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ORIGINAL ARTICLE

Geopolitical threats and the reversal of equity size premiums

Md Khaled Hossain Rafi[1] · **Syed Riaz Mahmood Ali**[2]

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Abstract
We examine how geopolitical threats affect U.S. equity portfolios across market capitalizations using daily returns from 1995 to 2024. Large and prime-cap portfolios generate significantly positive returns during heightened geopolitical tensions and yield 0.52% risk-adjusted excess returns during high-threat periods. Small and mid-cap portfolios show no response. Markov regime-switching analysis reveals that this effect intensifies eight-fold during high-volatility states. Geopolitical threats represent unique uncertainty distinct from market volatility or economic policy uncertainty. Effects occur contemporaneously with no lagged adjustment and indicate rapid information processing. Results remain robust across alternative specifications and out-of-sample tests. Implementable trading strategies capitalize on these differential responses can generate substantial economic value. Our findings extend safe haven asset literature to intra-asset class dynamics and demonstrate how firm size moderates geopolitical risk responses with direct implications for strategic asset allocation during global uncertainty.

Keywords Geopolitical threats · Portfolio returns · Hedging · Safe haven · Conditional volatility · Trading strategy · Regime switching

JEL classification E60 · G01 · G11 · G21 · G30

Introduction

Geopolitical risks have emerged as critical determinants of investment decisions and market dynamics over the past few decades (Baker et al. 2016; Carney 2016). Recent events including the Russia-Ukraine conflict and U.S.-China trade tensions highlight the importance of understanding how these threats affect different segments of financial markets (Segnon et al. 2024). The impact of geopolitical risk on financial markets was dramatically illustrated during the 2022 Russian invasion of Ukraine. Despite broader market declines of over 21%, the S&P 500 index rose by 3.5–5.5% within a week of the invasion. This counterintuitive response highlights the complex and often surprising ways geopolitical events can affect different market segments. Thus, it raises crucial questions about which types of assets demonstrate resilience during geopolitical crises and why.Empirical evidence indicates that geopolitical risks can threaten financial stability through cascading effects on asset markets and international capital movements (Demirer et al. 2018).

The U.S. equity market provides an ideal laboratory given its global prominence and relative geopolitical insulation (Balcilar et al. 2018). Recent evidence demonstrates that certain specific sectors of the U.S. equity market deliver significantly positive returns during heightened geopolitical threats. This resilience largely stems from strong investor confidence in the United States' advantageous geopolitical position. This raises three questions: How do portfolios of varying market capitalizations respond to geopolitical threats? Which characteristics drive superior crisis performance? What are the portfolio management implications?

Notably, investors perceive large-cap and prime firms as more reliable and less risky during such periods. Previous

✉ Md Khaled Hossain Rafi
mdkhaledhossain.m.rafi@utu.fi

Syed Riaz Mahmood Ali
rmahmood@na.edu

1 Department of Accounting and Finance, Turku School of Economics, University of Turku, Turku, Finland

2 Department of Business Administration, North American University, Stafford, Texas, USA

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research shows that geopolitical risks prompt investors to liquidate holdings in emerging markets, leading to capital flows toward advanced economies (Caldara and Iacoviello 2022). We argue that during heightened geopolitical turmoil, investors not only favor advanced markets but also prioritize large, low-risk firms within these markets. To address these questions, we examine the U.S. equity market and analyze different size-based portfolios and their responses to geopolitical threats. We employ the geopolitical threat (GPT) component of geopolitical risk index of Caldara and Iacoviello (2022). It captures market anticipation of potential geopolitical events rather than actual occurrences. This threat-induced uncertainty typically generates stronger market responses than realized events. Our analysis focuses on 12 distinct portfolios based on market capitalization (large, prime, mid, small) and investment style (growth, value).

Extensive research documents the persistent size anomaly where small-cap stocks generally outperform large-cap stocks (Hirshleifer 2001; Schwert 2003). Evidence indicates that value companies achieve higher average returns than growth equities (De Bondt and Thaler 1985; Fama and French 1992). However, we demonstrate that these patterns reverse during periods of geopolitical threats. Specifically, we find that portfolios composed of large and prime-cap stocks yield significantly favorable returns during periods of elevated geopolitical threats while small and mid-cap portfolios show no such advantage. This differential response which intensifies during high-volatility regimes challenges conventional wisdom about size effects in asset pricing. It also has important implications for portfolio construction during periods of heightened global uncertainty.

Our study makes several significant contributions to the literature. First, we analyze the relationship between geopolitical threats and portfolio returns based on market capitalization to highlight how macro-level geopolitical threats influence micro-level portfolio decisions. Second, we examine the impact of geopolitical threats on portfolio selection and asset allocation within U.S. size-based portfolios and demonstrate that geopolitical threats positively affect returns of large and prime-cap portfolios but not small and mid-cap portfolios. Third, we provide insights into portfolio volatility by identifying geopolitical threats as potential early indicators of future volatility and shifts in investor risk appetite.

Our methodological approach encompasses several innovative elements. We examine 12 distinct portfolios based on market capitalization and growth/value characteristics, providing a nuanced understanding of how different market segments respond to geopolitical threats. We employ Markov regime-switching models to analyze how portfolio returns respond to geopolitical threats under different volatility regimes. We investigate the impact of geopolitical threats on conditional volatility and optimal hedge ratios, test the robustness of our findings against alternative uncertainty measures, and develop practical trading strategies based on geopolitical threat indicators.

Our empirical findings reveal that large and prime-cap portfolios demonstrate a significant positive relationship with geopolitical threats. This effect is strengthened during high-volatility regimes. This relationship remains robust across different sample periods, specification tests, and alternative uncertainty measures. We find that these portfolios exhibit safe haven properties during periods of extreme geopolitical tension. Moreover, they generate positive returns precisely when market volatility is the highest. We also document that while geopolitical threats significantly impact the conditional volatility of large and prime-cap portfolios, investors appear to adjust their holdings rapidly with no evidence of lagged effects. These insights translate into effective trading strategies that capitalize on the differential response of market segments to geopolitical developments.

The remainder of this paper is organized as follows. Section 2 provides a theoretical framework and discusses relevant literature. Section 3 describes our data sources, variables, and methodological approach. Section 4 presents our main empirical findings and analysis. Finally, Section 5 concludes with a discussion of implications for investment practice and directions for future research.

Theoretical framework and literature review

Geopolitical risk significantly influences asset pricing and investor behavior. Caldara and Iacoviello (2022) demonstrate that geopolitical threats create market uncertainty while Pástor and Veronesi (2013) show such uncertainty increases risk premiums and affects capital allocation. Importantly, anticipated geopolitical events generate stronger market responses than realized events because uncertainty amplifies emotional investor reactions (Sunstein and Zeckhauser 2011). This threat-induced uncertainty prompts firms to delay investment decisions. It follows real options theory where waiting value increases under uncertainty (Bernanke 1983; Bloom 2009).

The size effect literature documents that small firms typically outperform large firms due to higher risk premiums (Banz 1981; Fama and French 1992). However, this relationship may reverse during crisis periods when investor preferences shift dramatically. We identify four theoretical channels explaining this reversal. First, large firms benefit from superior analyst coverage and information processing capabilities during uncertain periods. Second, large firms maintain greater debt capacity and cash reserves that provide operational buffers during crises. Third, flight-to-quality behavior increases institutional investor demand for large-cap stocks during uncertainty. Fourth, geographic and business line diversification provides natural hedging against localized geopolitical risks. These mechanisms suggest that traditional size premiums could reverse during geopolitical stress, with large-cap stocks demonstrating superior performance precisely when uncertainty peaks. This connects to safe haven asset literature where safe havens exhibit positive or uncorrelated performance with other assets during market stress (Baur and Lucey 2010).[1] While gold and sovereign bonds traditionally serve as safe havens during crises (Baur and McDermott 2010), we extend this framework to examine intra-asset class dynamics within equity markets.

Our theoretical framework predicts that large-cap stocks function as equity market safe havens during geopolitical crises. Unlike traditional safe havens that provide cross-asset diversification, large-cap stocks offer relative safety within equity allocations. This aligns with flight-to-liquidity theory where investors prefer liquid, well-known assets during uncertainty periods. The combination of superior information processing, financial flexibility, institutional preference, and operational diversification creates a confluence of factors that should drive capital toward large-cap stocks when geopolitical threats intensify. Building on this theoretical foundation, we hypothesize that large and prime-cap portfolios demonstrate positive responses to geopolitical threats while small and mid-cap portfolios do not. This relationship intensifies during high-volatility regimes when flight-to-quality behavior peaks. Finally, large-cap portfolios exhibit safe haven properties and show amplified positive responses during extreme geopolitical threat periods beyond their normal performance.

[1] It is important to distinguish between "safe haven" and "hedge" properties as defined by Baur and Lucey (2010). A hedge provides protection during normal market conditions through negative or low correlation with the underlying asset while a safe haven offers protection specifically during periods of market stress or crisis. Our analysis focuses on safe haven properties and examines whether large-cap portfolios demonstrate positive or uncorrelated returns precisely when geopolitical threats intensify rather than providing consistent hedging benefits across all market conditions.

Data and methodology

Geopolitical threat and its time-series properties

We utilize the geopolitical threat index developed by Caldara and Iacoviello (2022) as our measure of geopolitical risk. This index captures the dynamic fluctuations of global geopolitical risk through automated textual analysis of geopolitical-related articles from 11 leading national and international newspapers. We specifically use the daily Geopolitical Threat (GPT) component rather than the Act component as threats have been shown to have greater economic impacts through their uncertainty-amplifying effects (Caldara and Iacoviello 2022; Rafi and Ali 2025).[2] Throughout this paper, we refer to this measure as GPT (Geopolitical Threat) and its daily changes as ΔGPT. Evidence suggests that financial markets suffer more from anticipation of geopolitical events than from their actual occurrence (Salisu et al. 2021). Unlike broader measures such as the Economic Policy Uncertainty index of Baker et al. (2016), the GPT index focuses specifically on geopolitical tensions and responds distinctively to events such as the Russia-Ukraine conflict and Crimean annexation.

Table 1 shows that stationarity tests (ADF) on both the level of and change in GPT (ΔGPT) reject unit roots at 1%. It justifies the use of ΔGPT in our regressions (Dickey and Fuller 1979; Hamilton 2016). The level series exhibits strong positive first-order autocorrelation (0.621). It indicates persistence of elevated threat episodes whereas ΔGPT shows significant negative first-order autocorrelation (−0.438) which reflects rapid mean reversion after spikes. From Fig 1, visual inspection confirms pronounced level-series peaks at 9/11 (2001), Iraq War (2003), Russia-Ukraine war (2022) etc. ΔGPT oscillates tightly around zero (mean 0.014) which corroborates its stationarity and suitability for impact analysis on financial returns.

[2] Caldara and Iacoviello (2022) refer to geopolitical threat index as the Geopolitical Risk Threat (GPRT) index. For simplicity and consistency, we use the abbreviation GPT throughout this paper while referring to the same measure. The index is available at: https://www.matteoiacoviello.com/gpr.htm

Test assets

We analyze 12 distinct portfolios based on market capitalization and growth or value characteristics from the MSCI USA Index series (Data source: LSEG Workspace). Large Cap portfolios represent the MSCI USA Large Cap 300 Index that comprises the 300 largest companies in the U.S. market. Prime Cap portfolios refer to the MSCI USA Prime Market 750 Index which encompasses the 750 largest U.S. companies representing approximately 85% of total U.S. market capitalization. This category sits between traditional large-cap and mid-cap classifications and offers a broader representation of established firms.[3] Mid Cap portfolios track the MSCI USA Mid Cap 450 Index that represents mid-sized companies. Small Cap portfolios correspond to the MSCI USA Small Cap 1750 Index. Within each size segment, growth and vlue subcategories are constructed based on fundamental variables including price-to-book ratio, forward price-to-earnings ratio, and dividend yield.

We use daily data from 1995 to 2024. The sample period captures post-Cold War financial markets with major geopolitical events including 9/11, Iraq war, financial crisis, Crimean annexation, and Russia-Ukraine conflict. The mid-1990s marked a structural shift in the U.S. equity market with the emergence of the internet boom, significant regulatory changes following the 1996 National Securities Markets Improvement Act, and the acceleration of globalization (Campbell et al. 2001). Forbes and Rigobon (2002) also note that post-1995 market data benefits from improved liquidity and market efficiency. Thus, it enhances the reliability of our statistical inferences. The ending period is considered the latest data period while writing the paper.

To isolate geopolitical threat effects, we control for macroeconomic factors influencing equity returns including inflation changes (ΔCPI, change in the U.S. consumer price index), unemployment rate changes (ΔUNP, change in the U.S. unemployment rate), bond yield spread changes (Δ BYS, calculated as the 10-year treasury constant maturity minus 2-year treasury constant maturity), term premium changes (ΔTP, based on the U.S. ACM treasury term premia), and trade volume changes (ΔTV, the change in the U.S. retail trade volume).[4] Robustness tests employ alternative uncertainty measures including change in Bekaert economic uncertainty index (ΔBEX) of Bekaert et al. (2022),[5] change in macroeconomic uncertainty index (ΔUNC) of Jurado et al. (2015),[6] change in economic policy uncertainty index (ΔEPU) of Baker et al. (2016),[7] and change in market volatility measured by the CBOE volatility index (ΔVIX)[8] to ensure results are not driven by general uncertainty or market volatility.

Descriptive statistics

Table 1 reports that mid and small-cap indices show higher daily returns (0.05%–0.07%) than large-cap indices (0.03%–0.04%), with correspondingly higher risk (SD of 1.2–1.5.2.5 vs. 1.2–1.3.2.3). Growth indices consistently outperform value across all capitalization segments. The geopolitical threat (GPT) metric exhibits high volatility (mean = 105.07, SD = 58.74) with rapid intensification followed by normalization (ΔGPT mean ≈ 0). All variables demonstrate stationarity via ADF tests (significant at 1%), though GPT level (−42.24) shows stronger persistence than ΔGPT (−75.52) and market indices (−70.82 to −74.00). This is confirmed by autocorrelation of 0.621 for GPT level. It indicates threat persistence while ΔGPT (−0.341) shows mean-reversion.

[3] To provide context for the Prime Cap category, it is important to note that this classification differs from traditional academic categorizations. While the Russell 1000 typically captures the largest 1,000 U.S. companies and the S&P 500 focuses on 500 large-cap stocks, the MSCI USA Prime Market 750 Index occupies a middle ground, encompassing more companies than the S&P 500 but fewer than the Russell 1000. This classification allows us to examine a distinct segment that bridges the gap between pure large-cap exposure and broader market representation, providing unique insights into how mid-tier large companies respond to geopolitical threats compared to the very largest firms (Large Cap 300) and smaller market segments.

