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Teflon Capitalism: Geopolitical Risk and Investment Funds

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Keywords

geopolitical risk, investment funds, portfolio reallocations, stock markets

JEL Classification

F3, F5, G1, G3

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Teflon Capitalism: Geopolitical Risk and Investment Funds*

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October 18, 2026

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1 INTRODUCTION

The truth is that stocks can handle most conflicts, despite us being told how much they hate uncertainty.

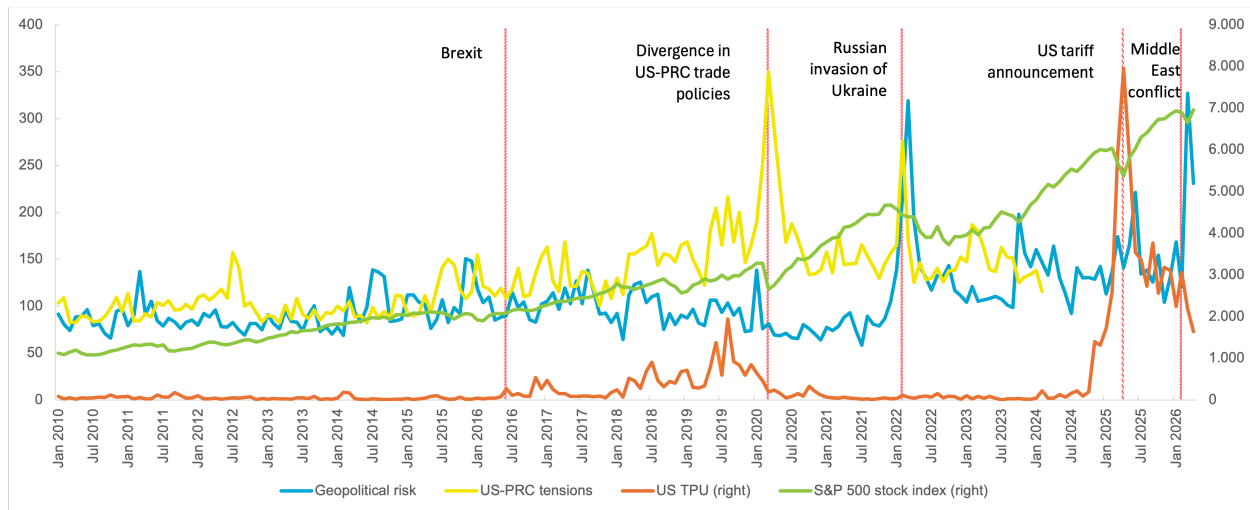
Stuart Kirk, 2024

Geopolitical risk (GPR) has become an increasingly prominent feature of the global economy. A broader quest for national autonomy accompanied by increased protective measures saw policy uncertainty skyrocket in 2025. Evidence abounds that a realignment of energy, trade and defense policies on the grounds of national strategic considerations fueled the fragmentation of global value chains and international financial flows. Declines in trade, investment, capital flows and growth amid rising inflation may result from national agendas taking precedence over global collaboration (Aiyar et al. 2023; Góes and Bekkers 2022; Gopinath et al. 2025; Fernández-Villaverde et al. 2024; Niepmann and Shen 2025; Pradhan et al. 2025). These dynamics drag down asset prices of exposed firms as shown by IMF (2025), Gonçalves et al. (2025), Hirshleifer et al. (2025) and Yilmazkuday (2024). Yet, in the aggregate, markets defy the gloom akin to a notion of Teflon capitalism (The Economist 2025). The Dax, S&P 500, and Nikkei stock market indices rose by 90%, 130%, and 170% respectively, over January 2020 to May 2026—a period of major geopolitical frictions (Figure 1).

What explains markets' resilience in face of major geopolitical upheaval? We conjecture that the risk-taking behavior of certain investors accounts for the muted stock market reaction. To study this hypothesis, we zoom into investment funds as a major investor category, holding about one third of global investable markets. Detailed data on funds' portfolio allocations combined with a measure of investee firms' GPR exposure help shed light on markets' response to global GPR shifts.

We document that funds' portfolio reallocations amid GPR shocks are key to understand the seeming market calm. The analysis proceeds in two steps. First, we show that funds pivot into stocks of more GPR-exposed firms when GPR increases, irrespective of the geographic source of GPR shocks. A two-standard deviation increase leads funds to raise the valuation-adjusted portfolio shares in stocks of more GPR-exposed firms by three basis points, equal to one fifth of funds' median portfolio shares. The effect is largely driven by extreme GPR episodes, such as

Figure 1: Geopolitical risk, policy uncertainty, and stock markets



PRC = People's Republic of China, TPU = trade policy uncertainty.

Sources: Baker et al. 2016, Caldara and Iacoviello 2022, Rogers et al. 2024, CEIC.

after the Russian invasion of Ukraine. Dynamics in specific industries do not drive the results, e.g., defense or the manufacturing of dual goods that could have been expected to attract higher demand after GPR shocks. Large fund domiciles like the United States (US) and Luxembourg, firms headquartered in any particular economy or funds belonging to large asset management companies do not account for the results either. Similarly, results do not depend on firm characteristics other than GPR exposure.

Second, we clarify what attracts funds into GPR-exposed firms when global GPR-related events unfold. We gauge that more GPR-exposed firms experience a larger decline in stock prices, in line with IMF (2025), Hirshleifer et al. (2025), Yilmazkuday (2024), and Crosignani et al. (2025). This decline in valuations of otherwise sound assets raises expected returns, incentivizing funds to purchase equities at depressed prices akin to search for yield. This search for yield-driven demand for GPR-exposed firms' stocks is what makes valuations swiftly recover, leaving financial markets seemingly calm, as if coated by Teflon. That is, investment funds—traditionally recognized as threat to financial stability—can help soften the blow to stock markets after GPR-injected volatility (Borensztein and Gelos 2003; Dahlhaus and Vasishtha 2014; Davis and Zlate 2023; Jotikasthira et al. 2012). Applying the same analytical framework to

bond funds does not see bond prices decline upon GPR shocks materializing, implying that the pivot into GPR-exposed firms is unique to equity funds.

Funds' search for yield is more pronounced for lower-performing funds, consistent with the risk-taking behavior of weak banks (Blattner et al. 2023; Acharya 2009). Higher risk-taking capacity—measured by large fund size and cash buffers as well as increased inflows prior to GPR shocks—also induces funds to allocate into GPR-exposed stocks more significantly. We show that when funds pivot into GPR-exposed stocks it yields more concentrated portfolios—in terms of fewer equities, industries, and firm headquarter countries—and a higher portfolio concentration index. We show that funds' pivot into GPR-exposed stocks yields more concentrated portfolios in terms of fewer equities, industries, and countries that investee firms are headquartered in, and a higher portfolio concentration index. Funds balance higher concentration with increased cash holdings to insure against downside risks.

Further, we contrast the behavior of fund managers with ultimate investors: When stock valuations of more GPR-exposed funds fall upon GPR impact, fund managers increase holdings in GPR-exposed stocks. In contrast, ultimate investors shift away from such funds. This dichotomy may reflect retail investors' well-documented behavior of pro-cyclical selling due to myopic loss aversion (Frazzini and Lamont 2008).

The analysis relies on a highly granular dataset combining investment funds' portfolio allocations with investee firm characteristics. We obtain a detailed dataset of funds' stock-level allocations from EPFR's Global "Dynamic Equity Holdings"—constituting to our knowledge this dataset's first use for academic research. We extract stock-level portfolio allocations for the period 2011:M1–2025:M3. Portfolio allocations are strictly positive, confining the initial analysis to reallocations along the intensive margin, with results later confirmed for an expanded dataset that includes zero allocations and hence the extensive margin. Our dataset covers both holding values and portfolio shares. We use the latter two to back out share prices, allowing us to control for valuation changes and thus isolate funds' active portfolio reallocations. The data covers 12,324 equities issued by 12,019 investee firms, held in the portfolios of 5,515 equity funds. Data at monthly frequency is essential to identify fund portfolio shifts in response to GPR shocks. Lower frequency data could fail to detect fund managers' swift responses. We supplement funds'

portfolio allocations with further information about funds, such as assets under management (AUM), cash shares and ultimate investor inflows from EPFR's "Fund Flows" database.

We merge the portfolio allocations with data on investee firms' GPR exposures. We derive our measures of firm-specific GPR exposures from quarterly earnings call transcripts obtained from S&P Capital IQ, similar to Hassan et al. (2019) and Clayton et al. (2025). The main exposure measure is the ratio of relevant keywords as specified in Caldara and Iacoviello (2022) to the total number of words in each transcript. For robustness, we use several variations of keyword counting, also using industry averages excluding the respective firm to remedy endogeneity concerns. Results are robust to the use of dummies defined if exposure exceeds the 25th, 50th, or 75th percentiles. We finally merge other firm and macroeconomic country characteristics as well as global GPR developments. Text-based indices provided in foundational work by Caldara and Iacoviello (2022) serve as GPR shifters in our regression framework. Data on firm characteristics comprise headquarter residence, industry, and employment as well as several balance sheet and profit and loss characteristics.

Using this merged dataset, we estimate panel regressions, relating fund-stock-level portfolio shares to firms' GPR exposure interacted with the global GPR shifter, controlling for firm, industry, country, and fund characteristics. The latter comprise fund size, past performance, and valuation changes computed as the change in share prices. Fund-stock and fund-time fixed effects absorb a wide-range of potential confounders such as time-varying fund characteristics common to all stocks a fund is invested in, and funds' time-invariant preferences for any particular equities. Country-time fixed effects in selected specifications isolate the supply effect of GPR shocks on fund portfolio allocations. They also disentangle allocations across equities from those across countries. Additional industry-time fixed effects eliminate cross-industry shifts as confounders. Controls for global economic policy uncertainty and oil price uncertainty ensure that our results hold irrespective of contemporaneous shifts in global policy uncertainty.

A series of placebo analyses demonstrate the empirical relevance of our exposure measure, and highlight parallel trends between more and less GPR-exposed firms in the absence of GPR shifts. These tests compare results during placebo time periods with low GPR, in a placebo sample containing only exchange traded funds (ETFs) with little room for any portfolio reallocations, and through firms' GPR exposure randomization. Further, we decompose the GPR exposure measure

into separate themes, and find that GPR shifts induce funds to invest mostly in firms exposed to a beginning or an escalation of war.

Our insights build on several strands of literature covering repercussions of GPR for macroeconomic accounts, global financial integration, and investor behavior. GPR shocks—proxied by innovations in GPR indices—and rising geopolitical fragmentation—measured by geopolitical distance—tend to lower output and drive inflation up, as discussed by Caldara et al. (2026), Iacoviello and Tong (2026), Fernández-Villaverde et al. (2024), Aiyar et al. (2023), Bondarenko et al. (2024), and Ambrosino et al. (2024). Firm-level investment declines sharply as GPR rises, notably for firms with low cash positions (Le and Tran 2021; Wang et al. 2024; Sheng et al. 2025). Such investment declines are likely tied to firms changing financing conditions in response to GPR shocks (Akyildirim et al. 2026; Paltalidis and Zhang 2025; Roy et al. 2024; Tang and Huang 2025). A commensurate drop in firm-level innovation suppresses economic growth (Dissanayake et al. 2018). Besides lower investment, Caldara and Iacoviello (2022) find a contraction in employment, confirmed by Hassan et al. (2019) at the firm level. Our work draws attention to how international investors reallocate equity portfolios in response to GPR-induced firm-level dynamics, and points at the implications for financial market stability.

Immediately relevant for our setup is the sensitivity of firms' equity prices to GPR shocks. We demonstrate that such shocks imply a decline in firms' equity valuations, in turn raising expected returns. Higher yields then attract investment funds to buy GPR-exposed firms' stocks, helping restore market valuations. This is because investors demand additional compensation in the form of higher expected returns for stocks susceptible to GPR shocks (Chen et al. 2026; Hirshleifer et al. 2025). Thus, GPR shocks do not inflict permanent scarring to asset prices, while short-lived price volatility does ensue. This asset price-GPR link is grounded in work by Yilmazkuday (2024), Hentov et al. (2018), D'Orazio et al. (2024), Beirne and Renzhi (2026), IMF (2025), Zhang et al. (2024), Huang et al. (2023), Federle et al. (2024), Zaremba et al. (2022), Crosignani et al. (2025), Cheng et al. (2024), Salisu et al. (2022), Sheng et al. (2025), Rafi and Ali (2025), and Gonçalves et al. (2025), all of whom corroborate the initial drop in asset prices and rise in expected returns as GPR shocks unfold. The equity pricing reaction is more pronounced for geopolitical threats than acts, emphasizing the market salience of GPR-signals.

