2001). This methodological approach ensures that the crash risk measures reflect firm-specific factors rather than broad market movements. The framework begins with an expanded market model regression that incorporates stock and market returns from adjacent weeks to compute residuals, which are subsequently used to ascertain the firm-specific returns. The measures included are the following.

Firstly, the Binary Crash Risk Indicator (N_CRASH) is coded “1” if a firm's weekly returns drop at least 3.09 standard deviations below its mean in a given year, representing extreme negative movements.

Secondly, and the main crash risk measure, the Negative Coefficient of Skewness (NCSKEW) is calculated by normalizing the negative third moment of weekly returns by the cubed standard deviation of these returns. It identifies the asymmetry in the return distribution, with more negative values indicating a higher crash risk.

Lastly, the Down-to-Up Volatility (DUVOL) Ratio compares the standard deviation of weekly returns in down weeks against up weeks, expressed as a logarithmic ratio. Higher values suggest an increased likelihood of stock price crashes, focusing on differences in volatility rather than skewness of returns.

Despite the extensive development of theories surrounding stock price crash risk, a significant gap remains in the empirical investigation of this subject, particularly in relation to the interactions between geopolitical risk and foreign ownership. This gap is especially striking given the crucial need to understand how firms, along with their external monitors, respond to mitigate future crash risks and protect shareholder value (Habib et al., 2018). While some studies have explored the relationships between stock price crash risk, geopolitical risk and foreign ownership, these investigations do not comprehensively examine the interplay of all three factors combined.

Another crucial factor increasingly linked to crash risk is geopolitical risk. To comprehend geopolitical risk effectively, it is essential to begin with the etymology of geopolitics. The term "geopolitics," originating from Ancient Greek, combines "geo" (earth, land) and "politikos" (of citizens, pertaining to the state). Donald S. Spencer (1998) defines geopolitics as “the branch of geography that elucidates the relationship between geographical realities and international affairs.” Alternatively, it can also be interpreted more broadly to encompass the strategic efforts of nations to control and compete for new territories (Flint, 2021).

Geopolitical risks are frequently cited by policymakers, investors and the media as key determinants of economic decisions. A 2017 Gallup Survey revealed that 75% of investors worry about geopolitical risk, highlighting its relevance for major central banks and institutions, including the European Central Bank, Federal Reserve, Bank of England, International Monetary Fund and World Bank.

Geopolitical tensions primarily manifest through two channels, both of which contribute to financial instability. First, they operate directly via financial mechanisms, triggered by restrictions on cross-border capital flows and payments. This encompasses the imposition of capital controls, financial sanctions and the freezing of international assets. Second, geopolitical tensions increase uncertainty, heightening investor concerns about future restrictions, the intensification of conflicts, or potential expropriations, all of which negatively affect firm-level stock performance (IMF, *Global Financial Stability Report*, April 2023). Thus, geopolitical risk act as a catalyst for negative volatility within markets, precipitating substantial capital outflows in the short term, thereby leading to financial instability (Caldara & Iacoviello, 2022; He et al., 2022).

In 2018, Caldara and Iacoviello constructed a Geopolitical Risk (GPR) index that quantifies the prevalence of adverse geopolitical events by measuring the frequency of newspaper articles discussing these events, becoming the main reference in this domain having demonstrated its applicability in capturing the economic effects of geopolitical tensions (Caldara & Iacoviello, 2022). The index is defined as the proportion of the number of articles mentioning adverse geopolitical events to the total number of articles analysed.

The GPR index is further categorized into two components: geopolitical threats (GPT) and geopolitical acts (GPA). GPT encompasses search categories one to five - war risks, peace threats, military buildups, nuclear threats and terrorist threats - capturing the anticipation of geopolitical events. GPA covers categories six to eight - beginning of war, escalation of war and terrorist acts - focusing on the actual occurrences of such events. While spikes in GPT and GPA generally coincide with the realization of geopolitical acts, there are instances where GPT surges even in the absence of corresponding geopolitical acts. Additionally, a country-specific version of the GPR has been developed, necessitating the mention of both GPR - related terms and the specific country in the analysed articles.

The focus on GPR as the primary index of uncertainty in this study is justified not only due to its relevance in measuring geopolitical risks but also because of its demonstrated efficacy in influencing stock market dynamics, particularly in relation to crash risk. The literature on GPR is relatively recent, reflecting the rise in geopolitical tensions and conflicts in recent years. Nonetheless, several key conclusions have emerged regarding the relationship between geopolitical risk and stock price crash risk, with scholars attempting to identify the channels driving the GPR-real economy link, particularly through the stock market.

Firstly, empirical evidence suggests that GPR, as an external macroeconomic uncertainty, can lead to the accumulation of negative news being withheld by management. This information asymmetry increases the risk of future stock price crashes (Xu et al., 2023), aligning with agency theory, where performance-sensitive compensation schemes incentivize managers to conceal adverse news. From a macroeconomic perspective, GPR has also been found to influence gold price volatility (Gkillas, Gupta, & Pierdzioch, 2020) and increase the possibility of recessions (Clance, Gupta, & Wohar, 2019; Francis, Owyang, & Soques, 2022).

Secondly, at the firm level, GPR has been associated with a decline in bank stability and profitability (Alsagr & Almazor, 2020; Phan, Tran, & Iyke, 2022), leading to tighter credit supply to the private sector and reduced financing opportunities for non-financial firms (Zhou, Gozgor, Huang, & Lau, 2020).

Thirdly, numerous studies have shown that GPR exerts a strong and statistically significant effect on stock returns. Agoraki, Kouretas and Laopodis (2022), for example, analyse the impact of both geopolitical risks and economic policy uncertainty on stock returns using an unbalanced panel dataset of 22 countries from 1985 to 2020. Their findings indicate that GPR significantly reduces stock returns by 10.53% to 42.14% of the sample mean, a more pronounced impact than that of economic policy uncertainty.

Additionally, Nana Xu, Zhifang He, Fangzhao Zhou, Wenjie Ding, and Jiaqi Chen (2023), in their study of 17,669 firm-year observations across 2,632 firms in China from 2009 to 2019, posit that increased exposure to geopolitical risk is significantly associated with higher stock price crash risk. Similarly, Fiorillo, Meles, Pellegrino, and Verdoliva (2024), in their analysis of 4,402 unique firms (comprising 39,821 firm-years) across 64 countries between 2010 and 2021, conclude that higher GPR increases the frequency of stock price crashes.

Finally, Salisu, Lasisi, and Tchankam (2022) contend that GPR primarily drives stock price crashes through geopolitical threats (GPT) - expectations of future geopolitical tensions - rather than through geopolitical acts (GPA), or the actual realization and escalation of these tensions. Their analysis, covering G7 economies and Switzerland from 2005 to 2021, highlights the importance of perceived risks over realized events in influencing market dynamics.

In summary, geopolitical risk is a critical factor with substantial effects on financial markets, contributing to heightened volatility and more frequent stock price crashes, primarily due to the accumulation of concealed bad news by management. The literature underscores not only the need for further empirical research, which this study seeks to address, but also the absence of studies exploring the role of foreign ownership in this relationship, particularly in the European context. Based on these insights, two hypotheses have been developed to guide this investigation.

H1: GPR causes stock price crashes to occur more frequently.

H2: GPR causes stock price crashes to occur more frequently, driven mainly by geopolitical threats (GPT) rather than geopolitical acts (GPA).

Foreign ownership plays a crucial role in this dynamic. In today's globalized economy, where cross-border investments are increasingly common, foreign ownership introduces additional layers of complexity and volatility, especially in the context of geopolitical risk. Foreign investors, who are often exposed to political and economic uncertainties in their home countries or regions, may react more swiftly to geopolitical events, either by withdrawing capital or reallocating investments to safer assets. This heightened sensitivity can amplify the effects of GPR on stock price crashes, as the external shocks affecting foreign investors can ripple through to the companies they invest in, leading to more pronounced market fluctuations.

Thus, foreign ownership may serve as a conduit through which geopolitical risk impacts stock price crash risk, potentially exacerbating market instability. This relationship is particularly relevant in regions like Europe, where geopolitical tensions are prevalent and foreign investment plays a significant role in domestic markets. By examining how foreign ownership interacts with GPR, this study aims to fill the gap in the literature that has yet to fully explore the intersection of these two factors.

Foreign ownership refers to the equity stakes in domestic companies held by investors from other countries. This ownership can manifest in various forms, such as direct investments by multinational corporations, portfolio investments by institutional investors and individual investments by foreign nationals. Foreign Direct Investment (FDI) is widely recognized as a crucial facilitator of global economic integration, enhancing economic growth for both the investor's home country and the host country. It provides the investing nation with access to new markets and resources while boosting the host country's economic performance through job creation and technology transfer (Pandya, 2008).

Foreign investors are significant external shareholders who can influence a firm's decision-making processes. They possess the ability to monitor management's activities through large-scale transactions and typically maintain a stable, long-term investment perspective (Park & Lee, 2006). Due to their superior access to and analysis of a company's internal information, foreign investors often outperform domestic institutional or individual investors in this regard. They act as “information intermediaries”, disseminating intrinsically valuable information about the firms in which they invest to other market participants. This role enhances the stability and efficiency of resource allocation in medium - and long-term capital markets (Jiang & Kim, 2004; Ahn et al., 2005).

However, prior literature has shown varied results regarding the effect of foreign ownership on stock price crash risk.

On one hand, some research suggests a negative association between foreign ownership and crash risk (Kim et al. 2011a, 2011b, 2014, 2019; Callen & Fang 2015). This is because foreign investors are expected to introduce more effective monitoring and better governance practices, which reduce agency costs and information asymmetry (Shleifer & Vishny, 1986). Financial regulations and the adoption of accounting standards, such as the International Financial Reporting Standards (IFRS), have been identified as important factors affecting stock price crash risk (DeFond et al., 2014), as they diminish irrational decisions and enhance the reliability and transparency of accounting information (Jeon, 2003; Chung et al., 2004).

