A Dissertation on

# Geopolitical risk and the cross-section of fund returns

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by

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# Abstract

This study examines the pricing implications of geopolitical risk on the cross-section of fund returns. We estimate fund exposure to the geopolitical risk index and find that funds with negative exposure (i.e., in the most negative beta quintile) generate 6.27% higher annualized risk-adjusted returns compared to those with positive exposure (i.e., in the most positive beta quintile). This finding is consistent with the predictions of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM), which posits that geopolitical risk is a state variable. According to ICAPM, increase in geopolitical risk adversely affects future investment opportunities and consumption; consequently, funds positively correlated with geopolitical risk act as hedge assets. The heightened demand for these assets drives up their prices, leading to lower expected future returns. We further examine whether funds in our sample posses the ability to successfully time geopolitical risk. We find that approximately 4.76% of active funds exhibit a significant positive correlation between the geopolitical risk timing coefficient and geopolitical risk beta, suggesting that timing skill is more prevalent among top-performing funds. These results indicate that investors who are averse to geopolitical risk demand compensation for holding negatively exposed funds and are willing to pay a premium for funds with positive exposure. Our findings have important implications for asset pricing, portfolio allocation, and risk management, particularly for investors seeking to understand the relationship between geopolitical risk and expected asset returns.



JEL Classification: G11; G12; C13; C21; C58; E20; E30

Keywords: Geopolitical risk; Cross-section of fund returns; ICAPM; Return predictability; Mutual funds; Hedge funds

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## Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning. I confirm that I have not used generative artificial intelligence tools to create any original content submitted as part of this research component. I have only used AI tools to assist in understanding published research articles and to help improve grammar and language. This use was in accordance with the guidelines set by Auckland University of Technology, and all content has been critically reviewed and edited by me.

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# Chapter 1

# Introduction

The rise of geopolitical uncertainties has emerged as a key factor contributing to systematic risk, significantly affecting investment decisions and market behaviour. Empirical evidence shows that heightened geopolitical tensions increase investor risk aversion, leading to a shift toward safe-haven assets (Baur & Smales, 2020), disruptions in global supply chains (Izzeldin et al., 2023), and increased market volatility (OECD, 2024; Smales, 2021). In addition, geopolitical shocks have been associated with increased funding and credit costs (IMF, 2023), bank instability (Phan et al., 2022) and reduced firm-level corporate investments in the United States (US) (Wang et al., 2023). Studies also indicate that geopolitical risks affect the predictability of asset returns (Yilmazkuday, 2024) and cause volatility spillovers between the commodity and stock markets (Smales, 2021). These complex relationships highlight the need to factor geopolitical risk into financial analysis and asset pricing.

Beyond financial impacts, geopolitical tensions also affect international trade and cross-border investments, critical components of the global economic system (OECD, 2022). According to the IMF's Global Financial Stability Report (IMF, 2023), rising geopolitical tensions disrupt trade flows and tighten global credit conditions, weakening macroeconomic and financial stability. Recent quantitative analysis by McKinsey & Co. (2025) shows that political misalignments negatively affect bilateral trade and investment flows (Grant & Haider, 2024)[1]This has led to an increase in the concentration of capital

[1]The geopolitical distance metric developed by McKinsey & Co. (2025) is based on UN voting patterns from 2022 to 2025 that quantifies political alignment between nations on a scale of 0–10. A lower value of geographical distance indicates a closer alignment between the nations.

flows between geopolitically aligned nations, reducing the benefits of cross-border investing and fragmenting global markets (Blackrock, 2025). In addition, heightened tensions in critical global supply regions, like the Middle East and the Asia-Pacific, have led to volatile commodity prices and increased shipping costs, directly impacting inflation and economic growth (OECD, 2024; RBNZ, 2024). Events like the war between Russia and Ukraine, the strained relations between the US and China, the dispute between Israel and Hamas in Gaza, and increasing cyber-attacks have reaffirmed the relevance of understanding the influence of geopolitical issues on financial stability and international trade.[2]

In response, institutional investors like sovereign wealth funds, central banks, and other major players now incorporate geopolitical risk assessments in their asset allocation decisions (Blackrock, 2025; Invesco, 2024). Organisations with international exposure are also adjusting their investment strategies to mitigate risks like trade barriers, cyber threats, and the potential US-China economic decoupling (S&P Global, 2025). This growing integration of geopolitical risk into investment decision-making reflects the need to protect asset values and ensure stable returns (Crosignani et al., 2025). Against this background, a pertinent question emerges: Can geopolitical uncertainty be regarded as a state variable influencing future consumption and investment decisions while also being priced as an undiversifiable risk?

Merton's (1973) intertemporal capital asset pricing model (ICAPM) suggests that state variables which broadly affect investment opportunities and the overall economic environment faced by investors should be reflected as priced risk factors in expected asset returns. Geopolitical risk, due to its far-reaching impact on market conditions and investor decision-making, emerges as a strong candidate for such a state variable. A growing body of empirical literature highlights the significance of state variables in shaping asset returns in Merton's (1973) ICAPM framework. Studies on volatility risk (Ang et al., 2006), uncertainty shocks (Bloom, 2009), aggregate systemic risk (Allen et al., 2012), policy uncertainty (Gomes et al., 2012; Pastor & Veronesi, 2012, 2013), time-varying macroeconomic uncertainty (Bali et al., 2017; Jurado et al., 2015) and

[2]The report published by Blackrock (2025) geopolitical risk dashboard has rated geopolitical tensions to a high likelihood following the US-China strategic competition with their tariff wars and battle on artificial intelligence technology causing sustained disruption to critical infrastructure.

economic policy uncertainty (Ali et al., 2022; Baker et al., 2016; Brogaard & Detzel, 2015) consistently show that economic uncertainty and volatility shocks are closely linked to asset prices and their subsequent returns. These findings reinforce that state variables like volatility, policy, and political uncertainty are priced as an undiversifiable risk.[3]

Several studies have explored the impact of geopolitical risk on various asset classes. For instance, Yilmazkuday (2024) show how geopolitical shocks affect stock returns and risk transmission mechanisms across advanced and emerging markets. Liu et al. (2019) and Mignon and Saadaoui (2023) highlight the influence of geopolitical tensions on commodity markets, while Su et al. (2021) examine the complex bidirectional effects of geopolitical risk and renewable energy dynamics. Additionally, Ma et al. (2022) find that geopolitical threats have significant predictive power for excess stock returns, especially during economic expansions. Zhang et al. (2022) demonstrate that geopolitical risk significantly raises global stock market volatility. Phan et al. (2022) link geopolitical risk to reduced bank stability through weaker profitability and heightened systemic risk. Despite these findings, the role of geopolitical risk in the performance of managed funds remains largely unexplored. In 2023, US-registered investment organisations possessed $33.9 trillion in assets and catered to over 120 million individuals, with mutual funds representing a substantial portion of US corporate stock ownership (Institute., I. C., 2024). Considering the significant size of investments in funds and their macro-financial significance, understanding the influence of geopolitical risk on fund return dynamics is essential. This study tries to address this gap by analysing the influence of geopolitical risk on the performance of managed funds.

In this study, we provide several findings on geopolitical risk that expand the literature. Despite the analysis of geopolitical risks acrossFirst, we find that geopolitical risk is priced in the cross-section of fund returns. The geopolitical risk premium is negative which is statistically and economically significant based on a sample of 37,149 available funds over 335 months from 1994 to 2021. This evidence lends support to the idea that managed fund returns are driven by geopolitical risk factor, and risk-averse fund investors are willing to pay a premium to hedge geopolitical risk For each fund month, we run a

[3]Undiversifiable, or systematic risk, refers to the market-wide risk that diversification cannot eliminate. In models like the ICAPM (Merton, 1973), state variables capture these broad economic conditions, linking them to systematic risk.

time series regression of fund excess returns over the past 36 months on the changes in US GPR index while controlling for Carhart (1997) risk factors statistically significant at the 5% level in our baseline regression. The regression coefficient on the GPR changes index captures the fund's GPR beta. When the funds are sorted into quintiles by their GPR beta, the bottom quintile outperforms the top quintile by 0.523% ($t$-statistic = $-2.58$) in the subsequent month's returns. We confirm this negative relationship between the GPR beta and fund's subsequent month performance in Fama and MacBeth (1973) regressions controlling for fund characteristics. Our time-series findings are robust using both value-weighted and equal-weighted excess and gross fund returns. Additionally, our Fama and MacBeth (1973) regression results remain consistent using additional index betas and when alternative index betas are included alongside GPR beta as control variables. We find that GPR is a priced systematic risk, which is equivalent to an additional risk premium of around 6.27% annually.

We additionally examine the effect of fund characteristics through bivariate portfolio analysis. The results show that large funds and older funds tend to exhibit a consistent pattern in excess returns and alphas, while funds with high flows have slightly different performances compared to those with low flows. Also, funds with high downside risk display significantly lower next-month excess returns than those with low downside risk. Moreover, we evaluate the cross-sectional effect of GPR beta on the return distribution using quantile regressions. The findings indicate that the adverse impact of GPR beta is most evident in underperforming funds, especially within the lower quantiles (5th to 25th). In contrast, its effect diminishes and becomes insignificant in the upper quantiles. This pattern suggests that underperforming funds are more vulnerable to GPR than high-performing funds, highlighting the variation in GPR pricing across the performance spectrum. We also examine whether the negative relationship between GPR and fund returns relates to variations in managerial skill. Using the skill-based R-squared classification measure of Titman and Tiu (2011), we categorise funds into high-skill and low-skill groups. The negative return spread between Q5 and Q1 portfolios is statistically significant only among high-skill funds, exhibiting a spread of $-0.167\%$ ($t$-statistic = $-1.94$). Conversely, the spread is insignificant among low-skill funds ($-0.040\%$, $t$-statistic = $-0.95$). This suggests that high-skilled funds are more exposed to geopolitical risk due to their active strategies.

To better understand the managerial-skill explanation, we evaluate the timing ability of fund managers to exploit GPR fluctuations using three timing tests. First, we present a GPR timing model based on the foundational market timing test by Henriksson and Merton (1981), following Chen et al. (2021) at the individual fund level to present the cross-sectional $t$-statistic for the GPR timing coefficient under the normality assumption. We find that around 3.28% of the funds exhibit a $t$-statistic exceeding a 5% significance level in the extreme right tail under normality, contrary to a statistically significant concentration in the extreme left tail with 17.47% of the overall funds displaying a $t$-statistic below $-2.33$. Second, we assess the macro-timing ability of funds following the market timing test of Bali et al. (2014) using pooled panel regression. We find a positive and significant macro-timing coefficient (0.029, $t$-statistic = 5.45) for active funds, suggesting superior timing ability during periods of high GPR index. Moreover, the percentage of positive and significant macro-timing coefficients for active funds (4.76%) is higher than that of passive funds (2.11%). Finally, we employ quantile regression to assess whether GPR timing skill differs across the distribution of fund performance. The GPR timing coefficient is negative and significant in the lower quantiles but positive and highly significant in the upper quantiles, suggesting that only top-performing managers can effectively time GPR. This supports our earlier results that GPR timing skill is mainly found in active fund managers who leverage GPR to achieve higher returns.

Our study makes three core contributions. First, we provide comprehensive evidence that geopolitical risk is a systematically priced factor in the cross-section of managed fund returns. While prior research has shown that certain systematic risks are positively associated with performance, GPR commands a negative premium in the cross-section of fund returns. A negative return differential between low and high GPR betas indicates that investors need additional compensation to remain invested in funds with negative GPR exposure. Conversely, investors are inclined to pay a premium for funds with positive GPR exposure, as these assets are perceived as a hedge against such risks. This aligns with the predictions of ICAPM frameworks of Merton (1973), Campbell (1993, 1996), and Chen (2002). This finding addresses a gap in asset pricing literature and equips investors with actionable insights to incorporate geopolitical risk into their portfolio allocation and risk management strategies.

Second, we integrate Markov switching regressions, quantile regression models, and macro timing tests at the fund level. We capture how pricing effects vary across market regimes. We also document how different managers respond to shifts in geopolitical uncertainty. This multifaceted methodological approach lets us identify state-dependent patterns in fund performance that traditional linear models cannot detect. Third, we build on existing findings regarding fund timing by showing that only a minority of active managers can tactically adjust their geopolitical exposures to earn significant excess returns under uncertainty. This result refines our understanding of timing skill in the presence of geopolitical risk. It also highlights the limits of managerial ability in complex market environments.

This study proceeds as follows: Chapter 2 includes the literature review for pricing implications on systematic risk factors and timing ability of fund managers. Chapter 3 describes our data. Chapter 4 presents the methodology and empirical findings of the study. Chapter 5 includes robustness and supplementary checks. Chapter 6 provides concluding remarks of the study.

# Chapter 2

# Literature Review

## 2.1 Literature on pricing implications of systematic risk factors

From a theoretical perspective, the asset pricing implications of systematic risk factors originate from Merton's (1973) ICAPM framework, which posits that investors require compensation for market risks and risks associated with future investment opportunities and consumption. Building on this foundation, Bernanke (1983) emphasised that heightened uncertainty leads firms to delay irreversible investment. Campbell (1993, 1996) later extended the ICAPM framework into a discrete-time setting, offering more practical, testable implications by sidestepping the empirical difficulties posed by consumption data. Chen (2002) further demonstrated that volatility is directly connected to asset risk premiums, with investors favouring higher values for assets that hedge against systematic volatility, consistent with ICAPM predictions.

Building on these foundations, empirical studies have extensively explored the interplay between distinct systematic risks and returns in asset pricing.[4] For example, Bali et al. (2012, 2014) find that systematic risk and state variable macroeconomic uncertainty

[4] A partial list in fund literature includes Carhart (1997), Fung and Hsieh (1997, 2001, 2004), Ackermann et al. (1999), Liang (1999, 2001), Berk and Green (2004), G. J. Jiang et al. (2007), Kacperczyk and Seru (2007), Kosowski et al. (2007), Fung et al. (2008), Brown et al. (2008, 2009, 2012), Patton (2009), Jagannathan et al. (2010), Aggarwal and Jorion (2010), Bali, Brown, and Caglayan (2011) and Bali et al. (2012, 2014), Huang et al. (2011), Chen et al. (2020), and Chen et al. (2021), among others.

exposures positively correlate with hedge fund returns. Additionally, the five-factor asset pricing model by Fama and French (2015) provides empirical support that systematic factors other than the market factor, such as size, book-to-market, profitability, and investment, carry a risk premium. Brogaard and Detzel (2015) find evidence of the positive effect of the state variable level economic policy uncertainty on stock returns and a contrasting negative risk premium to changes in uncertainty. Furthermore, the study by Brogaard et al. (2019) observes that increasing global political uncertainty leads to higher market volatility and appreciation of the US dollar.

On the contrary, empirical studies also find evidence that higher exposure to risks is associated with lower returns. For example, Ang et al. (2006) find that stocks with higher exposure to state variable volatility risk have lower expected returns, indicating that volatility is negatively priced. Moreover, general equilibrium models by Gomes et al. (2012) and Pastor and Veronesi (2012, 2013) highlight the impact of overall fiscal policies, policy uncertainty, and political factors on asset prices. For instance, Bali et al. (2017) find that investors demand a premium for holding stocks negatively exposed to economic uncertainty, consistent with the ICAPM predictions of Merton (1973) and Campbell (1993, 1996). Similarly, Agarwal et al. (2017) find a negative risk premium associated with volatility exposure in hedge funds, especially during periods of market turmoil. Furthermore, Rungmaitree et al. (2022) show that higher political risk is associated with lower hedge fund returns. Additionally, Ali et al. (2022) find that New Zealand's economic policy uncertainty is a priced and undiversifiable risk factor in the cross-section of managed fund returns.