Closely related to our work is the literature on the response of cross-border capital flows and capital allocation in response to GPR. Portfolio investments are decreasing in geoeconomical distance, as Catalán et al. (2024)'s gravity framework shows. Intensifying geopolitical dynamics weigh on cross-border portfolio and bank capital allocations, resulting in suppressed inflows and increased outflows, with a 'flight to safety' from Emerging Markets to Advanced Economies (Monetary and Department 2023; Feng et al. 2023). Declines in equity flows materialize faster and are most pronounced, reflecting greater sensitivity to political uncertainty (Chari et al. 2022).

Further differentiating by capital type, FDI has been shown to reallocate in reaction to shifting global supply chains (Aiyar et al. 2023; Avendano et al. 2026; Aiyar and Ohnsorge 2024). The reconfiguration patterns entail a concentration among geopolitically aligned countries (Gopinath et al. 2025; Kallen 2025). Similarly, cross-border bank flows fall markedly as GPR rises (Pradhan et al. 2025; Catalán and Tsuruga 2023). Niepmann and Shen (2025) show that banks partly offset the reduction in cross-border lending through lending by foreign affiliates. However, cross-border bank credit may shift towards more risky borrowers (Casanova et al. 2024). Portfolio investments also exhibit some alignment with geopolitical blocs as geopolitical distance increases (Airaudo et al. 2025). We add to this literature by zooming into the GPR-driven reallocation of portfolio equity held in investment funds' portfolios, highlighting the market-stabilizing force of relatively risk-loving agents.

Prior work studies the link between GPR and financial integration through the lens of fund portfolio reallocations. Converse and Mallucci (2025) find that bond funds substitute away from geopolitically high-risk countries, with investments concentrating in fewer countries more geopolitically aligned with the funds' domicile. Choi and Havel (2025) confirm that the substitution effect is concentrated in Emerging Markets. This literature focuses on cross-country reallocations along geopolitical alignments. Our work, in contrast, employs more granular data and focuses on the allocation of investment funds across individual securities. We explicitly control for country-time heterogeneity and can thus focus on fund managers' stock-level portfolio shifts as different from reallocations across countries. Based on our granular approach, we confirm an increase in portfolio concentration after GPR shifts, as also highlighted by Converse and Mallucci (2025) and Crosignani et al. (2025).

Studies employing stock-level fund holdings are scarce. Funds domiciled in the PRC have been shown to scale back market risk exposure and increase cash positions as GPR increases (Liu et al. 2024). Huang (2025) shows that US-PRC trade developments lead US equity mutual funds to allocate away from PRC-based equities in favor of less risky Asian destinations, while PRC-domiciled funds maintain US exposure. US funds also shift domestic allocations towards firms with lower exposure to the bilateral relations. Crosignani et al. (2025) also report that US mutual funds allocate away from stocks of US exporters to the People's Republic of China (PRC) when export controls are imposed. This contrasts with our findings based on a global sample at the fund-stock level beyond the US and the PRC. We find no evidence that investment funds reallocate away from exposed firms. Instead, funds seek to invest more in GPR-exposed firms as their stocks become cheaper when GPR materializes, helping restore valuations after GPR events. Our results thus highlight a new and complementary mechanism explaining equity market resilience amid geopolitical turmoil.

Our findings contrast with previous characterizations of funds as amplifiers of capital outflows from Emerging Markets, thus undermining financial stability. Early work by Borensztein and Gelos (2003) studies the role of funds in abetting financial crises by accelerating capital outflows. More recently, Davis and Zlate (2023) show that funds enabled capital outflows during the COVID-19 pandemic. In contrast, our work is aligned with the literature revealing a contrarian trading strategy against price pressures, suppressing capital outflows rather than amplifying them, and thus contributing to valuation stabilization. Besides outright contrarian funds, those with rule-based allocations like target-date-funds acted as a stabilizing force during the COVID-19 pandemic (Parker and Sun 2025; Wei et al. 2015). Similarly, funds using swing pricing mechanically help stabilize stock valuations (Ma et al. 2025). Index funds and those absorbing investor flows internally are also known to trade against price pressures, thus stabilizing markets (Goetzmann and Massa 2003; Chernenko and Sunderam 2016). Our work thus calls attention to the benefit of investment funds in absorbing system-wide GPR shocks.

Finally, we seek to enrich the understanding of fund portfolios' sensitivity to policy-related shocks. Alok et al. (2022), Hou and Wang (2022), Hassan et al. (2024), Converse and Mallucci (2023), and te Kaat and Raabe (2025) study the response of fund portfolios to economic policy

uncertainty, country, sovereign, and biodiversity risks.¹ The portfolio reallocation in response to various shocks also makes funds important conduits for the international spillover of climate, monetary policy, and the global financial cycle (Davis and Zlate 2023; Converse et al. 2023). We underline the sensitivity of portfolio allocations to GPR as a new policy dimension, with knock-on effects for financial markets and cross-country flows.

This paper proceeds as follows. In section 2, we present the dataset and summary statistics. Section 3 describes our identification strategy and section 4 presents the results, including robustness checks. Section 5 explores the underlying mechanism. To distinguish the funds' portfolio reallocation from ultimate investor responses to GPR shocks, section 6 studies how such shocks drive ultimate investor flows. We conclude with section 7. Data details and further robustness checks are documented in the Appendix.²

2 DATA

A uniquely assembled dataset of detailed equity fund allocations combined with investee firms' GPR exposures, standard firm and country characteristics, as well as global GPR shocks underpins our analyses. We describe each dataset in turn, followed by summary statistics.

2.1 Fund-Stock-Level Portfolios

To our knowledge we are the first to use EPFR Global's "Dynamic Equity Holdings" for academic research. It records funds' monthly share holdings in a stock, in terms of both the value and number of shares.³ This granularity enables us to study GPR-induced portfolio reallocations at the fund-stock level.

We clean the raw data in three steps. First, we exclude all equities with missing identifier (ISIN code), allowing us to merge the fund-stock-level data with the other datasets presented below. Second, we remove duplicate entries with the same combination of fund identifier, stock identifier,

¹ Capital controls, corporate transparency, currency denomination, and fund performance are also known to affect allocations (Forbes et al. 2016; Gelos and Wei 2005; Maggiori et al. 2020; Broner et al. 2006; Camanho et al. 2022).

² The Appendix is available at <http://dx.doi.org/10.22617/WPS260459-2>.

³ Fund-stock allocations are self-reported by fund managers to EPFR Global, and not computed by the data provider. Funds that report allocations only at lower frequency, or that report only flows into funds without any portfolio breakdown do not feature in the "Dynamic Equity Holdings" dataset. EPFR Global's internal consistency checks and checks against publicly available data help guard against any misreporting, and thus measurement error.

and report date to eliminate measurement error. Finally, we restrict the sample period to January 2011 to March 2025. After cleaning, the fund-stock-level panel includes 9,702 unique funds and 44,385 unique investee equities, which is issued by 36,549 unique firms.⁴

EPFR Global’s “Dynamic Equity Holdings” dataset contains strictly positive portfolio allocations only, implying that by default we study the intensive margin of portfolio adjustments. To also capture the extensive margin, in section D, we construct an expanded dataset inclusive of zero allocations. To this end, we fill in the gaps to obtain a strongly balanced fund-stock panel dataset. Using this larger dataset, we find our results unchanged. We take this as reassurance for our baseline analysis to proceed only with the smaller dataset.

We obtain portfolio shares by scaling the fund-stock-level holding value by a fund’s total holding value. In our regressions, following Forbes et al. (2016), we use the month-over-month growth rate of portfolio shares as our main dependent variable. As portfolio shares tend to take very small numbers, we compute growth rates as changes in the inverse hyperbolic sine (IHS)-transformed portfolio share, and not as log-differences. As explained in Norton (2022) and Aihounton and Henningsen (2021), marginal effects of IHS transformations are well-defined at zero as well as close to zero, i.e., they are closer to identity when the values of a variable approach zero. The natural logarithm, in contrast, becomes negative and large in absolute terms. Another advantage of the IHS-growth rate, in contrast to log-differences, is that it is defined at zero (Bellemare and Wichman 2020; Burbidge et al. 1988), so we can use the same dependent variable for the analysis in our smaller dataset (only considering the intensive margin) and the expanded one (considering both the extensive and intensive margin). For robustness, we also employ the absolute change in fund-stock-level portfolio shares as dependent variable.

Portfolio shares can change due to two forces: (i) active reallocations by fund managers and (ii) changes in stock prices (valuation effects). As we are interested in how fund managers reallocate portfolios due to GPR shocks, we need to control for valuation changes. For this, we derive stock prices as the ratio of a fund’s holding value in a stock and the numbers of shares held in that stock.⁵ We include the IHS-transformed growth rate of these stock prices as a control in most of

⁴ Zooming in active funds sample, there are 5,549 active funds investing in 38,832 equities from 32,849 firms.

⁵ While this approach yields variation in stock prices for the same stock across funds, we confirm that this variation is negligible, with the average stock-month standard deviation across funds amounting to \$0.22 compared to the min-max range of \$1.84.

our regressions. Growth rates in portfolio shares and stock prices are winsorized at the 1% and 99% levels to mitigate the impact of outliers.

The “Dynamic Equity Holdings” dataset also contains time-invariant information about funds, including domicile, the asset management company, and whether it is an Exchange Traded Fund (ETF) or an actively-managed fund. Our main analysis focuses on the latter because only managers of actively-managed funds can reallocate their portfolios, in contrast to ETFs that passively track a benchmark. We obtain fund-level time-varying variables from EPFR’s “Fund Flows” database previously used in several studies (e.g., Bettendorf and Karadimitropoulou 2023; Converse and Mallucci 2023; Converse et al. 2023; Forbes et al. 2016; Koepke and Paetzold 2024; te Kaat et al. 2026). In particular, we extract data on funds’ assets under management (total net assets), cash shares, ultimate investor flows scaled by assets under management, and fund returns. To smooth the latter two variables, which have extreme standard deviations, we compute 3-months moving averages. The fund flow variable is additionally winsorized at the 1% and 99% levels to eliminate any remaining outliers.

2.2 Earnings Call Transcripts

We obtain our measure of the firm-specific GPR exposure from publicly traded firms’ global earnings call transcripts. Relative to regulatory filings, such as 10-K forms, the interactive nature of earnings calls—an exchange between analysts and management—entails more contextual and even sentimental information (Hassan et al. 2019; Clayton et al. 2025). It is this contextual information that makes earnings calls ideal to gauge firms’ exposure to GPR. While the calls typically start with a management presentation prepared ex-ante, it is the subsequent question-and-answer session that allows analysts and investors to raise new developments including any recent GPR shocks, e.g., enquiring how a firm considers adapting supply chains amid geopolitical turmoil.

S&P Capital IQ is our source of earnings calls transcripts, accessed via Wharton Research Data Service. The transcripts benefited from preliminary cleaning and verification by human editors. We use this processed version for higher accuracy, covering 503,911 scripts from 20,023 companies over the period January 2011 to March 2025.

Using the earnings calls transcripts, we construct measures of firm-level GPR exposure using the keyword search method pioneered by Caldara and Iacoviello (2022). For each transcript, we assess the number of relevant keywords outlined in Caldara and Iacoviello (2022) and scale it by the total number of words in the transcript (see Table A2 of Online Appendix A). Besides all GPR-related keywords, we construct the following GPR exposure measures by sub-topic, as also defined by Caldara and Iacoviello (2022): war threats, peace threats, military buildups, nuclear threats, terror threats, beginning of war, escalation of war, terror acts.

Regular earnings calls are held at quarterly frequency. Irregular calls may be scheduled as well, albeit infrequent. We retain the transcripts of all calls, regular and irregular. Thus, we usually encounter one earnings call and hence one transcript per firm-quarter.⁶ Yet, for the few cases of multiple calls per quarter, we compute the exposure measure for each transcript as described above, and then average across all transcripts in a firm-quarter. To explore nonlinearities in our overall exposure measure, we compute dummies that take a value of one when a firm's GPR exposure exceeds the 25th, 50th, and 75th percentile of the sample distribution, respectively, otherwise zero. In a robustness check we use a variation of the GPR exposure measure in line with Appendix E3 of Caldara and Iacoviello (2022), constructed by counting the joint occurrence of risk-related and geopolitical keywords within a 10-word window in the earnings call transcript.⁷

2.3 Firm Balance Sheet Data

We merge the aforementioned data with a range of firm-level data obtained from Compustat Global via Wharton Research Data Services, a key provider of standardized financial statement information for publicly listed companies. The information covers firm characteristics, like headquarter locations and industry (SIC) codes, as well as financial indicators such as total assets, equity-to-asset ratios, liquidity-to-asset ratios, and returns on assets. Table 1 lists balance sheet and profit and loss items used in this paper.