[4] All control variable data is downloaded from Federal Reserve Bank of St. Louis (FRED) webpage

[5] The index can be downloaded from: https://www.nancyxu.net/

[6] The index can be downloaded from: https://www.sydneyludvigson.com/

[7] The index can be downloaded from: https://www.policyuncertainty.com/

[8] The index can be downloaded from: https://www.cboe.com/

Table 1 Descriptive statistics and diagnostic tests

	Mean	SD	Min	Max	Unit Root	BG Test
Explained Variables						
Composite	0.04	1.17	−10.00	10.06	−73.25***	21.13***
Large	0.04	1.18	−10.00	10.13	−73.27***	22.00***
Large Growth	0.05	1.30	−9.64	10.18	−72.19***	11.99***
Large Value	0.03	1.15	−10.42	10.09	−74.00***	20.67***
Prime	0.04	1.18	−10.05	9.99	−73.09***	17.40***
Prime Growth	0.03	1.15	−10.60	10.02	−73.76***	17.37***
Prime Value	0.05	1.30	−9.63	9.96	−72.07***	7.99***
Mid	0.06	1.26	−10.66	10.02	−71.81***	1.12
Mid Growth	0.07	1.43	−12.01	9.16	−71.13***	0.60
Mid Value	0.05	1.20	−11.59	11.09	−72.22***	2.93*
Small	0.06	1.35	−11.51	9.36	−71.48***	7.40***
Small Growth	0.07	1.46	−11.15	9.72	−70.82***	0.14
Small Value	0.05	1.32	−13.28	8.92	−71.91***	19.12***
Explanatory Variables						
GPT Level[a]	105.07	58.74	7.89	703.49	−42.24***	
ΔGPT[b]	−0.00	0.49	−3.45	2.66	−75.52***	
Control Variables						
ΔCPI	0.19	0.28	−1.79	1.37	−10.50***	
ΔUNP	−0.12	7.90	−19.42	120.62	−12.04***	
ΔBYS	0.00	0.15	−1.61	1.48	−75.64***	
ΔTP	0.00	0.02	−0.18	0.36	−68.84***	
ΔTV	0.16	1.73	−12.58	15.79	−15.67***	
ΔEPU	−2.93	59.92	−248.13	291.95	−75.96***	
ΔVIX	−0.58	6.59	−31.41	49.60	−72.66***	
ΔBEX	−0.22	5.33	−72.82	47.21	−69.59***	

[a] First-order autocorrelation for GPT Level: 0.62

[b] First-order autocorrelation for ΔGPT: −0.34

This table shows the descriptive statistics for the explained, explanatory and control variables from 1995 to 2024. The daily data comprises of 5,077 daily observations. Here GPT is the geopolitical threat index developed by Caldara and Iacoviello (2022), ΔGPT is the change in daily geopolitical threat, Composite is the MSCI United States of America composite stock index, Large is the MSCI United States Large Cap 300 Index, Large Growth is the MSCI United States Large Capital Growth Index, Large Value is the MSCI United States Large Capital Value Index, Prime is the MSCI United States Prime Market 750 Index, Prime Growth is the MSCI United States Prime Capital Growth Index, Prime Value is the MSCI United States Prime Capital Value Index, Mid is the MSCI United States Mid Capital 450 Index, Mid Growth MSCI United States Mid Capital Growth Index, Mid Value is the MSCI United States Mid Capital Value Index, Small is the MSCI United States Small Cap 1750 Index, Small Growth is the MSCI United States Small Capital Growth Index, Small Value is the MSCI United States Small Capital Value Index. Among Controls, ΔTV is the change in the United States Retail Trade Volume, ΔCPI is the change in the US Consumer Price Index, ΔUNP is the change in the US unemployment rate, ΔBYS is the change in the 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity and ΔTP is the change in the United States, US ACM Treasury Term Premia FIT Yield 10Y, ΔBEX is the economic uncertainty index of Bekaert et al. (2022), ΔEPU is the economic policy uncertainty (EPU) index of Baker et al. (2016) and ΔVIX is the CBOE implied volatility index (VIX). BG Test refers to the Breusch-Godfrey test for serial correlation. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2 shows that all portfolio returns are positively and highly correlated and exhibit a cohesive market structure despite varying capitalization segments and investment styles. This high correlation suggests that common systematic risk factors drive returns across the market spectrum although the correlation coefficients' magnitude varies predictably with capitalization proximity.

Figure 2 shows the relationship between geopolitical threats and portfolio returns across four market-cap categories. The scatter plots reveal size-dependent patterns: large- and prime-cap portfolios exhibit modest positive relationships with geopolitical threats while mid- and small-cap portfolios show weaker associations. Linear trend lines underline this differential sensitivity, with larger firms showing more consistent positive responses. The scatter reveals increasing return dispersion from large- to small-cap during high geopolitical tension. This indicates that smaller firms have more volatile responses.

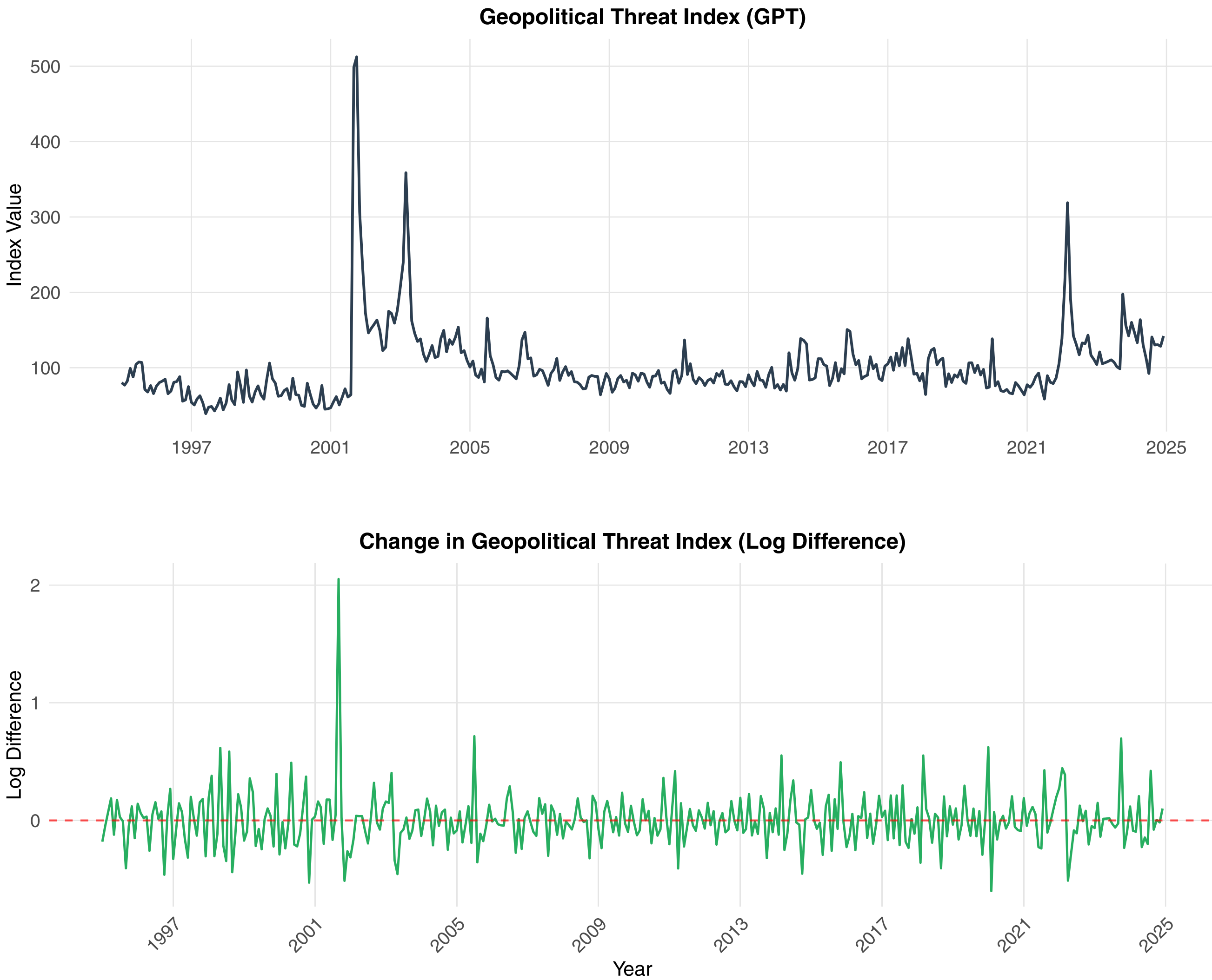

Fig. 1 Time series of the Geopolitical Threat Index (GPT) and Change in Geopolitical Threat Index (ΔGPT). This figure displays the daily Geopolitical Threat Index (GPT) developed by Caldara and Iacoviello (2022) and change in geopolitical threat (ΔGPT) from 1995 to 2024. The top panel shows the level of the index. Major geopolitical events such as the 9/11 attacks (2001), Iraq War (2003), Russia-Ukraine war (2022) etc. happened during this time. The bottom panel presents the day-to-day changes in the index (log differences) and demonstrates the high-frequency volatility in geopolitical threat perceptions. The sample spans from 1995 to 2024

Figure 3 shows individual time-series panels for each portfolio category. Large- and prime-cap portfolios are relatively stable with periodic volatility clustering, while mid- and small-caps have higher baseline volatility and stronger reactions during stress. Volatility spikes align with major geopolitical events in Fig 1, visually support the size-dependent flight-to-quality mechanism and reinforce that larger firms perform better in crises.

Breusch-Godfrey tests confirm serial correlation in 9 of 13 indices (1% level). It is most severe in large-caps (BG stat = 22.004) but absent in some mid-cap indices. The result suggests heterogeneous market efficiency. These findings necessitate Newey-West HAC standard errors in subsequent regression analyses to ensure valid statistical inference across multiple market regimes.

Empirical methodology

Core empirical framework

Our empirical strategy employs three complementary approaches to test differential portfolio responses to geopolitical threats. The baseline specification examines contemporaneous relationships:

$$\begin{aligned} R_t =& \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta CPI_t + \beta_3 \Delta UNP_t \\ &+ \beta_4 \Delta BYS_t + \beta_5 \Delta TP_t + \beta_6 \Delta TV_t + \varepsilon_t, \end{aligned} \tag{1}$$

where R_t represents daily portfolio returns, ΔGPT_t captures changes in the geopolitical threat index, and control variables include economic variables that are associated with uncertainty, geopolitical risk and stock markets (Arouri et al. 2016). We employ Newey-West HAC standard errors to address potential heteroskedasticity and serial correlation.

To examine safe haven properties during extreme geopolitical stress, we distinguish between normal and crisis period responses using an interaction specification that builds upon Equation 1:

$$R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2(\Delta GPT_t \times \text{High GPT Dummy}_t) + \beta_3 \Delta CPI_t + \beta_4 \Delta UNP_t + \beta_5 \Delta BYS_t + \beta_6 \Delta TP_t + \beta_7 \Delta TV_t + \varepsilon_t. \tag{2}$$

The High GPT Dummy equals one for the highest 10th percentile threat days, decomposing total response into baseline and crisis components. Coefficient β_1 captures normal period responses (identical to Table 3 results), while β_2 measures additional response during extreme events. This incremental effect represents the safe haven premium investors pay when geopolitical threats reach crisis levels. Positive and significant β_2 indicates amplified performance during extreme periods and confirms safe haven characteristics. This interaction approach follows established methodologies for examining conditional factor effects during market stress (Baur and Lucey 2010).

Linear specifications assume time-invariant parameters, potentially missing structural breaks and regime changes in uncertainty states (Hamilton 2016). We address this limitation using a two-state Markov regime-switching model capturing time-varying effects across volatility conditions:

$$R_t = \beta_0 + \beta_{s_t,1} \Delta GPT_t + \beta_{s_t,2} \Delta CPI_t + \beta_{s_t,3} \Delta UNP_t + \beta_{s_t,4} \Delta BYS_t + \beta_{s_t,5} \Delta TP_t + \beta_{s_t,6} \Delta TV_t + \varepsilon_t, \tag{3}$$

where $s_t \in \{1, 2\}$ follows a Markov process and distinguishes high and low volatility regimes with $\varepsilon_t \sim N(0, \sigma^2_{s_t})$. This approach captures how geopolitical threat effects vary with market conditions. We select the two-state specification based on BIC optimization across 2–4 state models, achieving optimal parsimony while capturing fundamental distinctions between normal and stressed market conditions (Ang and Bekaert 2002; Hamilton 2016).

Model selection was based on Bayesian Information Criterion (BIC) comparison across specifications with 2, 3 and 4 regimes. The two-state model achieved the lowest BIC values across portfolios (average BIC: −12,847 for 2-state vs. −12,821 for 3-state vs. −12,798 for 4-state models). This indicates optimal balance between model fit and parsimony while avoiding over-parameterization.

Volatility dynamics and temporal analysis

After establishing the impact of geopolitical threats on portfolio returns, we examine whether geopolitical threats affect return volatility. Following Nelson (1991), we estimate an EGARCH(1, 1) model where both conditional mean and variance depend on changes in the daily GPT index:

$$R_t = \beta_0 + \beta_1 \Delta \mathrm{GPT}_t + \beta_2 \Delta \mathrm{CPI}_t + \beta_3 \Delta \mathrm{UNP}_t + \beta_4 \Delta \mathrm{BYS}_t + \beta_5 \Delta \mathrm{TP}_t + \beta_6 \Delta \mathrm{TV}_t + \beta_7 z_{t-1} + \beta_8 \left(|z_{t-1}| - \sqrt{\frac{2}{\pi}} \right) + \beta_9 \ln \left(\sigma^2_{t-1} \right) + \varepsilon_t, \tag{4}$$

where coefficients (β_7, β_8, β_9) represent EGARCH specifications capturing current and lagged conditional volatility effects. This specification allows us to assess how geopolitical threats specifically influence volatility clustering and asymmetric responses which is crucial for investment decisions, security valuation, and risk management (Poon and Granger 2003).

In our EGARCH specification, portfolio returns are not demeaned prior to estimation as the model includes an intercept term that captures the unconditional mean return. The asymmetry parameter β_8 captures the leverage effect where negative return innovations have a disproportionately larger impact on conditional volatility than positive innovations of the same magnitude. When β_8 is significantly negative, it indicates that negative shocks increase volatility more than positive shocks. This reflects the typical asymmetric volatility response observed in equity markets. The persistence parameter β_9 measures how long volatility shocks persist, with values closer to unity indicating high volatility persistence.

Unlike the daily GPT index that reflects only previously published news and thus may lag markets' immediate reactions, the monthly GPT index aggregates all incidents within each calendar month and provides no information on their exact timing. This aggregation obscures the alignment between discrete news-driven spikes in threat and contemporaneous market returns and helps explain why no U.S. market portfolio exhibits a statistically significant monthly-frequency relationship with GPT.[9] To verify that geopolitical threat effects occur contemporaneously rather than following predictable patterns, we augment our baseline return regression with three-period leads and lags of the daily GPT index employing the following specifications:

$$R_t = \beta_0 + \beta_1 \Delta \mathrm{GPT}_t + \beta_2 \Delta \mathrm{GPT}_{t-1} + \beta_3 \Delta \mathrm{GPT}_{t-2} + \beta_4 \Delta \mathrm{GPT}_{t-3} + \beta_5 \Delta \mathrm{GPT}_{t+1} + \beta_6 \Delta \mathrm{GPT}_{t+2} + \beta_7 \Delta \mathrm{GPT}_{t+3} + \varepsilon_t. \tag{5}$$

This specification tests whether portfolio adjustments occur with market timing lags or reflect immediate responses

[9] For monthly frequency analysis, we found no statistically significant relationship between geopolitical threats and portfolio returns. These results are not reported in the main tables due to their consistent insignificance but are available in Appendix Table A5 for completeness. This lack of monthly effect underscores our finding that investors adjust their portfolios rapidly in response to geopolitical developments rather than exhibiting persistent monthly patterns.

Table 2 Correlation matrix

Variables	Com	Large	Large Growth	Large Value	Prime	Prime Growth	Prime Value	Mid	Mid Growth	Mid Value	Small	Small Growth	Small Value
Composite	1.000												
Large	0.997*	1.000											
Large Growth	0.956*	0.997*											
Large Value	0.958*	0.956*	0.965*	1.000									
Prime	0.947*	0.958*	0.951*	0.838*	1.000								
Prime Growth	0.903*	0.997*	0.998*	0.962*	0.951*	1.000							
Prime Value	0.912*	0.958*	0.966*	0.998*	0.843*	0.967*	1.000						
Mid	0.892*	0.959*	0.950*	0.839*	0.998*	0.953*	0.845*	1.000					
Mid Growth	0.878*	0.947*	0.941*	0.901*	0.904*	0.959*	0.922*	0.919*	1.000				
Mid Value	0.858*	0.903*	0.906*	0.919*	0.807*	0.924*	0.944*	0.819*	0.965*	1.000			
Small	0.997*	0.912*	0.896*	0.794*	0.936*	0.912*	0.810*	0.956*	0.948*	0.832*	1.000		
Small Growth	0.958*	0.892*	0.883*	0.837*	0.860*	0.904*	0.859*	0.880*	0.959*	0.908*	0.932*	1.000	
Small Value	0.959*	0.878*	0.875*	0.870*	0.804*	0.896*	0.894*	0.821*	0.950*	0.950*	0.862*	0.976*	1.000

This table presents the pairwise Pearson correlation coefficients for daily returns of twelve MSCI United States equity portfolios alongside the composite index over the 1995-2024 period (5077 observations). Composite is the MSCI United States of America composite stock index, Large is the MSCI United States Large Cap 300 Index, Large Growth is the MSCI United States Large Capital Growth Index, Large Value is the MSCI United States Large Capital Value Index, Prime is the MSCI United States Prime Market 750 Index, Prime Growth is the MSCI United States Prime Capital Growth Index, Prime Value is the MSCI United States Prime Capital Value Index, Mid is the MSCI United States Mid Capital 450 Index, Mid Growth MSCI United States Mid Capital Growth Index, Mid Value is the MSCI United States Mid Capital Value Index, Small is the MSCI United States Small Cap 1750 Index, Small Growth is the MSCI United States Small Capital Growth Index, Small Value is the MSCI United States Small Capital Value Index. All correlations marked with * are significant at the 5% level

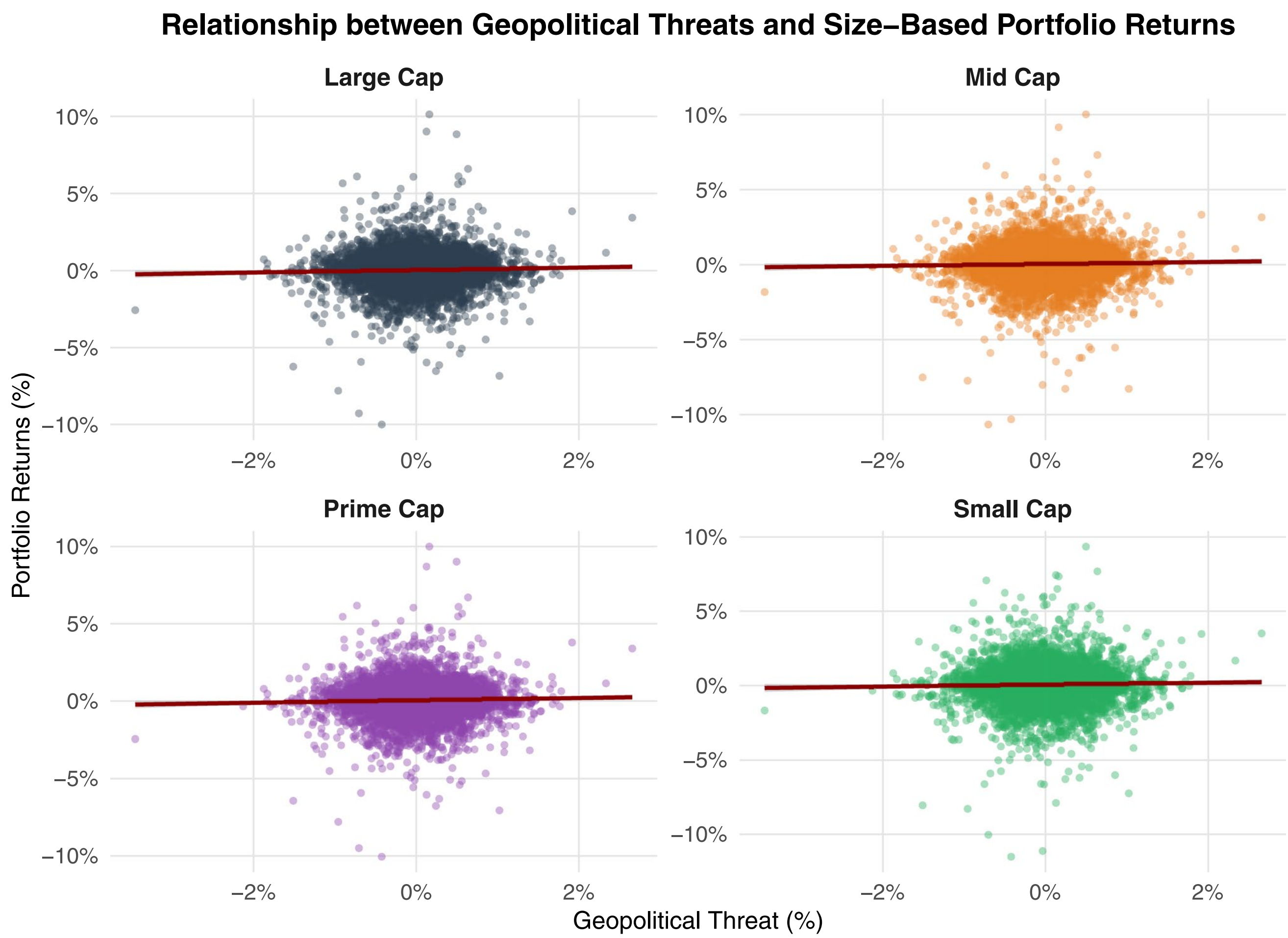

Fig. 2 A scatter plot to demonstrate the relationship between geopolitical threats and size-based portfolio returns. This figure presents scatter plots examining the relationship between daily changes in geopolitical threats and portfolio returns across four main market capitalization categories from 1995 to 2024. Each panel displays the relationship for a specific portfolio type: Large Cap (MSCI USA Large Cap 300 Index), Prime Cap (MSCI USA Prime Market 750 Index), Mid Cap (MSCI USA Mid Cap 450 Index) and Small Cap (MSCI USA Small Cap 1750 Index)

to threat announcements. The inclusion of lead terms addresses potential anticipation effects, while lag terms capture delayed adjustment patterns.

Robustness tests and economic significance

To ensure geopolitical threats represent unique risk factors distinct from general uncertainty, we compare against established uncertainty indices:

$$R_t = \beta_0 + \beta_1 \Delta \mathrm{GPT}_t + \beta_2 \Delta \mathrm{EPU}_t + \beta_3 \Delta \mathrm{VIX}_t + \beta_4 \Delta \mathrm{BEX}_t + \varepsilon_t, \tag{6}$$

where ΔEPU_t represents economic policy uncertainty by Baker et al. (2016), ΔBEX_t captures market volatility (CBOE implied volatility) and ΔBEX_t measures economic uncertainty by Bekaert et al. (2022). This specification isolates the unique effects of geopolitical threats while controlling for broader policy uncertainty, market volatility, and economic uncertainty.

We examine economic implications for portfolio management by analyzing how geopolitical threats affect optimal hedge relationships between portfolios:

$$h_t^* = \theta_0 + \theta_1 \Delta \mathrm{GPT}_t + \varepsilon_t, \tag{7}$$

where h_t^* represents the monthly minimum-variance hedge ratio calculated as $h_t^* = \frac{\rho_{gn,t}\sigma_{g,t}}{\sigma_{n,t}}$ with $\rho_{gn,t}$ denoting correlation between portfolio pairs and $\sigma_{g,t}, \sigma_{n,t}$ representing their respective standard deviations. This analysis reveals how geopolitical developments alter cross-portfolio risk relationships.

To evaluate predictive power, we conduct recursive forecasting using 70%−30%, 50%−50%, and 30%−70% sample splits. We estimate forecast models using:

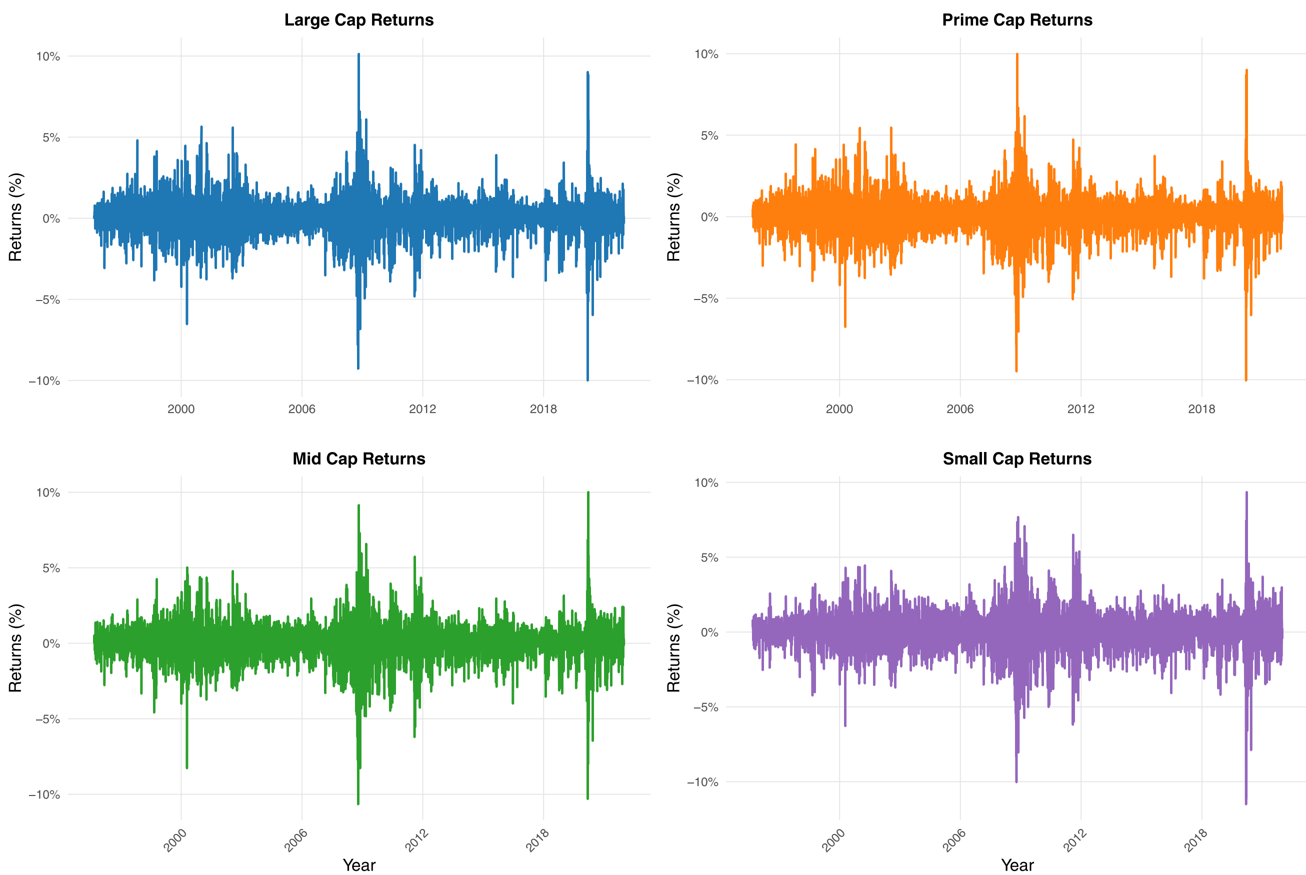

Fig. 3 Time series of portfolio returns by market capitalization. This figure presents individual time series plots for daily returns across four main market capitalization categories. Each panel highlights the distinct volatility patterns and temporal dynamics characteristic of different market segments. Large Cap returns are represented at upper left using blue line, prime Cap returns are represented at upper right using orange line, mid Cap returns are represented at lower left using green lineand small Cap returns are represented at lower right using purple line. The sample period spans from 1995 to 2024

$$R_t = \beta_0 + \beta_1 \Delta \mathrm{GPT}_t + \varepsilon_t. \tag{8}$$

and evaluate forecast accuracy through the Mincer and Zarnowitz (1969) regression:

$$\mathrm{Forecast}_t = b_0 + b_1 R_t + e_t, \tag{9}$$

where unbiased forecasts require $b_0 = 0$ and $b_1 = 1$. This approach tests whether geopolitical threat information provides genuine out-of-sample predictive content beyond in-sample fitting.

Finally, we develop four systematic strategies based on geopolitical signals: (1) high GPT levels (top 10th percentile), (2) positive threat changes (ΔGPT > 0), (3) combined high levels and positive changes, and (4) joint high GPT and high ΔGPT conditions. Performance evaluation includes both nominal and risk-adjusted return differences relative to benchmark portfolios, providing practical investment applications of our empirical findings.

Empirical findings

Differential response across market capitalizations

Our first hypothesis predicts that large and prime-cap portfolios respond positively to geopolitical threats while smaller portfolios do not. Table 3 offers strong supporting evidence. Large-cap portfolios exhibit statistically significant positive loadings on geopolitical threats ranging from 6.6 to 7.1 basis points (t-statistics: 1.96–2.12.96.12). Contrastly, small-cap coefficients remain statistically indistinguishable from zero across all periods. This differential response pattern has substantial economic implications. If we consider a one-standard-deviation increase in geopolitical threats, large-cap portfolios will generate additional returns of 33–36 basis points, while small-caps show no meaningful response. Over the 30-year sample period with approximately 25 extreme geopolitical events annually, this translates to 825–900 basis points of cumulative outperformance for large-caps during crisis periods.

Table 3 Impact of geopolitical threats on portfolio returns across different time periods

Portfolio	1995-2024	2005-2024	2015-2024
Panel A: Large-Cap Portfolios			
Large	0.069** (2.12)	0.076** (2.02)	0.107** (2.09)
Large Growth	0.071** (1.96)	0.078** (2.00)	0.126** (2.18)
Large Value	0.066** (2.07)	0.075* (1.91)	0.086* (1.75)
Panel B: Prime-Cap Portfolios			
Prime	0.066** (2.03)	0.074* (1.93)	0.103** (2.00)
Prime Growth	0.062** (1.97)	0.071* (1.81)	0.080 (1.61)
Prime Value	0.069* (1.89)	0.076* (1.93)	0.123** (2.15)
Panel C: Mid-Cap Portfolios			
Mid	0.052 (1.49)	0.061 (1.45)	0.079 (1.47)
Mid Growth	0.057 (1.43)	0.066 (1.51)	0.104* (1.84)
Mid Value	0.046 (1.39)	0.054 (1.26)	0.052 (0.91)
Panel D: Small-Cap Portfolios			
Small	0.051 (1.38)	0.058 (1.24)	0.057 (0.90)
Small Growth	0.056 (1.38)	0.057 (1.20)	0.074 (1.14)
Small Value	0.047 (1.30)	0.059 (1.21)	0.038 (0.59)
Composite	0.066** (2.04)	0.073* (1.92)	0.103** (2.01)

This table presents the coefficients for the change in geopolitical threat index (ΔGPT) from regressions estimated using the equation:$R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta CPI_t + \beta_3 \Delta UNP_t + \beta_4 \Delta BYS_t + \beta_5 \Delta TP_t + \beta_6 \Delta TV_t + \varepsilon_t$,where the dependent variable is the daily return on the US equity portfolios from 1995 to 2024. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). The t-statistics are reported in parentheses. Control variables change in the U.S. Consumer Price Index (ΔCPI), change in the U.S. Unemployment Rate (ΔUNP), change in the 10-Year Treasury Constant Maturity minus 2-Year Treasury Constant Maturity (ΔBYS), change in the U.S. ACM Treasury Term Premia FIT Yield 10-Year (ΔTP), Change in the United States Retail Trade Volume (ΔTV) are included in all specifications but not reported for brevity. Complete regression results including all control variables are provided in Appendix Table A1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

The consistency of this pattern across three distinct sample periods, including the post-financial crisis era, demonstrates robustness beyond sample-specific effects. Notably, the effect strengthens in recent periods (2015-2024), suggesting that modern market structure and institutional investor behavior amplify rather than diminish these size-based flight-to-quality dynamics. The absence of significant effects for mid and small-cap portfolios cannot be attributed to insufficient statistical power, as these portfolios exhibit higher volatility and larger standard errors. Instead, this null result supports our theoretical framework about the information processing advantages, financial flexibility, and institutional preferences that benefit large firms during uncertainty simply don't extend to smaller market segments.