On the other hand, various papers posit that higher foreign ownership might be associated with higher stock price crash risk. This is because foreign investors seeking short-term gains may divest to capitalize on market movements and demand excessive dividends, leading to overall instability in corporate management and inefficient resource allocation. Porter (1992) found that foreign investors focus on short-term performance and exert heavy pressure on management to report high profits, as their investment horizon is often short-term. Furthermore, foreign investors are exposed to agency problems due to the separation of ownership and control, which can induce corporate managers to pursue their own benefits at the expense of other shareholders (Jensen & Meckling, 1976; Chen et al., 2017).

Zhi-xiong Huang, Qi Tang, and Siming Huang (2020) have shown that foreign investors significantly increase stock price crash risk in China, based on a sample of 18,727 firm-year observations from 2006-2016. Similarly, Xuan Vinh Vo (2020) demonstrates the same trend in Vietnam, analysing 287 nonfinancial firms over the period 2007-2015. Finally, Jae Won Shin (2019) posits that foreign investors' ownership is positively correlated with future stock price crash risk in South Korea, with a sample consisting of 18,322 firm-year observations from 2001-2015.

In summary, while foreign ownership can enhance governance and reduce stock price crash risk through improved monitoring and better information dissemination, it can also heighten crash risk when driven by short-term profit motives, market instability, or heightened agency problems. The net effect of foreign ownership on stock price crash risk remains a nuanced and debated issue in the literature. Importantly, prior studies have largely overlooked the connection between foreign ownership and geopolitical risk. Therefore, my final hypothesis is as follows:

H3: Foreign ownership augments the impact of GPR on stock price crash risk.

3. Methodology & Sample

3.1. Methodology

This thesis employs a quantitative research design, utilizing a longitudinal dataset spanning a seventeen-year period from 2004 to 2020 inclusive. The dataset is sourced from the STOXX Europe 600 index, which tracks the performance of large -, mid -, and small-cap companies across 17 European countries, maintaining a fixed total of 600 constituents. As the index covers more than 80% of the most liquid stocks in Europe, it serves as a robust and representative proxy for the European equity market (Gonçalves et al., 2023).

The sample was refined by obtaining the most recent components list from the index's official website, using the ISIN code and ticker symbol for each company. The final sample size was reduced from 600 to 463 firms after the exclusion of 137 financial institutions, which were deemed outside the scope of this study. Financial institutions possess fundamentally distinct balance sheet structures, characterized by a predominance of financial assets and liabilities, and a primary focus on liquidity and leverage management. This configuration makes them particularly sensitive to market fluctuations and interest rate changes, potentially skewing the patterns observed in non-financial sectors. By excluding these institutions, the analysis remains concentrated on firms whose financial dynamics are more aligned with the central theme of this thesis, ensuring clearer and more relevant insights. Additionally, firm-year observations where companies experienced significant financial distress - specifically, where the control variable LEV was negative - were removed to prevent potential biases in the results.

Financial data for European listed companies were sourced from Bloomberg, while geopolitical risk data were obtained from the GPR index developed by Caldara and Iacoviello. Ownership data were collected from Moody's Orbis, a comprehensive resource for company information, and used to identify the top 10 shareholders for each firm to determine whether they were foreign investors. Foreign ownership was then calculated as the proportion of shares held by foreign investors, following the methodology of Xuan Vinh Vo (2020). The decision to focus on the top 10 shareholders per company is grounded in existing literature, which indicates that large shareholders exert the most significant influence on corporate governance and decision-making. Their investment behaviours are also more likely to impact stock price crash risk, particularly in response to geopolitical events (Huang, Z., Tang, Q., & Huang, S., 2020). The final dataset comprises 463 companies across 17 countries and 8 industries, resulting in a total of 5,045 firm-year observations.

3.2. Sample

Table A.I presents the distribution of firms by country, while Table A.II categorizes them by sector. The data reveals that Great Britain, France, Germany, Switzerland and Sweden collectively account for more than two-thirds of the sample. In terms of industry sectors, the Industrial, Consumer Non-cyclical and Consumer Cyclical sectors together constitute over two-thirds of the sample.

The first set of variables presented are the crash risk measures, which represent the dependent variables in this study. Stock price crash risk is defined as a significant and extreme decline in stock prices, characterized by negative skewness in the distribution of returns for individual stocks (Chen et al., 2001; Kim et al., 2014; Callen & Fang, 2015a). This phenomenon is often driven by idiosyncratic factors, most notably the sudden release of previously withheld negative information by managers (Hutton et al., 2009). Based on existing empirical research, the literature identifies three primary measures of firm-specific crash risk, all derived from weekly returns calculated as residuals from the market model (Chen et al., 2001).

The analysis begins with the following expanded market model regression:

$$r_{i,t} = \alpha_i + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \varepsilon_{i,t\ (1)} \qquad (1)$$

where $r_{i,t}$ and $r_{m,t}$ represent the returns for stock *i* and market index *m* in week *t*, respectively. The firm-specific weekly returns ($R_{i,t}$) are then derived from the residuals ($\varepsilon_{i,t}$) obtained from Equation (1):

$$R_{i,t} = \ln(1 + \varepsilon_{i,t}) \tag{2}$$

The first and primary measure, proposed by Chen et al. (2001), is based on skewness (NCSKEW). This measure captures the asymmetry in the return distribution and is widely used in the literature. Negative skewness values indicate that the data are skewed to the left, implying a greater risk of extreme negative returns. NCSKEW is calculated by taking the negative of the third moment of firm-specific weekly returns for each year and normalizing it by the standard deviation of firm-specific weekly returns raised to the third power:

$$NCSKEW_{i,T} = -\frac{n(n-1)^{\frac{3}{2}} \sum_{i=1}^{n} R_{i,t}^{3}}{(n-1)(n-2)(\sum_{i=1}^{n} R_{i,t}^{2})^{\frac{3}{2}}} \tag{3}$$

where *n* represents the number of available weekly returns for stock *i* in fiscal year *T*. The denominator normalizes the skewness, allowing for the comparison of stocks with varying levels of price volatility. A more negative NCSKEW value suggests a higher likelihood of extreme negative returns, reflecting an elevated crash risk. This measure is advantageous due to its simplicity in computation and interpretation, making it a popular choice for researchers.

The second measure of crash risk is the Down-to-Up Volatility (DUVOL) Ratio, also introduced by Chen et al. (2001). DUVOL is calculated by comparing the standard deviations of firm-specific weekly returns in "down" weeks versus "up" weeks within a given year:

$$DUVOL_{i,T} = \left(\frac{(n_{up} - 1) \sum_{down} R_{i,t}^{2}}{(n_{down} - 1) \sum_{up} R_{i,t}^{2}}\right) \tag{4}$$

where n_{down} *and* n_{up} represent the number of weeks during fiscal year *T* when the firm-specific return is below or above the mean value, respectively. This metric, calculated as the logarithm of the ratio of the standard deviation of "down" returns to that of "up" returns, suggests that a higher DUVOL corresponds to a greater likelihood of crash occurrences. Unlike NCSKEW, DUVOL is not based on the third moment, making it less sensitive to the influence of a small number of extreme negative returns (Callen & Fang, 2013).

The third measure is a binary crash risk indicator, which is coded as one if a firm experiences one or more firm-specific weekly returns falling at least 3.09 standard deviations below its mean value in a given year, and zero otherwise. According to Fiordelisi, Ricci, and Santilli (2023) and Hutton et al. (2009), the threshold of 3.09 standard deviations represents the 0.1% tail of the return distribution. This binary variable serves as an indicator of substantial stock price drops occurring within a week.

Weekly data for each company and the corresponding market returns were extracted from the Bloomberg database. For most companies, data was available for the majority of the 52 weeks, with minimal instances of missing data, primarily due to data scarcity or specific dates when the stock market was closed, such as holidays or other exceptional circumstances.

The second set of data comprises the independent variables in this thesis: the geopolitical risk and foreign ownership.

The first independent variable obtained from the GPR index, was developed in 2018 by Caldara and Iacoviello. This index quantifies the occurrence of adverse geopolitical events by analysing the frequency of relevant newspaper articles. The index is defined as the ratio of:

$$GPR \ \alpha \ \frac{G}{U} \tag{5}$$

where *G* represents the number of articles mentioning adverse geopolitical events and *U* denotes the total number of articles analysed, with a monthly frequency. Although a daily version of the index (GPRD) is available, this study mainly utilizes the monthly index to minimize data complexity and reduce potential noise that could arise from short-term fluctuations in daily data. The daily GPRD index was employed in robustness checks. This ensures that the results are not driven by the choice of frequency.

The GPR index is available in two versions: a historical version, dating back to 1900, and a more recent version, which is employed in this study, starting from 1985, which expands the source base to include newspapers such as the Chicago Tribune, Los Angeles Times, New York Times, Wall Street Journal, Philadelphia Inquirer, Daily Telegraph, Financial Times, The Guardian, and The Globe and Mail.

To identify articles discussing adverse geopolitical events, Caldara and Iacoviello employed a sophisticated query using two sets of keywords. The first set includes topic-specific words related to war, nuclear issues and terrorism, while the second set comprises words indicating either a "threat" or an "act" associated with these topics. This dual-bag approach ensures that only relevant and specific articles are captured. The selection of these topic words resulted from a meticulous process involving definitions intrinsic to geopolitical phenomena, textual analysis of approximately 44,000 front-page articles from the New York Times spanning 1900 to 2020, and an in-depth review of key historical periods and the language used by newspapers to describe geopolitical events. To refine the search and avoid false positives, articles containing words associated with non-relevant contexts, such as movies, anniversaries, obituaries and books, are deliberately excluded. Additionally, the methodology accounts for the evolution of language over time, ensuring the index remains accurate across different eras.