⁶ One earnings call only is held in 82.9%, two calls in 14.8%, and three calls in 2.3% of firm-quarters, respectively.

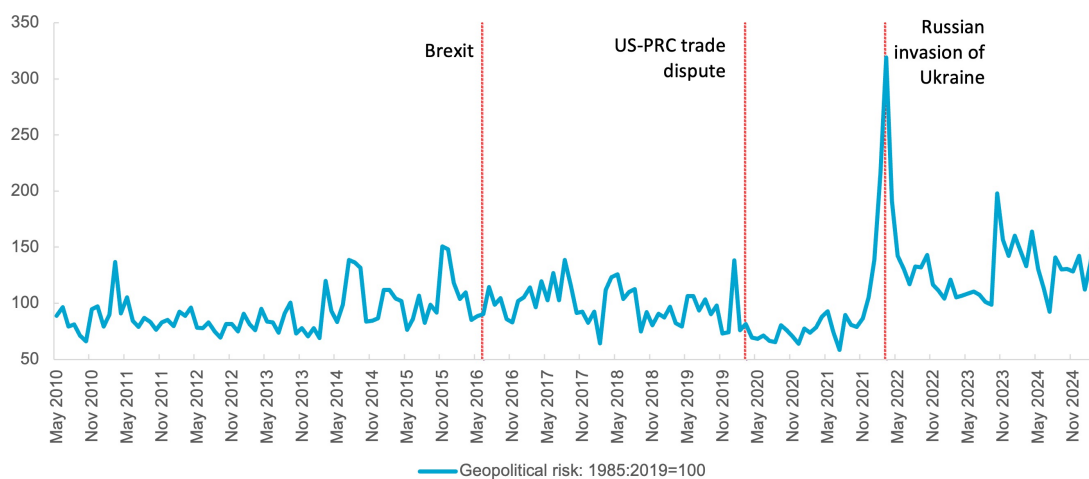
⁷ Prior to merging datasets, the number of joint-occurrences is zero for 65.9% of firm-quarter observations, one for 15.3% of observations, two for 7.2% of observations, and greater than two for 11.6% of observations.

2.4 GPR and Other Global Factors

We obtain our principal measure of global GPR shocks from Caldara and Iacoviello (2022). The authors construct an index based on major anglophone newspapers, equal to 100 for the average over 1985–2019. Figure 2 reveals significant time variation in the index. For most of the 2010–2018 period, the index fluctuates in a relatively narrow range—typically between 70 and 120—reflecting a generally stable geopolitical environment with intermittent short-lived shocks triggered by regional conflicts and political instability. The year 2020 constitutes a regime shift, when the index rises permanently and peaks at the onset of Russia’s war in Ukraine in early 2022. We explore non-linearities in selected robustness checks, replacing the continuous GPR index with a dummy equal to one when the change in GPR exceeds 1 or 2 standard deviations.

In addition to this global GPR index, our empirical analyses account for other global factors that could drive portfolio reallocations. Specifically, we incorporate the oil price uncertainty index of Abiad and Qureshi (2023) and the global economic policy uncertainty index of Baker et al. (2016), which track fluctuations in policy-related uncertainty that may affect firms’ production, investment, and trading decisions.

Figure 2: Geopolitical risk index



PRC = People’s Republic of China.
Source: Caldara and Iacoviello 2022.

2.5 Summary Statistics

The final estimation sample, a fund-stock-level panel dataset, encompasses 5,515 unique funds investing in 12,324 unique equities issued by 12,019 firms,⁸ constituting about 25 million observations in total. Table 1 presents the variables at the heart of our analysis. The main dependent variable—growth in fund-stock-specific portfolio shares—shows substantial variability: $\Delta IHS(Share)$ averages at -0.15%, ranging from -26.4% to 25.6%. Our main control variable for valuation effects, $\Delta IHS(SharePrice)$, averages at 0.13% and ranges from -33.7% to 28.7%.

Firm-level GPR exposure—the main regressor—stands at 0.01% of all words in the average firm’s earnings call transcript. Keywords in the subtopics “beginning of war” and “escalation of war” constitute the bulk of mentions. As for average standard firm-level controls, log-assets stand at 9.6, equity shares at 37.7%, liquidity ratios at 39%, and return on assets at 10.3%.

The GPR index (GPR_t) spans the range of 58 to 319 and averages around 113. Measures of policy uncertainty, including oil price uncertainty (OPU) and global economic policy uncertainty (EPU), display even larger variability, reflecting episodic spikes in global uncertainty.

Finally, the average fund-level cash share is equal to 1.4%, and 70% of funds have a positive performance over a 3-months rolling window in the sample period. The average fund experienced investor outflows during the sample period and the average fund size stands at almost \$23 billion, with a range of 0 to almost \$1.4 trillion.

Our sample spans stocks issues by firms in a broad range of industries and countries. Manufacturing firms account for the largest share of observations (about 40%), followed by services, including financial and other services (37.8%). Firms in the transportation and retail sectors together represent 10% of the sample. The sample covers firms headquartered in 86 countries. While US firms account for two thirds of observations, other developed economies are also well-represented, including the United Kingdom (3.6%), Canada (2.4%), France (2.1%), Germany (2.1%), and Japan (2%). Among emerging and developing economies, India has the largest presence, accounting for 5.4% of the sample.

⁸ Henceforth we use “securities” and “firms” interchangeably for ease of reference. Dropping firms issuing multiple equities leaves results unchanged, as documented in column (3) of Table B4). Firms with multiple equities account for around 7% of the final sample.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Median	Max	Unit
$\Delta IHS(Share)_{f,j,s,t}$	24,296,754	-0.15	5.62	-26.43	-0.01	25.60	%
$\Delta IHS(SharePrice)_{f,j,s,t}$	24,296,754	0.13	10.41	-33.70	0.45	28.73	%
GPR_t	24,296,754	113.24	38.53	58.42	106.81	318.96	-
OPU_t	24,296,754	106.81	54.26	17.43	96.07	357.82	-
$GEPU_t$	24,296,754	227.51	58.92	92.17	220.85	473.28	-
One SD increase _t	24,296,754	0.11	0.31	0.00	0.00	1.00	0/1
Two SD increase _t	24,296,754	0.05	0.21	0.00	0.00	1.00	0/1
$Exposure_{s,t-3}$	24,296,754	0.01	0.00	0.00	0.00	0.03	%
$I\{> 25\}_{s,t-3}$	24,296,754	0.76	0.43	0.00	0.55	1.00	0/1
$I\{> 50\}_{s,t-3}$	24,296,754	0.51	0.50	0.00	0.00	1.00	0/1
$I\{> 75\}_{s,t-3}$	24,296,754	0.25	0.44	0.00	1.00	1.00	0/1
$Exposure_{s,t-3}^{War Threats}$	24,296,754	0.00	0.00	0.00	0.00	0.03	%
$Exposure_{s,t-3}^{Peace Threats}$	24,296,754	0.00	0.00	0.00	0.00	0.01	%
$Exposure_{s,t-3}^{Military Buildup}$	24,296,754	0.00	0.00	0.00	0.00	0.01	%
$Exposure_{s,t-3}^{Nuclear Threats}$	24,296,754	0.00	0.00	0.00	0.00	0.01	%
$Exposure_{s,t-3}^{Terrorist Threats}$	24,296,754	0.00	0.00	0.00	0.00	0.02	%
$Exposure_{s,t-3}^{Beginning of War}$	24,296,754	0.00	0.00	0.00	0.00	0.05	%
$Exposure_{s,t-3}^{Escalation of War}$	24,296,754	0.00	0.00	0.00	0.00	0.03	%
$Exposure_{s,t-3}^{Terrorist Act}$	24,296,754	0.00	0.00	0.00	0.00	0.01	%
$\ln(Asset)_{s,t-12}$	17,395,612	9.57	2.36	0.53	9.37	21.40	ln(\$ million)
Equity Share _{s,t-12}	17,395,587	37.70	25.82	-592.49	38.24	99.98	%
Liquidity _{s,t-12}	13,906,597	38.97	21.44	0.00	36.42	126.12	%
ROA _{s,t-12}	16,770,298	10.27	13.04	-814.06	10.45	250.80	%
Net Assets _{f,j,t-1}	21,124,620	22,967.66	102,751.10	0.05	1,447.29	1,367,450	\$ million
Cash Share _{f,j,t-1}	5,388,459	1.39	2.31	-35.42	0.85	60.97	%
NAV _{f,j,t-1}	20,709,306	0.70	0.46	0.00	1.00	1.00	0/1
Flows _{f,j,t-1}	21,139,529	-0.14	2.94	-14.02	-0.16	11.54	%

GPR = geopolitical risk, OPU = oil price uncertainty, IHS = inverse hyperbolic sine, SD = standard deviation, ROA = return on assets, NAV = net asset value.

Notes: Summary statistics for key variables in the empirical analysis, defined as in Table A1. The data cover the period 2011:M1-2025:M3. Subscript f refers to fund, j to fund domiciles, s refers to security, and t refers to time.

Source: Authors' calculations.

3 REGRESSION FRAMEWORK

We estimate the following regressions at the fund-stock-level for our sample of actively-managed funds:

$$\Delta Share_{f,j,s,t} = \alpha_{f,j,t} + \alpha_{f,j,s} + \beta \cdot (GPR_t \times Exposure_{s,t-3}) + \gamma \cdot Exposure_{s,t-3} + \epsilon_{f,j,s,t}, \quad (1)$$

where $\Delta Share_{f,j,s,t}$ is the month-over-month IHS-transformed growth of the portfolio share that fund f , domiciled in country j , allocates to stock s . The main variable of interest is the interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and the GPR exposure of the firm issuing a specific stock s . We define GPR exposure as the share of words in a firm's earnings call pertaining to geopolitics, with details explained in section 2. To avoid simultaneity, the measure enters the specification with a 3-months lag, thus ensuring that it captures the exposure before GPR shocks materialize. This is because GPR exposure is constructed quarterly, and merged into the fund-stock dataset monthly, with the same GPR exposure value assigned to all months in a quarter.⁹

As the change in portfolio shares can be driven by valuation changes as well as active fund portfolio rebalancing, we control for the former by adding the IHS-difference in stock prices to all regressions.

$\alpha_{f,j,t}$ are fund-time fixed effects absorbing fund-specific time-varying influences, such as funds' risk-taking appetite, size or return. These fixed effects also absorb fund-level inflows from ultimate investors, thus helping differentiate funds' active portfolio reallocations from ultimate investors' decision to reallocate across funds. $\alpha_{f,j,s}$ are fund-stock-level fixed effects allowing to control for funds' preferences for specific equities. To further separate the asset allocation across equities from the allocation across countries, we include country-time fixed effects absorbing time-varying country-specific factors in some specifications. Similarly, some regressions encompass industry-time fixed effects to eliminate cross-industry shifts in portfolio allocations as confounder. Standard errors are double clustered at the fund and stock level to account for potential correlations for

⁹ We do know the month an earnings call was held in, but keep the derived exposure measure quarterly as explained in section 2. Thus, when an earnings call occurred in 2022:M6, we merge the corresponding exposure measure to 2022:M4–2022:M6. Hence, to assess the impact on share reallocation in 2022:M6, a 1 or 2-month lag would still suffer from simultaneity.

the same fund across equities or stock across funds. As we show, sensitivity checks using other clustering options leave the results virtually unchanged.

Our measure of firms' GPR exposure could be endogenous if correlated with other firm characteristics. We detect evidence for such correlation, albeit small (Table E1). To guard against confounding effects, we follow Roberts and Whited (2013) and horserace the double interaction of interest with interactions of the GPR index with other relevant firm characteristics.¹⁰ Estimated effects remain unchanged, meaning that the non-random treatment assignment does not undermine our identification. In a similar vein, other global factors, encompassing economic policy or oil price uncertainty, could also bias our estimates. We thus also estimate specifications in which we control for the interactions of GPR exposure with these aggregate variables.