Figures 2 and 3 strongly support our empirical findings. Figure 2 shows a progressive weakening of positive associations from large- to small-cap portfolios, with trend lines highlighting the size-dependent pattern. Figure 3 adds temporal context, showing larger portfolios maintain more stable volatility profiles that align with their role as safe havens during geopolitical uncertainty. Together, these visuals intuitively confirm the statistical results and clarify the practical implications of size-dependent flight-to-quality behavior.

Safe haven properties during extreme geopolitical threats

Our safe haven hypothesis requires evidence of amplified positive response during extreme geopolitical periods beyond normal performance. Table 4 results validats this prediction decisively. Large-cap portfolios exhibit additional crisis responses of 15.4–20.0 basis points, beyond their already positive baseline responses of 6.6 to 7.1 basis points shown in Table 3, during extreme threat periods with statistical significance at conventional levels across most specifications. These amplification effects represent genuine safe haven premiums. During the approximately 12 extreme geopolitical events per year (top 10th percentile days), large-cap portfolios outperform their own normal response by 185–240 basis points annually. This crisis premium persists even after controlling for general market volatility and economic uncertainty, indicating that geopolitical threats create unique demand for large-cap equity exposure.

The absence of safe haven properties in mid and small-cap portfolios strengthens our argument. If general market dynamics drove these results, we would observe similar amplification across size segments. Instead, the concentration of safe haven effects in large and prime-cap portfolios supports our theoretical channels. It states that only the largest firms possess the combination of information advantages, financial resources, and institutional investor appeal necessary to attract crisis-driven capital flows. The temporal stability of these effects deserves emphasis. Safe haven premiums remain remarkably consistent across our three sample periods. This finding suggests that the underlying economic mechanisms transcend specific market regimes or regulatory changes.

Regime-dependent amplification

Our volatility regime analysis provides the most compelling evidence for large-cap safe haven properties. Table 5 demonstrates that geopolitical threat responses amplify dramatically during high-volatility regimes and large-cap coefficients increase from statistically insignificant 2.2 basis points during calm periods to highly significant 17.9 basis points during volatile periods. This eight-fold amplification demonstrates that safe haven demand emerges precisely when market stress peaks. The regime-switching framework captures a fundamental behavioral shift. During normal periods geopolitical developments represent background noise. On contrary, during volatile periods they trigger immediate capital reallocation toward perceived safety.

The conditional nature of these effects addresses potential reverse causality concerns. If large-cap outperformance mechanically caused measured geopolitical threats, we would observe consistent effects across volatility regimes. Instead, the regime-dependent pattern suggests that genuine flight-to-quality behavior drives our results and it is activated only when market conditions heighten investor risk aversion. Remarkably, some small-cap portfolios also show positive loadings during high-volatility regimes but these effects are smaller and less consistent. This suggests that while extreme market stress may create some generalized equity demand, the preference for large-caps remains dominant during geopolitical crises. This conditional relationship highlights the importance of dynamic asset allocation strategies that consider both geopolitical developments and prevailing market volatility.

Volatility dynamics and threat specificity

Beyond return impacts, geopolitical threats significantly influence volatility dynamics. Table 6 reveals that large and prime-cap portfolios exhibit stronger volatility responses to geopolitical threats, with coefficients ranging from 0.052 to 0.076 (t-statistics: 1.94–2.75.94.75). This creates a complex risk-return tradeoff. While these portfolios benefit from positive return effects during threats, they simultaneously experience heightened volatility.

Large growth and prime value portfolios exhibit the strongest volatility responses to geopolitical threats, with coefficients of 0.074 (t-statistic: 2.48) and 0.076 (t-statistic:

Table 4 Safe haven properties during high geopolitical threat periods

Portfolio	1995-2024	2005-2024	2015-2024
Panel A: Large-Cap Portfolios			
Large	0.223** (2.02)	0.276** (2.31)	0.225* (1.67)
Large Growth	0.220* (1.82)	0.283** (2.30)	0.232 (1.53)
Large Value	0.218** (2.03)	0.265** (2.14)	0.213* (1.65)
Panel B: Prime-Cap Portfolios			
Prime	0.217** (1.97)	0.270** (2.23)	0.218 (1.62)
Prime Growth	0.209* (1.95)	0.255** (2.05)	0.202 (1.55)
Prime Value	0.221* (1.79)	0.279** (2.25)	0.228 (1.53)
Panel C: Mid-Cap Portfolios			
Mid	0.188 (1.59)	0.217 (1.61)	0.184 (1.30)
Mid Growth	0.208 (1.53)	0.231 (1.64)	0.211 (1.43)
Mid Value	0.164 (1.47)	0.206 (1.51)	0.151 (1.01)
Panel D: Small-Cap Portfolios			
Small	0.204 (1.61)	0.225 (1.59)	0.135 (0.82)
Small Growth	0.227 (1.64)	0.237 (1.61)	0.167 (0.98)
Small Value	0.179 (1.46)	0.218 (1.42)	0.096 (0.57)
Composite	0.217** (1.98)	0.272** (2.25)	0.220 (1.64)

This table presents the additional response of portfolios to geopolitical threats during extreme periods (top 10th percentile GPT days) beyond their normal response reported in Table 3. The regression model is as follows: $R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2(\Delta GPT_t \times \text{High GPT Dummy}_t) + \beta_3 \Delta CPI_t + \beta_4 \Delta UNP_t + \beta_5 \Delta BYS_t + \beta_6 \Delta TP_t + \beta_7 \Delta TV_t + \varepsilon_t,$ where the dependent variable is the daily return on the US equity portfolios from 1995 to 2024. A High GPT Dummy equals 1 when geopolitical threats are in the highest 10th percentile, otherwise the value is 0. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). The t-statistics are reported in parentheses. Control variables change in the U.S. Consumer Price Index (ΔCPI), change in the U.S. Unemployment Rate (ΔUNP), change in the 10-Year Treasury Constant Maturity minus 2-Year Treasury Constant Maturity (ΔBYS), change in the U.S. ACM Treasury Term Premia FIT Yield 10-Year (ΔTP), Change in the United States Retail Trade Volume (ΔTV) are included in all specifications but not reported for brevity. Complete regression results including all control variables are provided in Appendix Table A2. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table 5 Regime-dependent effects of geopolitical threats on portfolio returns

Portfolio	High volatility regime	Low volatility regime
Panel A: Large-Cap Portfolios		
Large	0.179** (2.02)	0.022 (0.83)
Large Growth	0.165* (1.86)	0.019 (0.68)
Large Value	0.226* (1.83)	0.026 (1.05)
Panel B: Prime-Cap Portfolios		
Prime	0.179* (1.93)	0.021 (0.81)
Prime Growth	0.226* (1.76)	0.024 (0.98)
Prime Value	0.169* (1.80)	0.018 (0.62)
Panel C: Mid-Cap Portfolios		
Mid	0.210* (1.65)	0.007 (0.27)
Mid Growth	0.183 (1.42)	0.017 (0.56)
Mid Value	0.178 (1.25)	0.013 (0.52)
Panel D: Small-Cap Portfolios		
Small	0.181** (1.99)	0.020 (0.76)
Small Growth	0.179** (2.02)	0.022 (0.83)
Small Value	0.165* (1.86)	0.019 (0.68)
Composite	0.181** (1.99)	0.020 (0.76)

This table presents the coefficients for ΔGPT from a two-state Markov regime-switching model estimated using the equation: $R_t = \beta_0 + \beta_{s_t,1}\Delta GPT_t + \beta_{s_t,2}\Delta CPI_t + \beta_{s_t,3}\Delta UNP_t + \beta_{s_t,4}\Delta BYS_t + \beta_{s_t,5}\Delta TP_t + \beta_{s_t,6}\Delta TV_t + \varepsilon_t$, where s_t indicates a discrete regime variable taking values in {1,2} following a 2-state Markov process for different regime states; $\varepsilon_t \sim N(0, \sigma^2_{s_t})$. We evaluated two-regime models with regime-dependent variances. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). The t-statistics are reported in parentheses. Control variables change in the U.S. Consumer Price Index (ΔCPI), change in the U.S. Unemployment Rate (ΔUNP), change in the 10-Year Treasury Constant Maturity minus 2-Year Treasury Constant Maturity (ΔBYS), change in the U.S. ACM Treasury Term Premia FIT Yield 10-Year (ΔTP), Change in the United States Retail Trade Volume (ΔTV) are included in all specifications but not reported for brevity. Complete regression results including all control variables are provided in Appendix Table A3. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table 6 Impact of geopolitical threats on conditional volatility

Portfolio	ΔGPT Effect	EGARCH parameters		
	Mean equation	z_{t-1}	$\lvert z_{t-1}\rvert - \sqrt{2/\pi}$	$\ln(\sigma^2_{t-1})$
Panel A: Large-Cap Portfolios				
Large	0.052* (1.94)	−0.089*** (−5.17)	0.447*** (26.11)	0.934*** (170.10)
Large Growth	0.074** (2.48)	−0.083*** (−4.82)	0.422*** (26.36)	0.947*** (202.52)
Large Value	0.065*** (2.61)	−0.079*** (−4.49)	0.444*** (24.88)	0.934*** (178.51)
Panel B: Prime-Cap Portfolios				
Prime	0.060** (2.14)	−0.092*** (−5.34)	0.441*** (25.31)	0.935*** (168.69)
Prime Growth	0.070*** (2.75)	−0.078*** (−4.57)	0.434*** (24.79)	0.937*** (183.58)
Prime Value	0.076** (2.49)	−0.090*** (−5.31)	0.408*** (26.15)	0.951*** (206.30)
Panel C: Mid-Cap Portfolios				
Mid	0.047 (1.53)	−0.094*** (−5.86)	0.399*** (22.91)	0.946*** (187.46)
Mid Growth	0.044 (1.22)	−0.095*** (−5.90)	0.381*** (22.56)	0.955*** (204.50)
Mid Value	0.046* (1.67)	−0.092*** (−6.12)	0.384*** (23.19)	0.954*** (222.81)
Panel D: Small-Cap Portfolios				
Small	0.039 (1.12)	−0.085*** (−5.31)	0.419*** (22.88)	0.942*** (175.09)
Small Growth	0.026 (0.67)	−0.088*** (−5.08)	0.397*** (20.95)	0.942*** (157.86)
Small Value	0.037 (1.23)	−0.069*** (−4.78)	0.417*** (24.90)	0.951*** (242.58)

This table presents the EGARCH model results showing the effect of geopolitical threats on conditional volatility. The model is estimated using the equation: $R_t = \beta_0 + \beta_1\Delta GPT_t + \beta_2\Delta CPI_t + \beta_3\Delta UNP_t + \beta_4\Delta BYS_t + \beta_5\Delta TP_t + \beta_6\Delta TV_t + \beta_7 z_{t-1} + \beta_8(\lvert z_{t-1}\rvert - \sqrt{2/\pi}) + \beta_9 \ln(\sigma^2_{t-1}) + \varepsilon_t$. The t-statistics are reported in parentheses. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). The t-statistics are reported in parentheses. Control variables change in the U.S. Consumer Price Index (ΔCPI), change in the U.S. Unemployment Rate (ΔUNP), change in the 10-Year Treasury Constant Maturity minus 2-Year Treasury Constant Maturity (ΔBYS), change in the U.S. ACM Treasury Term Premia FIT Yield 10-Year (ΔTP), Change in the United States Retail Trade Volume (ΔTV) are included in all specifications but not reported for brevity. Complete results for all portfolios including growth and value subcategories are provided in Appendix Table A6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table 7 Impact of geopolitical threats on returns using alternative measures of market uncertainty

Portfolio	Daily data				Monthly data				
	ΔGPT	ΔEPU	ΔVIX	ΔBEX	ΔGPT	ΔEPU	ΔVIX	ΔBEX	ΔUNC
Panel A: Large-Cap Portfolios									
Large	0.050** (2.21)	−0.000 (−0.39)	−0.129*** (−69.93)	−0.011*** (−4.78)	0.039 (0.26)	−0.000 (−0.27)	−0.147*** (−15.75)	−0.000 (−0.03)	−0.046 (−0.55)
Large Growth	0.050* (1.90)	−0.000 (−0.63)	−0.136*** (−64.25)	−0.014*** (−5.42)	0.043 (0.24)	−0.001 (−1.06)	−0.159*** (−14.00)	−0.001 (−0.05)	0.014 (0.14)
Large Value	0.050** (2.12)	−0.000 (−0.06)	−0.121*** (−63.49)	−0.007*** (−3.18)	0.025 (0.17)	0.001 (0.82)	−0.134*** (−14.51)	−0.001 (−0.10)	−0.115 (−1.39)
Panel B: Prime-Cap Portfolios									
Prime	0.047** (2.08)	−0.000 (−0.44)	−0.129*** (−70.33)	−0.012*** (−5.11)	0.045 (0.30)	−0.001 (−0.57)	−0.149*** (−16.14)	−0.002 (−0.28)	−0.042 (−0.51)
Prime Growth	0.046** (1.99)	−0.000 (−0.09)	−0.121*** (−63.81)	−0.008*** (−3.46)	0.013 (0.09)	0.001 (0.62)	−0.135*** (−14.83)	−0.002 (−0.27)	−0.108 (−1.31)
Prime Value	0.047* (1.82)	−0.000 (−0.69)	−0.137*** (−65.04)	−0.015*** (−5.77)	0.064 (0.35)	−0.002 (−1.36)	−0.162*** (−14.27)	−0.004 (−0.32)	0.013 (0.12)
Panel C: Mid-Cap Portfolios									
Mid	0.033 (1.30)	−0.000 (−0.57)	−0.132*** (−64.51)	−0.015*** (−5.93)	0.065 (0.39)	−0.002* (−1.81)	−0.161*** (−15.70)	−0.013 (−1.27)	−0.021 (−0.23)
Mid Growth	0.035 (1.17)	−0.000 (−0.82)	−0.144*** (−59.47)	−0.019*** (−6.44)	0.150 (0.71)	−0.004** (−2.36)	−0.177*** (−13.45)	−0.019 (−1.43)	−0.000 (−0.00)
Mid Value	0.030 (1.18)	−0.000 (−0.11)	−0.120*** (−58.59)	−0.011*** (−4.24)	−0.052 (−0.32)	−0.000 (−0.30)	−0.145*** (−14.49)	−0.009 (−0.86)	−0.062 (−0.69)
Panel D: Small-Cap Portfolios									
Small	0.032 (1.14)	0.000 (0.00)	−0.136*** (−59.70)	−0.016*** (−5.82)	0.091 (0.49)	−0.001 (−1.05)	−0.162*** (−14.10)	−0.019* (−1.68)	−0.009 (−0.08)
Small Growth	0.047** (2.11)	−0.000 (−0.29)	−0.129*** (−70.56)	−0.011*** (−4.81)	0.154 (0.71)	−0.002 (−1.39)	−0.174*** (−12.98)	−0.028** (−2.07)	0.010 (0.08)
Small Value	0.050** (2.21)	−0.000 (−0.39)	−0.129*** (−69.93)	−0.011*** (−4.78)	0.012 (0.06)	−0.000 (−0.34)	−0.150*** (−13.29)	−0.012 (−1.04)	−0.040 (−0.39)
Composite	0.047** (2.11)	−0.000 (−0.29)	−0.129*** (−70.56)	−0.011*** (−4.81)	0.038 (0.26)	−0.000 (−0.09)	−0.147*** (−15.87)	−0.002 (−0.18)	−0.045 (−0.53)

This table presents regression results (utilizing both daily and monthly data) using different uncertainty measures estimated using the equation: $R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta EPU_t + \beta_3 \Delta VIX_t + \beta_4 \Delta BEX_t + \beta_5 \Delta UNC_t + \varepsilon_t$, where the dependent variable is the daily and monthly return on the US equity portfolios from 1995 to 2024 respectively. ΔGPT is the change in geopolitical threat, ΔEPU is the economic policy uncertainty index of Baker et al. (2016), ΔVIX is the CBOE implied volatility index, ΔBEX is the economic uncertainty index of Bekaert et al. (2022), and ΔUNC is the macroeconomic uncertainty index of Jurado et al. (2015). For daily data, we implement the regression without ΔUNC because this index provides the monthly data. The t-statistics are reported in parentheses. Complete results for all uncertainty measures including ΔEPU, ΔVIX, ΔBEX, and ΔUNC are provided in Appendix Table A4.***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

2.49), respectively. In contrast, mid and small-cap portfolios generally demonstrate weaker volatility responses. The EGARCH parameters are highly significant across all portfolios, indicating strong asymmetric volatility responses and persistence. These findings imply that while geopolitical threats positively affect returns for large and prime-cap portfolios, they also introduce additional volatility.

Uniqueness of geopolitical threats

Table 7 demonstrates that geopolitical threats represent fundamentally different uncertainty from other risk measures. While large-cap portfolios load positively on geopolitical threats (coefficients 0.046–0.050), they exhibit strongly negative relationships with VIX (−0.120 to −0.144) and economic uncertainty (−0.007 to −0.019). This stark contrast confirms that geopolitical threats trigger unique investor behaviors not captured by general market or policy uncertainty measures.

The contrasting coefficients between geopolitical threats and alternative uncertainty measures highlight the unique nature of geopolitical risk. While ΔGPT exhibits positive relationships with large and prime-cap returns (coefficients ranging from 0.046 to 0.050), both VIX and BEX show strong negative relationships (coefficients of −0.120 to −0.144 for VIX and −0.007 to −0.019 for BEX). This pattern suggests that geopolitical threats trigger fundamentally different investor behaviors compared to general market or economic uncertainty. The insignificant coefficients for EPU further underscore that geopolitical risk represents a unique dimension of uncertainty that cannot be subsumed by broader policy uncertainty measures.

Temporal response pattern

Our lead-lag analysis in Table 8 reveals no significant relationships at various leads and lags, indicating that portfolio adjustments occur contemporaneously with threat announcements rather than following predictable timing patterns. This immediate response supports efficient market principles and suggests that geopolitical information is rapidly incorporated into prices.

Our analysis of monthly frequency data in Appendix Table A5 reveals a notable contrast to our daily results. None of the portfolios exhibit statistically significant relationships with geopolitical threats at the monthly frequency. The coefficients for ΔGPT are negative but statistically insignificant across all portfolios, ranging from −0.099 (Mid Growth) to −0.234 (Mid Value). This absence of monthly effects combined with our findings on lead-lag relationships in Table 8 strongly suggests that investors adjust their holdings rapidly in response to geopolitical developments rather than exhibiting persistent monthly patterns. This temporal dimension of market response provides valuable insights into the speed of information processing during geopolitical events, supporting efficient market perspectives. Interestingly, term premium (ΔTP) maintains its significant positive relationship with returns at the monthly frequency, suggesting its role as a more persistent driver of returns compared to geopolitical threats.

Table 8 The lead-lag relationship between geopolitical threat (GPT) and portfolio returns

Portfolio	ΔGPT_{t-1}	ΔGPT_{t-2}	ΔGPT_{t-3}	ΔGPT_{t+1}	ΔGPT_{t+2}	ΔGPT_{t+3}
Panel A: Large-Cap Portfolios						
Large	0.034	0.025	0.011	−0.025	−0.029	−0.035
	(1.00)	(0.73)	(0.32)	(−0.73)	(−0.84)	(−1.03)
Large Growth	0.041	0.021	0.027	−0.018	−0.027	−0.035
	(1.08)	(0.56)	(0.71)	(−0.48)	(−0.70)	(−0.94)
Large Value	0.027	0.030	−0.006	−0.033	−0.031	−0.034
	(0.80)	(0.88)	(−0.18)	(−0.99)	(−0.92)	(−1.01)
Panel B: Prime-Cap Portfolios						
Prime	0.035	0.025	0.012	−0.027	−0.026	−0.036
	(1.03)	(0.74)	(0.34)	(−0.78)	(−0.75)	(−1.06)
Prime Growth	0.028	0.030	−0.006	−0.037	−0.030	−0.033
	(0.82)	(0.90)	(−0.19)	(−1.10)	(−0.91)	(−1.00)
Prime Value	0.042	0.022	0.029	−0.018	−0.021	−0.038
	(1.11)	(0.57)	(0.76)	(−0.48)	(−0.56)	(−1.02)
Panel C: Mid-Cap Portfolios						
Mid	0.043	0.026	0.017	−0.036	−0.008	−0.043
	(1.16)	(0.72)	(0.47)	(−0.98)	(−0.21)	(−1.19)
Mid Growth	0.053	0.023	0.042	−0.016	0.009	−0.056
	(1.26)	(0.54)	(1.01)	(−0.38)	(0.22)	(−1.35)
Mid Value	0.033	0.031	−0.006	−0.055	−0.027	−0.033
	(0.93)	(0.89)	(−0.18)	(−1.58)	(−0.79)	(−0.93)
Panel D: Small-Cap Portfolios						
Small	0.052	0.036	0.004	−0.053	−0.009	−0.049
	(1.32)	(0.92)	(0.10)	(−1.35)	(−0.24)	(−1.24)
Small Growth	0.062	0.031	0.018	−0.044	−0.003	−0.056
	(1.46)	(0.73)	(0.42)	(−1.03)	(−0.07)	(−1.33)
Small Value	0.040	0.041	−0.009	−0.062	−0.018	−0.042
	(1.06)	(1.07)	(−0.23)	(−1.62)	(−0.46)	(−1.09)
Composite	0.037	0.028	0.009	−0.026	−0.029	−0.032
	(1.09)	(0.82)	(0.27)	(−0.77)	(−0.86)	(−0.93)

This table presents the coefficients for lagged and lead values of ΔGPT from regressions estimated using the equation: $R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta GPT_{t-1} + \beta_3 \Delta GPT_{t-2} + \beta_4 \Delta GPT_{t-3} + \beta_5 \Delta GPT_{t+1} + \beta_6 \Delta GPT_{t+2} + \beta_7 \Delta GPT_{t+3} + \varepsilon_t$, where the dependent variable is the daily return on the US equity portfolios from 1995 to 2024. The contemporaneous effect ($\Delta \mathrm{GPT}_t$) is not shown because it has already been shown in Table 3. The t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Hedging and trading strategy implications

Geopolitical threats systematically alter optimal hedging relationships between portfolios of different capitalizations. Table 9 presents our analysis of optimal hedge ratios. The Large/Small combination shows the strongest effect (coefficient: 0.38, t-stat: 1.84), indicating that during geopolitical stress investors must substantially increase small-cap positions to hedge large-cap exposures. This finding has practical implications for institutional investors managing cross-size hedging strategies.

The varying magnitudes across portfolio combinations, from 0.04 for Large/Prime to 0.38 for Large/Small, provide a granular view of how geopolitical threats alter the cross-sectional risk structure of equity markets, with the effect intensifying as the capitalization distance between portfolios increases.

Our out-of-sample analysis in Table 10 confirms the robustness of our findings across various estimation windows. Large and prime-cap portfolios demonstrate superior forecast performance, with coefficients exceeding unity in the 70%–30% split (ranging from 1.96 to 2.77). This indicates a genuine predictive content rather than in-sample overfitting.

Finally, Table 11 translates our empirical insights into actionable investment approaches. Strategies based on high geopolitical threat signals generate substantial risk-adjusted excess returns for large-cap portfolios (0.52% concurrent returns). This demonstrates the economic value of incorporating geopolitical intelligence into investment decisions. The superior performance of large-cap focused strategies during crisis periods provides concrete evidence of their safe haven properties.

For institutional investors to manage large pools of capital such as pension funds or sovereign wealth funds, these magnitudes translate to meaningful performance improvements during crisis periods. The implementation requires monitoring real-time geopolitical developments and adjusting allocations accordingly. The particular emphasis is on increasing large-cap exposures when geopolitical tensions rise. For individual investors, our findings suggest maintaining a strategic overweight to large-cap stocks as a buffer against unexpected geopolitical shocks, particularly during periods of elevated global tensions. The effectiveness of these trading strategies underscores the practical significance of our findings for investment management during periods of heightened global uncertainty.

Concluding remarks

This study demonstrates that geopolitical threats affect U.S. equity markets through systematic size-dependent channels. Large and prime-cap portfolios generate significantly positive returns during geopolitical stress, while small and mid-cap portfolios show no response. This relationship intensifies eight-fold during high-volatility regimes and confirms that flight-to-quality behavior emerges precisely when market stress peaks. Our findings reverse traditional size effects during crisis periods. Large-cap portfolios exhibit 6.6–7.1.6.1 basis points additional daily returns per unit geopolitical threat increase and are amplified to 15.4–20.0.4.0 basis points during extreme events. Over our 30-year sample, this translates to substantial cumulative outperformance during crisis periods. The contemporaneous nature of responses indicates efficient information processing rather than predictable timing patterns.

While focusing on the U.S. equity market yields useful insights given its global role and relative geopolitical insulation, this geographic focus may limit generalizability. Future research should test whether the same size-dependent flight-to-quality patterns occur in other developed markets (e.g., Europe, Japan, Australia) and in emerging markets with different geopolitical exposures.

Theoretically, our results validate predictions based on large firms' information processing advantages, financial flexibility, institutional preferences, and operational diversification. We extend safe haven literature from cross-asset to intra-asset class dynamics. We show that certain equity segments serve as relative refuges during geopolitical crises. Practically, our trading strategies generate 0.52% risk-adjusted excess returns during high-threat periods that demonstrate genuine economic value. The consistency across multiple sample periods and robustness against alternative uncertainty measures suggest fundamental rather than transitory phenomena.

Our visual analysis reinforces the empirical conclusions. Time-series plots show geopolitical events produce distinct,

Table 9 Hedging ratio: impact of geopolitical threat on the US equity portfolio combinations

Portfolio	θ_1	θ_0
Large/Prime	0.043 (1.63)	0.995*** (538.08)
Large/Mid	0.269* (1.91)	0.876*** (88.25)
Large/Small	0.379* (1.84)	0.762*** (52.88)
Prime/Mid	0.226* (1.94)	0.897*** (109.33)
Prime/Small	0.341* (1.81)	0.781*** (58.94)
Mid/Small	0.139 (1.10)	0.876*** (98.73)

This table presents the coefficients for ΔGPT from the hedge ratio analysis of optimal hedge position for each portfolio, calculated monthly as the minimum-variance hedge ratio, using the equation: $h_t^* = \frac{\rho_{gn,t}\sigma_{g,t}}{\sigma_{n,t}}$, where $\rho_{gn,t}$ is the correlation of one asset and the other assets within the portfolio in month t, and $\sigma_{g,t}$ and $\sigma_{n,t}$ are standard deviations of one asset and the other assets within the portfolio 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 the following equation: $h_t^* = \theta_0 + \theta_1 \Delta GPT_t + \varepsilon_t$, where h_t^* is the optimum hedge ratio and ΔGPT is the change in geopolitical threat for month *t*. The t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table 10 Regression coefficients between out-of-sample forecast values and real values for different combinations

	50–50% Split				70–30% Split				30–70% Split			
Portfolio	Forecast	t-stat	Constant	t-stat	Forecast	t-stat	Constant	t-stat	Forecast	t-stat	Constant	t-stat
Panel A: Large-Cap Portfolios												
Large	1.215**	(2.09)	0.052**	(2.32)	2.333**	(2.52)	−0.00293	(−0.08)	1.404**	(2.26)	0.00431	(0.17)
Large Growth	1.249**	(2.07)	0.055**	(2.22)	2.754**	(2.49)	−0.0154	(−0.33)	1.196**	(2.19)	0.00475	(0.17)
Large Value	1.182**	(1.96)	0.048**	(2.17)	1.959**	(2.31)	0.00284	(0.09)	1.727**	(2.19)	0.00774	(0.34)
Panel B: Prime-Cap Portfolios												
Prime	1.295**	(2.04)	0.049**	(2.05)	2.350**	(2.44)	−0.0140	(−0.35)	1.439**	(2.17)	−0.00048	(−0.02)
Prime Growth	1.254*	(1.89)	0.046**	(1.99)	1.967**	(2.19)	−0.00573	(−0.17)	1.797**	(2.10)	0.00078	(0.03)
Prime Value	1.331**	(2.05)	0.0518*	(1.95)	2.768**	(2.45)	−0.0283	(−0.55)	1.204**	(2.11)	0.00254	(0.08)
Panel C: Mid-Cap Portfolios												
Mid	0.907*	(1.73)	0.0091	(0.19)	2.406*	(1.93)	−0.0721	(−0.96)	1.710*	(1.67)	−0.0378	(−0.61)
Mid Growth	1.084*	(1.85)	0.00526	(0.10)	2.795**	(2.14)	−0.0897	(−1.07)	1.240	(1.64)	−0.0093	(−0.18)
Mid Value	0.829	(1.49)	−0.0096	(−0.17)	1.948	(1.53)	−0.0499	(−0.72)	2.417	(1.57)	−0.0601	(−0.83)
Panel D: Small-Cap Portfolios												
Small	1.049	(1.43)	0.0025	(0.05)	1.898	(1.51)	−0.0676	(−0.81)	1.224	(1.41)	−0.0266	(−0.43)
Small Growth	1.023	(1.45)	0.0113	(0.19)	2.165*	(1.66)	−0.0851	(−0.90)	0.705	(1.28)	0.0133	(0.29)
Small Value	0.942	(1.34)	−0.022	(−0.30)	1.561	(1.25)	−0.0480	(−0.65)	2.697	(1.46)	−0.107	(−1.01)
Composite	1.238**	(2.02)	0.056**	(2.48)	2.355**	(2.45)	−0.00355	(−0.10)	1.372**	(2.16)	0.0112	(0.46)

This table presents the values of regression coefficients of the out-of-sample regression model. Panels A-C present out-of-sample forecast performance based on the equation: $\text{Forecast}_t = b_0 + b_1 R_t + e_t$, where Forecast_t is the estimated or forecasted out-of-sample values of US equity portfolio returns of 12 different categories based on market capitalization in time t and R_t is the daily actual US equity portfolio returns based on market capitalization at time t. Results are shown for three different estimation windows: 50%–50%, 70%–30%, and 30%–70%. The t-statistics are reported in parentheses. Following Mincer and Zarnowitz (1969), we regress the forecasted values on actual realized returns to evaluate forecast performance. This specification tests whether forecasts are unbiased (intercept = 0) and efficient (slope = 1). While some literature suggests reversing the dependent and independent variables to address potential errors-in-variables problems (Forbes and Rigobon 2002), our approach maintains consistency with the traditional forecast evaluation framework. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table 11 Trading strategies for different scenarios of geopolitical threats

Panel A: Concurrent (in percentage)

Index	$\Delta GPT > 0$		High GPT		High GPT & $\Delta GPT > 0$		High GPT & High ΔGPT	
	Nominal	Risk-adjusted	Nominal	Risk-adjusted	Nominal	Risk-adjusted	Nominal	Risk-adjusted
Large-Cap Portfolios								
Large	0.066	0.032	0.518	0.524	0.495	0.519	−0.150	−0.141
Large Growth	0.850	0.043	3.252	1.532	2.399	0.598	2.279	−0.647
Large Value	−0.795	−0.574	−2.516	−1.730	−1.814	−0.845	−2.942	−1.665
Prime-Cap Portfolios								
Prime	0.310	0.224	0.299	0.329	0.260	0.309	0.377	0.618
Prime Growth	−0.636	−0.414	−2.661	−1.871	−2.024	−1.072	−2.771	−1.383
Prime Value	1.162	0.252	2.976	1.357	2.148	0.461	3.121	0.464
Mid-Cap Portfolios								
Mid	1.511	0.795	−0.799	−0.991	−1.049	−1.261	2.923	2.862
Mid Growth	2.541	0.618	1.480	−0.128	0.578	−1.034	7.447	4.372
Mid Value	0.212	0.093	−3.305	−2.852	−3.080	−2.658	−2.200	−1.947
Small-Cap Portfolios								
Small	0.964	0.013	−1.427	−1.855	−0.254	−1.116	4.104	0.653
Small Growth	2.270	0.377	1.365	−0.599	2.078	−0.466	8.600	2.330
Small Value	−0.536	−0.959	−4.417	−3.936	−2.882	−2.681	−0.740	−3.243

Panel B: Prior (in percentage)

Index	$\Delta GPT > 0$		High GPT		High GPT & $\Delta GPT > 0$		High GPT & High ΔGPT	
	Nominal	Risk-adjusted	Nominal	Risk-adjusted	Nominal	Risk-adjusted	Nominal	Risk-adjusted
Large-Cap Portfolios								
Large	−0.098	−0.098	0.042	0.062	−0.201	−0.197	−0.344	−0.348
Large Growth	1.577	0.970	2.756	1.920	3.313	2.892	0.125	0.585
Large Value	−1.886	−1.625	−2.728	−2.479	−3.898	−3.997	−1.009	−1.350
Prime-Cap Portfolios								
Prime	0.173	0.135	0.140	0.170	−0.092	−0.093	−0.110	−0.167
Prime Growth	−1.496	−1.274	−2.543	−2.285	−3.564	−3.675	−0.276	−0.623
Prime Value	1.726	1.074	2.787	1.975	3.222	2.825	−0.121	0.329
Mid-Cap Portfolios								
Mid	1.613	1.143	0.761	0.617	0.527	0.506	1.013	0.891
Mid Growth	2.411	1.221	2.970	1.859	2.658	2.258	−1.714	−1.057
Mid Value	0.560	0.427	−1.431	−1.248	−1.706	−1.696	3.488	3.311
Small-Cap Portfolios								
Small	1.412	0.715	−0.161	−0.444	−0.059	−0.010	1.960	2.085
Small Growth	2.645	1.305	1.696	0.671	1.772	1.492	−0.103	0.578
Small Value	−0.014	−0.314	−1.997	−1.930	−1.901	−1.718	3.862	3.765

This table shows the performance of hedging/trading strategies based on geopolitical threat-related trading signals. We report both normal and risk-adjusted return differences from the benchmark return (portfolio returns-benchmark return). Panel A demonstrates the concurrent return differences and Panel B demonstrates the prior return differences. $\Delta GPT > 0$ indicates the state when geopolitical threat change is greater than 0, and High GPT indicates when geopolitical threat is above the top 10%. A high ΔGPT indicates when the change in geopolitical threat is above the top 10%

size-dependent responses with larger firms exhibiting the stability expected of safe-haven assets. Scatter plots reveal a progressive weakening of the relationship from large- to small-cap and illustrate how market capitalization moderates sensitivity to geopolitical risk.

As geopolitical tensions continue shaping investment landscapes, understanding size-dependent crisis responses becomes crucial for portfolio management. Our findings provide both theoretical insight and practical tools for constructing resilient portfolios during global uncertainty, offering valuable guidance for navigating increasingly turbulent environments.

Appendix Tables

Table A1 Complete regression results for the impact of geopolitical threats on portfolio returns across different time periods

Portfolio	1995-2024							2005-2024							2015-2024						
	ΔGPT	ΔCPI	ΔUNP	ΔBYS	ΔTP	ΔTV	Cons	ΔGPT	ΔCPI	ΔUNP	ΔBYS	ΔTP	ΔTV	Cons	ΔGPT	ΔCPI	ΔUNP	ΔBYS	ΔTP	ΔTV	Cons
Panel A: Large-Cap Portfolios																					
Large	0.069**	0.016	0.006**	−0.284***	14.437***	0.019*	0.033*	0.076**	0.029	0.005**	−0.241*	14.88***	0.010	0.037	0.107**	0.173	0.006**	−0.226	10.87***	0.001	0.022
	(2.12)	(0.26)	(2.38)	(−2.58)	(19.99)	(1.83)	(1.70)	(2.02)	(0.46)	(2.09)	(−1.67)	(19.88)	(0.84)	(1.62)	(2.09)	(1.43)	(2.13)	(−0.80)	(11.90)	(0.10)	(0.59)
L. Growth	0.071**	0.018	0.007***	−0.251**	13.727***	0.028**	0.041*	0.078**	0.032	0.006**	−0.216	13.64***	0.013	0.046**	0.126**	0.173	0.006**	−0.226	9.19***	0.004	0.040
	(1.96)	(0.27)	(2.60)	(−2.05)	(17.04)	(2.43)	(1.86)	(2.00)	(0.49)	(2.23)	(−1.46)	(17.75)	(1.08)	(2.00)	(2.18)	(1.27)	(1.97)	(−0.71)	(8.91)	(0.32)	(0.96)
L. Value	0.066**	0.012	0.004*	−0.313***	15.240***	0.010	0.025	0.075*	0.026	0.004*	−0.268*	16.20***	0.006	0.026	0.086*	0.173	0.005**	−0.228	12.68***	−0.003	0.002
	(2.07)	(0.21)	(1.90)	(−2.92)	(21.67)	(0.95)	(1.31)	(1.91)	(0.39)	(1.77)	(−1.79)	(20.91)	(0.47)	(1.11)	(1.75)	(1.49)	(2.07)	(−0.84)	(14.46)	(−0.25)	(0.05)
Panel B: Prime-Cap Portfolios																					
Prime	0.066**	0.015	0.006**	−0.287***	14.696***	0.020*	0.037*	0.074*	0.027	0.005**	−0.234	15.12***	0.010	0.039*	0.103**	0.164	0.006**	−0.228	10.96***	0.001	0.024
	(2.03)	(0.26)	(2.46)	(−2.60)	(20.32)	(1.95)	(1.86)	(1.93)	(0.41)	(2.11)	(−1.61)	(19.95)	(0.89)	(1.72)	(2.00)	(1.35)	(2.11)	(−0.81)	(12.01)	(0.11)	(0.64)
P. Growth	0.062**	0.010	0.004*	−0.308***	15.404***	0.010	0.029	0.071*	0.022	0.004*	−0.255*	16.36***	0.006	0.029	0.080	0.167	0.005**	−0.224	12.79***	−0.003	0.004
	(1.97)	(0.17)	(1.94)	(−2.89)	(21.99)	(1.01)	(1.52)	(1.81)	(0.32)	(1.76)	(−1.69)	(20.94)	(0.49)	(1.23)	(1.61)	(1.41)	(2.00)	(−0.82)	(14.40)	(−0.27)	(0.10)
P. Value	0.069*	0.020	0.007***	−0.262**	14.070***	0.030***	0.043**	0.076*	0.031	0.006**	−0.215	13.95***	0.014	0.049**	0.123**	0.163	0.006**	−0.233	9.25***	0.005	0.042
	(1.89)	(0.30)	(2.69)	(−2.13)	(17.41)	(2.58)	(1.98)	(1.93)	(0.47)	(2.27)	(−1.43)	(17.96)	(1.15)	(2.08)	(2.15)	(1.21)	(1.99)	(−0.74)	(9.14)	(0.34)	(1.02)
Panel C: Mid-Cap Portfolios																					
Mid	0.052	0.012	0.007***	−0.311***	15.992***	0.027**	0.054***	0.061	0.012	0.006**	−0.206	16.31***	0.014	0.053**	0.079	0.119	0.005*	−0.239	11.45***	0.002	0.034
	(1.49)	(0.19)	(2.71)	(−2.65)	(20.74)	(2.41)	(2.58)	(1.45)	(0.17)	(2.09)	(−1.28)	(19.47)	(1.08)	(2.09)	(1.47)	(0.93)	(1.90)	(−0.80)	(11.90)	(0.18)	(0.86)
M. Growth	0.057	0.027	0.009***	−0.330**	15.785***	0.040***	0.057**	0.066	0.030	0.007**	−0.216	15.48***	0.019	0.060**	0.104*	0.105	0.006*	−0.271	9.52***	0.006	0.053
	(1.43)	(0.37)	(2.96)	(−2.44)	(17.79)	(3.07)	(2.37)	(1.51)	(0.40)	(2.35)	(−1.30)	(17.85)	(1.43)	(2.29)	(1.84)	(0.79)	(1.93)	(−0.87)	(9.47)	(0.46)	(1.30)
M. Value	0.046	−0.004	0.005**	−0.293***	16.249***	0.013	0.048**	0.054	−0.003	0.005	−0.196	17.18***	0.007	0.044*	0.052	0.139	0.005	−0.207	13.42***	−0.004	0.012
	(1.39)	(−0.06)	(2.04)	(−2.63)	(22.21)	(1.24)	(2.45)	(1.26)	(−0.03)	(1.64)	(−1.19)	(20.12)	(0.52)	(1.71)	(0.91)	(1.04)	(1.60)	(−0.66)	(13.26)	(−0.31)	(0.28)
Panel D: Small-Cap Portfolios																					
Small	0.051	−0.008	0.007***	−0.260**	17.773***	0.028**	0.057**	0.058	−0.004	0.005*	−0.123	18.08***	0.013	0.051*	0.057	0.118	0.005	−0.183	13.46***	0.004	0.022
	(1.38)	(−0.12)	(2.59)	(−2.07)	(21.55)	(2.31)	(2.55)	(1.24)	(−0.05)	(1.78)	(−0.68)	(19.37)	(0.92)	(1.82)	(0.90)	(0.80)	(1.63)	(−0.53)	(12.03)	(0.27)	(0.47)
S. Growth	0.056	0.001	0.008***	−0.283**	17.579***	0.040***	0.062**	0.057	0.005	0.006**	−0.123	17.33***	0.019	0.061**	0.074	0.093	0.005*	−0.214	12.04***	0.009	0.041
	(1.38)	(0.02)	(2.87)	(−2.06)	(19.51)	(3.07)	(2.55)	(1.20)	(0.06)	(1.99)	(−0.68)	(18.44)	(1.33)	(2.15)	(1.14)	(0.61)	(1.65)	(−0.60)	(10.44)	(0.63)	(0.88)
S. Value	0.047	−0.019	0.005**	−0.237*	18.002***	0.014	0.050**	0.059	−0.011	0.005	−0.142	18.83***	0.005	0.041	0.038	0.146	0.005	−0.151	14.88***	−0.004	0.000
	(1.30)	(−0.29)	(2.06)	(−1.95)	(22.47)	(1.22)	(2.32)	(1.21)	(−0.13)	(1.45)	(−0.66)	(19.61)	(0.36)	(1.41)	(0.59)	(0.95)	(1.45)	(−0.42)	(12.90)	(−0.24)	(0.00)
Composite	0.066**	0.011	0.006**	−0.293***	14.630***	0.019*	0.034*	0.073*	0.026	0.005**	−0.234	15.06***	0.010	0.039*	0.103**	0.168	0.006**	−0.227	10.92***	0.001	0.023
	(2.04)	(0.19)	(2.38)	(−2.68)	(20.37)	(1.83)	(1.77)	(1.92)	(0.41)	(2.10)	(−1.61)	(19.91)	(0.89)	(1.69)	(2.01)	(1.39)	(2.12)	(−0.80)	(11.98)	(0.11)	(0.63)

This table presents the complete regression results estimated using the equation: $R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta CPI_t + \beta_3 \Delta UNP_t + \beta_4 \Delta BYS_t + \beta_5 \Delta TP_t + \beta_6 \Delta TV_t + \varepsilon_t$, where the dependent variable is the daily return on US equity portfolios. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). Control variables include: Change in the U.S. Consumer Price Index (ΔCPI), change in the U.S. Unemployment Rate (ΔUNP), change in the 10-Year Treasury Constant Maturity minus 2-Year Treasury Constant Maturity (ΔBYS), change in the U.S. ACM Treasury Term Premia FIT Yield 10-Year (ΔTP), and change in the United States Retail Trade Volume (ΔTV). Results are presented for three sample periods: the full sample (1995-2024), and two sub-periods (2005-2024 and 2015-2024). The t-statistics are reported in parentheses below each coefficient. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table A2 Consolidated regression results for the impact of high geopolitical threat interactions on portfolio returns across different time periods