The GPR index is further categorized into two components: geopolitical threats (GPT) and geopolitical acts (GPA). GPT encompasses search categories one to five - war risks, peace threats, military buildups, nuclear threats and terrorist threats - capturing the anticipation of geopolitical events. GPA covers categories six to eight - beginning of war, escalation of war and terrorist acts - focusing on the actual occurrences of such events.

The GPR, GPT and GPA measures were extracted from the Caldara and Iacoviello database at a monthly frequency, while the GPRD measure was obtained at a daily frequency. To ensure consistency across these different frequencies, the average of the observations for all measures was calculated over each fiscal year. This averaging process reduces the impact of short-term fluctuations and outliers, making the data more stable and reliable for analysis. Furthermore, the logarithmic transformation of these averages is applied to stabilize variance, minimize the influence of extreme values and improve data normality. These adjustments enhance the performance and interpretability of the model, allowing for more robust and meaningful insights (Fiorillo, Meles, Pellegrino, & Verdoliva, 2024).

The second independent variable, foreign ownership, refers to the equity stakes in domestic companies held by international investors. Data on ownership were obtained from Moody's Orbis platform, with a focus on identifying the top 10 shareholders to determine the controlling shareholders. For each company, the dataset includes the total number of shareholders, the location of the firm, the country of origin of each of the top 10 shareholders and their respective ownership percentages, collected annually. Foreign ownership was then calculated as the proportion of shares held by foreign investors, following the methodology outlined by Xuan Vinh Vo (2020) and defined as FIO. Table A.III presents the distribution of foreign ownership proportions by country. As expected, the countries with the highest representation in the sample, as shown in Table A.I, also exhibit the most comprehensive data on investor ownership.

The third and final set of variables comprises the control variables used in this thesis to account for additional predictors of stock price crash risk. Consistent with prior research on crash risk (Callen & Fang, 2013; Chen et al., 2001; Jang & Kang, 2019; Kim et al., 2011), these control variables were sourced from the Bloomberg database and include several key firm-specific metrics.

Firm Size LN(Total Assets): This variable represents the natural logarithm of a company's total assets, serving as a proxy for firm size. Larger firms generally have greater resources to absorb external shocks and mitigate risks, potentially reducing their vulnerability to stock price crashes. However, large firms are often subject to greater regulatory scrutiny and public attention, which may amplify the market's reaction to negative information, as suggested by agency theory (Jin & Myers, 2006). The balancing effect of size on crash risk is therefore nuanced and must be carefully considered in light of both resource availability and public visibility.

Leverage (LEV): The debt-to-equity ratio is used to measure a company's financial leverage, providing insight into its capital structure. Highly leveraged firms, particularly those facing geopolitical instability, may be more susceptible to increased borrowing costs, financial distress and ultimately stock price crashes. This relationship is consistent with previous findings indicating that firms with higher leverage are more vulnerable to adverse events (Graham, Harvey, & Rajgopal, 2005).

Profitability (EBIT/Total Assets): Profitability, calculated as the ratio of earnings before interest and taxes (EBIT) to total assets, reflects a company's ability to generate operating income relative to its asset base. Firms with higher profitability are generally better equipped to weather geopolitical shocks and financial instability, thereby reducing the likelihood of a stock price crash. Furthermore, high profitability indicates operational efficiency and resilience, allowing firms to manage external risks more effectively (Kim et al., 2014). Given the heightened uncertainty associated with geopolitical risk (Caldara & Iacoviello, 2022), profitability serves as a critical buffer against crash risk.

Volatility (STDEV): The annualized standard deviation of weekly stock returns is employed to measure stock price volatility, a direct indicator of a firm's exposure to market risk. High volatility is often associated with increased uncertainty and sensitivity to adverse events, particularly in the context of geopolitical tensions (Xu et al., 2023). Firms with higher STDEV are more likely to experience sharp declines in stock prices in response to geopolitical events, which makes this a crucial control variable for analysing crash risk. This measure was calculated using Stata, based on the weekly returns data sourced for each company.

Analyst Coverage (T_Analyst): This variable represents the number of analysts issuing buy, hold or sell recommendations for the company's stock. Analyst coverage is a useful proxy for market visibility and investor attention, with firms receiving more coverage being subject to greater market scrutiny. Greater visibility can lead to both positive and negative impacts - on one hand, it enhances transparency and information flow, which may mitigate crash risk. On the other hand, increased attention can amplify market reactions to negative news, particularly in periods of heightened geopolitical risk (Kim et al., 2011a).

To account for foreign ownership models, the control variables were adjusted by removing Profitability and T_Analyst and introducing Return on Assets (ROA), in line with the existing literature (Xuan Vinh Vo, 2020 and Huang, Z., Tang, Q., & Huang, S., 2020).

Return on Assets (ROA): ROA replaces profitability as the preferred measure of operational efficiency, following established literature. It captures a firm's ability to generate income relative to its total assets, indicating how effectively the firm utilizes its resources. Firms with higher ROA are generally more resilient to external shocks, including geopolitical risks, thereby reducing the likelihood of a stock price crash. ROA provides a more comprehensive measure of operational efficiency in the context of foreign ownership.

In conclusion, the variables employed in this study are categorized into three distinct groups: dependent variables, independent variables and control variables. The dependent variables are represented by the crash risk measures - NCSKEW, DUVOL and N_CRASH. The independent variables include geopolitical risk measures - GPR, GPT, GPA and GPRD - along with foreign ownership (FIO). The control variables consist of LN(Total Assets), LEV, Profitability, STDEV, T_Analyst and ROA. A comprehensive overview of these variables is provided in Table A.IV.

Table A.V presents the descriptive statistics for the variables, with the winsorization technique, providing insights into the number of observations, mean, standard deviation, minimum, median, maximum, as well as the 1st and 99th percentiles, skewness and kurtosis. To mitigate the influence of significant outliers, a winsorization technique was applied at the 1% level to both tails of the distribution for all variables, except those expressed in logarithmic form, as suggested in the literature (Fiorillo, Meles, Pellegrino, & Verdoliva, 2024). This approach effectively reduced kurtosis in several control variables, most notably LEV, where kurtosis markedly decreased from 5,668 to 14.595, underscoring the utility of this method in stabilizing data distribution.

The analysis of crash risk measures reveals distinct distribution patterns. The NCSKEW and DUVOL metrics, with means of 0.065 and 0.263, respectively, exhibit distributions that closely approximate normality. Both metrics are characterized by slight positive skewness (0.498 for NCSKEW and 0.169 for DUVOL) and moderate kurtosis (5.002 for NCSKEW and 3.719 for DUVOL), suggesting relatively stable behaviour with only minor deviations. In contrast, N_CRASH, with a mean of 0.124, displays substantial positive skewness (2.447) and elevated kurtosis (7.589), indicating that while stock price crashes are infrequent, they tend to be severe when they do occur.

The second independent variable, FIO, presents an average of 0.288 with a standard deviation of 0.381, indicating substantial variability in foreign ownership proportion across firms. The minimum value of 0 and maximum value of 1 illustrate the full range of foreign ownership, from firms with no foreign investment to those fully owned by foreign investors. The skewness of 0.959 and kurtosis of 2.273 indicate a moderate rightward skew, suggesting that while many companies have low or moderate foreign ownership, a smaller subset of firms has significantly higher levels of foreign ownership. This variability highlights the diverse roles foreign investors play in European firms, ranging from minority shareholders to major controlling entities.

Turning to the geopolitical variables, LN(GPR), LN(GPT) and LN(GPRD) demonstrate slight positive skewness and near-normal kurtosis, suggesting fairly symmetrical distributions with some higher outliers. For example, LN(GPR) has a mean of 4.543 and skewness of 0.552, while LN(GPRD) shows similar skewness (0.64) with a mean of 4.538. On the other hand, LN(GPA) is characterized by slight negative skewness (-0.143) and heavier tails, as indicated by its kurtosis of 3.329, possibly reflecting the presence of more extreme low values within the dataset.

Regarding the control variables, LN(Total Assets), with a mean of 9.053, exhibits a nearly symmetric distribution, with slight negative skewness (-0.188) and moderate kurtosis (2.798), indicating a balanced distribution across most companies. In contrast, variables such as LEV, Profitability, STDEV, T_Analyst and ROA exhibit substantial positive skewness and high kurtosis, reflecting the presence of significant outliers and a pronounced right tail.

LEV, for instance, has a skewness of 2.913 and a kurtosis of 14.595, suggesting that a few highly leveraged firms disproportionately affect the overall distribution, increasing the likelihood of extreme values. Profitability shows a skewness of 0.894 and a kurtosis of 6.141, highlighting that most firms demonstrate moderate profitability, but a few outliers with exceptionally high profitability pull the distribution toward the right. Similarly, STDEV has a skewness of 1.363 and a kurtosis of 4.858, indicating that while most companies experience relatively stable volatility, some firms are subject to significantly higher levels of market risk, distorting the overall volatility landscape. T_Analyst has a skewness of 0.233 and a kurtosis of 2.299, demonstrating that most firms have moderate analyst coverage, but a few outliers with very high coverage create a right-tailed distribution. Lastly, ROA presents a skewness of 1.14 and kurtosis of 7.054, reflecting that while most companies exhibit moderate efficiency in utilizing their assets, a small number of firms significantly outperform, leading to a pronounced rightward skew and higher kurtosis.