Finally, while not performing a classical difference-in-differences analysis, firms more rather than less exposed to geopolitical risks should—in the absence of aggregate geopolitical changes—exhibit similar dynamics. We establish parallel trends by means of three placebo regressions as follows: First, we estimate our baseline specification on a sample period without any significant GPR shocks. Second, we estimate our regressions on a sample of ETFs. ETFs passively track a benchmark, limiting the scope for active portfolio reallocations across equities. Third, we randomize GPR exposure akin to synthetic placebo regressions, as in Bednarek et al. (2021). Our estimated effects disappear in all three setups, confirming no structural difference across equities when the regression design turns GPR exposure irrelevant.

4 RESULTS

4.1 Baseline Results

In this subsection, we present our baseline results for equation 1. The interaction coefficient of interest is positive and statistically significant at the 1% level in both columns (1) and (2) of Table 2. Column (1) includes fund-time fixed effects only, and column (2) adds fund-stock fixed effects.

These effects are economically significant: A two-standard deviation increase in GPR accelerates the change in portfolio shares for more (75th percentile) relative to less (25th

¹⁰These characteristics are only available at annual frequency. Thus, they enter the specification with a lag of 12 months to capture their state before any GPR shocks materialize.

percentile) exposed firms by three basis points (bp). Given that portfolio share changes have a median of close to zero, this translates into 3 bp higher portfolio shares on average, equal to one fifth of the median portfolio share in our sample. Large variability in GPR shocks amplifies these effects. For instance, the GPR index has risen by 5 standard deviations during Russia's war in Ukraine. For such extreme episodes, the impact on portfolio shares reached up to 8 bp. These effects reflect active portfolio rebalancing as we control for stock price changes.

The coefficient on the exposure variable itself is negative and statistically significant, meaning that outside of heightened GPR periods more exposed firms lose portfolio shares relative to less exposed ones. For episodes with an average GPR level, the marginal effect is close to zero,¹¹ whereas for extreme GPR events, the marginal effect becomes positive, statistically significant, and large in absolute terms. Specifically, for the maximum GPR level during our sample period that occurred after the Russian invasion of Ukraine (318.96), the marginal effect with respect to firm-level exposure is equal to 42.1,¹² implying that a one-SD increase in exposure ($=0.002$) leads to a 8 bp higher portfolio share ($=0.002 \times 42.1$).

In column (3), we introduce country-time fixed effects to isolate shifts in portfolio shares across individual equities, and not across countries. Results stand confirmed, albeit at the cost of slightly decreased economic and statistical significance. The same applies when we add industry-time fixed effects in column (9) of Table B4 to guard against any bias arising from funds' time-varying preferences for certain industries.

In columns (4)-(6) of Table 2, we replace the continuous firm-level GPR exposure by dummies that take values of one when a firm's GPR exposure exceeds the 25th percentile, median, and 75th percentile of the in-sample distribution, respectively. The double interaction of interest retains its statistical significance for all three, meaning results hold uniformly across the exposure distribution.

The above reported results for equity funds contrast with the response of bond funds. In section C, we apply the same analytical framework to bond funds, and find no statistically significant response to GPR shocks. As we elaborate in section 5, the differential response of stock and bond prices (and hence expected returns) to swings in GPR is key to discerning this dichotomy.

¹¹The mean of GPR is 113.24, so the marginal effect in column (2) becomes: $-24.936 + 0.210 \times 113.24 = -1.16$.

¹² $= -24.936 + 0.210 \times 318.96 = 42.05$.

Table 2: Baseline Results

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IHS(Share Price)_{f,j,s,t}$	0.215*** (0.012)	0.217*** (0.012)	0.214*** (0.012)	0.217*** (0.012)	0.217*** (0.012)	0.217*** (0.012)
$Exposure_{s,t-3}$	-24.549*** (7.842)	-24.936*** (8.335)	-24.007*** (8.248)			
$GPR_t \times Exposure_{s,t-3}$	0.198*** (0.072)	0.210*** (0.080)	0.195** (0.080)			
$I\{> 25\}_{s,t-3}$				-0.085*** (0.027)		
$GPR_t \times I\{> 25\}_{s,t-3}$				0.001** (0.000)		
$I\{> 50\}_{s,t-3}$					-0.075*** (0.026)	
$GPR_t \times I\{> 50\}_{s,t-3}$					0.001*** (0.000)	
$I\{> 75\}_{s,t-3}$						-0.060* (0.031)
$GPR_t \times I\{> 75\}_{s,t-3}$						0.001* (0.000)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	No	Yes	Yes	Yes	Yes	Yes
Country-Time FE	No	No	Yes	No	No	No
Observations	24,344,966	24,296,754	24,296,449	24,296,754	24,296,754	24,296,754
R-squared	0.264	0.304	0.308	0.304	0.304	0.304

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR (columns 1-3), as defined in Section 2. Columns (4)-(6) replace the continuous exposure measure with dummies that take a value of one when it exceeds the 25th, median or 75th percentile of the distribution. All lower-order variables of the double interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions further control for valuation effects by adding the IHS-growth in security-level stock prices, as well as (depending on column) fund-time, fund-security, and country-time fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

4.2 Addressing Identification Concerns and Robustness Checks

In this section, we address several identification concerns and present multiple robustness checks: First, we address potential endogeneity of the GPR exposure measure. Second, we account for other global uncertainty measures that may correlate with GPR. Third, we conduct placebo tests, and end with additional checks on sample composition and alternative constructions of the dependent variable, GPR exposure measure, and GPR index. We summarize the latter results in this subsection, and delegate details to section B.

4.2.1 Endogeneity in GPR exposure

Our firm-level GPR exposure variable could be endogenous if correlated with other firm characteristics such as firm size, capitalization, liquidity, and profitability. Yet, Table E1 shows that these correlations are weak, with a maximum correlation of 11.2% between a firm's GPR exposure and liquidity. Nevertheless, we corroborate that any correlations do not affect our results. In Table 3, we introduce these characteristics in their interactions with the GPR index, first sequentially in columns (1)–(4) and then simultaneously in column (5). In all specifications, our baseline coefficient remains statistically significant at least at the 5% level. A coefficient magnitude ranging from 0.17 to 0.20 also suggests stability with respect to the baseline coefficient of 0.21 (Table 2, column (2)). This stability reassures us that results are unbiased with respect to other firm characteristics.

Table 3: Controlling for Non-Randomness in Geopolitical Risk Exposure

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$				
	(1)	(2)	(3)	(4)	(5)
$GPR_t \times Exposure_{s,t-3}$	0.192** (0.086)	0.190*** (0.086)	0.197** (0.099)	0.174** (0.089)	0.197** (0.098)
$GPR_t \times \ln(Asset)_{s,t-12}$	-0.000 (0.000)				0.000 (0.000)
$GPR_t \times Equity\ Share_{s,t-12}$		0.000 (0.000)			-0.000** (0.000)
$GPR_t \times Liquidity_{s,t-12}$			0.000 (0.000)		-0.000** (0.000)
$GPR_t \times ROA_{s,t-12}$				-0.000* (0.000)	-0.000*** (0.000)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes	Yes	Yes
Observations	17,367,177	17,367,152	13,880,569	16,742,483	13,867,562
R-squared	0.318	0.318	0.320	0.320	0.320

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1–2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. Specifications include firm-specific financial variables interacted with the aggregate GPR index to control for any non-randomness of GPR exposure. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions further control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

4.2.2 Accounting for other global uncertainties

Endogeneity concerns may also apply to the global GPR index, as it could capture other global uncertainties. To isolate global risk sentiment purely related to GPR, we control for the interactions of global economic policy uncertainty as well as oil price uncertainty with the firm-level GPR exposure. We first control for each of the interactions separately in columns (1)-(2) of Table 4, then jointly in column (3). To ensure comparability across different risk indices, we standardize them.

Reassuringly, the GPR double interaction of interest remains statistically significant across all specifications, and clearly dominates the effects of the other two uncertainty measures. Besides the GPR index, variations in economic policy uncertainty also tend to alter fund portfolios. Specifically, rising economic policy uncertainty induces funds to invest more into GPR-exposed firms (column 1), but this effect disappears when we include all interactions jointly in column (3). Therefore, GPR turns out to be the only global shifter that drives our benchmark results in a robust manner.

Table 4: Controlling for Alternative Sources of Risk

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$		
	(1)	(2)	(3)
$GPR_t \times Exposure_{s,t-3}$	8.401*** (3.111)	6.502** (3.118)	7.086** (3.098)
$GEPU_t \times Exposure_{s,t-3}$	4.852* (2.628)		4.212 (2.743)
$OPU_t \times Exposure_{s,t-3}$		4.093 (2.531)	3.166 (2.651)
Fund-Time FE	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes
Observations	24,296,754	24,296,754	24,296,754
R-squared	0.304	0.304	0.304

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The outcome variable is the IHS-growth in fund-security-specific portfolio shares. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. Other global factors measuring oil price and economic policy uncertainty are included in the regression as well, interacted with the firm-level GPR exposure. All global variables are standardized by subtracting the mean and scaling by the standard deviation. The lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions further control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

4.2.3 Placebo Analyses

The key identifying assumption underlying our analysis is that more rather than less GPR-exposed firms have similar dynamics in the absence of major GPR swings. In this subsection, we establish such parallel trends by means of three types of placebo regressions, i.e., regressions over placebo time periods, for placebo funds, and using placebo exposure measures. These specifications lend support to the relevance of the GPR exposure as we measure it, as it is systematically and thus non-randomly aligned with GPR shifts.

First, we split the sample into three periods: (i) low to moderate GPR events with limited spillover to global trade and finance (pre 2014); (ii) elevated, but not systematic geoeconomic and political fragmentation, trade dynamics, and Brexit (2014–2019); (iii) high and systemic GPR with persistently higher uncertainty and global spillovers (2020–2025). Figure 2 of section 2.4 highlights these time windows, and the first three columns of Table 5 summarize the results for each. Our baseline results only survive in the latter period. For the two pre-2020 time periods, our interaction of interest is not statistically different from zero. This helps confirm the salience of GPR shifts for portfolio allocations, and implies no systematic difference between more rather than less GPR-exposed firms in the absence of treatment. Importantly, in the 2020–2025 period, funds reallocate towards GPR-exposed firms primarily when GPR rises to extreme levels. Specifically, in the last three columns of Table 5, we further split the post-2020 sample along the GPR distribution into low, medium, and high risk corresponding to the in-sample distribution up to the 25th percentile, 25th to 75th percentile, and above the 75th percentile, respectively. Only GPR shifts above the 75th percentile (GPR exceeding a value of 120) yield statistically significant results.

Another approach to test for the relevance of GPR shifts and GPR-specific exposure is to check for the response of ETFs to GPR shifts. ETFs are mostly passive with only a small tracking error, and have thus little room to deviate from the respective benchmark. Hence, we should detect only a limited portfolio reallocation, if any. We estimate the baseline specification for an ETF sample only, controlling for the change in portfolio shares of the respective benchmark. We compute the latter as the monthly average growth rate in stock-level portfolio shares for the active equity funds with the same benchmark. Table 6 shows the results of this ETF-centered exercise.

Table 5: Sub-Samples by Time Period

Dependent Variable	2011-2013	2014-2019	2020-2025	2020-2025 $GPR_t < 80$	2020-2025 $80 \leq GPR_t < 120$	2020-2025 $GPR_t \geq 120$
	$\Delta IHS(Share)_{f,j,s,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$GPR_t \times Exposure_{s,t-3}$	-0.600 (1.576)	0.280 (0.199)	0.194** (0.082)	-0.535 (0.941)	-0.645 (0.434)	0.222** (0.112)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	310,306	6,320,019	17,647,488	3,205,087	6,288,889	7,971,911
R-squared	0.487	0.352	0.292	0.352	0.360	0.306

GPR = geopolitical risk.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. The sample is split into a pre-2014, 2014-19, and post-2019 period (columns 1-3). In columns (4)-(6), the latter is further split into periods of GPR below 80, between 80 and 120, and above 120. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

In columns (1)-(3), the interaction between aggregate GPR and firm-level exposure is not statistically significant. Conversely, when we saturate our baseline regression run on the active equity funds sample with the respective benchmark—where that benchmark is computed based on the monthly average growth rate in stock-level portfolio shares for ETF equity funds—our main results survive, as columns (4)-(6) of Table 6 show. The coefficient size in absolute terms is 45 times larger for active funds than for ETFs, meaning the effects of GPR on ETFs are not only statistically, but also economically weaker, as per our hypothesis.

