International Review of Financial Analysis 90 (2023) 102835

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Geopolitical threats, equity returns, and optimal hedging

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ARTICLE INFO

Keywords:
Geopolitical threats
Asset returns
Hedging
Safe heaven
Exchange-traded fund (ETF)

ABSTRACT

In this paper, we demonstrate that the U.S. equity market and a few specific sectors produce significantly positive returns during high geopolitical threats, even with the presence of standard controls, whereas other major markets around the world fail to exhibit such results. We use the geopolitical threats (GPT) index of Caldara and Iacoviello (2022). We extend our study by examining the equity returns during extremely high geopolitical threats and find the results significantly positive for the U.S. equity market and two specific sectors- information technology and financials. The results of our investigation are likewise supported by the lead-lag regression and the Markov regime-switching model. Our results are robust in the presence of various alternative measures of market uncertainty indices, for instance, economic policy uncertainty, economic uncertainty, macroeconomic uncertainty etc., on a daily basis. However, the return on equity was not robust when conditional volatility and monthly frequency were considered. We also investigate and find the optimal hedging implications for investors during the presence of geopolitical threats. We find a considerable hedge alternative between the US market and gold and further explore how Geopolitical threats affect Gold and different US sectoral Exchange-traded funds (ETFs).

1. Introduction

The importance of geopolitical risk has increased over the past three decades as a result of wars, terrorist attacks, conflict situations, and tensions that endanger the stable and peaceful development of international relations (Caldara & Iacoviello, 2022). For instance, the recent Russian invasion of Ukraine on February 24 in 2022 caused a peak in geopolitical threats that week (see Fig. 1). Geopolitical risk is a major factor in influencing investment choices, which in turn has an impact on the flow of capital across international borders (Feng, Han, Vigne, & Xu, 2022). The literature shows that there is a negative association between geopolitical risk and equity returns around the world (see, Ahmed, Hasan, & Kamal, 2022; Kamal, Ahmed, & Hasan, 2023). However, the S&P 500 index and the vanguard technology stock index (VGT), in fact, rallied by more than 3.5% and 5%, respectively, from the day before the Russian invasion to the end of that week. It is worth noting that the S&P 500 index fell by more than 21% during the first half of 2022. The largest market around the world for investments is the U.S. equity market which investors find confidence in, especially during the major world political tensions since the U.S.A., as a nation, is distant from conflict zones while also having the highest protection level through its defense capability. These facts leave us few questions. What is the association between geopolitical threats and equity returns around the world? How do various sectors and other asset classes respond to changes in geopolitical threats? What is the optimal hedge ratio, if any, for investors during high geopolitical threats? In this paper, we study major equity markets around the world along with other asset classes followed by equity market sectors in answering these questions.

Boutchkova, Doshi, Durnev, and Molchanov (2012) differentiate between domestic political uncertainty and global political risks. The latter is also known as geopolitical risks (GPR) which are viewed as significant drivers for stock market investors, market makers, businesses, and central banks. Bank of England marks geopolitical risks (GPR) as one of the three uncertainties known as the "uncertainty trinity" that might have severe detrimental economic consequences (Carney, 2016). The World Bank, the International Monetary Fund, and the European Central Bank emphasize and track the risks coming from geopolitical tensions. Current literature recognizes the equity market response to geopolitical risk (GPR) around the world. The knowledge we have so far, which is also intuitive, is about negative returns in equity

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https://doi.org/10.1016/j.irfa.2023.102835
Received 10 March 2023; Received in revised form 21 July 2023; Accepted 1 August 2023
Available online 4 August 2023

markets in response to higher geopolitical instability (Dimic, Orlov, & Piljak, 2015; Jones & Banning, 2009; Kapar & Buigut, 2020; Li & Born, 2006; Mei & Guo, 2004; Nippani & Medlin, 2002). Choudhry (2010) shows the responses of the U.S. stock prices to the events of World War II. News of prolonged war caused the market decline and higher volatility while news of Allied victory resulted in higher returns with a fall in volatility. Using market-based odds on the probability of removal of Saddam Hussein from power, Amihud and Wohl (2004) also find similar results. The literature also finds associations between political risk and asset prices (Berkman, Jacobsen, & Lee, 2011; Kelly, Pastor, & Veronesi, 2016; Pastor & Veronesi, 2012; Pástor & Veronesi, 2013), the cost of debt for the government (Huang, Wu, Yu, & Zhang, 2015) and corporations (Bekaert, Harvey, Lundblad, & Siegel, 2016). Higher political risk is associated with the stock markets in terms of lower liquidity (Cox & Griffith, 2018) and higher volatility (Brogaard, Dai, Ngo, & Zhang, 2019).

Caldara and Iacoviello (2022) explore the economic consequences of geopolitical risk (GPR) consisting of the uncertainty of possible wars, terrorist acts, and conflicts between nations. The study also suggests that GPR has notable impacts on corporations and financial markets through adverse effects on investments, employment, and downside risks. There are also studies on the detrimental effects of GPR on equity returns and bond spreads (Rigobon & Sack, 2005) and volatility in the stock markets (Choi, 2022). However, Salisu, Lasisi, and Tchankam (2022) show that geopolitical threats (GPT), which include military build-ups, threats of war, terrorism, etc., have a greater adverse effect on stock returns than geopolitical acts (i.e., the actual occurrence of adverse events). Russia's invasion of Ukraine in 2022 significantly increases GPT as a consequence of the resurgence in geopolitical competition and tensions among world leaders. This leads to the need for research in the field of geopolitical threats and their impacts on the equity markets overall and at the sector level along with portfolio implications for the investors. It is an important learning mechanism for investors and risk managers to be able to differentiate between geopolitical threats and acts since a precise analysis of this would allow them to properly assess the components of their portfolio risks. Investors would like to mitigate potential adverse effects on their portfolios stemming from drastic geopolitical events by investing in stable and strong markets which also ensures a sense of safety and eliminates fear and insecurity (Ciner, Gurdgiev, & Lucey, 2013). We show in this paper that there are safe haven equity markets and specific sectors that investors can utilize to hedge against such GPT.

There are some contributions in the literature about lower equity market returns and higher volatility to terror attacks (Brounen & Derwall, 2010; Chesney, Reshetar, & Karaman, 2011; Goel, Cagle, & Shawky, 2017; Nikkinen, Pynnönen, Ranta, & Vähämaa, 2011). However, the characteristic of such attacks determines the magnitude and duration of market responses. An attack in a wealthy, democratic nation that is perceived to be less risky causes a stronger response (Drakos, 2009; Karolyi & Martell, 2006). The market response is typically the highest in the nation where the attack takes place (Balcilar, Gupta, Pierdzioch, & Wohar, 2018; Brounen & Derwall, 2010). Drakos (2009) and Nikkinen and Vähämaa (2010) show that investor sentiment goes down during terror attacks. Our study does not concentrate on terror attacks only; rather we focus on overall geopolitical threats.

From the current literature, the safe haven properties of gold are evident (Baur & Lucey, 2010; Ciner et al., 2013). Li and Lucey (2017) also consider all four precious metals. However, Batten, Ciner, and Lucey (2010) argue that, unlike other precious metals, gold markets do not show higher volatility caused by similar factors. The hedging and safe haven properties of gold are studied concerning stock market indices (Baur & McDermott, 2010; Gürgün & Ünalmis, 2014), bond market indices (Agyei-Ampomah, Gounopoulos, & Mazouz, 2014; Baur & Lucey, 2010), exchange rates (Reboredo, 2013a) and oil prices (Junttila, Pesonen, & Raatikainen, 2018; Reboredo, 2013b). There are also studies on the positive association between economic policy uncertainty and gold prices (Beckmann, Berger, & Czudaj, 2019) and the role of sentiment on the futures prices of precious metals (Smales, 2014; Smales & Lucey, 2018). There are some studies on the responses of the commodity markets to the volatility in geopolitical risks. For instance, Brandt and Gao (2019) show that geopolitical news causes a strong

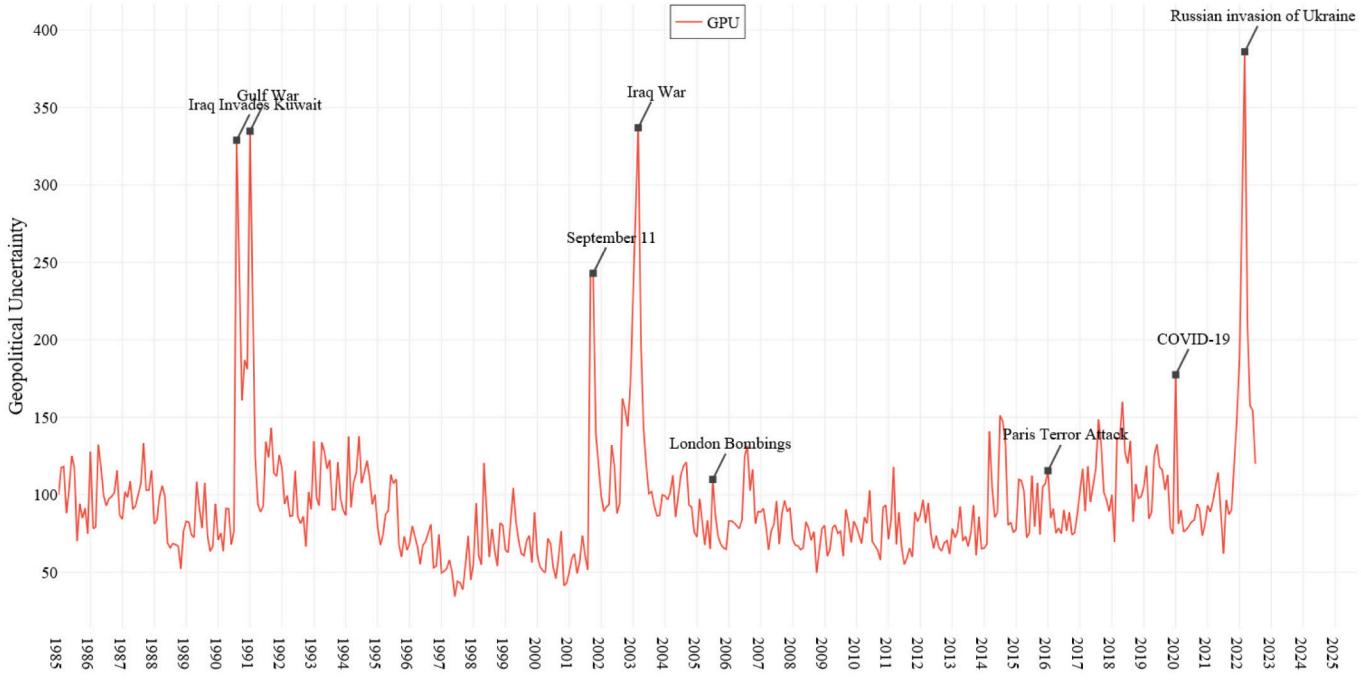

Fig. 1. Geopolitical threat index.
This figure shows the GPT Index from 1985 to 2018. Source: "Measuring Geopolitical Threat" by Dario Caldara and Matteo at https://www2.bc.edu/matteo-iacoviello/GPT.htm

immediate impact and results in greater uncertainty for crude oil prices and trading activity. Kollias, Kyrtsou, and Papadamou (2013) exhibit the negative impact of geopolitical risk on both oil and stock markets. Chesney et al. (2011) study the relationship between rare events, such as terror attacks, on precious metals. However, there is not much sector-level study on the association between geopolitical risk and equity market returns. Our study contributes to this part of the literature.

We use the geopolitical threat index of Caldara and Iacoviello (2022) to find the relationship between asset returns and geopolitical threats to find safe haven equity markets and sectors for potential hedges by investors. Our contribution is six-fold in this paper. First, we show that only U.S.A, which has strong defense capability and is distant from the conflict zones, exhibits significantly positive returns during high geopolitical threats while other countries demonstrate insignificant associations. Our results are significant both with and without the presence of the control variables- changes in inflation, unemployment rate, credit spread, term premium, and trade volume. Second, we further investigate the relationship between geopolitical threats and equity returns at the sector level and find that several sectors show a significantly positive association with such threats. Third, we show that the U.S. market and two sectors- information technology, and financial demonstrate a positive association with extremely high geopolitical threats. Fourth, we use the Markov regime-switching model with two volatility regimes- high and low and show that several sectors show a significantly positive association with geopolitical threats during the high volatility regime and several other sectors during the low volatility regime. Fifth, we study the association of geopolitical threats with equity returns at the sector level under the presence of alternative measures of market uncertainty indices- economic policy uncertainty, economic uncertainty, macroeconomic uncertainty, and implied volatility both on a daily and monthly basis to reinforce our results. Sixth, to find optimal hedge ratios as portfolio implications for the investors, we construct portfolio pairs consisting of the U.S. market with other major equity markets around the world and also with other asset classes, e.g., gold, silver, etc. We also show optimal hedge ratios for portfolio pairs of gold with various sectors and find that investors can hedge against geopolitical threats using gold and information technology stocks.

Our results demonstrate that the US market shows a better hedge against geopolitical threats than other counties and assets. The Chinese market also shows good hedging prospects against the geopolitical threat in the most recent sample (in Appendix). Interestingly, both countries have strong defense systems and are geographically distant from the conflict zones of the recent Russian invasion. Therefore, investors feel safe investing in these two countries' equity markets. Our results also demonstrate that the information technology, Communication, and Material sectors show a good hedge against the geopolitical threat in the U.S. market. This indicates that investors prefer to shift their investments to specific sectors and safer places during higher geopolitical threats. We also show that information technology and financial sectors can be considered safe havens since these sectors are resilient in showing better performance during extremely high geopolitical threats.

Our results are consistent while using the Markov regime-switching model with two volatility regimes- high and low. Using changes in inflation, unemployment rate, credit spread, term premium, and trade volume as control variables, we show that the shift in the geopolitical threat index primarily determines the equity returns of the whole market and several sectors in the U.S. The results show that the information technology and communication sectors perform well in both high- and low-volatility regimes. Energy and materials sectors exhibit positive returns during the high volatility regime while utility and healthcare sectors serve as effective hedges during the low volatility conditions.

To check the robustness of our results, we further study the equity returns at the sectoral level both on a daily and monthly basis considering the economic policy uncertainty (EPU) index by Baker, Bloom, and Davis (2016), the economic uncertainty (Unc) index by Bekaert and Mehl (2019), the macroeconomic uncertainty index (MacroUnc) by Jurado, Ludvigson, and Ng (2015), and the CBOE implied volatility index (VIX) as the alternative measures of market uncertainty indices. It is worth noting that while all these alternative measures show negative relationships with the returns in the U.S. equity market as a whole, a significantly positive relationship exists between a geopolitical threat (GPR Threat) and the U.S. equity returns even after adjusting for these alternative measures of uncertainty. The directions of the associations are also applicable in sector-level returns. The relationship is moderately significant on a daily basis for the whole U.S. market and three sectors-information technology, communication, and utilities. However, the return on equity was not robust when conditional volatility and monthly frequency were considered.

We examine and report the influence of geopolitical threats on the optimal hedge ratios in the full sample (1985–2021) and three subsamples. To find the portfolio implications for the investors regarding the geopolitical threats, we first construct hedge ratios in pairs of the U.S. market with other major markets around the world and various other asset classes, i.e., gold, silver, palladium, platinum, copper, bond, and U.S. dollar index. We find a considerable hedge alternative between the US market and gold and further explore how Geopolitical threats affect Gold and different US sectoral Exchange Trading Funds (ETFs). Our results show that the gold and information technology ETF displays the greatest asset pairings to counter the geopolitical threat in the long run since the results are significant only for the full sample period (2005–2022). We employ the Benjamini and Hochberg (1995) procedure to control the false discovery rate to establish a threshold for the acceptable rate of false discoveries across all the characteristics under study. Our results indicate that the overall US market, and the ETFs of information technology, and utility sectors still remain significant after controlling for false discovery in the presence of all other control variables. Investors may benefit from these findings to reconstruct their portfolios during various levels of geopolitical threats.

The paper proceeds as follows: section 2 presents the data used for our study, section 3 provides the methodology used, section 4 describes the results and their robustness checks along with portfolio implications for the investors followed by section 5 which depicts some general discussion and the concluding part of the paper.

2. Data

2.1. Geopolitical risk

As a measure of geopolitical risk, we employ the GPR Threat index created by Caldara and Iacoviello (2022). According to the authors, geopolitical risk is the danger posed by events like wars, terrorist attacks, and conflicts between states, all of which threaten to disrupt the otherwise steady flow of international relations. The approach that underpins this index is based on textual analysis of articles published in the media. This index is significant and draws academics' attention since it directly captures the dynamic fluctuations of global geopolitical risk through an automated search for geopolitical-related content from the electronic archives of 11 top national and international English newspapers. The GPR's raw data are calculated by dividing the number of articles that mention geopolitical risk by the overall number of articles that are published each month. Several studies have recently employed this index in their empirical analysis (for example, Liu, Ma, Tang, and Zhang (2019); Baur and Smales (2020); Liu, Han, and Xu (2021); Feng et al. (2022), etc.).