4. Empirical Results

4.1 Baseline Results of Geopolitical Risk and Stock Price Crash Risk

The baseline results examining the relationship between geopolitical risk and stock price crash risk are present here, specifically testing two hypotheses: first, that higher GPR increases the frequency of stock price crashes, and second, that GPR-driven stock price crashes are primarily influenced by geopolitical threats (GPT) rather than geopolitical acts (GPA).

To address potential inconsistencies in the regression model assumptions, validation tests were conducted. Table A.VI presents the results of the variance inflation factors (VIF), which show no evidence of multicollinearity among the regressors, as all VIF values are low, with a mean of 1.58 - well below the threshold of 10. Additionally, the same table displays the results of the Hausman and Wooldridge tests. The Hausman test strongly supports the use of the fixed effects (FE) model over the random effects model, while the Wooldridge test provides robust evidence of serial correlation among the residuals. Non-stationarity is not a concern, as demonstrated in Table A.VII. However, the presence of residual autocorrelation in the models may undermine their precision, potentially leading to inconsistent and biased estimates. Robustness tests will be performed to further assess and mitigate potential issues related to endogeneity.

When analysing the Pairwise Correlation Matrix in Table A.VIII, several key relationships become apparent. Firstly, the crash risk measures show strong positive correlations, as expected, since they capture related aspects of stock price crash risk across different dimensions. Notably, NCSKEW and DUVOL exhibit the highest correlation at 0.907, indicating a significant overlap in how they represent crash risk.

Secondly, the geopolitical risk variables demonstrate strong positive correlations, which is anticipated since they capture similar elements of geopolitical uncertainty. However, the negative correlation between LN(GPT) and LN(GPA) of -0.086 suggests differing dynamics between geopolitical threats and actual acts, underscoring the importance of the second hypothesis (H2), which distinguishes between these two aspects of geopolitical risk.

Thirdly, FIO shows weak correlations with most other variables, implying that foreign ownership does not strongly interact with many of the crash risk or control variables. This aligns with prior findings in the literature that suggest the influence of foreign ownership on stock price crash risk is more nuanced and may depend on specific contexts or external factors, such as geopolitical risk.

Lastly, the control variables reveal interesting dynamics. LN(Total Assets) exhibits a strong positive correlation with T_Analyst (0.625), suggesting that larger firms tend to attract more analyst coverage, likely due to their increased market visibility and investor interest. Conversely, LN(Total Assets) shows a negative correlation with Profitability (-0.327), indicating that larger firms may not be as profitable relative to their size, possibly due to increased overhead, inefficiencies or differing financial structures. Additionally, ROA is negatively correlated with LN(Total Assets) (-0.270), reinforcing this notion observed in Profitability. LEV also presents a weak positive correlation with LN(Total Assets) (0.205), implying that larger organizations tend to take on more debt, which is consistent with the financial leverage literature. Moreover, STDEV positively correlates with crash risk measures, reflecting that firms with higher volatility are more prone to extreme negative returns.

Table I presents the results of pooled ordinary least squares (OLS) and fixed effects (FE) regressions. The dependent variables in these regressions are the crash risk measures: NCSKEW, DUVOL and N_CRASH.

For columns 1 to 3, the estimation of the effect of geopolitical risk on stock price crash risk was calculated using the following Equation, without firm and year fixed effects:

$$\begin{aligned} Crash\ Risk_{i,t} = {} & \alpha_i + \beta_1 LN(GPR)_t + \beta_2 LN(Total\ Assets)_{i,t} + \beta_3 LEV_{i,t} \\ & + \beta_4 Profitability_{i,t} + \beta_5 STDEV_{i,t} + \beta_6 T\_Analyst_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

The analysis reveals that LN(GPR) is statistically significant only in the DUVOL regression, with a coefficient of 0.391 at the 1% significance level. By contrast, the coefficients for NCSKEW (0.191) and N_CRASH (-0.006) are not statistically significant, with the negative coefficient for N_CRASH appearing counterintuitive. This suggests that while fluctuations in geopolitical risk have a limited overall impact on crash risk, they exert a more substantial influence on downside volatility (DUVOL).

Similarly, LN(Total Assets) is statistically significant solely in the DUVOL regression, with a coefficient of 0.022, significant at the 5% level. This finding implies that larger firms tend to experience higher downside volatility, although this relationship does not hold for NCSKEW or N_CRASH. In contrast, LEV does not demonstrate statistical significance in any of the models, indicating that leverage does not play a critical role in explaining crash risk in this context. Profitability exhibits strong statistical significance across all crash risk measures, with negative coefficients (-2.256 for NCSKEW, -2.077 for DUVOL and -0.321 for N_CRASH), reinforcing the notion that more profitable firms are less likely to encounter stock price crashes. STDEV is significant in predicting both DUVOL and N_CRASH, with coefficients of -1.393 and 0.614, respectively, both significant at the 10% level. However, the opposing signs of these coefficients complicate the interpretation of STDEV's influence, suggesting that its impact may differ across the various crash risk measures. Lastly, T_Analyst consistently shows statistical significance across all regressions, with positive coefficients. For NCSKEW and DUVOL, the coefficients (0.009 and 0.007, respectively) are significant at the 1% level, while for N_CRASH, the coefficient (0.002) is significant at the 10% level. These results imply that greater analyst coverage is associated with heightened crash risk, likely due to increased scrutiny and broader dissemination of information about the firm.

Building on these findings, columns 4 to 6 present the regression results after incorporating firm and year fixed effects, offering a more refined understanding of the model's outcomes. To address heteroskedasticity, robust standard errors were applied (Wooldridge, 2010). The inclusion of fixed effects modifies Equation 6 as follows:

$$\begin{aligned} Crash\ Risk_{i,t} = {} & \alpha_i + \beta_1 LN(GPR)_t + \beta_2 LN(Total\ Assets)_{i,t} + \beta_3 LEV_{i,t} \\ & + \beta_4 Profitability_{i,t} + \beta_5 STDEV_{i,t} + \beta_6 T\_Analyst_{i,t} + \gamma FirmFE \\ & + \theta YearFE + \varepsilon_{i,t} \end{aligned} \tag{7}$$

In the OLS model, LN(GPR) is statistically significant only for DUVOL. However, after the introduction of FE, LN(GPR) becomes statistically significant at the 1% level for

NCSKEW, though it remains insignificant for N_CRASH. This shift suggests that geopolitical risk exerts a significant influence on crash risk measures when accounting for firm-specific and temporal factors.

The inclusion of fixed effects further reinforces the role of independent variables. LN(Total Assets) becomes statistically significant in both the DUVOL regression at the 5% level, with an increased coefficient of 0.102, and in the NCSKEW regression, with a coefficient of 0.111. This supports the theory that larger firms tend to face greater stock price crash risk or that this risk is magnified in larger companies. Conversely, LEV remains non-significant across all regressions, while Profitability continues to demonstrate strong significance, with negative coefficients of -3.380 for NCSKEW and -3.450 for DUVOL, reaffirming that more profitable companies are less vulnerable to crash risk.

STDEV is now significant across all regressions: at the 5% level for NCSKEW (coefficient of 3.667), at the 10% level for DUVOL (-2.520) and at the 1% level for N_CRASH (2.589). Despite the statistical significance, the opposing signs across measures warrant caution in interpreting STDEV's overall effect on crash risk. Finally, T_Analyst remains consistently significant, with coefficients increasing to 0.026 for NCSKEW and 0.019 for DUVOL, reinforcing the idea that increased analyst coverage is associated with heightened crash risk, likely due to greater scrutiny and the broader dissemination of information.

In conclusion, these findings provide robust support for the first hypothesis (H1), indicating that heightened geopolitical risk significantly increases the likelihood of stock price crashes.

Table I – OLS & FE Regressions of GPR on Stock Price Crash Risk

Variables	(1) NCSKEW	(2) DUVOL	(3) N_CRASH	(4) NCSKEW	(5) DUVOL	(6) N_CRASH
LN(GPR)	0.191	0.391***	-0.006	0.733***	0.601***	0.070
	(0.126)	(0.103)	(0.045)	(0.204)	(0.163)	(0.079)
LN(Total Assets)	0.002	0.022**	-0.007	0.111**	0.102**	0.011
	(0.013)	(0.010)	(0.005)	(0.053)	(0.044)	(0.018)
LEV	-0.001	-0.008	0.000	-0.016	-0.021	-0.003
	(0.010)	(0.008)	(0.004)	(0.016)	(0.013)	(0.006)
Profitability	-2.256**	-2.077***	-0.321*	-3.380***	-3.450***	-0.271
	(0.461)	(0.377)	(0.166)	(0.735)	(0.615)	(0.265)

STDEV	0.701	-1.393*	0.614*	3.667**	-2.520*	2.589***
	(0.952)	(0.777)	(0.342)	(1.704)	(1.322)	(0.590)
T_Analyst	0.009***	0.007***	0.002**	0.026***	0.019***	0.004**
	(0.002)	(0.002)	(0.001)	(0.005)	(0.005)	(0.002)
Constant	-0.941	-1.661***	0.183	-4.825***	-3.463***	-0.455
	(0.602)	(0.492)	(0.217)	(1.270)	(1.016)	(0.480)
Firm FE	No	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
N	3,951	3,951	3,954	3,951	3,951	3,954
R^2	0.019	0.032	0.003			
Adjusted R^2	0.017	0.030	0.002			
Within R^2				0.038	0.040	0.018
Between R^2				0.054	0.099	0.000
Overall R^2				0.022	0.034	0.007

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Standard errors in parentheses for columns 1 to 3, while robust standard errors for columns 4 to 6. The R^2 represents the proportion of the variance in the dependent variable that is explained by the independent variables. The Adjusted R^2 is a modified version of R^2 that adjusts for the number of predictors in the model. The Within R^2 shows the proportion of variation in the dependent variable explained by the regressors within each firm, the Between R^2 focus on dynamics between firms and the Overall R^2 combines both Within and Between R^2.