Finally, we test the relevance of our GPR exposure measure through synthetic placebo regressions, similar to Bednarek et al. (2021). For this, we randomize the firm-level GPR exposure variable in 1,000 draws using the mean and standard deviation of the actual GPR exposure. Randomizing exposure severs any economically meaningful link between GPR shocks and firms' GPR exposure, leading any systematic interaction to vanish. We then estimate our baseline regression on the resulting 1,000 random samples, and plot the corresponding interaction coefficient of interest in Figure 3. In 914 out of 1,000 placebo regressions, the interaction coefficient is not statistically significant at the 10% level. Thus, GPR shifts produce no

Table 6: Null Effects for ETFs

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$					
	ETF			non-ETF		
	(1)	(2)	(3)	(4)	(5)	(6)
$GPR_t \times Exposure_{s,t-3}$	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)	0.078** (0.039)	0.091** (0.042)	0.085** (0.042)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	No	Yes	Yes	No	Yes	Yes
Country-Time FE	No	No	Yes	No	No	Yes
Observations	35,362,158	35,325,851	35,325,676	17,285,360	17,252,654	17,252,371
R-squared	0.957	0.959	0.959	0.348	0.387	0.389

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. Columns (1)-(3) are based on ETF (passive) funds, whereas columns (4)-(6) restrict the analysis to non-ETF (active) funds. All regressions control for the corresponding change in portfolio shares of the respective benchmark, as explained in the main text. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time, country-time, and fund-security fixed effects (depending on column). Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

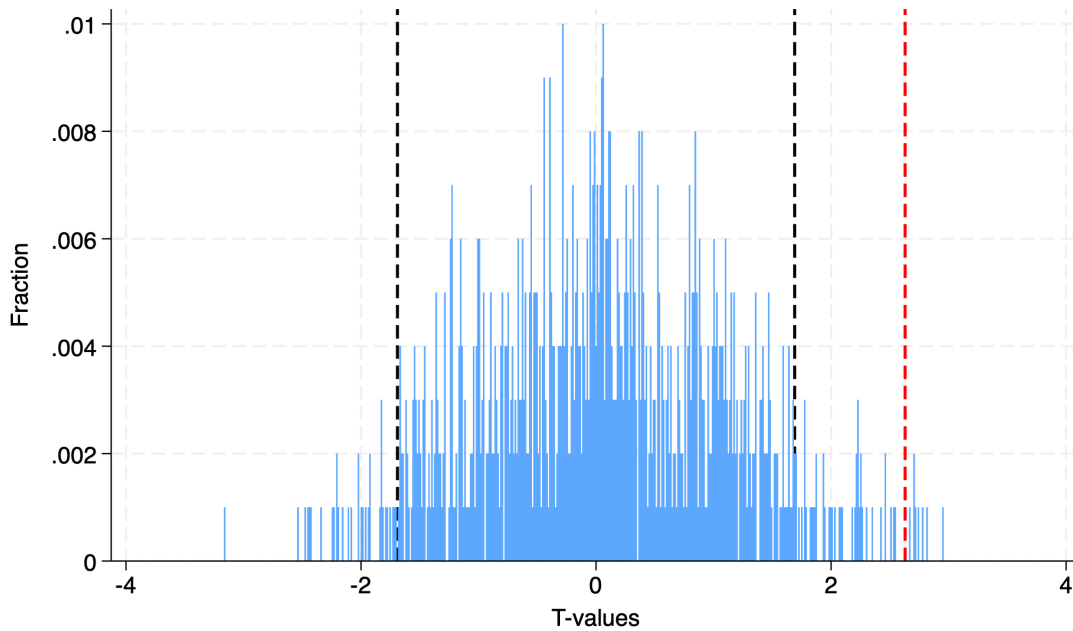
statistically significant effect if exposure is randomized, lending further support to the relevance of the GPR exposure as we measure it. This also means that the identifying variation in our main analysis indeed stems from systemic and non-random alignment between GPR exposure and aggregate GPR shifts.

4.2.4 Additional robustness checks

We conduct a range of additional robustness checks, as detailed in section B and summarized here as follows. First, in Table B1, we measure GPR shifts by alternative variables—the change instead of the level of the index of Caldara et al. (2026), dummies that equal one when the change exceeds 1 or 2 standard deviations of its distribution, and the country-specific GPR indexes of major economies (US, United Kingdom, Germany, Japan and PRC) instead of the global aggregate GPR. For all these cases, our results remain statistically significant.

Second, in columns (1)-(8) of Table B2, we use subcategories of firm-level GPR exposure instead of the overall measure. As defined in section 2, subcategories relate to war threats, peace threats, military buildup, nuclear threats, terrorist threats, beginning of wars, escalation of wars, and

Figure 3: Distribution of t-values for randomizing the exposure variable



Note: The red vertical line denotes the t-value associated with our benchmark coefficient from Table 2. Source: Authors' calculations.

terrorist acts. We find that GPR shifts have the strongest impact on firms exposed to a beginning or an escalation of wars (columns 6 and 7). This is consistent with the benchmark analysis showing a significantly stronger GPR impact during extreme spikes such as the onset of Russia's war in Ukraine.

Third, we examine alternative measures of firms' GPR exposure by constructing a joint occurrence measure as per section 2.2. We turn the measure into a dummy equal to one when a firm's average share of GPR-relevant occurrence exceeds zero. Our main results are unaffected, as per column (1) of Table B3. Returning to the baseline GPR exposure measure, our results remain equally unaffected when we compute a firm's GPR exposure as the average or median of all firms' exposures in the same industry or industry-country pair, respectively, excluding the firm itself to reduce endogeneity concerns, with results reported in columns (2)-(5) of Table B3.

Fourth, we estimate weighted least squares regressions using funds' size as weight, we use an alternative dependent variable or different clustering strategies, we drop dominant fund domiciles and asset management companies from the sample, and we saturate the regressions with industry-

time fixed effects to control for any time-varying industry preferences of funds. The latter captures funds seeking to take advantage of rising expected returns in specific industries, such as defense and dual use goods manufacturing, that may grow faster when GPR shocks occur. As Tables B4 and B5 show, our baseline results remain statistically significant. We also establish that our results stay unchanged when purging firms issuing multiple equities from our sample (Column 3 in Table B4). This ensures a one-to-one mapping between the fund portfolio holdings and investee firms.

Fifth, we interact our double interaction of interest with industry dummies to gauge how specific industries account for our results. As Table B6 shows, no particular industry drives our results. In line with evidence from using industry-time fixed effects, our results are not driven by specific industries, such as defense, which could have been conceived to attract investments as geopolitical relations evolve.

Finally, we contrast results of small with large firms. Large firms are often touted as “national champions” and as such enjoy government subsidies or other support in times of crises. Thus, large firms’ equities could attract greater demand from funds during GPR events, and thus drive our results. As Table B7 shows, this concern is unwarranted, however, as our results hold both in sub-samples of small firms (in the lowest 80% of the country-year-specific total asset distribution) and large firms (top 20%).

5 EXPLORING THE MECHANISM

Why does rising GPR lead funds to invest more in GPR-exposed firms? In this section, we document that GPR shocks lower stock prices, and raise expected returns, attracting funds to invest in GPR-exposed equities. This is in line with Yilmazkuday (2024) and IMF (2025), and suggests equity funds’ search for yield as the main driver of our results. It is this search for yield that amplifies the results for funds with a poor return profile and higher risk-taking capacity. The search for yield ultimately contributes to higher portfolio concentrations after GPR shocks. This loss of diversification is offset by an increase in cash positions.

5.1 Stock Price Response to GPR

We run the following regression to document the decline in stock prices of GPR-exposed firms after GPR shocks:

$$\Delta SharePrice_{s,t} = \alpha_s + \alpha_t + \omega \cdot (GPR_t \times Exposure_{s,t-3}) + \epsilon_{s,t}, \quad (2)$$

where the dependent variable is the change in the IHS-transformed stock prices of stock s in month t . The main regressor of interest is the interaction between the global GPR index interacted with the firm-level GPR exposure, as defined in section 2. All regressions encompass time and stock fixed effects, and standard errors are clustered at the stock level.

Table 7: Return Responses

Dependent Variable	$\Delta IHS(Share Price)_{s,t}$			
	(1)	(2)	(3)	(4)
$GPR_t \times Exposure_{s,t-3}$	-1.817*** (0.284)			
$GPR_t \times I\{> 25\}_{s,t-3}$		-0.005*** (0.001)		
$GPR_t \times I\{> 50\}_{s,t-3}$			-0.005*** (0.001)	
$GPR_t \times I\{> 75\}_{s,t-3}$				-0.006*** (0.001)
Time FE	Yes	Yes	Yes	Yes
Security FE	Yes	Yes	Yes	Yes
Observations	548,787	548,787	548,787	548,787
R-squared	0.221	0.221	0.221	0.221

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in security-specific share prices. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for time and security fixed effects. Standard errors are clustered at the security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

Table 7, column (1), confirms that the valuation compression upon GPR shock materialization is more pronounced for more GPR-exposed firms. The estimate implies a stock price differential between more and less exposed firms of 24 bp for each two standard deviation increase in the GPR index. This effect is large, accounting for more than half of the median monthly stock price

change of 0.45%. This result also holds when we transform the continuous exposure measure into dummies that take values of one when a firm's exposure lies above the 25th, median, or 75th percentile of the in-sample distribution (columns 2-4), meaning that effects apply uniformly across the GPR exposure distribution.

Lower stock prices imply higher expected returns assuming that firm fundamentals remain unchanged. We corroborate unchanged fundamentals by estimating firm-level regressions of returns on assets, firm size (log of total assets), and log-employment on the interaction between lagged GPR and firms' lagged GPR exposure. Table E2 of Appendix E presents the results. Columns (1), (3) and (5) show one-year lags, and columns (2), (4) and (6) exhibit two-year lags. We do not detect a differential response of firm fundamentals to heightened GPR. The only exception—with an estimate that is only significant at the 10% level—is the size of a firm that decreases slightly for more exposed firms in the year after the GPR increase. However, this effect on firm size is transitory, as it already turns statistically insignificant in the second year after the GPR shock. Thus, firm fundamentals of GPR-exposed firms remain unchanged amid GPR shocks, implying higher expected returns and suggesting that search for yield is the main driver underlying our results.

5.2 Risk-Taking Capacity Determines Funds' Pivot Into GPR-Exposed Equities

To the extent that search for yield is the main mechanism underlying our baseline evidence, we should find that our results are amplified by funds with a greater risk-taking capacity and a poorer performance record, consistent with the literature on financial institutions' risk-taking (Acharya 2009; Blattner et al. 2023). We investigate this hypothesis by expanding equation 1 with a triple interaction involving the GPR index, stock-level GPR exposure and different fund-level characteristics:

$$\begin{aligned} \Delta Share_{f,j,s,t} = & \alpha_{f,j,t} + \alpha_{f,j,s} + \alpha_{s,t} + \theta \cdot (GPR_t \times Exposure_{s,t-3} \times Fund\ Char_{f,j,t-1}) \\ & + \gamma \cdot (Exposure_{s,t-3} \times Fund\ Char_{f,j,t-1}) + \epsilon_{f,j,s,t}, \end{aligned} \quad (3)$$

We consider three measures of funds' risk-taking capacity in the matrix $FundChar_{f,j,t-1}$: (i) the 1-month lagged fund size as proxied by assets under management, (ii) 1-month lagged inflows

over a 3-months rolling window, scaled by assets under management, and (iii) the 1-month lagged cash share. Larger funds can be expected to have a greater risk-taking capacity due to several features. First, larger funds are often distinguished by a more diversified investor base, lowering risk of concentrated redemption claims. Second, these funds often have more sophisticated risk management, achieving a higher return given risk (Vidal-García et al. 2018). Third, lower expense ratios mean that any losses from more risky bets do not lower profits by as much as for smaller funds. Similarly, funds with larger inflows and higher cash shares are likely associated with higher resilience to redemption claims, allowing these funds to take additional risks.

Moreover, a poor track record tends to increase funds' risk appetite to catch up with benchmarks (Acharya 2009; Blattner et al. 2023). For this, we include in the matrix $FundChar_{f,j,t-1}$ a dummy that takes the value of one for positive returns in the three months preceding month t , else zero.

Equation 3 bestows an important advantage relative to equation 1 from the baseline analysis. We can now add stock-time fixed effects to eliminate the impact of time-varying stock-level characteristics, such as firms' demand for equity financing. This separation of demand for and supply of equity financing from investment funds helps mitigate the risk of residual confounders, thus strengthening the identification significantly.

