Geopolitical Risk in Financial Markets: Evidence from Mutual Fund Flows

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Abstract

This paper investigates how geopolitical risk is reflected in mutual fund flows and asset prices. We find in a sample of international equity funds that higher exposure to geopolitical rivals is associated with lower fund flows around major geopolitical events. Using the flow spread between the low- and high-exposure funds, we define a new measure of geopolitical risk called GPFS. We find that GPFS commands a significant risk premium in the cross section of stock returns after 2016, but not before. The premium is concentrated among big firms and those with foreign revenues. Additional evidence supports a risk-based interpretation.

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For most of the time since World War II, countries around the globe steadily integrated their trade and supply chains. Economists generally agree that this era of globalization created substantial welfare gains, as it brings more products at lower prices to consumers, and opens up broader markets to companies. Yet, when domestic economies integrate so deeply with global markets, they also become highly exposed to foreign nations—including those that are not aligned geopolitically. This exposure is innocuous when international relations are stable and geopolitics do not disrupt business exchanges. Recently, however, rising geopolitical tensions have fundamentally changed the global economic landscape. Events like the US-China trade conflict and the Russia-Ukraine war have led to the scrutinization of economic interdependence. Because nations now weaponize trade links, supply chains, and financial networks, the vulnerability to geopolitical shocks can easily offset, or even outweigh, the traditional gains from trade.

The impact of geopolitical tensions on the world economy has attracted a lot of attention. A large and growing literature documents that these tensions have real economic consequences (see Mohr and Trebesch (2025) for a survey). As for financial markets, however, there is an ongoing debabe on whether, and how, geopolitical risk influences asset prices. In particular, there is little evidence on how these tensions alter the capital allocation decisions of investors, and whether such shifts drive risk premia. Recent studies give conflicting answers. Some papers find that news-based geopolitical risk indices forecast market premiums and drive cross-sectional asset returns (Sheng, Sun, and Wang, 2025; Gonçalves, Melone, and Ricciardi, 2026), whereas other studies question their relevance for risk premia (Hirshleifer, Mai, and Pukthuanthong, 2025; Bianchi et al., 2026).

In this paper, we study geopolitical risk through the lens of mutual fund flows and asset prices. We examine U.S. international equity funds and compare the flows between funds with high and low exposure to U.S. geopolitical rivals. Intuitively, if investors take into account geopolitical risk in their investment decisions, then when they perceive an increase in risk, we should observe more outflows from high-exposure funds than from low-exposure ones. This is exactly what we find. Leveraging this flow behavior, we construct a novel measure of geopolitical risk called the Geopolitical Flow Spread (GPFS), which, in contrast to the existing news-based measures, directly reflects investors' perception. We then examine the asset pricing implications of GPFS. We measure firms' exposure to geopolitical risk using their loadings on GPFS (i.e. GPFS beta); then we explore their relation to stock returns. Intuitively, If those fund flow shifts captured by GPFS reflect risk considerations rather than a temporary investor overreaction (Bianchi et al., 2024), then stocks with high GPFS beta should command a risk premium. We show that this is indeed the case, but only in the post-2016 period. Overall, our results are consistent with the notion that investors increasingly view geopolitics as a key variable in capital allocation, and they demand hedging against related risk.

We begin our analysis by obtaining a sample of U.S. international equity mutual funds from Morningstar. We compute a measure of geopolitical exposure for these funds based on their portfolio holdings. Specifically, we use the foreign exposure of a fund, in combination with the ideal points computed by Bailey, Strezhnev, and Voeten (2017), to assess the fund's exposure to geopolitical rivals. The foreign exposure data reveal the fraction of fund assets invested in each country's equity, which is computed by Morningstar based on the headquarter location of the stock's company. And the ideal points provide a measure of the geopolitical alignment of any other country with the U.S.. We then sort funds into portfolios based on quintiles of the geopolitical exposure and analyze their fund flows.

We follow Dou, Kogan, and Wu (2026) in computing the flow shocks for each fund. Then we define our measure of geopolitical risk, GPFS, as the average fund flow shocks in the lowest geopolitical exposure quintile minus the average fund flow shocks in the highest quintile. Our measure is based on the intuition that investment in international funds with high exposure to geopolitical rivals should be particularly sensitive to variation in geopolitical tensions. When geopolitical tensions rise, there will be more capital flowing out of the high exposure funds. We confirm this intuition empirically by examining the time series of GPFS, and we show that the ups and downs of this measure coincide well with prominent geopolitical events.

After establishing the link between GPFS and geopolitical tensions, we move on to examine its asset pricing implications. In the cross section of U.S. stocks, we show that GPFS beta has strong explanatory power in the post-2016 period. First, we sort stocks into quintile portfolios based on their GPFS beta. We find that the zero cost portfolio that is long stocks in the highest GPFS beta quintile and short stocks in the lowest GPFS beta quintile has average annual returns of 16.4%. We confirm that this premium does not reflect loadings on well-known factors, as we run the time series regressions of the portfolio return on various benchmark risk factors. The residuals remain positive and highly significant. These findings hold for the period from 2017 to 2024. In the period before 2016, there is no significant return spread between high- and low-GPFS-beta stocks.

To complement our portfolio analysis, we also perform Fama-MacBeth regressions, which allow us to control for more stock characteristics that are known to predict stock returns. We confirm that the explanatory power of GPFS beta persists even after controlling for a range of characteristics like size, value, momentum, etc.. And we also find that the return premium associated with GPFS beta mainly comes from big stocks, which are more likely to have international businesses.

Finally, we show that GPFS beta is positively correlated with the supply chain exposure to geopolitical rivals and also the revenue dependence on foreign customers. We also find that active equity funds tilt their portfolio holdings away from stocks with higher GPFS betas, suggesting that the source of GPFS premium is due to some institutional investors shunning away from the high-beta stocks.

Literature. This paper mainly contributes to the literature studying geopolitical risk premia. Most existing studies apply textual analysis to news articles to measure geopolitical tensions and study the impact on financial markets. After Caldara and Iacoviello (2022) introduce a news-based geopolitical risk (GPR) index, Gonçalves, Melone, and Ricciardi (2026) examine the asset pricing implications. They find that geopolitical threats (GPT) and acts (GPA) have different asset pricing implications: only GPT links to capital allocation and risk premia. Hirshleifer, Mai, and Pukthuanthong (2025) refine this approach by applying a semi-supervised topic model to extract a specific "War" discourse factor. They show that the War factor is priced in the cross-section of asset returns. Sheng, Sun, and Wang (2025) also construct a news-based index that captures trade uncertainty, and they show that it successfully predicts market excess returns. Compared with these studies, our distinctive contribution is to propose a flow-based measure of geopolitical risk. It reflects the revealed preferences of fund investors by tracking the flow differential between funds with high and low exposure to U.S. geopolitical rivals. And our asset pricing results complement prior studies and help resolve some of their disagreement.

The rest of the paper is organized as follows. Section 1 describes the data and sample construction. Section 2 explains the construction of GPFS. Section 3 presents the asset pricing tests using GPFS. Section 4 provides evidence on the underlying mechanism. Section 5 concludes.

1 Data

In this section, we present the data used in our analysis, which come from several sources. We also briefly describe the process for sample construction, highlighting key steps and filters. For the final cleaned sample, we provide major summary statistics. Omitted details and variable definitions, as well as auxiliary tables and figures, are given in Appendix.

Data on international mutual funds. The main contribution of this paper is to provide a novel approach to measuring geopolitical risk based on mutual fund flows. To that end, we collect data on international open-end equity mutual funds domiciled in the U.S. from the Morningstar database. We include both actively managed funds and passive funds (but exclude ETFs). For funds with multiple share classes, we use the oldest share class as our unit of observation and aggregate any variables to fund level if necessary across all share classes using the total net asset (TNA) as weight. To address the incubation bias (Evans, 2010), we exclude the first 36 months of observations for each fund share since its inception.

Our final sample consists of 1687 funds (with 4188 distinct share classes) and spans the period from January 2000 to December 2024. Among the sampled funds, only 91 are passive funds and the rest are active funds. Table 1 reports major descriptive statistics. These funds are on average 11.5 years old, and they manage 1.49 billion dollars in assets, of which nearly 90 percent are equities. The median fund has a monthly excess return of 0.78%, with alpha ranging from -0.32% to -0.30% depending on the factor models being used. The average Sharpe ratio is 0.58, in line with the literature. The average (median) fund flow is negative, -0.091% (-0.364%) per month, suggesting that most funds are witnessing outflows in this period.

To measure the geopolitical exposure of these international funds, we obtain information on their portfolio holdings. In particular, we use the foreign exposure data computed by Morningstar, which gives the fraction of fund assets invested in each country. [1] As shown in Table 2, international funds, though restricted by their mandates, still have considerable investment in domestic stocks, averaging about 15% of fund assets. As for foregin exposure, Japan and the UK account for around 11%. Investment in China represents about 6.4%. France and Germany capture about 4-5% each. The top 10 countries together account for more than 70% of fund investment. Figure 1 shows the time series variation of the investment positions in major countries.

Next, we combine the foreign exposure data with the geopolitical alignment data,

[1] Mornignstar determines the country of domicle for a stock based on its underlying company's headquarter location, as well as the business region.

which we describe below, to define the geopolitical exposure of each fund as follows:

$$GP\_exposure_{i,t} = \frac{\sum_{c \in C} w_{i,c,t} \, d_{c,t}}{\sum_{c \in C} w_{i,c,t}},$$

where $w_{i,c,t}$ denotes the percentage of fund i assets invested in the equity of country c at time t, and $d_{c,t}$ denotes the geopolitical distance between country c and the U.S.. According to our calculation, the average *GP_exposure* for our sampled funds is 1.48, with a standard deviation of 0.67.

Data on geopolitical alignment. We measure geopolitical alignment using the ideal points compiled by Voeten (2021), which follows the methodology developed by Bailey, Strezhnev, and Voeten (2017). The underlying idea is to translate countries' voting behavior at the United Nations General Assembly (UNGA) into numerical values that reflect their foreign policy stance. If two countries vote similarly on many issues, they will have similar ideal points. Conversely, countries with distinct voting decisions on various issues will have very different ideal points. We use the baseline ideal points computed using the votes cast on the final passage of all resolutions, which have various themes including colonialism, disarmament, human rights, nuclear weapons, and economic development. [2] Then we define the geopolitical distance between the U.S. and any other country as the absolute difference between their respective ideal points.

$$d_{c,t} = \left| \mathrm{IP}_{c,t} - \mathrm{IP}_{US,t} \right| .$$

As an illustration, Figure A.1 shows the ideal points for the five permanent members of the United Nations Security Council (P5).

Data on supply chain exposure and foreign sales. We measure the supply chain ex-

[2] Not all resolutions are treated equal in the estimation of ideal points. Each resolution is weighted according to its informativeness about ideological differences. Some resolutions are more effective in separating countries with respect to their geopolitical alignment and thus receive greater weight in the estimation.

posure of U.S. industries using the Inter-Country Input Output (ICIO) data released by the Organization for Economic Cooperation and Development (OECD). The ICIO data show the inputs each sector in each country buys from every other sector in every other country. Through the IO analysis described in Baldwin, Freeman, and Theodorakopoulos (2023), we compute the Leontief matrix from the ICIO data, which reveals for each sector the required inputs from every other country-sector for each unit of production. This allows us to compute a supply-chain-based measure of geopolitical exposure for the U.S. industries. We use data from Factset Revere to measure firms' revenues from foreign countries.

Other data. We also download stock return data from the CRSP and the firm financial variables from the Compustat. The Geopolitical Risk Index (GPR) and its threat (GPRT) and act (GPRA) components come from Caldara and Iacoviello (2022). The Economic Policy Uncertainty Index (EPU) is from Baker, Bloom, and Davis (2016). The VIX data are from the CBOE. The global common volatility measure (COVOL) is from Engle and Campos-Martins (2023), and the news-based war discourse risk indicator (WAR) is from Hirshleifer, Mai, and Pukthuanthong (2025b).

2 Construction of the GPFS

2.1 Share-level fund flow shocks

We construct fund flow shocks at the share-class level to account for heterogeneity in investor composition within funds. We first compute share-level net flows using the standard asset-based flow identity,

$$F_{i,k,t} = \frac{\text{TNA}_{i,k,t} - \text{TNA}_{i,k,t-1} \times (1 + R_{i,k,t})}{\text{TNA}_{i,k,t-1}},$$

where $\text{TNA}_{i,k,t}$ denotes total net assets and $R_{i,k,t}$ is the net return of share class k of fund i in month t. We restrict the estimation sample to share classes with TNA of at least $15 million. We also exclude observations within the first 36 months of the share's inception date to address incubation bias. These filters are applied only in the estimation of flow factors and do not affect the construction of geopolitical exposure or the main analysis sample.

We then model share-level flows as

$$F_{i,k,t} = a + b_1 \,\text{ExRet}_{i,k,t} + b_2 \,\text{ExRet}_{i,k,t-1} + c\, F_{i,k,t-1} + \theta_t + \varepsilon_{i,k,t},$$

where $\text{ExRet}_{i,k,t}$ denotes the excess return of the share class k relative to the market return, and θ_t captures month fixed effect in fund flows. We define the share-level flow shock as

$$\text{flow}_{i,k,t} \equiv \theta_t + \varepsilon_{i,k,t},$$

which captures unexpected capital reallocations that are not explained by return chasing, flow persistence, or predictable market-wide dynamics. We observe share class assets under management and returns from 1990 to 2024 and use them to estimate the factor structure of mutual fund flows.

2.2 Geopolitical Flow Spread (GPFS)

We construct a Geopolitical Flow Spread (GPFS) to summarize differential investor flow responses across funds with different geopolitical exposures. In each month t, we sort funds into quintiles based on their geopolitical exposure $e_{i,t}$. Let $\mathcal{H}_t$ and $\mathcal{L}_t$ denote the sets of funds in the top and bottom quintiles of geopolitical exposure, respectively. We define GPFS as the difference in average fund flow shocks between low- and high-exposure funds:

$$\text{GPFS}_t = \overline{\text{flow}}_{\mathcal{L}_t,t} - \overline{\text{flow}}_{\mathcal{H}_t,t},$$

where $\overline{\text{flow}}_{\mathcal{L}_t,t}$ and $\overline{\text{flow}}_{\mathcal{H}_t,t}$ denote the cross-sectional averages of share-class flow shocks within the corresponding exposure groups. A positive value of GPFS_t indicates stronger investor outflows from high-exposure funds relative to low-exposure funds, or stronger relative inflows into low-exposure funds. We construct the GPFS factor from flow shocks and geopolitical exposure over the 2000–2024 period.[3]

2.3 Properties of the GPFS

Panel A of Table 3 reports summary statistics for the Geopolitical Flow Spread (GPFS). GPFS varies substantially over time and has a negative average value: its mean is -0.42, and its median is -0.38. Under our low-minus-high construction, this negative average indicates that, in normal periods, investor flows tend to move toward funds with higher geopolitical exposure. Positive GPFS realizations therefore capture episodes in which investors rebalance away from high-exposure funds and toward low-exposure funds.

Figure 2 plots the monthly GPFS from January 2000 to December 2024. The series fluctuates around a slightly negative level but displays sharp positive increases around geopolitical shocks of different types, including wars, sanctions, diplomatic conflicts, and technology-related tensions. Under the low-minus-high construction, these increases reflect defensive reallocations from high-exposure funds to low-exposure funds. The figure shows that GPFS captures discrete flow responses to periods of geopolitical stress, rather than a slowly moving component of aggregate risk.

To compare GPFS with existing risk measures, we convert each monthly index into a factor-like series using its monthly growth rate. We denote these factor-like series with the superscript "fac". Panel B of Table 3 shows that GPFS is only weakly correlated with

[3] Morningstar's equity country exposure data are sparse and less reliable prior to 2000.

these factors: its correlation is 0.04 with GPR^{fac}, GPT^{fac}, and GPA^{fac}, which are constructed from the Caldara and Iacoviello (2022) geopolitical risk, threats, and acts indices. Its correlations are similarly small with broader uncertainty factors: 0.06 with EPU^{fac}, constructed from the Global Economic Policy Uncertainty index of Baker, Bloom, and Davis (2016); 0.13 with ΔVIX; and 0.07 with WAR^{fac}, constructed from the war discourse risk measure of Hirshleifer, Mai, and Pukthuanthong (2025b).

By contrast, the news-based geopolitical risk factors are much more closely related to each other. GPR^{fac} is highly correlated with both GPT^{fac} and GPA^{fac}, with correlations close to one. WAR^{fac} is also moderately correlated with the three Caldara–Iacoviello-based factors. These patterns show that GPFS captures a distinct component of geopolitical risk, one reflected in international mutual fund flows rather than in news coverage or broad market uncertainty.

Figure 3 compares GPFS with the news-based geopolitical risk factors over the post-2017 period. GPFS and the news-based factors sometimes rise around the same geopolitical episodes, such as the Russia–Ukraine War and Russia energy sanctions, but their movements are not synchronized. The figure shows that GPFS shares geopolitical content with news-based measures while differing in timing and magnitude.

Table 4 examines this timing difference more formally using bidirectional Granger-causality tests. The evidence mainly runs from GPFS to the Caldara–Iacoviello-based factors: GPFS predicts GPR^{fac}, GPT^{fac}, and GPA^{fac} at longer lag lengths, while the reverse directions are not statistically significant. This lead–lag pattern suggests that GPFS captures portfolio adjustments that sometimes occur before geopolitical concerns become prominent in news-based risk measures.

3 Pricing Geopolitical Risk

3.1 The GPFS Beta Premium

We measure each stock's exposure to geopolitical risk by estimating its sensitivity to the negative of GPFS factor. Specifically, we regress the monthly excess returns of a stock to the negative of GPFS using a 24-month rolling window, requiring at least 12 monthly observations.

$$\text{ret}^{e}_{i,t-\tau} = \alpha_{i,t} + \beta^{\text{GPFS}}_{i,t} \times (-\text{GPFS}_{t-\tau}) + \varepsilon_{i,t-\tau}, \qquad \tau = 0, 1, \ldots, 23.$$

In June of each year, we sort stocks into quintiles based on their estimated GPFS betas. We use the average beta over the preceding January–June period for ranking and NYSE stocks to determine the breakpoints. The portfolios are held from July of year t to June of year $t+1$.

Figure 4 plots the cumulative returns of the long–short portfolio that buys stocks in the highest GPFS beta quintile and sells stocks in the lowest quintile. The portfolio performed poorly before 2017, with cumulative returns remaining flat or slightly negative. In contrast, returns rise sharply from 2017 onward, generating a sustained increase in cumulative performance over the subsequent years.

Table 5 reports average returns and single-factor alphas for portfolios sorted on GPFS beta. We estimate alphas using two benchmark returns: the CRSP market excess return and the value-weighted excess return of all U.S. international equity funds. The GPFS beta premium is absent before 2017. From 2001 to 2016, the high-minus-low portfolio earns -0.09% per month, with a t-statistic of -0.02, and its alphas relative to both benchmarks are statistically insignificant.

The post-2017 period shows a different pattern. From 2017 to 2024, the high-minus-low portfolio earns 16.42% per year, with a t-statistic of 3.19. Its alpha is 13.83% relative to the CRSP market benchmark and 15.36% relative to the international-equity-fund benchmark, with t-statistics of 2.84 and 3.08, respectively. The spread is driven mainly by the high-beta side of the sort: the high-beta portfolio's average excess return rises from 6.71% before 2017 to 22.29% after 2017, whereas the low-beta portfolio changes little, from 6.80% to 5.87%.

Table 6 shows that this post-2017 premium is not explained by standard equity factors. From 2017 to 2024, the high-minus-low alpha is 15.39% under the FF3 model, 14.84% under the FFC model, and 18.53% under the FF5 model. The corresponding t-statistics are 3.37, 3.15, and 4.12. Before 2017, the same alphas are small and statistically insignificant. These results show that the GPFS beta premium emerges only after 2017 and remains large after controlling for standard factor exposures.

Figure 5 compares the GPFS beta portfolio with portfolios sorted on betas to news-based geopolitical risk factors. For the news-based portfolios, we estimate stock betas from 36-month rolling regressions of monthly excess returns on the negatives of GPR^{fac}, GPT^{fac}, and GPA^{fac}, rebalance the beta-sorted portfolios monthly, and plot the cumulative returns of the high-minus-low portfolios. The GPR^{fac}, GPT^{fac}, and GPA^{fac} beta portfolios show a similar post-2020 upward pattern, but with smaller and less persistent cumulative gains than the GPFS beta portfolio. This pattern suggests that news-based measures contain related pricing information, but GPFS identifies the post-2020 premium more sharply.[4]

Figure 6 shows that higher GPFS betas predict persistently higher excess returns over the 12 months following portfolio formation, with no evidence of pre-trends or reversals. This pattern suggests that return predictability based on GPFS beta is unlikely to be driven by heterogeneous price pressure or liquidity shocks across stocks.

The divergence beginning in 2017 indicates that stocks with higher exposure to GPFS

[4]We use the historical version of the Caldara and Iacoviello (2022) geopolitical risk series to construct GPR^{fac}, GPT^{fac}, and GPA^{fac}, consistent with the long time-series tests in Gonçalves, Melone, and Ricciardi (2026).

earn systematically higher returns only in recent years. Since 2017, global markets have experienced sustained trade conflicts, sanctions, and regional military tensions, during which geopolitical risk became a persistent and economically significant concern for investors.

The absence of a premium before 2017 reduces concerns that the results reflect mechanical sorting or persistent cross-sectional characteristics unrelated to geopolitical risk. Instead, the evidence suggests that GPFS beta proxies for a priced dimension of geopolitical risk that becomes relevant when geopolitical tensions are sustained rather than episodic.

3.2 Cross-Sectional Pricing of GPFS Beta

We next ask whether the GPFS beta premium survives standard cross-sectional controls. Using the same GPFS beta estimates as in the portfolio tests, we estimate monthly Fama–MacBeth regressions of next-month stock excess returns on GPFS beta and stock-level controls:

$$r^e_{i,t+1} = \alpha_t + \lambda_t^{\mathrm{GPFS}} \beta_{i,t}^{\mathrm{GPFS}} + \boldsymbol{X}'_{i,t}\gamma_t + \varepsilon_{i,t+1}, \qquad \bar{\lambda}^{\mathrm{GPFS}} = \frac{1}{T}\sum_t \lambda_t^{\mathrm{GPFS}}.$$

The controls include log market capitalization, market beta, Pastor–Stambaugh liquidity beta, momentum, and short-term reversal.

Table 7 reports the average Fama–MacBeth slopes for January 2017 to November 2024. In the full sample, GPFS beta earns a positive premium in the univariate regression: the coefficient is 3.82, with a t-statistic of 1.97. The estimate becomes smaller and statistically insignificant after adding the standard controls.

The pricing result is concentrated among large stocks. For stocks above the NYSE median size breakpoint, the GPFS beta premium remains positive across all specifications. The coefficient is 7.22 in the univariate regression and remains 5.35 after including all controls, with t-statistics of 2.65 and 1.91, respectively. By contrast, the coefficients for small stocks are close to zero and statistically insignificant. This size pattern is consistent with the interpretation that GPFS captures geopolitical risk relevant for internationally integrated firms.

Next, we test whether GPFS beta is priced in a broader set of anomaly portfolios. We first estimate the factor loadings for each test portfolio from time-series regressions.

$$r^e_{j,t} = \alpha_j + \boldsymbol{\beta}_j' \boldsymbol{F}_t + \varepsilon_{j,t},$$

where $r^e_{j,t}$ is the excess return of test portfolio j, and $\boldsymbol{F}_t$ includes the standard equity factors and GPFS. We then run month-by-month cross-sectional regressions of contemporaneous portfolio returns on the estimated betas:

$$r^e_{j,t} = \lambda_{0,t} + \beta_j^{\text{GPFS}} \lambda_t^{\text{GPFS}} + \boldsymbol{\beta}_j^{\text{std}\prime} \boldsymbol{\lambda}_t^{\text{std}} + u_{j,t}, \qquad \bar{\lambda}^{\text{GPFS}} = \frac{1}{T} \sum_{t=1}^{T} \lambda_t^{\text{GPFS}}.$$

Table 8 reports the risk prices of the second-pass monthly cross-sectional regressions using the Hou–Xue–Zhang test portfolios as test assets. The GPFS beta is not priced before 2017. In Panel A, the average price of GPFS beta is negative and statistically insignificant across the FF3+GPFS, FFC+GPFS, and FF5+GPFS specifications. The coefficients range from -3.62 to -0.23, with t-statistics close to zero.

The post-2017 evidence is different. In Panel B, the average price of GPFS beta is positive in all three specifications. The coefficient is 16.28 in the FF3+GPFS model, 18.98 in the FFC+GPFS model, and 19.79 in the FF5+GPFS model. The corresponding t-statistics are 1.70, 2.55, and 2.71. These estimates show that portfolios with higher GPFS beta earn higher contemporaneous returns after 2017, even after controlling for standard equity factor exposures.

4 Supply-Side Geopolitical Exposure

4.1 Industry Foreign Reliance

We construct industry-level geopolitical exposure by combining the dependence of foreign production with the country-level geopolitical distance. The measure captures the extent to which an industry depends on inputs sourced from politically distant countries.

For each U.S. industry i and year t, we define exposure as

$$g_{i,t} = \mathbf{r}_{i,t}^{\top}\mathbf{d}_t,$$

where $\mathbf{r}_{i,t}$ is the vector of dependence on foreign production at the country-level and $\mathbf{d}_t$ is the vector of geopolitical distances relative to the United States. To construct $\mathbf{r}_{i,t}$, we obtain production linkages from the OECD Inter-Country Input–Output (ICIO) tables. For each year, we construct the technical coefficient matrix A and compute the Leontief inverse

$$L = (I - A)^{-1},$$

which captures both direct and indirect upstream production requirements.

For industry i, the i-th column of L summarizes the total input requirements needed to produce one unit of the final output. We define reliance on country c as

$$r_{i,c,t} = \frac{\sum_{k \in c} L_{ki,t}}{\sum_k L_{ki,t}},$$

which measures the share of total production requirements sourced from the country c, including higher-order supply-chain effects.

Figure A.2 in the Appendix shows upstream production dependence for U.S. manufacturing industries in 2017. Reliance is concentrated among a small set of major trading partners and differs between industries. This cross-sectional variation underlies our construction of industry-level geopolitical exposure.

4.2 Industry Exposure and Stock GPFS Betas

We examine whether stocks in industries that rely more heavily on geopolitically distant foreign suppliers exhibit greater sensitivity to geopolitical risk. We first assign industry-level geopolitical exposure to individual stocks. We standardize industry exposure $g_{i,t}$ within each year and denote the resulting measure by $g_{i,t}^{std}$. We then map OECD industries to historical NAICS classifications of stocks annually and assign each stock s the exposure of its matched industry $g_{i,t}^{std}$, denoted by $g_{s,t}$. To focus on relative exposure, we center stock-level exposure by removing the cross-sectional mean,

$$\tilde{g}_{s,t} = g_{s,t} - \bar{g}_t,$$

where $\bar{g}_t$ is the average exposure in all stocks in year t.

Figure 7 shows a monotonic relation between industry exposure and GPFS betas. The median demeaned exposure increases from -0.069 in the lowest beta quintile (Q1) to 0.063 in the highest quintile (Q5), a spread of 0.13 in standardized exposure. The shift is visible across the distribution rather than being driven by outliers. High-beta stocks are consistently drawn from industries with greater upstream reliance on geopolitically distant suppliers.

4.3 Industry Loadings on the GPFS Beta Portfolio

We examine whether industry geopolitical exposure is reflected in loadings on the GPFS portfolio. To do so, we regress industry excess returns on the market excess return and the GPFS portfolio return. The geopolitical exposure of the industry is constructed using OECD 50 industries and mapped to the Fama-French 49 industry classifications; the concordance is described in Table A.1. The sample spans July 2001 to December 2024 and uses 49 value-weighted Fama–French industry portfolios.

For each industry j, we estimate

$$R_t^j - r_t^f = \alpha_j + \beta_j^{\text{MKT}} \left(R_t^{\text{MKT}} - r_t^f \right) + \beta_j^{\text{GPFS}} R_t^{\text{GPFS}} + \varepsilon_t^j,$$

where t indexes months, R_t^j - r_t^f is the excess return of industry j, $R_t^{\text{MKT}} - r_t^f$ is the excess market return and R_t^{GPFS} is the return of the long–short portfolio formed by sorting stocks on $\beta_{s,t}^{GPFS}$. The coefficient β_j^{GPFS} captures the load of industry j in the GPFS portfolio.

Figure 8 reveals a strong positive cross-sectional relationship between industry GPFS betas and industry-level geopolitical exposure. Industries with greater upstream reliance on geopolitically distant suppliers load more heavily on the GPFS portfolio. The relation is economically large for the manufacturing industries. A one-unit increase in standardized exposure is associated with a 0.17 increase in GPFS beta (t = 3.27, $R^2 = 0.31$). In contrast, the slope is substantially lower among the non-manufacturing industries (0.07, $R^2 = 0.04$). The semiconductor and hardware industries exhibit the highest GPFS loadings in the cross section, reflecting their central role in geopolitical competition and supply-chain vulnerability.

5 Revenue-Based Geopolitical Exposure

5.1 Firm-Level Revenue Exposure

For each firm i and year t, we construct a revenue-based geopolitical exposure measure using FactSet geographic revenue disclosures. Let $w_{i,c,t}$ denote the fraction of firm i's total revenue attributed to country c in year t, and let $d_{c,t}$ denote the geopolitical distance between country c and the United States. We define firm-level geopolitical exposure as

$$\text{Exposure}_{i,t} = \frac{\sum_c w_{i,c,t}\, d_{c,t}}{\sum_c w_{i,c,t}}.$$

This measure is the revenue-weighted average geopolitical distance of a firm's disclosed revenue base. Firms earn higher exposure when a larger share of their revenue comes from countries that are more geopolitically distant from the United States. We normalize by covered revenue so that firms with incomplete country disclosure are not mechanically assigned lower exposure.

5.2 Revenue Exposure Portfolios

We construct portfolios sorted on firms' revenue-based geopolitical exposure. Exposure is measured at the firm level and assigned to individual stocks using the mapping between CRSP `permno` identifiers and underlying firms in FactSet. Detailed data construction and link procedures are described in Appendix A.

We first separate firms with zero foreign revenue from those with positive foreign revenue. Firms with zero foreign revenue form a dedicated zero-exposure portfolio (Q0), which we use as an additional reference when computing high-minus-low return spreads. Among firms with strictly positive revenue exposure, we sort stocks into quintiles (Q1–Q5) based on exposure measured at the end of June in year $t-1$. NYSE stocks with positive exposure determine the breakpoints. Portfolios are value-weighted and held from July of year t through June of year $t+1$.

We apply the same procedure to construct portfolios based on the revenue exposure of firms to China. Specifically, we measure firm-level China exposure as the share of revenue generated from China and assign it to individual stocks using the CRSP–FactSet link described above.

Figure 9 shows that cumulative return spreads are negligible before 2017 and become sizable thereafter, for both Q5–Q1 and Q5–Q0 portfolios and for aggregate and China-specific revenue exposure. The post-2017 increase in cumulative returns indicates that the pricing of revenue-based geopolitical exposure is concentrated in the recent period.

Table 9 quantifies the magnitude of this premium. The high-minus-low portfolio sorted on total revenue exposure earns 8.15% per year in excess returns, with a CAPM alpha of 7.58% and a Fama–French five-factor alpha of 5.18%. When exposure is measured using revenue shares to China, the premium increases to 10.25% per year, with a five-factor alpha of 6.53%, suggesting that exposure to geopolitically distant markets carries an even stronger pricing effect.

We extend this country-level sorting approach to a broader set of countries. For each country c, we measure exposure as the share of company revenue generated by c and lag it by one year. Each June, we restrict the sample to stocks with revenue exposure to the country c greater than 1 percent and classify these stocks into quintiles using the NYSE breakpoints. Portfolios are held from July of year t through June of year $t+1$. We compute the high-minus-low return spread (Q5–Q1) and require at least 30 stocks in both Q1 and Q5 in a given month.

Figure A.3 reports high-minus-low return spreads (Q5–Q1) across countries grouped by geopolitical classification, including geopolitical core economies, supply-chain economies, commodity exporters and U.S. allies. The spreads at the Country-level are substantially higher in absolute value in the post-2017 period than in the pre-2017 period. Before 2017, Q5–Q1 spreads were generally close to zero in most countries. After 2017, spreads become economically large in both directions and display pronounced heterogeneity among geopolitical groups.

In the post-2017 period, the largest positive spread appears in Iran at 16.5%, followed by China at 13.0% and India at 9.0%. In contrast, exposure to close U.S. allies such as Canada is associated with a spread of -11.5%, with similarly negative spreads for Italy (-9.0%) and France (-6.9%). These sign and magnitude patterns indicate that revenue dependence on geopolitically distant economies commands a positive premium, whereas exposure to countries more closely aligned with the United States is associated with a discount.

To examine whether revenue exposure and firm size condition the GPFS beta premium, we implement dependent double sorts for the post-2017 period in Table 10. Panel A first separates stocks by revenue-based geopolitical exposure. Stocks with zero revenue exposure are assigned to T0. Among stocks with positive exposure, we sort stocks into three groups, T1–T3, using 30/40/30 breakpoints based on revenue exposure measured at the end of June of year $t - 1$. Within each exposure group, we then sort stocks into quintiles based on their average GPFS beta over January–June of year t.

Panel B repeats the same exercise using firm size instead of revenue exposure. We first sort stocks into three size groups using 30/40/30 breakpoints based on size measured at the end of June of year t. Within each size group, we then sort stocks into quintiles based on GPFS beta. All portfolios are value-weighted and held from July of year t to June of year $t + 1$.

In Panel A of Table 10, the high-minus-low GPFS beta spread is small and statistically insignificant among zero-exposure stocks. The spread rises among firms with positive exposure and becomes largest in the highest exposure group. In T3, the Q5–Q1 spread reaches 22.63% per year, with a t-statistic of 3.12. In panel B, the Q5–Q1 spread is 17.40% per year in the largest size group, with a t-statistic of 3.48, while the corresponding spreads are smaller and statistically insignificant in the two smaller size groups. These results indicate that GPFS beta earns the strongest premium among firms whose revenue bases are more exposed to geopolitically distant markets and among large firms that are more integrated into global markets.

6 Fund Response to Geopolitical Risk

6.1 Portfolio Tilt

We examine whether active U.S. domestic equity funds tilt their holdings away from stocks with higher exposure to the GPFS factor. We estimate

$$w_{i,t}^{MF} - w_{i,t}^{mkt} = a + b_1 \beta_{i,t-1}^{GPFS} + b_2 \beta_{i,t-1}^{mkt} + \varepsilon_{i,t}.$$

We define $w_{i,t}^{MF}$ as the AUM-weighted portfolio weight of the stock i aggregated between active equity funds that hold the stock. The market weight $w_{i,t}^{mkt}$ is equal to the capitalization of the stock i divided by the total capitalization of the CRSP stock universe in the month t. The dependent variable $w_{i,t}^{MF} - w_{i,t}^{mkt}$ measures the deviation of the weight of the mutual fund portfolio from the weight of the market portfolio of the stock i in month t.

Table 11 reports the results. In the post period, the coefficient in $\beta_{i,t-1}^{GPFS}$ equals -0.026 (t = -3.83) when controlling for market beta. In the pre period, the corresponding estimate is -0.001 (t = -0.25), indicating that there is no systematic tilt once the market beta is included. The Fama–MacBeth regressions deliver similar post-period magnitudes and show no comparable effect in the pre period. The pattern indicates that the active domestic equity funds only tilt their portfolios away from high GPFS exposure stocks in the post period.

6.2 Portfolio Rebalance

This section examines whether active international equity funds adjust their country allocations in response to geopolitical risk. Using quarterly holdings, we construct country-level marginal reallocations that capture how funds redistribute portfolio weights across countries over time.

For each country c and quarter t, we define marginal reallocation as the change in the aggregate portfolio weight between quarters t and $t+1$. Specifically, the dependent variable is the average change in portfolio weights across all funds investing in country c, which captures the net reallocation of capital toward or away from that country. We then estimate the following panel regression:

$$\Delta w_{c,t+1} = \beta^{GPFS} \left(GPFS_t \times D_{c,t} \right) + \Gamma' X_{c,t} + \alpha_c + \tau_t + \varepsilon_{c,t+1},$$

where $\Delta w_{c,t+1}$ denotes the change in the aggregate portfolio weight allocated to country c in the following quarter. $GPFS_t$ is the geopolitical risk factor and $D_{c,t}$ is an indicator equal to one for countries with a geopolitical distance above the median in quarter t. The interaction term therefore captures the differential response of portfolio allocations to geopolitical risk for high-risk countries.

The control vector

$$X_{c,t} = (\Delta w_{c,t}, \Delta w_{c,t-1}, w_{c,t})$$

accounts for persistence in portfolio adjustments and mechanical rebalancing driven by existing portfolio weights. We include country fixed effects α_c to control for time-invariant country characteristics and time fixed effects τ_t to absorb global shocks affecting all countries simultaneously.

Table 12 shows that funds cut allocations more sharply to geopolitically distant countries when geopolitical risk rises after 2017. In the specification with both country and time fixed effects (column (4)), the interaction coefficient is -0.07 ($t = -2.44$), indicating stronger rebalancing away from countries that are less geopolitically aligned with the United States. The corresponding coefficient is close to zero before 2017, indicating that this pattern is specific to the recent period.

7 Conclusion

In this paper, we take a novel approach to studying geopolitical risk in financial markets. We propose a novel measure of geopolitical risk based on mutual fund flows. Within a sample of international equity funds, we find that the flow shocks to funds with high and low geopolitical exposure are strongly correlated with geopolitical events. Using the flow spread between high- and low-geopolitical-exposure funds, we define a new measure of geopolitical risk called GPFS.

Our analysis reveals that GPFS helps predict the cross section of stock returns in the years after 2016. Stocks with greater GPFS beta earn higher returns, even after controlling for prominent factors. For the period before 2016, however, there is no return difference between high- and low-GPFS-beta stocks. At the aggregate level, we show that GPFS positively predicts future market returns, supporting the idea that geopolitical risk is a systematic risk that commands a risk premium. The predictability persists for horizons up to three years and remains significant when including other stock market predictors.

We also provide evidence that supports a risk-based interpretation of our results. In particular, we find that active funds that invest in domestic markets systematically tilt away from stocks with high GPFS beta after 2016. The extent to which they underweight a stock relative to the market is positively correlated with the stock's GPFS beta. We also find that the GPFS risk premium is concentrated among big stocks and stocks with considerable exposure to foreign supply chains and customers. In sum, our results suggest that geopolitical risk is a distinct source of systematic risk in financial markets.

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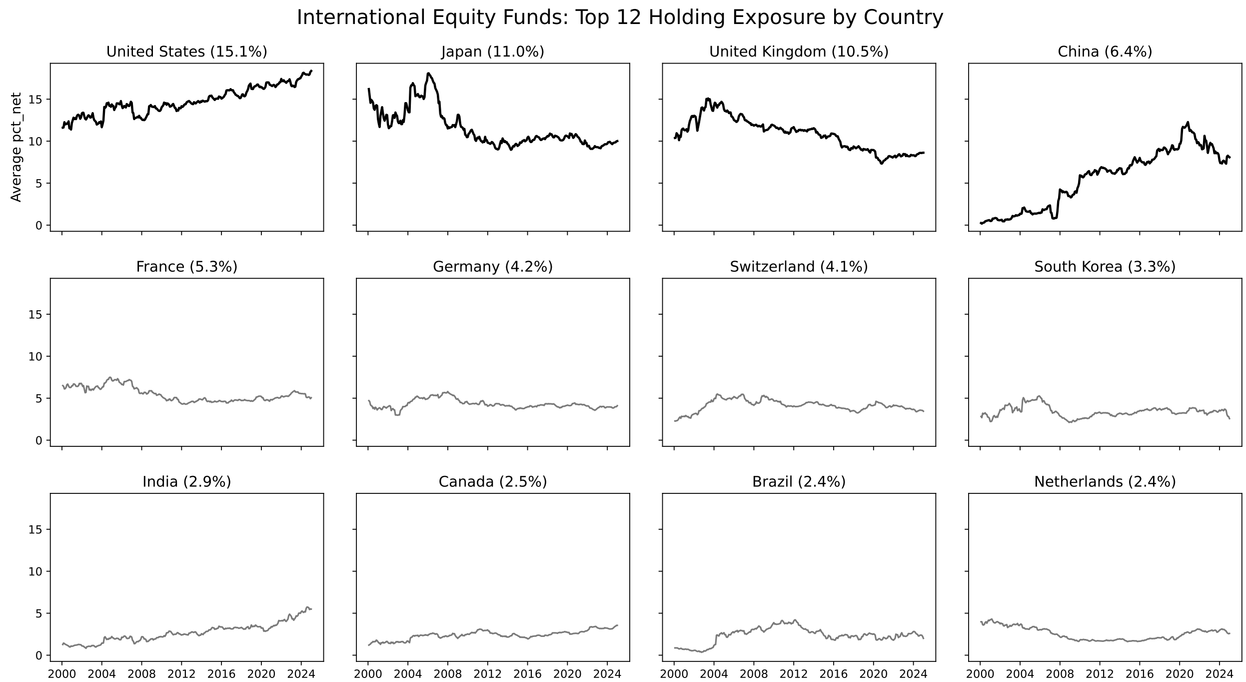

Figure 1: International Equity Fund Holdings by Country. This figure plots country-level portfolio weights of international equity funds from January 2000 to December 2024. The figure displays the 12 countries with the largest average exposure over the sample period. Country exposure is the fraction of fund net assets invested in equities domiciled in each country. Numbers in parentheses report each country's full-sample average portfolio weight, in percent.

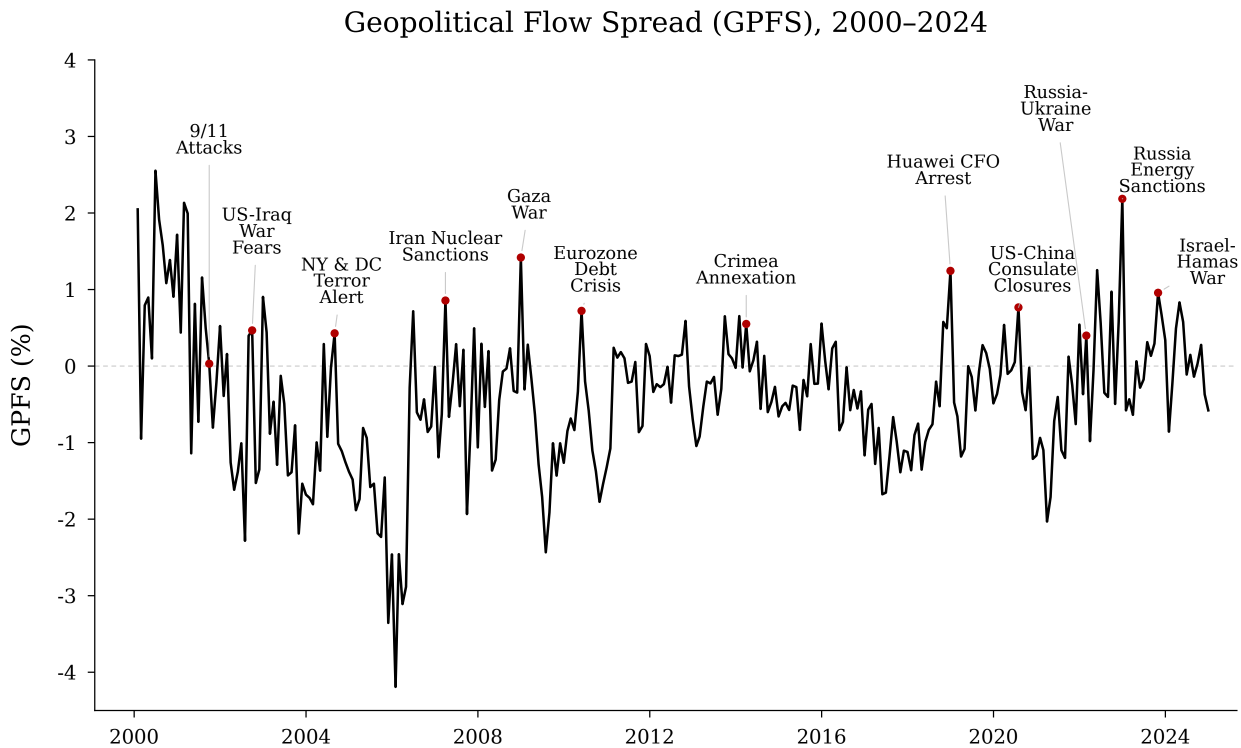

Figure 2: Geopolitical Flow Spread (GPFS). This figure plots the monthly Geopolitical Flow Spread (GPFS) from January 2000 to December 2024. Each month, international equity funds are sorted into quintiles based on geopolitical exposure. GPFS is defined as the difference in average share-class flow shocks between the lowest- and highest-exposure quintiles. Values are reported in percent per month. Red markers indicate geopolitical events that provide context for prominent GPFS movements.

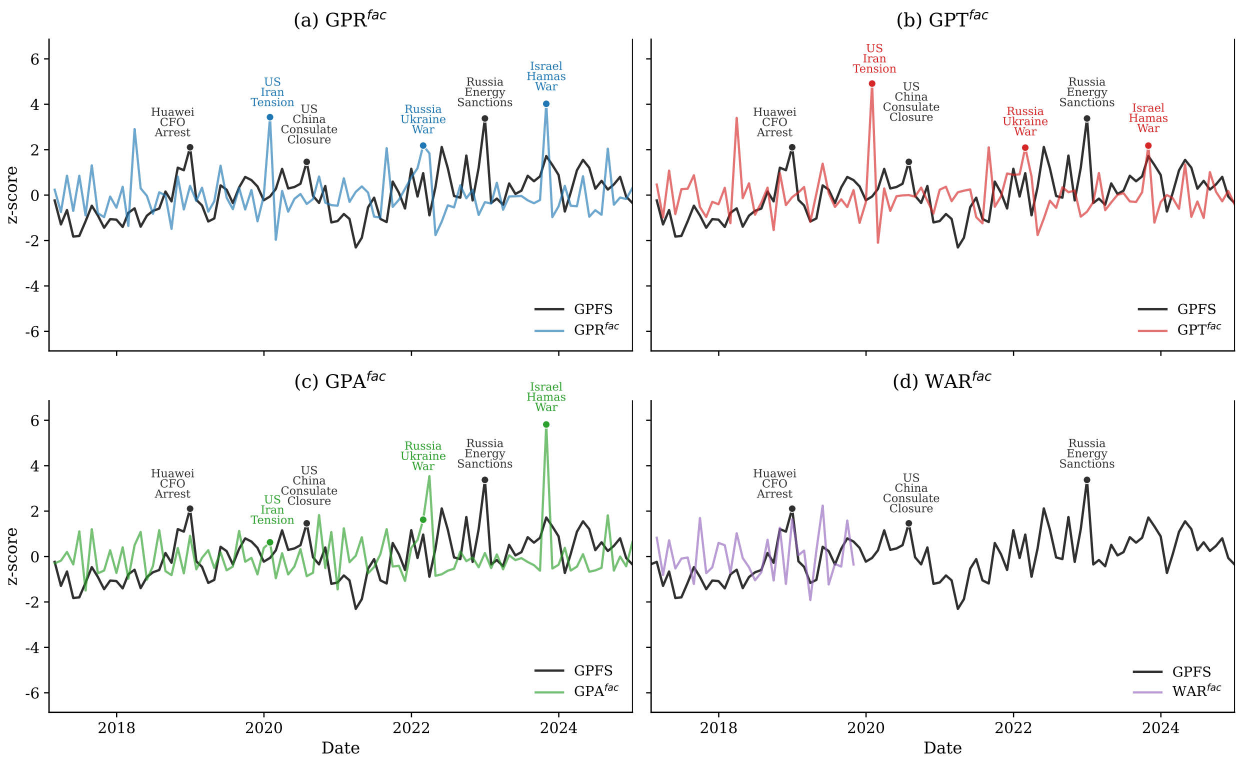

Figure 3: GPFS and News-Based Geopolitical Risk Measures. This figure compares GPFS with four news-based geopolitical risk measures over 2017–2024, with all series expressed as z-scores. GPFS is the fund-flow-based measure constructed from international equity mutual fund portfolio exposures. The news-based measures include the monthly growth rates of the geopolitical risk index (GPR^{fac}), geopolitical threats index (GPT^{fac}), and geopolitical acts index (GPA^{fac}) of Caldara and Iacoviello (2022), and the monthly growth rate of the war discourse risk measure (WAR^{fac}) of Hirshleifer, Mai, and Pukthuanthong (2025b). Event labels provide geopolitical context for prominent movements in GPFS or the corresponding news-based measures.

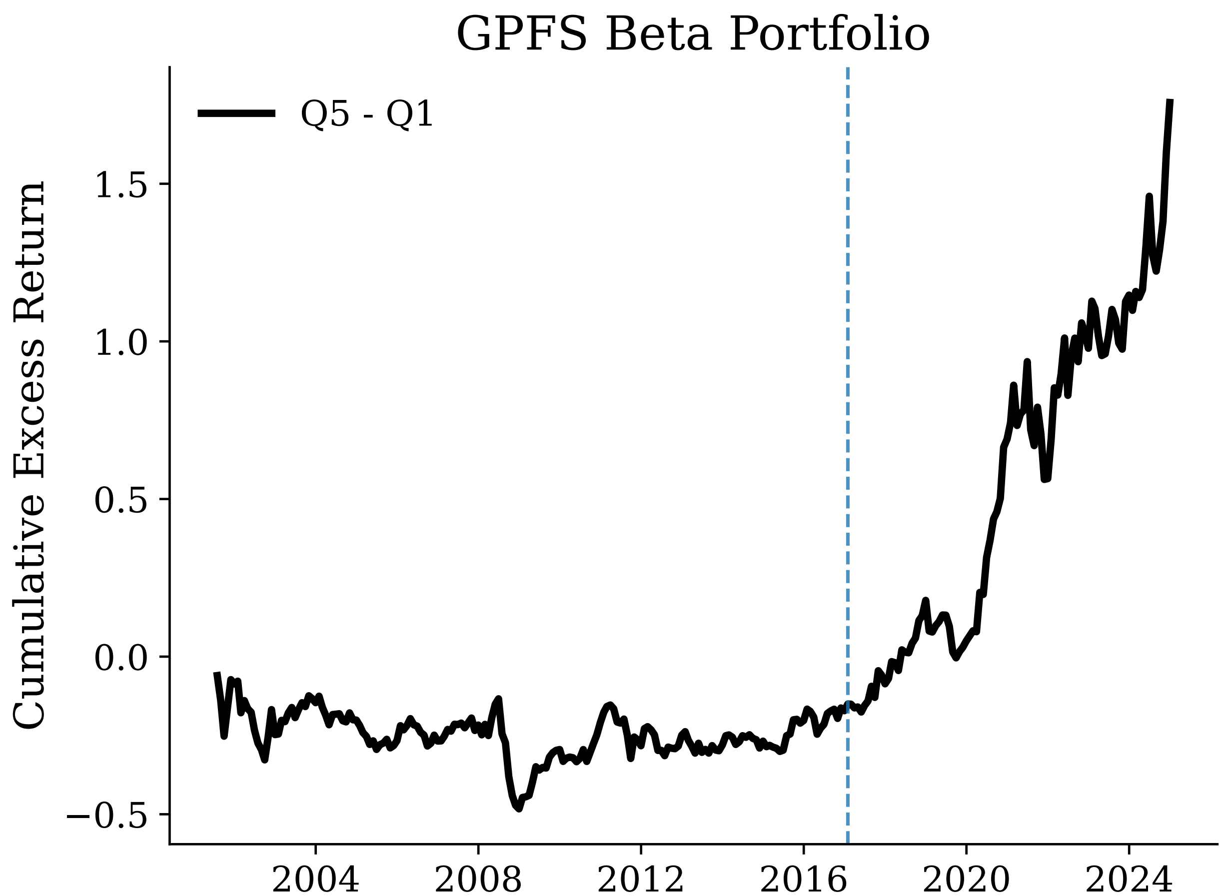

Figure 4: Cumulative Returns of the GPFS Beta Portfolio. This figure plots the cumulative return of a long–short portfolio that buys stocks in the highest quintile and sells stocks in the lowest quintile sorted on GPFS beta. GPFS betas are estimated using a 24 month rolling regression of monthly excess stock returns on the negative of GPFS, requiring at least 12 observations. Each June, stocks are sorted based on their average beta over the preceding January to June period using NYSE breakpoints, and portfolios are held from July of year t to June of year $t+1$. The sample covers July 2001 to December 2024. The vertical dashed line marks January 2017.

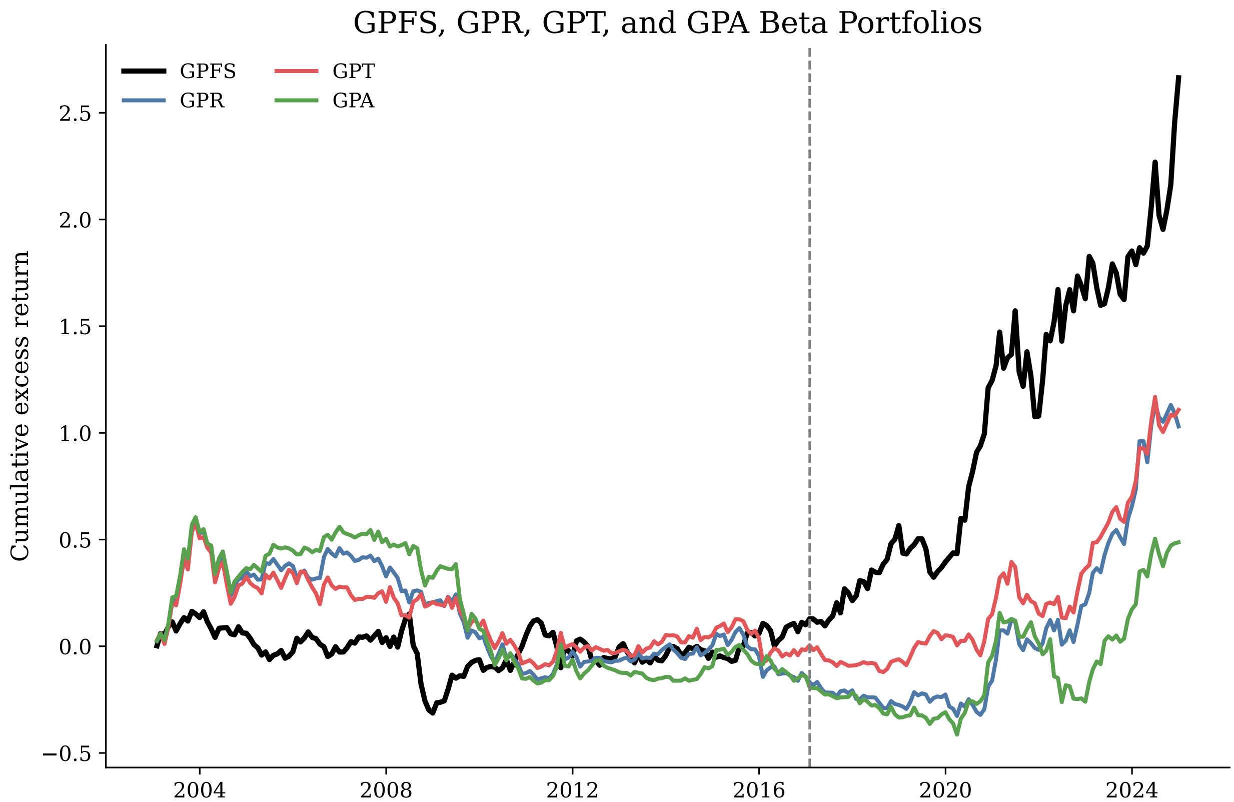

Figure 5: Cumulative Returns of Portfolios Sorted on Geopolitical Risk Indices. This figure plots the cumulative returns of long–short portfolios formed by sorting stocks on their betas with respect to GPFS and the news-based geopolitical risk measures GPR, GPT, and GPA from Caldara and Iacoviello (2022). GPFS betas are estimated from 24-month rolling regressions of monthly excess stock returns on the negative of GPFS; stocks are sorted each June using their average beta over the preceding January–June period, and portfolios are held for one year. Betas for GPR^{fac}, GPT^{fac}, and GPA^{fac} are estimated from 36-month rolling regressions of monthly excess stock returns on the negative growth rates of the corresponding news-based measures, with portfolios rebalanced monthly. The sample covers January 2003 to December 2024. The vertical dashed line marks January 2017.

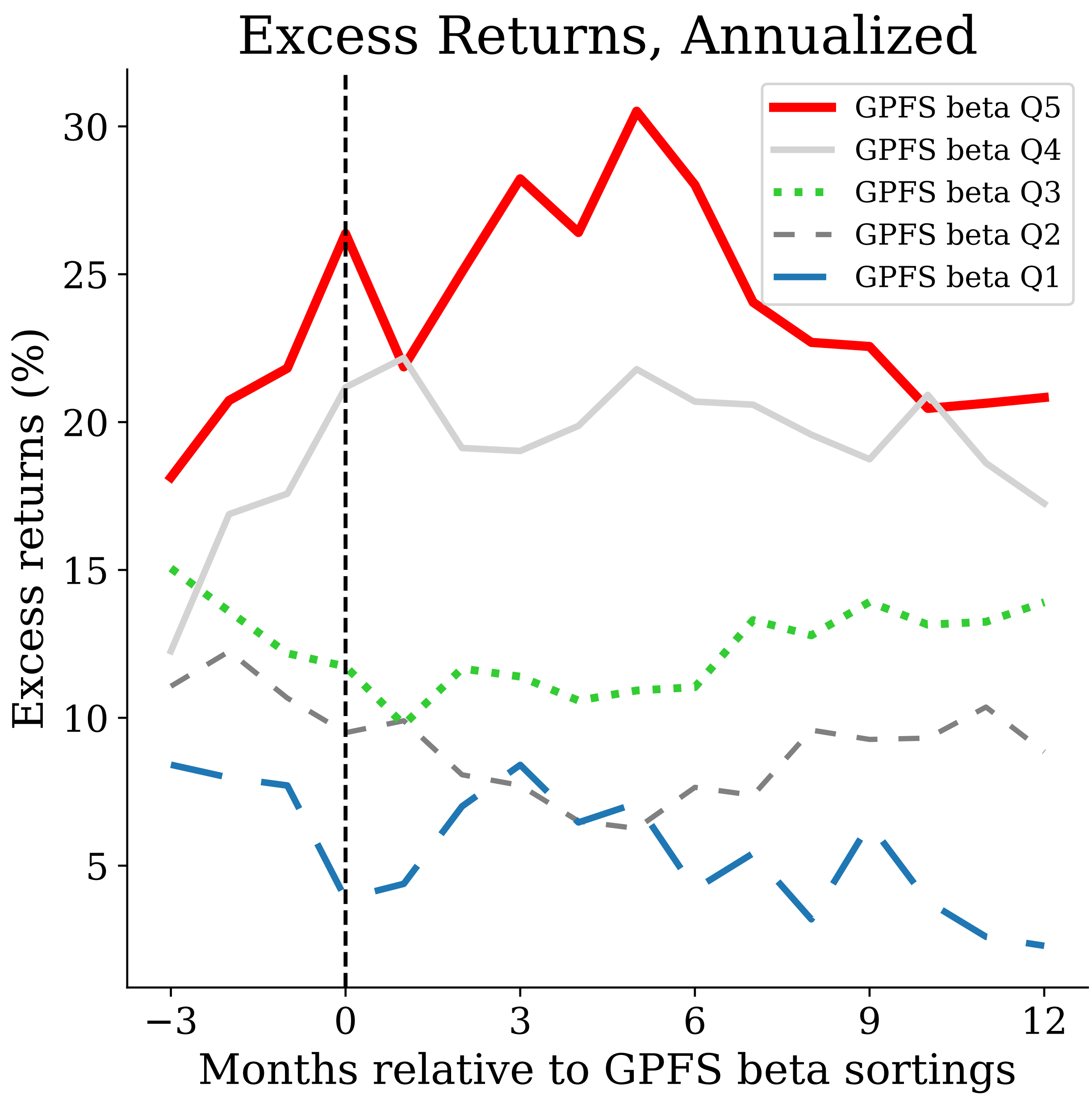

Figure 6: Event-Time Excess Returns of GPFS Beta Portfolios. This figure plots annualized value-weighted excess returns of quintile portfolios sorted on GPFS betas from three months before portfolio formation to twelve months after formation. GPFS betas are estimated using 24-month rolling regressions of stock returns on the negative of GPFS. In each month, stocks are sorted into quintiles based on their estimated GPFS betas using NYSE breakpoints. The sample spans January 2017 to December 2024. Portfolios are tracked in event time relative to the formation month and event-time returns are averaged across formation months. The vertical dashed line marks the portfolio formation month.

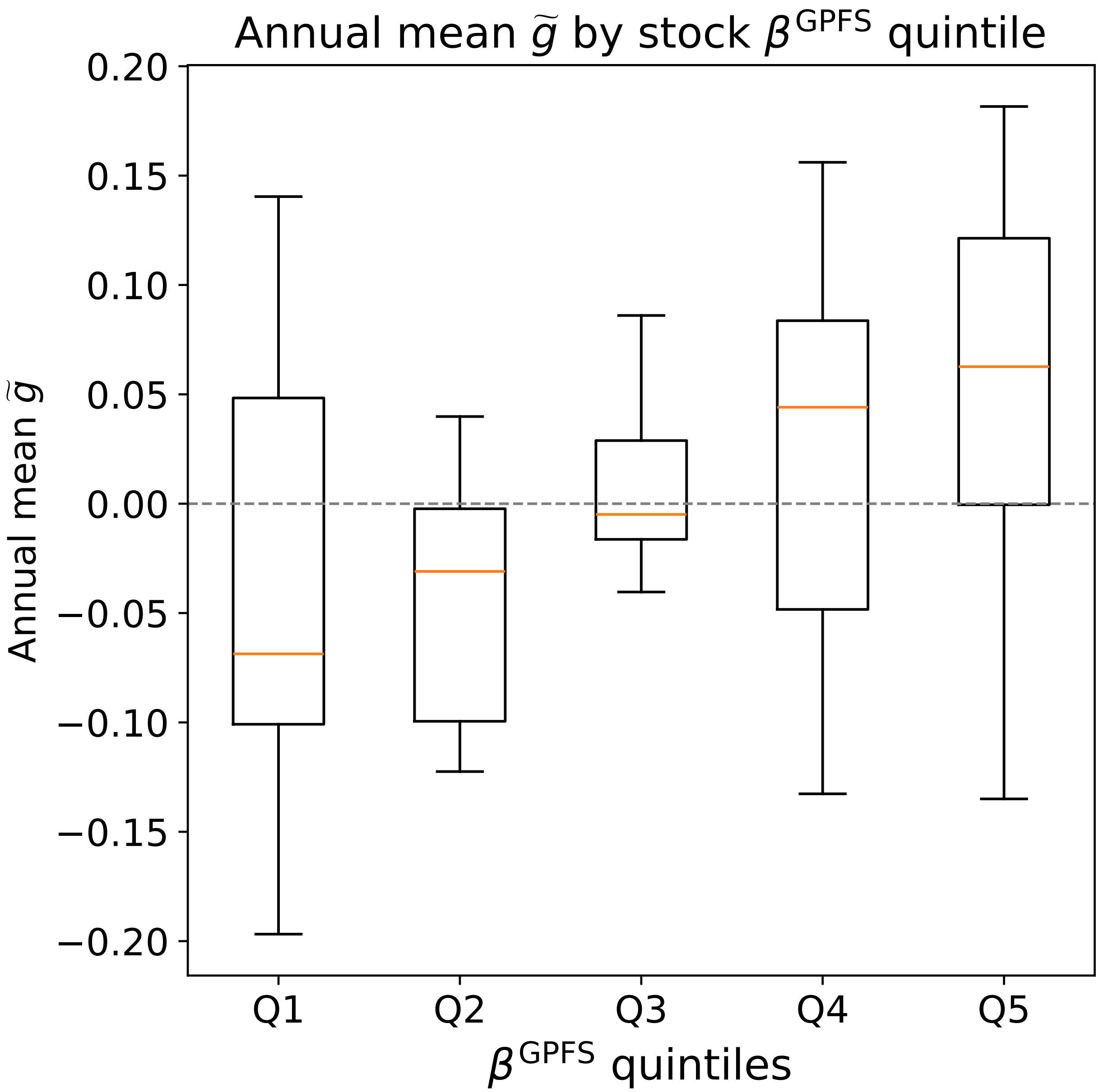

Figure 7: Industry Exposure by GPFS Beta Quintile. This figure displays box plots of annual mean standardized industry exposure $\tilde{g}$ across quintiles sorted on GPFS betas. Stock-level GPFS betas are estimated using 24-month rolling regressions of stock returns on the negative of GPFS. Each June, stocks are sorted into quintiles based on the average of their estimated betas over the preceding January to June period using NYSE breakpoints. The sample spans 2001 to 2022. Within each beta quintile, we compute the annual cross-sectional mean of standardized exposure, and the box plots summarize the time-series distribution of these annual group means. The dashed horizontal line marks zero standardized exposure.

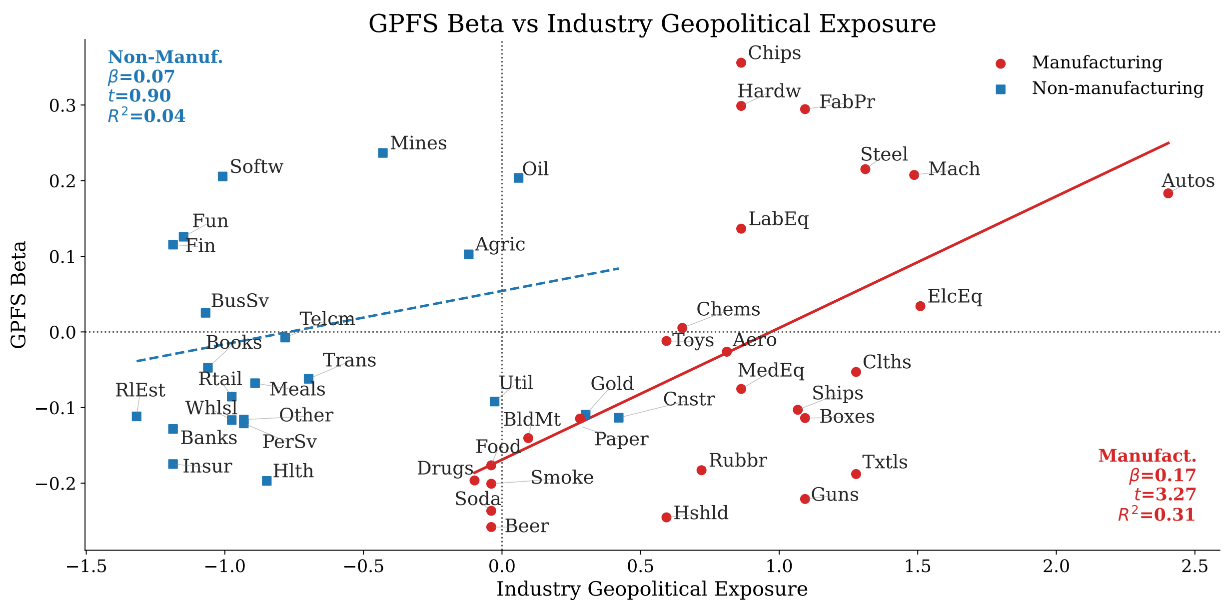

Figure 8: Industry GPFS Betas and Geopolitical Exposure. This figure plots industry GPFS loadings against industry geopolitical exposure. GPFS loadings are estimated from time-series regressions of industry excess returns on the market excess return and the GPFS portfolio return over the July 2001 to December 2024 period. Industry geopolitical exposure is constructed using OECD input–output data and mapped to the Fama–French 49 industry classification. Each point represents one industry. Manufacturing industries are shown in red and non-manufacturing industries in blue. Solid and dashed lines denote fitted values from separate cross-sectional regressions for manufacturing and non-manufacturing industries, respectively.

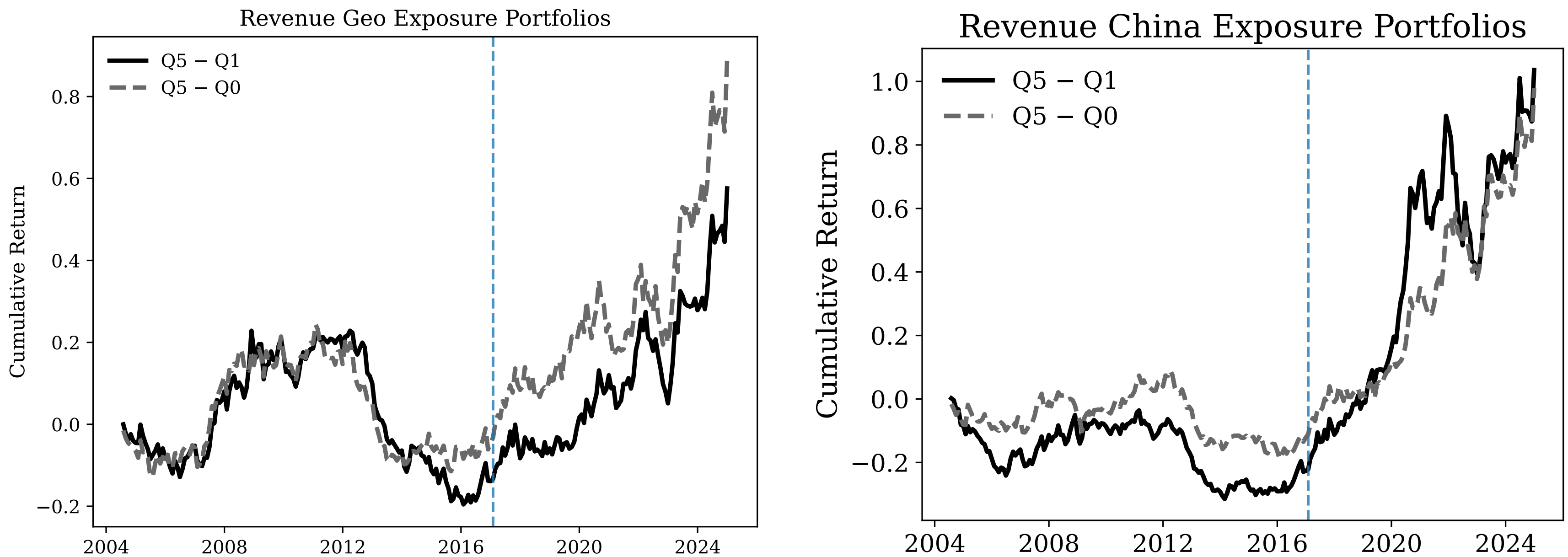

Figure 9: Cumulative Returns of Revenue-Based Geopolitical Exposure Portfolios. This figure plots cumulative returns of portfolios sorted on firms' revenue-based geopolitical exposure. Exposure is measured at the firm level using geographic revenue disclosures and assigned to individual stocks via the CRSP–FactSet link. Each June, firms with strictly positive exposure are sorted into quintiles based on exposure measured at the end of June in year $t-1$, with breakpoints determined using NYSE stocks with positive exposure. Firms with zero foreign revenue form a separate zero-exposure portfolio (Q0). Portfolios are value-weighted and held from July of year t through June of year $t+1$. The left panel reports returns for portfolios sorted on total revenue-based geopolitical exposure, and the right panel reports returns for portfolios sorted on revenue exposure to China. Solid lines denote the return difference between the highest and lowest quintiles (Q5 minus Q1), and dashed lines denote the return difference between the highest quintile and the zero-exposure portfolio (Q5 minus Q0). The sample spans July 2004 to December 2024. The vertical dashed line marks 2017.

Table 1: Summary Statistics of Fund Performance. This table reports mean, standard deviation, 25th percentile, median, and 75th percentile for fund performance measures of U.S. international equity mutual funds from January 2000 to December 2024. The sample uses each fund's oldest share class and includes fund-month observations with valid country exposure data, assets under management of at least $15 million, and at least three years since inception.

	Mean	SD	P25	Median	P75
TNA ($billion)	1.49	5.63	0.08	0.27	0.88
Excess return (%)	0.41	5.20	-2.53	0.78	3.51
Flow (monthly %)	-0.09	4.58	-1.46	-0.36	0.89
Equity share	0.89	0.51	0.92	0.96	0.99
Total risk	0.16	0.07	0.11	0.15	0.20
Sharpe ratio	0.58	1.35	-0.31	0.51	1.39
CAPM alpha (%)	-0.33	0.36	-0.52	-0.32	-0.13
Carhart alpha (%)	-0.31	0.33	-0.47	-0.30	-0.14
FF5 alpha (%)	-0.34	0.37	-0.52	-0.32	-0.17
Information ratio	-0.47	0.48	-0.70	-0.44	-0.19
Fund age (years)	11.45	9.46	4.23	9.18	16.40

Table 2: Summary Statistics of Fund Holding by Country. This table reports the mean, standard deviation, 25th percentile, median, and 75th percentile of country exposure for the top 15 countries by average exposure among U.S. international equity mutual funds from January 2000 to December 2024. Country exposure is the fraction of fund net assets invested in each country.

Country	Mean	SD	CS SD	TS SD	P25	Median	P75
United States	15.09	23.68	23.72	3.35	0.03	1.78	26.29
Japan	11.01	13.99	14.17	2.44	0.00	8.11	17.47
United Kingdom	10.49	9.29	9.20	2.73	2.22	9.62	16.70
China	6.40	12.43	9.92	2.43	0.00	1.56	6.36
France	5.28	5.02	5.01	1.54	0.00	4.58	8.80
Germany	4.24	4.22	4.16	1.42	0.00	3.53	7.05
Switzerland	4.11	4.15	4.04	1.39	0.00	3.23	6.81
South Korea	3.34	5.93	6.04	1.25	0.00	1.13	3.85
India	2.91	7.54	7.00	1.18	0.00	0.11	2.89
Canada	2.49	4.94	4.75	1.14	0.00	0.95	3.61
Brazil	2.44	5.52	5.02	1.12	0.00	0.42	2.69
Netherlands	2.40	2.71	2.65	1.16	0.00	1.75	3.76
Australia	2.12	3.73	3.51	0.93	0.00	0.89	3.27
Italy	1.48	1.94	1.94	0.80	0.00	0.77	2.39
Sweden	1.40	2.28	2.23	0.74	0.00	0.70	2.23

Table 3: Summary Statistics and Corelations Between Risk Indices. Panel A reports monthly descriptive statistics for the Geopolitical Flow Spread (GPFS), including the mean, median, standard deviation, and selected percentiles. Panel B reports pairwise Pearson correlations between GPFS and commonly used geopolitical risk and uncertainty measures. The sample spans January 2000 to December 2024, subject to data availability. GPFS is constructed from international equity mutual fund flows. GPR denotes the Geopolitical Risk Index of Caldara and Iacoviello (2022); GPT and GPA denote its threat and act components; EPU denotes the Global Economic Policy Uncertainty index of Baker, Bloom, and Davis (2016); VIX denotes the CBOE Volatility Index; and WAR denotes the news-based war discourse risk indicator of Hirshleifer, Mai, and Pukthuanthong (2025b). In Panel B, GPR^{fac}, GPT^{fac}, GPA^{fac}, EPU^{fac}, and WAR^{fac} are monthly growth rates of the corresponding indices, while ΔVIX is the monthly change in VIX.

Panel A. Descriptive Statistics

Variable	Mean	Median	Stdev	10th	25th	75th	90th
GPFS	-0.42	-0.38	0.92	-1.49	-0.99	0.13	0.58

Panel B. Correlation Structure

	GPFS	GPR^{fac}	GPT^{fac}	GPA^{fac}	EPU^{fac}	ΔVIX	WAR^{fac}
GPFS							
GPR^{fac}	0.04						
GPT^{fac}	0.04	0.89					
GPA^{fac}	0.04	0.95	0.74				
EPU^{fac}	0.06	0.28	0.19	0.30			
ΔVIX	0.13	0.17	0.12	0.19	0.35		
WAR^{fac}	0.07	0.35	0.37	0.34	-0.05	0.02	

Table 4: Granger Causality between GPFS and Geopolitical Risk Factors. This table reports bidirectional Granger-causality tests between the GPFS and news-based geopolitical factors. GPR^{fac}, GPT^{fac}, and GPA^{fac} are monthly growth rates in the Caldara and Iacoviello (2022) geopolitical risk index and its threat and act components; WAR^{fac} is the monthly growth rate in the Hirshleifer, Mai, and Pukthuanthong (2025b) war discourse risk measure. Entries are p-values from tests with lag lengths from one to six months. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Lag length (months)					
Direction	1	2	3	4	5	6
GPFS $\rightarrow$ GPR^{fac}	0.381	0.209	0.228	0.391	0.058*	0.000***
GPR^{fac} $\rightarrow$ GPFS	0.352	0.426	0.392	0.538	0.281	0.126
GPFS $\rightarrow$ GPT^{fac}	0.637	0.590	0.720	0.897	0.443	0.041**
GPT^{fac} $\rightarrow$ GPFS	0.339	0.588	0.400	0.567	0.277	0.264
GPFS $\rightarrow$ GPA^{fac}	0.243	0.108	0.128	0.245	0.020**	0.000***
GPA^{fac} $\rightarrow$ GPFS	0.499	0.465	0.528	0.677	0.420	0.159
GPFS $\rightarrow$ WAR^{fac}	0.143	0.227	0.210	0.242	0.355	0.302
WAR^{fac} $\rightarrow$ GPFS	0.775	0.648	0.806	0.527	0.257	0.262

Table 5: GPFS Beta–Sorted Portfolios. The table reports average monthly portfolio returns for portfolios sorted on estimated GPFS betas. For each stock, we estimate GPFS beta by regressing monthly excess returns on the negative of GPFS using a 24-month rolling window and requiring at least 12 observations. In June of each year, stocks are sorted into quintiles based on the average beta over the preceding January–June period, using NYSE breakpoints. Portfolios are value-weighted and held from July of year t to June of year $t + 1$. Columns (1) and (4) report average monthly excess returns; columns (2) and (5) report CAPM alphas; columns (3) and (6) report fund alphas relative to the value-weighted return of all international equity funds. H–L denotes the high-minus-low spread. Columns (1)–(3) use portfolio returns from July 2001 to December 2016, and columns (4)–(6) use portfolio returns from January 2017 to December 2024. Newey–West t-statistics are reported in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Period: 2001–2016			*B. Period: 2017–2024*		
	Excess Ret.	CAPM α	Fund α	Excess Ret.	CAPM α	Fund α
Low	6.80*	1.25	3.02	5.87	-6.24***	0.43
	[1.67]	[0.71]	[1.29]	[1.21]	[-2.71]	[0.16]
Q2	7.56**	2.15*	3.84**	10.87**	-2.10	5.17**
	[2.10]	[1.84]	[2.04]	[2.29]	[-1.17]	[1.98]
Q3	7.25*	1.59*	3.31*	12.80***	-0.12	7.02***
	[1.86]	[1.89]	[1.90]	[2.83]	[-0.07]	[2.94]
Q4	7.40	0.08	2.25	17.08***	3.06	10.74***
	[1.50]	[0.06]	[0.98]	[3.27]	[1.24]	[3.22]
High	6.71	-2.36	0.27	22.29***	7.59*	15.79***
	[1.01]	[-1.02]	[0.09]	[3.18]	[1.78]	[3.09]
H–L	-0.09	-3.60	-2.75	16.42***	13.83***	15.36***
	[-0.02]	[-1.24]	[-0.98]	[3.19]	[2.84]	[3.08]

Table 6: Factor Model Alphas for GPFS Beta-Sorted Portfolios. This table reports factor model alphas for value-weighted portfolios sorted on estimated GPFS betas. GPFS betas are estimated from 24-month rolling regressions of monthly excess stock returns on the negative of GPFS. Each June, stocks are sorted into quintiles based on their average beta over the preceding January–June period using NYSE breakpoints, and portfolios are held from July of year t to June of year $t+1$. H–L denotes the high-minus-low spread. Columns (1)–(3) report alphas for July 2001 to December 2016, and columns (4)–(6) report alphas for January 2017 to December 2024. FF3 α, FFC α, and FF5 α are alphas relative to the Fama–French three-factor, Fama–French–Carhart four-factor, and Fama–French five-factor models, respectively. Newey–West t-statistics are reported in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Period: 2001–2016			*B. Period: 2017–2024*		
	FF3 α	FFC α	FF5 α	FF3 α	FFC α	FF5 α
Low	0.97	0.91	-0.02	-6.36***	-6.33***	-7.61***
	[0.55]	[0.53]	[-0.01]	[-2.87]	[-2.85]	[-3.36]
Q2	2.19*	1.79*	-0.04	-2.25	-1.68	-2.37
	[1.93]	[1.65]	[-0.05]	[-1.28]	[-0.91]	[-1.33]
Q3	1.90**	1.69**	0.80	-0.30	-0.06	-1.23
	[2.47]	[2.02]	[1.02]	[-0.18]	[-0.04]	[-0.76]
Q4	0.34	0.34	0.09	2.40	2.35	2.61
	[0.26]	[0.27]	[0.07]	[0.95]	[0.90]	[1.11]
High	-2.14	-1.58	0.43	9.03**	8.51**	10.92***
	[-1.13]	[-0.82]	[0.22]	[2.33]	[2.13]	[2.94]
H–L	-3.11	-2.50	0.45	15.39***	14.84***	18.53***
	[-1.14]	[-0.89]	[0.16]	[3.37]	[3.15]	[4.12]

Table 7: Fama-Mecbeth Regressions. The table reports monthly Fama–MacBeth regressions of next-month excess stock returns (in percent) on GPFS betas and control variables. GPFS beta is estimated from rolling 24-month regressions of stock excess returns on the negative of GPFS. Market and liquidity betas are constructed analogously using the Fama–French market excess return and the Pastor–Stambaugh traded liquidity factor, respectively. *lnsize* is the log of market capitalization, *mom* is the cumulative stock return over months $t-11$ to $t-1$, and *rev* is the prior-month excess return. The sample covers January 2017 to November 2024. In all specifications, stocks are restricted to those with share prices above $5 and market capitalization above the NYSE 10th percentile breakpoint. Panel A reports results for the full sample, while Panels B and C report results for stocks below and above the NYSE median size breakpoint, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: All			*Panel B: Small*			*Panel C: Big*		
β^{GPFS}	3.82**	1.72	1.15	2.95	0.56	-0.17	7.22***	5.17**	5.35*
	[1.97]	[0.94]	[0.53]	[1.57]	[0.30]	[-0.08]	[2.65]	[1.99]	[1.91]
lnsize		0.10			0.18			0.13**	
		[1.25]			[1.57]			[2.11]	
β^{mkt}		0.31			0.32*			0.27	
		[1.61]			[1.66]			[1.27]	
β^{liq}			0.29			0.28			0.34
			[1.42]			[1.33]			[1.56]
mom			0.37*			0.34*			0.41
			[1.87]			[1.72]			[1.37]
rev			0.98			0.76			2.01*
			[1.36]			[1.07]			[1.82]
Observations	1723	1723	1722	990	990	989	733	733	733
R^2	0.008	0.029	0.032	0.007	0.020	0.029	0.018	0.048	0.066

Table 8: Factor Pricing of Hou–Xue–Zhang Test Portfolios. This table reports second-pass monthly cross-sectional regressions of Hou–Xue–Zhang test portfolio returns on estimated factor betas. The test assets are long–short portfolios from Hou et al. (2020), which cover 199 anomalies in six categories. Factor loadings are estimated in first-pass time-series regressions on FF3+GPFS, FFC+GPFS, and FF5+GPFS. GPFS is the return on the high-minus-low stock portfolio sorted on GPFS betas. Panel A reports results for June 2001 to December 2016, and Panel B reports results for January 2017 to December 2024. Reported coefficients are annualized prices of risk in percent. Newey–West t-statistics are reported in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: 2001–2016			*Panel B: 2017–2024*		
	FF3+GPFS	FFC+GPFS	FF5+GPFS	FF3+GPFS	FFC+GPFS	FF5+GPFS
β^{GPFS}	-3.48	-3.62	-0.23	16.28*	18.98**	19.79***
	[-0.64]	[-0.66]	[-0.05]	[1.70]	[2.55]	[2.71]
β^{MKT}	-4.79	-12.09*	1.53	4.55	2.38	1.74
	[-0.64]	[-1.89]	[0.20]	[0.68]	[0.35]	[0.30]
β^{SMB}	2.42	3.94	2.60	-8.62**	-9.27**	-6.62
	[0.78]	[1.29]	[0.85]	[-2.02]	[-2.21]	[-1.38]
β^{HML}	3.91	2.37	0.24	-4.07	-4.29	-7.64
	[1.21]	[0.74]	[0.07]	[-0.61]	[-0.64]	[-1.05]
β^{UMD}		-0.56			2.31	
		[-0.11]			[0.43]	
β^{RMW}			2.57			3.44
			[1.00]			[1.23]
β^{CMA}			4.90**			-0.85
			[2.56]			[-0.21]
Test assets	199	199	199	199	199	199
Months	186	186	186	96	96	96
Avg. N_t	199	199	199	199	199	199
Avg. R^2	0.405	0.442	0.469	0.499	0.532	0.547

Table 9: Revenue-Based Geopolitical Exposure Portfolios. The table reports average monthly returns for portfolios sorted on firms' revenue-based geopolitical exposure over January 2017 to December 2024. Firm-level exposure is defined as the revenue-weighted average geopolitical distance of a firm's foreign revenue base. Each June of year t, stocks with positive foreign revenue are sorted into quintiles (Q1–Q5) based on exposure measured at the end of June in year $t-1$, using NYSE breakpoints. Portfolios are value-weighted and held from July of year t to June of year $t+1$. Panel A reports portfolios sorted on total foreign revenue exposure, and Panel B reports portfolios sorted on revenue exposure to China. Columns report mean excess returns, CAPM alphas, and Fama–French five-factor alphas. Q5–Q1 denotes the high-minus-low spread. Newey–West t-statistics are reported in parentheses.

	Panel A: Revenue Geo Exposure			*Panel B: China Revenue Exposure*		
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio	Mean	CAPM α	FF5 α	Mean	CAPM α	FF5 α
Q1	9.99**	-3.73*	-2.89	8.17*	-3.93	-2.55
	(2.13)	(-1.70)	(-1.52)	(1.95)	(-1.27)	(-1.46)
Q2	9.98***	-1.90	-1.82	8.66*	-3.25*	-4.28*
	(2.60)	(-0.95)	(-1.04)	(1.94)	(-1.79)	(-1.93)
Q3	13.45**	-0.59	-0.18	12.54***	0.27	-0.57
	(2.35)	(-0.21)	(-0.12)	(2.69)	(0.15)	(-0.36)
Q4	13.53**	0.86	-0.75	13.44***	-0.06	0.40
	(2.56)	(0.48)	(-0.44)	(2.61)	(-0.04)	(0.36)
Q5	18.14***	3.85**	2.31	21.16***	6.32***	4.00**
	(3.43)	(1.98)	(1.45)	(3.52)	(2.66)	(2.52)
Q5-Q1	8.15**	7.58**	5.20*	12.99***	10.25**	6.55**
	(2.41)	(2.01)	(1.75)	(2.64)	(2.00)	(2.49)

Table 10: Double Sorts on Revenue Exposure, GPFS Beta, and Size. This table reports average monthly portfolio excess returns, in percent, for dependent double-sorted portfolios over January 2017 to December 2024. GPFS beta is estimated from 24-month rolling regressions of monthly stock excess returns on the negative of GPFS. Each June, stocks are first sorted by revenue-based geopolitical exposure in Panel A and by size in Panel B. In Panel A, stocks with zero revenue-based geopolitical exposure are assigned to T0. Among the remaining stocks with positive exposure, stocks are sorted into three groups, T1–T3, using 30/40/30 breakpoints based on revenue-based geopolitical exposure measured at the end of June of year $t-1$. In Panel B, all stocks are sorted into three size groups, T1–T3, using 30/40/30 breakpoints based on size measured at the end of June of year t. Within each group, stocks are then sorted into quintiles based on the average GPFS beta over January–June of year t. Portfolios are value-weighted and held from July of year t to June of year $t+1$. Newey–West t-statistics are reported in parentheses.

	Panel A: Foreign revenue × Beta				*Panel B: Size × Beta*		
	(1) T0	(2) T1	(3) T2	(4) T3	(5) T1	(6) T2	(7) T3
Q1	8.43	4.03	3.99	6.59	-1.33	10.01	5.79
	(1.45)	(0.66)	(0.74)	(0.96)	(-0.12)	(1.30)	(1.10)
Q2	8.34	9.30**	10.94**	9.03	11.33	9.28	9.90**
	(1.63)	(2.13)	(2.20)	(1.64)	(1.20)	(1.43)	(2.02)
Q3	8.26	8.61*	8.75*	15.32***	22.58*	13.29*	12.48**
	(1.40)	(1.77)	(1.72)	(2.67)	(1.75)	(1.66)	(2.32)
Q4	13.19*	9.92	10.70**	20.79***	10.74	11.34	14.54***
	(1.79)	(1.40)	(2.02)	(2.97)	(0.93)	(1.49)	(2.98)
Q5	17.37*	15.62*	24.31***	29.22***	11.28	13.06	23.19***
	(1.66)	(1.71)	(2.64)	(4.01)	(0.75)	(1.23)	(3.19)
Q5−Q1	8.94	11.59	20.31***	22.63***	12.61	3.06	17.40***
	(1.00)	(1.20)	(2.84)	(3.12)	(1.54)	(0.67)	(3.48)

Table 11: Portfolio Tilt and GPFS Exposure. This table reports regressions of portfolio tilt on GPFS exposure. Portfolio tilt $w_{i,t}^{MF} - w_{i,t}^{mkt}$ is defined as the difference between the AUM-weighted mutual fund portfolio weight $w_{i,t}^{MF}$ and the market portfolio weight $w_{i,t}^{mkt}$ for stock i in month t. The GPFS beta $\beta_{i,t-1}^{GPFS}$ and market beta $\beta_{i,t-1}^{mkt}$ are estimated from rolling 24-month return regressions on the negative of GPFS and market return. All variables are standardized to have zero mean and unit variance. Panel A reports panel regressions with time fixed effects and standard errors double clustered by stock and month. Panel B reports Fama–MacBeth cross-sectional regressions with Newey–West t-statistics. The pre period spans January 2001 to December 2016 and the post period spans January 2017 to December 2024.

	(1)	(2)	(3)	(4)
	Panel A. Panel + Time FE			
	2000-2016		2017-2024	
	$w_{i,t}^{MF} - w_{i,t}^{mkt}$		$w_{i,t}^{MF} - w_{i,t}^{mkt}$	
$\beta_{i,t-1}^{GPFS}$	-0.009^{*}	-0.001	-0.031^{***}	-0.026^{***}
	(-1.84)	(-0.25)	(-4.40)	(-3.83)
$\beta_{i,t-1}^{mkt}$		-0.021^{***}		-0.018^{**}
		(-3.71)		(-2.58)
Obs.	657,706	657,706	303,533	303,533
R^2	0.000	0.000	0.001	0.001
	Panel B. Fama–MacBeth			
	2000-2016		2017-2024	
	$w_{i,t}^{MF} - w_{i,t}^{mkt}$		$w_{i,t}^{MF} - w_{i,t}^{mkt}$	
$\beta_{i,t-1}^{GPFS}$	-0.017^{**}	-0.011	-0.035^{**}	-0.036^{**}
	(-2.41)	(-1.57)	(-2.31)	(-2.03)
$\beta_{i,t-1}^{mkt}$		-0.015^{**}		-0.007
		(-2.39)		(-0.58)
Avg. Obs.	3,653	3,653	3,161	3,161
Avg. R^2	0.002	0.003	0.003	0.005

Table 12: Fund Rebalancing Response to Geopolitical Risk. The table reports panel regressions of country-level marginal reallocations on geopolitical risk shocks. The dependent variable $\Delta w_{c,t+1}$ is the quarterly change in the aggregate portfolio weight allocated to country c. The main explanatory variable is the interaction between the GPFS and an indicator equal to one for countries with above-median geopolitical distance in quarter t. Control variables include lagged changes in portfolio weights $\Delta w_{c,t-1}$, $\Delta w_{c,t-2}$ and the current portfolio weight level $w_{c,t}$. Panel A reports results for the full sample, split into pre-2017 and post-2017 periods. Country and time fixed effects are included as indicated. Standard errors are clustered at the country level. t-statistics are reported in brackets.

	(1)	(2)	(3)	(4)
	2000-2016		2017-2024	
	$\Delta w_{c,t+1}$		$\Delta w_{c,t+1}$	
$GPFS_t \times D_{c,t}$	-0.04	-0.04	-0.03*	-0.07**
	[-1.52]	[-1.26]	[-1.94]	[-2.44]
$\Delta w_{c,t-1}$	-0.02	-0.01	-0.04	0.02
	[-0.68]	[-0.43]	[-1.01]	[0.48]
$\Delta w_{c,t-2}$	-0.06***	-0.06***	0.07	0.12**
	[-3.30]	[-3.76]	[1.44]	[2.02]
$w_{c,t}$	0.01	-0.58**	0.01	-2.58***
	[0.87]	[-2.43]	[0.20]	[-3.21]
Country FE	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Obs.	3234	3234	1519	1519
R^2	0.01	0.02	0.01	0.07

Appendix

A Mapping CRSP Stocks to FactSet Geographic Revenue Data

This appendix explains how we assign country-level revenue shares from FactSet to individual CRSP securities. The final output is a stock-year-country panel in which each `permno` is uniquely linked to a vector of geographic revenue shares measured as of June 30 of each year.

Step 1: Linking `permno` to FactSet entity identifiers.

We begin with the WRDS CRSP–FactSet linking table. For each year of company (i, t), we define the formation date as June 30 of year t. A link is considered valid if the formation date is within the interval $[\texttt{link\_bdate}, \texttt{link\_edate}]$. When multiple valid links exist for a given $(\texttt{permno}, t)$ due to overlapping intervals, we retain the link with the most recent start date (i.e., the largest `link_bdate`). This rule assigns the entity that is active and has been most recently established as of June 30,. After this filtering, each $(\texttt{permno}, t)$ is assigned to exactly one `entity_id`. We verify that the maximum number of entities per firm-year equals one.

Step 2: Linking entity identifiers to FactSet company identifiers.

We next map `entity_id` to `company_id` using FactSet's company history file. For each $(\texttt{entity\_id}, t)$, we again use June 30 as the reference date and retain records whose interval $[\texttt{start\_date}, \texttt{end\_date}]$ contains that date. If multiple company identifiers are valid for the same $(\texttt{entity\_id}, t)$, we retain the record with the most recent start date. This procedure ensures that firm reorganizations or identifier changes do not create duplicate mappings within a year. We confirm that each $(\texttt{entity\_id}, t)$ corresponds to a single `company_id` after filtering.

Step 3: Linking company identifiers to geographic revenue reports.

We then merge company identifiers with FactSet GeoRev report identifiers using the company–report history file. For each $(\texttt{company\_id}, t)$, we select the report whose effective interval contains June 30 of year t. If there are overlapping reports, we again retain the record with the most recent start date. The resulting dataset maps each firm-year to one geographic revenue report identifier.

Step 4: Expanding to country-level revenue shares.

Each report identifier is linked to country-level revenue items in the GeoRev report-item table. We extract the estimated revenue share (`est_percent`) for each ISO3 country code. This produces a firm-year-country panel (i, t, c) that contains the fraction of total revenue attributed to the country c.

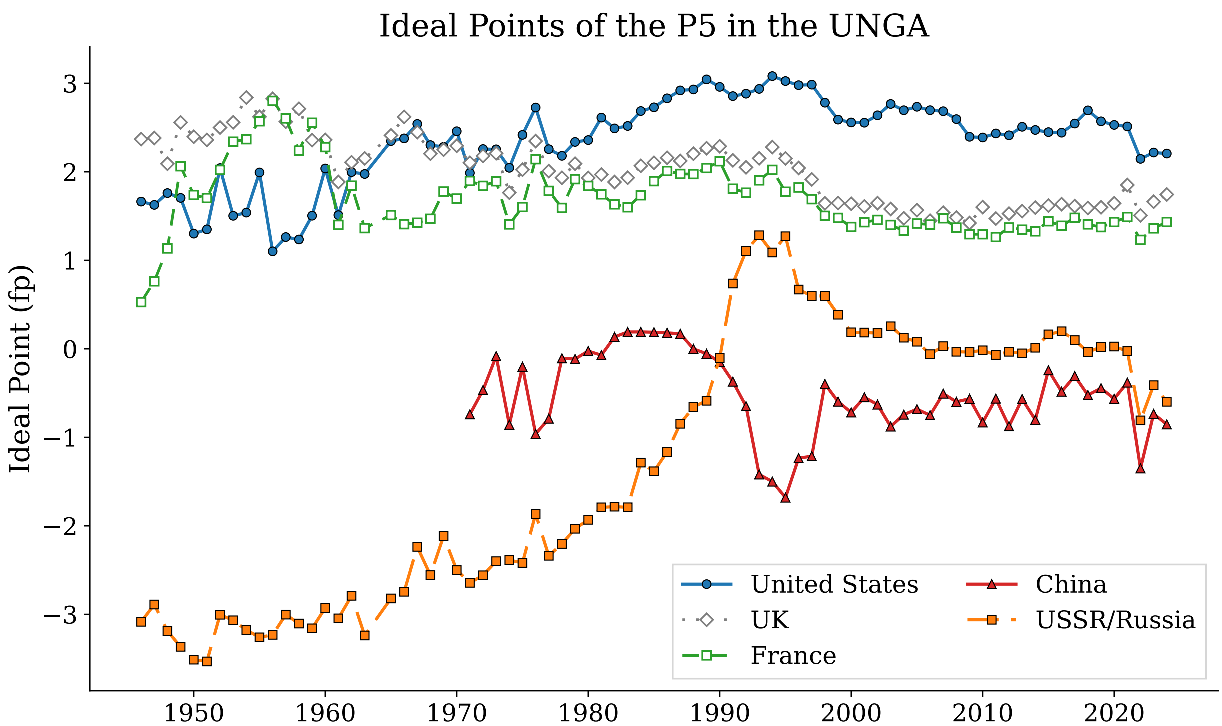

Figure A.1: UN General Assembly Ideal Points of the Permanent Five Members. This figure plots annual ideal point estimates for the permanent five members of the United Nations Security Council. Idealpoint estimates are based on votes on the final passage of General Assembly resolutions, including failed resolutions ("idealpointfp"). The sample spans 1946 to 2024. For China, the series begins in 1971, when the People's Republic of China replaced the Republic of China (Taiwan) as the representative of China in the United Nations.

	Basic non-ferrous	Refined petrol.	Vehicles	Basic iron&steel	Elec. eq.	Machinery nec	Fab. metal gds	Ships & boats	Oth. transp. eq.	Textiles	Plastics	Wood	Chemical gds	Pharma	Electronics	Oth. manuf.	Paper&print	Food	Oth. non-metal gds	Manuf. ave.
chn	1.9	.7	3.2	1.6	3.1	2.8	2.0	3.3	2.7	3.5	2.1	2.3	1.6	.8	3.6	2.5	2.0	1.2	1.4	2.2
can	6.0	7.1	2.3	2.5	2.2	1.6	2.1	1.4	1.2	1.0	1.3	2.5	1.5	.5	.7	1.2	1.7	1.2	1.2	2.1
mex	2.0	1.3	2.5	1.1	1.3	1.3	1.1	1.2	1.0	.5	.6	.5	.5	.1	.9	.6	.5	.7	.5	1.0
deu	1.0	.3	1.4	.7	.7	.9	.7	.7	.7	.6	.7	.4	.7	.9	.4	.5	.5	.3	.3	.7
jpn	.6	.2	2.1	.6	.7	1.0	.6	.8	.9	.4	.5	.4	.5	.4	.4	.4	.4	.3	.3	.6
kor	.4	.2	1.1	.6	.5	.7	.6	.6	.5	.4	.4	.3	.4	.2	.5	.3	.3	.2	.2	.4
gbr	.4	.3	.6	.4	.3	.4	.4	.4	.5	.4	.4	.2	.4	.8	.2	.3	.3	.3	.3	.4
bra	.6	.6	.4	.7	.4	.4	.6	.2	.4	.2	.2	.3	.2	.1	.1	.2	.3	.2	.2	.3
rus	1.2	.2	.3	.7	.5	.4	.6	.2	.2	.2	.2	.2	.2	.1	.1	.2	.1	.1	.2	.3
fra	.4	.1	.3	.2	.3	.2	.2	.3	1.0	.3	.4	.2	.4	.5	.1	.2	.2	.2	.1	.3
ita	.5	.1	.5	.3	.3	.4	.3	.3	.3	.3	.2	.2	.2	.4	.1	.2	.2	.1	.2	.3
ind	.2	.1	.3	.3	.2	.3	.3	.2	.2	.6	.3	.3	.2	.4	.1	.3	.2	.2	.2	.3
sau	.1	1.8	.1	.1	.1	.1	.1	.1	0	.1	.1	.1	.2	0	0	.1	.1	.1	.2	.2
irl	.1	.1	.1	.1	.1	.1	.1	.1	.1	.2	.2	.1	.2	1.2	.1	.1	.1	.1	.1	.2
che	.1	.1	.1	.1	.1	.1	.1	.2	.1	.2	.3	.1	.3	1.1	.1	.1	.1	.1	.1	.2
RoW	1.2	4.4	.4	.8	.6	.4	.5	.3	.3	.5	.5	.4	.7	.4	.2	.3	.4	.6	.8	.7
Foreign	22.0	21.1	19.0	14.8	14.7	14.1	13.6	13.0	12.7	11.9	11.1	10.7	10.6	10.3	10.0	9.9	9.4	8.4	8.2	12.9
usa	78.0	78.9	81.0	85.2	85.3	85.9	86.4	87.0	87.3	88.1	88.9	89.3	89.4	89.7	90.0	90.1	90.6	91.6	91.8	87.1

Figure A.2: U.S. Industry Foreign Production Reliance (2017). This figure reports the country-level share of total upstream production requirements for each U.S. industry in 2017. We construct the technical coefficient matrix A from the OECD Inter-Country Input–Output (ICIO) tables and compute the Leontief inverse $L = (I - A)^{-1}$, which captures both direct and indirect input linkages. For each U.S. industry j, the j-th column of L summarizes the total intermediate inputs required to produce one unit of final output. We aggregate these requirements by source country and compute

$$r_{c,j} = \frac{\sum_{k \in c} L_{kj}}{\sum_k L_{kj}},$$

which measures the fraction of total production requirements attributable to country c. Entries are reported in percent. Darker colors indicate greater reliance on inputs sourced from the corresponding country.

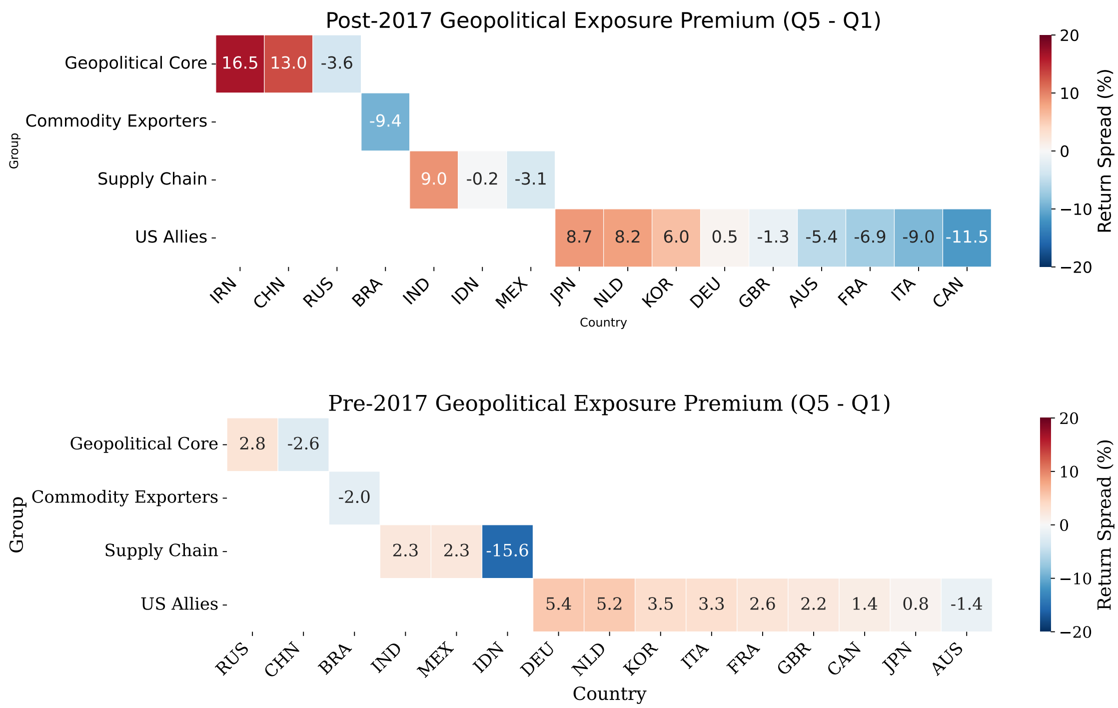

Figure A.3: Geopolitical Exposure Premium by Country. This figure reports the high-minus-low return spread (Q5 minus Q1) for portfolios sorted on country-specific revenue exposure. For each country c, exposure is measured as the share of firm revenue generated from country c, lagged by one year. Each June, we restrict the sample to stocks with revenue exposure to country c greater than 1 percent and sort these stocks into quintiles using NYSE breakpoints. Portfolios are held from July of year t through June of year $t+1$. We require at least 30 stocks in both Q1 and Q5 to compute the spread in a given month. The top panel reports average monthly spreads over January 2017 to December 2024, and the bottom panel reports spreads over July 2004 to December 2016. Countries are grouped according to the geopolitical classifications shown on the vertical axis. Color intensity reflects the magnitude of the return spread in percent.

Table A.1: Mapping between Fama–French 49 Industries and OECD ICIO Sectors.

FF49 Industry	Name	OECD Industry	Category
Beer	Food products	c10t12	Manufacturing
Food	Food products	c10t12	Manufacturing
Smoke	Food products	c10t12	Manufacturing
Soda	Food products	c10t12	Manufacturing
Clths	Textiles apparel leather	c13t15	Manufacturing
Txtls	Textiles apparel leather	c13t15	Manufacturing
Paper	Paper products & printing	c17_18	Manufacturing
Chems	Chemicals	c20	Manufacturing
Drugs	Pharmaceuticals	c21	Manufacturing
Rubbr	Rubber and plastics	c22	Manufacturing
BldMt	Non-metallic mineral products	c23	Manufacturing
Steel	Basic metals	c24a	Manufacturing
Boxes	Fabricated metal containers	c25	Manufacturing
FabPr	Fabricated metal products	c25	Manufacturing
Guns	Fabricated metal products	c25	Manufacturing
Chips	Computer electronic optical	c26	Manufacturing
Hardw	Computer electronic optical	c26	Manufacturing
LabEq	Computer electronic optical	c26	Manufacturing
MedEq	Medical equipment & optical instruments	c26	Manufacturing
ElcEq	Electrical equipment	c27	Manufacturing
Mach	Machinery and equipment	c28	Manufacturing
Autos	Motor vehicles	c29	Manufacturing
Aero	Air and spacecraft	c301	Manufacturing
Ships	Shipbuilding & other transport	c302t309	Manufacturing
Hshld	Furniture & other manufacturing	c31t33	Manufacturing
Toys	Furniture & other manufacturing	c31t33	Manufacturing
Agric	Agriculture and hunting	a01	Primary
Coal	Mining of coal and lignite	b05	Primary
Oil	Extraction of crude petroleum and natural gas	b06	Primary
Gold	Mining of metal ores	b07	Primary
Mines	Other mining and quarrying	b08	Primary
Util	Utilities	d	Primary
Cnstr	Construction	f	Services
Rtail	Wholesale & retail trade	g	Services
Whlsl	Wholesale & retail trade	g	Services
Trans	Land transport	h49	Services
Meals	Accommodation & food services	i	Services
Books	Publishing & media	j58t60	Services
Telcm	Telecommunications	j61	Services
Softw	IT services	j62_63	Services
Banks	Financial services	k	Services
Fin	Financial services	k	Services
Insur	Financial services	k	Services
RlEst	Real estate	l	Services
BusSv	Professional services	m	Services
Hlth	Human health	q	Services
Fun	Arts recreation	r	Services
Other	Other services	s	Services
PerSv	Other personal services	s	Services