The second hypothesis (H2) posits that GPR increases the frequency of stock price crashes, with this effect being primarily driven by geopolitical threats (GPT) rather than geopolitical acts (GPA). To test this hypothesis and corroborate existing findings on the impact of geopolitical factors on stock market dynamics, Equation (7) was re-estimated by substituting the primary regressor, LN(GPR), with the logarithms of GPT and GPA.

Table II presents the regression results, with columns 1 to 3 focusing on GPT and the remaining columns on GPA. The results indicate that the coefficients for both GPT and GPA are statistically significant at the 1% level for NCSKEW and DUVOL, while N_CRASH remains insignificant, as observed in the previous models. However, GPT exhibits notably stronger coefficients than GPA. For instance, the coefficient for NCSKEW(GPT) is 3.578, while NCSKEW(GPA) stands at 0.316.

These findings emphasize that geopolitical threats (GPT) have a more substantial impact on stock price crashes than geopolitical acts (GPA), suggesting that the uncertainty and fear surrounding geopolitical threats play a more decisive role in triggering stock price crashes than the actual realization of geopolitical events. This outcome confirms previous findings in the literature (Fiorillo, Meles, Pellegrino, and Verdoliva, 2024; Salisu, A. A., Lasisi, L., Tchankam, J. P., & Adediran, I. A., 2022).

Table II - Effect of GPT vs GPA on Stock Price Crash Risk

Variables	(1) NCSKEW (GPT)	(2) DUVOL (GPT)	(3) N_CRASH (GPT)	(4) NCSKEW (GPA)	(5) DUVOL (GPA)	(6) N_CRASH (GPA)
LN(GPT)	3.578***	2.935***	0.340			
	(0.994)	(0.796)	(0.383)			
LN(GPA)				0.316***	0.260***	0.030
				(0.088)	(0.070)	(0.034)
LN(Total Assets)	0.111**	0.102**	0.011	0.111**	0.102**	0.011
	(0.053)	(0.044)	(0.018)	(0.053)	(0.044)	(0.018)
LEV	-0.016	-0.021	-0.003	-0.016	-0.021	-0.003
	(0.016)	(0.013)	(0.006)	(0.016)	(0.013)	(0.006)
Profitability	-3.380***	-3.450***	-0.271	-3.380***	-3.450***	-0.271
	(0.735)	(0.615)	(0.265)	(0.735)	(0.615)	(0.265)
STDEV	3.667**	-2.520*	2.589***	3.667**	-2.520*	2.589***
	(1.704)	(1.322)	(0.590)	(1.704)	(1.322)	(0.590)
T_Analyst	0.026***	0.019***	0.004**	0.026***	0.019***	0.004**
	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)	(0.002)
Constant	-18.022***	-14.291***	-1.709	-2.871***	-1.860***	-0.269
	(4.892)	(3.910)	(1.880)	(0.772)	(0.621)	(0.285)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,951	3,951	3,954	3,951	3,951	3,954
Within R^2	0.038	0.040	0.018	0.038	0.040	0.018
Between R^2	0.054	0.099	0.000	0.054	0.099	0.000
Overall R^2	0.022	0.034	0.007	0.022	0.034	0.007

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses. The Within R^2 shows the proportion of variation in the dependent variable explained by the regressors within each firm, the Between R^2 focus on dynamics between firms and the Overall R^2 combines both Within and Between R^2.

4.2 Robustness Results of Geopolitical Risk and Stock Price Crash Risk

To further validate the baseline results with greater certainty, additional robustness tests are conducted only to the main crash risk measure (NCSKEW), as presented in Table A.IX. These tests aim to assess the reliability of the initial findings from Table I, particularly regarding Hypothesis 1 (H1).

First, to confirm that the positive relationship between GPR and stock price crash risk is not disproportionately driven by the most representative countries in the sample (Table A.I), the first robustness test excludes companies from Great Britain, France and Germany, which collectively account for nearly 50% of the sample (column 1). Second, to examine whether the results are skewed by countries with fewer companies, the second test excludes firms incorporated in countries falling within the lowest decile of the sample distribution (column 2). The third and fourth columns evaluate the regression while controlling for country and sector fixed effects, respectively. In column 5, the combined relevance of all fixed effects is tested. Additionally, column 6 presents result after excluding companies from the Industrial and Consumer Non-cyclical sectors, which represent 50% of the sample (Table A.II). In column 7, the independent variable T_Analyst is further examined by using Best_Analyst, a variable ranging from 1 (sell recommendation) to 5 (buy recommendation), to ensure the robustness and validity of the analyst recommendation data in the regression analysis. Lastly, column 8 employs an alternative specification of the GPR index, using the daily GPR values calculated as the logarithm of the average daily GPR values - LN(GPRD) - rather than the monthly values used in the baseline model.

Each of these tests' re-estimates Equation (7), with adjustments tailored to the specific robustness check, ensuring that the baseline findings hold across varying scenarios and conditions.

Across all regressions, LN(GPR) remains statistically significant, largely mirroring the earlier results, except for columns 3 and 4, where the individual effects of country and sector are isolated. These findings lead to several key conclusions. First, Hypothesis 1 (H1) is reinforced, as LN(GPR) consistently remains statistically significant with positive coefficients predominantly at the 1% level, except in column 7, where significance is observed at the 5% level. Second, neither country nor sector effects alone can account for the variations in the dependent variables. Third, T_Analyst emerges as a robust control variable, as Best_Analyst returns a negative coefficient, a result that aligns with expectations: a more favourable analyst rating (closer to 5) is associated with lower NCSKEW, while a lower rating (closer to 1) corresponds to higher NCSKEW, indicating that unfavourable ratings increase the crash risk measure and are linked to higher volatility. Lastly, the alternative specification of the GPR index, LN(GPRD), yields consistent and positive results, further confirming the robustness of the independent variable.

These findings are consistent with existing literature on the impact of GPR on stock price performance (Agoraki et al., 2022; Saâdaoui, Jabeur, & Goodell, 2023; Salisu et al., 2022) and market volatility (Yang et al., 2022; Zhang, He, He, & Li, 2023). The depth of this study, particularly its firm-level analysis, substantially strengthens both the first and second hypotheses (H1 and H2). These results contribute meaningful insights to the ongoing discourse on GPR and its effects on stock market dynamics.

Despite the robustness tests, the baseline results may still be subject to endogeneity bias, omitted variable bias and other unmeasured determinants of crash risk. Additionally, persistent effects may not be fully captured by the OLS or FE regressions. Relying solely on a firm fixed effects model is insufficient to comprehensively address endogeneity concerns. To mitigate this issue, a two-stage instrumental variable (IV) approach is employed.

The chosen instrument is the *Political Stability and Absence of Violence/Terrorism* index from the Worldwide Governance Indicators (WGI) database, provided by the World Bank. This index measures country-level perceptions of political instability and politically motivated violence, including terrorism, with values ranging from -2.5 to 2.5, where lower values indicate higher political instability. The index serves as a proxy for governance quality at the country level, and prior literature (Ferreira, Gomes, Lopes & Zhang, 2023) has identified it as a significant driver of geopolitical tensions. Importantly, the index is argued to have no direct link to stock price crash risk, thereby satisfying the exclusion restriction necessary for a valid IV (Fiorillo, Meles, Pellegrino, & Verdoliva, 2024).

The first stage regression is defined as follows:

$$LN(GPR)_t = \alpha_i + \beta_1 Stability_t + \psi_1 Controls_{i,t} + \gamma FirmFE + \theta YearFE + \varepsilon_{i,t} \quad (8)$$

where $Stability_t$ is the IV. In the second stage, Equation (7) is estimated after replacing the endogenous variable $LN(GPR)_t$ with the predicted values from the first stage regression:

$$Crash\ Risk_{i,t} = \alpha_i + LN(\hat{G}PR)_t + \psi_1 Controls_{i,t} + \gamma FirmFE + \theta YearFE + \varepsilon_{i,t} \quad (9)$$

Table III presents the results of the IV approach. The first-stage regression, displayed in column 1, confirms that the instrument is negatively related to GPR, presenting a coefficient of -0.021, statistically significant at the 1% level. This finding aligns with expectations, as lower stability index values correspond to increased political instability, thereby raising GPR. The Cragg-Donald Wald F-statistic strongly supports the instrument's validity, significantly surpassing the Stock and Yogo (2005) weak identification test critical value at the 10% level (75.973 compared to the threshold of 16.38).

The second-stage regression results, presented in columns 2 to 4, confirm that the coefficient for the predicted GPR value from the first stage remains positive and statistically significant at the 1% level for both NCSKEW and DUVOL, while N_CRASH remains insignificant, as consistently observed throughout this study.

Furthermore, all independent variables that were statistically significant in previous models maintain consistent results. LN(TotalAssets) exhibits a positive coefficient with 5% significance, Profitability maintains a negative coefficient with 1% significance, STDEV retains its mixed signs and significance at the 5% level for NCSKEW and 10% for DUVOL and T_Analyst remains significant at the 1% level with positive coefficients.

These findings further demonstrate that higher geopolitical risk significantly elevates the likelihood of stock price crashes, fully confirming the first hypothesis (H1), as similarly evidenced in previous literature (Fiorillo, Meles, Pellegrino, & Verdoliva, 2024).