Table 8 reports the results. Coefficient estimates in columns (1)–(3) show that funds with greater risk-taking capacity, i.e., larger funds and those with higher inflows and cash shares pivot more into GPR-exposed firms' equities as GPR rises. The corresponding triple interaction coefficients are statistically significant at least at the 5% level, with the exception of the cash share interaction, which is still positive in sign as hypothesized, albeit not statistically significant.

In column (4), we find further that funds with poorer performance records to amplify our results. The corresponding triple interaction coefficient is negative and statistically significant at the 1% level. Overall, funds with a greater risk-taking capacity and those with a poorer pre-GPR performance drive our baseline results, consistent with a search for yield driving funds' pivot into GPR-exposed stocks.

Table 8: Exploring Heterogeneity of Fund Characteristics

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$			
	(1)	(2)	(3)	(4)
$GPR_t \times Exposure_{s,t-3} \times \text{Net Assets}_{f,j,t-1}$	0.251*** (0.000)			
$GPR_t \times Exposure_{s,t-3} \times Flows_{f,j,t-1}$		0.008** (0.004)		
$GPR_t \times Exposure_{s,t-3} \times \text{Cash Share}_{f,j,t-1}$			0.031 (0.031)	
$GPR_t \times Exposure_{s,t-3} \times NAV_{f,j,t-1}$				-0.468*** (0.140)
Fund-Time FE	Yes	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes	Yes
Security-Time FE	Yes	Yes	Yes	Yes
Observations	21,079,138	20,657,072	5,313,394	20,657,072
R-squared	0.411	0.411	0.484	0.414

GPR = geopolitical risk, IHS = inverse hyperbolic sine, NAV = net asset value.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. The main regressor is the triple interaction between the aggregate GPR index of Caldara and Iacoviello (2022), a continuous measure of exposure to GPR, as defined in Section 2, and various fund characteristics. In column 1, total net assets are rescaled to millions. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted). All regressions encompass fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

5.3 Rising Portfolio Concentration

What does funds' pivot into GPR-exposed equities imply for portfolio concentration? We measure portfolio concentration in four ways: (i) number of equities in a fund's portfolio, (ii) the fund-level Herfindahl-Hirschman index (HHI) based on the holding values across all equities in a fund's portfolio, (iii) the number of industries the equities in a fund portfolio belong to, and iv) the number of countries the firms issuing the equities in a fund portfolio are headquartered in. We regress the logarithms of these variables on the interaction between the GPR index and a fund's GPR

exposure computed as the weighted average of the stock-level GPR exposure measure, with portfolio shares serving as weights:

$$Concentration_{f,j,t} = \alpha_{f,j} + \alpha_t + \theta \cdot (GPR_t \times Exposure_{f,j,t-3}) + \epsilon_{f,j,t}, \quad (4)$$

where $Concentration_{f,j,t}$ stands for the aforementioned measures of portfolio concentration.

We document results in Table 9. Columns (1)-(2) show that portfolio concentration rises after a GPR shock materializes, with the number of equities decreasing and the HHI increasing. The rise in concentration is mirrored by fewer industries and countries a fund holds positions in (columns 3-4). In column (5), we use the IHS-change in funds' cash shares as dependent variable, which we find to increase as a response to GPR shocks.¹³ In sum, funds consolidate portfolios into higher-yielding positions and balance the additional aggregate portfolio risk by raising cash holdings to protect the downside.

Table 9: Investigating Portfolio Concentration

Dependent Variable	ln(Num. ISIN) (1)	ln(HHI Holding Values) (2)	ln(Num. country) (3)	ln(Num. Industry) (4)	$\Delta IHS(\text{Cash})$ (5)
$GPR_t \times Exposure_{s,t-3}$	-1.100*** (0.093)	1.349*** (0.086)	-0.222*** (0.063)	-1.036*** (0.086)	11.840*** (3.158)
Time FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Observations	195,459	195,459	195,459	195,441	188,684
R-squared	0.933	0.900	0.945	0.919	0.013

GPR = geopolitical risk, IHS = inverse hyperbolic sine, HHI = Herfindahl-Hirschmann index.

Notes: These regressions are based on monthly fund-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variables are concentration measures of fund portfolios, as well as the IHS-change in cash shares. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for time and fund fixed effects, as well as fund-level inflows scaled by assets under management. Standard errors are double clustered at the fund level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

6 CONTRASTING FUND MANAGERS WITH ULTIMATE INVESTORS

The previous sections investigated how fund managers reallocate portfolios in response to geopolitical shocks. This section seeks to differentiate fund managers' behavior from ultimate

¹³This result is unchanged when we drop funds with negative cash shares from the analysis (i.e., funds that borrow).

investors holding shares in funds. For this, we switch from studying the GPR impact on funds' portfolio holdings to investors' flows into these funds. Our dataset obtained from EPFR comprises 9,464 funds months. Thus, the approach abstracts from fund managers' portfolio allocation decisions, and thus isolates the response of ultimate investors to GPR events.

We proceed with fund-level regressions as follows:

$$Flows_{f,j,t} = \alpha_{f,j} + \alpha_t + \theta \cdot (GPR_t \times Exposure_{f,j,t-3}) + \epsilon_{f,j,t}, \quad (5)$$

where the dependent variable is the monthly inflow into fund f , domiciled in country j , scaled by assets under management and winsorized at the 1% and 99% levels. The main variable of interest is the interaction between the GPR index and lagged fund-level GPR exposure, computed as the weighted average firm-level GPR exposure of all equities in a fund's portfolio, with portfolio shares serving as weights. The regressions are saturated with fund and time fixed effects, and the standard errors are clustered at the fund level.

Columns (1)-(3) of Table 10 reveal that the double interaction between the aggregate GPR index and fund-level GPR exposure enters negatively and statistically significant, implying that ultimate investors reduce their flows into more GPR-exposed funds. In columns (4)-(6), the result holds when replacing the continuous exposure measure with a high-exposure dummy that takes the value of one when the continuous value exceeds the in-sample median, zero otherwise. We conclude that fund managers and ultimate investor's responses to GPR are diametrically opposed. While fund managers seize the upside opportunity of compressed valuations as GPR shocks unfold, ultimate investors reduce holdings in GPR-exposed funds to protect their portfolios from additional downside risk from GPR shocks. This dichotomy is consistent with the well-documented behavior of retail investors exhibiting pro-cyclical selling during market stress due to myopic loss aversion compared to professional investors displaying counter-cyclical behavior, trading against temporary volatility (Frazzini and Lamont 2008; Bordalo et al. 2022; Duffie 2010).

Table 10: Fund Flow Responses

Dependent Variable	<i>Flows_{f,j,t}</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
$GPR_t \times FundExposure_{f,j,t-3}$	-4.577*** (0.638)	-3.556*** (0.601)	-3.666*** (0.650)			
$GPR_t \times HighExposure_{f,j,t-3}$				-0.005*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
Time FE	No	No	Yes	No	No	Yes
Fund FE	No	Yes	Yes	No	Yes	Yes
Observations	195,546	195,459	195,459	195,546	195,459	195,459
R-squared	0.005	0.145	0.155	0.004	0.145	0.155

GPR = geopolitical risk.

Notes: These regressions are based on monthly fund-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the ultimate investor flow into funds scaled by total net assets. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and either a continuous measure of funds' GPR exposure (columns 1-3), computed as the weighted average of all security-specific GPR exposures in the portfolio, or a dummy equal to one if this fund exposure exceeds the sample median (columns 4-6). All lower-order variables of this double interaction—unless spanned by the set of fixed effects—are included, but omitted for brevity. Regressions encompass time and fund fixed effects. Standard errors are clustered at the fund level and shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

7 CONCLUSION

This paper sheds light on the muted stock market response to GPR shocks. We focus on investment funds' stock holdings, and examine portfolio shifts in response to GPR shocks. Based on detailed monthly data of funds' stock allocations, we trace the effect of GPR shocks on stock prices and portfolio shares held in GPR-exposed firms. We document that equities issued by more GPR-exposed firms benefit from additional fund demand as GPR events materialize, with effects amplified during exceptionally high GPR episodes. This demand is driven by a drop (rise) in stock prices (expected returns) for more GPR-exposed firms' stocks, inviting funds to acquire shares in otherwise financially healthy entities. Thus, the GPR-induced valuation compression reverses instantly, explaining the seeming calm of stock markets thanks to the market-stabilizing force of yield-chasing investment funds. This contrasts with the procyclical behavior of ultimate investors, who we find divest from more GPR-exposed funds as GPR shocks unfold.

We show that funds' search for yield in GPR-exposed equities is most pronounced for funds with greater risk-taking capacity or worse performance track record. The search for yield also leads to increased portfolio concentrations, with associated risks balanced by larger cash holdings. Stock price reactions in particularly GPR-exposed industries like defense or dual use goods do not explain

our results. Similarly, dominant fund domiciles, firms headquartered in any particular economy, or funds belonging to the largest asset management companies do not account for the results. Results hold when accounting for various sources of policy uncertainty and remain robust to various fixed effects absorbing confounding variability, as well as a battery of other checks and placebo tests.

Overall, this work characterizes how GPR shapes equity funds' investment decisions, and establishes funds as risk-affine agents important to safeguard financial stability and ultimately financing for firms' real activity after GPR events. We invite future research to shed light on the sell side in markets: With funds purchasing GPR-exposed firms' stocks as GPR shocks unfold, fully understanding the financial stability repercussions of GPR hinges on identifying the investors most susceptible to fire-selling exposed assets. Another avenue for future research is the inquiry into cross-border spillovers. While funds soften the blow from GPR-injected volatility for equity markets in aggregate, portfolio reallocations into GPR-exposed firms may trigger significant cross-border flows. A high concentration of highly GPR-exposed firms in any particular economy would attract portfolio capital inflows from investment funds. Inversely, other economies with lower concentrations may see outflows. Net effects on any economy would depend not only on the cross-country distribution of highly GPR-exposed firms but also on ultimate investors' withdrawal from more GPR-exposed funds, in turn shaping fund allocations.

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A DATA APPENDIX

Table A1: Variable Definitions and Data Sources

Variable	Definition	Unit	Source
$\Delta IHS(Share)_{f,j,s,t}$	Monthly change in IHS-transformed portfolio share of fund f , domiciled in country j , allocated to stock s	%	EPFR
$\Delta IHS(SharePrice)_{f,j,s,t}$	Monthly change in IHS-transformed share prices of stock s invested in by fund f in domicile j	%	EPFR
GPR_t	Global GPR index constructed from articles in leading anglophone newspapers	-	Caldara and Iacoviello (2022)
OPU_t	The frequency of newspaper articles discussing oil-related uncertainty	-	Abiad and Qureshi (2023), Oil Price Uncertainty
$GEPU_t$	Global economic policy uncertainty constructed from 18 countries	-	Baker et al. (2016), Economic Policy Uncertainty
One SD increase _{t}	A dummy variable indicating a one standard deviation increase in the GPR index	0/1	Author calculated
Two SD increase _{t}	A dummy variable indicating a two standard deviation increase in the GPR index	0/1	Author calculated
$Exposure_{s,t-3}$	Firm-specific GPR exposure	%	author calculated based on earnings call texts and Caldara and Iacoviello (2022)
$I\{> 25\}_{s,t-3}$	A dummy variable indicating whether the firm's GPR exposure is above the 25% quantile	0/1	based on Caldara and Iacoviello (2022)
$I\{> 50\}_{s,t-3}$	A dummy variable indicating whether the firm's GPR exposure is above the 50% quantile	0/1	based on Caldara and Iacoviello (2022)
$I\{> 75\}_{s,t-3}$	A dummy variable indicating whether the firm's GPR exposure is above the 75% quantile	0/1	based on Caldara and Iacoviello (2022)
$Exposure_{s,t-3}^{War Threats}$	Firms' GPR exposure by topic: War Threats, based on topic-specific keywords	%	based on Caldara and Iacoviello (2022)
$Exposure_{s,t-3}^{Peace Threats}$	Firms' GPR exposure by topic: Peace Threats, based on topic-specific keywords	%	based on Caldara and Iacoviello (2022)
$Exposure_{s,t-3}^{Military Buildup}$	Firms' GPR exposure by topic: Military Buildup, based on topic-specific keywords	%	based on Caldara and Iacoviello (2022)
$Exposure_{s,t-3}^{Nuclear Threats}$	Firms' GPR exposure by topic: Nuclear Threats, based on topic-specific keywords	%	based on Caldara and Iacoviello (2022)
$Exposure_{s,t-3}^{Terrorist Threats}$	Firms' GPR exposure by topic: Terrorist Threats, based on topic-specific keywords	%	based on Caldara and Iacoviello (2022)
$Exposure_{s,t-3}^{Beginning of War}$	Firms' GPR exposure by topic: Beginning of War, based on topic-specific keywords	%	based on Caldara and Iacoviello (2022)
$Exposure_{s,t-3}^{Escalation of War}$	Firms' GPR exposure by topic: Escalation of War, based on topic-specific keywords	%	based on Caldara and Iacoviello (2022)
$Exposure_{s,t-3}^{Terrorist Act}$	Firms' GPR exposure by topic: Terrorist Act, based on topic-specific keywords	%	based on Caldara and Iacoviello (2022)
$\ln(Asset)_{s,t-12}$	Firms' reported total assets from the balance-sheet	ln(\$ million)	Compustat
Equity Share _{$s,t-12$}	The ratio of stockholder equity to total assets	%	Compustat
Liquidity _{$s,t-12$}	The ratio of current assets to total assets	%	Compustat
$ROA_{s,t-12}$	Return on assets, calculated as the share of EBITDA over total assets	%	Compustat
Total Net Assets _{$f,j,t-1$}	Total net assets	\$ million	EPFR
Flows _{f,j,t}	Fund inflows in the current month as a share of total net assets	%	EPFR
Cash Share _{$f,j,t-1$}	Share of cash held by a fund	%	EPFR
$NAV_{f,j,t-1}$	A dummy variable indicating whether the average fund performance in the past three months is positive	0/1	EPFR
$HHI_{f,t}$	Herfindahl–Hirschman index calculated at fund-time level based on holding values across equities	-	EPFR
Num. ISIN _{f,t}	The number of equities fund f holds at time t	-	EPFR
Num. Country _{f,t}	The number of countries fund f invested at time t	-	EPFR
Num. Industry _{f,t}	The number of industries (SIC) fund f invested at time t	-	EPFR
$\Delta IHS(Cash)_{f,t}$	Monthly changes in IHS-transformed cash share of fund f at time t	%	EPFR