The following are the reasons why we use the GPR index in our study: the GPR index permits us the incorporation of a broader range of geopolitical events than previous research and this index focuses entirely on geopolitical risk. For instance, the closet index is Baker et al. (2016)'s EPU index, which typically increases around presidential elections and fiscal policy disagreements. However, GPR doesn't change much when the economy is bad or when there are presidential elections,

but EPU does. In a similar vein, EPU does not react to Russia's takeover of Crimea in 2014 and the recent invasion of Ukraine in 2022 in the same way as GPR does. Another significant aspect of the GPR index is that, because it is derived exclusively from media sources, it should be independent of capital movements. We employ the daily Geopolitical Risk Threat (hereafter GPR Threat)[1] instead of Geopolitical Risk Act index of Caldara and Iacoviello (2022) and retrieved from Iacoviello's website. We consider the daily GPR Threat index, since many affluent countries' financial markets have been disproportionately harmed by GPR threats (such as war and terrorism) than by their actual occurrence of these events Salisu, Raheem, and Vo (2021). Additionally, Caldara and Iacoviello (2018) contend that GPR threats are worse for the economy than Act disasters, (p. 21) '… the act component of GPR leads to a resolution of the uncertainty around a particular set of events, as well as to a coordinated policy response that ends up giving protection on the worst possible outcomes. By contrast, threat shocks depress asset prices and economic activity because they increase uncertainty and send signals about future adverse events.'

2.2. Financial assets

Finding out how the values of various asset classes react to shifts in geopolitical risk is the fundamental goal of this research. Because each asset has a distinct supply and demand structure, it is interesting to consider them to understand how they might respond to risk elements like geopolitical risk. For instance, each of the asset classes—stocks and bonds—has its own distinguishing characteristics, and each asset class has a significantly distinct structure, payout, return, and risk profile (see, more details, Jones & Wilson, 2004; Reilly, Wright, & Chan, 2000 etc.). Because determining the present value of an asset requires considering two variables that are in a state of perpetual flux—the earnings stream and the discount rate—stock prices are more prone to wild swings than bond prices. In the case of precious metal, market demand may play a substantial impact in price fluctuations. For example, investors and central banks generally use gold as a form of investment or as a store of value; nevertheless, industrial demand for gold is very low. While silver has many industrial applications in electronics, printed circuit boards, and photography and is the best-known metal for conducting heat and electricity. Compared to gold continually costing more than silver, the price ratio between the two metals appears to be steadier.

On the other hand, the automotive industry is the single largest consumer of palladium and platinum since these metals are utilized as catalytic convertors in this sector. It's possible that the increased industrial demand for palladium and platinum is also to blame for the dramatic shifts in the value of these precious metals relative to one another. The areas where the precious metals are mined could potentially be the cause of variations in the relative value of palladium and platinum. Therefore, a commodity that is mined in a nation that is seen as geopolitically risky is likely to react to changes in geopolitical risk differently than metals extracted in safer environments (Baur & Smales, 2020). Similarly, a commodity with a larger industrial demand would react to changes in geopolitical risk differently than a commodity whose demand is predominantly driven by investment.

Initially, we use daily price data of major equity markets (G7 countries) around the world, five major precious metal (gold, silver, copper, palladium and platinum) spot prices, bonds, and dollar prices. After that, we use 11 US ETFs price data which are ITech ETF, Communication ETF, Consumer Staples ETF, Consumer Discretionary ETF, Energy ETF, Financial ETF, Health ETF, Industry ETF, Material ETF, Real State ETF, and Utility ETF. Though we create our whole sample period (for non-ETF assets) from 1985 to 2021, our main analysis is based on the sample period from 2005 to 2021 for two reasons. First, after 2005, information flows much more rapidly due to the rapid changes in information technology. Second, ETF data are available from around that period. However, we also conduct whole sample data analysis as well as many subsample analyses which are reported in the appendix section.

2.3. Control variables

We consider several well-established macro variables like *the Consumer Price*, *Unemployment Rate*, *Bond Yield*, *Term Premium,* and *Trade volume* which indicates the total retail trade volume. We observe that only *Term Premium* has a significant positive impact on most of the assets' return which is consistent with the result of Baur and Smales (2020). For robustness check, we also consider a broader range of other uncertainty indices (see Table 7) as controls in both daily and monthly frequency. We observe that only the GRT index has a positive and significant relationship with the US stock returns and the other uncertainty indices have negative relations when they are used as a control.

2.4. Description of data

Table 1 shows the descriptive statistics of variables that we analyzed in this research. We see from the unit root test that all the variables are stationary with a high level of significance. In panel A, we observe that the Russian stock market has the highest standard deviation in return which is almost 2.5% and the Chinese market has the highest max value in return which is 74%. The lowest standard deviation in return is in the Australian market among the equities which is 0.9% and among other assets, the bond return has the lowest standard deviation. Panel B reports the descriptive statistics of 11 US ETFs. We observe that Energy ETFs have the highest standard deviation which is around 2% and consumer staples have the lowest standard deviation which is around 0.9%.

Table 2 reports the correlation between all country's equity indices, precious metals, bonds, and dollar returns. In panel A, we see that France and German have the highest correlation which is almost 80%. We also observe that bond has a negative correlation with almost all assets. A negative stock-bond correlation is beneficial for the majority of investors since it increases diversity within a typical portfolio. Panel B also demonstrates the correlation values with different EFTs with other assets. We see that all ETFs are positively correlated with each other but negatively correlated with gold and bond. Fig. 1 plots the GPT monthly risk index to show the different occurrences that cause geopolitical threats. We see the September eleven terror attack, the US occupation of Iraq, and the Russian war on Ukrain cause a significant geopolitical threat within the last two decades. However, Russian war on Ukrain is the cause of the highest geopolitical threat among them.

The trading hours of stock exchanges throughout the world vary. Therefore, using daily closing prices causes the underestimation of the underlying correlations between stock markets. The non-synchroneity issue is avoided by some researchers using weekly or monthly data (see Longin and Solnik (1995) and Ramchand and Susmel (1998)). The problem with small samples (due to weekly and monthly frequency) is that the low-frequency data make multivariate modeling ineffective, particularly when parameters are time-varying (see Martens and Poon (2001)). Additionally, weekly and monthly statistics are unable to depict the dynamism of daily connections. On the other hand, several researchers make use of daily non-synchronous returns (Hamao, Masulis, and Ng (1990) and Koutmos and Booth (1995)). These studies cannot tell a contemporaneous association from a spillover. In our study, we mainly use daily frequency data to avoid the problem of small samples. However, in alternative measures of the market uncertainty table (Table 7), we include both daily and monthly frequency.

[1] Caldara and Iacoviello (2022) classified the actions such as "risk of war", "fear of war", "military threat", "threat of war", and "threat of terrorism" as geopolitical threats and tensions, while "beginning of the war", "air strike", "heavy casualties", "terrorist act" etc. are considered as geopolitical events and acts.

Table 1
Descriptive statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max	Unit root
ΔGPT Threat	9738	0.00012	0.49386	−3.45264	2.65504	−144.92***
Equity Markets (1985 to 2021)						
USA	9742	0.00033	0.01138	−0.22900	0.10957	−103.26***
China	7915	0.00030	0.02225	−0.18427	0.74517	−83.873***
Japan	9742	0.00008	0.01252	−0.15810	0.12865	−89.527***
UK	9742	0.00019	0.01086	−0.13029	0.09384	−92.154 ***
France	9085	0.00016	0.01354	−0.13098	0.10595	−90.207***
Switzerland	8830	0.00023	0.01110	−0.11143	0.10788	−86.835***
Germany	9742	0.00029	0.01384	−0.13710	0.10797	−94.852 ***
Canada	9742	0.00022	0.00972	−0.13176	0.11294	−93.639***
Australia	7809	0.00019	0.00961	−0.10203	0.06766	−84.575***
Russia	6959	0.00035	0.02489	−0.48292	0.23204	−71.510***
Gold	9742	0.00019	0.00964	−0.10162	0.07382	−91.816***
Silver	9742	0.00013	0.01714	−0.23672	0.13665	−90.826***
Palladium	9218	0.00032	0.02008	−0.17859	0.16961	−82.191***
Platinum	9742	0.00013	0.01449	−0.17277	0.11728	−89.489***
Copper	9742	0.00020	0.01633	−0.10796	0.29054	−90.610 ***
Bond	9742	−0.0000	0.00303	−0.03500	0.03797	−79.207***
Dollar	8437	0.00001	0.00494	−0.03056	0.02520	−80.664***
Exchange Traded Funds (ETF) (2005 to 2021)						
Energy	4578	0.00018	0.01905	−0.22096	0.15783	−69.760***
Information Technology	4578	0.00049	0.01364	−0.14487	0.10449	−69.809***
Healthcare	4578	0.00036	0.01079	−0.11713	0.11139	−68.678***
Communications	4578	0.00018	0.01265	−0.12126	0.13079	−67.546***
Industry	4578	0.00029	0.01360	−0.12173	0.11247	−66.751***
Materials	4578	0.00028	0.01529	−0.13130	0.11181	−67.733***
Utility	4578	0.00024	0.01155	−0.11907	0.12226	−68.746***
Consumer Discretion	4578	0.00040	0.01330	−0.13963	0.10494	−65.314***
Financial	4578	0.00013	0.01762	−0.17652	0.14907	−73.556***
Real Estate	4578	0.00017	0.01875	−0.21712	0.15706	−77.044***
Consumer Staples	4578	0.00030	0.00893	−0.09810	0.08654	−68.422***
Controls						
Δ Trade Volume	9672	0.171	1.633	−12.579	15.791	−12.810***
Δ CPI	9716	0.225	0.266	−1.786	1.367	−7.901***
Δ Unemployment	9716	−0.159	6.644	−19.416	120.624	−13.627***
Δ Bond Yield Spread	8866	−0.0001	0.15701	−1.79176	2.19723	−88.958***
Δ Term Premium	9742	−0.0001	0.01904	−0.25732	0.35746	−88.715***

Here ΔGPT Threat is the change in daily geopolitical threat, US is the SP500 return, China is the Shanghai SE A Share Price Index return, Japan is the Tokyo Stock Exchange return, UK is the FTSE 100 return, France is the France CAC 40, Switzerland is the Swiss Market (SMI) return, Germany is the DAX Performance return, Canada is the Toronto Stock Exchange Composite Index, Australia is the Standard and Poor's Australian Stock Exchange 200, Russia is the MSCI Russia from 1985 to 2021. All ETFs are from Vanguard ETFs' daily returns from 2005 to 2021. Among Controls Δ Trade Volume is the change in the United States Retail Trade Volume, Δ CPI is the change in the US Consumer Price Index, Δ Unemployment is the change in the US unemployment rate, Δ Bond Yield Spread is the change in the 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity and Δ Term Premium is the change in the United States, US ACM Treasury Term Premia FIT Yield 10Y.

3. Methodology

To examine how changes in the geopolitical threat affect various assets, we utilize the simple regression model with the following specification:

$$R_t = \beta_0 + \beta_1 \Delta\text{GPT Threat}_t + \beta_2 \Delta\text{CPI}_t + \beta_3 \Delta\text{UNEMP}_t + \beta_4 \Delta\text{Bond Yield Spred}_t + \beta_5 \Delta\text{Term Premium}_t + \beta_6 \Delta\text{Trade volume}_t + \varepsilon_t \quad (1)$$

R_t is the assets return (Ln difference) in time t (source: DataStream), ΔGPT Threat is the Ln difference of geopolitical threat index (from Caldara & Iacoviello, 2022), *CPI* is the US monthly consumer price index (source: DataStream), *UNEMP* is the US monthly unemployment rate (source: DataStream), *Bond Yield Spread* is the 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity (source: Fred), *Term Premium* is the United States, US ACM Treasury Term Premia FIT Yield 10-Year (source: DataStream), *Trade volume* is the United States, Retail Trade, Total, Volume, Total Retail Trade (Volume) (source: DataStream).

Baur and McDermott (2010) argue that investors should be aware of the difference between a robust and weak hedge or safe haven, as investors should expect higher returns at periods of increased geopolitical risk if there is a positive correlation between asset classes, which can improve market stability by limiting overall losses. We, like Baur and Smales (2020), adhere to Baur and McDermott's (2010) hedging and safe-haven concepts of hedge and safe haven to fit the context of geopolitical threats to analyze the characteristics of market reactions to changes in geopolitical threats, where if an asset's returns are positively correlated (uncorrelated) with changes in geopolitical threat, it is a strong (weak) hedge against that risk. Similarly, during times of severe geopolitical threat, an asset is a strong (weak) safe haven against a geopolitical threat if its returns are positively correlated (uncorrelated) with changes in geopolitical threat.

After analyzing how the geopolitical threat affects different assets, in this section, we examine the impact of GPT on US ETF return during extremely tumultuous geopolitical eras. For this purpose, we use the following model:

$$R_{it} = \alpha + \beta_3(\Delta GPT_t \times HiGPT_t) + Controls_t + e_{it} \quad (2)$$

with controls as before and where $HiGPT_t$ is a dummy which is one if month t has a value of the Geopolitical threat index in its highest decile.

Whether geopolitical threat has an impact on return volatility as well, in this part, we look at the additional estimation of model 1 that was derived using an EGARCH (1,1) specification (Nelson, 1991). The conditional variance equation and the mean equation both take changes in geopolitical threat into account. The formula for the conditional

Table 2
Correlation matrix among major variables.

Panel A: Correlation of country indices and other Assets

	ΔGPT Threat	USA	China	Japan	UK	France	Switzerland	Germany	Canada	Australia	Russia	Palladium	Platinum	Gold	Silver	Bond	Dollar
ΔGPT Threat	1.000																
USA	0.040*	1.000															
China	0.006	0.097*	1.000														
Japan	0.000	0.149*	0.115*	1.000													
UK	0.026	0.577*	0.064*	0.286*	1.000												
France	0.026	0.598*	0.061*	0.273*	0.802*	1.000											
Switzerland	0.026	0.532*	0.049*	0.280*	0.739*	0.771*	1.000										
Germany	0.027	0.606*	0.059*	0.260*	0.709*	0.826*	0.753*	1.000									
Canada	0.030*	0.763*	0.050*	0.218*	0.533*	0.508*	0.441*	0.484*	1.000								
Australia	−0.010	0.227*	0.138*	0.498*	0.342*	0.314*	0.317*	0.307*	0.271*	1.000							
Russia	0.002	0.308*	0.090*	0.235*	0.416*	0.405*	0.353*	0.391*	0.315*	0.287*	1.000						
Palladium	−0.004	0.150*	0.063*	0.125*	0.127*	0.105*	0.094*	0.094*	0.145*	0.179*	0.129*	1.000					
Platinum	0.002	0.139*	0.065*	0.113*	0.104*	0.080*	0.047*	0.063*	0.152*	0.190*	0.164*	0.558*	1.000				
Gold	−0.019	−0.004	0.047*	0.026	0.048*	−0.003	−0.045*	0.005	0.147*	0.071*	0.134*	0.373*	0.478*	1.000			
Silver	0.000	0.123*	0.046*	0.078*	0.109*	0.080*	0.060*	0.072*	0.186*	0.140*	0.188*	0.317*	0.429*	0.727*	1.000		
Bond	−0.007	−0.362*	−0.028*	−0.054*	−0.178*	−0.197*	−0.177*	−0.202*	−0.160*	−0.083*	−0.130*	−0.038*	−0.031*	0.108*	0.001	1.000	
Dollar	−0.010	−0.177*	−0.019	−0.037*	−0.005	0.001	0.029*	−0.001	−0.079*	−0.058*	−0.106*	−0.114*	−0.128*	−0.302*	−0.231*	−0.066*	1.000

Panel B: Correlation of ETFs and other Assets

	ΔGPT Threat	Energy	Itech	Healthcare	Communication	Industry	Materials	Utility	Consumer Discretion	Financial	Real Estate	Consumer staples	Palladium	Platinum	Gold	Silver	Bond	Dollar
ΔGPT Threat	1.000																	
Energy	0.029*	1.000																
Itech	0.047*	0.617*	1.000															
Healthcare	0.027	0.590*	0.774*	1.000														
Com.	0.040*	0.621*	0.797*	0.736*	1.000													
Industry	0.029	0.748*	0.829*	0.773*	0.789*	1.000												
Materials	0.031*	0.796*	0.782*	0.718*	0.743*	0.898*	1.000											
Utility	0.041*	0.565*	0.569*	0.641*	0.620*	0.643*	0.623*	1.000										
Con Dis	0.030*	0.642*	0.872*	0.768*	0.823*	0.884*	0.811*	0.585*	1.000									
Financial	0.029*	0.656*	0.726*	0.687*	0.737*	0.851*	0.777*	0.569*	0.813*	1.000								
Real Estate	0.019	0.546*	0.652*	0.609*	0.670*	0.741*	0.687*	0.627*	0.742*	0.819*	1.000							
Cons stap.	0.023	0.577*	0.713*	0.776*	0.730*	0.765*	0.710*	0.751*	0.751*	0.680*	0.657*	1.000						
Palladium	−0.004	0.199*	0.133*	0.127*	0.132*	0.166*	0.200*	0.139*	0.138*	0.105*	0.085*	0.095*	1.000					
Platinum	0.002	0.182*	0.130*	0.104*	0.128*	0.155*	0.197*	0.128*	0.129*	0.099*	0.096*	0.098*	0.558*	1.000				
Gold	−0.019	0.091*	−0.004	−0.024	0.000	0.000	0.099*	0.048*	−0.022	−0.063*	0.009	−0.001	0.373*	0.478*	1.000			
Silver	0.000	0.212*	0.112*	0.080*	0.109*	0.133*	0.230*	0.109*	0.104*	0.071*	0.110*	0.072*	0.317*	0.429*	0.727*	1.000		
Bond	−0.007	−0.319*	−0.315*	−0.283*	−0.272*	−0.373*	−0.351*	−0.145*	−0.325*	−0.368*	−0.203*	−0.246*	−0.038*	−0.031*	0.108*	0.001	1.000	
Dollar	−0.010	−0.231*	−0.138*	−0.125*	−0.160*	−0.187*	−0.265*	−0.164*	−0.152*	−0.143*	−0.156*	−0.134*	−0.114*	−0.128*	−0.302*	−0.231*	−0.066*	1.000

*$p < 0.05$.

variance

$$R_t = \beta_c + \beta_1 \Delta\text{GPT Threat}_t + \beta_2 \Delta\text{CPI}_t + \beta_3 \Delta\text{UNEMP}_t + \beta_4 \Delta\text{Bond Yield Spred}_t + \beta_5 \Delta\text{Term Premium}_t + \beta_6 \Delta\text{Trade volume}_t + \varepsilon_t \quad (3A)$$

$$log(\sigma_t^2) = \lambda_c + \alpha_0 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_0 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \gamma_0 log(\sigma^2{}_{t-1}) + \lambda_1 \Delta\text{GPT Threat}_t + \lambda_2 \Delta\text{CPI}_t + \lambda_3 \Delta\text{UNEMP}_t + \lambda_4 \Delta\text{Bond Yield Spred}_t + \lambda_5 \Delta\text{Term Premium}_t + \lambda_6 \Delta\text{Trade volume}_t + \varepsilon_t \quad (3B)$$

The term $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is the standardized value that helps in interpreting the magnitude and the persistence of the estimated variable. If its coefficient $\gamma_i \neq 0$ and significant, the impact is asymmetric. If $\Sigma\gamma_i < 0$ and significant, then the leverage effect is present. Thus, term $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is the asymmetrical effect term. On the other hand, the absolute value of the standardized lagged residual $\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}$ symmetrical effect term. In the case of a positive shock (when the term $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is Positive), the shock impact on the conditional variance, and when this term is negative (the leverage effect is present). The estimated coefficients are reported in Appendix Table A5 (Panel A and Panel B). The GARCH coefficient (λ2) for each asset is not statistically significant for GPT threat indicating a low degree of volatility persistence.