Table III – Two-Stage Instrumental Variables Approach (IV)

Variables	(1) First Stage LN(GPR)	(2) Second Stage NCSKEW	(3) Second Stage DUVOL	(4) Second Stage N_CRASH
Stability	-0.021***			
	(0.002)			
LN(GPR)		0.733***	0.601***	0.070
		(0.203)	(0.162)	(0.078)
LN(Total Assets)	-0.020	0.111**	0.102**	0.011
	(0.015)	(0.053)	(0.044)	(0.018)
LEV	-0.001	-0.016	-0.021	-0.003
	(0.003)	(0.016)	(0.013)	(0.006)
Profitability	-0.300**	-3.380***	-3.450***	-0.271
	(0.137)	(0.733)	(0.613)	(0.264)
STDEV	0.406	3.667**	-2.520*	2.589***
	(0.267)	(1.698)	(1.318)	(0.588)

T_Analyst	0.001	0.026***	0.019***	0.004**
	(0.001)	(0.005)	(0.005)	(0.002)
Constant	0.826***	-5.474***	-3.520***	-0.408
	(0.127)	(1.262)	(1.011)	(0.478)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster SE	Firm	Firm	Firm	Firm
N	3,954	3,951	3,951	3,954
Number of Clusters	387	387	387	387
Cragg-Donald Wald F-statistic 1st stage	75.973			
Stock–Yogo size of nominal 10%	16.38			
Centered R^2	0.003	0.140	0.141	0.126
Uncentered R^2	0.999	0.145	0.239	0.248

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses. The Centered R^2 indicates the proportion of variation in the dependent variable explained by the regressors after accounting for the mean of the dependent variables. The Uncentered R^2 measures the proportion of variation in the dependent variable explained by the regressors without subtracting the mean from the dependent variable.

4.3 The Moderating Role of Foreign Ownership

Previously, it was demonstrated that geopolitical risk significantly increases the likelihood of future stock price crashes, with geopolitical threats playing a more prominent role than geopolitical acts. In an increasingly globalized world, where capital markets are more interconnected than ever, and geopolitical tensions are driving nations into distinct geopolitical blocs, it becomes essential to investigate whether foreign ownership, through foreign direct investment (FDI), might amplify or mitigate geopolitical risks, thereby moderating the likelihood of future stock price crashes.

As discussed in the literature review, the current body of research presents conflicting evidence on this topic. Some studies suggest that foreign ownership has a stabilizing effect on crash risk, owing to the expectation that foreign investors bring more effective monitoring mechanisms and improved corporate governance practices. These factors reduce the likelihood of irrational decisions and enhance the reliability and transparency of accounting information (Jeon, 2003; Chung et al., 2004). Conversely, other studies argue that foreign ownership may contribute to instability. Such investors, often driven by short-term gains, may divest in response to market fluctuations and demand excessive dividends, which can destabilize corporate management and lead to inefficient resource allocation (Porter, 1992). Additionally, agency problems stemming from the separation of ownership and control may incentivize corporate managers to prioritize their own interests over those of shareholders (Jensen & Meckling, 1976; Chen et al., 2017).

Given these conflicting perspectives, it is essential to clarify the relationship between foreign ownership and crash risk. Hypothesis 3 (H3) posits that foreign ownership increases the likelihood of stock price crashes, through its impact on GPR. To test this hypothesis, a new independent variable, FIO (Foreign Investor's Ownership), is introduced, representing the proportion of foreign ownership in a firm, with data sourced from the Orbis Moody's database. Profitability and T_Analyst are removed from the control variables and replaced by ROA, which is more frequently used in related studies (Huang et al., 2020; Ho, 2020). Accordingly, Equation 7 is modified as follows:

$$\begin{aligned} Crash\ Risk_{i,t} = {} & \alpha_i + \beta_1 LN(GPR)_t + \beta_2 FIO_{i,t} + \beta_3 LN(Total\ Assets)_{i,t} + \beta_4 LEV_{i,t} \\ & + \beta_5 STDEV_{i,t} + \beta_6 ROA_{i,t} + \gamma FirmFE + \theta YearFE + \varepsilon_{i,t} \qquad (10) \end{aligned}$$

Table IV presents the regression results incorporating firm and year fixed effects. In the first three columns, LN(GPR) is statistically significant for both NCSKEW and DUVOL at the 1% level, with coefficients of 0.787 and 0.661, respectively. FIO also shows statistical significance at the 1% level for NCSKEW and the 5% level for DUVOL, with coefficients of 0.164 and 0.099, respectively, while N_CRASH remains insignificant across all specifications.

The control variables exhibit consistent behaviour across the regressions. LN(Total Assets) and ROA remain significant for both crash risk measures, with coefficients of 0.142 and 0.132 at the 1% level for size, and -0.011 at the 1% level for profitability. This suggests that larger companies are more vulnerable to crash risk, while more profitable firms exhibit lower susceptibility. LEV is significant only in the DUVOL regression, with a negative coefficient of -0.025 at the 5% level, indicating that less leveraged companies are less prone to crash risk. Additionally, STDEV is significant at the 1% level for NCSKEW, with a coefficient of 5.591, reflecting that firms with higher volatility are more likely to experience stock price crashes.

In columns 4 to 6, Equation 10 is further modified to include an interaction term:

$$Crash\ Risk_{i,t} = \alpha_i + \beta_1 LN(GPR)_t + \beta_2 LN(GPR)_t \times FIO_{i,t} + \beta_3 LN(Total\ Assets)_{i,t} + \beta_4 LEV_{i,t} + \beta_5 STDEV_{i,t} + \beta_6 ROA_{i,t} + \gamma FirmFE + \theta YearFE + \varepsilon_{i,t} \quad (11)$$

The results remain consistent with prior findings, but the introduction of the interaction term between LN(GPR) and FIO adds an important dimension and layer of complexity to the analysis. The interaction term is statistically significant for both NCSKEW (at the 1% level, with a coefficient of 0.036) and DUVOL (at the 5% level, with a coefficient of 0.022). This indicates that the combined influence of geopolitical risk and foreign ownership significantly amplifies the likelihood of stock price crashes.

This interaction term is particularly crucial as it suggests that the impact of GPR on crash risk is not homogeneous across all firms but is significantly influenced by their level of foreign ownership. The positive and significant coefficients for the interaction term demonstrate that as foreign ownership increases, the effect of geopolitical risk on crash risk intensifies. In other words, firms with a higher proportion of foreign investors are more susceptible to geopolitical risks, leading to a greater likelihood of stock price crashes when geopolitical tensions escalate.

These findings provide empirical support for the third hypothesis (H3), confirming that foreign ownership amplifies the effect of geopolitical risk on stock price crash risk. This underscores the interconnectedness of global investment dynamics and geopolitical uncertainties, and further clarifies the role of foreign ownership in exacerbating crash risk, consistent with the findings of Huang, Tang, & Huang (2020) and Xuan Vinh Vo (2020).

Table IV – The Moderating Role of Foreign Ownership

Variables	(1) NCSKEW	(2) DUVOL	(3) N_CRASH	(4) NCSKEW	(5) DUVOL	(6) N_CRASH
LN(GPR)	0.787***	0.661***	0.062	0.779***	0.656***	0.060
	(0.202)	(0.160)	(0.080)	(0.202)	(0.160)	(0.080)
FIO	0.164***	0.099**	0.030			
	(0.049)	(0.040)	(0.021)			
LN(GPR)*FIO				0.036***	0.022**	0.007
				(0.011)	(0.009)	(0.005)
LN(Total Assets)	0.142***	0.132***	0.011	0.142***	0.132***	0.011
	(0.043)	(0.035)	(0.016)	(0.043)	(0.035)	(0.016)
LEV	-0.028	-0.025**	-0.008	-0.028	-0.025**	-0.008

	(0.017)	(0.011)	(0.006)	(0.017)	(0.011)	(0.006)
STDEV	5.591***	-0.612	3.101***	5.594***	-0.611	3.101***
	(1.820)	(1.349)	(0.577)	(1.820)	(1.349)	(0.577)
ROA	-0.011***	-0.011***	-0.000	-0.011***	-0.011***	-0.000
	(0.004)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
Constant	-5.065***	-3.847***	-0.380	-5.025***	-3.823***	-0.373
	(1.187)	(0.941)	(0.474)	(1.186)	(0.941)	(0.474)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,043	5,043	5,045	5,043	5,043	5,045
Within R^2	0.025	0.027	0.016	0.025	0.027	0.016
Between R^2	0.059	0.130	0.004	0.059	0.130	0.004
Overall R^2	0.019	0.033	0.007	0.019	0.033	0.007

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses. The Within R^2 shows the proportion of variation in the dependent variable explained by the regressors within each firm, the Between R^2 focus on dynamics between firms and the Overall R^2 combines both Within and Between R^2.

4.4 Geopolitical Risk Channels: Terrorism and Military Conflicts

To conclude the empirical analysis, this study examines potential channels through which geopolitical risk influences stock price crash risk. Three significant geopolitical events were selected, based on the Caldara and Iacoviello indices, to investigate the specific mechanisms driving stock price crashes. These events were chosen with a focus on Great Britain, the largest representation in the sample, accounting for 21% of the total observations.

The selected events include: (1) the 2005 London Bombings, (2) the 2014 Annexation of Crimea by Russia, and (3) the surge in Terrorist Attacks on British soil in 2015. These events represent two primary channels of geopolitical risk, as identified by Caldara and Iacoviello (2022): terrorism and military conflicts. Columns 1, 2 and 3 of Table V present the analysis of each event using the primary crash risk measure, NCSKEW. In each case, the interaction between the geopolitical event and companies based in Great Britain is captured through binary variables. This analysis provides critical insights into how specific types of geopolitical risk - namely terrorism and military conflicts - affect stock price crash risk for firms exposed to these events.

Equation 11 is further refined to include the new interaction terms, as shown in Table V. Across all three regressions both LN(GPR) and the interaction term between geopolitical risk and foreign ownership show strong statistical significance at the 1% level, with positive coefficients. The control variables maintain consistent behaviour with previous analyses.