Portfolio	1995-2024							2005-2024							2015-2024						
	ΔGPT	ΔCPI	ΔUNP	ΔBYS	ΔTP	ΔTV	Cons	ΔGPT	ΔCPI	ΔUNP	ΔBYS	ΔTP	ΔTV	Cons	ΔGPT	ΔCPI	ΔUNP	ΔBYS	ΔTP	ΔTV	Cons
Panel A: Large-Cap Portfolios																					
Large	0.215*	0.974	0.184	−0.285***	14.39***	−0.264	0.0381	0.215*	0.974	0.184	−0.285***	14.39***	−0.264	0.0381	0.225*	0.175	0.006**	−0.202	10.92***	0.001	0.009
	(1.94)	(0.12)	(0.24)	(−2.59)	(19.94)	(−0.28)	(1.17)	(1.94)	(0.12)	(0.24)	(−2.59)	(19.94)	(−0.28)	(1.17)	(1.67)	(1.44)	(2.15)	(−0.71)	(11.95)	(0.10)	(0.23)
L. Growth	0.216*	−4.161	−0.0715	−0.254**	13.68***	−0.458	0.0268	0.216*	−4.161	−0.0715	−0.254**	13.68***	−0.458	0.0268	0.232	0.175	0.006**	−0.199	9.25***	0.004	0.027
	(1.75)	(−0.47)	(−0.08)	(−2.07)	(16.99)	(−0.43)	(0.74)	(1.75)	(−0.47)	(−0.08)	(−2.07)	(16.99)	(−0.43)	(0.74)	(1.53)	(1.28)	(1.99)	(−0.63)	(8.96)	(0.32)	(0.62)
L. Value	0.209*	6.375	0.448	−0.313***	15.19***	0.001	0.0501	0.209*	6.375	0.448	−0.313***	15.19***	0.001	0.0501	0.213*	0.174	0.005**	−0.207	12.71***	−0.003	−0.010
	(1.94)	(0.82)	(0.61)	(−2.92)	(21.62)	(0.00)	(1.59)	(1.94)	(0.82)	(0.61)	(−2.92)	(21.62)	(0.00)	(1.59)	(1.65)	(1.50)	(2.09)	(−0.76)	(14.50)	(−0.25)	(−0.29)
Panel B: Prime-Cap Portfolios																					
Prime	0.209*	1.279	0.286	−0.288***	14.65***	−0.251	0.0457	0.209*	1.279	0.286	−0.288***	14.65***	−0.251	0.0457	0.218	0.166	0.006**	−0.205	11.01***	0.001	0.011
	(1.89)	(0.16)	(0.38)	(−2.61)	(20.26)	(−0.26)	(1.40)	(1.89)	(0.16)	(0.38)	(−2.61)	(20.26)	(−0.26)	(1.40)	(1.62)	(1.37)	(2.13)	(−0.72)	(12.05)	(0.12)	(0.30)
P. Growth	0.200*	6.663	0.477	−0.308***	15.35***	0.0497	0.0557*	0.200*	6.663	0.477	−0.308***	15.35***	0.0497	0.0557*	0.202	0.168	0.005**	−0.205	12.82***	−0.003	−0.008
	(1.86)	(0.86)	(0.65)	(−2.89)	(21.94)	(0.05)	(1.77)	(1.86)	(0.86)	(0.65)	(−2.89)	(21.94)	(0.05)	(1.77)	(1.55)	(1.42)	(2.03)	(−0.75)	(14.44)	(−0.26)	(−0.21)
P. Value	0.213*	−3.878	0.0947	−0.264**	14.02***	−0.476	0.0359	0.213*	−3.878	0.0947	−0.264**	14.02***	−0.476	0.0359	0.228	0.165	0.006**	−0.207	9.30***	0.005	0.029
	(1.72)	(−0.43)	(0.11)	(−2.15)	(17.35)	(−0.44)	(0.99)	(1.72)	(−0.43)	(0.11)	(−2.15)	(17.35)	(−0.44)	(0.99)	(1.53)	(1.22)	(2.00)	(−0.66)	(9.14)	(0.34)	(0.68)
Panel C: Mid-Cap Portfolios																					
Mid	0.178	3.045	0.785	−0.312***	15.93***	−0.161	0.0844**	0.178	3.045	0.785	−0.312***	15.93***	−0.161	0.0844**	0.184	0.120	0.005*	−0.220	11.48***	0.002	0.023
	(1.51)	(0.36)	(0.97)	(−2.65)	(20.67)	(−0.16)	(2.43)	(1.51)	(0.36)	(0.97)	(−2.65)	(20.67)	(−0.16)	(2.43)	(1.30)	(0.94)	(1.92)	(−0.74)	(11.93)	(0.18)	(0.58)
M. Growth	0.200	−1.690	0.933	−0.332**	15.73***	−0.526	0.0829**	0.200	−1.690	0.933	−0.332**	15.73***	−0.526	0.0829**	0.211	0.107	0.006*	−0.248	9.56***	0.006	0.041
	(1.47)	(−0.17)	(1.01)	(−2.46)	(17.73)	(−0.45)	(2.08)	(1.47)	(−0.17)	(1.01)	(−2.46)	(17.73)	(−0.45)	(2.08)	(1.43)	(0.80)	(1.95)	(−0.80)	(9.52)	(0.46)	(0.98)
M. Value	0.154	8.206	0.620	−0.292***	16.18***	0.309	0.0848***	0.154	8.206	0.620	−0.292***	16.18***	0.309	0.0848***	0.151	0.139	0.005	−0.194	13.43***	−0.004	0.003
	(1.37)	(1.02)	(0.81)	(−2.62)	(22.14)	(0.32)	(2.58)	(1.37)	(1.02)	(0.81)	(−2.62)	(22.14)	(0.32)	(2.58)	(1.01)	(1.04)	(1.61)	(−0.62)	(13.29)	(−0.30)	(0.08)
Panel D: Small-Cap Portfolios																					
Small	0.204	3.791	0.861	−0.260**	17.69***	0.198	0.0909**	0.204	3.791	0.861	−0.260**	17.69***	0.198	0.0909**	0.135	0.119	0.005	−0.170	13.48***	0.004	0.014
	(1.61)	(0.42)	(1.00)	(−2.07)	(21.47)	(0.18)	(2.45)	(1.61)	(0.42)	(1.00)	(−2.07)	(21.47)	(0.18)	(2.45)	(0.82)	(0.80)	(1.64)	(−0.49)	(12.06)	(0.28)	(0.30)
S. Growth	0.227	−0.717	1.036	−0.285**	17.50***	−0.203	0.0913**	0.227	−0.717	1.036	−0.285**	17.50***	−0.203	0.0913**	0.167	0.094	0.005*	−0.197	12.07***	0.010	0.032
	(1.64)	(−0.07)	(1.10)	(−2.07)	(19.44)	(−0.17)	(2.25)	(1.64)	(−0.07)	(1.10)	(−2.07)	(19.44)	(−0.17)	(2.25)	(0.98)	(0.61)	(1.66)	(−0.55)	(10.47)	(0.63)	(0.66)
S. Value	0.179	8.396	0.686	−0.235*	17.91***	0.677	0.0896**	0.179	8.396	0.686	−0.235*	17.91***	0.677	0.0896**	0.096	0.146	0.005	−0.142	14.89***	−0.004	−0.005
	(1.46)	(0.95)	(0.82)	(−1.93)	(22.39)	(0.64)	(2.49)	(1.46)	(0.95)	(0.82)	(−1.93)	(22.39)	(0.64)	(2.49)	(0.57)	(0.96)	(1.46)	(−0.40)	(12.92)	(−0.23)	(−0.11)
Composite	0.209*	1.402	0.266	−0.295***	14.58***	−0.268	0.0421	0.209*	1.402	0.266	−0.295***	14.58***	−0.268	0.0421	0.220	0.170	0.006**	−0.204	10.96***	0.001	0.011
	(1.90)	(0.18)	(0.35)	(−2.69)	(20.32)	(−0.28)	(1.30)	(1.90)	(0.18)	(0.35)	(−2.69)	(20.32)	(−0.28)	(1.30)	(1.64)	(1.40)	(2.14)	(−0.72)	(12.02)	(0.11)	(0.28)

This table presents the additional response of portfolios to geopolitical threats during extreme periods (top 10th percentile GPT days) beyond their normal response reported in Table 3. The complete regression model is as follows: $R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2(\Delta GPT_t \times \text{High GPT Dummy}_t) + \beta_3 \Delta CPI_t + \beta_4 \Delta UNP_t + \beta_5 \Delta BYS_t + \beta_6 \Delta TP_t + \beta_7 \Delta TV_t + \varepsilon_t$, where the dependent variable is the daily return on US equity portfolios. The key explanatory variable is the change in the geopolitical threat index interacted with a high GPT dummy variable ($\Delta GPT \times \text{High GPT Dummy}$). A high GPT Dummy is 1 when geopolitical threats have the highest 10% values otherwise the value is 0. Control variables include: Change in Inflation (ΔCPI), Unemployment rate (ΔUNP), change in Bond Yield Spread (ΔBYS), change in Term Premium (ΔTP), and Change in Trade Volume (ΔTV). Results are presented for three sample periods: the full sample (1995-2024), and two sub-periods (2005-2024 and 2015-2024). The t-statistics are reported in parentheses below each coefficient. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively. For brevity, we use ΔGPT to refer to $(\Delta GPT \times \text{High GPT Dummy}_t)$ to fit everything in the same table

Table A3 Detailed Markov Chain Regime-Switching Regression Results

Portfolio	ΔGPT		ΔCPI		ΔUNP		ΔBYS		ΔTP		ΔTV		cons	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Panel A: High Volatility Regime														
Composite	0.181**	(1.99)	0.027	(1.36)	−0.031	(−0.23)	0.008**	(2.03)	−0.593*	(−1.71)	19.906***	(12.60)	−0.059	(−1.19)
Large	0.179**	(2.02)	0.028	(1.40)	−0.027	(−0.20)	0.009**	(2.07)	−0.520	(−1.57)	19.477***	(12.42)	−0.058	(−1.20)
Large Growth	0.165*	(1.86)	0.036*	(1.79)	0.028	(0.20)	0.009**	(2.13)	−0.309	(−1.04)	16.457***	(10.02)	−0.033	(−0.65)
Large Value	0.226*	(1.83)	0.025	(0.91)	−0.012	(−0.07)	0.008	(1.59)	−1.020*	(−1.89)	22.777***	(11.52)	−0.076	(−1.16)
Prime	0.179*	(1.93)	0.028	(1.40)	−0.024	(−0.17)	0.009**	(2.06)	−0.528	(−1.50)	19.922***	(12.39)	−0.062	(−1.22)
Prime Growth	0.226*	(1.76)	0.027	(0.96)	−0.014	(−0.08)	0.009	(1.63)	−1.029*	(−1.81)	22.894***	(11.36)	−0.079	(−1.16)
Prime Value	0.169*	(1.80)	0.038*	(1.76)	0.026	(0.17)	0.010**	(2.07)	−0.365	(−1.09)	17.306***	(9.79)	−0.043	(−0.81)
Mid	0.210*	(1.65)	0.045*	(1.75)	−0.000	(−0.00)	0.011**	(2.12)	−0.608	(−1.17)	22.295***	(10.74)	−0.082	(−1.15)
Mid Growth	0.183	(1.42)	0.058*	(1.88)	0.005	(0.03)	0.011*	(1.83)	−0.366	(−0.80)	21.634***	(9.36)	−0.071	(−1.00)
Mid Value	0.013	(0.52)	0.008	(0.73)	−0.038	(−0.77)	0.004	(0.91)	−0.159**	(−2.10)	10.956***	(14.96)	0.084***	(5.18)
Small	0.181**	(1.99)	0.027	(1.36)	−0.031	(−0.23)	0.008**	(2.03)	−0.593*	(−1.71)	19.906***	(12.60)	−0.059	(−1.19)
Small Growth	0.179**	(2.02)	0.028	(1.40)	−0.027	(−0.20)	0.009**	(2.07)	−0.520	(−1.57)	19.477***	(12.42)	−0.058	(−1.20)
Small Value	0.165*	(1.86)	0.036*	(1.79)	0.028	(0.20)	0.009**	(2.13)	−0.309	(−1.04)	16.457***	(10.02)	−0.033	(−0.65)
Panel B: Low Volatility Regime														
Composite	0.020	(0.76)	0.025*	(1.90)	0.003	(0.05)	0.000	(0.12)	−0.188**	(−2.28)	9.019***	(11.64)	0.078***	(4.57)
Large	0.022	(0.83)	0.024*	(1.90)	0.011	(0.22)	0.000	(0.00)	−0.191**	(−2.31)	9.021***	(11.73)	0.077***	(4.52)
Large Growth	0.019	(0.68)	0.018	(1.25)	0.001	(0.01)	0.001	(0.17)	−0.210**	(−2.20)	10.278***	(12.18)	0.084***	(4.37)
Large Value	0.026	(1.05)	0.007	(0.67)	−0.014	(−0.28)	0.001	(0.19)	−0.197**	(−2.53)	9.662***	(13.29)	0.059***	(3.60)
Prime	0.021	(0.81)	0.027**	(2.07)	0.006	(0.11)	0.001	(0.16)	−0.202**	(−2.44)	9.165***	(11.66)	0.081***	(4.73)
Prime Growth	0.024	(0.98)	0.007	(0.66)	−0.017	(−0.36)	0.001	(0.23)	−0.198**	(−2.57)	9.858***	(13.79)	0.062***	(3.87)
Prime Value	0.018	(0.62)	0.021	(1.59)	−0.004	(−0.07)	0.003	(0.46)	−0.209**	(−2.25)	10.326***	(11.04)	0.093***	(4.72)
Mid	0.007	(0.27)	0.016	(1.03)	−0.022	(−0.40)	0.005	(1.22)	−0.24***	(−2.77)	10.742***	(12.27)	0.100***	(5.48)
Mid Growth	0.017	(0.56)	0.029**	(2.24)	−0.010	(−0.16)	0.009**	(2.57)	−0.31***	(−3.01)	11.021***	(11.50)	0.115***	(5.74)
Mid Value	0.178	(1.25)	0.025	(0.90)	0.011	(0.06)	0.008	(1.48)	−2.079**	(−2.01)	23.868***	(10.29)	−0.058	(−0.75)
Small	0.020	(0.76)	0.025*	(1.90)	0.003	(0.05)	0.000	(0.12)	−0.188**	(−2.28)	9.019***	(11.64)	0.078***	(4.57)
Small Growth	0.022	(0.83)	0.024*	(1.90)	0.011	(0.22)	0.000	(0.00)	−0.191**	(−2.31)	9.021***	(11.73)	0.077***	(4.52)
Small Value	0.019	(0.68)	0.018	(1.25)	0.001	(0.01)	0.001	(0.17)	−0.210**	(−2.20)	10.278***	(12.18)	0.084***	(4.37)

This table presents the coefficients estimated using Equation: $R_t = \beta_0 + \beta_{s_t,1}\Delta GPT_t + \beta_{s_t,2}\Delta CPI_t + \beta_{s_t,3}\Delta UNP_t + \beta_{s_t,4}\Delta BYS_t + \beta_{s_t,5}\Delta TP_t + \beta_{s_t,6}\Delta TV_t + \varepsilon_t$, where s_t indicates a discrete regime variable taking values in {1,2} following a 2-state Markov process for different regime states; $\varepsilon_t \sim N(0, \sigma^2_{s_t})$. We evaluated two-regime models with regime-dependent variances. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). The t-statistics are reported in parentheses. Control variables change in the U.S. Consumer Price Index (ΔCPI), change in the U.S. Unemployment Rate (ΔUNP), change in the 10-Year Treasury Constant Maturity minus 2-Year Treasury Constant Maturity (ΔBYS), change in the U.S. ACM Treasury Term Premia FIT Yield 10-Year (ΔTP), Change in the United States Retail Trade Volume (ΔTV) are included in all specifications but not reported for brevity. Complete regression results including all control variables are provided in Appendix Table A7. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table A4 Consolidated regression results for alternative measures of market uncertainty using daily and monthly data

Panel A: Daily Data (1995-2024)