While existing studies offer mixed evidence on the pricing of systematic risks and state variables, geopolitical risk presents a unique challenge due to its uncertain nature that can lead to abrupt repricing of assets, tighter financial conditions, and declines in future investment opportunities, particularly when combined with macro-financial vulnerabilities (IMF, 2024). These dynamics align with the ICAPM framework (Merton, 1973), in which risks negatively affect expected consumption and investment opportunities demand compensation. Similarly, Gopinath (2024) provides empirical evidence that trade and investment flows are increasingly fragmenting along geopolitical lines, changing global capital allocation patterns and amplifying investor uncertainty. These findings suggest that geopolitical risk can be regarded as a systematic risk factor and may carry a negative premium, particularly for assets with higher exposure to geopolitical shocks.

Extending this perspective, early research studies on geopolitical risks document that elevated geopolitical risks lead to financial fragmentation, impair cross-border capital flows, and affect banks' funding costs and profitability, thereby hindering economic activity (see, for example, Zhang et al. (2022)). Further studies show that geopolitical risks contribute significantly to volatility in equity (Liu et al., 2019) and commodity markets (Smales, 2021) and have predictive power over stock returns and bad volatility, particularly in emerging markets (Balcilar et al., 2018; Ma et al., 2022). For example, Yilmazkuday (2024) finds that GPR shocks negatively affect stock prices in advanced and emerging economies, while Umar et al. (2022) show that the effect of GPR on global asset returns is highly related to asset-type and condition-specific. Notably, the tangible effects of geopolitical risks are evident in fluctuations in oil prices, investment, inflation, economic activity, and trade (see also Caldara, Conlisk, et al. (2022), Mignon and Saadaoui (2023), and Wang et al. (2023)). These findings suggest that geopolitical risk is a state variable and, given its pervasive effects across the economy and financial markets, can be viewed as a systematic risk.

Building on these empirical findings and linking them to Merton's (1973) ICAPM framework, assets with positive exposure to geopolitical risk are expected to act as hedges for investors during periods of heightened geopolitical fluctuations. For example, Fund A, which has a positive beta (i.e. positively exposed), would be considered a safer investment, offering more stability when geopolitical risk increases. Investors would, therefore demand such assets, as they tend to perform better when future conditions deteriorate due to elevated geopolitical tensions. In contrast, Fund B is a riskier investment with a negative beta (i.e. negatively exposed) to geopolitical risk. Investors will avoid such assets as their payoff will be worse during situations of higher geopolitical risk. Consequently, investors will only be willing to hold these assets if they are compensated with higher expected returns. These assets will only attract investors when prices are heavily discounted, resulting in higher future expected returns. This relationship between geopolitical risk and asset pricing highlights the need for investors to be compensated for holding assets with significant negative exposure to geopolitical uncertainty, especially during times of heightened geopolitical risks is consistent with Merton's (1973) ICAPM framework leading to the following hypothesis:

**Hypothesis 1**: Funds with negative exposure to geopolitical risk should earn higher risk-adjusted expected returns.

## 2.2 Literature on the timing ability of fund managers

In the evolving literature on fund managers' market timing ability, early studies by Treynor and Mazuy (1966) laid the groundwork with their quadratic performance evaluation model, demonstrating that market timing ability is reflected in strategic risk exposure shifts. Building on this, Henriksson and Merton (1981) refined the approach by incorporating parametric and non-parametric techniques, showing how fund managers adjust their market exposure in anticipation of changing returns. However, both studies find limited evidence of successful market timing among mutual fund managers. Jagannathan and Korajczyk (1986) pointed out that managers lacking genuine timing skills might still appear successful if their strategies involve nonlinear payoffs, which do not necessarily contribute to actual performance improvements. Ferson and Schadt (1996) further emphasised that active adjustments in risk factor exposures significantly affect returns beyond what a simple index return can capture. Carhart (1997) contributes to this narrative by using net alpha as a metric for managerial ability. His work employs a four-factor model, extending the three-factor model by Fama and French (1993) with the momentum factor to isolate the abnormal return that managers generate after accounting for common risk exposures. His findings demonstrate that persistence in mutual fund performance is driven by their exposure to risk factors rather than successful market timing. Further studies examined persistence in mutual fund performance by analysing returns generated by funds for investors (Bollen & Busse, 2001; Zheng, 1999), offering empirical support that performance is mostly unpredictable. Fama and French (2010) reassess the evidence and determine that managers largely lack proficiency, finding signs of talent in only the upper tail of manager distributions. However, based on their gross alpha measure, this skill is economically negligible, indicating luck rather than talent.

Despite the widely accepted belief that mutual fund managers lack skill, a body of literature finds evidence of skill. Initial studies by Grinblatt and Titman (1989) find positive gross alphas for small and growth mutual funds. In their subsequent study, Grinblatt and Titman (1993) showed superior stock performance when owned by certain fund managers.

Kosowski et al. (2006) employ bootstrap analysis, finding evidence indicating that 10% of managers have skill. G. J. Jiang et al. (2007) provide fresh insights by introducing a holdings-based approach to evaluate market timing, revealing positive timing abilities for actively managed US equity funds. L. W. Chen et al. (2013) further explore style-timing abilities, identifying growth timing adjustments as a key driver of abnormal returns for growth-oriented mutual funds. Berk and van Binsbergen (2015) challenge the notion of mutual fund managers lacking timing ability, noting frequent traders exhibit significant market timing skills. These studies suggest mutual fund managers can effectively adjust market exposure based on market conditions.

However, in a recent study, Jiang et al. (2021) tested mutual fund flow performance using Bayesian investors and past performance signals, finding high economic uncertainty disrupts the link between managers' ability and fund performance, leading to inefficient capital allocation due to the inability to distinguish skill from luck. Literature also emphasises that hedge fund managers exhibit superior market timing abilities compared to mutual fund counterparts. Chen (2007) finds market timing skills vary across hedge fund styles, with strategies such as convertible arbitrage and global macro demonstrating stronger timing ability. Bali et al. (2014) find empirical evidence that mutual funds lack macro-timing ability demonstrated by hedge funds. Osinga et al. (2021) revealed a positive relationship between factor-timing and alpha generation, with approximately 34% of hedge funds showing significant market timing skills. Hedge funds benefit from a less restrictive regulatory environment, allowing more aggressive strategies and higher returns compared to heavily regulated mutual funds (Agarwal et al., 2018; Jorion & Schwarz, 2019). Building on these varied arguments, our GPR timing tests extend previous insights to geopolitical risk, expecting top-performing funds to successfully navigate geopolitical risk, leading to the following hypothesis:

**Hypothesis 2**: Fund managers possess the skills to time geopolitical risk.

# Chapter 3

# Data

The data employed in our study is sourced from the Refinitiv Lipper for Investment Management (LIM) database. The detailed classification framework underlying this database is grounded in the Lipper Global Classification (LGC) guidelines, which standardise fund categorisation into an asset universe by evaluating the investment objectives, asset type, and geographic exposure of the funds (Lipper, 2019).[5] In our study, we utilise a dataset starting from January 1994 to November 2021, yielding a sample period of 335 months. After excluding funds with monthly AUM under US$ 1 million and less than 12 months since inception, the final sample includes a total of 37,149 available funds with approximately 3.79 million observations. The sample consists of US-domiciled mutual funds, hedge funds, and exchange-traded funds (ETFs) classified as asset universe on the LIM database, with a total AUM of US$ 16.3 trillion as of November 2021.[6] Within

[5]Globally, the LIM database compiles comprehensive fund-level survivorship bias-free data for institutional investors domiciled in more than 50 countries, encompassing over 335,000 share classes (Lipper, 2020). These include mutual funds, closed-end funds, exchange-traded funds (ETFs), hedge funds, retirement funds, domestic pension and insurance products. LIM database compiles fund-level information, including monthly returns, assets under management (AUM), inception date, redemption date, asset universe, asset type, domicile, and geographical focus, among others. In addition, according to LGC guidelines, each fund is further classified into multiple asset types, including equity, bond, mixed assets, and alternatives, among others, based on its exposure to each asset class and the best available fund description provided by LIM (Lipper, 2019).

[6]According to the Investment Company Institute (2022) factbook (refer p.22), the total net assets of US-registered investment companies stood at US$ 34.6 trillion at year-end 2021. This includes US$ 27 trillion in mutual funds, US$ 7.2 trillion in exchange-traded funds (ETFs), and smaller amounts in closed-end funds (US$ 309 billion) and unit investment trusts (US$ 95 billion). The ICI factbook

these categories, funds are further segmented by asset type, including equity, mixed assets, and alternatives. Equity funds invest primarily in stock markets, mixed assets funds strategically balance variable income and fixed income securities, and alternative funds typically engage in derivative-based strategies or invest in non-traditional asset classes (Lipper, 2019). The average fund size in our sample for November 2021 is approximately US$ 988 million. Although this is lower than the average size of US-registered mutual funds, estimated at over US$ 3 billion as of year-end 2021 (Institute., I. C., 2022), it remains reflective of institutional-scale investment vehicles, particularly when including hedge funds and ETFs. Compared to previous studies such as Fama and French (2010), Berk and van Binsbergen (2015), Pastor et al. (2015), Sun et al. (2018), Cuthbertson et al. (2022), and Mateus et al. (2024), our dataset is comparable in terms of sample size, temporal coverage, and asset categorisation. These studies similarly employ large-scale fund datasets to examine performance, factor models, and determinants of fund flows, highlighting the robust foundation and suitability of our data for empirical analysis and aligning well with the fund literature.

We include a set of explanatory control variables in our Fama and MacBeth (1973) cross-sectional regressions and Machado & Santos Silva's (2019) quantile regressions via moments method approach (MM–QR) to validate the parametric test results in a complex setting that simultaneously controls for various effects or fund characteristics. We include fund size, fund age, fund flows, downside risk, return volatility, geographical focus dummy, and fund-type dummies. Previous studies in the fund literature provide empirical evidence for including these variables to understand the effects of fund characteristics on systematic risk factors.[7]

Fund size is measured by total monthly assets under management (AUM) in US$ million. Previous studies find that large-sized funds benefit from greater resources and economies of scale to exhibit operational efficiency and distinct performance dynamics. Fund age is the average number of months in the fund's existence since its inception.

excludes hedge funds as they are not regulated investment companies under the Investment Company Act of 1940.

[7]See, for example, Gruber (1996); Sirri and Tufano (1998); Chevalier and Ellison (1999); Wermers (2000); Berk and Green (2004); Chen et al. (2004); Bali et al. (2007); Huang et al. (2007, 2021); Bali et al. (2014), among others.

Studies suggest that longer-established funds may benefit from accrued expertise and investor confidence, highlighting that a fund's maturity may reflect superior management capabilities (Gruber, 1996; Sirri & Tufano, 1998).

Fund flows are calculated monthly based on the flow measure of Franzoni and Schmalz (2017). We define monthly fund flows as:

$$\text{Net flow}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \times (1 + R_{i,t})}{\text{TNA}_{i,t-1}} \tag{3.1}$$

where Net flow$_{i,t}$ represents the fund flow of fund $i$ in month $t$, TNA$_{i,t}$ is the total net assets of fund $i$ at the end of month $t$, TNA$_{i,t-1}$ is the total net assets of fund $i$ at the start of month $t$, and $R_{i,t}$ denotes the return of fund $i$ during month $t$. Franzoni and Schmalz (2017) demonstrate that monthly fund flows can effectively capture investor sentiment and liquidity conditions often reflected in trading behaviour (also see Barberis et al. (2005); Huang et al. (2007, 2021)). Downside risk is measured at the fund level as the absolute value of 5% Value at Risk (VaR), following the methodology of Ali et al. (2021), which captures the magnitude of extreme losses computed over a rolling 12-month window of fund returns. This approach is supported by previous research highlighting the role of tail risk in asset pricing (Ang et al., 2006) and comprehensive reviews of downside risk measurement (Post & van Vliet, 2006). Return volatility is measured as the standard deviation of the fund's monthly gross returns over the trailing 12-month period. Studies by Huang et al. (2007, 2021) suggest that return volatility influences the fund flow-performance relationship and helps isolate the impact of risk-adjusted performance from random return fluctuations.

In addition, we use the "geographical focus" data provided by LGC guidelines to categorise the funds as either Domestic or International focused. A fund is designated with a specific geographic focus if it allocates a minimum of 50% of its exposure to that country or region (Lipper, 2019). For instance, if a fund meets this threshold for its home country, it is classified as "Domestic." Conversely, if no single country reaches that 50% level, meaning the fund's exposure is spread out across multiple countries, it is considered "International" focused. Following this, for each fund, we assign a geographical focus dummy variable equal to 1 if it is categorised as domestic and 0 if it is categorised as international. Furthermore, we use the 'asset universe' data provided by LGC guidelines to identify the fund type in our sample to assign dummies (Lipper, 2019). We assign a mutual fund dummy equal to 1 if the asset universe belongs to the mutual fund and 0 otherwise; a hedge fund dummy equal to 1 if the asset universe belongs to the hedge fund and 0 otherwise; and an exchange-traded fund dummy equal to 1 if asset universe belongs to exchange-traded fund, and 0 otherwise.

Using the variance inflation factor (VIF), we test multicollinearity for our explanatory variables. A frequently referenced rule of thumb is regression literature texts, which state that a VIF value of more than 10 indicates a potential multicollinearity issue that may warrant a reconsideration of the model specification (Montgomery et al., 2021). Nonetheless, O'Brien (2007) notes that higher VIF values may be acceptable under certain conditions. Meanwhile, Belsley et al. (1980) suggest that a VIF in the range of 5 to 10 suggests moderate multicollinearity and requires closer scrutiny. In contrast, a VIF below 5 is generally regarded as indicative of minimal multicollinearity. The VIF values in our model specification with all the explanatory variables taken together range from 1 to 4.27 with a mean VIF of 1.84, which indicates no multicollinearity issues.