The key contribution here lies in the interaction terms, which uncovers how specific geopolitical events further amplify crash risk for British firms. For the first event (London Bombings), the interaction term is significant at the 10% level; for the second event (Crimea Annexation), it is significant at 5%; and for the third event (2015 Terrorist Attacks), it shows significance at the 1% level. In all cases, the coefficients of the interaction terms are positive, indicating that each of these geopolitical events intensified crash risk for Great Britain-based companies.

In conclusion, this analysis provides empirical evidence that terrorism and military conflicts are two primary drivers of geopolitical risk, contributing significantly to stock price crashes. The interaction terms demonstrate a clear mechanism through which geopolitical instability, as observed during major events such as the London Bombings, Crimea Annexation and 2015 Terrorist Attacks, amplifies crash risk for firms with high exposure to these geopolitical shocks. These findings highlight the importance of considering both broad geopolitical trends and event-specific risks when assessing market and firm-level vulnerabilities to stock price crashes and reinforce H1 results.

Table V – Geopolitical Risk Channels

Variables	(1) NCSKEW	(2) NCSKEW	(3) NCSKEW
LN(GPR)	0.786***	0.782***	0.784***
	(0.203)	(0.203)	(0.202)
LN(GPR)*FIO	0.038***	0.035***	0.033***
	(0.011)	(0.011)	(0.011)
London_Bombings_2005&2006*GB_Company	0.177*		
	(0.104)		
Annexation_of_Crimea_2014*GB_Company		0.338**	
		(0.163)	
Terrorist_Attacks_2015*GB_Company			0.453***
			(0.151)
LN(Total Assets)	0.143***	0.143***	0.144***
	(0.043)	(0.043)	(0.043)
LEV	-0.027	-0.028*	-0.029*

	(0.017)	(0.017)	(0.017)
STDEV	5.592***	5.622***	5.665***
	(1.818)	(1.823)	(1.836)
ROA	-0.011***	-0.011***	-0.011***
	(0.004)	(0.004)	(0.004)
Constant	-5.071***	-5.045***	-5.067***
	(1.192)	(1.186)	(1.189)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	5,043	5,043	5,045
Within R^2	0.026	0.026	0.027
Between R^2	0.061	0.061	0.062
Overall R^2	0.019	0.020	0.020

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses. The Within R^2 shows the proportion of variation in the dependent variable explained by the regressors within each firm, the Between R^2 focus on dynamics between firms and the Overall R^2 combines both Within and Between R^2.

5. Conclusion

This thesis explores the intricate relationship between geopolitical risk (GPR) and stock price crash risk, with a particular focus on how foreign ownership moderates this connection. As geopolitical tensions escalate and the international order weakens, GPR has become an increasing concern for regulators, investors and stakeholders alike.

The analysis utilizes a dataset of 463 non-financial companies from the STOXX Europe 600 index, covering a seventeen-year period (2004-2020 inclusive), with financial data sourced from Bloomberg, GPR data from the Caldara and Iacoviello index and ownership data from Moody’s Orbis.

Firstly, initial results from the ordinary least squares (OLS) regression revealed that only the DUVOL crash risk measure was statistically significant at the 1% level, with a positive coefficient of 0.391. The introduction of the fixed effects (FE) regression model, accounting for both firm and year effects, yielded stronger results, thus providing support that GPR significantly increases the frequency of stock price crashes - Hypothesis 1 (H1). NCSKEW became significant at the 1% level, with a positive coefficient of 0.733, while the DUVOL coefficient increased to 0.601. N_CRASH remained insignificant. The control variables offered valuable insights: LN(TotalAssets) showed a positive coefficient of 0.142 at the 5% level, suggesting that larger firms are more vulnerable to crash risk. Profitability, with a 1% significance level, exhibited negative coefficients (-0.011), indicating that firms with higher liquidity are less likely to experience crash risk during periods of geopolitical uncertainty. T_Analyst, also significant at 1%, had positive coefficients (0.026 for NCSKEW and 0.019 for DUVOL), implying that greater analyst coverage increases crash risk. LEV remained insignificant, while STDEV showed mixed results - positive for NCSKEW (5.591) and negative for DUVOL (-2.520).

Secondly, it was demonstrated that geopolitical threats (GPT) play a more significant role than geopolitical acts (GPA) in driving stock price crashes - Hypothesis 2 (H2). By substituting LN(GPR) with LN(GPT) and LN(GPA), the analysis revealed that GPT had substantially larger coefficients: 3.578 for NCSKEW and 2.935 for DUVOL, compared to GPA's lower coefficients of 0.316 and 0.260. Control variables behaved similarly to those in the FE regression, and these findings strongly supported H2, affirming that GPT is the dominant driver of crash risk, in alignment with previous literature (Fiorillo, Meles, Pellegrino, & Verdoliva, 2024).

To further validate the findings for H1, a series of robustness tests were conducted, focusing on NCSKEW. These tests included excluding firms from Great Britain, France and Germany, which collectively represent 50% of the sample, as well as firms from countries in the lowest decile of the sample. Additionally, tests were conducted to control for country, for sector fixed effects, for all fixed effects and an alternative analyst variable, Best_Analyst, was used in place of T_Analyst to explore variations in analyst coverage. Despite these adjustments, LN(GPR) consistently remained significant, reinforcing the robustness of the results.

To address concerns of endogeneity, a two-stage instrumental variable (IV) approach was employed, using the *Political Stability and Absence of Violence/Terrorism index* from the Worldwide Governance Indicators (WGI) database. This index served as a valid instrument for geopolitical tensions, as it has no direct connection to stock price crashes. The second-stage regression confirmed that GPR remained positive and significant for both NCSKEW (0.787) and DUVOL (0.661), while N_CRASH remained insignificant. These findings conclusively demonstrate that heightened geopolitical risk significantly increases the likelihood of stock price crashes, fully validating Hypothesis 1 (H1), consistent with previous studies (Xu, He, Zhou, Ding, and Chen, 2023).

Thirdly, the interaction between geopolitical risk and foreign ownership (FIO) provides further clarity on the role of FIO in stock price crash risk. Consistent with prior literature suggesting that foreign investors may amplify market sensitivity to geopolitical events (Huang, Tang, & Huang, 2020; Vo, 2020), results indicate that FIO magnifies the impact of GPR on crash risk – Hypothesis 3 (H3). By removing T_Analyst and replacing Profitability with ROA, in line with established methodologies, the interaction term between GPR and FIO had positive coefficients of 0.036 for NCSKEW and 0.022 for DUVOL, significant at the 1% and 5% levels, respectively, while N_CRASH remained insignificant. Control variables exhibited consistent behaviour with previous models.

Finally, when examining the key channels of GPR, particularly terrorism and military conflicts, these factors were shown to be major drivers of crash risk. By interacting binary variables for the year of the event and the company's ISO code (in this case, Great Britain), the analysis demonstrated that events such as the 2005 London Bombings, the 2014 Annexation of Crimea and the 2015 Terrorist Attacks in Great Britain significantly increased crash risk for British companies. The coefficients for these interactions were positive and significant: 0.177 at the 10% level for the London Bombings, 0.338 at the 5% level for Crimea Annexation and 0.453 at the 1% level for the 2015 Terrorist Attacks, further emphasizing the role of these events in elevating crash risk for firms in Great Britain and reinforcing H1 results.

In conclusion, this thesis confirms that GPR, particularly in the form of geopolitical threats, substantially increases the likelihood of stock price crashes, with foreign ownership further amplifying this risk. It addresses several key gaps in the literature by providing the first comprehensive analysis of how GPR and foreign ownership interact to influence stock price crashes, using a unique European dataset. It also highlights the importance of differentiating between geopolitical threats and acts in assessing crash risk, and analyses key geopolitical events, such as the London Bombings, Crimea's Annexation and Terrorist Attacks of 2015, to illustrate the channels through which geopolitical risk manifests in financial markets.

However, several limitations must be acknowledged. The dataset is unbalanced due to missing values for some companies, and the choice of variables, particularly, ownership data, was constrained by data availability. Future research could benefit from: examining a broader time period that includes ongoing geopolitical tensions such as the war in Ukraine and the conflict in Israel; expanding the dataset to a global scale; and analysing specifically how the different levels of FIO influence GPR effects on stock price crash risk.

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Appendix

Table A.I - Country Composition

Country	Total by Country	%	Cumulative
GB	93	20.09	20.09
FR	63	13.61	33.69
DE	57	12.31	46.00
CH	46	9.94	55.94
SE	46	9.94	65.87
NL	32	6.91	72.79
IT	22	4.75	77.54
DK	20	4.32	81.86
ES	18	3.89	85.75
FI	17	3.67	89.42
NO	13	2.81	92.22
BE	9	1.94	94.77
IE	7	1.51	95.68
LU	7	1.51	97.19
AT	5	1.08	98.27
PL	5	1.08	99.35
PT	3	0.65	100.00
Total	463	100.00	

Table A.II - Sector Composition

Sector	Total by Sector	%	Cumulative
Industrial	119	25.70	25.70
Consumer, Non-cyclical	115	24.84	50.54
Consumer, Cyclical	79	17.06	67.60
Basic Materials	39	8.42	76.03
Communications	37	7.99	84.02
Utilities	29	6.26	90.28
Technology	25	5.40	95.68
Energy	20	4.32	100.00
Total	463	100.00	

Table A.III – Foreign Ownership Proportion by Country

Country	Total by Country	%	Cumulative
GB	1,499	20.74	20.74
FR	1,008	13.95	34.69
DE	950	13.14	47.83
CH	731	10.11	57.94
SE	561	7.76	65.7
NL	474	6.56	72.26
IT	374	5.17	77.43
ES	306	4.23	81.66
DK	289	4.00	85.66
FI	272	3.76	89.42
NO	187	2.59	92.01
BE	136	1.88	93.89
IE	119	1.65	95.54
LU	102	1.41	96.95
AT	85	1.18	98.13
PL	84	1.16	99.29
PT	51	0.71	100.00
Total	7,228	100.00	