To check the impact of the other alternate measures of market uncertainties we formulate the following regression equation:

$$R_t = \beta_0 + \beta_1 \Delta\text{GPT Threat}_t + \beta_2 \Delta\text{Unc}_t + \beta_3 \Delta\text{MacroUnc}_t + \beta_4 \Delta\text{EPU}_t + \beta_5 \Delta\text{VIX}_t + \varepsilon_t \quad (4)$$

Where the ΔUnc_teconomic uncertainty index of Bekaert and Mehl (2019), $\Delta\text{MacroUnc}_t$ is the macroeconomic uncertainty index of Jurado et al. (2015), ΔEPU_t is the economic policy uncertainty (EPU) index of Baker et al. (2016) and ΔVIX is the CBOE implied volatility index (VIX) at time t.

To find the portfolio hedge implication, we consider the case of an investor who is presently invested in US and Gold asset portfolios with one US or Gold asset and one other different asset. The optimal hedge position for each portfolio is calculated monthly as the minimum-variance hedge ratio $h_t^* = \frac{\rho_{gn,t}\sigma_{g,t}}{\sigma_{n,t}}$, where $\rho_{gn,t}$ is the US stock (for panel A) and Gold (for Panel B) assets and other assets correlation in month *t*, and $\sigma_{g,t}$and $\sigma_{n,t}$standard deviations of US stock or gold assets and other assets for month *t*, respectively. After calculating the optimal hedge ratios for each month, we then examine the effect of geopolitical threats on the hedge ratios of different portfolios (asset pairs) by using:

$$h_t^* = \theta_0 + \theta_1 GPT_t + \varepsilon_t \quad (5)$$

Where h_t^* is the optimum hedge ratio and *GPT* is the geopolitical threat for month *t*.

The impact of geopolitical threat on the ideal hedging ratios is presented in Table 8. We generally see that when geopolitical threat is high, the number of hedge positions that should be taken in a given asset should be low. This is shown by estimates that are negative for θ_1.

The fact that the results discussed above are based on linear specifications with the assumption that the model parameters are time-invariant makes them significantly weaker because they do not account for potential structural breaks and regime changes that might lead to different levels of uncertainty in a regime-switching environment and affect the relationship between the GPT threat and stock market. The impacts of GPT threat on stock markets during regime switching, as in Eq. 6, would therefore be worthwhile to research.

$$R_t = \alpha_0 + \varphi_{st1} \Delta\text{GPT Threat}_t + \varphi_{st2} \Delta\text{GPT Threat}_{t-1} + \varphi_{st3} \Delta\text{CPI}_t + \varphi_{st4} \Delta\text{UNEMP}_t + \varphi_{st5} \Delta\text{Bond Yield Spred}_t + \varphi_{st6} \Delta\text{Term Premium}_t + \varphi_{st7} \Delta\text{Trade volume}_t + \varepsilon_t \quad (6)$$

Where $\varepsilon_t \sim N(0,\sigma_{st}^2)$ where S_t is a discrete regime variable taking values in {1,2, ….n} following a n -state Markov process. We evaluated two-regime models with regime-dependent **constant** variances.

To analyze the impact of Geopolitical Threats on various assets and sectors we apply the simple time series regression model with major five controls. Later we also introduce a few related uncertainty and risk indices as additional controls. Additionally, first, we introduce a high Geopolitical Threat dummy to address the impact during extremely tumultuous geopolitical states. This model is important to find out safe-haven assets during extremely high geopolitical threat situations. Second, we introduce EGARCH (1,1) specification to find out the impact of geopolitical threats on the volatility of the different asset classes. Volatility is regarded as an indicator of the degree of uncertainty in asset price swings. Markowitz (1952) utilized it more precisely as a risk indicator. An analytical solution for volatility is utilized in risk management, portfolio optimization, and hedging, where there is a growing requirement for an accurate forecast of volatility. Therefore, we think that this model is relevant in this paper. Third, we apply Markov Chain Regime Switching Approach with the same controls to find out how the impact works in the different volatility regimes. In periods of financial stability as opposed to financial crises, several economic time series exhibit distinct behaviors. Hence the results from this approach are relevant and informative. Finally, to check the impact of the Geopolitical Threat on the optical hedge ratio, we find the optimal hedge position for each portfolio by calculating the monthly minimum-variance hedge ratio and checking the effect of Geopolitical Threat on them. This approach also demonstrates how the monthly dynamic change of correlations among the asset classes differs due to changes in Geopolitical Threat.

4. Results

4.1. Hedging geopolitical threat

In this section, we conduct a series of regressions (Eq.1) between changes in Geopolitical threat (ΔGPT Threat) and different asset returns (G7 countries' stock indices, precious metals, bonds, and dollars) in different subsamples. Table 3 (see related Tables Appendix 1, 2, and 3) presents the regression coefficients of ΔGPT threat and other controls with their associated standard error in the parenthesis. We find that the coefficient of ΔGPT threat is positive and significant in the case of the US market in the 2005–2021 sample. We also conduct similar regression in other sample periods like 2015–2021, 1995–2021, and 1985–2021 which are reported in Appendix Tables 1, 2, and 3 respectively. The results demonstrate that the US market is showing a good hedge in the recent samples. All samples after 1995 (when information flows rapidly and investors quickly shift their investment towards the US market) generate regression coefficients related with ΔGPT threat are positive and significant. In Table 3 the ΔGPT threat coefficient is 0.000937 with an associated standard error of 0.000347 which is significant at a 5% level of significance. Similar results are evident in Appendix Table 1 and 2 which validates the US market's good hedging capacity against geopolitical threats in comparison to other counties and assets.

Based on the facts presented above, it can be deduced that the market in the US possesses a considerable capacity for geopolitical risk hedging. This is likely due to the fact that the US equities market is one of the largest and most diverse in the world, consisting of a wide array of sectors and businesses that provide investors with a variety of possibilities for hedging against geopolitical risks. Investors in the US equities market may protect themselves against the potential negative effects of

Table 3
Relationship between geopolitical threat (GPT) and asset returns (2005–2021).

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
Panel A: Equity Markets								
USA	**0.000937****						0.000272	4524
	(0.000347)						(0.000180)	
	0.000870*	0.000157	0.0000602**	−0.00180	0.176***	0.000172	0.000281	4118
	(0.000343)	(0.000578)	(0.0000226)	(0.00129)	(0.00685)	(0.000105)	(0.000209)	
China	0.000215						0.000195	4524
	(0.00043)						(0.000225)	
	0.000286	0.000192	0.0000141	0.000187	0.0318***	0.0000165	0.000151	4074
	(0.000452)	(0.000763)	(0.0000298)	(0.00170)	(0.00904)	(0.000139)	(0.000275)	
UK	0.000576						0.0000980	4524
	(0.000326)						(0.000169)	
	0.000460	−0.000120	0.0000321	−0.00163	0.139***	0.000158	0.0000630	4118
	(0.000330)	(0.000557)	(0.0000218)	(0.00124)	(0.00660)	(0.000102)	(0.000201)	
France	0.000714						0.000113	4524
	(0.000390)						(0.000202)	
	0.000555	0.0000346	0.0000178	−0.00151	0.173***	0.000101	0.000118	4074
	(0.000390)	(0.000658)	(0.0000257)	(0.00146)	(0.00779)	(0.000120)	(0.000237)	
Germany	0.000708						0.000262	4524
	(0.000382)						(0.000198)	
	0.000536	−0.000135	0.0000478	−0.00116	0.165***	0.000220	0.000265	4074
	(0.000382)	(0.000645)	(0.0000252)	(0.00143)	(0.00763)	(0.000117)	(0.000232)	
Canada	**0.000629***						0.000178	4524
	(0.000314)						(0.000163)	
	0.000582	0.00122*	0.0000617**	−0.00192	0.133***	0.000173	−0.0000456	4029
	(0.000320)	(0.000545)	(0.0000212)	(0.00122)	(0.00642)	(0.000100)	(0.000194)	
Australia	−0.000198						0.000132	4524
	(0.000307)						(0.000159)	
	−0.000183	0.00108	0.0000287	0.000323	0.0551***	0.0000972	−0.000130	4074
	(0.000327)	(0.000551)	(0.0000215)	(0.00123)	(0.00652)	(0.000100)	(0.000199)	
Russia	0.0000846						0.000133	4524
	(0.000631)						(0.000327)	
	0.000203	0.00221*	0.000120**	−0.00212	0.145***	0.000368	−0.000149	4074
	(0.000657)	(0.00111)	(0.0000433)	(0.00247)	(0.0131)	(0.000202)	(0.000400)	
Switzerland	0.000567						0.000162	4524
	(0.000306)						(0.000159)	
	0.000434	0.000782	0.0000313	−0.000854	0.111***	0.000112	−0.0000565	4074
	(0.000311)	(0.000525)	(0.0000205)	(0.00117)	(0.00621)	(0.0000956)	(0.000189)	
Panel B: Other Assets								
Gold	−0.000417						0.000322	4524
	(0.000318)						(0.000165)	
	−0.000448	0.000562	0.0000241	−0.0000697	−0.0467***	0.0000304	0.000151	4074
	(0.000337)	(0.000569)	(0.0000222)	(0.00127)	(0.00673)	(0.000104)	(0.000205)	
Silver	−0.0000323						0.000263	4524
	(0.000561)						(0.000291)	
	−0.000171	0.00145 (0.00101)	0.0000505	0.000608	−0.00132	0.000265	−0.000113	4074
	(0.000600)		(0.0000395)	(0.00225)	(0.0120)	(0.000184)	(0.000365)	
Palladium	−0.000217						0.000551	4524
	(0.000609)						(0.000316)	
	−0.0000419	0.000649	−0.0000172	−0.00105	0.0682***	0.000231	0.000329	4074
	(0.000640)	(0.00108)	(0.0000421)	(0.00240)	(0.0128)	(0.000197)	(0.000389)	
Platinum	0.0000474						0.0000313	4524
	(0.000438)						(0.000227)	
	0.000116	0.00138	0.0000571	0.000135	0.0285**	0.000277	−0.000296	4074
	(0.000468)	(0.000789)	(0.0000308)	(0.00176)	(0.00935)	(0.000144)	(0.000285)	
Copper	0.000102						0.000236	4524
	(0.000485)						(0.000251)	
	0.000171	0.00332***	0.0000354	−0.00137	0.111***	0.000112	−0.000376	4074
	(0.000511)	(0.000862)	(0.0000337)	(0.00192)	(0.0102)	(0.000157)	(0.000311)	
Bond	−0.0000406						−0.0000329	4524
	(0.0000812)						(0.0000421)	
	0.00000359	−0.000199**	−0.000009**	0.000285	−0.0930***	−0.0000317*	0.00000164	4074
	(0.0000442)	(0.0000745)	(0.000002)	(0.000166)	(0.000883)	(0.0000136)	(0.0000269)	
Dollar	−0.0000996						0.0000545	4524
	(0.000134)						(0.0000696)	
	−0.000104	−0.000378	−9.84e-08	−0.000632	0.0107***	0.0000152	0.000074	4074
	(0.000143)	(0.000241)	(0.000009)	(0.000537)	(0.00286)	(0.000044)	(0.0000870)	

This table presents the coefficients estimated using Eq. 1 (with and without control) where the dependent variable is the daily return on equity markets (USA, China, UK, France, Germany, Canada, Australia, Russia, Switzerland), and other assets (gold, silver, palladium, platinum, copper, bond and dollar) from 2005 to 2021. The key explanatory variable is the change in the geopolitical threat index (ΔGPT Threat). The set of control variables includes Changes in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, change in Term Premium, and Change in Trade Volume. Standard errors are in parentheses and ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels respectively.

geopolitical events by allocating their capital to companies and sectors that are less vulnerable to them. Previous findings are corroborating our results, for instance, during the US subprime crisis, Chudik and Fratzscher (2012) showed that investors acted in a way called "flight to safety." This caused financial capital to move from emerging market economies to bond markets in the USA and other advanced economies. The findings of Chudik and Fratzscher (2012) is also supported by Feng et al. (2022), who demonstrates that, in the context of rising geopolitical risk at the aggregate level, capital flows for both developed and developing nations experience considerable contractions, indicating a flight-home impact. In particular, the extent of the fluctuations in capital flows experienced by emerging economies in response to geopolitical risk is greater. In a recent study, Boubaker, Goodell, Pandey, and Kumari (2022) find that the US market experienced a positive and statistically significant cumulative abnormal return on the day of the invasion of Ukraine on February 24, 2022, whereas the majority of the sampled countries' stock markets were significantly impacted by this geopolitical event on that event date. The US's distance from warring countries is one of the reasons, the authors point out in their paper for this positive market reactions in the US market. However, based on our results, by supporting findings of Chudik and Fratzscher (2012) and Feng et al. (2022), we argue that the US market acts as a hedge during times of high geopolitical risk. Previous evidence also demonstrates that the US market is a good hedge against inflation too (see Salisu, Ndako, & Akanni, 2020).

We contend, however, that investors now find safety in the US equity market and shift their investments there relatively fast because of the country's beneficial geopolitical location and advanced defense technologies. The US has not suffered any major terrorist attacks since September 11, 2001, further contributing to the country's relative geopolitical stability. The US government's efforts to prevent terrorist activities around the world, especially the US Army's anti-terrorist operations, may have created a positive impression of US's geopolitical stability in the minds of investors. As a result, this market exhibits higher returns than other markets and assets. In the most recent sample of 2015–2021, the Chinese market likewise exhibits favorable hedging chances against the geopolitical threat (Appendix Table 1). Given China's rapid ascent both militarily and economically, this is not particularly surprising. Both the US and Chinese market's positive movement against geopolitical threats validates that investors feel safe

Table 4
Relationship between geopolitical threat (GPT) and US ETF returns (2005–2021).

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
Information Technology	**0.00125****						0.000465*	4511
	(0.000393)						(0.000203)	
	0.00125**	0.000469	0.000074**	−0.00227	0.175***	0.000266*	0.000445	
	(0.000393)	(0.000668)	(0.000026)	(0.00150)	(0.00788)	(0.000123)	(0.000238)	4029
	0.000975**						0.000163	
	(0.000365)						(0.000189)	4511
	0.000924*	0.000093	0.000077**	−0.00119	0.136***	0.000272*	0.000140	
Communication	**(0.000372)**	(0.00063)	(0.00002)	(0.00142)	(0.00747)	(0.000117)	(0.000226)	4029
	0.000410						0.000290*	
	(0.000257)						(0.000133)	4511
	0.000384	0.000287	0.0000416*	−0.000147	0.0979***	0.000118	0.000254	
Consumer Staples	(0.000266)	(0.000453)	(0.0000177)	(0.00101)	(0.00534)	(0.000083)	(0.000161)	4029
	0.000764*						0.000372	
Consumer Discretionary	**(0.000384)**						(0.000199)	4511
	0.000774*	−0.000320	0.00008***	−0.00170	0.174***	0.00033**	0.000466*	
	(0.000385)	(0.000656)	(0.00002)	(0.00147)	(0.00773)	(0.00012)	(0.000234)	4029
	0.00112*						0.000172	
Energy	**(0.000549)**						(0.000285)	4511
	0.000912	0.00138	0.00012***	−0.00261	0.265***	0.000205	−0.0000619	
	(0.000551)	(0.000937)	(0.000036)	(0.00210)	(0.0110)	(0.000172)	(0.000334)	4029
	0.00100*						0.000114	
Financial	**(0.000509)**						(0.000264)	4511
	0.000831	0.000329	0.0000566	−0.00168	0.263***	0.000159	0.000134	
	(0.000509)	(0.000866)	(0.0000338)	(0.00194)	(0.0102)	(0.000159)	(0.000309)	4029
	0.000585						0.000359*	
Healthcare	(0.000310)						(0.000161)	4511
	0.000507	0.000352	0.000065**	−0.000840	0.133***	0.000124	0.000329	
	(0.000313)	(0.000529)	(0.000020)	(0.00118)	(0.00626)	(0.000096)	(0.000191)	4029
	0.000738						0.000272	
Industry	(0.000393)						(0.000204)	4511
	0.000703	−0.00000	0.0000461	−0.000529	0.208***	0.000153	0.000337	
	(0.000388)	(0.0006)	(0.000025)	(0.00146)	(0.00775)	(0.000119)	(0.000236)	4029
	0.000921*						0.000266	
Material	**(0.000441)**						(0.000229)	4511
	0.000918*	0.000522	0.000081**	−0.000514	0.214***	0.000200	0.000236	
	(0.000441)	(0.000744)	(0.000029)	(0.00166)	(0.00881)	(0.000136)	(0.000268)	4029
	0.000651						0.000144	
Real Estate	(0.000541)						(0.000281)	4511
	0.000612	0.0000172	0.0000644	−0.000560	0.151***	0.000234	0.000111	
	(0.000573)	(0.000967)	(0.0000378)	(0.00215)	(0.0115)	(0.000176)	(0.000349)	4029
	0.000910**						0.000228	
Utility	**(0.000333)**						(0.000173)	4511
	0.000979	0.00159	0.000129***	−0.00231	0.261***	0.000234	−0.0000663	
	(0.000548)	(0.000925)	(0.000036)	(0.00206)	(0.0110)	(0.000169)	(0.000334)	4029

This table presents the coefficients estimated using Eq1 (with and without control) where the dependent variable is the daily return on different sectoral ETF returns from 2005 to 2021. The key explanatory variable is the change in the geopolitical threat index (ΔGPT Threat). The set of control variables includes Change in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, change in Term Premium, Change in Trade Volume. Standard errors are in parentheses and ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels respectively.

investing in these two countries' equity markets due to their distant geographical location from the conflict zone and strong defense capability.