For our analysis, we will use the current US GPR index developed by Caldara and Iacoviello (2022). The authors construct the index using 10 major international newspapers through textual analysis, searching for around 200 keywords related to geopolitical tensions and events. This study documents that the index shows spikes during major geopolitical events such as the Gulf War, 9/11, the 2003 invasion of Iraq, the 2014 Russia-Ukraine crisis, the Paris terrorist attacks and Russia's most recent invasion of Ukraine, indicating heightened geopolitical risks during these periods. This index is used in many studies in the literature for its standardised, replicable formulation based on newspaper coverage of geopolitical events, along with its capacity to identify both global and country-specific risk factors relevant to asset pricing and macro-financial dynamics.[8]

As our objective is to analyse the pricing implications of GPR on managed fund returns, we include the recognised standard risk factors found in the extensively referenced frameworks of the 1960s Capital Asset Pricing Model (CAPM), Sharpe (1964), Fama and French (1993), and Carhart (1997) (CH-4) in empirical asset pricing literature. For this purpose, we obtain risk factor data from Jensen et al. (2023), who developed global factor

[8]See for example Balcilar et al. (2018), Baur and Smales (2020), Caldara, Conlisk, et al. (2022), Liu et al. (2019), Ma et al. (2022), Smales (2021), Umar et al. (2022), Wang et al. (2023), Wang et al. (2023), and Zhang et al. (2022), among others.

data for 153 factors clustered into 13 themes in 93 countries. We extract data from the website for value-weighted CH-4 risk factors like (1) market (MKT): excess return on the value-weighted US equity market portfolio; (2) size (SMB): the market equity factor constructed using return differential between small and large firms; (3) book-to-market (HML): book-to-market equity factor constructed using the return differential between portfolios of 'value' and 'growth' stocks; and (4) momentum (MOM): constructed using past 12-month returns (excluding the most recent month), taking the difference between 'winners' and 'loser' stocks.[9]

**Table 1: Summary statistics**

This table reports the statistics for the variables of the funds in the sample. Fund size is measured by total monthly assets under management (AUM) in US$ million. Fund age is the average number of months in the fund's existence. Monthly return is the average of monthly gross fund returns. Fund flows are calculated monthly based on the flow measure of Franzoni and Schmalz (2017)(equation (3.1)). Downside risk is measured at the fund level as the absolute value of 5% Value at Risk (VaR), following the methodology of Ali et al. (2022). Return volatility is measured as the standard deviation of the fund's monthly gross returns over the trailing 12-month period.

| | Mean | Median | p5 | p95 | SD |
|---|---|---|---|---|---|
| Fund size (million) | 494.38 | 51.20 | 2.10 | 2157.80 | 1702.27 |
| Fund age (months) | 113.97 | 88.00 | 19.00 | 280.00 | 102.58 |
| Monthly return (%) | 0.68 | 0.93 | -6.97 | 7.06 | 4.21 |
| Fund flows (%) | 0.83 | 0.36 | -7.21 | 11.05 | 9.96 |
| Downside risk (%) | 5.76 | 4.79 | 1.28 | 11.7 | 3.65 |
| Return volatility (%) | 3.77 | 3.50 | 1.30 | 7.03 | 1.76 |

The summary statistics of the funds in our sample reported in Table 1, show that the average fund in our sample has an AUM value of US$ 494 million and a lifespan of 9.5 years (114 months) since its inception. The fund age varies from 3 to 23 years (19 to 280 months), with a standard deviation of 8.5 years. These are broadly comparable to those reported in prior studies for US-based funds, which document average fund sizes ranging from US$ 300–600 million and typical fund ages between 7–10 years (Berk & van Binsbergen, 2015; Bollen & Busse, 2005; Pastor et al., 2015). The mean monthly

[9]Risk factor data for the United States and documentation on construction is available at https://jkpfactors.com/factor-returns.

fund return is 0.68% (average annualised return of 8.5%), which corresponds closely with Bessembinder et al. (2023), who report average monthly returns of 0.77% for US equity mutual funds. Our average return volatility of 3.77% and average downside risk of 5.76% were both measured over the trailing 12-month window.

The average monthly fund flow of 0.83% is consistent with the patterns observed in studies examining fund flow dynamics, indicating moderate investor sensitivity to past fund performance and market conditions (Cuthbertson et al., 2022; Franzoni & Schmalz, 2017). Additionally, the wide gap between the mean and median fund sizes (494 million vs. 51.20 million) indicates a right-skewed distribution caused by only a few large funds, as further evidenced by a high standard deviation of 1702.27 commonly observed in fund-size data (Guercio et al., 2010; Pastor et al., 2015). The correlation matrix in Table 2 indicates that, although most of the coefficients are weak, fund age exhibits a moderate correlation with fund size (0.246), consistent with the findings that older, established funds generally manage larger asset bases (Pastor et al., 2015). Further, return volatility demonstrates a strong correlation with downside risk (0.874), implying that funds with increased volatility are subject to more significant downside risks (Ali et al., 2021).

**Table 2: Correlation matrix between variables**

This table presents the correlation matrix between the variables. Fund size is measured by total monthly assets under management (AUM) in US$ million. Fund age is the average number of months in the fund's existence. Monthly return is the average of monthly gross fund returns. Fund flows are calculated monthly based on the flow measure of Franzoni and Schmalz (2017)(equation (3.1)). Downside risk is measured at the fund level as the absolute value of 5% Value at Risk (VaR), following the methodology of Ali et al. (2022). Return volatility is measured as the standard deviation of the fund's monthly gross returns over the trailing 12-month period. Values in bold are statistically significant at 1% or below.

| | Variables | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| 1 | Fund size (million) | 1 | | | | | |
| 2 | Fund Age (months) | **0.246** | 1 | | | | |
| 3 | Monthly return (%) | **0.016** | **0.019** | 1 | | | |
| 4 | Monthly fund flow (%) | **-0.015** | **-0.112** | **0.046** | 1 | | |
| 5 | Downside risk (%) | **-0.020** | 0.001 | **-0.062** | **-0.028** | 1 | |
| 6 | Return volatility (%) | **-0.010** | **0.007** | **0.049** | **-0.004** | **0.874** | 1 |

# Chapter 4

# Methodology and empirical results

## 4.1 Univariate and bivariate portfolio level sorts

We employ a series of parametric and non-parametric tests to determine the predictive power of GPR in the cross-section of managed fund returns within our sample. We initially utilise portfolio sorts to investigate the relationship between beta calculated using changes in the GPR index and fund excess returns. Starting in February 1996, each month, we construct five value-weighted return portfolios of funds based on the beta calculated using changes in the GPR index, which represents the exposure to changes in US GPR. These betas are derived from a rolling window using Ang et al. (2006), encompassing the most recent 36 months, including the current month, with the initial rolling window covering the period from February 1994 to January 1996. Subsequently, we track the portfolio returns for each quintile portfolio the following month (beginning in February 1996). Each quintile portfolio is adjusted monthly to create a series of returns from February 1996 to November 2021. We employ a two-stage approach, following Chen et al. (2021), to determine the GPR beta for each fund. Initially, we estimate a baseline model that regresses the fund excess returns on the CH-4 risk factors. In the next step, we perform a second regression on the fund excess returns that include the changes in the GPR index along with the CH-4 risk factors found to be statistically significant at the 5% confidence level in the baseline model. We then measure the GPR beta as the coefficient of the GPR changes index obtained from the second-stage regression. For each month $t$, we conduct the following time series regression for each fund that has a minimum of 24 return observations within the 36-month rolling window:

$$R_{i,t} = \alpha_{i,t} + \beta^G \Delta GPR_t + \beta' f_t + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the excess returns (beyond the one-month T-bill rate) of the fund $i$ in month $t$, $\Delta\mathrm{GPR}_t$ is the changes in the current US GPR index values in month $t$ and $\beta^G$ is the GPR beta for the fund $i$ in month $t$ and the vector $f_t$ includes the CH-4 factors, namely MKT, SMB, HML, and MOM, that are statistically significant at the 5% confidence level in the baseline model. For month $t$, the rolling window spans from month $t - 35$ to month $t$. We then track the returns for the quintile portfolios in the month following portfolio formation. These portfolios are rebalanced monthly.

**Table 3: Quintile portfolio summary statistics**

This table reports the statistics for each quintile portfolio constructed based on the $\beta^G$ calculated using equation (1). Fund size is measured by total monthly assets under management (AUM) in US$ million. Fund age is the average number of months in the fund's existence. Monthly return is the average of monthly gross fund returns. Fund flows are calculated monthly based on the flow measure of Franzoni and Schmalz (2017)(equation (3.1)). Downside risk is measured at the fund level as the absolute value of 5% Value at Risk (VaR), following the methodology of Ali et al. (2022). Return volatility is measured as the standard deviation of the fund's monthly gross returns over the trailing 12-month period.

| Portfolios | Q1 | Q2 | Q3 | Q4 | Q5 |
|---|---|---|---|---|---|
| Fund size (million) | 484.87 | 673.43 | 725.02 | 630.89 | 466.29 |
| Fund Age (months) | 118.68 | 144.91 | 148.68 | 146.57 | 124.67 |
| Monthly return (%) | 0.85 | 0.71 | 0.62 | 0.53 | 0.36 |
| Fund flows (%) | 0.42 | 0.31 | 0.23 | 0.13 | -0.04 |
| Downside risk (%) | 6.12 | 5.64 | 5.39 | 5.66 | 6.14 |
| Return volatility (%) | 4.75 | 3.97 | 3.60 | 3.14 | 2.86 |

The results of statistics of the quintile portfolios sorted based on $\beta^G$ calculated using equation (1) reported in Table 3 shows distinct variations across quintiles. The Q3 funds have the highest average AUM value at 725.02 US$ million and a longer average age at 148.68 months. Monthly returns consistently decrease from 0.85% in Q1 to 0.36% in Q5. Fund flow declined from 0.42% in Q1 to -0.04% in Q5. Return volatility is highest in Q1 at 4.75% and gradually decreases to 2.86% by Q5. Conversely, downside risk exhibits a clear trend, with Q3 funds registering the lowest level at 5.39%, in contrast to marginally higher levels in Q1 (6.12%) and Q5 (6.14%).

### Table 4: Univariate value-weighted portfolio analysis based on GPR beta

This table reports the average next-month fund excess returns, CAPM alphas, and CH-4 alphas of five quintile portfolios based on the $\beta^G$ calculated using equation (1). Value-weighted excess return portfolios are constructed using funds in each quintile from the lowest (Q1) to the highest (Q5) based on their GPR index betas. The row "Q5 – Q1" represents the spread between Portfolio 5 and Portfolio 1. The monthly risk-adjusted returns (alphas) are presented based on CAPM and the CH-4 model, which accounts for market (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors, with all returns and alphas reported in monthly percentage terms. Newey and West (1987) adjusted $t$-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| Quintiles | Average $\beta^G$ in each quintile | Next-month excess return (%) | Next-month CAPM alpha (%) | Next-month CH-4 alpha (%) |
|---|---|---|---|---|
| Q1 | -1.089 | 0.869 | 0.473 | 0.460 |
| | | (5.02) | (3.83) | (3.62) |
| Q2 | -0.330 | 0.690 | 0.287 | 0.277 |
| | | (4.31) | (3.58) | (3.34) |
| Q3 | -0.022 | 0.609 | 0.220 | 0.217 |
| | | (3.95) | (2.60) | (2.67) |
| Q4 | 0.293 | 0.513 | 0.186 | 0.179 |
| | | (3.50) | (1.60) | (1.58) |
| Q5 | 1.297 | 0.346 | 0.061 | 0.058 |
| | | (1.79) | (0.57) | (0.56) |
| Q5-Q1 - High-Low | | **-0.523*** ** | **-0.412** ** | **-0.402** ** |
| | | **(-2.58)** | **(-2.30)** | **(-2.19)** |
| No. of obs. | 310 | 310 | 310 | 310 |
| Adjusted R-squared (Q5-Q1) | | | 7.44% | 7.23% |

The results of the univariate portfolio analysis reported in Table 4 present the average $\beta^G$ for each quintile, the subsequent month's excess return, and the average CAPM and CH-4 alphas. The average $\beta^G$ exhibits a monotonic increase from $-1.089$ in the lowest quintile (Q1) to 1.297 in the highest quintile (Q5). Higher sensitivity of a fund to geopolitical risk index changes is associated with lower excess returns in the subsequent month. The lowest quintile portfolio (Q1) exhibits an average $\beta^G$ of $-1.089$, resulting in an average monthly return of 0.869%. On the contrary, funds in the highest quintile (Q5) exhibit an average $\beta^G$ of 1.297, resulting in an average monthly return of 0.346%. This clear monotonic decrease in returns across increasing $\beta^G$ quintiles supports our hypothesis 1 that funds more sensitive to geopolitical risk should earn higher risk-adjusted expected returns.

The apparent negative spread of $-0.523\%$ per month ($t$-statistic = $-2.58$) between Q5 and Q1, equivalent to an additional risk premium of around 6.27% annually, is direct empirical evidence that geopolitical risk is a priced systematic factor in fund returns. This finding indicates that investors demand additional compensation for investing in funds with negative exposure to the GPR index. Overall, our findings for the US funds align with prior evidence documented by Bali et al. (2017) in the context of US stock returns and Ali et al. (2022) for NZ institutional investment returns.

In addition, to examine the relationship between the fund characteristics and $\beta^G$ obtained from equation (1), we construct bivariate portfolio sorts. We first divide the funds into two groups based on fund characteristics (like fund size, fund age, fund flows, downside risk, return volatility, and geographical focus) and then sort funds within each group into quintile portfolios according to $\beta^G$. We define the high and low groups using the median of each characteristic for continuous fund characteristics like fund size, fund age, fund flows, downside risk, and return volatility. Funds above (below) the median are classified as the high (low) group. Within each group, funds are further sorted into $\beta^G$–based quintile portfolios. For the categorical variable geographical focus of the fund, we classify the sample into domestic (low) and international (high) based on the 'geographical focus' data provided by LGC guidelines (Lipper, 2019) to categorise the funds as either Domestic or International focused and then sort into quintile portfolios based on $\beta^G$ within each group. This bivariate sorting procedure allows us to assess whether the cross-sectional relationship between $\beta^G$ and fund returns vary systematically with key fund characteristics.

## Table 5: Bivariate value-weighted portfolio analysis (subsample analysis) based on GPR beta and fund characteristics

This table reports the next-month returns, CAPM alphas, and CH-4 alphas of Q5 (high), Q1 (low), and Q5 and Q1 (high − low) for bivariate-sorted quintiles portfolios using $\beta^G$ from equation (1) and a second fund-specific characteristic (fund size, fund age, fund flows, downside risk, return volatility, and geographical focus). The monthly risk-adjusted returns (alphas) are presented based on CAPM and the CH-4 model, which accounts for market (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors, with all returns and alphas reported in monthly percentage terms. Newey–West Newey and West (1987) adjusted $t$-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| | Next-month excess return (%) | | | Next-month CAPM alpha (%) | | | Next-month CH4 alpha (%) | | |
|---|---|---|---|---|---|---|---|---|---|
| | High | Low | High-Low | High | Low | High-Low | High | Low | High-Low |
| Fund size | -0.464** | -0.438*** | -0.026 | -0.616*** | -0.576*** | -0.040 | -0.623*** | -0.576*** | -0.047 |
| | (-2.30) | (-2.36) | (-0.56) | (-2.69) | (-2.73) | (-0.78) | (-2.65) | (-2.66) | (-0.91) |
| Fund age | -0.462** | -0.431** | -0.031 | -0.605*** | -0.580*** | -0.025 | -0.611*** | -0.583*** | -0.028 |
| | (-2.29) | (-2.23) | (-0.84) | (-2.65) | (-2.65) | (-0.55) | (-2.61) | (-2.59) | (-1.59) |
| Fund flows | -0.471*** | -0.432** | -0.040 | -0.651*** | -0.526** | -0.125 | -0.668*** | -0.520** | -0.149 |
| | (-2.55) | (-2.19) | (-0.26) | (-3.32) | (-2.36) | (-0.80) | (-3.36) | (-2.31) | (-1.04) |
| Downside risk | -0.470*** | -0.044 | -0.425*** | -0.594*** | -0.026 | -0.567*** | -0.592*** | -0.023 | -0.567*** |
| | (-2.92) | (-0.51) | (-2.68) | (-3.49) | (-0.30) | (-3.49) | (-3.38) | (-0.27) | (-3.41) |
| Return volatility | -0.457** | -0.407** | -0.050 | -0.629*** | -0.505** | 0.124 | -0.646*** | -0.498** | 0.149 |
| | (-2.49) | (-2.07) | (0.34) | (-3.21) | (-2.30) | -0.81 | (-3.24) | (-2.25) | -1.07 |
| Geographical focus | -0.409 | -0.340 | -0.070 | -0.796** | -0.658** | -0.138 | -0.779** | -0.614** | -0.165 |
| | (-1.38) | (-1.47) | (-0.30) | (-2.49) | (-2.38) | (-0.55) | (-2.36) | (-2.29) | (-0.69) |

Table 5 presents the results of the bivariate-sorted portfolios based on the $\beta^G$ ranks and fund-specific characteristics like fund size, age, fund flows, downside risk, return volatility and geographical focus for portfolios Q5–Q1. Fund size and fund age-based bivariate Q5–Q1 results follow a consistent pattern. Large funds have a next-month excess return spread of $-0.464\%$ ($t$-statistic = $-2.30$) compared to $-0.438\%$ ($t$-statistic = $-2.36$) for small funds. Similarly, the CAPM alphas are $-0.616\%$ for large funds and $-0.576\%$ for small funds, while the CH-4 alphas are $-0.623\%$ and $-0.576\%$, respectively. In addition, old funds have a next-month excess return of $-0.462\%$ ($t$-statistic = $-2.29$), slightly different to $-0.431\%$ ($t$-statistic = $-2.23$) for young funds. Similarly, the CAPM alphas are $-0.605\%$ for old funds and $-0.580\%$ for young funds, while the CH-4 alphas are $-0.611\%$ and $-0.583\%$, respectively.