Table A.IV - Variables Description

Variables	Min
Crash Risk Measures	
NCSKEW	The negative coefficient of skewness, defined as the ratio of the third moment of firm-specific weekly returns to the cube standard deviation, multiplied by minus one
DUVOL	The down-to-up volatility, defined as the natural logarithm of the ratio of the standard deviation of weekly returns in the "down weeks" to the standard deviation of weekly returns in the "up weeks". Up (down) weeks refer to weeks when the firm-specific stock return is above (below) fiscal year average
N_CRASH	The number of crashes in a given fiscal year. A crash occurs each time a firm-specific weekly return is 3.09 standard deviations below the firm's average residual

	return
Geopolitical Risk Measures	
LN(GPR)	The natural logarithm of the annualized monthly GPR index
LN(GPA)	The natural logarithm of the annualized monthly GPA index
LN(GPT)	The natural logarithm of the annualized monthly GPT index
LN(GPRD)	The natural logarithm of the annualized daily GPR index
Control Variables	
LNTotalAssets	The natural logarithm of total assets
LEV	The leverage ratio, defined as total debt to total shareholder's equity
Profitability	Profitability, defined as ratio of EBIT to total assets
T_Analyst	Total number of recommendations made by analysts
STDEV	The yearly standard deviation of stock returns, computed on weekly basis
ROA	Return on Assets, defined as ratio of net income to total assets
Binary Variables	
GB_Company	Indicates if a company's ISO code is from Great Britain (1 for yes, 0 for no)
London_Bombings_2005&2006	Indicates for 1, if the year is 2005 or 2006, and 0 if not
Annexation_of_Crimea_2014	Indicates for 1, if the year is 2014, and 0 if not
Terrorist_Attacks_2015	Indicates for 1, if the year is 2015, and 0 if not

Table A.V - Summary Statistics with Winsorization Technique Applied

Variables	Obs	Mean	Std. Dev.	Min	Median	Max	p1	p99	Skew.	Kurt.
NCSKEW	6,698	.065	1.023	-4.831	.035	6.4	-2.147	2.996	.498	5.002
DUVOL	6,696	.263	.823	-4.643	.255	4.541	-1.576	2.361	.169	3.719
N_CRASH	7,822	.124	.335	0	0	2	0	1	2.447	7.589
FIO	7,228	.288	.381	0	.037	1	0	1	.959	2.273
LN(GPR)	7,871	4.543	.129	4.348	4.541	4.863	4.348	4.863	.552	2.956

LN(GPT)	7,871	4.546	.15	4.315	4.508	4.811	4.315	4.811	.23	1.717
LN(GPA)	7,871	4.499	.271	3.898	4.483	5.092	3.898	5.092	-.143	3.329
LN(GPRD)	7,871	4.538	.126	4.356	4.536	4.858	4.356	4.858	.64	3.118
LN(TotalAssets)	5,766	9.053	1.715	2.569	9.003	13.171	4.987	12.515	-.188	2.798
LEV	5,712	1.862	1.597	.194	1.444	10.803	.195	10.722	2.913	14.595
Profitability	5,695	.034	.037	-.077	.028	.176	-.077	.176	.894	6.141
STDEV	6,705	.042	.017	.018	.037	.103	.018	.103	1.363	4.858
T_Analyst	4,746	18.76	9.665	1	18	41	1	41	.233	2.299
ROA	5,545	6.518	6.882	-12.491	5.506	35.879	-12.452	35.818	1.14	7.054

Table A.VI - Variance Inflation Factor (VIF), Hausman and Wooldridge Tests

Variables	VIF
(1) LN(GPR)	1.18
(2) LN(TotalAssets)	2.06
(3) LEV	1.08
(4) Profitability	2.11
(5) STDEV	1.27
(6) T_Analyst	1.82
(7) ROA	2.06
(8) FIO	1.05
Mean VIF	1.58
Hausman p-value	0.000
Wooldridge p-value	0.000

Table A.VII - Fischer-type Augmented Dickey Fuller (ADF) Tests for one lag with time trend

Variables	p-value
(1) NCSKEW	0.000
(2) DUVOL	0.000
(3) N_CRASH	0.000
(4) LN(TotalAssets)	0.000
(5) LEV	0.000
(6) Profitability	0.000
(7) STDEV	0.8338
(8) T_Analyst	0.000
(9) ROA	0.000
(10) FIO	0.000

Table A.VIII - Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) NCSKEW	1.000													
(2) DUVOL	0.907	1.000												
	(0.000)													
(3) N_CRASH	0.579	0.396	1.000											
	(0.000)	(0.000)												
(4) LN(GPR)	-0.012	0.016	-0.015	1.000										
	(0.322)	(0.197)	(0.180)											
(5) LN(GPT)	0.015	0.019	0.042	0.612	1.000									
	(0.235)	(0.114)	(0.000)	(0.000)										
(6) LN(GPA)	-0.028	0.005	-0.054	0.729	-0.086	1.000								
	(0.023)	(0.654)	(0.000)	(0.000)	(0.000)									
(7) LN(GPRD)	-0.013	0.012	-0.016	0.999	0.612	0.724	1.000							
	(0.271)	(0.324)	(0.157)	(0.000)	(0.000)	(0.000)								
(8) LN(TotalAssets)	0.095	0.139	0.011	-0.054	0.063	-0.118	-0.056	1.000						
	(0.000)	(0.000)	(0.406)	(0.000)	(0.000)	(0.000)	(0.000)							
(9) LEV	0.031	0.026	-0.003	-0.007	-0.016	0.001	-0.005	0.205	1.000					
	(0.022)	(0.054)	(0.847)	(0.618)	(0.238)	(0.921)	(0.708)	(0.000)						
(10) Profitability	-0.086	-0.103	-0.013	0.052	0.004	0.058	0.055	-0.327	-0.170	1.000				
	(0.000)	(0.000)	(0.311)	(0.000)	(0.744)	(0.000)	(0.000)	(0.000)	(0.000)					

(11) STDEV	0.005	-0.056	0.047	-0.385	-0.281	-0.248	-0.378	-0.113	0.073	-0.180	1.000			
	(0.673)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(12) T_Analyst	0.102	0.121	0.022	-0.104	-0.052	-0.077	-0.108	0.625	0.130	-0.130	-0.097	1.000		
	(0.000)	(0.000)	(0.137)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(13) ROA	-0.074	-0.084	0.014	0.086	0.038	0.073	0.087	-0.270	-0.236	0.712	-0.185	-0.099	1.000	
	(0.000)	(0.000)	(0.300)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(14) FIO	0.052	0.031	0.052	-0.076	0.106	-0.182	-0.081	0.040	0.034	-0.076	0.049	0.153	-0.065	1.000
	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	

Note: P-values in parentheses.

Table A.IX - Robustness Checks

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW
LN(GPR)	0.808***	0.697***	0.169	0.175	0.733***	1.185***	0.517**	
	(0.286)	(0.207)	(0.175)	(0.177)	(0.217)	(0.290)	(0.204)	
LN(GPRD)								0.752***
								(0.209)
LN(Total Assets)	0.064	0.101*	0.013	-0.011	0.111**	0.284***	0.189***	0.111**
	(0.070)	(0.053)	(0.016)	(0.014)	(0.053)	(0.077)	(0.051)	(0.053)
LEV	-0.018	-0.016	-0.011	-0.002	-0.016	-0.026	-0.029*	-0.016
	(0.026)	(0.016)	(0.011)	(0.011)	(0.017)	(0.017)	(0.016)	(0.016)
Profitability	-4.215***	-3.178***	-2.736***	-2.072***	-3.380***	-2.999***	-2.659***	-3.380***
	(1.014)	(0.751)	(0.517)	(0.496)	(0.737)	(0.905)	(0.736)	(0.735)
STDEV	2.046	3.615**	0.684	1.183	3.667**	6.471***	2.414	3.667**
	(2.301)	(1.746)	(1.363)	(1.423)	(1.795)	(2.249)	(1.702)	(1.704)
T_Analyst	0.030***	0.026***	0.008***	0.010***	0.026***	0.026***		0.026***
	(0.007)	(0.005)	(0.003)	(0.002)	(0.005)	(0.007)		(0.005)
Best_Analyst							-0.182***	
							(0.031)	
Constant	-4.769***	-4.561***	-0.979	-0.875	-5.474***	-8.636***	-8.636***	-4.916***
	(1.764)	(1.287)	(0.871)	(0.869)	(1.399)	(1.810)	(1.810)	(1.294)
Firm FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	No	Yes	No	No	No
Sector FE	No	No	No	Yes	Yes	No	No	No
N	2,287	3,814	3,951	3,951	3,951	1,906	3,942	3,951
R^2			0.044	0.036	0.140		0.039	
Adjusted R^2							0.041	
Within R^2	0.038	0.035				0.061		0.038
Between R^2	0.053	0.052				0.072		0.054
Overall R^2	0.023	0.021				0.027		0.022

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses. The Within R^2 shows the proportion of variation in the dependent variable explained by the regressors within each firm, the Between R^2 focus on dynamics between firms and the Overall R^2 combines both Within and Between R^2. Test 1 excludes Great Britain, France & Germany. Test 2 excludes countries with firms count below the 10th percentile. Test 3 & Test 4 are fixed country and sector, respectively. Test 5 with all fixed effects. Test 6 excluding sectors Industrial & Consumer, Non-Cyclical. Test 7 substituting T_Analyst with Best_Analyst. Test 8 with LN(GPRD).