Portfolio	ΔGPT	t-stat	ΔEPU	t-stat	ΔVIX	t-stat	ΔBEX	t-stat	cons	t-stat
Composite	0.047**	(2.11)	−0.000	(−0.29)	−0.129***	(−70.56)	−0.011***	(−4.81)	−0.040***	(−3.04)
Large	0.050**	(2.21)	−0.000	(−0.39)	−0.129***	(−69.93)	−0.011***	(−4.78)	−0.040***	(−3.03)
Large Growth	0.050*	(1.90)	−0.000	(−0.63)	−0.136***	(−64.25)	−0.014***	(−5.42)	−0.036***	(−2.62)
Large Value	0.050**	(2.12)	−0.000	(−0.06)	−0.121***	(−63.49)	−0.007***	(−3.18)	−0.045***	(−3.31)
Prime	0.047**	(2.08)	−0.000	(−0.44)	−0.129***	(−70.33)	−0.012***	(−5.11)	−0.037***	(−2.82)
Prime Growth	0.046**	(1.99)	−0.000	(−0.09)	−0.121***	(−63.81)	−0.008***	(−3.46)	−0.042***	(−3.13)
Prime Value	0.047*	(1.82)	−0.000	(−0.69)	−0.137***	(−65.04)	−0.015***	(−5.77)	−0.034**	(−2.45)
Mid	0.033	(1.30)	−0.000	(−0.57)	−0.132***	(−64.51)	−0.015***	(−5.93)	−0.022*	(−1.65)
Mid Growth	0.035	(1.17)	−0.000	(−0.82)	−0.144***	(−59.47)	−0.019***	(−6.44)	−0.023	(−1.47)
Mid Value	0.030	(1.18)	−0.000	(−0.11)	−0.120***	(−58.59)	−0.011***	(−4.24)	−0.025*	(−1.89)
Small	0.032	(1.14)	0.000	(0.00)	−0.136***	(−59.70)	−0.016***	(−5.82)	−0.025*	(−1.71)
Small Growth	0.047**	(2.11)	−0.000	(−0.29)	−0.129***	(−70.56)	−0.011***	(−4.81)	−0.040***	(−3.04)
Small Value	0.050**	(2.21)	−0.000	(−0.39)	−0.129***	(−69.93)	−0.011***	(−4.78)	−0.040***	(−3.03)

Panel B: Monthly Data (1995-2024)

Portfolio	ΔGPT	t-stat	ΔEPU	t-stat	ΔVIX	t-stat	ΔBEX	t-stat	ΔUNC	t-stat	cons	t-stat
Composite	0.038	(0.26)	−0.000	(−0.09)	−0.147***	(−15.87)	−0.002	(−0.18)	−0.0447	(−0.53)	−0.022	(−0.39)
Large	0.039	(0.26)	−0.000	(−0.27)	−0.147***	(−15.75)	−0.000	(−0.03)	−0.046	(−0.55)	−0.022	(−0.38)
Large Growth	0.043	(0.24)	−0.001	(−1.06)	−0.159***	(−14.00)	−0.001	(−0.05)	0.014	(0.14)	−0.063	(−0.90)
Large Value	0.025	(0.17)	0.001	(0.82)	−0.134***	(−14.51)	−0.001	(−0.10)	−0.115	(−1.39)	0.025	(0.44)
Prime	0.045	(0.30)	−0.001	(−0.57)	−0.149***	(−16.14)	−0.003	(−0.28)	−0.042	(−0.51)	−0.023	(−0.41)
Prime Growth	0.013	(0.09)	0.001	(0.62)	−0.135***	(−14.83)	−0.002	(−0.27)	−0.108	(−1.31)	0.021	(0.38)
Prime Value	0.064	(0.35)	−0.001	(−1.36)	−0.162***	(−14.27)	−0.004	(−0.32)	0.013	(0.12)	−0.062	(−0.89)
Mid	0.065	(0.39)	−0.002*	(−1.81)	−0.161***	(−15.70)	−0.013	(−1.27)	−0.021	(−0.23)	−0.034	(−0.55)
Mid Growth	0.150	(0.71)	−0.004**	(−2.36)	−0.177***	(−13.45)	−0.019	(−1.43)	−0.000	(−0.00)	−0.055	(−0.68)
Mid Value	−0.052	(−0.32)	−0.000	(−0.30)	−0.145***	(−14.49)	−0.009	(−0.86)	−0.062	(−0.69)	−0.002	(−0.04)
Small	0.091	(0.49)	−0.001	(−1.05)	−0.162***	(−14.10)	−0.0193*	(−1.68)	−0.009	(−0.08)	−0.0436	(−0.62)
Small Growth	0.154	(0.71)	−0.002	(−1.39)	−0.174***	(−12.98)	−0.028**	(−2.07)	0.010	(0.08)	−0.059	(−0.72)
Small Value	0.012	(0.06)	−0.000	(−0.34)	−0.150***	(−13.29)	−0.012	(−1.04)	−0.040	(−0.39)	−0.022	(−0.32)

This table presents the complete regression results estimated using different frequency data. Panel A uses daily data and Panel B uses monthly data. We present coefficients from the models: $R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta EPU_t + \beta_3 \Delta VIX_t + \beta_4 \Delta BEX_t + \varepsilon_t (daily data),\ and R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta EPU_t + \beta_3 \Delta VIX_t + \beta_4 \Delta BEX_t + \beta_5 \Delta UNC_t + \varepsilon_t$ (*monthly data*), where the dependent variable is the return on US equity portfolios. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). Other variables include economic policy uncertainty index (ΔEPU), CBOE implied volatility index (ΔVIX), Bekaert economic uncertainty index (ΔBEX), and macroeconomic uncertainty index (ΔUNC, monthly data only). The t-statistics are reported in parentheses below each coefficient. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table A5 Monthly frequency regression results for the relationship between geopolitical threats and portfolio returns with macroeconomic controls

Portfolio	ΔGPT		ΔCPI		ΔUNP		ΔBYS		ΔTP		ΔTV		cons	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Composite	−0.144	(−0.68)	2.365	(0.33)	0.174	(0.25)	−0.463	(−0.98)	10.53***	(3.70)	−0.142	(−0.16)	0.0469	(1.56)
Large	−0.142	(−0.68)	2.041	(0.28)	0.0819	(0.12)	−0.388	(−0.82)	10.23***	(3.60)	−0.134	(−0.15)	0.0430	(1.43)
Large Growth	−0.170	(−0.70)	−2.606	(−0.31)	−0.226	(−0.28)	0.0238	(0.04)	9.59***	(2.91)	−0.280	(−0.27)	0.0310	(0.89)
Large Value	−0.122	(−0.61)	6.910	(1.01)	0.399	(0.60)	−0.804*	(−1.80)	11.05***	(4.11)	0.087	(0.10)	0.0555*	(1.96)
Prime	−0.142	(−0.67)	2.415	(0.33)	0.187	(0.26)	−0.319	(−0.67)	10.42***	(3.65)	−0.113	(−0.12)	0.0506*	(1.68)
Prime Growth	−0.139	(−0.70)	7.311	(1.06)	0.424	(0.63)	−0.745*	(−1.66)	11.01***	(4.08)	0.150	(0.17)	0.0609**	(2.14)
Prime Value	−0.155	(−0.63)	−2.296	(−0.27)	−0.0502	(−0.06)	0.092	(0.17)	10.01***	(3.01)	−0.296	(−0.28)	0.0404	(1.15)
Mid	−0.153	(−0.65)	4.547	(0.56)	0.699	(0.88)	0.0098	(0.02)	11.24***	(3.52)	0.024	(0.02)	0.0897***	(2.66)
Mid Growth	−0.099	(−0.35)	0.0771	(0.01)	0.841	(0.89)	0.391	(0.62)	12.00***	(3.15)	−0.328	(−0.27)	0.0890**	(2.21)
Mid Value	−0.234	(−1.07)	9.388	(1.24)	0.538	(0.73)	−0.467	(−0.95)	10.72***	(3.62)	0.484	(0.51)	0.0888***	(2.84)
Small	−0.128	(−0.51)	6.161	(0.71)	0.760	(0.91)	0.165	(0.29)	14.51***	(4.30)	0.384	(0.36)	0.0973***	(2.73)
Small Growth	−0.098	(−0.34)	1.803	(0.18)	0.934	(0.98)	0.462	(0.72)	14.96***	(3.89)	−0.011	(−0.01)	0.0980**	(2.41)
Small Value	−0.174	(−0.74)	10.58	(1.31)	0.586	(0.74)	−0.162	(−0.31)	14.29***	(4.50)	0.859	(0.85)	0.0955***	(2.85)

This table presents the coefficients estimated using Equation: $R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta CPI_t + \beta_3 \Delta UNP_t + \beta_4 \Delta BYS_t + \beta_5 \Delta TP_t + \beta_6 \Delta TV_t + \varepsilon_t$, where the dependent variable is the monthly return on the US equity portfolios from 1995 to 2024. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). The set of control variables includes Change in Inflation (ΔCPI), Unemployment rate (ΔUNP), change in Bond Yield Spread (ΔBYS), change in Term Premium (ΔTP), and Change in Trade Volume (ΔTV). The t-statistics are reported in parentheses below each coefficient. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

Table A6 Detailed Result on the Effect of Geopolitical Threat on Conditional Volatility

Panel A: Geopolitical Threats and Controls

	ΔGPT	t-stat	ΔCPI	t-stat	ΔUNP	t-stat	ΔBYS	t-stat	ΔTP	t-stat	ΔTV	t-stat	Constant
Large	0.0520*	(1.94)	1.212	(0.18)	0.0187	(0.03)	−0.137	(−1.39)	9.105***	(15.51)	1.063	(1.21)	−0.0287
Large Value	0.0646***	(2.61)	4.308	(0.67)	0.0738	(0.13)	−0.125	(−1.28)	8.395***	(15.48)	0.0447	(0.07)	−0.0223
Large Growth	0.0744**	(2.48)	1.877	(0.24)	0.1471	(0.23)	−0.288**	(−2.44)	9.185***	(13.25)	0.460	(0.38)	−0.0365
Prime	0.0601**	(2.14)	1.252	(0.20)	−0.0001	(−0.00)	−0.142	(−1.46)	8.697***	(16.02)	1.375*	(1.66)	−0.0284
Prime Value	0.0761**	(2.49)	0.425	(0.06)	0.0871	(0.14)	−0.279**	(−2.39)	9.252***	(13.28)	0.502	(0.41)	−0.0461
Prime Growth	0.0697***	(2.75)	1.033	(0.16)	0.2324	(0.40)	−0.133	(−1.37)	8.314***	(14.69)	0.151	(0.21)	−0.0171
Mid	0.0472	(1.53)	4.011	(0.52)	0.0401	(0.06)	−0.255**	(−2.57)	10.56***	(16.17)	1.015	(1.33)	−0.0341
Mid Value	0.0457*	(1.67)	3.388	(0.52)	−0.0014	(−0.00)	−0.191**	(−2.10)	9.115***	(14.33)	1.187	(1.32)	−0.0266
Mid Growth	0.0437	(1.22)	−3.164	(−0.36)	0.2292	(0.32)	−0.391***	(−3.29)	10.63***	(13.95)	0.558	(0.55)	−0.0501
Small	0.0387	(1.12)	4.392	(0.52)	−0.0674	(−0.09)	−0.335***	(−3.16)	12.17***	(15.60)	1.973**	(2.40)	−0.0286
Small Value	0.0374	(1.23)	6.856	(0.92)	−0.1653	(−0.26)	−0.273***	(−2.93)	10.37***	(14.15)	1.436	(1.35)	−0.0160
Small Growth	0.0258	(0.67)	1.780	(0.18)	0.1281	(0.15)	−0.346***	(−2.83)	13.81***	(16.24)	1.222	(1.30)	−0.0359

Panel B: Conditional Variance Coefficients

	z_{t-1}	t-stat	$\lvert z_{t-1}\rvert - \sqrt{2/\pi}$	t-stat	$\ln(\sigma^2_{t-1})$	t-stat	Constant
Large	−0.0889***	(−5.17)	0.447***	(26.11)	0.934***	(170.10)	0.0446***
Large Value	−0.0785***	(−4.49)	0.444***	(24.88)	0.934***	(178.51)	0.0388***
Large Growth	−0.0828***	(−4.82)	0.422***	(26.36)	0.947***	(202.52)	0.0479***
Prime	−0.0915***	(−5.34)	0.441***	(25.31)	0.935***	(168.69)	0.0433***
Prime Value	−0.0902***	(−5.31)	0.408***	(26.15)	0.951***	(206.30)	0.0443***
Prime Growth	−0.0778***	(−4.57)	0.434***	(24.79)	0.937***	(183.58)	0.0358***
Mid	−0.0944***	(−5.86)	0.399***	(22.91)	0.946***	(187.46)	0.0415***
Mid Value	−0.0923***	(−6.12)	0.384***	(23.19)	0.954***	(222.81)	0.0283***
Mid Growth	−0.0950***	(−5.90)	0.381***	(22.56)	0.955***	(204.50)	0.0451***
Small	−0.0847***	(−5.31)	0.419***	(22.88)	0.942***	(175.09)	0.0528***
Small Value	−0.0694***	(−4.78)	0.417***	(24.90)	0.951***	(242.58)	0.0383***
Small Growth	−0.0875***	(−5.08)	0.397***	(20.95)	0.942***	(157.86)	0.0650***

This table presents the EGARCH model results showing the effect of geopolitical threats on conditional volatility. The model is estimated using the equation: $R_t = \beta_0 + \beta_1 \Delta GPT_t + \beta_2 \Delta CPI_t + \beta_3 \Delta UNP_t + \beta_4 \Delta BYS_t + \beta_5 \Delta TP_t + \beta_6 \Delta TV_t + \beta_7 z_{t-1} + \beta_8(\lvert z_{t-1}\rvert - \sqrt{2/\pi}) + \beta_9 \ln(\sigma^2_{t-1}) + \varepsilon_t$. The t-statistics are reported in parentheses. The key explanatory variable is the change in the geopolitical threat index (ΔGPT). The t-statistics are reported in parentheses. Control variables change in the U.S. Consumer Price Index (ΔCPI), change in the U.S. Unemployment Rate (ΔUNP), change in the 10-Year Treasury Constant Maturity minus 2-Year Treasury Constant Maturity (ΔBYS), change in the U.S. ACM Treasury Term Premia FIT Yield 10-Year (ΔTP), Change in the United States Retail Trade Volume (ΔTV) are included in all specifications but not reported for brevity. Complete results for all portfolios including growth and value subcategories are provided in Appendix Table A8. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively

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Declarations

Conflict of interest The authors have no competing interests to declare.

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Dr. Riaz is an Assistant Professor in the Department of Business Administration at North American University, Stafford, Texas, USA. He did his Doctoral studies at Åbo Akademi University and defended his thesis in 2021. His dissertation topic was related to Asset Pricing, Portfolio Management, and Behavioral Finance. His current research focuses on various topics related to Financial Economics, Equity Market, Asset Pricing, Behavioral Finance, etc. He published articles in a few well-recognized international journals like the International Review of Financial Analysis, the International Review of Economics and Finance, The North American Journal of Economics and Finance, The Quarterly Review of Economics and Finance, Emerging Markets Finance and Trade, and Asia-Pacific Journal of Accounting & Economics. He is also a reviewer of a few renowned journals like The European Journal of Finance, Finance Research Letters, International Review of Economics and Finance, Financial Innovation, and Global Business Review.

Mr. Rafi is a Doctoral Researcher in the Department of Accounting and Finance under the Turku School of Economics at the University of Turku, Turku, Finland. He did his Master's in Finance and Investment from Germany. His research expertise encompasses the intersection of empirical asset pricing, behavioral finance, and macroeconomic uncertainty, with particular emphasis on quantifying the impact of economic policy & macroeconomic uncertainty and geopolitical risks along with sustainability and climate considerations on financial markets. He has published papers in wellrecognized international journals. His work contributes to the growing literature on how exogenous risk factors influence cross-sectional asset returns and market efficiency during periods of economic and geopolitical instability. As an active member of the academic community, Mr. Rafi serves as a reviewer for several reputable financial journals, where he contributes to maintaining rigorous standards in academic publishing.