Furthermore, funds with high flows have a subsequent month's excess return of $-0.471\%$ ($t$-statistic = $-2.55$), in contrast to $-0.432\%$ ($t$-statistic = $-2.19$) for funds with low flows. The CAPM alphas are $-0.651\%$ for high-flow funds and $-0.526\%$ for low-flow funds, whereas the CH-4 alphas are $-0.668\%$ and $-0.520\%$, respectively. Similarly, funds exhibiting high return volatility demonstrate a subsequent month's excess return of $-0.457\%$ ($t$-statistic = $-2.49$) contrary to $-0.407\%$ ($t$-statistic = $-2.07$) for funds with low volatility, with CAPM alphas of $-0.629\%$ versus $-0.505\%$ and CH-4 alphas of $-0.646\%$ compared to $-0.498\%$. The minimal variances in magnitude indicate no significant performance variations between these funds. Also, international funds (high geographical focus) and domestic funds (low geographical focus) show similar results, with no statistically significant return spread observed between the Q5–Q1 portfolios. These sub-sample results confirm that the negative relation between GPR sensitivity and fund performance persists across different fund characteristics. This consistency further strengthens the argument that geopolitical risk represents a systematic risk factor that is priced negatively and investors demand a premium, as stated in hypothesis 1.

In contrast to the above fund characteristics, funds with high downside risk exhibit a next-month excess return of $-0.470\%$ ($t$-statistic = $-2.92$), while those with low downside risk report $-0.044\%$ ($t$-statistic = $-0.51$), yielding a statistically significant high–low returns of around $-0.425\%$ ($t$-statistic = $-2.68$). Similarly, the CAPM & CH-4 alphas for high-low downside risk funds are $-0.568\%$ and $-0.569\%$, respectively. The statistically significant disparities between high and low prove that funds exhibiting more downside risk substantially underperform than those with less downside risk. Among all characteristics, downside risk appears to amplify the adverse impact of GPR exposure. Funds with high downside risk and high $\beta^G$ suffer the most pronounced underperformance, reinforcing our hypothesis that investors require a premium for holding funds more exposed to uncertainty stemming from geopolitical shocks when it is coupled with tail risk.

## 4.2 Markov-Switching dynamic regression

We employ a two-state Markov-switching dynamic regression model to capture how the relationship between the US GPR index and value-weighted Q5–Q1 excess fund returns differs across unobserved regimes. While univariate analysis provides an average effect of changes in GPR on excess returns, the Markov-switching model indicates that this relationship is regime-dependent. Markov-switching models have been used in previous studies to identify regime shifts in market returns, recognising two separate (high and low) states (Hamilton & Lin, 1996; Hamilton & Susmel, 1994; Kim et al., 2004; Mayfield, 2004; Schaller & Norden, 1997). The basic structure of our Markov-switching model based on Hamilton's (1989) framework is as follows:

$$R_t = \beta_{st} \cdot \text{GPR}_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_{st}^2) \tag{2}$$

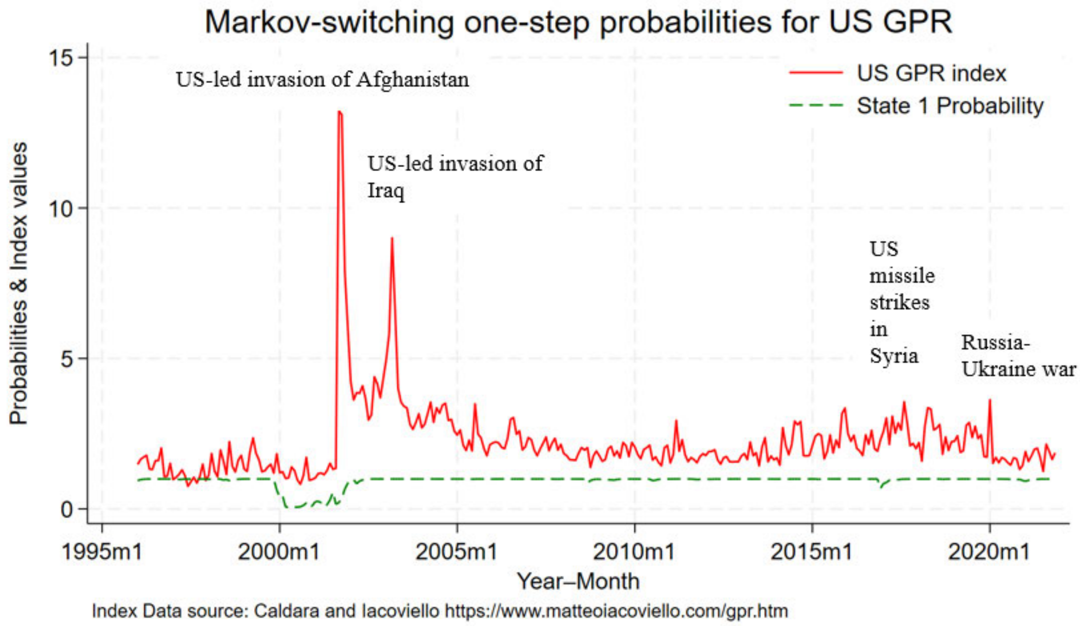
where $R_t$ denotes the return differential between Q5–Q1 portfolios for each month in our sample at time $t$, $\text{GPR}_t$ is the US GPR index value in month $t$, and $\beta_{st}$ is the state-dependent coefficient that captures how US GPR index values affect Q5–Q1 returns differently across states or regimes. The unobserved state $s_t \in \{1, 2\}$ evolves according to a first-order Markov chain. This means that the probability of transitioning to a given state depends only on the current state:

$$P(s_t = j \mid s_{t-1} = i) = p_{ij}, \quad i, j \in \{1, 2\}.$$

The transitional probabilities $p_{ij}$ summarise the persistence within each regime. For example, $p_{11}$ is the probability of staying in state 1, $p_{22}$ is the probability of staying in state 2, and $p_{12}$ and $p_{21}$ indicate the likelihood of switching from one regime to the other.

**Figure 1: Transitional probabilities in regimes**

The figure shows the US GPR index (dash line) and the one-step probabilities for State 1 (dotted line) from the Markov-Switching dynamic regression equation (2) over the sample period in our study, estimated using the value-weighted Q5–Q1 portfolio monthly excess returns. Based on the state-specific standard deviations reported in Figure 1, State 1 is the normal regime.




The results of the Markov-Switching model reported in Figure 1 indicate notable variations across two states. Conceptually, a state with a lower standard deviation is the normal regime, and the other state is the turbulent regime. Accordingly, State 1 is the normal regime, which is less volatile, compared to State 2, which is the turbulent regime, which is more volatile. Accordingly, State 1 exhibits lower instability (standard deviation = 1.70) than State 2 (standard deviation = 5.25). In State 1, the coefficient of the GPR index is negative and statistically significant, thereby suggesting that increased GPR is associated with lower Q5–Q1 returns when the markets are relatively stable. This finding directly supports our hypothesis 1 that funds with higher sensitivity to GPR should earn higher risk-adjusted expected returns which is consistent with Merton's (1973) ICAPM framework. It is also consistent with Pastor and Veronesi (2012, 2013), who argue that investors can assess and price political and policy-related risk when markets are calm and more information-efficient. In contrast, during State 2, the coefficient is negative but statistically insignificant, implying that the impact of GPR is less noticeable during more volatile periods. The difference in statistical significance suggests that during periods of high volatility, individual risk factors such as GPR have a reduced prevalence due to the dominance of broad systemic uncertainty (Bloom, 2009; Chen, 2002).

**Table 6: Markov-switching dynamic regression**

This table reports the results of a two-state Markov-switching dynamic regression model using equation (2) on state-dependent value-weighted Q5–Q1 portfolio monthly excess returns. The coefficients of state 1 and state 2 correspond to the US GPR index. The probabilities of persistence of regimes are interpreted as follows: $p(\mathrm{S1} \to \mathrm{S1}) = p_{11}$; $p(\mathrm{S1} \to \mathrm{S2}) = p_{12}$; $p(\mathrm{S2} \to \mathrm{S2}) = p_{22}$; and $p(\mathrm{S2} \to \mathrm{S1}) = p_{21}$. State-specific standard deviations reflect differing instability. A higher value of $p$ indicates greater persistence in that regime. A state with a lower standard deviation is the normal regime, and the other state is the turbulent regime.

| | State-dependent variable Q5–Q1 excess return | |
|---|---|---|
| | S.D. of the index | GPR index (Coeff.) |
| State 1 | 1.70 | **-0.087**** |
| (Normal Regime) | | **(-2.22)** |
| State 2 | 5.25 | -0.408 |
| (Turbulent Regime) | | (-0.58) |
| $p(\mathrm{S1} \to \mathrm{S1})$ | | 99.61% |
| $p(\mathrm{S1} \to \mathrm{S2})$ | | 0.39% |
| $p(\mathrm{S2} \to \mathrm{S2})$ | | 94.16% |
| $p(\mathrm{S2} \to \mathrm{S1})$ | | 5.84% |

The transitional probabilities show that both states are highly persistent, which means the system does not frequently switch once it enters a regime. But a higher $p_{11}$ value of 99.61% indicates that the market is in State 1 most of the time (Figure 1 ). A relative lesser $p_{22}$ value of 94.16% signifies that State 2 is less frequent but quite persistent once entered, indicating that the market can remain more volatile for an extended period. The Markov-Switching results reinforce the notion that geopolitical risk is a consistently priced factor in fund returns, particularly during stable market conditions. The findings are consistent with univariate analysis, confirming that the negative and significant effect of GPR is more pronounced in the normal regime when the markets are not overshadowed by broader volatility.

## 4.3 Fama and MacBeth regression

Fama and MacBeth (1973) cross-sectional regressions methodology is widely used in fund literature as a benchmark approach to formally test the cross-sectional link between fund characteristics and returns.[10] We perform Fama and MacBeth's (1973) cross-sectional regressions of fund excess returns on $\beta^G$, along with various fund characteristics and dummies as control variables. This provides complementary evidence to the results obtained from the portfolio-sorting approach (Hou et al., 2020). In our baseline specification Model 1, we estimate the predictive power of the GPR index beta computed from equation (1) on the fund excess returns. In Model 2, we extend the analysis by incorporating a suite of fund-specific controls. These include the log of fund size, log of fund age, fund flows, downside risk, return volatility and geographical focus dummy. In Model 3, fund type-specific dummies represent mutual, hedge, and exchange-traded funds.

We run the following cross-sectional regression equation of fund excess returns on the $\beta^G$ and control variables:

$$R_{t+1} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}^G_{i,t} + \lambda' \mathbf{x}'_{i,t} + e_{i,t} \tag{3}$$

where $R_{t+1}$ is the monthly excess return (beyond the monthly T-bill rate) in the month $t+1$, $\lambda$ is the coefficient of $\hat{\beta}^G$ estimated from the regression model in equation (1), and $\lambda'$ is the vector of control variables $\mathbf{x}'_{i,t}$. The control variables include fund size, fund age, fund flows, downside risk, return volatility and fund-type dummies (refer to Chapter 3). We obtain monthly US business cycle data from the National Bureau of Economic Research (NBER) to determine if the association between GPR and fund returns fluctuates across different business cycle phases. Utilising this data, we categorise each month in our sample as either an expansion or a contraction month. We subsequently subset the complete

[10] See, for example, Bali et al. (2014), Bali et al. (2021), Li and Rossi (2021), Chen et al. (2021), Bessembinder et al. (2023), Yang and Du (2023), among others.

sample, generating two separate datasets, and we run Model 3 specification for each subset to obtain different coefficient estimates for expansion (Model 4) and contraction (Model 5) periods.

Table 7 reports the average intercepts and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions using equation (3). Model 1 reveals a negative and significant association between $\beta^G$ and subsequent fund returns (coefficient = –0.073; $t$-statistic = –2.62). This is consistent with Merton's (1973) ICAPM and aligns with recent findings by Umar et al. (2022), who provide empirical evidence that geopolitical risk significantly affects global asset returns. In Model 2, after controlling for fund characteristics, the negative impact of $\beta^G$ remains significant (coefficient = –0.055; $t$-statistic = –2.28). The magnitude is economically and statistically significant, with a one standard deviation increase (1.15, see Table 16) in $\beta^G$ corresponding to a 0.063 ($1.15 \times 0.055$) percentage point reduction in its relative sample mean in monthly fund returns. Interestingly, after incorporating fund-type dummies in Model 3, the results continue to show a consistent negative relationship (coefficient = –0.054; $t$-statistic = –2.24). This suggests that our findings are robust to including various control variables and fixed effects, supporting our hypothesis that funds with greater exposure to GPR earn higher risk-adjusted expected returns.

Additionally, using NBER's US business cycle months data, we split the whole sample into two additional models. During expansion periods (Model 4), the negative association is pronounced and significant (coefficient = –0.064; $t$-statistic = –2.52), consistent with prior studies suggesting that geopolitical risks exert stronger effects in stable economic times (Bloom, 2009; Pastor & Veronesi, 2013). Conversely, during contractions (Model 5), the effect becomes positive but insignificant (coefficient = 0.052; $t$-statistic = 0.85), indicating geopolitical risks are overshadowed by broader market distress. The adjusted $R^2$ values range from 0.020 (Model 1) to 0.250 (Model 5), indicating strong explanatory power. These results contribute to the growing literature on the negative influence of systematic risk factors on investment returns (Ali et al., 2022; Bali et al., 2017). Our findings have important implications for portfolio management and strategic asset allocations, highlighting the importance of actively incorporating geopolitical risk assessments in investment decisions (Balcilar et al., 2018; Crosignani et al., 2025).

## Table 7: Fama and MacBeth regression of fund returns on GPR beta and control variables

This table reports the average intercept and average slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of next-month fund excess returns on five different models. In Model 1, we run the regression using next-month fund excess returns on the $\beta^G$ calculated using equation (1). In Model 2, along with the GPR index beta, we add control variables namely (1) log of fund size; (2) log of fund age; (3) fund flows is calculated monthly based on the flow measure of Franzoni and Schmalz (2017)(equation (3.1)); (4) downside risk is measured at the fund level as the absolute value of 5% Value at Risk (VaR) following the methodology of Ali et al. (2022); (5) return volatility is measured as the standard deviation of the fund's monthly gross returns over the trailing 12-month period; and (6) geographical focus dummy equal to 1 if the fund is classified as Domestic using the LGC guidelines and 0 if it is considered International. In Model 3, we extend Model 2 by adding fund type dummies based on the 'asset universe' data provided by LGC guidelines: a mutual fund dummy equal to 1 if the asset universe belongs to a mutual fund, a hedge fund dummy equal to 1 if it belongs to a hedge fund, and an exchange-traded fund dummy equal to 1 if it belongs to an ETF and 0 otherwise under each dummy. In Models 4 and 5, we subset the full sample based on NBER-based US business cycle (expansion and contraction) months and run the Model 3 specification separately on each subset. Model 4 reports the results for the expansion months subset, and Model 5 reports the results for the contraction months subset. Newey and West (1987) adjusted t-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| | Dependent variable: Next-month excess return | | | | |
|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| | Coeff. | Coeff. | Coeff. | Coeff. | Coeff. |
| Intercept | 0.522** | -0.202** | -0.020 | -0.013 | -0.090 |
| | (2.39) | (-2.08) | (-0.24) | (-0.15) | (-0.27) |
| $\beta^G$ | **-0.073*** ** | **-0.055** ** | **-0.054** ** | **-0.064** ** | 0.052 |
| | **(-2.62)** | **(-2.28)** | **(-2.24)** | **(-2.52)** | (0.85) |
| Fund size | | 0.006 | 0.008 | **0.011** ** | -0.023 |
| | | (1.22) | (1.61) | **(2.31)** | (-0.94) |
| Fund age | | **0.055*** ** | **0.048*** ** | **0.049*** ** | 0.036 |
| | | **(3.64)** | **(3.31)** | **(3.14)** | (1.17) |
| Fund flows | | **0.002* ** | **0.002** ** | -0.013 | 0.002 |
| | | (1.90) | (2.02) | (-0.15) | (0.52) |

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Downside risk | | 0.018 | 0.023 | 0.028 | -0.026 |
| | | (0.64) | (0.85) | (0.98) | (-0.28) |
| Return volatility | | **0.110**** | **0.119**** | **0.139**** | -0.081 |
| | | (1.97) | (2.11) | (2.48) | (-0.30) |
| Geographical focus dummy | | -0.036 | 0.001 | -0.020 | 0.214 |
| | | (-0.54) | (0.02) | (-0.33) | (0.72) |
| Mutual fund type dummy | | | **-0.153*** | -0.103 | -0.664 |
| | | | (-1.70) | (-1.2) | (-1.43) |
| Hedge fund type dummy | | | -0.079 | -0.081 | -0.059 |
| | | | (-0.86) | (-0.91) | (-0.12) |
| Exchange-traded fund type dummy | | | **-0.172*** | -0.121 | -0.693 |
| | | | (-1.88) | (-1.45) | (-1.28) |
| No. of obs. | 2,916,845 | 2,916,845 | 2,916,845 | 2,667,829 | 249,016 |
| Adjusted $R^2$ | 0.020 | 0.178 | 0.190 | 0.184 | 0.250 |

## 4.4 Predictive regression

We further examine the predictive power of GPR betas for future fund performance using Q5–Q1 quintile portfolio sorts and Fama and MacBeth (1973) cross-sectional regressions over 3- and 6-month horizons. This analysis helps assess whether GPR exposure consistently forecasts excess returns and risk-adjusted performance across extended holding periods. Tables 8 and 9 present our predictive regression analysis results examining the relationship between GPR exposure and future fund performance over the $n$-month ahead fund excess returns and alphas (CAPM and CH-4). The risk premium linked to funds with negative exposure to the GPR persists for up to six months. In Table 8, we find that the negative performance differential between high and low $\beta^G$ funds persists across extended horizons. Over the next 3 months, the excess return spread between Q5 and Q1 funds is –0.479% ($t$-statistic = –2.36), and –0.472% ($t$-statistic = –2.31) over the next 6 months. This underperformance remains statistically significant even after adjusting for standard risk factors: CAPM alphas are –0.634% and –0.625%, while CH-4 alphas are –0.641% and –0.630%, over the next 3 and 6 months, respectively. The persistence of the risk premium aligns with Chen (2002) and Merton's (1973) ICAPM, where state variables like uncertainty or macro risk alter future investment opportunity sets, thereby requiring compensation in asset prices. These findings support our hypothesis 1, suggesting that the GPR is priced over the 6-month horizon.

In Table 9, in Model 1, the $\beta^G$ slope coefficients range from –0.061 (3-month ahead) to –0.050 (6-month ahead), implying that a one standard deviation increase in $\beta^G$ (1.15) is associated with a 0.058 to 0.070 percentage point reduction in next-month excess fund returns, relative to its sample mean. In Model 2, after including fund-level controls such as size, age, flows, downside risk, volatility, and geographical focus, the coefficients remain negative and statistically significant (–0.042 to –0.046), corresponding to a 0.048 to 0.053 percentage point reduction in future returns for each standard deviation increase in $\beta^G$. In Model 3, the results remain robust after adding fund-type dummies, with $\beta^G$ coefficients ranging from –0.040 to –0.045. This consistency across specifications reinforces the finding that geopolitical risk is a priced and forward-looking risk factor with predictive power that persists even after accounting for fund characteristics and styles. Overall, these results strongly support hypothesis 1 and align with ICAPM theory (Merton, 1973), indicating that GPR negative exposure predicts future fund performance persistently.

## Table 8: Predictive regression on univariate value-weighted portfolio analysis based on GPR beta

This table reports the results of predictive regressions of the $n$-month ahead excess returns, CAPM alphas and CH-4 alphas for the spread between Q5–Q1 quintile portfolios sorted on $\beta^G$ using equation (1). Quintile 1 (Q1) represents the portfolio of funds with the lowest $\beta^G$, while quintile 5 (Q5) includes those with the highest $\beta^G$. For each holding period, the excess returns of the high-minus-low (Q5–Q1) portfolios over the next 3 and 6 months are reported in the first row. The monthly risk-adjusted returns (alphas) are presented for each holding period based on CAPM and the CH-4 model, which accounts for market (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors, with all returns and alphas expressed in monthly percentage terms. Newey and West (1987) adjusted $t$-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| | Q5 - Q1 excess returns | |
|---|---|---|
| | 3-month ahead | 6-month ahead |
| Excess return (%) | **-0.479**** | **-0.472**** |
| | **(-2.36)** | **(-2.31)** |
| CAPM alpha (%) | **-0.634***** | **-0.625***** |
| | **(-2.78)** | **(-2.73)** |
| CH-4 alpha (%) | **-0.641***** | **-0.630**** |
| | **(-2.74)** | **(-2.67)** |

### Table 9: Fama and MacBeth predictive regression of fund returns on GPR beta and control variables

This table reports the n-month ahead average intercept and average slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of next-month fund excess returns on three different models. In Model 1, we run the regression using next-month fund excess returns on the $\beta^G$ calculated using equation (1). In model 2, along with the $\beta^G$, we add control variables namely (1) log of fund size; (2) log of fund age; (3) fund flows which is calculated monthly based on the flow measure of Franzoni and Schmalz (2017)(equation (3.1)); (4) downside risk measured using the 5% Value at Risk (VaR) based on the methodology in Ali et al. (2022); (5) return volatility based on standard deviation of cumulative return over the trailing 12-month period; and (6) geographical focus dummy equal to 1 if the fund is classified as Domestic using the LGC guidelines and 0 if it is considered International. In Model 3, we extend Model 2 by adding fund type dummies based on the 'asset universe' data provided by LGC guidelines: a mutual fund dummy equal to 1 if the asset universe belongs to a mutual fund, a hedge fund dummy equal to 1 if it belongs to a hedge fund, and an exchange-traded fund dummy equal to 1 if it belongs to an ETF and 0 otherwise under each dummy. Newey and West (1987) adjusted t-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| | Dependent variable: n−month ahead excess return | | | | | |
|---|---|---|---|---|---|---|
| | 3-month ahead | | | 6-month ahead | | |
| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| Intercept | 0.515** | -0.083 | -0.048 | 0.524** | -0.078 | 0.104 |
| | (2.39) | (-0.84) | (-0.60) | (2.47) | (-0.79) | (1.19) |
| $\beta^G$ | **-0.061**** | **-0.042*** | **-0.040*** | **-0.050**** | **-0.046**** | **-0.045**** |
| | **(-2.43)** | **(-1.82)** | **(-1.76)** | **(-2.22)** | **(-2.14)** | **(-2.09)** |
| Fund size | | 0.008 | 0.010 | | 0.008 | 0.010 |
| | | (1.27) | (1.63) | | (1.04) | (1.32) |

| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
|---|---|---|---|---|---|---|
| Fund age | | **0.040***** | **0.032**** | | **0.041***** | **0.032**** |
| | | **(2.64)** | **(2.18)** | | **(2.65)** | **(2.16)** |
| Fund flows | | 0.000 | 0.001 | | 0.001 | 0.001 |
| | | (0.55) | (0.62) | | (1.08) | (1.20) |
| Downside risk | | -0.000 | 0.003 | | 0.001 | 0.003 |
| | | (-0.01) | (0.10) | | (0.05) | (0.12) |
| Return volatility | | 0.085 | **0.094*** | | 0.079 | 0.087 |
| | | (1.51) | (1.66) | | (1.49) | (1.64) |
| Geographical focus dummy | | -0.035 | 0.006 | | -0.033 | -0.002 |
| | | (-0.49) | (0.09) | | (-0.47) | (-0.03) |
| Mutual fund type dummy | | | -0.014 | | | **-0.162*** |
| | | | (-0.15) | | | (-1.79) |
| Hedge fund type dummy | | | 0.046 | | | -0.089 |
| | | | (0.51) | | | (-0.95) |
| Exchange-traded fund type dummy | | | -0.063 | | | **-0.203**** |
| | | | (-0.66) | | | **(-2.29)** |
| No. of obs. | 2,916,842 | 2,916,842 | 2,916,842 | 2,916,839 | 2,916,839 | 2,916,839 |
| Adjusted $R^2$ | 0.018 | 0.156 | 0.168 | 0.015 | 0.133 | 0.144 |

## 4.5 Quantile regression

Koenker and Bassett (1978) describe the quantile regression method as an extension of ordinary least squares (OLS) that precisely calculates rates of change throughout the whole distribution of the response variable. In contrast to OLS, which concentrates solely on the conditional mean, quantile regression offers a more thorough examination by calculating the impacts of predictors over several quantiles. This is especially beneficial when the response variable demonstrates heterogeneity, as OLS may either understate or overstate the effects of predictor variables on the response variable (Badshah, 2012; Koenker, 2004; Koenker & Hallock, 2001). While the Fama and MacBeth (1973) regression framework provides useful mean effect estimates by averaging cross-sectional relationships over time, it does not account for heterogeneity across the distribution of returns or unobserved fund-level characteristics. Thus, the quantile regression approach is particularly well-suited for identifying asymmetric relationships between predictor variables and fund performance, capturing tail behaviour and providing a more refined understanding than mean-based approaches.

Studies in asset pricing literature increasingly use quantile regression to explore how predictors behave in extreme cases, such as underperforming or outperforming funds, which is especially valuable for understanding phenomena like tail risk, downside exposure, or return persistence. Recent applications of the MM–QR framework include Belloni et al. (2023), who propose a high-dimensional latent panel quantile regression model with an application to asset pricing, highlighting the importance of accounting for both observable characteristics and latent factors when analysing the entire distribution of asset returns. Furthermore, Urbizu et al. (2024) employ the MM–QR approach to investigate the asymmetric effects of firms' ESG risk exposure on stock volatility, demonstrating the versatility of this method in capturing heterogeneous relationships in financial data.

As an additional test to understand the heterogeneity of our predictors across the entire distribution of fund excess returns, we implement a quantile regression via the moments method approach (MM–QR) equation for panel data developed by Machado and Santos Silva (2019) at the fund level. This method helps us capture the individual fund fixed effects across the panel, an extension of the He (1997) restricted location-scale model to estimate the quantile coefficients. We run two models across different quantiles for potential non-linear effects along the distribution. In Model 1, we examine the effect of the predictor $\beta^G$ calculated using equation (1) on the response variable. In Model 2, we add control variables like the log of fund size, the log of fund age, fund flows, downside risk, and return volatility as predictors along with $\beta^G$. We run the following MM–QR approach quantile regression equation:

$$\mathcal{Q}_\tau \left( R_{t+1} \mid \alpha_i, X_{it} \right) = \alpha_i + \widetilde{\beta}(\tau)' X_{it} \tag{4}$$

where $\mathcal{Q}_\tau(\cdot)$ denotes the $\tau$th quantile of the response variable $R_{t+1}$, which is the next-month excess returns (beyond the monthly T-bill rate), $\alpha_i$ is a fund-specific fixed effect capturing unobserved heterogeneity across funds, and the vector of coefficients $\widetilde{\beta}(\tau)$ of the predictor variable $X_{it}$ varies with $\tau$, allowing us to estimate the coefficients at different points (quantiles) of the conditional distribution of $R_{t+1}$. In Model 1, $X_{it}$ is the predictor variable $\beta^G$ calculated using equation (1). In Model 2, $X_{it}$ is the vector of predictor variables $\beta^G$ and the control variables.

The results reported in Table 10 provide evidence supporting hypothesis 1, suggesting that higher GPR exposure leads to lower future returns, particularly among underperforming funds. In Model 1, the coefficient for $\beta^G$ is negative and significant at lower quantiles (5th to 25th), indicating that increasing geopolitical risk exposure often reduces next-month excess returns for underperforming funds. This suggests that the underperforming funds might lack the skill to effectively mitigate the impact of heightened GPR, making them particularly vulnerable to systematic risks (Bali et al., 2017; Pastor & Veronesi, 2013). In contrast, this effect reduces in magnitude and ultimately becomes positive and significant at the upper quantiles (above the 80th), indicating that well-performing funds may not be adversely affected by, and could even experience slight benefits from, heightened geopolitical risk. This finding could indicate that the top-performing funds possess the skill to navigate increased geopolitical uncertainty, offering preliminary evidence for hypothesis 2 (Berk & van Binsbergen, 2015).

## Table 10: Quantile regression with GPR beta and control variables

This table reports the results of the panel method-of-moments quantile regression (MM–QR) approach specification calculated using equation (4) (refer to section 4.5). The response variable is the subsequent month's excess fund returns. In Model 1, we run the panel MM–QR equation with only the $\beta^G$ calculated using equation (1) as the predictor. In Model 2, we run the panel MM–QR equation after including additional control variables like the log of fund size, the log of fund age, fund flows, downside risk and return volatility as predictors along with $\beta^G$. p-values are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| Response variable – Next-month excess return | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 (with controls) | | | | | |
| $\tau$ | $\beta^G$ | $\beta^G$ | Fund size | Fund age | Fund flows | Downside risk | Return volatility |
| 0.05 | -0.190*** | -0.187*** | -0.331*** | 1.243*** | 0.008 | 0.779*** | 0.948*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.157) | (0.000) | (0.000) |
| 0.10 | -0.149*** | -0.153*** | -0.312*** | 1.023*** | 0.006 | 0.602*** | 0.842*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.153) | (0.000) | (0.000) |
| 0.15 | -0.127*** | -0.133*** | -0.300*** | 0.892*** | 0.005 | 0.496*** | 0.779*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.158) | (0.000) | (0.000) |
| 0.20 | -0.110*** | -0.118*** | -0.291*** | 0.789*** | 0.004 | 0.414*** | 0.729*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.175) | (0.000) | (0.000) |
| 0.25 | -0.096*** | -0.105*** | -0.284*** | 0.705*** | 0.003 | 0.346*** | 0.688*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.207) | (0.000) | (0.000) |
| Median | -0.044*** | -0.058*** | -0.257*** | 0.394*** | 0.001 | 0.095*** | 0.539*** |
| | (0.000) | (0.006) | (0.000) | (0.000) | (0.735) | (0.000) | (0.000) |

| | Model 1 | Model 2 (with controls) | | | | | |
|---|---|---|---|---|---|---|---|
| | $\beta^G$ | $\beta^G$ | Fund size | Fund age | Fund flows | Downside risk | Return volatility |
| 0.75 | 0.001 | -0.019 | -0.235*** | 0.139** | -0.001 | -0.110*** | 0.416*** |
| | (0.866) | (0.522) | (0.000) | (0.026) | (0.720) | (0.000) | (0.000) |
| 0.80 | 0.012*** | -0.009 | -0.229*** | 0.075 | -0.002 | -0.161*** | 0.385*** |
| | (0.001) | (0.778) | (0.000) | (0.274) | (0.642) | (0.000) | (0.000) |
| 0.85 | 0.025*** | 0.002 | -0.223*** | 0.002 | -0.002 | -0.220*** | 0.350*** |
| | (0.000) | (0.958) | (0.000) | (0.979) | (0.575) | (0.000) | (0.000) |
| 0.90 | 0.041*** | 0.015 | -0.215*** | -0.083 | -0.003 | -0.288*** | 0.309*** |
| | (0.000) | (0.712) | (0.000) | (0.327) | (0.516) | (0.000) | (0.000) |
| 0.95 | 0.066*** | 0.032 | -0.206*** | -0.195* | -0.004 | -0.378*** | 0.255*** |
| | (0.000) | (0.486) | (0.000) | (0.043) | (0.460) | (0.000) | (0.000) |
| No. of obs. | 2,916,845 | 2,916,845 | 2,916,845 | 2,916,845 | 2,916,845 | 2,916,845 | 2,916,845 |

In Model 2, when we include control variables, the $\beta^G$ stays negative and significant for funds at lower quantiles (5th to 25th), while its effect at upper quantiles becomes mainly insignificant. This indicates that the adverse impact of geopolitical risk on underperformers is significant, but high-performing funds are less influenced when fund-level characteristics are considered. When we look at the coefficients for control variables, fund size is consistently negative and statistically significant across quantiles, indicating that larger funds generally demonstrate lower excess returns in the subsequent month. This aligns with the findings of Chen et al. (2004), who report a negative correlation between fund size and performance as they tend to face liquidity constraints. Conversely, fund age positively affects returns at lower quantiles, suggesting that more established funds exhibit superior performance in the left tail, although this benefit diminishes at higher quantiles. This finding reflects that experienced fund managers and stable investor bases allow funds to manage risk better in volatile environments (Ferreira et al., 2012). Fund flows exhibit no significance with excess returns, although downside risk negatively impacts the upper tail. Ultimately, return volatility positively influences next month's returns across all quantiles, although the impact of this effect diminishes at the upper quantiles. Overall, these results indicate a differentiated influence of GPR exposure across the different sections of the return distribution, supporting our hypothesis 1 and providing initial empirical evidence for hypothesis 2.

## 4.6 Fund-skill and GPR beta performance

We use a methodology to divide our fund sample into high-skill and low-skill subsets using the framework developed by Titman and Tiu (2011) as applied in Chen et al. (2021) to show managerial skill that improves fund performance during GPR fluctuations. This test aims to investigate whether the negative relation between GPR sensitivity and performance is concentrated more among high-skill managers, as they are potentially better equipped to navigate geopolitical uncertainty. We expect that if the skill enables managers to better anticipate and respond to change in GPR, then the negative association between the future returns and GPR should be more pronounced within a high-skill subset of funds.

We first compute the $R^2$ by regressing the fund's excess returns against the CH-4 factors: MKT, SMB, HML, and MOM for funds with at least 24 return observations within a 36-month rolling window. Following Chen et al. (2021), funds with an $R^2$ below the median are classified as high skill and low skill otherwise. This classification is based on the notion that skilled managers generate alpha through active management while relying less on systematic risk exposures, as previously documented in the literature.[11] For each skill subset, we follow the method described in section 4.1 to estimate the $\beta^G$ using equation (1) and construct quintile portfolios sorted by $\beta^G$ for univariate analysis. In addition, we conduct Fama and MacBeth (1973) regressions, as described in section 4.3, for three models on each subset individually. This approach assists us in evaluating whether the risk-return relationship linked to GPR is primarily driven by differences in managerial skill.

Table 11 reports the univariate results for high-skill and low-skill funds. For high-skill funds, the subsequent month's excess returns and risk-adjusted alphas decline monotonically from quintile Q1 to Q5. The return spread between funds with the highest and lowest GPR sensitivity for the subsequent month's excess returns, as indicated in a row "Q5 – Q1," is –0.167% ($t$-statistic = –1.94). This negative and statistically significant spread provides direct support to hypothesis 1, indicating that higher sensitivity to geopolitical risk reduces subsequent fund returns, particularly for high-skill managers. These results are consistent with the predictions in theoretical models, highlighting that significant exposure to systematic risks commands a premium (Merton, 1973; Pastor & Veronesi, 2013). In contrast, the low-skill fund subset shows minimal variation across quintiles, with a "Q5–Q1" spread of –0.040% in excess returns ($t$-statistic = –0.95) and similarly statistically insignificant alphas (both CAPM and CH-4 alphas). The findings indicate that the negative association between GPR sensitivity and fund performance is predominantly observed among high-skill funds, suggesting that skilled managers' active strategies to manage GPR inadvertently expose them to market uncertainties, influencing their fund performance.

[11] See, for example, Ackermann et al. (1999), Agarwal et al. (2009), Cremers and Petajisto (2009), Fama and French (2010), among others.

## Table 11: Univariate value-weighted portfolio analysis based on GPR beta for high-skill funds and low-skill funds

This table reports the univariate results of high-skill and low-skill funds. We partition the fund sample into high-skill and low-skill funds according to the Titman and Tiu (2011) hedge fund skill measure. Following Chen et al. (2021), in each month for each fund with at least 24 observations over the past 36 months, we estimate the $R^2$ by regressing the fund excess returns over the market (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors. A fund is classified as a high-skill fund if its $R^2$ is below the median level. It reports the average next-month fund excess returns, CAPM alphas and CH-4 alphas of five quintiles portfolios based on the $\beta^G$ calculated using equation (1) for high-skill and low-skill fund subsets. Value-weighted excess return portfolios are constructed using funds in each quintile in each subset from the lowest (Q1) to the highest (Q5) based on their GPR index betas. The row "Q5 – Q1" represents the spread between portfolio 5 and portfolio 1. The monthly risk-adjusted returns (alphas) are presented based on CAPM and the CH-4 model, which accounts for market (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors, with all returns and alphas reported in monthly percentage terms. Newey and West (1987) adjusted $t$-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| Quintiles | High-skill funds | | | Low-skill funds | | |
|---|---|---|---|---|---|---|
| | Next-month excess return (%) | CAPM alpha (%) | CH-4 alpha (%) | Next-month excess return (%) | CAPM alpha (%) | CH-4 alpha (%) |
| Q1 | 0.845 | 0.278 | 0.270 | 0.840 | 0.180 | 0.180 |
| | (4.83) | (3.96) | (3.95) | (4.69) | (3.52) | (3.47) |
| Q2 | 0.814 | 0.287 | 0.284 | 0.829 | 0.211 | 0.222 |
| | (4.09) | (3.97) | (3.96) | (3.66) | (3.70) | (4.37) |
| Q3 | 0.742 | 0.204 | 0.193 | 0.783 | 0.174 | 0.184 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (3.66) | (2.74) | (2.55) | (3.54) | (3.88) | (4.62) |
| Q4 | 0.722 | 0.157 | 0.139 | 0.758 | 0.148 | 0.158 |
| | (3.34) | (1.88) | (1.65) | (3.42) | (3.33) | (3.99) |
| Q5 | 0.678 | 0.108 | 0.100 | 0.800 | 0.160 | 0.170 |
| | (3.07) | (1.16) | (1.05) | (3.43) | (3.32) | (3.59) |
| Q5–Q1 – High–Low | **-0.167*** | **-0.170*** | **-0.170**** | -0.040 | -0.020 | -0.010 |
| | **(-1.94)** | **(-1.94)** | **(-1.97)** | (-0.95) | (-0.47) | (-0.24) |
| No. of obs. | 310 | 310 | 310 | 310 | 310 | 310 |
| Adjusted $R^2$ (Q5–Q1) | | 3.09% | 2.99% | | 5.78% | 5.69% |

In addition, Table 12 illustrates a significant difference in the influence of geopolitical risk exposure on the cross-sectional performance of high-skill and low-skill funds. In high-skill funds, the coefficient for $\beta^G$ consistently exhibits a negative and statistically significant value across all three models, varying from –0.073 in Model 1 to –0.056 in Model 3, which suggests that one standard deviation increase in GPR results in an estimated drop of around 0.06 to 0.08 percentage points relative to its sample mean in returns for the next month. On the contrary, low-skill funds demonstrate weaker and less compelling evidence: although the coefficient is negative (about –0.037 in Model 1), it becomes statistically insignificant upon the inclusion of additional control variables (Models 2 and 3). These results support our assertion in hypothesis 1, and the adverse effects linked to GPR sensitivity are far more pronounced among high-skill funds.

## 4.7 GPR timing

We present a GPR timing model based on the foundational market timing test by Henriksson and Merton (1981), in which fund managers tactically modify their market exposure in expectation of increased (or decreased) returns. The purpose of this test is to evaluate whether fund managers in our sample possess the ability to dynamically adjust their exposure to GPR in anticipation of future returns. This analysis directly addresses hypothesis 2, which posits that fund managers possess the skills to time GPR. Given that the changes in the GPR index by itself do not fully represent investment performance, we investigate the dynamics of fund exposure to the GPR factor, as indicated by the return differential between portfolios containing funds with low $\beta^G$ (Q1) and those with high $\beta^G$ (Q5). Previous studies have applied similar frameworks, reinforcing the significance of dynamic risk management in performance evaluation.[12]

[12] Similar methodology is also used in a different context by Jagannathan and Korajczyk (1986), Cohen et al. (2003), Y. Chen and Liang (2007), Bali, Cakici, and Whitelaw (2011), Cao et al. (2013), Bali et al. (2014), Caglayan and Ulutas (2014), among others.

**Table 12: Fama and MacBeth regression of fund returns on GPR beta and control variables for high-skill funds and low-skill funds**

This table reports the average intercept and average slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of next-month fund excess returns of high-skill and low-skill funds. We partition the fund sample into high-skill and low-skill funds according to the Titman and Tiu (2011) hedge fund skill measure. Following Chen et al. (2021), in each month for each fund with at least 24 observations over the past 36 months, we estimate the $R^2$ by regressing the fund excess returns over the market (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors. A fund is classified as a high-skill fund if its $R^2$ is below the median level. In Model 1, we run the regression using next-month fund excess returns on the $\beta^G$ calculated using equation (1). In model 2, along with the GPR index beta, we add control variables namely (1) log of fund size; (2) log of fund age; (3) fund flows which is calculated monthly based on the flow measure of Franzoni and Schmalz (2017)(equation (3.1)); (4) downside risk measured using the 5% Value at Risk (VaR) based on the methodology in Ali et al. (2022); (5) return volatility based on standard deviation of cumulative return over the trailing 12-month period; and (6) geographical focus dummy equal to 1 if the fund is classified as Domestic using the LGC guidelines and 0 if it is considered International. In Model 3, we extend Model 2 by adding fund type dummies based on the 'asset universe' data provided by LGC guidelines: a mutual fund dummy equal to 1 if the asset universe belongs to a mutual fund, a hedge fund dummy equal to 1 if it belongs to a hedge fund, and an exchange-traded fund dummy equal to 1 if it belongs to an ETF and 0 otherwise under each dummy. Newey and West (1987) adjusted t-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| | Dependent variable: Next month excess return | | | | | |
|---|---|---|---|---|---|---|
| | High-skill funds | | | Low-skill funds | | |
| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| Intercept | 0.468** | -0.215* | 0.034 | 0.556** | -0.123 | -0.063 |
| | (2.25) | (-1.84) | (0.37) | (2.44) | (-1.15) | (-0.55) |

| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
|---|---|---|---|---|---|---|
| $\beta^G$ | **-0.073**** | **-0.058**** | **-0.056*** | **-0.037*** | -0.024 | -0.023 |
| | **(-2.20)** | **(-1.99)** | **(-1.93)** | **(-1.76)** | (-1.32) | (-1.30) |
| Fund size | | 0.009 | 0.011* | | **0.008***** | **0.008***** |
| | | (1.49) | (1.87) | | (3.30) | (3.15) |
| Fund age | | **0.067***** | **0.055***** | | **0.015**** | **0.016**** |
| | | (3.01) | (2.62) | | (2.15) | (2.18) |
| Fund flows | | 0.002 | **0.002*** | | 0.001 | 0.001 |
| | | (1.60) | (1.73) | | (1.04) | (1.08) |
| Downside risk | | 0.020 | 0.025 | | 0.020 | 0.020 |
| | | (0.69) | (0.91) | | (0.68) | (0.68) |
| Return volatility | | 0.090 | **0.099*** | | **0.179**** | **0.179**** |
| | | (1.62) | (1.77) | | (2.49) | (2.49) |
| Geographical focus dummy | | -0.059 | -0.003 | | **0.056*** | 0.037 |
| | | (-0.79) | (-0.04) | | (1.79) | (1.47) |
| Mutual fund type dummy | | | **-0.202**** | | | -0.060 |
| | | | (-2.06) | | | (-0.58) |
| Hedge fund type dummy | | | -0.124 | | | -0.001 |
| | | | (-1.36) | | | (0.02) |
| Exchange-traded fund type dummy | | | **-0.330***** | | | 0.005 |

| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
|---|---|---|---|---|---|---|
| | | | (-3.45) | | | (0.04) |
| No. of obs. | 1,453,753 | 1,453,753 | 1,453,753 | 1,463,092 | 1,463,092 | 1,463,092 |
| Adjusted $R^2$ | 0.025 | 0.175 | 0.189 | 0.016 | 0.253 | 0.255 |

We implement this investigation following Chen et al. (2021) at the individual fund level instead of the fund index level, as not all funds are anticipated to effectively time GPR. We are mainly interested in whether diversity in fund GPR timing skills correlates with the cross-sectional dispersion in fund $\beta^G$ and performance. For each fund with a minimum of 24 monthly return observations, we run the following GPR timing regression:

$$
\begin{aligned}
R_{i,t} = \alpha_{1,t} + \beta^G \, \Delta GPR_t \\
+ \gamma\big(gpr\_factor_t \times I.(gpr\_factor_t > \overline{gpr\_factor_t})\big) \\
+ \beta' f_t + \varepsilon_{i,t}
\end{aligned}
\tag{5}
$$

where $R_{i,t}$ is the excess return (beyond the monthly T-bill rate) of fund $i$ in month $t$, and $\Delta\text{GPR}_t$ is the change in the current US GPR index value in month $t$. The variable gpr-factor$_t$ is the tradable GPR factor, which is the difference between the average excess returns of low (Q1) and high (Q5) $\beta^G$-sorted fund portfolios, and $I$ is a dummy variable equal to 1 when the tradable GPR factor is greater than its time series mean, and 0 otherwise. The risk factors included in the vector $f_t$ are the same as in equation (1). The coefficient $\gamma$ reflects the fund manager's ability to time GPR. A fund manager capable of timing GPR would augment the fund's exposure to the tradable GPR factor during periods of high factor returns, resulting in a positive $\gamma$ in equation (5). We therefore identify $\gamma$ as the GPR timing coefficient. We expect that a subset of managers, especially those who demonstrate superior performance, will exhibit positive and significant GPR timing coefficients reflecting the successful timing of GPR signals.

Table 13 reports the cross-sectional distribution of the $t$-statistic for the GPR timing coefficient $\gamma$ calculated using equation (5). The results show the percentage of $t$-statistics that exceed the predetermined cut-off values under the normal distribution assumption. In our sample, 3.08% of the funds exhibit a $t$-statistic exceeding 1.65 (i.e., 5% significance level in the right tail under normality). In comparison, 3.67% of the funds display a $t$-statistic below –1.65 (i.e., 5% significance level in the left tail under normality). A total of 17.47% of the overall funds display $t$-statistics below –2.33, indicating a significantly greater concentration in the extreme left tail, whereas only 4.72% of funds have $t$-statistics above 2.33. This variation suggests that although a small fraction of managers appear to successfully time GPR, consistent with hypothesis 2, most fund managers generally exhibit negative GPR timing coefficients. Furthermore, when analysed by asset type, alternative funds show a higher percentage of extreme negative $t$-statistics (21.49% below –2.33) than equity funds (16.13%), exhibiting variations in investment approaches and risk profiles across asset categories. While these inferences are drawn under the normality assumption, fund returns are not normally distributed (see, for example, Fung and Hsieh (1997)), thereby prompting further tests to check for the macro-timing ability of funds in our sample.

In our second test, to assess the macro-timing ability of funds, we examine whether funds actively adapt their exposures to fluctuations in the GPR index. The purpose is to establish whether such dynamic exposure reflects macro-timing skills, particularly among active funds. We anticipate a positive relation for active funds in contrast to passive funds, as active funds would be more inclined to capitalise on fluctuations in the GPR index. This serves as an additional test of hypothesis 2 and helps distinguish whether this skill is more prevalent among actively managed strategies.

For this, we categorise the funds in our sample as active or passive based on their 12-month rolling idiosyncratic volatility values. Specifically, we calculate the idiosyncratic volatility for each fund based on a 12-month rolling window and categorise the funds every year into active or passive based on the idiosyncratic volatility values at the start of the year. The fund is classified as active if the idiosyncratic volatility at $t$ – year start exceeds the 75th percentile of all the $t$ – year January values. Additionally, we categorise a fund as passive if its idiosyncratic volatility at $t$ – year January is below the 25th percentile of all the $t$ – year January values. Consequently, to test the capacity of active funds to anticipate fluctuations in the GPR index, we follow the market timing test of (Ali et al., 2022; Bali et al., 2014) to estimate the following pooled panel regressions:

$$R_{i,t} = \alpha + \beta_1 \, \mathrm{GPR}_t + \beta_2 \, \mathrm{GPR}_t^{high} + \varepsilon_{i,t} \tag{6}$$

where $R_{i,t}$ is the excess return (beyond the monthly T-bill rate) of fund $i$ in month $t$, and $\mathrm{GPR}_t$ is the GPR index value in month $t$. The variable $\mathrm{GPR}_t^{high}$ is equal to $\mathrm{GPR}_t$ if $\mathrm{GPR}_t$ is higher than the time series median US GPR index value, and 0 otherwise. In equation (6), we focus on the regression parameter $\beta_2$, which reflects the macro-timing ability of fund managers. If active funds indeed capitalise on fluctuations in the GPR index, one could expect a positive and significant $\beta_2$ value for active funds, indicating better macro-timing ability, whereas this coefficient would be negative for passive funds.

**Table 13: The cross-sectional distribution of the $t$-statistic of the GPR timing coefficient**

This table presents the cross-sectional distribution of fund-level $t$-statistics for the GPR timing coefficient $\gamma$ across funds with a minimum of 24 monthly excess return observations calculated using equation (5). The numbers in parentheses are the significance levels under the normality assumptions.

| Asset type | Number of funds | T $\leq$ -2.33 | T $\leq$ -1.96 | T $\leq$ -1.65 | T $\leq$ -1.28 | T $\geq$ 1.28 | T $\geq$ 1.65 | T $\geq$ 1.96 | T $\geq$ 2.33 |
|---|---|---|---|---|---|---|---|---|---|
| | | (1%) | (2.5%) | (5%) | (10%) | (10%) | (5%) | (2.5%) | (1%) |
| All funds | 30,674 | 17.47% | 3.27% | 3.67% | 6.10% | 4.49% | 3.08% | 2.65% | 4.72% |
| Equity | 21,701 | 16.13% | 3.39% | 3.78% | 6.07% | 4.50% | 3.28% | 2.97% | 5.28% |
| Mixed assets | 6,214 | 20.34% | 2.91% | 3.46% | 6.40% | 4.36% | 2.48% | 1.51% | 3.17% |
| Alternatives | 2,759 | 21.49% | 3.12% | 3.30% | 5.62% | 4.71% | 2.83% | 2.68% | 3.84% |

Table 14 presents the predicted values of $\beta_2$ along with their respective $t$-statistics, calculated using pooled panel regressions explained in equation (6) to assess macro-timing proficiency. The $t$-statistics are calculated using robust standard errors clustered at the fund level, accounting for within-fund correlation over time by one component of the two-way clustering recommendations by Petersen (2009). For active funds, the $\beta_2$ coefficient is positive (0.029) and statistically significant ($t$-statistic = 5.45), suggesting that active funds have superior market timing ability during periods of high GPR index. Conversely, passive funds display a substantially negative $\beta_2$ coefficient value (–0.045 with a $t$-statistic = –13.27), indicating that they do not adjust their exposures to take advantage during high GPR index periods. In addition, a higher percentage of active funds exhibit positive and significant $\beta_2$ estimates compared to passive funds (4.76% vs. 2.11%). Overall, the results in Panel B confirm hypothesis 2, implying that active funds display better market timing ability than passive funds. This is consistent with the broader literature indicating that skilled managers can effectively time systematic risk factors, particularly under macroeconomic uncertainties (Ali et al., 2022; Bali et al., 2017).

In our third test, we employ a panel quantile regression using the method-of-moments (MM–QR). We estimate two models, as outlined in equation (4) in section 4.5, across different quantiles to examine the effect of the predictor variable GPR timing $\gamma$ on the response variable. In Model 1, we run the panel MM–QR equation with only GPR timing $\gamma$ as the predictor of the response variable $R_{t+1}$, which is the next month's excess returns (beyond the monthly T-bill rate). In Model 2, we add the predictor $\beta^G$, calculated using equation (1), to the GPR timing $\gamma$. This test aims to investigate whether the impact of GPR timing ability, represented by $\gamma$, differs across various parts of the return distribution. In contrast to mean-based models, this technique enables us to determine whether GPR timing is especially beneficial or detrimental for funds at the highest and lowest points of performance. We anticipate that $\gamma$ will exhibit a positive association with fund returns in the upper quantiles, suggesting stronger timing skills among top-performing managers. This test extends our earlier analysis and is closely linked to hypothesis 2, helping us to assess whether GPR timing ability is concentrated in the upper tail of fund performance.

**Table 14: Macro-timing tests**

This table presents the macro-timing ability of funds. We first classify each fund each month as active or passive based on its 12-month rolling idiosyncratic volatility. The fund is classified as active if the idiosyncratic volatility at $t$ – year start exceeds the 75th percentile of all the $t$ – year January values. Additionally, we categorise a fund as passive if its idiosyncratic volatility at $t$ – year January is below the 25th percentile of all the $t$ – year January values. Next, we estimate $\beta_2$ using equation (6) for the pooled panel data and report the $t$-statistics using robust standard errors clustered at the fund level, accounting for within-fund correlation over time by one component out of the two-way clustering recommendations by Petersen (2009). Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| | Active funds | Passive funds |
|---|---|---|
| $\beta_2$ | **0.029*** ** | **-0.045*** ** |
| $t$-statistic | **(5.45)** | **(-13.27)** |
| No. of obs. | 1,303,745 | 823,984 |
| $R^2$ (%) | 0.06 | 0.22 |
| Percentage of funds with positive and significant $\beta_2$ | 4.76% | 2.11% |
| No. of funds | 36,514 | 20,265 |

The results of quantile regression using the GPR timing coefficient $\gamma$ as predictor variables are reported in Table 15. It shows distinct variations in the influence of the GPR timing coefficient $\gamma$ on the fund excess returns across quantiles. In Model 1, at lower quantiles, $\gamma$ is negative, indicating a lack of ability to effectively time GPR, leading to poor subsequent returns. This finding aligns with prior evidence that underperforming or less skilled managers often fail to capitalise on macroeconomic signals (Berk & van Binsbergen, 2015). In contrast, a positive and statistically significant $\gamma$ at the top quantiles (75th and above) suggests a proficient GPR timing capability, resulting in higher excess returns for top-performing funds. These results are consistent with hypothesis 2, implying that certain managers can dynamically adjust their portfolios to benefit from geopolitical risk (Ali et al., 2022; Chen et al., 2021).

**Table 15: Quantile regression with GPR timing coefficient and GPR beta**

This table reports the results of the panel method-of-moments quantile regression (MM–QR) approach with GPR timing coefficient $\gamma$ calculated using equation (5). The response variable is the subsequent month's excess fund returns. In Model 1, we run the panel MM–QR equation with only the GPR timing coefficient $\gamma$ as the predictor. In Model 2, we run the panel MM–QR equation after including the $\beta^G$ calculated using equation (1) along with the GPR timing coefficient $\gamma$. p-values are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| | Response variable: Next-month excess return | | |
|---|---|---|---|
| | Model 1 | Model 2 | |
| $\tau$ | $\gamma$ | $\gamma$ | $\beta^G$ |
| 0.05 | -0.209*** | -0.205*** | -0.176*** |
| | (0.000) | (0.000) | (0.000) |
| 0.10 | -0.154*** | -0.152*** | -0.138*** |
| | (0.000) | (0.000) | (0.000) |
| 0.15 | -0.124*** | -0.121*** | -0.116*** |
| | (0.000) | (0.000) | (0.000) |
| 0.20 | -0.101*** | -0.099*** | -0.100*** |
| | (0.000) | (0.000) | (0.000) |
| 0.25 | -0.081*** | -0.080*** | -0.086*** |
| | (0.000) | (0.000) | (0.000) |
| Median | -0.011*** | -0.011*** | -0.037*** |
| | (0.000) | (0.000) | (0.000) |
| 0.75 | 0.049*** | 0.048*** | 0.005 |
| | (0.000) | (0.000) | (0.000) |
| 0.80 | 0.064*** | 0.063*** | 0.016*** |
| | (0.000) | (0.000) | (0.000) |
| 0.85 | 0.081*** | 0.081*** | 0.028*** |
| | (0.000) | (0.000) | (0.000) |
| 0.90 | 0.103*** | 0.102*** | 0.044*** |
| | (0.000) | (0.000) | (0.000) |
| 0.95 | 0.138*** | 0.136*** | 0.068*** |

| | Model 1 | Model 2 | |
|---|---|---|---|
| | $\gamma$ | $\gamma$ | $\beta^G$ |
| | (0.000) | (0.000) | (0.000) |
| No. of Obs. | 2,862,051 | 2,862,051 | 2,862,051 |

The findings are largely consistent after adding $\beta^G$ calculated using equation (1), in Model 2 alongside $\gamma$. Both $\beta^G$ and $\gamma$ display negative coefficients at the lower tail and positive coefficients at the upper tail, reinforcing that higher GPR exposure negatively impacts weaker funds with lower excess returns but positively influences the fund with higher excess returns. This pattern confirms the view that GPR can act as a differentiating factor, where skilled managers exploit volatility while less adept funds suffer (Bali et al., 2017; Umar et al., 2022). Overall, the timing tests reveal considerable disparity in fund managers' capacity to successfully manage geopolitical risk, with the majority displaying ineffective timing skills, whereas a small proportion show superior skills in capitalising on geopolitical uncertainty to achieve better returns. Such heterogeneity is consistent with hypothesis 2, demonstrating that timing skill is concentrated among top performers, as predicted by skill-based asset pricing studies (Titman & Tiu, 2011).

# Chapter 5

# Robustness and supplementary tests

To evaluate the robustness of our univariate (section 4.1) and cross-sectional (section 4.3) results, we run two additional sets of tests. First, we re-estimate Model 3 of Fama and MacBeth's (1973) cross-sectional regressions (refer to section 4.3) under two distinct approaches. In approach 1, we calculate $\beta$ values for each of the three additional indices separately using equation (1) by replacing the US GPR index and then run Model 3 with those $\beta$ values. Besides the US-based country-specific index, we include additional measures of geopolitical risk, like the global GPR index, which serves as an overall indicator of global geopolitical uncertainty. This global index comprises two distinct sub-indices: the GPR Acts (GPRA) Index, which measures the impact of specific acts with geopolitical implications, and the GPR Threats (GPRT) Index, which assesses the perceived severity and probable consequences of these events (Caldara & Iacoviello, 2022). By comparing the results of the US-based country-specific index with these three alternative indices individually, we can cross-validate our earlier results and ascertain the impact of various dimensions of geopolitical risk on fund returns in our sample.

In approach 2, we calculate $\beta$ values for each of the three alternative indices separately using equation (1) by replacing the US GPR index and then run Model 3 with those $\beta$ values as control variables along with the $\beta^G$ values. For alternative indices, we include the NVIX (news volatility index), which measures variations in news sentiment and functions as an indicator of market uncertainty (Fang et al., 2018). We also use the PLS index and the war discourse index, developed by Hirshleifer et al. (2023), using a two-step Partial Least Squares (PLS) methodology that consolidates signals from 14 media discourse topics derived using a semi-supervised LDA technique. The war discourse index (one of the 14 topics in the PLS index), in contrast, breaks down specific coverage focused on war-related themes by tracking the frequency and weight of war seed words (such as "conflict", "tension" and "war") in media articles. These indices not only indicate the intensity of media coverage on 14 media discourse topics over 160 years but also serve as a powerful indicator of market returns, with increases in the war index specifically correlated with significant spikes in subsequent excess returns (Hirshleifer et al., 2023). We intend to evaluate the robustness of our main GPR findings by incorporating these additional and alternative risk index proxies. If our findings are consistent across various indices, it would further substantiate that geopolitical risk is a systematic risk factor impacting fund performance beyond the limitations of a single index or methodology.

Table 16 reports the summary statistics between the US GPR betas and the betas of other indices. It indicates that the US GPR beta has a mean of 0.03 and a standard deviation of 1.15, reflecting little average risk with some variation across funds. Conversely, the global GPR beta and its sub-indices, GPRA beta and GPRT beta, show greater mean values and higher variation, indicating the vulnerability to broad geopolitical uncertainties. Their strong correlations with the US GPR index, as reported in Table 17 (0.987 for global GPR, 0.913 for GPRA, and 0.812 for GPRT), imply that these indices serve as effective additional indicators to the US-specific index. Conversely, the War index, PLS 14 index, and NVIX index have much lower correlations with the US GPR index, with values of 0.394, 0.179, and –0.019, respectively. This weak association implies that these indices reflect different elements of market uncertainty and hence act as alternate proxies for robustness checks.