To investigate thoroughly, we run the same regression model (Eq.1) for the US ETFs returns in Table 4. The results demonstrate that IT, Communication, and Material ETFs are showing a good hedge against the geopolitical threat. Geopolitical threat coefficient against the IT ETF is 0.00125 (standard error of 0.000393), significant at the 5% level of confidence, and with all controls. Likewise, Communication and Material ETF have a geopolitical threat coefficient of 0.000975 (standard error 0.000365) and 0.000924 (standard error 0.000372) respectively with all controls and significant at a 10% level of confidence. Without controls, these coefficients are significant at a 5% level of confidence. These findings suggest that investors are choosing to invest in the IT, communication, and material industries while investing in the US market in order to counter the geopolitical threat.

4.2. Safe haven properties

After identifying the US market as potential hedges against the geopolitical threat, we now focus on determining if they also serve as safe havens, or whether the established linkages hold during times of high geopolitical threat. We would anticipate that states of geopolitical threat that are especially pertinent to a worldwide audience and thus produce a higher number of newspaper stories are consistent with high levels of GPT. Therefore, it's probable that more assets react to GPT at these times. Using Eq. 2, we show that there are traces of hedging capability of the US market during the extremely high geopolitical threat change states. Our findings are presented in Table 5. In Eq. 2, we use a dummy variable named *HiGPT* where we consider 1 when that particular period is within 10% highest geopolitical threat. In Table 5, we observe that not only does the coefficient of $(\Delta GPT_t \times HiGPT_t)$ against the overall US market shows a positive and significant result but in the case of the ITech and Financial ETFs, $(\Delta GPT_t \times HiGPT_t)$

Table 5
Relationship between geopolitical threat (GPT) and US ETF returns in the top 10% Threat States sample (Safe haven properties).

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
USA (S&P 500)	**0.00128***						0.000143 (0.000191)	4524
	(0.000616)							
	0.0013*	0.000173	0.0000605**	−0.00179	0.176***	0.000170	0.000142	4074
	(0.000612)	(0.000579)	(0.0000226)	(0.00129)	(0.00685)	(0.000105)	(0.000218)	
Information Technology	**0.00177***						0.000287 (0.000215)	4511
	(0.000696)							
	0.00189**	0.000301	0.0000675**	−0.00193	0.174***	0.000216	0.00025	4074
	(0.000702)	(0.000664)	(0.0000259)	(0.00148)	(0.00786)	(0.000121)	(0.000250)	
Communication	0.00104						0.0000583 (0.0002)	4511
	(0.000647)							
	0.00107	−0.000060	0.0000714**	−0.000994	0.135***	0.000234*	0.0000290	4074
	(0.000665)	(0.000630)	(0.0000246)	(0.00140)	(0.00745)	(0.000115)	(0.000237)	
Consumer Staples	0.000681						0.000222 (0.000141)	4511
	(0.000456)							
	0.00134*	0.000173	0.0000605**	−0.00179	0.176***	0.000170	0.000455 (0.000269)	4074
	(0.000612)	(0.000579)	(0.0000226)	(0.00129)	(0.00685)	(0.000105)		
Consumer Discretionary	0.0013 (0.00068)						0.000241 (0.00021)	4511
	0.00140*	−0.000456	0.0000764**	−0.00141	0.173***	0.000270*	0.000324	4074
	(0.000688)	(0.000651)	(0.0000254)	(0.00145)	(0.00770)	(0.000119)	(0.000245)	
Energy	0.000749						0.0000964	4511
	(0.000974)						(0.000301)	
	0.000339	0.00159	0.000129***	−0.00234	0.261***	0.000232	−0.000104	4074
	(0.000978)	(0.000925)	(0.0000361)	(0.00206)	(0.0110)	(0.000169)	(0.000348)	
Financial	**0.00196***						−0.0000841	4511
	(0.000902)						(0.000279)	
	0.00134*	0.000173	0.0000605**	−0.00179	0.176***	0.000170	0.000142	4074
	(0.000612)	(0.000579)	(0.0000226)	(0.00129)	(0.00685)	(0.000105)	(0.000218)	
Healthcare	0.000721						0.000286 (0.00017)	4511
	(0.00055)							
	0.000806	0.000362	0.0000656**	−0.000838	0.133***	0.000123	0.000245	4074
	(0.000559)	(0.000529)	(0.0000207)	(0.00118)	(0.00626)	(0.0000964)	(0.000199)	
Industry	0.00128						0.000142 (0.000215)	4511
	(0.000696)							
	0.00140*	0.0000165	0.0000465	−0.000518	0.208***	0.000151	0.000193	4074
	(0.000692)	(0.000655)	(0.0000256)	(0.00146)	(0.00775)	(0.000119)	(0.000246)	
Material	0.000923						0.000173 (0.000242)	4511
	(0.000782)							
	0.00106	0.000534	0.0000817**	−0.000522	0.215***	0.000198	0.000126	4074
	(0.000787)	(0.000745)	(0.0000291)	(0.00166)	(0.00882)	(0.000136)	(0.000280)	
Real Estate	0.00176						−0.0000337	4511
	(−0.00095)						(0.000297)	
	0.00192	0.0000429	0.0000651	−0.000531	0.151***	0.000232	−0.0000856	4074
	(0.00102)	(0.000967)	(0.0000378)	(0.00215)	(0.0114)	(0.000176)	(0.000364)	
Utility	0.000994						0.000128 (0.000183)	4511
	(−0.00059)							
	0.000930	0.000237	0.0000422	−0.000999	0.0840***	0.000213*	0.000107	4074
	(0.000625)	(0.000591)	(0.0000231)	(0.00132)	(0.00700)	(0.000108)	(0.000223)	

This table presents the coefficients estimated using Eq. 2 (with and without control) where the dependent variable is the daily return on different sectoral ETF returns from 2005 to 2021 on top 10% GPT states. The key explanatory variable is the change in the geopolitical threat index (ΔGPT Threat). The set of control variables includes Change in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, change in Term Premium, Change in Trade Volume. Standard errors are in parentheses and ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels respectively.

coefficients are also showing a positively significant outcome. Therefore, Itech and the Financial sector ETFs are two assets that can be considered as safe havens assets against the geopolitical threat.

According to Mather and Lighthall (2012), people who are stressed tend to focus more on positive information and disregard bad information. Therefore, investors who are under pressure can remember their prior success in US stock investment which may be risker than bonds and gold. Additionally, stocks have higher expected income than gold and bond which are considered safe haven assets during highly uncertain periods (see Baur & McDermott, 2010). Evidence also shows that a highly volatile asset like Bitcoin can be a safe haven against political and economic uncertainties in the US (Umar, Su, Rizvi, & Shao, 2021).

4.3. The US ETF returns under different regime

When we looked at how the US ETF returns were affected under different volatility regimes (high and low) by changes in the geopolitical threat index (ΔGPT Threat), we discovered consistency with the previous findings. Table 6 displays the estimated coefficients for the Markov Switching Model under two volatility regimes, with the return on the US equity markets and several sectoral ETF returns as the dependent variables (January 2005 to May 2021). The shift in the ΔGPT Threat index is the primary determinant here, whereas changes in inflation (ΔCPI), changes in the unemployment rate (UNEMP), change in credit spread, change in term premium, and change in trade volume are included in the group of control variables.

We found indication of an effect on the return of the overall US ETF because of a shift in ΔGPT Threat during the high volatility regime, where we did not use any control. Without controls, the ΔGPT threat coefficient is 0.0014 with an associated standard error of 0.0005 which is significant at a 1% level of significance. As a result, the US aggregate market has shown to be a strong hedge in the environment of high volatility conditions. This extremely substantial GPT threat, however, did not persist when controls were implemented. In contrast, the US aggregate ETF coefficient is positive and statistically significant with all controls under conditions of low volatility regime.

When examining the sectoral ETF return, we discovered a heterogeneous impact due to the shift of ΔGPT Threat. Consistent with earlier findings, ETFs in the IT, Communication, and Materials sectors demonstrate a strong hedge against the ΔGPT Threat. Furthermore, Utility, Energy, and Health ETF provide a fair indication of hedging capacity at different volatility regimes. The IT ETF appears to be the best performing ETF sector in the US against the ΔGPT Threat in terms of return, since it performs well in both high and low volatility regimes. In the high volatility regime, the coefficient of ΔGPT threat for IT ETF is extremely significant without control, and the value of the coefficient is still positive. However, when we look at the situation in conditions of low volatility, we see the clear picture of hedging capacity of IT ETF, where the return is positive and significant without control. This proves that the ΔGPT Threat apparently had no impact on IT EFT returns under either regime in the US market.

The communication ETF similarly demonstrated an effective hedge against the ΔGPT Threat, displaying positive and highly substantial returns in both high and low volatility regimes. In high volatility environments, the energy and material ETFs both perform well, while the utility and health ETFs serve as effective hedges in low volatility conditions. Results show that the US ETF's returns are unaffected by a shift in geopolitical risk. In other words, the US ETF market investment is a good way to protect against risks in geopolitical events.

In addition, we analyzed the influence of geopolitical threat on the conditional volatility of both the aggregate US ETF market and the US sectoral ETF market, which is shown in Table A5 in the appendix. With the exception of a mild impact on consumer staples, we were unable to discern any impact of the GPR threat on the sectoral ETF conditional volatility.

4.4. Alternative measures of market uncertainty

In their study, Baur and Smales (2020) point out the possibility of combining the information obtained from many alternative measures of risk with that of a single uncertainty index measure through omitted variables. Therefore, it is likely that the quantification of Geopolitical threat (GPT Threat) that is used in this study combines information regarding market uncertainty that is already available via other factors that were left out of the analysis. As an example, Baur and Smales (2020) has mentioned different types of risk indices, for instance, International Country Risk Guide (ICRG) index provided by the PRS group, economic policy uncertainty (EPU) index constructed by Baker et al. (2016), investor sentiment (BW_Sent) index by Baker and Wurgler (2006, 2007), the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), which might be correlated each other. Therefore, it is probable that changes in GPR threat are related with shifts in BW_Sent as a result of the influence of terrorism on attitudes. However, Baur and Smales (2020) finally confirmed that, with the exception of EPU and VIX, the metrics appear to be positively correlated.

After analyzing the US ETF's market return in relation to shifts in Geopolitical threat (ΔGPT Threat), we therefore further investigate the ETF's performance in light of shifts in Geopolitical threat (ΔGPT Threat) by controlling a variety of other alternative measures of market uncertainty. Table 7 presents the regression coefficients of ΔGPT Threat after controlling different alternative measures of market uncertainty with their associated standard error in the parenthesis. By adding the additional uncertainty measures to our previous model, we aim to investigate whether the various uncertainty measures have an impact on our results. First, we conduct our analysis on a daily time series basis with general uncertainties (Panel A of Table 7), then we do the same including all variables as controls from Table 4 (Panel B of Table 7), and finally, we run a regression of panel A on monthly data using different alternative uncertainty metrics (Panel C of Table 7). Along with the geopolitical threat (GPT Threat) index, we also consider the economic policy uncertainty (EPU) index by Baker et al. (2016), the economic uncertainty (Unc) index by Bekaert and Mehl (2019), the macroeconomic uncertainty index (MacroUnc) by Jurado et al. (2015), and the CBOE implied volatility index (VIX) as the alternative measures of market uncertainty indices.

Panel A demonstrates that the returns for the US ETF are significantly influenced by changes in financial market uncertainty (Unc and VIX) on a daily basis. Changes in EPU have a small but noticeable impact on a small portion of the US ETF market on a daily basis. In tandem with the return of the US ETF market as a whole, the value of all sectoral ETFs on the US market declines significantly when Unc and VIX rise. All coefficient values are negative, with a 1% level of significance. The US ETF as a whole and each sectoral ETF likewise react similarly to changes in the remaining two indices (MacroUnc and EPU), with the exception of a very small number of values that are statistically significant. Consequently, the Unc and VIX play a significant role on a daily basis in determining the return of the US ETF market. It is noteworthy that a positive relationship exists between geopolitical threat (GPR Threat) and the returns of US ETFs even after adjusting for these other measures of uncertainty. On a daily basis, however, this relationship is only moderately significant for the whole US ETF market and the IT, communication, and utilities sectors. This findings is consistent with our previous outcome. This indicates that GPR Threat detects crucial moments for the values of the US ETF on a daily basis that are unrelated to developments in the financial markets, in politics, or in the business cycle as a whole. Panel B shows that the GPR threat loses significance on the U.S. S&P 500 index and communications sector after controlling for all other variables while remaining unchanged for the information technology and the utility sectors.

With the exception of GPR Threat, we observe a nearly identical pattern of relationship between the returns for the US ETF and various alternative measures of uncertainty indices (Unc, MacroUnc, EPU, and

Table 6
Impact of GPT on US ETF returns under regime switching.

	Regimes	ΔGPT Threat	ΔGPT Threat, t - 1	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	p_{low|low}	p_{low|high}	p_{high|low}	p_{high|high}
USA (S&P 500)	High	**0.0004***							0.001***	0.9828	0.0172	0.0477	0.9523
		(0.0002)							(0.0001)				
		0.0027**	0	−0.0003	0.0001**	−0.0319***	0.2548***	0.0003	−0.0014*				
		(0.0013)	(0.0018)	(0.0005)	(0)	(0.0121)	(0.0206)	(0.0003)	(0.0007)	0.9535	0.0465	0.0129	0.9871
	Low	**0.0025****							−0.0014**	0.9828	0.0172	0.0477	0.9523
		(0.0012)							(0.0007)				
		0.0005**	0.0003	0	0	0.0002	0.1207***	0.0002***	0.0008***				
		(0.0002)	(0.0003)	(0.0004)	(0)	(0.0007)	(0.0067)	(0)	(0.0001)	0.9535	0.0465	0.0129	0.9871
Information Technology	High	0.0003							0.0012***	0.9863	0.0137	0.0425	0.9575
		(0.0003)							(0.0002)				
		0.0044***	−0.0004	0.0008	0.0001**	−0.0333***	0.2343***	0.0003	−0.0013*				
		(0.0015)	(0.0015)	(0.0016)	(0.0001)	(0.0114)	(0.0211)	(0.0003)	(0.0008)	0.9586	0.0414	0.0127	0.9873
	Low	**0.0043*****							−0.0014*	0.9863	0.0137	0.0425	0.9575
		(0.0014)							(0.0008)				
		0.0005	0.0008**	0	0	−0.0001	0.1336***	0.0003*	0.001***				
		(0.0004)	(0.0003)	(0.0007)	(0.0001)	(0.0044)	(0.008)	(0.0001)	(0)	0.9586	0.0414	0.0127	0.9873
Communication	High	**0.0006***							0.0007***	0.9885	0.0115	0.0504	0.9496
		(0.0003)							(0.0002)				
		0.0034*	0.0005	−0.0014	0.0001*	−0.0471***	0.2169***	0.0004	−0.0017*				
		(0.0019)	(0.0019)	(0.0021)	(0.0001)	(0.0174)	(0.0264)	(0.0004)	(0.001)	0.9416	0.0584	0.0115	0.9885
	Low	**0.0028***							−0.002**	0.9885	0.0115	0.0504	0.9496
		(0.0016)							(0.0009)				
		0.0007**	0.0005*	0.0004	0.0001*	0.0007	0.1029***	0.0002*	0.0006***				
		(0.0003)	(0.0003)	(0.0006)	(0)	(0.001)	(0.0082)	(0.0001)	(0.0002)	0.9416	0.0584	0.0115	0.9885
Consumer Staples	High	0.0002							0.0006***	0.983	0.017	0.0839	0.9161
		(0.0002)							(0.0001)				
		0.0003	0.0004	−0.0001	0	0.0012	0.0549***	0.0001	0.0007***				
		(0.0002)	(0.0002)	(0.0004)	(0)	(0.0007)	(0.0067)	(0.0001)	(0.0001)	0.9818	0.0182	0.0933	0.9067
	Low	0.0017							−0.0013*	0.983	0.017	0.0839	0.9161
		(0.0013)							(0.0007)				
		0.0006	−0.0022	−0.0004	0.0001	−0.0301**	0.1705***	0.0002	−0.0012*				
		(0.0014)	(0.0015)	(0.0015)	(0)	(0.0131)	(0.0197)	(0.0003)	(0.0007)	0.9818	0.0182	0.0933	0.9067
Consumer Discretionary	High	0.0004							0.001***	0.9899	0.0101	0.0288	0.9712
		(0.0003)							(0.0001)				
		0.0005	0.0006*	−0.0006	0	0.0006	0.1362***	0.0004**	0.0009***				
		(0.0003)	(0.0003)	(0.0006)	(0)	(0.0009)	(0.0083)	(0.0002)	(0.0002)	0.9916	0.0084	0.0286	0.9714
	Low	**0.0022***							−0.0012*	0.9899	0.0101	0.0288	0.9712
		(0.0013)							(0.0007)				
		0.0021	−0.0009	−0.0005	0.0001**	−0.0564***	0.2532***	0.0004	−0.001				
		(0.0015)	(0.0015)	(0.0017)	(0.0001)	(0.0136)	(0.0221)	(0.0003)	(0.0008)	0.9916	0.0084	0.0286	0.9714
Energy	High	0.0007							0.0005**	0.9957	0.0043	0.0213	0.9787
		(0.0005)							(0.0002)				
		0.0007	0.0003	0.0016*	0.0001*	−0.0014	0.2333***	0.0004	0.0002				
		(0.0005)	(0.0005)	(0.0009)	(0.0001)	(0.0013)	(0.0117)	(0.0003)	(0.0003)	0.9956	0.0044	0.0291	0.9709
	Low	0.0026							−0.0014	0.9957	0.0043	0.0213	0.9787
		(0.0026)							(0.0014)				
		0.0037	0.0026	−0.0003	0.0001	−0.0529	0.3452***	0.0002	−0.0019				
		(0.0033)	(0.0032)	(0.0031)	(0.0001)	(0.0375)	(0.0488)	(0.0004)	(0.0018)	0.9956	0.0044	0.0291	0.9709
Financial	High	0.0004							0.0007***	0.9897	0.0103	0.0379	0.9621
		(0.0003)							(0.0002)				