Source: Authors.

Table A2: Keywords in Caldara and Iacoviello (2022)

Topic sets	Phrases
War words	war OR conflict OR hostilities OR revolution* OR insurrection OR uprising OR revolt OR coup OR geopolitical
Peace words	peace OR truce OR armistice OR treaty OR parley
Military words	military OR troops OR missile* OR "arms" OR weapon* OR bomb* OR warhead*
Nuclear bigrams	"nuclear war*" OR "atomic war*" OR "nuclear missile*" OR "nuclear bomb*" OR "atomic bomb*" OR "h-bomb*" OR "hydrogen bomb*" OR "nuclear test" OR "nuclear weapon"
Terrorism words	terror* OR guerrilla* OR hostage*
Actor words	allie* OR enem* OR insurgen* OR foe* OR army OR navy OR aerial OR troops OR rebels
Threat/act sets	Phrases
Threat words	threat* OR warn* OR fear* OR risk* OR concern* OR danger* OR doubt* OR crisis OR troubl* OR disput* OR tension* OR imminen* OR inevitable OR footing OR menace* OR brink OR scare OR peril*
Peace disruption words	threat* OR menace* OR reject* OR peril* OR boycott* OR disrupt*
Buildup words	buildup* OR build-up* OR sanction* OR blockad* OR embargo OR quarantine OR ultimatum OR mobiliz*
War begin words	begin* OR start* OR declar* OR begun OR began OR outbreak OR "broke out" OR breakout OR proclamation OR launch*
Actor fight words	advance* OR attack* OR strike* OR drive* OR shell* OR offensive OR invasion OR invad* OR clash* OR raid* OR launch*
Terrorism act words	attack OR act OR bomb* OR kill* OR strike* OR hijack*
Geopolitical terms	war, military, terror*, geopolitical, conflict, "Middle East", Iraq, Iran, Syria, Libya, Ukrain*, Russia*, Venezuela, coup, expropriation, confiscation, nationalism, security, protest*, country, countries, political, retaliation, unrest, geograph*, troop*, sanction, sanctions, embargo, wars, warfare, army, navy, weapon*, combat, missile*, immigration, diplomacy
Risk-related terms	uncertain*, variab*, chance*, possib*, pending, doubt*, prospect*, bet, bets, betting, exposed, likel*, threat*, probab*, unknown*, potential, concern*, tension*, issue*, instability, cautio*, fear*, volatil*, varying, unclear, speculative, hesitant, headwind*, backlog*, dispute, disrupt*, worry*, worries, hurdle*, obstacle*, disturbance*, hostile*, unrest, conflict, pressure*, crisis, trigger*, impact, peril*, effect*, acts, attack*, incident*

Notes: The truncation character (*) denotes a search including all possible endings of a word, e.g. "threat*" includes "threat" or "threats" or "threatening".

Source: Caldara and Iacoviello (2022)

B ROBUSTNESS CHECKS IN DETAIL

Here we provide details on the robustness checks performed in section 4.2. First, we replace the GPR index in levels by its first difference. As shown in column (1) of Table B1, this slightly reduces the statistical significance of our double interaction of interest, but leaves the coefficient estimate statistically significant nevertheless. Then, we study extreme GPR episodes. To this end, we define two dummies that take the value of one when GPR increases by at least 1 or 2 standard deviations, respectively. As columns (2)-(3) show, results enter statistically significantly.

Table B1: Robustness Checks: Alternative Geopolitical Risk measures

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta GPR_t \times Exposure_{s,t-3}$	0.188** (0.089)							
One SD increase $\times Exposure_{s,t-3}$		19.391** (7.575)						
Two SD increase $\times Exposure_{s,t-3}$			22.186** (10.653)					
$GPR_t^{USA} \times Exposure_{s,t-3}$				8.147** (3.406)				
$GPR_t^{GBR} \times Exposure_{s,t-3}$					14.764** (6.244)			
$GPR_t^{DEU} \times Exposure_{s,t-3}$						20.530*** (7.333)		
$GPR_t^{JPN} \times Exposure_{s,t-3}$							51.986*** (16.736)	
$GPR_t^{PRC} \times Exposure_{s,t-3}$								22.875*** (8.281)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,296,754	24,296,754	24,296,754	24,296,754	24,296,754	24,296,754	24,296,754	24,296,754
R-squared	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304

Notes: GPR = geopolitical risk, IHS = inverse hyperbolic sine, SD = standard deviation.

These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The outcome variable is the IHS-growth in fund-security-specific portfolio shares. Across specifications, we interact alternative GPR indices with the continuous measure of exposure to GPR, as defined in Section 2. Column (1) uses the change of the aggregate GPR index, and column (2) and (3) employ a dummy indicating a one- or two-standard deviation increase in the index, respectively. Columns (4)-(8) adopt country-specific aggregate GPR indices for the US, UK, Germany, Japan and the PRC obtained from Caldara and Iacoviello (2022). All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses.

*, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

Furthermore, we zoom into GPR indexes specific to five major economies—the PRC, Germany, Japan, UK and US. Statistically significant coefficients in columns (4)-(8) show that that economy-specific GPR increases also prompt investment funds to rebalance toward more GPR-exposed firms.

Second, we test for robustness to sub-components of firm-level GPR exposure. In columns (1)-(8) of Table B2, we break down the aggregate GPR index that we used in the main body of the paper into its eight sub-components. The results show that it is mainly the exposure to a beginning and an escalation of a war that drives our results. This in line with the dynamics of the aggregate GPR index, which spikes substantially at the onset of the Russian invasion of Ukraine (Figure 2).

Table B2: Robustness Checks: Topic-specific Geopolitical Risk Exposure

	war threats	peace threats	military buildup	nuclear threats	terrorist threats	beginning of war	escalation of war	terrorist acts
Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GPR_t \times Exposure_{s,t-3}^{Topic}$	-0.094 (0.145)	-0.089 (0.343)	0.103 (0.432)	-0.106 (0.152)	-0.104 (0.152)	0.412*** (0.114)	0.334*** (0.106)	-0.233 (0.403)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,296,754	24,296,754	24,296,754	24,296,754	24,296,754	24,296,754	24,296,754	24,296,754
R-squared	0.304	0.304	0.304	0.304	0.304	0.304	0.304	0.304

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. Across specifications, we interact the topic-specific GPR risk exposures (based on topic-specific keywords) with the aggregate GPR index of Caldara and Iacoviello (2022). All lower-order variables of the interactions—unless spanned by the set of fixed effects—are also included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

Third, in Table B3, we employ alternative measures of firms' GPR exposure. In column (1), we base our exposure variable on the joint occurrences measure of Caldara and Iacoviello (2022). Specifically, given that most joint occurrence shares equal zero, we define a dummy equal to one when the average joint occurrence share exceeds zero. Columns (2)-(5) of Table B3 use as alternative exposure measures the means and medians of the baseline exposure variable in industry and industry-country bins. To alleviate endogeneity concerns, we exclude the exposure of the firm in question. The double interaction of interest remains positive and statistically significant across all specifications, indicating that our results hold irrespective of how we define firms' GPR exposure.

Fourth, in Table B4, test for variations in the dependent variable, weighting, clustering, fixed effects and fund sample composition. First among these, we replace the dependent variable

Table B3: Robustness Checks: Alternative Geopolitical Risk Exposure Measures

	occurrence	industry mean	industry median	industry-country mean	industry-country median
Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$				
	(1)	(2)	(3)	(4)	(5)
$GPR_t \times Exposure_{s,t-3}$	0.000* (0.000)	1.288*** (0.411)	1.378*** (0.412)	0.858*** (0.204)	0.727*** (0.197)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes	Yes	Yes
Observations	24,296,754	24,296,714	24,296,714	24,124,713	24,124,713
R-squared	0.304	0.304	0.304	0.303	0.303

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. Across specifications, we interact alternative measures of firm-level exposure to GPR with the aggregate GPR index of Caldara and Iacoviello (2022). Column (1) adopts the joint occurrence measure outlined in the Appendix of Caldara and Iacoviello (2022). Columns (2) and (4) use industry and industry-by-country means of the GPR exposure variable excluding the firm itself, and columns (3) and (5) use the corresponding median. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

(expressed as change in the IHS-transformed portfolio share) by the absolute change. Column (1) suggests that this reduces statistical significance of the estimate only marginally.

We then estimate weighted least squares regressions, with weights equal to the logarithm of a fund's assets under management. This might be important because from a firm perspective, it is more beneficial when a large than a small investor increases its investments. As column (2) shows, the estimate of interest remains significant. In column (3), we drop from the sample all firms issuing multiple equities to ensure a one-to-one match between firms and equities. Again, our results are unaffected.

In columns (4)-(8), we cluster the standard errors at the stock level, fund level, time level, stock-time level, and industry-time level, respectively. The interaction between the GPR index and firm-level GPR exposure remains highly significant in all cases. Given higher statistical significance levels across columns (4)-(8), our baseline results in Table 3—generated using double clustered standard errors—appear conservative.

In column (9), we finally saturate our baseline regression with industry-time fixed effects to ensure that we identify portfolio reallocations across individual equities, and not across industries. Our coefficient of interest remains statistically significant, but decreases somewhat. This implies

that our baseline results estimated without industry-time fixed effects partially reflect reallocations across industries. These reallocations, however, do not seem to be strong enough for any particular industry to drive our results entirely, as we detail below and show in Table B6.

Table B4: Robustness Checks: Alternative Specifications

Dependent Variable	$\Delta Share_{f,j,s,t}$ (1)	WLS (by asset size)	1:1 match	cl(s)	cl(f)	cl(t)	cl(s-t)	cl(industry, f)	industry-time FE
		(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$GPR_t \times Exposure_{i,t-3}$	0.005** (0.002)	0.159** (0.079)	0.194** (0.081)	0.210*** (0.080)	0.210*** (0.021)	0.210*** (0.065)	0.210*** (0.065)	0.211*** (0.054)	0.158** (0.080)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,296,754	21,124,739	22,596,185	24,296,754	24,296,754	24,296,754	24,296,754	24,294,339	24,294,339
R-squared	0.282	0.277	0.230	0.304	0.304	0.304	0.304	0.304	0.305

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. Column (1) uses the changes of portfolio shares in levels as dependent variable, and column (2) adopts weighted least squares, with the logarithm of a fund's assets serving as weights. Column (3) drops firms issuing multiple securities. Columns (4)-(8) employ different clustering strategies. Column (9) includes industry-time fixed effects. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are also included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

Fifth, in Table B5, we first drop the largest fund domicile countries in our sample (by number of observations), i.e., the US, Luxembourg, Ireland and the UK. In columns (5)–(8) of the same table, we drop the largest asset management companies, i.e., Vanguard, Fidelity, Dimensional Fund Advisors, and Geode Capital Management. In all cases, our baseline effects are largely unchanged, providing reassurance that they are not driven by funds associated with specific asset management companies or domiciles.