**Table 16: Summary statistics of additional and alternative index betas**

This table reports the results of the summary statistics using additional and alternative index betas. The beta for each index is calculated using equation (1) by replacing the respective changes in the index values in place of the changes in GPR index (refer to section 4.1).

| | Mean | Median | p5 | p95 | SD |
|---|---|---|---|---|---|
| US GPR beta | 0.03 | -0.01 | -1.48 | 1.46 | 1.15 |
| Global GPR beta | 0.09 | -0.01 | -3.60 | 3.54 | 2.91 |
| GPRA beta | -0.01 | -0.02 | -3.25 | 2.73 | 2.17 |
| GRPT beta | 0.09 | 0.00 | -2.93 | 3.07 | 2.47 |
| War index beta | 0.04 | 0.01 | -0.50 | 0.58 | 0.41 |
| PLS index beta | 0.08 | 0.02 | -1.94 | 2.24 | 1.32 |
| NVIX beta | -0.14 | -0.05 | -0.74 | 0.21 | 0.30 |

**Table 17: Correlation matrix between additional and alternative indices**

This table reports the correlation matrix between additional and alternative indices. All values are statistically significant at 1% or below.

| | Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| 1 | US GPR index | 1 | | | | | | |
| 2 | Global GPR index | 0.987 | 1 | | | | | |
| 3 | GPRA index | 0.812 | 0.802 | 1 | | | | |
| 4 | GRPT index | 0.913 | 0.936 | 0.544 | 1 | | | |
| 5 | War index | 0.394 | 0.419 | 0.428 | 0.345 | 1 | | |
| 6 | PLS index | 0.179 | 0.193 | 0.216 | 0.148 | 0.693 | 1 | |
| 7 | NVIX index | -0.019 | -0.015 | -0.031 | 0.002 | 0.115 | 0.139 | 1 |

Additionally, Table 18 shows that swapping the $\beta^G$ with the global GPR, GPRA, or GPRT betas yields consistently negative and considerable impact on the subsequent month's excess returns, thus supporting the fact that funds more vulnerable to geopolitical risk exhibit underperformance. These findings reaffirm hypothesis 1, demonstrating that GPR sensitivity to fund performance is robust to similar indices highly correlated with the US GPR index. The coefficient of the global GPR beta is –0.027 ($t$-statistic = –2.48), implying that one standard deviation (2.91) rise in the global GPR beta results in a 0.08 percentage point decrease (–0.027 $\times$ 2.91) in the following month's return.

Comparable effects are observed for GPRA (coefficient = –0.043, $t$-statistic = –2.85) and GPRT (coefficient = –0.027, $t$-statistic = –1.97), mirroring earlier findings for the US GPR beta. Furthermore, including the War index, PLS 14 index, or NVIX index in Model 3 does not change the US GPR beta's negative and statistically significant relation with next month's fund excess returns, with coefficients ranging from –0.08 to –0.10, all significant at the 1% level. This indicates that the initial findings for US GPR exposure remain robust, even after controlling for alternative indices of uncertainties.

In our second test, we replicate the univariate quintile-sorting approach outlined in section 4.1, but instead of employing value-weighted portfolios, we create equal-weighted portfolios for each $\beta^G$ quintile calculated using equation (1) and check the results for both excess and gross fund returns. This ensures that substantial funds do not overshadow portfolio performances and enables us to ascertain whether the inverse correlation between GPR exposure and subsequent performance persists when all funds are weighted equally (Asness et al., 2018; Fama & French, 2010). The GPR betas are identical; excess returns, CAPM alphas, and CH-4 alphas are now uniformly aggregated across funds within each quintile.

The results presented in Table 19 support the initial findings from the value-weighted analysis. The return differential between Q5 and Q1 consistently displays a negative and statistically significant trend in excess and gross returns. The Q5–Q1 differential return, as indicated in Panel A, is –0.459% for excess returns, whereas for gross returns presented in Panel B, it is –0.524%. The negative spreads show that funds with higher GPR betas (Q5) consistently underperform those with the lowest (Q1), even under the equal-weighted approach consistent with our hypothesis 1. These results indicate that the negative relation between GPR index exposure and fund performance is robust across different weighting parameters, which aligns with evidence that genuine priced risk factors persist regardless of portfolio construction (Asness et al., 2018).

## Table 18: Fama and MacBeth regression using additional and alternative index betas with control variables

This table reports the average intercept and average slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of next-month fund excess returns using model 3 (refer to Section 4.3). For additional indices, we replace $\beta^G$ with global GPR beta (column 1), GPR acts beta (column 2) and GPR threats beta (column 3) in model 3 specification and then run the regression. For alternative indices, we add war index beta (column 4), PLS index beta (column 5) and NVIX beta (column 6) as an additional control variable in model 3 specification and then run the regression. In model 3 specification we have control variables namely (1) log of fund size; (2) log of fund age; (3) fund flows which is calculated monthly based on the flow measure of Franzoni and Schmalz (2017)(equation (3.1)); (4) downside risk measured using the 5% Value at Risk (VaR) based on the methodology in Ali et al. (2022); (5) return volatility based on standard deviation of cumulative return over the trailing 12-month period; (6) geographical focus dummy equal to 1 if the fund is classified as Domestic as per the LGC guidelines and 0 if it is considered International; (7) fund type dummies based on the 'asset universe' data provided by LGC guidelines: a mutual fund dummy equal to 1 if the asset universe belongs to a mutual fund, a hedge fund dummy equal to 1 if it belongs to a hedge fund, and an exchange-traded fund dummy equal to 1 if it belongs to an ETF and 0 otherwise under each dummy. Newey and West (1987) adjusted t-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

| | Dependent variable: Next-month excess return | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Coeff. | Coeff. | Coeff. | Coeff. | Coeff. | Coeff. |
| Intercept | 0.049 | 0.044 | -0.003 | -0.034 | 0.029 | -0.033 |
| | (0.49) | (0.41) | (-0.03) | (-0.31) | (0.27) | (-0.31) |
| $\beta^G$ | | | | **-0.077*** ** | **-0.087*** ** | **-0.098*** ** |
| | | | | **(-2.61)** | **(-3.34)** | **(-2.98)** |

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Global GPR beta | -0.027** | | | | | |
| | (-2.48) | | | | | |
| GPR acts beta | | -0.043*** | | | | |
| | | (-2.85) | | | | |
| GPR threats beta | | | -0.027* | | | |
| | | | (-1.97) | | | |
| War index beta | | | | 0.123 | | |
| | | | | (1.09) | | |
| PLS index beta | | | | | 0.014 | |
| | | | | | (0.70) | |
| NVIX beta | | | | | | -0.031 |
| | | | | | | (-0.26) |
| Fund size | 0.005 | 0.005 | 0.005 | 0.005 | 0.006 | 0.005 |
| | (0.79) | (0.76) | (0.82) | (0.92) | (1.02) | (0.87) |
| Fund age | 0.050*** | 0.039** | 0.049*** | 0.063*** | 0.049*** | 0.057** |
| | (2.84) | (2.03) | (3.24) | (3.22) | (2.93) | (2.56) |
| Fund flows | 0.003** | 0.003** | 0.003** | 0.003** | 0.002** | 0.003** |
| | (2.31) | (2.31) | (2.28) | (2.15) | (2.22) | (2.12) |
| Downside risk | 0.020 | 0.020 | 0.022 | 0.022 | 0.013 | 0.021 |
| | (0.66) | (0.64) | (0.69) | (0.71) | (0.43) | (0.67) |

|  | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Return volatility | 0.092 | 0.095 | 0.092 | 0.089 | 0.083 | 0.089 |
|  | (1.38) | (1.41) | (1.38) | (1.36) | (1.25) | (1.34) |
| Geographical focus dummy | 0.001 | 0.002 | -0.004 | -0.018 | -0.003 | -0.007 |
|  | (0.02) | (0.03) | (-0.06) | (-0.24) | (-0.04) | (-0.09) |
| Mutual fund type dummy | -0.160 | -0.117 | -0.095 | -0.155 | -0.147 | -0.105 |
|  | (-1.49) | (-1.05) | (-0.95) | (-1.53) | (-1.35) | (-0.98) |
| Hedge fund type dummy | -0.072 | -0.024 | -0.006 | -0.054 | -0.054 | -0.013 |
|  | (-0.63) | (-0.20) | (-0.05) | (-0.48) | (-0.49) | (-0.10) |
| Exchange-traded fund type dummy | -0.115 | -0.074 | -0.047 | -0.124 | -0.100 | -0.064 |
|  | (-1.04) | (-0.65) | (-0.48) | (-1.23) | (-0.92) | (-0.59) |
| No. of Obs. | 1,953,906 | 1,953,906 | 1,953,906 | 1,953,906 | 1,953,906 | 1,953,906 |
| Adjusted $R^2$ | 0.198 | 0.194 | 0.197 | 0.217 | 0.214 | 0.212 |

## Table 19: Univariate equal-weighted portfolio analysis based on GPR beta

This table reports the average next-month fund excess returns, CAPM alphas and CH-4 alphas of five quintiles portfolios based on the $\beta^G$ calculated as per equation (1). Equal-weighted excess return portfolios are constructed using funds in each quintile from the lowest (Q1) to the highest (Q5) based on their $\beta^G$. The row "Q5 – Q1" represents the spread between Portfolio 5 and Portfolio 1. The monthly risk-adjusted returns (alphas) are presented based on CAPM and the CH-4 model, which accounts for market (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors, with all returns and alphas reported in monthly percentage terms. Panel A reports the results of equal-weighted excess fund returns. Panel B reports the results of equal-weighted gross fund returns. Newey and West (1987) adjusted $t$-statistics are provided in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Equal-weighted excess returns based portfolio analysis

| Quintiles | Average $\beta^G$ in each quintile | Next-month excess return (%) | Next-month CAPM alpha (%) | Next-month CH-4 alpha (%) |
|---|---|---|---|---|
| Q1 | -1.089 | 0.820 | 0.426 | 0.399 |
| | | (4.99) | (3.69) | (3.43) |
| Q2 | -0.330 | 0.698 | 0.296 | 0.268 |
| | | (4.28) | (3.59) | (3.32) |
| Q3 | -0.022 | 0.619 | 0.233 | 0.214 |
| | | (3.48) | (2.97) | (2.86) |
| Q4 | 0.293 | 0.545 | 0.193 | 0.184 |
| | | (3.02) | (1.65) | (1.59) |
| Q5 | 1.297 | 0.361 | 0.091 | 0.090 |
| | | (1.99) | (0.63) | (0.62) |
| Q5-Q1 - High-Low | | **-0.459*** ** | **-0.335** ** | **-0.309** ** |
| | | **(-2.64)** | **(-2.43)** | **(-2.34)** |
| No. of obs. | 310 | 310 | 310 | 310 |
| Adjusted $R^2$ (Q5-Q1) | | | 8.62% | 8.38% |

Panel B: Equal-weighted gross returns based portfolio analysis

| Quintiles | Average $\beta^G$ in each quintile | Next-month excess return (%) | Next-month CAPM alpha (%) | Next-month CH-4 alpha (%) |
|---|---|---|---|---|
| Q1 | -1.089 | 0.953 | 0.568 | 0.459 |
| | | (6.17) | (4.13) | (3.85) |
| Q2 | -0.330 | 0.811 | 0.426 | 0.397 |
| | | (4.81) | (3.93) | (3.24) |
| Q3 | -0.022 | 0.682 | 0.384 | 0.347 |
| | | (3.97) | (3.15) | (2.97) |
| Q4 | 0.293 | 0.578 | 0.267 | 0.211 |
| | | (3.23) | (2.56) | (2.13) |
| Q5 | 1.297 | 0.429 | 0.129 | 0.121 |
| | | (2.51) | (1.69) | (1.63) |
| Q5-Q1 - High-Low | | **-0.524*** ** | **-0.439*** ** | **-0.338** ** |
| | | **(-2.76)** | **(-2.61)** | **(-2.48)** |
| No. of obs. | 310 | 310 | 310 | 310 |
| Adjusted $R^2$ (Q5-Q1) | | | 9.43% | 9.16% |

# Chapter 6

# Conclusion

This study explores the relationship between US geopolitical risk and fund performance by investigating how exposure to US geopolitical risk affects the risk-adjusted returns on a sample of 37,149 US-based funds. The study employed a range of parametric and non-parametric tests, including univariate, multivariate, Markov-Switching dynamic regression model, Fama and MacBeth (1973) and quantile regressions to isolate and understand the correlation between the GPR beta and subsequent fund returns. In addition, both individual-level and macro-timing tests were conducted to examine the ability of fund managers to actively time their exposure to geopolitical risk.

The analysis shows that funds with negative exposure to geopolitical risk consistently generate 6.27% higher risk-adjusted returns annually compared to funds with positive exposure. Regime-dependent tests further reveal that the adverse impact of geopolitical risk is most pronounced during stable market periods, while cross-sectional and predictive regressions confirm that higher GPR exposure is associated with lower future returns even after controlling for various fund-specific characteristics. Furthermore, quantile regression results suggest that the detrimental effects of heightened GPR exposure are particularly significant among underperforming funds. In contrast, top-performing funds appear to mitigate these risks more effectively through superior managerial skills. In addition, timing tests reveal that approximately 4.26% of active funds successfully time their exposure to geopolitical risk, highlighting the heterogeneous nature of managerial responses. Our estimates survive a battery of robustness tests using alternative geopolitical risk index betas and equal-weighted portfolios, demonstrating that the baseline results display the negative effect of geopolitical risk on future fund performance. The findings indicate that geopolitical risk is a crucial state variable in asset pricing models. The findings contribute to the asset pricing literature by extending the discussion on systematic risk factors to include geopolitical risk.

The implications of these findings are multifaceted. They offer practical insights for investors and fund managers, underlining the need for careful risk management in a more geopolitically volatile landscape. The evidence indicating that funds with reduced exposure to geopolitical risk generate superior risk-adjusted returns highlights the advantages of integrating geopolitical risk evaluations into asset allocation and risk management strategies for investors and portfolio managers. The study underlines the importance of policymakers and regulators monitoring geopolitical developments and their impact on financial markets, facilitating more proactive risk management and regulatory measures. The study supports the view that geopolitical risk is a significant state variable in asset pricing, which further advocates the inclusion of geopolitical risk in existing risk assessment models and suggests avenues for refining theoretical frameworks to better account for geopolitical events.

Our focus is confined to US-based funds, while providing insights into this market, suggests the need to examine the generalisability of these findings in a global context. Additionally, the dataset from the Refinitiv Lipper for Investment Management (LIM) database does not include specific data points like management fees, incentive fees, and expense ratios that could further influence fund performance. Rather than detracting from our study, these aspects reinforce the robustness and contribution of our study while highlighting promising avenues for further refinement in future research.

Future studies may build on this study by examining the influence of geopolitical risk on alternative asset classes, such as bonds or international funds, to ascertain whether comparable risk premiums exist in these markets. Further research may also investigate the influence of GPR in emerging markets, where sensitivities to geopolitical events might vary from those in developed economies. Additionally, event-specific analysis could assess the influence of significant geopolitical shocks on fund performance by using option market data or trade volumes to capture market reactions in a different setting.

In conclusion, this study confirms that geopolitical risk is a priced factor in fund performance and provides a thorough basis for integrating these risks into investment strategies and asset pricing models. These findings contribute to a deeper understanding of the complex interplay between geopolitical uncertainty and financial market outcomes, facilitating better-informed decision-making and further academic exploration.

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