(*continued on next page*)

Table 6 (*continued*)

	Regimes	ΔGPT Threat	ΔGPT Threat, t - 1	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	p_{low|low}	p_{low|high}	p_{high|low}	p_{high|high}
Healthcare	Low	0.0019	−0.0016	0.0008	0.0001	−0.096***	0.3997***	0.0003	−0.0013				
		(0.0021)	(0.002)	(0.0031)	(0.0001)	(0.0237)	(0.0351)	(0.0004)	(0.0012)	0.9664	0.0336	0.0085	0.9915
		0.003							−0.0019				
		(0.0022)							(0.0012)	0.9897	0.0103	0.0379	0.9621
	High	0.0004	0.0001	−0.0005	0	0.0013	0.2046***	0.0001	0.0007***				
		(0.0003)	(0.0004)	(0.0006)	(0)	(0.001)	(0.0078)	(0.0001)	(0.0002)	0.9664	0.0336	0.0085	0.9915
		0.0011							−0.0017**				
		(0.0015)							(0.0008)	0.9431	0.0569	0.0118	0.9882
		0.0011	−0.0006	0.0002	0.0001**	−0.0359**	0.2047***	0.0002	−0.0017*				
		(0.0009)	(0.0015)	(0.0034)	(0.0001)	(0.0141)	(0.0229)	(0.0002)	(0.0008)	0.9359	0.0641	0.0118	0.9882
	Low	**0.0005***							0.0008***				
		(0.0003)							(0.0001)	0.9431	0.0569	0.0118	0.9882
		0.0005*	0.0005*	−0.0005	0	0.0001	0.1021***	0.0001	0.0009***				
		(0.0003)	(0.0003)	(0.0004)	(0)	(0.0018)	(0.0074)	(0.0001)	(0.0002)	0.9359	0.0641	0.0118	0.9882
Industry	High	0.0019							−0.0016**				
		(0.0014)							(0.0007)	0.9551	0.0449	0.0157	0.9843
		0.0004	0.0003	−0.0003	0	0.0014	0.1536***	0.0001	0.0009***				
		(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0009)	(0.0081)	(0.0001)	(0.0002)	0.9885	0.0115	0.0398	0.9602
Industry	Low	0.0004							0.001***				
		(0.0003)							(0.0002)	0.9551	0.0449	0.0157	0.9843
		0.0015	−0.0006	−0.0002	0.0001**	−0.0545***	0.3066***	0.0004	−0.0011				
		(0.0016)	(0.0015)	(0.0027)	(0)	(0.0145)	(0.0227)	(0.0002)	(0.0007)	0.9885	0.0115	0.0398	0.9602
	High	**0.0035***							−0.0017*				
		(0.0018)							(0.001)	0.9609	0.0391	0.0108	0.9892
		0.0002	0.0002	0.0004	0	0.0013	0.1581***	0.0001	0.0008***				
		(0.0004)	(0.0004)	(0.0007)	(0)	(0.0013)	(0.0091)	(0.0001)	(0.0002)	0.9875	0.0125	0.0435	0.9565
Material	Low	0.0003							0.0009***				
		(0.0004)							(0.0002)	0.9609	0.0391	0.0108	0.9892
		0.0029	−0.001	−0.0001	0.0001**	−0.0103	0.2782***	0.0004	−0.0016*				
		(0.0018)	(0.0018)	(0.0016)	(0.0001)	(0.0082)	(0.0228)	(0.0004)	(0.0008)	0.9875	0.0125	0.0435	0.9565
Real Estate	High	0.0001							0.0006***				
		(0.0002)							(0.0002)	0.9947	0.0053	0.0212	0.9788
		0.0002	0.0002	−0.0003	0.0001	0.0017	0.0103	0.0002	0.0007***				
		(0.0002)	(0.0004)	(0.0007)	(0.0001)	(0.0012)	(0.0086)	(0.0001)	(0.0002)	0.9945	0.0055	0.0213	0.9787
	Low	0.0036							−0.0014				
		(0.0026)							(0.0014)	0.9947	0.0053	0.0212	0.9788
		0.002	−0.002	0.0003	0.0001	−0.038*	0.3422***	0.0004	−0.0011				
		(0.0028)	(0.0029)	(0.0018)	(0.0001)	(0.0206)	(0.0369)	(0.0006)	(0.0013)	0.9945	0.0055	0.0213	0.9787
Utility	High	**0.0005***							0.0006***				
		(0.0003)							(0.0001)	0.9943	0.0057	0.0639	0.9361
		0.0055*	0.0011	−0.0012	0.0001	−0.0656***	0.2474***	0.0004	−0.0026*				
		(0.0028)	(0.0028)	(0.0026)	(0.0001)	(0.0189)	(0.0309)	(0.0004)	(0.0014)	0.9423	0.0577	0.006	0.994
	Low	**0.0061****							−0.0035**				
		(0.0029)							(0.0017)	0.9943	0.0057	0.0639	0.9361
		0.0005*	0.0001	−0.0004	0	0.0007	0.019**	0.0002	0.0007***				
		(0.0003)	(0.0003)	(0.0005)	(0)	(0.001)	(0.0079)	(0.0001)	(0.0002)	0.9423	0.0577	0.006	0.994

This table presents the coefficients estimated using Markov Switching Model under two regimes with Eq. 1 (with and without control) where the dependent variable is the return on equity markets (USA) and different sectoral ETF returns (J 2005 to 2021). The key explanatory variable is the change in the geopolitical threat index (ΔGPT Threat). The set of control variables includes Changes in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, changes in Term Premium, and Change in Trade Volume. *p_{i|j}*is the probability of being in regime *i* at time $t + 1$ given that the market was in regime j at time t. Robust standard errors are in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Table 7
Alternative measures of market uncertainty.

Panel A: Daily Frequency

	USA (S&P500)	Itech	Energy	Healthcare	Comm.	Industry	Materials	Utility	Con. Dis.	Financial	Real Estate	Con. Stap.
	0.000545*	0.000841**	0.000536	0.000244	0.000623*	0.000250	0.000439	0.000692*	0.000387	0.000469	0.000271	0.000147
ΔGPT Threat	(0.000242)	(0.000285)	(0.000474)	(0.000240)	(0.000293)	(0.000298)	(0.000348)	(0.000309)	(0.000289)	(0.000429)	(0.000505)	(0.000212)
	−0.0575***	−0.0529***	−0.0975***	−0.0338***	−0.0490***	−0.0717***	−0.0629***	−0.0310***	−0.0621***	−0.0865***	−0.0592***	−0.0302***
ΔUnc	(0.00446)	(0.00524)	(0.00873)	(0.00442)	(0.00540)	(0.00548)	(0.00641)	(0.00569)	(0.00531)	(0.00790)	(0.00929)	(0.00390)
	−0.00603	−0.00213	−0.0184*	−0.00140	−0.0115*	−0.0115*	−0.0137*	−0.00853	−0.0107*	−0.0111	−0.0126	−0.00464
ΔMacro Unc	(0.00392)	(0.00461)	(0.00768)	(0.00388)	(0.00475)	(0.00482)	(0.00564)	(0.00501)	(0.00467)	(0.00695)	(0.00817)	(0.00342)
	−0.0992***	−0.111***	−0.109***	−0.0848***	−0.0886***	−0.102***	−0.114***	−0.0617***	−0.100***	−0.113***	−0.102***	−0.0641***
ΔVIX	(0.00216)	(0.00254)	(0.00423)	(0.00214)	(0.00262)	(0.00266)	(0.00311)	(0.00276)	(0.00257)	(0.00383)	(0.00450)	(0.00189)
	−0.00153*	−0.00329***	−0.00241	−0.000714	−0.000929	−0.00184*	−0.00197	0.000290	−0.00192*	−0.00182	0.000210	−0.000226
ΔEPU	(0.000702)	(0.000826)	(0.00138)	(0.000696)	(0.000851)	(0.000864)	(0.00101)	(0.000897)	(0.000837)	(0.00124)	(0.00146)	(0.000614)
	0.000330**	0.000555***	0.000142	0.000410***	0.000208	0.000337*	0.000325	0.000232	0.000445**	0.000138	0.000169	0.000311**
Constant	(0.000125)	(0.000147)	(0.000245)	(0.000124)	(0.000152)	(0.000154)	(0.000180)	(0.000160)	(0.000149)	(0.000222)	(0.000261)	(0.000109)
N	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214
R-sq	0.557	0.515	0.327	0.454	0.403	0.486	0.441	0.222	0.482	0.369	0.233	0.390
adj. R-sq	0.557	0.515	0.326	0.453	0.402	0.485	0.441	0.221	0.482	0.368	0.232	0.390

Panel B: Daily Frequency with all other controls

	U.S.	Energy	Info. Tech.	Healthcare	Comm.	Industrial	Materials	Utility	Cons. Dis.	Financial	Real Estate	Cons. Stap.
ΔGPT Threat	**0.000474***	0.000430	**0.000791****	0.000172	0.000546	0.000238	0.000418	**0.000703***	0.000342	0.000350	0.000159	0.000118
	(0.000241)	(0.000472)	**(0.000286)**	(0.000242)	(0.000298)	(0.000295)	(0.000348)	**(0.000316)**	(0.000289)	(0.000424)	(0.000515)	(0.000215)
Δ CPI	0.000295	0.00124	0.000513	0.000557	0.0000457	0.0000541	0.000629	0.000303	−0.000373	0.000289	0.000140	0.000302
	(0.000410)	(0.000805)	(0.000487)	(0.000412)	(0.000508)	(0.000502)	(0.000592)	(0.000539)	(0.000493)	(0.000723)	(0.000878)	(0.000367)
Δ UNEMP	0.0000266	0.0000875**	0.0000301	0.0000408*	0.0000467*	0.0000149	0.0000537*	0.0000245	0.0000485*	0.0000126	0.0000334	0.0000176
	(0.0000163)	(0.0000321)	(0.0000194)	(0.0000164)	(0.0000202)	(0.0000200)	(0.0000236)	(0.0000215)	(0.0000196)	(0.0000288)	(0.0000350)	(0.0000146)
Δ BYP	−0.00166	−0.00199	−0.00182	−0.000786	−0.000752	−0.000351	−0.000264	−0.000900	−0.00120	−0.00114	−0.000368	0.000119
	(0.000916)	(0.00180)	(0.00109)	(0.000921)	(0.00113)	(0.00112)	(0.00132)	(0.00120)	(0.00110)	(0.00162)	(0.00196)	(0.000819)
Δ TP	0.0744***	0.141***	0.0620***	0.0530***	0.0410***	0.103***	0.103***	0.0212**	0.0643***	0.142***	0.0418***	0.0322***
	(0.00521)	(0.0102)	(0.00619)	(0.00524)	(0.00646)	(0.00639)	(0.00753)	(0.00685)	(0.00627)	(0.00919)	(0.0112)	(0.00466)
Δ TV	0.0000707	0.0000212	0.000118	0.0000721	0.000139	0.0000470	0.000102	0.000153	0.000179*	−0.0000079	0.000133	0.0000340
	(0.0000754)	(0.000148)	(0.0000896)	(0.0000758)	(0.0000934)	(0.0000925)	(0.000109)	(0.0000992)	(0.0000907)	(0.000133)	(0.000162)	(0.0000675)
Δ UNC	−0.0451***	−0.0656***	−0.0451***	−0.0263***	−0.0437***	−0.0526***	−0.0429***	−0.0289***	−0.0519***	−0.0581***	−0.0549***	−0.0258***
	(0.00474)	(0.00930)	(0.00562)	(0.00476)	(0.00587)	(0.00581)	(0.00684)	(0.00623)	(0.00569)	(0.00835)	(0.0101)	(0.00424)
Δ MacUnc	−0.00708	−0.0228**	−0.00359	−0.00274	−0.0144**	−0.0122*	−0.0148*	−0.00907	−0.0139**	−0.0122	−0.0141	−0.00550
	(0.00404)	(0.00793)	(0.00480)	(0.00406)	(0.00500)	(0.00495)	(0.00584)	(0.00531)	(0.00485)	(0.00712)	(0.00865)	(0.00361)
Δ VIX	−0.0973***	−0.107***	−0.108***	−0.0833***	−0.0873***	−0.0986***	−0.111***	−0.0612***	−0.0989***	−0.109***	−0.101***	−0.0633***
	(0.00217)	(0.00427)	(0.00258)	(0.00218)	(0.00269)	(0.00266)	(0.00314)	(0.00286)	(0.00261)	(0.00383)	(0.00465)	(0.00194)
Δ EPU	−0.00140*	−0.00203	−0.00308***	−0.000592	−0.000973	−0.00173*	−0.00180	0.000395	−0.00191*	−0.00158	0.0000244	−0.000229
	(0.000696)	(0.00137)	(0.000827)	(0.000700)	(0.000862)	(0.000854)	(0.00101)	(0.000915)	(0.000837)	(0.00123)	(0.00149)	(0.000623)
_cons	0.000143	−0.000181	0.000299	0.000199	0.0000287	0.000211	0.0000907	0.000113	0.000344	−0.0000125	−0.0000349	0.000159
	(0.000146)	(0.000287)	(0.000173)	(0.000147)	(0.000181)	(0.000179)	(0.000211)	(0.000192)	(0.000175)	(0.000258)	(0.000313)	(0.000131)
N	4029	4029	4029	4029	4029	4029	4029	4029	4029	4029	4029	4029
R-sq	0.584	0.362	0.534	0.474	0.413	0.520	0.470	0.227	0.504	0.408	0.241	0.402
adj. R-sq	0.583	0.360	0.532	0.472	0.412	0.519	0.469	0.225	0.503	0.407	0.239	0.400

Panel C: Monthly frequency

	US	Itech	Energy	Healthcare	Comm.	Industry	Materials	Utility	Con. Dis.	Financial	Real Estate	Con. Stap.
ΔGPT Threat	0.00232	0.00215	0.00449	0.00101	**0.00585***	**0.00701***	0.00678	−0.000801	0.00340	0.00391	0.00425	−0.000156

(*continued on next page*)

Table 7 (*continued*)

Panel C: Monthly frequency

	US	Itech	Energy	Healthcare	Comm.	Industry	Materials	Utility	Con. Dis.	Financial	Real Estate	Con. Stap.
	(−0.00211)	(0.00310)	(0.00478)	(0.00314)	**(0.00272)**	**(0.00313)**	(0.00363)	(0.00285)	(0.00347)	(0.00389)	(0.00465)	(0.00235)
ΔUnc	−0.0728***	−0.0671***	−0.206***	−0.0391*	−0.0710***	−0.0965***	−0.105***	−0.0324	−0.0897***	−0.121***	−0.0749**	−0.0188
	(−0.0124)	(0.0183)	(0.0282)	(0.0185)	(0.0161)	(0.0185)	(0.0214)	(0.0168)	(0.0205)	(0.0229)	(0.0275)	(0.0139)
ΔMacro Unc	−0.00383	−0.00136	−0.0102	0.000826	−0.00767*	−0.00777	−0.00946	−0.00660	−0.00759	−0.00779	−0.0104	−0.00344
	(−0.00286)	(0.00417)	(0.00642)	(0.00422)	(0.00365)	(0.00421)	(0.00487)	(0.00383)	(0.00466)	(0.00522)	(0.00625)	(0.00315)
ΔVIX	−0.0904***	−0.104***	−0.0704**	−0.0905***	−0.0847***	−0.107***	−0.116***	−0.0566***	−0.0981***	−0.0852***	−0.0963***	−0.0882***
	(−0.0102)	(0.0149)	(0.0230)	(0.0151)	(0.0131)	(0.0151)	(0.0175)	(0.0137)	(0.0167)	(0.0187)	(0.0224)	(0.0113)
ΔEPU	−0.00115*	−0.00278***	−0.000884	−0.000838	−0.000422	−0.00117	−0.000968	0.000383	−0.00110	−0.00112	0.000855	0.0000738
	(−0.000496)	(0.000724)	(0.00112)	(0.000733)	(0.000635)	(0.000731)	(0.000847)	(0.000667)	(0.000811)	(0.000908)	(0.00109)	(0.000548)
Constant	0.000318***	0.000568***	0.000155	0.000320*	0.000237*	0.000366**	0.000367*	0.000252*	0.000510***	0.000154	0.000208	0.000362***
	(−0.0000861)	(0.000127)	(0.000196)	(0.000128)	(0.000111)	(0.000128)	(0.000148)	(0.000117)	(0.000142)	(0.000159)	(0.000190)	(0.0000960)
N	215	208	208	208	208	208	208	208	208	208	208	208
R-sq	0.609	0.482	0.467	0.321	0.485	0.546	0.513	0.226	0.451	0.433	0.276	0.391
adj. R-sq	0.6	0.469	0.454	0.304	0.472	0.534	0.501	0.207	0.438	0.419	0.258	0.376

Panel A shows the presents the coefficients estimated using Eq. 4 where the independent variables include the geopolitical threat (GPT) index, the economic policy uncertainty (EPU) index of Baker et al. (2016), the economic uncertainty (Unc) index of Bekaert and Mehl (2019), the macroeconomic uncertainty index (MacroUnc) of Jurado et al. (2015), and the CBOE implied volatility index (VIX). Panel B reports a comprehensive multiple regression analysis including all variables from Table 4 and panel A of this table. Panel C presents the same regression coefficients of panel A in the monthly frequency. ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% level respectively. Sample Period: 2005–2021.

VIX) when we examine the monthly frequency of the coefficient value (Panel C). Again, as seen in Panel C, monthly fluctuations in measures of financial market uncertainty (Unc and VIX) have a large impact on returns for the US ETF. When Unc and VIX increase, both the value of the US ETF market as a whole and of all sectoral ETFs on the US market decrease noticeably. Notably, even after controlling for these other measures of uncertainty, a positive association still persists between geopolitical threat (GPR Threat) and the returns of US ETFs when monthly frequency is considered. However, the significance of these positive relationships diminishes over the course of a month, and is only statistically significant (at the 10% level) between communication and the industry ETF. In light of this, the monthly frequency results also suggest that GPR Threat recognizes times of critical importance for the prices of US ETFs that are unconnected to movements in the financial markets.

4.5. *Portfolio implications*

After proving the substantial hedging probabilities of US ETF returns against geopolitical risk through different analyses, we examine the economic consequences of the findings by evaluating the portfolio implications in this section. The influence of geopolitical risk on the optimal hedging ratios is reported in Table 8. In Panel A of Table 8, we present the impact of geopolitical threat on the US and other asset portfolio hedge ratios in full sample (1985–2021) and three subsamples, whereas impact of geopolitical threat on Gold and ETFs portfolios hedge ratios are described on Panel B in full sample and three subsamples. Since ETF data is available from 2005, we cannot consider major events that occurs before 2005. For example, Gulf war, Iraq war, Sep 11 attack etc. However, there are few major events that happens within that subsample periods. For example: London Bombing (2005–2010), Paris Terror Attack (2010–2016), Covid 19 (2016–2021). We see that impact of geopolitical threat over hedge ratios varies over different subsamples.

We usually see that when there is a lot of political uncertainty, the number of hedge positions that should be taken in a given asset goes down. In Table 8, the negative estimates for Theta1 suggest that the optimal hedging position in a given asset should be reduced as geopolitical uncertainty increases. Panel A shows that the US and other asset portfolios' hedge ratios are not significantly negatively impacted by geopolitical uncertainty, with the US-Gold and US-Palladium being the best asset pairings. Panel A further demonstrates that the geopolitical threat has a little or no impact on US and precious metal hedge ratios, as in the majority of cases of the asset pairs we observed a positive theta1 value. A positive and strong correlation (at 5% level of significance) between the US and Gold asset pairs, indicating a good hedge alternative for two asset class combinations with the US market.

Since we found that the best asset pair was the US and Gold, we looked at how Geopolitical Threat affected Gold and different US sectoral ETFs in Panel B. Interestingly, we discovered positive theta1 values for every sectoral ETF we examined, with the exception of the energy ETF, where the correlation between the gold and IT ETFs is quite highly positively significant. As a result, the gold and IT ETF displays the greatest asset pairings to counter the geopolitical threat. Investors may benefit from the findings since the ensuing hedging techniques would require fewer expensive and smaller hedge positions at such times.

It is interesting to notice that gold and palladium have less hedging prospect against U.S. S&P 500 index over time while only copper was significant for hedging for the period between 1997 and 2009 only. From panel B it is evident that the information technology sector possesses significant hedging prospect for investors in the full sample period of 2005 to 2021. However, this sector is not significant in terms of hedging prospects in any of the subsamples. Therefore, it is visible that this sector is a long-term hedging tool coupled with gold for investors.

Numerous studies have looked at the hedging efficiency of stock index futures contracts (see, for instance, Lindahl (1992), Junkus and Lee (1985), Figlewski, 1984, Graham and Jennings (1987), and Holmes

Table 8
Portfolio implications.

Panel A: Impact of Geopolitical Threat on hedge ratios of portfolios with the US and other countries/asset

Portfolio (Asset Pairs)	Full Sample: 1985–2021		Sub-sample: 1985–1997		Sub-sample: 1997–2009		Sub-sample: 2009–2021	
	θ_0	θ_1	θ_0	θ_1	θ_0	θ_1	θ_0	θ_1
US - China	0.0107	−0.2296	−0.0121	0.7713	−0.0141	−1.8811**	0.0471	0.6944
US - UK	0.4169***	−0.0335	0.3039***	0.3822	0.4671***	−0.1699	0.4762***	−0.6407
US - France	0.3622***	−0.2891	0.1943***	−1.2116	0.4115***	−0.1402	0.4408***	−0.228
US - Germany	0.3256***	−0.4557	0.1125***	−0.4415	0.4197***	−0.6165	0.4372***	−0.6923
US - Canada	0.8606***	0.6773	0.8907***	2.0105	0.7907***	0.5973	0.8992***	−0.665
US - Australia	0.1080***	0.1926	0.0595*	1.096	0.0969***	−0.36	0.1409***	0.3686
US - Russia	0.1507***	−0.1331	−0.0265	0.8931	0.1008***	0.5534	0.2210***	−0.7795*
US - Switzerland	0.3769***	−0.2082	0.1604***	−1.0511	0.4230***	−0.2432	0.4800***	−0.138
US - Japan	0.0657***	0.8953	0.0644***	0.8063	0.0691***	0.8543	0.0625	1.1828
US - Gold	−0.0842***	1.4661**	−0.1328***	2.4712*	−0.1045***	1.8461	−0.0094	0.4577
US - Silver	−0.0085	0.4581	−0.0306*	0.9027	−0.033	0.6099	0.0379*	−0.0647
US - Palladium	0.0230**	0.5699*	−0.0265	2.1120**	0.0289**	−0.0512	0.0615***	0.2116
US - Platinum	0.0271***	0.1792	−0.0194	0.8315	0.0225	−0.1128	0.0806***	0.1762
US - Copper	0.1286***	0.1596	0.0325	−0.955	0.1483***	1.6926**	0.2009***	−0.313
US - Bond	−0.5501***	0.2199	0.5010***	4.681	−0.7534***	−5.2293	−1.3836***	−1.5893
US - Dollar	0.0032	−0.0639	0.1118**	0.2818	0.2842***	−0.3392	−0.3394***	−0.2473

Panel B: Impact of Geopolitical Threat on hedge rations of portfolios with Gold and ETFs

Portfolio (Asset Pairs)	Full Sample: 2005–2022		Sub-sample: 2005–2010		Sub-sample: 2010–2016		Sub-sample: 2016–2021	
	θ_0	θ_1	θ_0	θ_1	θ_0	θ_1	θ_0	θ_1
Gold - Energy	0.0873***	−0.1599	0.1520***	0.2017	0.1148***	−0.2773	−0.0033	−0.5622
Gold - ITech	−0.0103	1.3431**	−0.0013	0.3737	0.027	1.2043	−0.0596*	1.6619
Gold - Communication	0.0207	0.5637	0.0309	−0.6767	0.0417	0.6795	0.0004	1.1916
Gold - Consumer Staples	0.0204	1.0321	−0.0326	−0.8177	0.0657	1.3402	0.0606	0.8011
Gold - Consumer Discretionary	−0.0289	1.0721	−0.0172	0.6718	0.0087	0.7691	−0.0581	1.7693
Gold - Financial	−0.0601***	0.1710	−0.0084	0.1551	−0.0238	0.0908	−0.1389***	−0.4187
Gold - Healthcare	−0.0134	0.4125	−0.0282	0.2131	0.0318	0.6285	−0.0173	0.0677
Gold - Industry	0.0007	0.5758	0.0441	−0.1227	0.0619	0.8145	−0.0973***	0.3409
Gold - Material	0.0861***	0.5752	0.1489***	0.2639	0.1259***	0.0989	−0.0261	1.0346
Gold - Real State	0.0567***	0.4972	0.031	0.3625	0.0810**	0.0537	0.0692**	0.5788
Gold - Utility	0.0900***	0.5490	0.0828*	1.1088	0.1302**	0.0913	0.0685**	−0.2523

The table reports the effect of Geopolitical Threat on the optimal hedge ratios for each asset via Eq. (5). The significance of coefficients is based on Newey-West standard errors with five lags. ***, **, * and represent significance at 1, 5, and 10% levels, respectively. In panel A, the first subsample starts on 1985 and ends on 1997, the second subsample starts on 1997 and ends on 2009, and the third subsample starts on 2009 and ends on 2021. In panel B, the first subsample starts on 2005 and ends on 2010, the second subsample starts on 2010 and ends on 2016-, and the third subsample starts on 2016 and ends on 2021.

(1996)). Ex-post hedging efficacy assumes that the hedger has complete knowledge of how to spot and futures prices will behave in the future and can thus determine the ideal hedge ratio for the next period using this historical data. These researches have mostly focused on examining the efficiency of hedging when the portfolio to be hedged mimics a broad market index.

4.6. Assessing statistical significance

We have evaluated the statistical significance of our discoveries by employing conventional t-statistics and associated *p*-values. For instance, Table 7's t-statistics examine the null hypothesis of no significance for various factors such as changes in GPR Threat, macroeconomic uncertainty, economic policy uncertainty, etc. One possible concern is the potential issue of data snooping. The multiple comparison problem, as described by Bonferroni (1936) and Dunn (1959), suggests that some of the predictive characteristics we identify may be purely coincidental due to the simultaneous study of numerous variables. For instance, when considering a 5% significance level, approximately 5% of the characteristics we investigate could appear significant by chance alone. However, we have addressed this problem by presenting results for all variables examined, including those that prove to be less predictive (e.g., changes in unemployment). Additionally, our extensive historical sample restricts the number of variables we can analyze, thereby limiting the extent of data snooping. Nevertheless, it is crucial to exercise caution in assigning statistical significance to individual characteristics without proper consideration.

The utilization of the Bonferroni adjustment helps manage the risk of committing a Type I error when testing multiple variables, establishing a stringent threshold for statistical significance. This could explain why it is infrequently employed in empirical studies. In our case, the Bonferroni adjustment proves valuable in determining whether to accept or reject the null hypothesis of zero predictability for each characteristic individually. However, by adhering to the Bonferroni criteria, there is a higher probability of committing a Type II error.[2] An alternative method is to control the proportion of rejections that are anticipated to be Type I errors or false discoveries, meaning they mistakenly reject the null hypothesis of zero predictability. Essentially, this approach guarantees that only a very small fraction, such as 10%, of all the rejections made can be attributed to Type I errors.

We employ the Benjamini and Hochberg (1995) procedure to control the false discovery rate. The core idea of this procedure is to establish a threshold for the acceptable rate of false discoveries across all the characteristics under study. It aims to determine the number of predictive characteristics that can be considered within this predefined threshold. To implement this procedure, we arrange all 10 characteristic variables in ascending order based on their *p*-values. Then, we compare each p-value with its corresponding adjusted p-value, calculated as (α X

[2] Santa-Clara and Valkanov (2003) address the limitations of Bonferroni approach and decide not to use it in their paper.

Table 9
False discovery tests.

Panel A: Comparison of *p*-values and adjusted p-values for panel B of Table 7

	ΔGPT Threat	Δ CPI	Δ UNEMP	Δ BYP	Δ TP	Δ TV	Δ UNC	Δ MacUnc	Δ VIX	Δ EPU
US	0.053	0.003	0.5	0.08	0	0.5	0	0.257	0	0.033
	0.06	0.04	0.09	0.07	0.01	0.1	0.02	0.08	0.03	0.05
Energy	0.382	0.857	0.39	0.288	0	0.451	0	0.011	0	0.142
	0.07	0.1	0.08	0.06	0.01	0.09	0.02	0.04	0.03	0.05
Information technology	0.006	0.011	0.36	0.102	0	0.543	0	0.906	0	0
	0.05	0.06	0.08	0.07	0.01	0.09	0.02	0.1	0.03	0.04
Healthcare	0.501	0.019	0.601	0.424	0	0.422	0	0.984	0	0.344
	0.08	0.04	0.09	0.07	0.01	0.06	0.02	0.1	0.03	0.05
Communications	0.073	0.666	0.588	0.515	0	0.941	0	0.019	0	0.234
	0.05	0.09	0.08	0.07	0.01	0.1	0.02	0.04	0.03	0.06
Industrial	0.434	0.001	0.967	0.802	0	0.969	0	0.039	0	0.033
	0.07	0.04	0.09	0.08	0.01	0.1	0.02	0.06	0.03	0.05
Materials	0.244	0.081	0.849	0.873	0	0.571	0	0.051	0	0.061
	0.07	0.06	0.09	0.1	0.01	0.08	0.02	0.04	0.03	0.05
Utility	0.028	0.129	0.998	0.479	0.002	0.471	0	0.088	0	0.704
	0.04	0.06	0.1	0.08	0.03	0.07	0.01	0.05	0.02	0.09
Consumer Discretionary	0.256	0.006	0.843	0.295	0	0.333	0	0.047	0	0.015
	0.07	0.04	0.1	0.08	0.01	0.09	0.02	0.06	0.03	0.05
Financial	0.421	0.001	0.873	0.527	0	0.611	0	0.162	0	0.17
	0.07	0.04	0.1	0.08	0.01	0.09	0.02	0.05	0.03	0.06
Real Estate	0.776	0.007	0.88	0.896	0	0.721	0	0.177	0	0.944
	0.07	0.04	0.08	0.09	0.01	0.06	0.02	0.05	0.03	0.1
Consumer Staples	0.599	0.075	0.959	0.857	0	0.644	0	0.265	0	0.657
	0.06	0.04	0.1	0.09	0.01	0.07	0.02	0.05	0.03	0.08

Panel B: Significance at 10% level

	ΔGPT Threat	Δ CPI	Δ UNEMP	Δ BYP	Δ TP	Δ TV	Δ UNC	Δ MacUnc	Δ VIX	Δ EPU
US	True	True	False	False	True	False	True	False	True	True
Energy	False	False	False	False	True	False	True	True	True	False
Information technology	True	True	False	False	True	False	True	False	True	True
Healthcare	False	True	False	False	True	False	True	False	True	False
Communications	False	False	False	False	True	False	True	True	True	False
Industrial	False	True	False	False	True	False	True	True	True	True
Materials	False	False	False	False	True	False	True	False	True	False
Utility	True	False	False	False	True	False	True	False	True	False
Consumer Discretionary	False	True	False	False	True	False	True	True	True	True
Financial	False	True	False	False	True	False	True	False	True	False
Real Estate	False	True	False	False	True	False	True	False	True	False
Consumer Staples	False	False	False	False	True	False	True	False	True	False

Panel A reports all the p-values and adjusted p-values for each of the characteristic variables for S&P 500 index and sectoral ETFs in the U.S. First rows show the p-values whereas the second rows report the adjusted p-values following Benjamini and Hochberg (1995) procedure to control the false discovery rate. Since there are 10 variables, the adjusted *p*-values are calculated using the formula: (α X rank) / 10.
Panel B reports whether the p-values are lower or higher than the adjusted p-values for all the characteristic variables for panel B of Table 7. If the p-value is less than the adjusted p-value then "True" is reported and "False" if otherwise.

rank) / 10 where α is 0.10 for a 10% significance level. We follow a stepwise approach, starting with the variable possessing the highest p-value. If the p-value exceeds the adjusted p-value, we conclude that the variable is not statistically significant. However, once we encounter a variable with a p-value lower than the adjusted p-value, we consider this variable and all those with lower p-values as significant. For the characteristic with the lowest p-value, this adjustment aligns with the Bonferroni method. We apply the false discovery tests to all the characteristic-related findings presented in panel B of Table 7.

Panel A of Table 9 reports all the p-values and adjusted p-values for each of the characteristic variables for S&P 500 index and sectoral ETFs in the U.S. First rows show the p-values whereas the second rows report the adjusted p-values following Benjamini and Hochberg (1995) procedure to control the false discovery rate. Panel B reports whether the p-values are lower or higher than the adjusted p-values for all the characteristic variables for panel B of Table 7. If the p-value is less than the adjusted p-value then "True" is reported and "False" if otherwise. It is interesting to notice that changes in GRP threat for S&P 500 index, the ETF of information technology, and the ETF of utility sectors still remain significant after controlling for false discovery.

5. Discussions and concluding remarks

The geopolitical tensions around the world soared due to the Russian invasion of Ukraine in 2022. While the literature recognizes the negative association between geopolitical risks and equity returns around the world, Salisu et al. (2022) show that geopolitical threats (GPT) have a greater adverse effect on stock returns than geopolitical acts. Therefore, using the geopolitical threat index of Caldara and Iacoviello (2022), we study the relationship between geopolitical threats (GPT) and asset returns to find equity markets and sectors that can be considered safe havens for potential hedges by investors. We find that the U.S. equity market and a few individual sectors produce significantly positive returns during high geopolitical threats while other major markets around the world fail to exhibit such results. Our results are significant both with and without the presence of the control variables- changes in inflation, unemployment rate, credit spread, term premium, and trade volume.

We also investigate the associations between geopolitical threats and the returns of the U.S. market during extremely high geopolitical threats and find the results significantly positive. The same is true for the

relationships of geopolitical threats with two sectors- information technology, and financials. Markov regime-switching model, with two volatility regimes- high and low, demonstrates that several sectors show a significantly positive association with geopolitical threats during the high volatility regime while some others during the low volatility regime. On a daily basis, our findings are also robust in the presence of alternative metrics of market uncertainty indices, such as economic policy uncertainty, economic uncertainty, and macroeconomic uncertainty, among others. However, when conditional volatility and monthly frequency were taken into account, the return on equity was not robust. It is important to find the portfolio implications for investors, particularly the optimal hedge ratios. We construct portfolios of the U.S. market pairing with other major equity markets around the world and other asset classes, e.g., gold, silver, etc., in the full sample (1985–2021) and three subsamples. The result is significant in the case of the pair of the U. S. market and gold only. Therefore, in the second stage, we construct portfolios of gold paring with the sectors in the equity market and find that the gold and information technology ETF displays the greatest asset pairings to counter the geopolitical threat in the long run since the results are significant only for the full sample period (2005–2022). We employ the Benjamini and Hochberg (1995) procedure to control the false discovery rate to establish a threshold for the acceptable rate of false discoveries across all the characteristics under study. Our findings suggest that even after adjusting for false discovery in the presence of all other control factors, the US market as a whole, as well as the ETFs of the information technology and utility sectors, continue to be significant.

While our study contributes to the literature in several ways, i.e., finding safe haven equity markets and sectors, if any, for investors, and potential hedge opportunities to protect their portfolios against geopolitical threats by holding the equity market index or stocks from individual sectors in combination with precious metals, there is scope for future research in this field. One avenue of further study could be to find associations of geopolitical threats with derivative securities, e.g., options and futures in the equity market. Another important way of potential investigation is to search for hedging opportunities for investors using derivatives in combination with stocks from different sectors and/or precious metals.

Data availability

Data will be made available on request.

Appendix A. Appendix

A.1. Relationship between geopolitical threat (GPT) and asset returns (2015–2021)

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
Panel A: Equity Markets								
USA	**0.00132****						0.000365 (0.000259)	1916
	(0.000469)							
	0.00125**	0.00165	0.00006**	−0.00277	0.141***	0.000076	0.0000953	1754
	(0.000462)	(0.00106)	(0.00002)	(0.00267)	(0.00821)	(0.00010)	(0.000340)	
China	**0.00135***						−0.0000278	1916
	(0.000563)						(0.000311)	
	0.00137*	0.000908	0.0000206	−0.000901	0.0396***	−0.0000741	−0.000218	
	(0.000580)	(0.00133)	(0.0000296)	(0.00335)	(0.0103)	(0.000134)	(0.000427)	1710
	0.000535						0.0000695	
	(0.000434)						(0.000240)	1916
	0.000391	0.000645	0.0000323	−0.00418	0.113***	0.0000671	−0.0000180	1710
UK	(0.000443)	(0.00102)	(0.0000226)	(0.00256)	(0.00788)	(0.000103)	(0.000326)	
	0.000740 (0.000517)						0.000208 (0.000285)	1916
France	0.000506	0.000891	0.0000147	−0.00522	0.127***	−0.0000245	0.000116	
	(0.000523)	(0.00120)	(0.0000267)	(0.00302)	(0.00930)	(0.000121)	(0.000385)	1710
	0.00108* (0.000528)						0.000182 (0.000292)	1916
	0.000771	0.000831	0.0000484	−0.00634*	0.125***	0.000111	0.0000574	
Germany	(0.000538)	(0.00123)	(0.0000275)	(0.00310)	(0.00956)	(0.000125)	(0.000396)	1710
	0.000629 (0.000408)						0.000181 (0.000225)	1916
	0.000601	0.00191	0.000061**	−0.00219	0.110***	0.0000908	−0.000163	
Canada	(0.000427)	(0.00102)	(0.000022)	(0.00246)	(0.00761)	(0.000101)	(0.000314)	1669
	−0.000473							
	(0.000417)						0.000161 (0.000230)	1916
	−0.000386	0.00105	0.0000242	−0.00440	0.0720***	−0.0000231	−0.000138	
Australia	(0.000447)	(0.00102)	(0.0000228)	(0.00258)	(0.00794)	(0.000104)	(0.000329)	1710
	0.000639 (0.000910)						0.000182 (0.000502)	1916
	0.000166	0.000588	0.0000401*	−0.00184**	0.115***	0.000105	0.0000576	
Russia	(0.000208)	(0.000403)	(0.0000171)	(0.000662)	(0.00533)	(0.000068)	(0.000136)	1710
	0.000644 (0.000414)						0.000146 (0.000229)	1916
	0.000495	0.00200*	0.0000367	−0.00401	0.0853***	0.0000166	−0.000288	
Switzerland	(0.000432)	(0.000991)	(0.0000221)	(0.00250)	(0.00768)	(0.000100)	(0.000318)	1710
Panel B: Other Assets								
	−0.000295							
	(0.000359)						0.000241 (0.000198)	1916
Gold	−0.000318	−0.000354		−0.00203	−0.0557***	0.000015	0.000360	
	(0.000375)	(0.000860)	0.0000093(0.00001)	(0.00216)	(0.00667)	(0.00008)	(0.000276)	1710
	0.000481 (0.000655)						0.000185 (0.000362)	1916
	0.000337	0.000618	0.0000209	−0.00590	−0.0276*	0.000153	0.0000838	
Silver	(0.000701)	(0.00161)	(0.0000358)	(0.00405)	(0.0125)	(0.000162)	(0.000516)	1710
	−0.000152							
Palladium	(0.000904)						0.000528 (0.000499)	1916

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(*continued*)

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
	−0.0000287	−0.000427	−0.0000485	−0.000428	0.0527**	0.0000535	0.000647	
	(0.000935)	(0.00214)	(0.0000478)	(0.00540)	(0.0166)	(0.000217)	(0.000689)	1710
	−0.000370							
	(0.000646)						−0.000102 (0.000356)	1916
	−0.000292	0.000644	0.0000374	−0.00473	0.0292*	0.000162	−0.000216	
Platinum	(0.000692)	(0.00159)	(0.0000353)	(0.00399)	(0.0123)	(0.000160)	(0.000510)	1710
	0.00000584							
	(0.000539)						0.000209 (0.000298)	1916
	0.0000267	0.00219	0.0000115	0.0000662	0.0634***	−0.0000725	−0.000103	
Copper	(0.000573)	(0.00131)	(0.0000293)	(0.00331)	(0.0102)	(0.000133)	(0.000422)	1710
	−0.0000905						−0.0000601	
	(0.000114)						(0.0000632)	1916
	−0.0000254	−0.000244*	−0.000006*	0.000398	−0.0748***	−0.0000219	0.0000185	
Bond	(0.0000538)	(0.000123)	(0.000002)	(0.000311)	(0.000957)	(0.000012)	(0.0000396)	1710
	−0.000199						0.0000713	
	(0.000170)						(0.0000937)	1916
	−0.000220	−0.0000629	0.00000802	−0.00332**	0.0217***	0.0000429	−0.00000101	
Dollar	(0.000180)	(0.000413)	(0.0000092)	(0.00104)	(0.00321)	(0.000041)	(0.000133)	1710

This table presents the coefficients estimated using Eq. 1 (with and without control) where the dependent variable is the daily return on equity markets (USA, China, UK, France, Germany, Canada, Australia, Russia, Switzerland), and other assets (gold, silver, palladium, platinum, copper, bond and dollar) from 2015 to 2021. The key explanatory variable is the change in the geopolitical threat index (ΔGPT Threat). The set of control variables includes Changes in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, change in Term Premium, and Change in Trade Volume. Standard errors are in parentheses and ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels respectively.

A.2. Relationship between geopolitical threat (GPT) and asset returns (1995–2021)

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
Panel A: Equity Markets								
USA	**0.000661***						0.000308*	7134
	(0.000284)						(0.000140)	
	0.000641*	−0.000037	0.0000573**	−0.00275**	0.171***	0.000200*	0.000343*	6495
	(0.000286)	(0.000527)	(0.0000212)	(0.000971)	(0.00647)	(0.0000926)	(0.000175)	
	0.000117						0.000220	7134
China	(0.000394)						(0.000194)	
	0.000156	0.000166	0.000000851	0.00137	0.0295**	0.0000107	0.000239	
	(0.000416)	(0.000766)	(0.0000308)	(0.00141)	(0.00940)	(0.000135)	(0.000254)	6451
	0.000224						0.000125	
	(0.000272)						(0.000134)	7134
	0.000252	−0.000350	0.0000314	−0.00227*	0.139***	0.000176*	0.000144	
UK	(0.000278)	(0.000512)	(0.0000205)	(0.000942)	(0.00628)	(0.0000899)	(0.000169)	6451
	0.000142 (0.000333)						0.000171 (0.000164)	7134
France	0.000185	−0.000252	0.0000256	−0.00304**	0.175***	0.000183	0.000175	
	(0.000338)	(0.000622)	(0.0000250)	(0.00115)	(0.00763)	(0.000109)	(0.000206)	6451
	0.000167 (0.000344)						0.000265 (0.000169)	7134
	0.000193	−0.000488	0.0000515*	−0.00226	0.181***	0.000260*	0.000273	
Germany	(0.000348)	(0.000641)	(0.0000257)	(0.00118)	(0.00787)	(0.000113)	(0.000212)	6451
	0.000414 (0.000253)						0.000223 (0.000125)	7134
	0.000598	0.00121*	0.0000622**	−0.00192	0.133***	0.000176	−0.0000391	
Canada	(0.000318)	(0.000538)	(0.0000211)	(0.00121)	(0.00638)	(0.0000995)	(0.000192)	4088
	−0.000278 (0.000234)						0.000193 (0.000115)	7134
	−0.000206	0.000912*	0.0000349	0.000388	0.0512***	0.000155	−0.0000463	
Australia	(0.000248)	(0.000457)	(0.0000183)	(0.000840)	(0.00560)	(0.0000802)	(0.000151)	6451
	−0.000532 (0.000604)						0.000347 (0.000298)	6959
Russia	0.000166	0.000588	0.0000401*	−0.00184**	0.115***	0.000105	0.0000576	
	(0.000208)	(0.000403)	(0.0000171)	(0.000662)	(0.00533)	(0.0000685)	(0.000136)	6288
	0.000212 (0.000272)						0.000211 (0.000134)	7134
	0.000157	0.000443	0.0000259	−0.00229*	0.117***	0.000116	0.0000439	
Switzerland	(0.000280)	(0.000516)	(0.0000207)	(0.000949)	(0.00633)	(0.0000905)	(0.000171)	6451
Panel B: Other Assets								
	−0.000283 (0.000241)						0.000223 (0.000119)	7134
Gold	−0.000328	0.000749	0.0000243	−0.000248	−0.0449***	0.0000171	0.0000650	
	(0.000254)	(0.000468)	(0.0000188)	(0.000862)	(0.00575)	(0.0000823)	(0.000155)	6451
	0.00000768 (0.000423)						0.000218 (0.000208)	7134
	−0.0000205	0.00165*	0.0000507	0.000931	−0.00492	0.000214	−0.000149	
Silver	(0.000451)	(0.000831)	(0.0000334)	(0.00153)	(0.0102)	(0.000146)	(0.000275)	6451
	0.000300 (0.000518)						0.000372 (0.000255)	7134
	0.000401	0.000761	−0.0000397	0.000299	0.0643***	0.000158	0.000205	
Palladium	(0.000548)	(0.00101)	(0.0000405)	(0.00186)	(0.0124)	(0.000177)	(0.000334)	6451
	0.000227 (0.000351)						0.000122 (0.000173)	7134
	0.000314	0.00135	0.0000494	0.000112	0.0275**	0.000237	−0.000183	
Platinum	(0.000375)	(0.000690)	(0.0000277)	(0.00127)	(0.00847)	(0.000121)	(0.000229)	6451
Copper	−0.000127 (0.000381)						0.000160 (0.000188)	7134

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(*continued*)

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
	−0.0000355	0.00303***	0.0000334	−0.000331	0.107***	0.000102	−0.000417	
	(0.000401)	(0.000739)	(0.0000297)	(0.00136)	(0.00907)	(0.000130)	(0.000245)	6451
	−0.0000283						−0.0000104	
	(0.0000699)						(0.0000344)	7134
	0.000000492	−0.000113	−0.00000798*	0.000383**	−0.109***	−0.0000162	0.00000604	
Bond	(0.0000430)	(0.0000792)	(0.00000318)	(0.000146)	(0.000971)	(0.0000139)	(0.0000262)	6451
	−0.000135 (0.000115)						0.0000216 (0.0000567)	7134
	−0.000118	−0.00036	−0.0000018	−0.00113**	0.0160***	0.0000012	0.0000449	
Dollar	(0.000122)	(0.000225)	(0.000009)	(0.000414)	(0.00276)	(0.000039)	(0.000074)	6451

This table presents the coefficients estimated using Eq. 1 (with and without control) where the dependent variable is the daily return on equity markets (USA, China, UK, France, Germany, Canada, Australia, Russia, Switzerland), and other assets (gold, silver, palladium, platinum, copper, bond and dollar) from 1995 to 2021. The key explanatory variable is the change in the geopolitical threat index (ΔGPT Threat). The set of control variables includes Changes in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, change in Term Premium, and Change in Trade Volume. Standard errors are in parentheses and ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels respectively.

A.3. Relationship between geopolitical threat (GPT) and asset returns (Whole sample: 1985–2021)

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
Panel A: Equity Markets								
	0.000362						0.000330**	
	(0.000233)						(0.000115)	9738
USA	0.000320	−0.000285	0.0000380	−0.00329***	0.143***	0.0000711	0.000417**	
	(0.000243)	(0.000470)	(0.00002)	(0.000773)	(0.00622)	(0.00008)	(0.000158)	8608
	0.000152						0.000302	
	(0.000513)						(0.000250)	7915
China	0.000199	0.000640	0.0000366	0.000999	0.0335**	0.000177	0.000200	
	(0.000548)	(0.00104)	(0.000041)	(0.00192)	(0.0128)	(0.000181)	(0.000337)	7168
	−0.0000465						0.000181	
	(0.000223)						(0.000110)	9738
UK	−0.0000168	−0.000474	0.0000167	−0.00197**	0.127***	0.0000903	0.000247	
	(0.000233)	(0.000450)	(0.000019)	(0.000739)	(0.00595)	(0.000076)	(0.000152)	8799
	0.0000105 (0.000292)						0.000160 (0.000142)	9085
France	0.0000518	−0.000496	0.0000179	−0.00257**	0.160***	0.000169	0.000225	
	(0.000302)	(0.000573)	(0.000024)	(0.000917)	(0.00741)	(0.000103)	(0.000193)	8224
	0.0000643 (0.000284)						0.000286* (0.000140)	9738
Germany	0.0000923	−0.000707	0.0000361	−0.00182	0.167***	0.000215*	0.000364	
	(0.000294)	(0.000568)	(0.000024)	(0.000933)	(0.00751)	(0.000096)	(0.000191)	8799
	0.000176 (0.000200)						0.000219* (0.0000986)	9738
Canada	0.000166	0.000588	0.0000401*	−0.00184**	0.115***	0.000105	0.0000576	
	(0.000208)	(0.000403)	(0.000017)	(0.000662)	(0.00533)	(0.000068)	(0.000136)	8799
	−0.000265						0.000187 (0.000109)	7809
	(0.000223)							
Australia	−0.000211	0.000849	0.0000342	0.000382	0.0502***	0.000140	−0.0000347	
	(0.000237)	(0.000448)	(0.000018)	(0.000825)	(0.00549)	(0.000078)	(0.000145)	7070
	−0.000532						0.000347 (0.000298)	6959
	(0.000604)							
Russia	−0.000505	0.00201	0.000123**	0.000299	0.143***	0.000468*	−0.0000421	
	(0.000634)	(0.00116)	(0.000046)	(0.00214)	(0.0142)	(0.000204)	(0.000386)	6288
	0.000173 (0.000242)						0.000234* (0.000118)	8830
Switzerland	0.0000951	0.0000222	0.0000194	−0.00166*	0.108***	0.000121	0.000144	
	(0.000253)	(0.000477)	(0.000020)	(0.000760)	(0.00616)	(0.000086)	(0.000161)	7989
Panel B: Other Assets								
	−0.000155						0.000185 (0.0000977)	9738
	(0.000198)							
Gold	−0.000152	0.000621	0.0000320	0.000475	−0.0358***	0.0000978	0.0000261	
	(0.000212)	(0.000410)	(0.000017)	(0.000673)	(0.00542)	(0.000069)	(0.000138)	8799
	−0.000122						0.000130 (0.000174)	9738
	(0.000352)							
Silver	−0.000146	0.00128	0.0000477	0.00180	0.0123	0.000228	−0.000168	
	(0.000377)	(0.000729)	(0.000031)	(0.00120)	(0.00965)	(0.000124)	(0.000246)	8799
	0.000361 (0.000430)						0.000319 (0.000209)	9218
Palladium	0.000538	0.000222	−0.0000421	0.000629	0.0669***	0.000200	0.000255	
	(0.000457)	(0.000871)	(0.000036)	(0.00140)	(0.0113)	(0.000152)	(0.000294)	8347
	0.000444 (0.000297)						0.000123 (0.000147)	9738
Platinum	0.000517	0.000869	0.0000370	0.000339	0.0328***	0.000176	−0.000101	
	(0.000320)	(0.000619)	(0.000026)	(0.00102)	(0.00819)	(0.000105)	(0.000209)	8799
	−0.000500						0.000203 (0.000165)	9738
	(0.000335)							
Copper	−0.000581	0.00209**	0.0000196	−0.00127	0.102***	0.000118	−0.000267	
	(0.000359)	(0.000695)	(0.000029)	(0.00114)	(0.00919)	(0.000118)	(0.000234)	8799
	−0.0000456						−0.00000911	9738
Bond	(0.0000621)						(0.0000307)	

(*continued on next page*)

(*continued*)

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
Dollar	−0.0000411 (0.0000492)	−0.000131 (0.0000950)	−0.000007 (0.000004)	0.000312* (0.000156)	−0.106*** (0.00126)	−0.0000281 (0.000016)	0.00000936 (0.0000320)	8799
	−0.000153 (0.000111)						0.0000112 (0.0000537)	8437
	−0.000169 (0.000118)	−0.000467* (0.000221)	−0.000004 (0.000009)	−0.00108** (0.000402)	0.0171*** (0.00282)	−0.0000005 (0.000039)	0.000076 (0.0000735)	7644

This table presents the coefficients estimated using Eq. 1 (with and without control) where the dependent variable is the daily return on equity markets (USA, China, UK, France, Germany, Canada, Australia, Russia, Switzerland), and other assets (gold, silver, palladium, platinum, copper, bond and dollar) from 1985 to 2021. The key explanatory variable is the change in the geopolitical threat index (ΔGPT Threat). The set of control variables includes Change in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, change in Term Premium, Change in Trade Volume. Standard errors are in parentheses and ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels respectively.

A.4. Relationship between geopolitical threat (GPT) and US ETF returns (2015–2021)

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
Information Technology ETF	**0.00190**** **(0.000588)**						0.000684* (0.000325)	1903
	0.00191** **(0.000599)**	**0.00266 (0.0014)**	**0.0000853* (0.00003)**	**−0.00639 (0.00345)**	**0.139*** (0.0107)**	**0.000161 (0.000141)**	**0.000277 (0.000440)**	**1669**
Communication ETF	**0.00134**** **(0.000508)**						0.000159 (0.000281)	1903
	0.00126* (0.000521)	0.00187 (0.0012)	0.000083** (0.00002)	−0.00208 (0.00300)	0.109*** (0.00929)	0.000168 (0.000123)	−0.000214 (0.000383)	1669
Consumer Staples ETF	0.000588 (0.000387)						0.000251 (0.000214)	1903
	0.000592 (0.000410)	0.00168 (0.0009)	0.000055** (0.00002)	−0.00193 (0.00236)	0.0796*** (0.00730)	0.0000876 (0.000096)	−0.0000621 (0.000301)	1669
Consumer Discretionary ETF	**0.00108* (0.000521)**						0.000487 (0.000288)	1903
	0.00125** **(0.000393)**	0.00046 (0.0006)	0.0000748* (0.00002)	−0.0022 (0.00150)	0.175*** (0.00788)	0.000266* (0.000123)	0.000445 (0.000238)	1669
Energy ETF	0.00137 (0.000814)						0.0000100 (0.000450)	1903
	0.00114 (0.000823)	0.00408* (0.001)	0.000147*** (0.00004)	−0.0000053 (0.00474)	0.239*** (0.0147)	0.000102 (0.000194)	−0.000873 (0.000605)	1669
Financial ETF	0.00101 (0.000603)						0.000312 (0.000333)	1903
	0.000749 (0.000568)	0.00283* (0.001)	0.000077** (0.00002)	−0.00266 (0.00327)	0.233*** (0.0101)	0.0000312 (0.000134)	−0.000105 (0.000417)	1669
Health ETF	**0.00121**** **(0.000466)**						0.000369 (0.000258)	1903
	0.00115* (0.000478)	0.00084 (0.001)	0.000069** (0.00002)	−0.00276 (0.00276)	0.116*** (0.00850)	0.0000522 (0.000111)	0.000279 (0.000352)	1669
Industry ETF	0.000943 (0.000531)						0.000294 (0.000293)	1903
	0.000839 (0.000523)	0.00158 (0.0012)	0.0000561* (0.000026)	−0.00231 (0.00302)	0.171*** (0.00929)	0.000050 (0.000121)	0.0000692 (0.000385)	1669
Material ETF	0.000958 (0.000554)						0.000315 (0.000306)	1903
	0.000938 (0.000548)	0.00144 (0.0012)	0.000078** (0.000028)	0.000484 (0.00317)	0.171*** (0.00975)	0.0000651 (0.000127)	0.000131 (0.000404)	1669
Real Estate ETF	0.000483 (0.000543)						0.000152 (0.000300)	1903
	0.000493 (0.000577)	0.00090 (0.0013)	0.0000571 (0.000029)	−0.000928 (0.00333)	0.0906*** (0.0103)	0.0000721 (0.000134)	−0.000102 (0.000425)	1669
Utility ETF	0.000940 (0.000499)						0.000247 (0.000276)	1903
	0.00108* (0.000541)	0.00015 (0.0012)	0.0000424 (0.000027)	−0.00222 (0.00312)	0.0633*** (0.00962)	0.000161 (0.000125)	0.000178 (0.000398)	1669

This table presents the coefficients estimated using Eq. 1 (with and without control) where the dependent variable is the daily return on different sectoral ETF returns from 2015 to 2021. The key explanatory variable is the change in the geopolitical threat threat index (ΔGPT Threat). The set of control variables includes Change in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, change in Term Premium, Change in Trade Volume. Standard errors are in parentheses and ***, **, and * indicate statistical significance at the 0.1%, 1%, and 5% levels respectively.

A.5. Effect on conditional volatility

	ΔGPT Threat	ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
Panel A: Mean Model								
USA (S&P 500)	0.0032						0.0003 **	208
	(0.0034)						(0.0002)	
	0.0039	0.0005	0.0001 ***	−0.0070	0.1159 ***	0.0002 **		
	(0.0033)	(0.0005)	(0.0000)	(0.0071)	(0.0318)	(0.0001)	0.0003 (0.0002)	208
	0.0041						0.0006 ***	
	(0.0041)						(0.0002)	208
Information Technology	0.0049	0.0007	0.0001 ***	−0.0072	0.1333 ***	0.0003 **	0.0004 **	
ETF	(0.0039)	(0.0006)	(0.0000)	(0.0084)	(0.0378)	(0.0001)	(0.0002)	208
	0.0054							
	(0.0039)						0.0002 (0.0002)	208
	0.0065 *	0.0002	0.0001 ***	−0.0014	0.0802 **	0.0003 ***		
Communication ETF	(0.0038)	(0.0006)	(0.0000)	(0.0081)	(0.0364)	(0.0001)	0.0002 (0.0002)	208
	0.0009						0.0004 ***	
	(0.0028)						(0.0001)	208
	0.0015	0.0006	0.0000 **	−0.0027		0.0001 *	0.0002 *	
Consumer Staples ETF	(0.0028)	(0.0004)	(0.0000)	(0.0060)	0.0293 (0.0269)	(0.0001)	(0.0001)	208
	0.0043						0.0005 **	
	(0.0044)						(0.0002)	208
Consumer Discretionary	0.0052	−0.0002	0.0001 ***	−0.0119	0.1847 ***	0.0004 ***	0.0005 **	
ETF	(0.0042)	(0.0006)	(0.0000)	(0.0089)	(0.0403)	(0.0001)	(0.0002)	208
	0.0046							
	(0.0063)						0.0003 (0.0003)	208
	0.0059	0.0010	0.0001 ***	−0.0231 *	0.3322 ***			
Energy ETF	(0.0057)	(0.0009)	(0.0000)	(0.0122)	(0.0549)	0.0002 (0.0002)	0.0001 (0.0003)	208
	0.0017							
	(0.0048)						0.0002 (0.0002)	208
	0.0017	0.0004	0.0001 **	−0.0069	0.2524 ***			
Financial ETF	(0.0044)	(0.0007)	(0.0000)	(0.0094)	(0.0426)	0.0001 (0.0001)	0.0001 (0.0002)	208
	0.0014						0.0003 **	
	(0.0037)						(0.0002)	208
	0.0025	0.0008	0.0001 ***	−0.0032				
Health ETF	(0.0037)	(0.0006)	(0.0000)	(0.0079)	0.0240 (0.0357)	0.0002 (0.0001)	0.0002 (0.0002)	208
	0.0057						0.0004 **	
	(0.0044)						(0.0002)	208
	0.0059	0.0002	0.0001 **	−0.0092	0.2022 ***	0.0002 *	0.0004 *	
Industry ETF	(0.0042)	(0.0006)	(0.0000)	(0.0089)	(0.0402)	(0.0001)	(0.0002)	208
	0.0064						0.0005 **	
	(0.0049)						(0.0002)	208
	0.0074	0.0007	0.0001 ***	−0.0081	0.2082 ***	0.0003 **		
Material ETF	(0.0046)	(0.0007)	(0.0000)	(0.0098)	(0.0440)	(0.0001)	0.0003 (0.0002)	208
	0.0029							
	(0.0049)						0.0002 (0.0002)	208
	0.0039	0.0008	0.0001 **	−0.0121		0.0003 **		
Real Estate ETF	(0.0049)	(0.0007)	(0.0000)	(0.0104)	0.0632 (0.0468)	(0.0001)	0.0000 (0.0003)	208
	−0.0011						0.0003 **	
	(0.0031)						(0.0001)	208
	−0.0004	0.0009 *	0.0000 **	−0.0054	−0.0504 *	0.0003 ***		
Utility ETF	(0.0030)	(0.0005)	(0.0000)	(0.0064)	(0.0289)	(0.0001)	0.0001 (0.0002)	208

	ΔGPT Threat	eGARCH Coefficients				ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
		constant	alpha	beta	gamma							
Panel B: Conditional Variance Model												
	0.0017										0.0029	
	(0.0108)										***	207
											(0.0005)	
USA (S&P 500)		0.0051	−0.0010	−0.0520	−0.0010	−0.0031			−0.2232	−0.0006	0.0531	
	0.0102	***	**	***	***	**	0.0001	0.0225	***	**	***	
	(0.0084)	(0.0006)	(0.0004)	(0.0064)	(0.0003)	(0.0013)	(0.0000)	(0.0178)	(0.0813)	(0.0002)	(0.0062)	207
	0.0008										0.0037	
	(0.0110)										***	
											(0.0005)	206
		0.0050		−0.0473	−0.0010				−0.2580	−0.0006	0.0495	
Information	0.0017	***	−0.0004	***	**	−0.0023	0.0001	0.0260	***	**	***	
Technology ETF	(0.0089)	(0.0007)	(0.0004)	(0.0073)	(0.0004)	(0.0014)	(0.0001)	(0.0190)	(0.0871)	(0.0002)	(0.0070)	206
											0.0032	
Communication	0.0034										***	
ETF	(0.0098)										(0.0004)	206

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(*continued*)

	ΔGPT Threat	eGARCH Coefficients				ΔCPI	ΔUNEMP	Δ Bond Yield Spread	Δ Term Premium	Δ Trade Volume	Constant	N
		constant	alpha	beta	gamma							
	0.0061	0.0048 ***	−0.0005	−0.0451 ***	−0.0009 ***	−0.0055 ***	0.0000	0.0142	−0.2085 ***	−0.0003	0.0479 ***	
	(0.0076)	(0.0007)	(0.0003)	(0.0066)	(0.0003)	(0.0012)	(0.0000)	(0.0166)	(0.0743)	(0.0002)	(0.0064)	206
	0.0009										0.0016 ***	
	(0.0066)										(0.0003)	204
		0.0042	−0.0006	−0.0446		−0.0024			−0.1382		0.0460	
Consumer Staples ETF	0.0104 **	***	**	***	−0.0001	***	0.0000	0.0120	***	−0.0002	***	
	(0.0051)	(0.0004)	(0.0002)	(0.0045)	(0.0002)	(0.0007)	(0.0000)	(0.0105)	(0.0483)	(0.0001)	(0.0044)	204
	0.0012										0.0036 ***	
	(0.0107)										(0.0005)	206
Consumer		0.0041		−0.0402	−0.0006	−0.0057			−0.2509	−0.0006	0.0437	
Discretionary	0.0141 *	***	0.0003	***	**	***	0.0001	0.0421 **	***	**	***	
ETF	(0.0085)	(0.0007)	(0.0004)	(0.0065)	(0.0003)	(0.0013)	(0.0000)	(0.0184)	(0.0855)	(0.0002)	(0.0064)	206
	−0.0018										0.0074 ***	
	(0.0241)										(0.0011)	206
		0.0053		−0.0412		−0.0140			−0.5165	−0.0011	0.0522	
	0.0084	***	0.0016	**	−0.0006	***	0.0001	0.0900 **	**	*	***	
Energy ETF	(0.0215)	(0.0018)	(0.0013)	(0.0160)	(0.0008)	(0.0033)	(0.0001)	(0.0455)	(0.2078)	(0.0006)	(0.0155)	206
	0.0043										0.0064 ***	
	(0.0226)										(0.0010)	207
		0.0090		−0.0816	−0.0015	−0.0102			−0.4727	−0.0010	0.0883	
	0.0261	***	0.0003	***	**	***	0.0001	0.0862 **	**	*	***	
Financial ETF	(0.0191)	(0.0015)	(0.0009)	(0.0148)	(0.0007)	(0.0029)	(0.0001)	(0.0408)	(0.1830)	(0.0005)	(0.0144)	207
	−0.0012										0.0023 ***	
	(0.0075)										(0.0003)	207
		0.0045	−0.0006	−0.0454	−0.0006	−0.0021			−0.1799		0.0466	
	0.0085	***	**	***	***	**	0.0000	0.0180	***	−0.0002	***	
Health ETF	(0.0057)	(0.0005)	(0.0003)	(0.0052)	(0.0002)	(0.0009)	(0.0000)	(0.0122)	(0.0556)	(0.0002)	(0.0050)	207
	−0.0018										0.0036 ***	
	(0.0119)										(0.0005)	204
		0.0055		−0.0508		−0.0044			−0.2826	−0.0006	0.0548	
	0.0101	***	−0.0007	***	−0.0006	**	0.0001	0.0401 *	***	**	***	
Industry ETF	(0.0103)	(0.0010)	(0.0005)	(0.0100)	(0.0004)	(0.0017)	(0.0001)	(0.0215)	(0.0995)	(0.0003)	(0.0098)	204
	−0.0026										0.0048 ***	
	(0.0140)										(0.0006)	207
		0.0044		−0.0377		−0.0091			−0.3351	−0.0007	0.0445	
	0.0093	***	−0.0006	***	−0.0006	***	0.0000	0.0345	***	**	***	
Material ETF	(0.0119)	(0.0010)	(0.0006)	(0.0092)	(0.0004)	(0.0018)	(0.0001)	(0.0248)	(0.1123)	(0.0003)	(0.0090)	207
	0.0122										0.0074 ***	
	(0.0305)										(0.0014)	206
		0.0111		−0.1047		−0.0205				−0.0015	0.1146	
	0.0297	***	−0.0002	***	−0.0008	***	0.0000	0.0227	−0.3600	**	***	
Real Estate ETF	(0.0258)	(0.0020)	(0.0013)	(0.0204)	(0.0009)	(0.0039)	(0.0002)	(0.0556)	(0.2500)	(0.0007)	(0.0198)	206
	−0.0022										0.0026 ***	
	(0.0116)										(0.0005)	205
		0.0031	−0.0011	−0.0288		−0.0051	0.0001		−0.2419	−0.0006	0.0325	
	0.0074	***	**	***	−0.0005	***	**	0.0378 *	**	**	***	
Utility ETF	(0.0102)	(0.0010)	(0.0005)	(0.0099)	(0.0003)	(0.0017)	(0.0001)	(0.0214)	(0.0988)	(0.0003)	(0.0097)	205

Panel A, presents the coefficients estimated using Eq. 3 (A), and Panel B using Eq.3 (B), presents the coefficients estimated using the EGARCH (1,1) specifications where the dependent variable is the return on equity markets (USA), and different sectoral ETF returns (January 2005 to May 2022). The key explanatory variable is the change in the geopolitical threat index (ΔGPT Threat). The set of control variables includes Changes in Inflation (ΔCPI), Unemployment rate ((ΔUNEMP), change in Credit Spread, change in Term Premium, and Change in Trade Volume. Robust standard errors are in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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