Table B5: Robustness Checks: Dropping Major Domiciles and Asset Management Companies

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Dropping Domiciles				Panel B: Dropping Asset Managers			
	US	LU	GB	IE	Vanguard	Fidelity	Dimensional	Geode
$GPR_t \times Exposure_{s,t-3}$	0.371*** (0.119)	0.202*** (0.078)	0.202** (0.080)	0.212*** (0.082)	0.266*** (0.092)	0.226*** (0.077)	0.212*** (0.083)	0.218*** (0.082)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,357,778	22,363,201	22,883,729	23,153,211	18,087,942	22,439,446	23,193,910	23,041,535
R-squared	0.378	0.293	0.293	0.303	0.324	0.307	0.308	0.310

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1–2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. We drop one major domicile or fund manager/family from the sample at a time. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

Sixth, we examine whether our results are driven by firms in specific industries. To this end, we interact the global GPR index not only with firms' GPR exposure but also with industry dummies, with industries corresponding to one-letter SIC codes and using the largest industry—manufacturing—as omitted reference category. Column (3) of Table B6 shows that all of the triple interactions are not statistically different from zero, implying that our results are not driven by any particular industry. Specific industries like defense and dual use good manufacturing typically attract larger investor attention during GPR shocks, leading us to conjecture increased fund allocations into associated companies. We thus zoom into these industries in particular. While column (1) defines defense to include both core industries like weapon manufacturing and adjacent industries like aerospace & aviation, we construct, in column

(2), a dual-use industry dummy that further includes industries like semiconductors, chemicals, materials, and advanced instruments. In both cases, we do not detect any amplified effect.

Table B6: Robustness Checks: Industry Heterogeneity

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$		
	(1)	(2)	(3)
$GPR_t \times Exposure_{s,t-3}$	0.219*** (0.082)	0.222*** (0.084)	0.255* (0.147)
$GPR_t \times Exposure_{s,t-3} \times Defense_s$	-0.227 (0.340)		
$GPR_t \times Exposure_{s,t-3} \times Dual\ Use_s$		-0.232 (0.276)	
$GPR_t \times Exposure_{s,t-3} \times Agriculture_s$			-0.621 (0.911)
$GPR_t \times Exposure_{s,t-3} \times Construction_s$			-0.017 (0.441)
$GPR_t \times Exposure_{s,t-3} \times Energy_s$			-0.108 (0.318)
$GPR_t \times Exposure_{s,t-3} \times Finance_s$			-0.236 (0.209)
$GPR_t \times Exposure_{s,t-3} \times Mining_s$			-0.287 (0.417)
$GPR_t \times Exposure_{s,t-3} \times Non-Classified_s$			0.879 (0.624)
$GPR_t \times Exposure_{s,t-3} \times Retail_s$			-0.519 (0.367)
$GPR_t \times Exposure_{s,t-3} \times Service_s$			0.054 (0.233)
$GPR_t \times Exposure_{s,t-3} \times Transportation_s$			-0.134 (0.283)
$GPR_t \times Exposure_{s,t-3} \times Wholesale_s$			0.129 (0.279)
Fund-Time FE	Yes	Yes	Yes
Fund-Security FE	Yes	Yes	Yes
Observations	24,296,754	24,296,754	24,294,339
R-squared	0.304	0.304	0.304

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. The main regressor is the triple interaction between the aggregate GPR index of Caldara and Iacoviello (2022), a continuous measure of exposure to GPR, as defined in Section 2, and different industry indicators. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

Finally, in Table B7, we estimate our baseline regression corresponding to equation 1 on two distinct sub-samples: one comprising smaller firms, defined as those in the lowest 80% of the country-year-specific total asset distribution, and one encompassing only large firms in the top 20%. This is important because large firms often benefit from special government support during crises—

including business disruptions due to GPR events—, upholding these firms’ status as ‘national champions’. Focusing only on the lowest 80% thus helps guard against large firms driving our results. The results show that related concerns are unwarranted, with the double interaction of interest being positive and statistically significant in both sub-samples. Although the coefficient magnitude is larger in the large firm sub-sample, the difference between large and smaller firms is not statistically significant at conventional levels (unreported).

Table B7: Small vs. Large Firms

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$	
	Large Firms (1)	Small Firms (2)
$GPR_t \times Exposure_{s,t-3}$	0.266* (0.147)	0.175*** (0.056)
Fund-Time FE	Yes	Yes
Fund-Security FE	Yes	Yes
Observations	10,800,404	13,477,465
R-squared	0.347	0.335

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1-2025:M3. The dependent variable is the IHS-growth in fund-security-specific portfolio shares. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. Large firms are defined those with total assets in the top 20% in a country-year bin, and smaller firms are those in the lowest 80%. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors’ calculations.

C BOND FUNDS

This paper studies how GPR shocks induce portfolio rebalancing of equity funds, and shows that funds allocate more into GPR-exposed stocks as GPR rises. In this section, we apply the same analytical framework to bond funds. For this, we construct a sample of individual holdings of 1,916 bond funds worldwide investing in 1,732 fixed-income securities, based on the EPFR Fixed Income Flows and Holdings dataset. This dataset provides monthly fund-security-level information on bond holdings for a large cross-section of globally domiciled mutual funds and ETFs. All variables remain defined as in the main text, with the valuation control computed as the IHS-growth in bond prices, which we source from the Wharton Research Data Service Bond Returns database and merge to the bond-fund-level data.

Table C1 portrays the results. The coefficient of interest on the interaction between GPR and firms' GPR exposure is statistically insignificant throughout all specifications. Hence, bond funds do not reallocate portfolios across individual securities in response to GPR shocks. Why do bond fund managers seemingly ignore GPR shocks? In section 5, we show that equity funds' search for yield is the main driver for the pivot into GPR-exposed firms, as stock prices (expected returns) of more GPR-exposed firms decline (increase), offering an attractive investment opportunity. This price reaction for equities contrasts with bonds, whose prices are known to be less volatile (Jordà et al. 2019). In fact, unreported regressions indicate that GPR shocks leave bond prices of more rather than less exposed firms largely unchanged, consistent with risk premia adjustments primarily affecting equities as residual claims. This explains why bond funds' cross-security portfolio allocations prove insensitive to GPR shifts.

Table C1: Bond Fund Analysis

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IHS(Bond Price)_{f,j,s,t}$	0.098*** (0.012)	0.095*** (0.016)	0.094*** (0.015)	0.095*** (0.016)	0.095*** (0.016)	0.095*** (0.016)
$Exposure_{s,t-3}$	-3.542 (2.507)	-2.171 (2.432)	-2.271 (2.485)			
$GPR_t \times Exposure_{s,t-3}$	0.009 (0.019)	-0.006 (0.018)	-0.002 (0.018)			
$I\{> 25\}_{s,t-3}$				0.009 (0.008)		
$GPR_t \times I\{> 25\}_{s,t-3}$				-0.000 (0.000)		
$I\{> 50\}_{s,t-3}$					-0.014* (0.007)	
$GPR_t \times I\{> 50\}_{s,t-3}$					0.000 (0.000)	
$I\{> 75\}_{s,t-3}$						-0.008 (0.007)
$GPR_t \times I\{> 75\}_{s,t-3}$						0.000 (0.000)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	No	Yes	Yes	Yes	Yes	Yes
Country-Time FE	No	No	Yes	No	No	No
Observations	2,503,772	2,499,844	2,490,584	2,499,844	2,499,844	2,499,844
R-squared	0.397	0.444	0.446	0.445	0.445	0.445

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security (bond)-level data from EPFR covering the period 2018:M10-2025:M3. The outcome variable is the IHS-growth in fund-bond-specific portfolio shares. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR (columns 1-3), as defined in Section 2. Columns (4)-(6) replace the continuous exposure measure with dummies that take a value of one when it exceeds the 25th, median or 75th percentile of the distribution. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in bond prices (coefficient omitted either), as well as fund-time, country-time, and fund-security fixed effects. Standard errors are double clustered at the fund and bond level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

D PORTFOLIO ADJUSTMENTS AT EXTENSIVE AND INTENSIVE MARGINS

EPFR data only encompass strictly positive portfolio allocations, implying that, by default, our analysis in the main body of the paper exclusively studies the intensive margin of portfolio adjustments. However, fund managers can also open new positions or close existing ones. To explore these adjustment margins, we identify the missing positions and fill these with zeros. For instance, for a position held by a fund over the period 2012:M1–2017:M5, we create data points for the same stock in the period before 2012:M1 and after 2017:M5, and set these new data points to zero.

We repeat the baseline regressions for this expanded dataset. Columns (1)–(3) of Table D1 show that our baseline results stand. In columns (4) and (5), we directly contrast adjustments at the intensive and extensive margin, and find only the former to drive our results. This vindicates our choice to focus on the smaller dataset and thus the intensive margin in the main body of the paper, coincidentally also more convenient for faster computations.

Table D1: Portfolio Reallocations at the Extensive and Intensive Margin

Dependent Variable	$\Delta IHS(Share)_{f,j,s,t}$			Extensive	Intensive
	(1)	(2)	(3)		
$GPR_t \times Exposure_{s,t-3}$	0.081* (0.043)	0.077* (0.046)	0.076* (0.046)	-0.005 (0.013)	0.083** (0.041)
Fund-Time FE	Yes	Yes	Yes	Yes	Yes
Fund-Security FE	No	Yes	Yes	Yes	Yes
Country-Time FE	No	No	Yes	No	No
Observations	49,271,199	49,246,994	49,246,896	49,246,994	49,246,994
R-squared	0.095	0.114	0.116	0.023	0.157

GPR = geopolitical risk, IHS = inverse hyperbolic sine.

Notes: These regressions are based on monthly fund-security-level data from EPFR covering the period 2011:M1–2025:M3. The data is compiled as balanced panel, filling in zeros when a fund does not hold any particular securities. The dependent variables in columns (1) to (3) are the IHS-growth in fund-security-specific portfolio shares. In columns (4) and (5), we calculate the IHS-growth of portfolio shares along the extensive and intensive margin, respectively. Specifically, for the extensive margin, we set the dependent variable from columns (1)–(3) equal to zero when it changes along the intensive margin, and for the intensive margin, we set it equal to zero when it changes along the extensive margin. The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. All lower-order variables of the interactions—unless spanned by the set of fixed effects—are included, but omitted for brevity. The regressions control for valuation effects by adding the IHS-growth in security-level stock prices (coefficient omitted), as well as fund-time, country-time, and fund-security fixed effects. Standard errors are double clustered at the fund and security level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.

E ADDITIONAL TABLES

Table E1: Correlation Matrix for Firm Fundamentals and GPR-exposure

Variables	Exposure _{s,t-3}
$\ln(\text{Asset})_{s,t-12}$	-0.029
Equity Share _{s,t-12}	-0.002
Liquidity _{s,t-12}	0.112
ROA _{s,t-12}	-0.042

ROA = return on assets. Notes: This table displays the correlation matrix between firms' fundamentals and the GPR-exposure measure constructed based on the earnings call transcripts.

Source: Authors' calculations.

Table E2: Effects on Firm Fundamentals

Dependent Variable	ROA		ln(Asset)		ln(Employee)	
	(1)	(2)	(3)	(4)	(5)	(6)
$GPR_{t-1} \times Exposure_{s,t-1}$	-0.675 (1.244)		-0.082* (0.046)		0.027 (0.060)	
$GPR_{t-2} \times Exposure_{s,t-1}$		-0.540 (1.653)		-0.081 (0.052)		-0.067 (0.056)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,553	33,853	42,007	35,094	39,430	33,064
R-squared	0.762	0.753	0.983	0.984	0.978	0.980

GPR = geopolitical risk, ROA = return on assets.

Notes: These regressions are based on annual firm-level data sourced from Compustat Global covering the period 2011-2025. The dependent variables are firm-level fundamentals (return on assets, total assets, and number of employees). The main regressor is the double interaction between the aggregate GPR index of Caldara and Iacoviello (2022) and a continuous measure of exposure to GPR, as defined in Section 2. The regressions also encompass firm and time fixed effects. Standard errors are clustered at the firm level and shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations.