Geopolitical Risk in Financial Markets: Evidence from Mutual Fund Flows

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Abstract

We investigate how geopolitical risk is reflected in mutual fund flows and asset prices. We show, in a sample of international equity funds, higher exposure to geopolitical rivals is associated with lower fund flows around major geopolitical events. Based on the flow differential between the high- and low-exposure funds, we propose a novel geopolitical risk factor called Geopolitical Flow Spread (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 explanation.

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For most of the time since World War II, countries around the globe have steadily integrated their trade and supply chains. Economists generally agree that this era of globalization creates 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 geopolitically aligned. This exposure is innocuous when international relations are stable, and geopolitics does not disrupt business exchanges. Recently, however, rising geopolitical tensions have significantly impacted the global economy. Events like the US-China trade conflict and the Russia-Ukraine war have led to increased scrutiny of economic interdependence. There is a growing recognition among business community that the vulnerability to geopolitical shocks can 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 debate on whether, and how, geopolitical tensions influence asset pricing. In particular, there is limited 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 premium and drive cross-sectional asset returns (Gonçalves, Melone, and Ricciardi, 2026; Sheng, Sun, and Wang, 2025), whereas other studies question their relevance for risk premia (Hirshleifer, Mai, and Pukthuanthong, 2025a; Bianchi et al., 2024).

In this paper, we study the effects of geopolitical risk through the lens of mutual fund flows and asset prices. We examine U.S. international equity funds and compare the fund flows between those with high and low exposure to U.S. geopolitical rivals. Presumably, if investors incorporate geopolitical risk into their investment decisionmaking, then an increase in perceived risk should lead to more pronounced outflows from high-exposure funds compared to 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 reflect investors' perception. We then investigate the asset pricing implications of GPFS. We measure firms' exposure to geopolitical risk using their loadings on GPFS (i.e., GPFS beta) and examine their relation to stock returns. Intuitively, if those fund flow shifts captured by GPFS embody systematic risk considerations rather than overreactions to geopolitical news (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 support the notion that investors increasingly shift from viewing geopolitics as episodic to seeing it as structural, treating geopolitical risk as an important factor in capital allocation and asset pricing.

We begin our analysis by constructing a sample of U.S. international equity mutual funds from Morningstar spanning the period from 2001 to 2025. For these funds, we define a measure of geopolitical exposure based on their underlying portfolio holdings. Specifically, we measure a fund's geopolitical exposure as the weighted average of the geopolitical distances between the U.S. and the countries in which the fund invests, using the country-level holdings as weights. We obtain the holdings data from Morningstar, which provides the fraction of fund assets invested in each country. [1] To capture geopolitical distance, we exploit the ideal points computed by Bailey, Strezhnev, and Voeten (2017) and define the geopolitical distance of a country (with respect to the U.S.) as the absolute difference between the country's ideal point and that of the U.S. [2] The intuition underlying our geopolitical exposure measure is straightforward: a fund allocated more heavily

[1] Morningstar determines the "nationality" of a stock based on the headquarter's location of the underlying company.

[2] Bailey, Strezhnev, and Voeten (2017) compute the ideal points based on United Nations General Assembly votes. Through a spatial model, they map each country's foreign policy stance onto a single dimension that reflects its position toward the liberal international order.

to countries with greater geopolitical distance to the U.S. will exhibit a higher exposure. Finally, we sort funds into quintile portfolios every quarter based on their geopolitical exposure and then examine their fund flows.

Because raw fund flows are inherently persistent and heavily driven by fund performance, we filter out the part of flows attributable to past flows and performance. Specifically, we adopt the approach by Dou, Kogan, and Wu (2026) to extract fund flow shocks that are orthogonal to the effects of flow persistence and lagged returns; these filtered shocks are arguably reflecting unexpected innovations, such as sudden shifts in geopolitical risk. We focus on these flow shocks and define our measure of geopolitical risk, the Geopolitical Flow Spread (GPFS), as the average fund-flow shock among funds in the lowest geopolitical exposure quintile minus the average fund-flow shock among those in the highest quintile. Intuitively, when geopolitical tensions rise and investors perceive an increased risk, international funds with high exposure to geopolitical rivals should experience disproportionately large capital flight relative to their low-exposure peers, driving our GPFS measure upward. We confirm this intuition empirically by evaluating the time series of GPFS: we demonstrate that its steepest spikes closely align with prominent, identifiable geopolitical events throughout our sample period.

While international equity funds provide a setting where geopolitical exposure is relatively easy to measure and investors' capital reallocations can be observed, it remains unclear whether the capital flow shifts captured by GPFS translate into a systematic risk premium or merely reflect temporary investor overreactions. Therefore, we turn to the domestic equity market to examine the asset pricing implications of GPFS. As shown by Demirci et al. (2022), in addition to direct investment in foreign assets, holding domestic stocks can also expose investors to foreign markets (and hence to geopolitical risk). If geopolitical risk drives equilibrium asset prices, then GPFS should command a risk premium in the cross section of stock returns.

As is customary, we focus on U.S. stocks that are ordinary common shares listed on the NYSE, AMEX, or NASDAQ. We measure an individual stock's exposure to geopolitical risk using its GPFS beta, which we estimate by running rolling-window time-series regressions of stock excess returns on the GPFS factor. After sorting stocks into quintile portfolios based on GPFS beta, we uncover a salient structural break: From 2001 to 2016, a long-short portfolio that is long stocks in the highest GPFS beta quintile and short those in the lowest quintile has an average annualized return close to zero (and not statistically significant). From 2017 to 2025, however, this long-short portfolio yields a remarkable average annualized return of 16.4%, which is both economically large and statistically significant. The increased long-short return is primarily driven by the long leg: while the excess returns of the low-GPFS-beta portfolio remain flat at approximately 6% throughout the sample period, the average excess return of the high-GPFS-beta portfolio surge from 6.7% in the pre-2016 era to 22.3% after 2017.

Interestingly, this stark contrast before and after 2017 echoes the observation by John Mearsheimer, a leading expert on international relations. As he mentioned in a recent interview, during the "*unipolar moment*", the financial community showed virtually no interest in geopolitics because it "*didn't matter for business people all around the world*". Around 2017, however, as "*we move from unipolarity into multipolarity*", people in the financial world became very interested in talking to him. Hedge fund managers want to hear his opinion on particular issues, "*so they can figure out for themselves where they should invest their money*". [3] Professor Mearsheimer's experience accords remarkably well with our findings.

We conduct a battery of robustness checks. First, we confirm that this post-2017 return spread does not reflect exposure to well-known risk factors: when we run time-series regressions of the long-short portfolio returns on various benchmark factor models, the resulting alphas remain virtually unchanged and highly statistically significant. Second, we find that the return spread between the extreme quintiles is remarkably persistent,

[3] See `https://youtu.be/adBv52vkrSY?si=UqApjyZ-QagSFmcu` for the full interview.

with no discernible post-formation reversal patterns. Moreover, our results not only hold but actually become stronger when portfolios are value-weighted. This implies that our findings are not driven by obscure micro-cap anomalies, and it also suggests that geopolitical shocks matter for investor wealth. Finally, we show that this premium is concentrated among large-cap firms and those with significant foreign revenues—exactly the ones most vulnerable to geopolitical tensions. To complement our portfolio analysis, we also conduct Fama-MacBeth regressions, which allow us to control for a wide array of firm characteristics known to predict stock returns. The results show that the predictive power of GPFS beta remains robust and statistically significant even after controlling for a range of characteristics such as size, book-to-market ratio, and momentum.

To examine the primitive forces behind GPFS beta, we first follow Baldwin, Freeman, and Theodorakopoulos (2023) in exploiting the Inter-Country Input-Output (ICIO) data from the OECD to compute the look-through supply-chain reliance of U.S. industries on foreign countries. Combining that data with the country-level geopolitical distance, we obtain a supply-chain-based geopolitical exposure measure, which we show correlates moderately with GPFS beta. In addition, we utilize granular foreign revenue data from FactSet Revere to compute the fraction of sales from foreign markets for individual U.S. firms. Again, combining these foreign revenue dependencies with the geopolitical distance generates a revenue-based geopolitical exposure measure, which also exhibits a significant positive correlation with GPFS beta. After examining these two primary channels through which firms expose to geopolitical risk (that is, the upstream supply-chain reliance and the downstream revenue dependencies), we find that while both channels correlate with GPFS beta, neither of them alone can fully account for its variation or its asset prcing implications.

In additional tests. we show that after 2017, international equity funds respond to geopolitical shocks by tilting their portfolios away from countries with high geopolitical exposure. Also, domestic mutual funds systematically underweight high-GPFS-beta stocks, whereas no such institutional aversion exists in the pre-2016 era. Moreover, we find that firms significantly reduce corporate investment in response to GPFS spikes, and this effect is stronger among high-GPFS-beta firms—a pattern that, once again, emerges only after 2017. Finally, other than individual stocks, we also examine the cross section of anomaly portfolios. In accordance with other results, we find that GPFS beta possesses strong, statistically significant explanatory power for these benchmark portfolio returns during the post-2017 period.

Literature. This paper primarily contributes to the recent literature studying the asset pricing implications of geopolitical risk. Since the seminal work of Caldara and Iacoviello (2022), who developed a news-based geopolitical risk (GPR) index, a series of studies has examined its implications for asset prices. While Caldara and Iacoviello (2022) show that adverse shocks to the GPR index tend to induce immediate and persistent declines in aggregate stock prices, Bianchi et al. (2024) find the opposite, showing that most GPR spikes are not associated with stock market jumps. Instead, they find that only a handful of GPR events precede big drops in stock prices, which they argue are driven not by variations in risk premia, but rather by investors' subjective cash flow expectations overreacting to GPR news. In accordance with this study, Hirshleifer, Mai, and Pukthuanthong (2025b) find that GPR does not command any significant return premium in the cross-section of stocks. However, a recent paper by Gonçalves, Melone, and Ricciardi (2026) argues that geopolitical risk is indeed priced, but through a different risk measure. They build on Caldara and Iacoviello (2022)'s decomposition of GPR into a geopolitical threats (GPT) index and a geopolitical acts (GPA) index, and show that GPT is better aligned with the geopolitical risk perceptions and capital allocation decisions of investors and firms. Consequently, they find that GPT is priced across various asset cross-sections. In a similar spirit, Sheng, Sun, and Wang (2025) refine Caldara and Iacoviello (2022)'s approach by focusing exclusively on a single news source, The Wall Street Journal, and incorporating trade-war-related keywords into the index construction. They obtain a new geopolitical risk index and show that it successfully predicts aggregate stock market returns.

We make several contributions to this literature. First, we propose a novel approach to measuring geopolitical risk based on mutual fund flows. By tracking capital flows across different international equity funds with varying degrees of geopolitical exposure, we construct a measure of geopolitical risk that directly mirrors investors' actual perceptions rather than journalists' reporting. Second, we document a noteworthy structural break around 2017, which matches the geopolitical shift from unipolarity to multipolarity in international relations. This striking alignment between asset pricing dynamics and international relations has not been documented in any of the previous papers. Finally, our findings help resolve, at least in part, the ongoing debate in the literature. Our result that geopolitical risk was not priced prior to 2017 accords with Bianchi et al. (2024), suggesting that investors in this earlier era did not treat geopolitical risk as an important pricing factor. Even when the market showed some reaction to geopolitical shocks during this period, the impact was largely transitory, and the behavior of firms and institutional investors reveal that the primary market participants were simply not very concerned. In the post-2017 period, however, we find that investors have become far more attentive to these shocks. Firms and institutional investors are now responding much more strongly to geopolitical risks than before, a pattern that is consistent with Gonçalves, Melone, and Ricciardi (2026) and Sheng, Sun, and Wang (2025). In a sense, both sides of the literature are right; it is just that the underlying importance of geopolitical risk to investors has changed a lot over time.

Outline. 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. [4] 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, 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 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.[5] Then we define the geopolitical distance between

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

[5]Not all resolutions are treated equal in the estimation of ideal points. Each resolution is weighted ac-

the U.S. and any other country as the absolute difference between their respective ideal points.

$$d_{c,t} = |\text{IP}_{c,t} - \text{IP}_{US,t}| .$$

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 exposure 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).

cording 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.

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.[6]

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 re-

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

flect 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 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.

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

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.[7]

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 rever-

[7] 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).

sals. 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 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:

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

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 (Hou, Xue, and Zhang, 2020) 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.5 shows that U.S. manufacturing industries differ substantially in their upstream foreign production reliance. The average foreign share is 12.9%, but it reaches about 19–22% in basic iron, refined petroleum, and vehicles, while remaining below 10% in industries such as food and paper/print. The country composition also varies across industries: Canada is important for resource- and transport-related sectors, Mexico is prominent in vehicles, and China contributes more to electronics, machinery, textiles, and other manufacturing. These patterns indicate that industry exposure reflects both the intensity of foreign input reliance and the geopolitical identity of the supplying countries. This cross-sectional variation motivates our industry-level geopolitical exposure measure.

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.3. 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 Table A.4.

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.7 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 fund holdings, we aggregate portfolio weights at the country level and study whether geopolitical risk shocks lead funds to reallocate capital away from countries that are more geopolitically distant.

For each country c and quarter t, the dependent variable $\Delta w_{c,t+1}$ is the change in the aggregate portfolio weight allocated to country c from quarter t to quarter $t+1$. We estimate the following country-quarter 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 $GPFS_t$ denotes the geopolitical risk factor, and $D_{c,t}$ is the geopolitical distance between country c and the United States in quarter t. The interaction term captures whether funds reallocate differently from geopolitically distant countries when geopolitical risk rises.

The control vector includes the current portfolio weight, the country's contemporaneous stock-market return, and the geopolitical distance measure:

$$X_{c,t} = \left(w_{c,t}, R_{c,t+1}, D_{c,t} \right).$$

The current portfolio weight $w_{c,t}$ controls for mechanical mean reversion in portfolio allocations. The country return $R_{c,t+1}$ accounts for valuation effects in country-level portfolio weights. The distance measure $D_{c,t}$ controls for the direct relation between geopolitical distance and subsequent reallocations.

Table 12 reports the results separately for the pre-2017 and post-2017 periods. Before 2017, the interaction between $GPFS_t$ and $D_{c,t}$ is negative but statistically insignificant across all specifications. In the most complete specification, the coefficient is -0.06 with a t-statistic of -1.59. This indicates little evidence that geopolitical risk systematically affected country reallocations before the recent period.

In contrast, after 2017, the interaction coefficient becomes larger in magnitude and statistically significant. In the specification with all controls, the coefficient is -0.12 with a t-statistic of -2.31. Since the variables are standardized, this estimate implies that a one-standard-deviation increase in the interaction between geopolitical risk and geopolitical distance is associated with a 0.12-standard-deviation decline in the subsequent change in country portfolio weight. Economically, the result suggests that when geopolitical risk rises, funds reduce allocations more strongly to countries that are more geopolitically distant from the United States.

7 Conclusion

In this paper, we study how geopolitical risk is reflected in capital flows and asset prices, shedding new light on investors' perception of geopolitical tensions. While the extant literature relies heavily on news-based measures, we examine how capital actually moves across international mutual funds to construct a novel, flow-based measure of geopolitical risk. This measure allows us to avoid the semantic noise of the news-based measures and focus directly on investors' real decisions as they unfold in the capital markets.

Our main findings suggest that the investors' perception of geopolitics is not a static constant. We document a stark structural break around 2017 that coincides with a profound regime shift in international relations—the transition from post-Cold War unipolarity to a multipolar system. Documenting this pattern allows us to address the recent debate on the pricing of geopolitical risk. We contend that the conflicting findings in the literature are simply a product of different eras: Before 2017, geopolitical risk was indeed unpriced in the cross-section of stocks, and aggregate market drops following major geopolitical events were largely temporary—likely caused by overreactions in investor expectation as Bianchi et al. (2024) suggest. But after 2017, the situation changed. In this new era, investors stopped treating geopolitics as passing headline noise and began systematically incorporating it as an important pricing factor.

These findings carry important implications for how we build macro-finance models that feature geopolitical risk. They suggest that treating geopolitical risk as a static ingredient misses a prominent feature in the data. Under different regimes of international relations, geopolitical risk can have very different economic implications. We leave the development of such models to future research.

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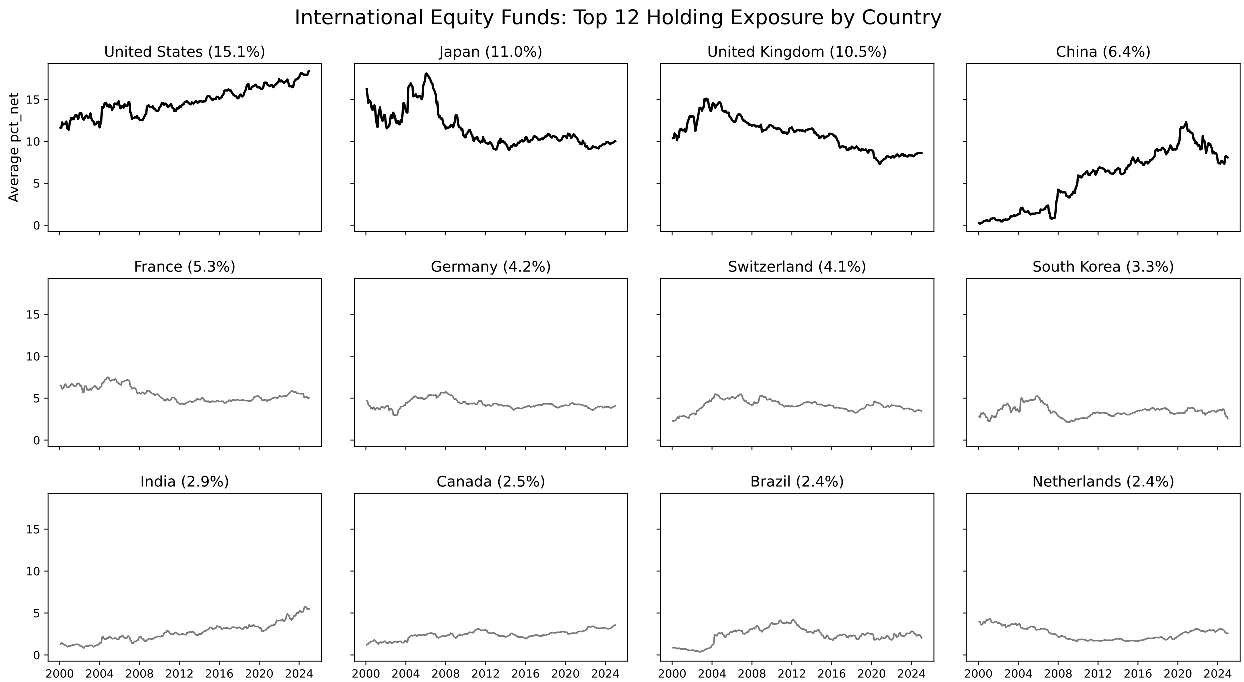

Figure 1: International Equity Fund Holdings by Country. This figure plots country-level portfolio weights of international equity funds from January 2000 to December 2024. The figure displays the 12 countries with the largest average exposure over the sample period. Country exposure is the fraction 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.

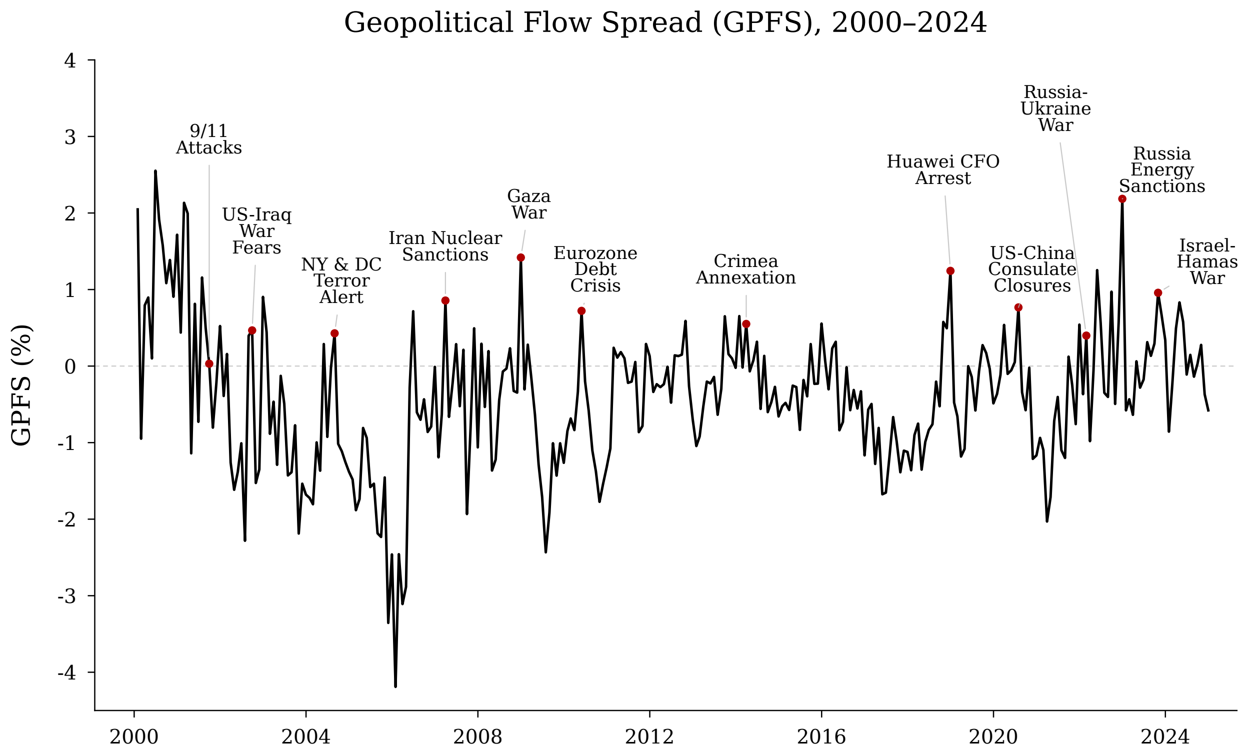

Figure 2: Geopolitical Flow Spread (GPFS). This figure plots the monthly Geopolitical Flow Spread (GPFS) from January 2000 to December 2024. Each month, international equity funds are sorted into quintiles based on geopolitical exposure. GPFS is defined as the difference in average share-class flow shocks 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.

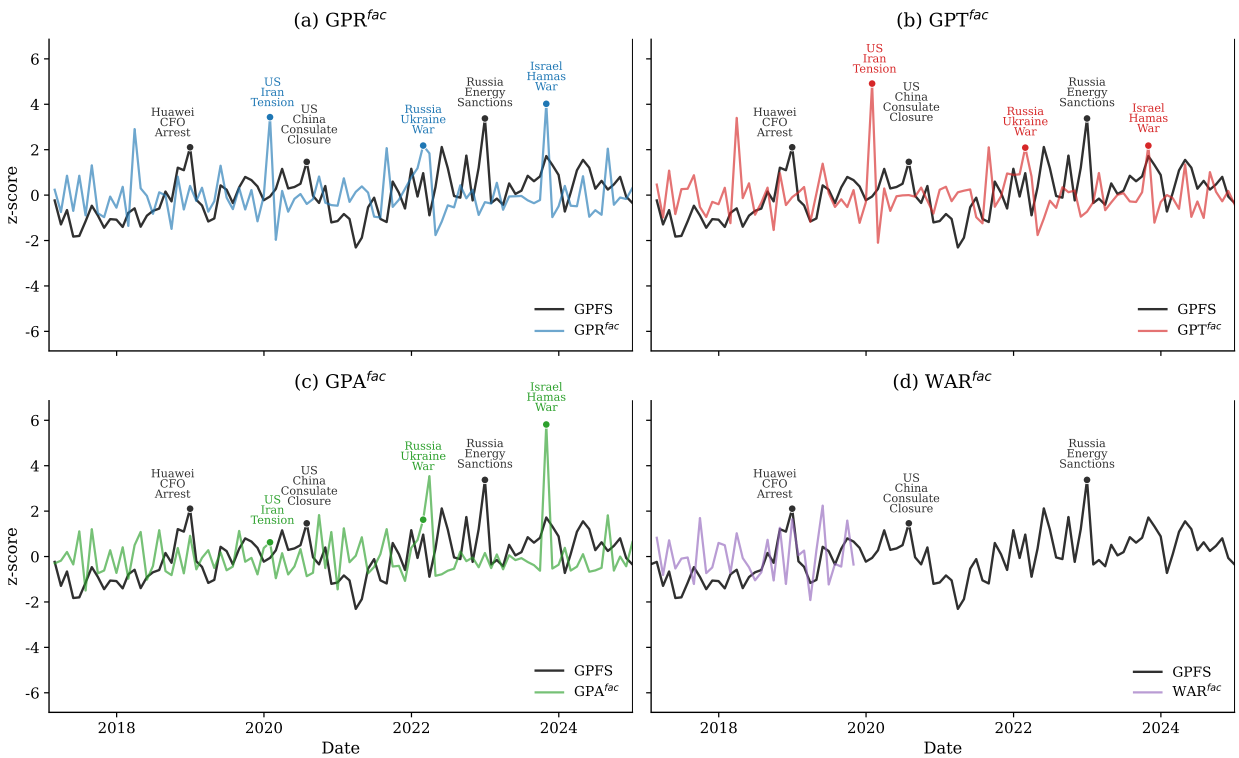

Figure 3: GPFS and News-Based Geopolitical Risk Measures. This figure compares GPFS with four news-based geopolitical risk measures over 2017–2024, with all series expressed as z-scores. GPFS is the fund-flow-based measure constructed from international equity mutual fund portfolio exposures. The news-based 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.

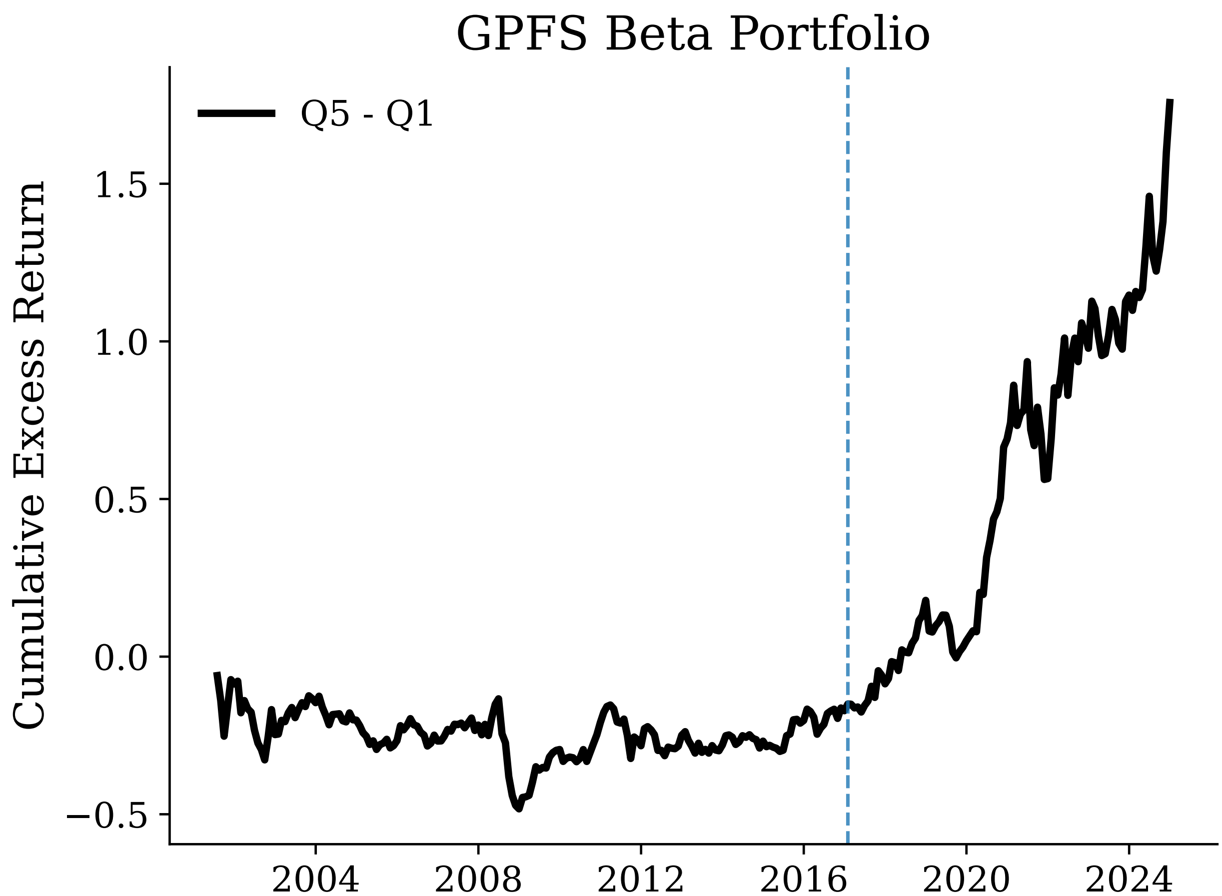

Figure 4: Cumulative Returns of the GPFS Beta Portfolio. This figure plots the cumulative return of a long–short portfolio that buys stocks in the highest quintile and sells stocks in the lowest quintile sorted on GPFS beta. GPFS betas are estimated using a 24 month rolling regression of monthly excess 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.

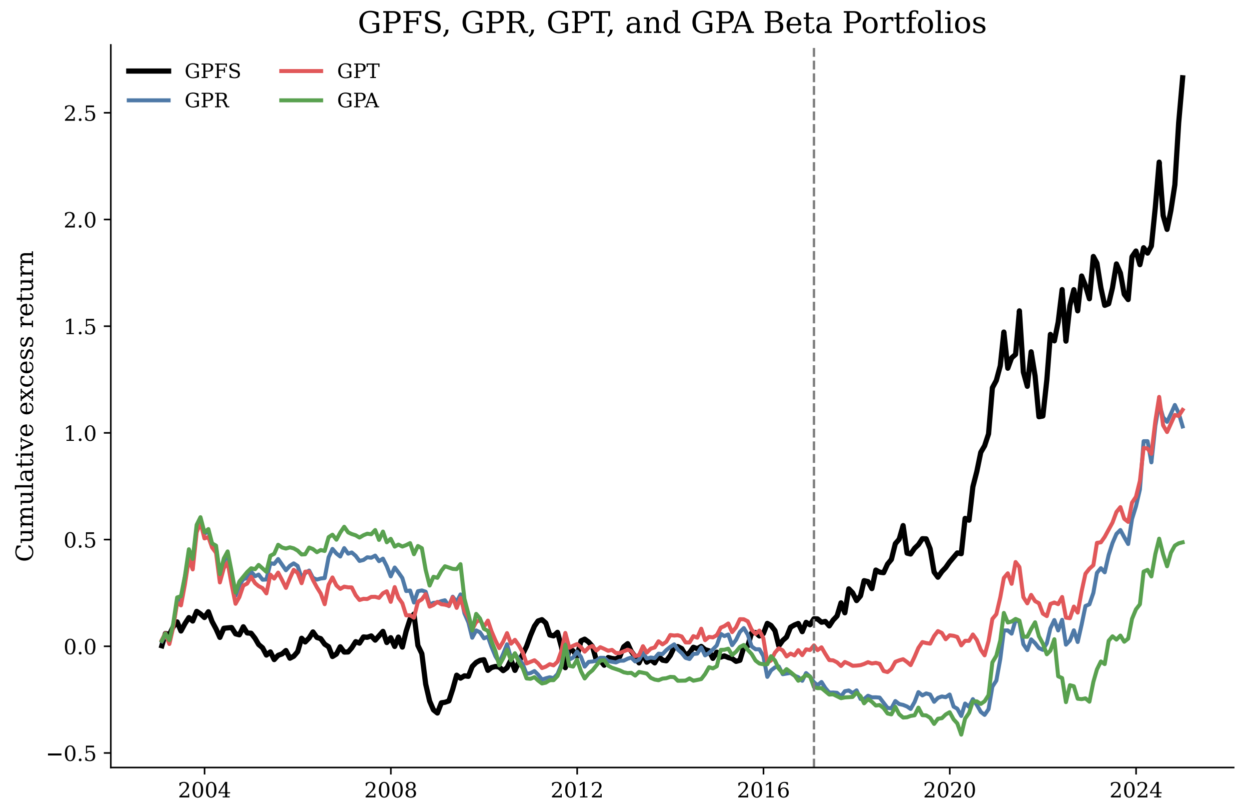

Figure 5: Cumulative Returns of Portfolios Sorted on Geopolitical Risk Indices. This figure plots the cumulative returns of long–short portfolios formed by sorting stocks on their betas with respect to GPFS and the news-based geopolitical risk measures GPR, GPT, and GPA from Caldara and Iacoviello (2022). 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.

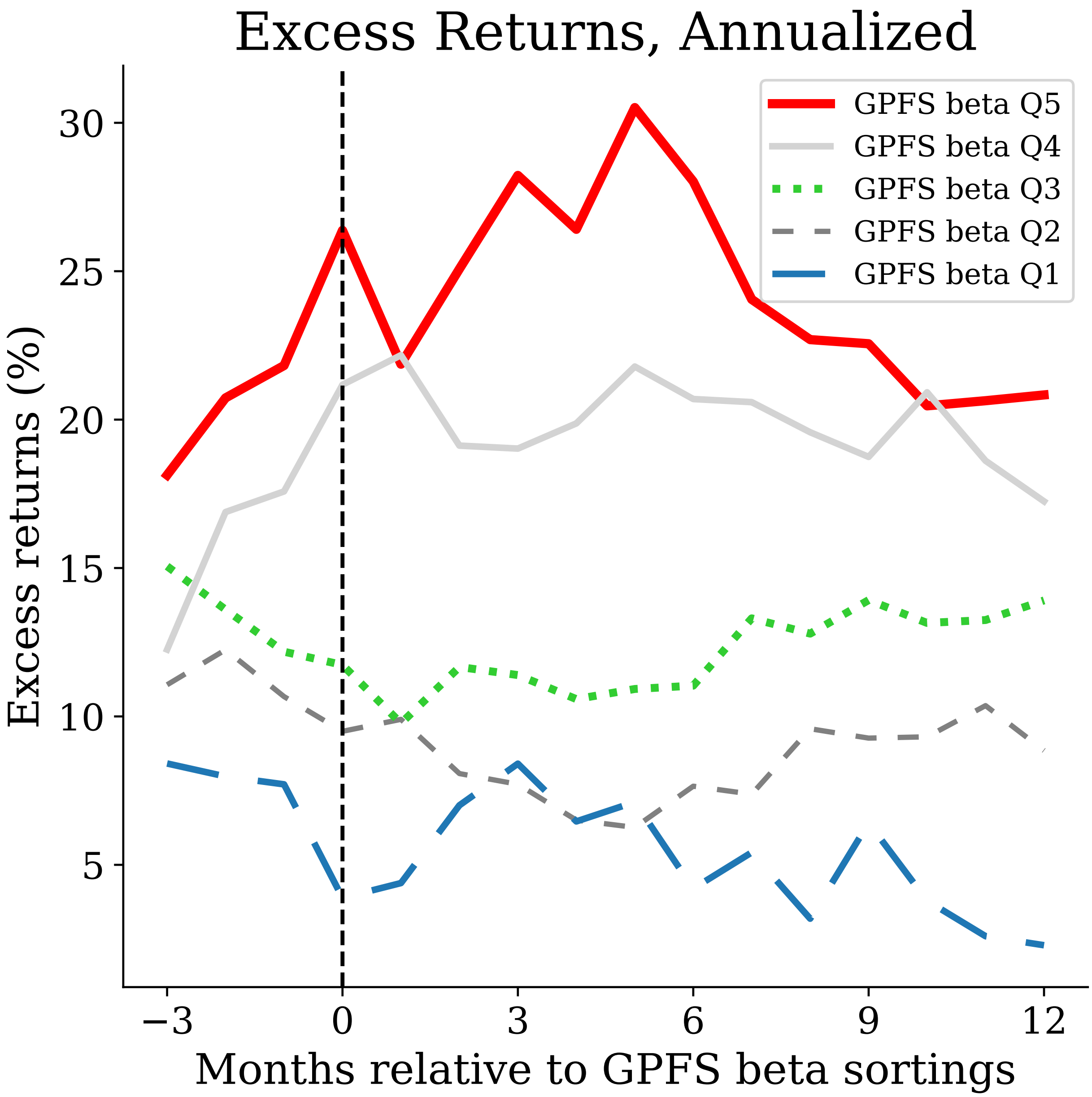

Figure 6: Event-Time Excess Returns of GPFS Beta Portfolios. This figure plots annualized value-weighted excess returns of quintile portfolios sorted on GPFS betas from three months before portfolio formation to twelve months after formation. GPFS betas are estimated using 24-month rolling regressions 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.

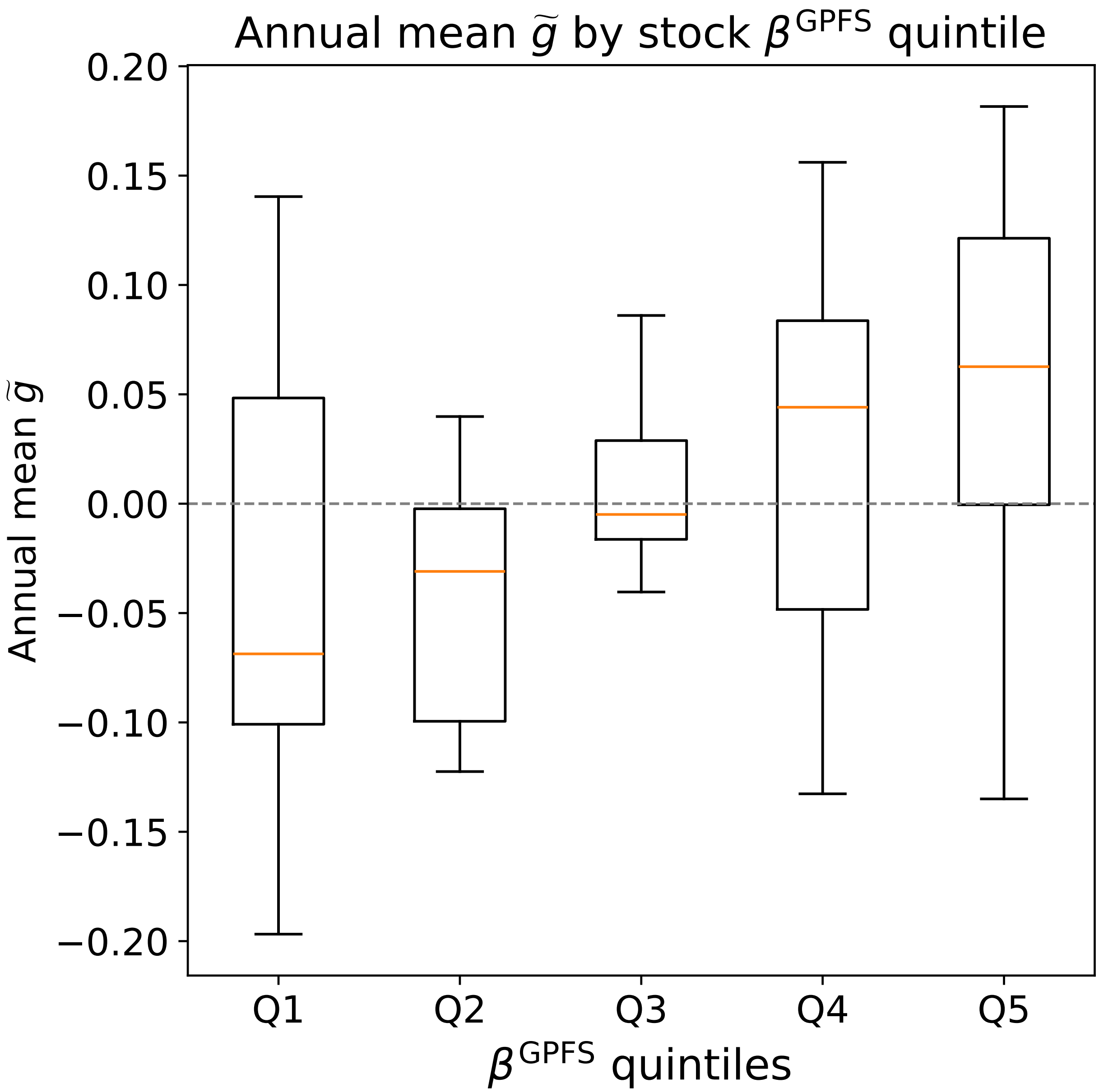

Figure 7: Industry Exposure by GPFS Beta Quintile. This figure displays box plots of annual mean standardized industry exposure $\tilde{g}$ across quintiles sorted on GPFS betas. Stock-level GPFS betas are estimated using 24-month rolling regressions of stock returns on the negative of GPFS. Each June, 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.

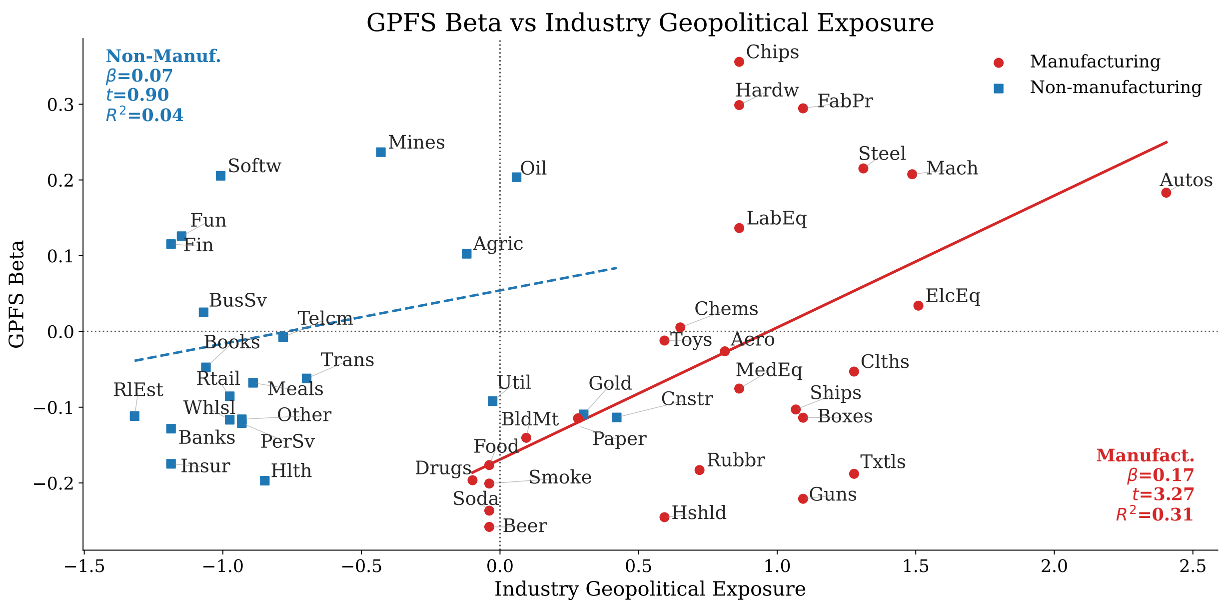

Figure 8: Industry GPFS Betas and Geopolitical Exposure. This figure plots industry GPFS loadings against industry geopolitical exposure. GPFS loadings are estimated from time-series regressions of industry excess returns on the market excess return and the GPFS portfolio return over the July 2001 to 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.

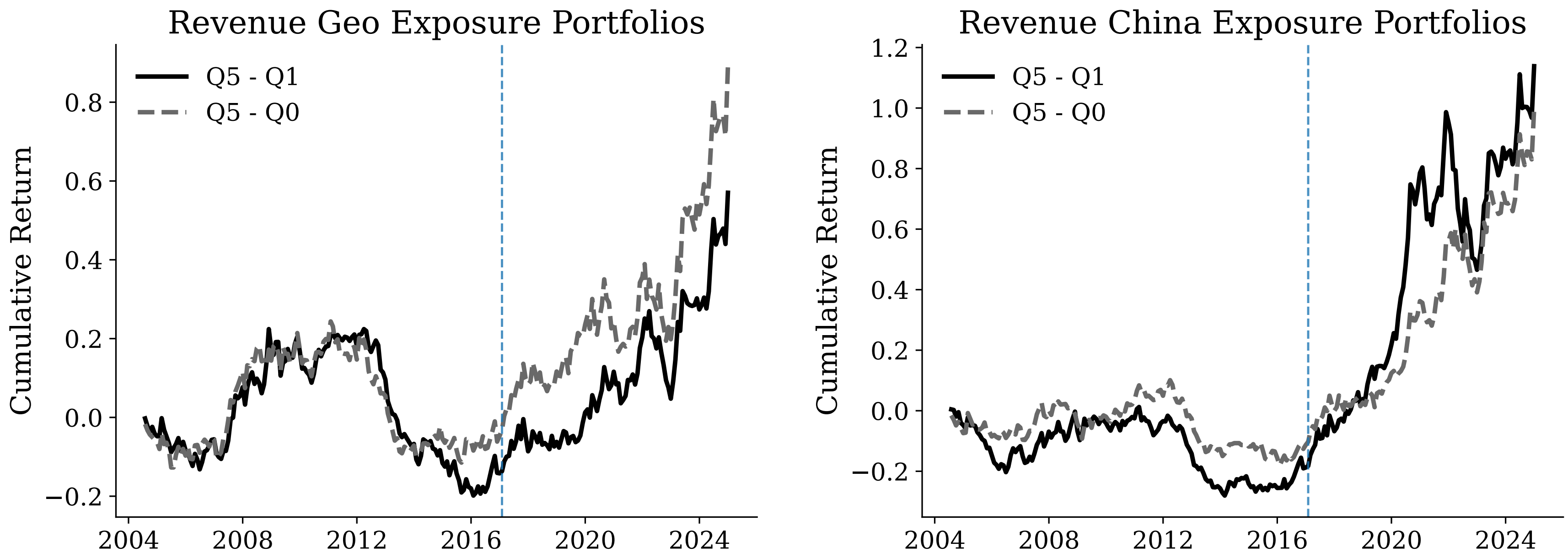

Figure 9: Cumulative Returns of Revenue-Based Geopolitical Exposure Portfolios. This figure plots cumulative returns of portfolios sorted on firms' revenue-based geopolitical exposure. Exposure is measured at the firm level using geographic revenue disclosures and assigned to individual stocks via the 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, Xue, and Zhang (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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Revenue Geo Exposure			*Panel B: China Revenue Exposure*		
	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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Foreign revenue × Beta				*Panel B: Size × Beta*		
	T0	T1	T2	T3	T1	T2	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 mutual fund portfolio tilts on lagged stock-level GPFS beta and market beta. The dependent variable is $w^{MF}_{i,t} - w^{mkt}_{i,t}$, where $w^{MF}_{i,t}$ is the AUM-weighted average portfolio weight of stock i among funds holding the stock, and $w^{mkt}_{i,t}$ is stock i's market-cap weight in the CRSP universe. Stock-level $\beta^{GPFS}_{i,t-1}$ and $\beta^{mkt}_{i,t-1}$ are estimated from 24-month rolling regressions of monthly excess returns, require at least 12 observations, and are lagged one month. Panel A reports panel regressions with month fixed effects and two-way clustered standard errors; Panel B reports monthly Fama–MacBeth regressions with Newey–West t-statistics. Columns (1)–(2) cover 2000–2016, and columns (3)–(4) cover 2017–2024. The dependent variable and explanatory betas are standardized to have mean zero and standard deviation one within each subperiod. t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)
	Panel A. Panel + Time FE			
	2000-2016		2017-2024	
	$w^{MF}_{i,t} - w^{mkt}_{i,t}$		$w^{MF}_{i,t} - w^{mkt}_{i,t}$	
$\beta^{GPFS}_{i,t-1}$	-0.009*	-0.001	-0.031***	-0.026***
	(-1.84)	(-0.25)	(-4.40)	(-3.83)
$\beta^{mkt}_{i,t-1}$		-0.021***		-0.018**
		(-3.71)		(-2.57)
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	
	$w^{MF}_{i,t} - w^{mkt}_{i,t}$		$w^{MF}_{i,t} - w^{mkt}_{i,t}$	
$\beta^{GPFS}_{i,t-1}$	-0.017**	-0.011	-0.035**	-0.036**
	(-2.41)	(-1.57)	(-2.31)	(-2.03)
$\beta^{mkt}_{i,t-1}$		-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 international equity fund's reallocation 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 the country geopolitical distance measure $D_{c,t}$ in quarter t. Control variables include the current portfolio weight level $w_{c,t}$, the country's compounded stock-market return $R_{c,t+1}$ in quarter $t+1$, and the geopolitical distance $D_{c,t}$. The sample is split into pre-2017 and post-2017 periods. The dependent variable and all regressors are standardized to have means of zero and standard deviations of one using the full-sample. All specifications include country and quarter fixed effects. Standard errors are two-way clustered by country and quarter. Newey–West t-statistics are reported in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: 2000–2016			*Panel B: 2017–2024*		
	$\Delta w_{c,t+1}$			$\Delta w_{c,t+1}$		
$GPFS_t \times D_{c,t}$	-0.04	-0.06	-0.06	-0.13**	-0.12**	-0.12**
	[-1.06]	[-1.56]	[-1.59]	[-2.23]	[-2.21]	[-2.31]
$w_{c,t}$	-0.78***	-0.70***	-0.70***	-2.16***	-2.16***	-2.16***
	[-2.86]	[-2.76]	[-2.79]	[-2.88]	[-2.87]	[-2.89]
$R_{c,t+1}$		0.76***	0.76***		0.03	0.03
		[3.30]	[3.36]		[0.94]	[0.98]
$D_{c,t}$			-0.15			0.13
			[-0.97]			[1.05]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3332	3332	3332	1519	1519	1519
R^2	0.02	0.07	0.07	0.06	0.06	0.06

Internet Appendix

"Geopolitical Risk in Financial Markets: Evidence from Mutual Fund Flows"

By Chenxi Zhang and Chao Zi

Contents

A Supplementary Empirical Results

This appendix reports supporting evidence for the paper's main result.

A.1 Geopolitical Distance and Fund Country Exposure

Table A.1 summarizes the UNGA voting data used to construct country-level geopolitical distance. Panel A shows that the General Assembly passes an average of 82 final-passage resolutions per year from 2000 to 2024. The largest issue categories are peace, security, and disarmament, with 23 resolutions per year, and Israel/Palestine and related regional conflict, with 20 resolutions per year, indicating that the voting data contain substantial information about international political alignment.

Panel B documents large cross-country dispersion in UNGA ideal points. The average annual cross-sectional standard deviation is 0.80, with an interquartile range from -0.62 to 0.70. Among the countries most relevant for U.S. international equity funds, the United States has the highest average ideal point, 2.51, while close U.S. allies such as the United Kingdom, Canada, France, Australia, Germany, and Japan range from 0.69 to 1.58. By contrast, Brazil, India, and China have lower average ideal points of -0.20, -0.37, and -0.65.

Figure A.1 shows that this cross-country dispersion is also time-varying. The United States, the United Kingdom, and France remain relatively aligned, although their ideal points drift downward after the early 1990s. The USSR/Russia series captures the geopolitical rupture around the end of the Cold War: Russia moves sharply upward as the Soviet bloc dissolves and relations with Western countries temporarily improve, before drifting downward again after the mid-1990s. China shows a different post-Cold-War pattern. Its ideal point falls sharply in the early 1990s, bottoms out in the mid-1990s, and then partially recovers as diplomatic and economic engagement with Western countries resumes. These patterns support treating geopolitical distance as a time-varying country characteristic rather than as a fixed country attribute.

Figure A.2 shows that the aggregate country weights of U.S. international equity funds broadly track global equity market-cap weights. This relation is especially strong for several large portfolio countries, including Japan, China, France, South Korea, India, Brazil, and the Netherlands. The evidence suggests that the average international equity fund portfolio is close to a diversified world equity portfolio, although deviations remain for some countries such as the United States, Germany, Switzerland, and Canada. This supports the interpretation of our exposure sorts: high- and low-exposure fund portfolios mainly capture geopolitical tilts around a diversified global allocation, rather than narrow bets on a few countries.

A.2 Flow-Based and News-Based Measures of Geopolitical Risk

Figure A.3 focuses on the post-2017 period and shows that GPFS and the news-based GPR index are related but far from synchronized. GPFS spikes around events with direct implications for international investors, such as the Huawei CFO arrest and Russia-related energy sanctions. In contrast, GPR responds most strongly to the onset of the Russia–Ukraine war and other news-intensive episodes, such as U.S.–Iran tensions. This difference suggests that GPFS captures a market-relevant, flow-based component of geopolitical risk that is distinct from news intensity.

Figure A.4 provides a long-run benchmark based on the historical GPR, GPT, and GPA series. The figure plots cumulative wealth indices for high-minus-low beta portfolios sorted on stock-level exposure to each news-based geopolitical risk measure. The GPT beta portfolio has the strongest long-run performance, while the GPR portfolio rises more unevenly and the GPA portfolio is weaker and more cyclical.

Consistent with the figure, the estimated annualized premium is largest for GPT, at 4.09% with a Newey–West t-statistic of 2.68. The corresponding estimate for GPR is smaller, at 2.95% with a t-statistic of 1.78, while GPA has an insignificant premium of

1.57% with a t-statistic of 0.92. These results suggest that the historical news-based measures contain some pricing information, mainly through the threat component, but the magnitudes are modest and differ substantially across components.

Table A.2 reports panel regressions of monthly share-class flows on lagged fund geopolitical exposure and its interaction with geopolitical-event indicators. The test asks whether investors withdraw more from geopolitically exposed funds when geopolitical risk becomes elevated. The interaction coefficient is negative in every specification, indicating that high-exposure funds receive lower flows during geopolitical-risk months. The evidence is especially precise in the post-2017 period. From 2017 to 2024, the interaction coefficient ranges from -0.23 for GPR to -0.38 for GPA, with t-statistics between -2.58 and -3.73. In the earlier 2000–2016 period, the estimates are also negative, ranging from -0.48 for GPR to -0.27 for WAR, but the statistical significance is weaker for some event definitions, especially GPA. Taken together, these results support interpreting fund flows as a market-based measure of perceived geopolitical risk. The response appears in both subsamples, but it is more consistently significant after 2017, suggesting that geopolitical exposure becomes more salient to fund investors in the recent period.

A.3 Mimicking GPFS with Equity Anomaly Portfolios

This section examines whether GPFS can be represented by a tradable factor constructed from equity anomaly portfolios. We construct SPCA mimicking factors for $-GPFS$ using monthly U.S. equity anomaly portfolio returns, following the supervised principal component analysis approach of Giglio, Xiu, and Zhang (2025). The test assets combine equal- and value-weighted anomaly portfolios from the Open Source Asset Pricing dataset of Chen and Zimmermann (2022) and the Jensen, Kelly, and Pedersen dataset from Jensen, Kelly, and Pedersen (2023). After requiring complete monthly returns from January 2000 to December 2024, the test-asset universe contains 3,010 OSAP decile portfolios based on 163 anomaly signals and 306 JKP long-short portfolios based on 153 anomaly signals.

The mimicking factors are estimated out of sample. For each specification, we use an expanding training window that begins in January 2000. Within each training window, SPCA first selects the anomaly portfolios most closely related to $-GPFS$, and then extracts a small number of components from the selected portfolios. We report four specifications that vary the number of SPCA factors and the fraction of anomaly portfolios retained in the supervised step: four factors using 10% of test assets, five factors using 10%, five factors using 20%, and six factors using 10%. The first out-of-sample mimicking-factor return is formed in July 2001 using data through June 2001, and the training window then expands by one month at a time. The portfolio weights are rescaled so that the fitted in-sample mimicking factor has an annualized volatility of 20%, close to that of the market factor.

Table A.5 reports annualized premia and benchmark alphas for these SPCA mimicking factors. The alpha specifications include CAPM, the intertemporal asset-pricing model of Chabi-Yo, Gonçalves, and Loudis (2025), FFC, and FF5. The final column reports the slope from regressing the high-minus-low stock GPFS-beta portfolio return on the mimicking factor, which measures whether the mimicking factor captures the same return variation as the GPFS-beta sort.

Panel A shows that the SPCA mimicking factors are strongly priced in the post-2017 period. Across specifications, the annualized premium ranges from 15.78% to 20.72%, with Newey–West t-statistics between 2.76 and 3.51. The benchmark alphas remain large after controlling for standard factor models and are statistically significant in most specifications. The mimicking factors also load positively on the high-minus-low GPFS-beta portfolio, with slopes between 0.258 and 0.383 and t-statistics between 1.86 and 3.91. These results indicate that GPFS-related return variation can be extracted from tradable equity anomaly portfolios and that this variation earns a sizable premium after 2017.

Panel B shows that the pricing result is much weaker before 2017. The mimicking factors still load positively and significantly on the high-minus-low GPFS-beta portfolio, indicating that they capture GPFS-related return variation. However, their annualized premia are small, ranging from 0.45% to 4.90%, and are statistically insignificant. The benchmark alphas are also close to zero and insignificant. Thus, the mimicking exercise supports the main finding: GPFS-related return variation is present in equity portfolios throughout the sample, but it becomes economically priced only in the post-2017 period.

A.4 Real Exposure Channels and GPFS Beta

Figure A.6 examines whether stock-level GPFS betas are systematically related to firms' geographic revenue exposure. For each year from 2017 to 2024, we sort stocks by revenue-based geopolitical exposure in Panel A and by China revenue exposure in Panel B. We report China exposure separately because China is both a large destination in U.S. international equity portfolios and a country with large geopolitical distance from the United States. Firms with zero exposure are placed in Q0, while positive-exposure firms are sorted into quintiles using NYSE breakpoints. We then compute the June market-cap-weighted average standardized GPFS beta within each portfolio.

The figure shows that firms with greater revenue-based exposure tend to have higher GPFS betas. In both panels, zero-exposure firms have negative average betas, whereas the highest-exposure firms have positive betas. The difference between the highest-exposure and zero-exposure groups is large and statistically significant: the Q5–Q0 difference is 1.00 for revenue-based geopolitical exposure and 0.89 for China revenue exposure, with confidence intervals that exclude zero. The China result shows that the relation between revenue exposure and GPFS beta is not driven only by the composite geopolitical-distance measure; it is also visible for a single economically important and geopolitically distant country. Although the pattern is not strictly monotonic across all intermediate quintiles, the contrast between zero-exposure and high-exposure firms is economically and statistically clear. This evidence supports the interpretation that GPFS beta is connected to firms' geographic revenue exposure.

Figure A.8 compares GPFS beta portfolios with portfolios formed using firm-level revenue-based geopolitical exposure and industry-level supply-chain geopolitical exposure. All three series rise after 2020, indicating that geopolitical exposure becomes more strongly priced in the recent period. The increase is much stronger for GPFS, while the revenue- and industry-based portfolios display weaker cumulative returns.

The comparison also highlights the different scope of the three exposure measures. Firms with no reported foreign revenue are assigned zero exposure, which limits the effective cross-sectional variation in the revenue-based sort. Industry-level supply-chain exposure captures upstream production reliance, but it is measured at a coarser industry level and depends on input-output tables that are released with a lag, so the measure cannot be updated to the most recent years. GPFS is instead constructed directly from mutual fund flows and therefore provides a broader and more timely measure of market-perceived geopolitical risk. The revenue- and industry-based portfolios serve as useful validation tests, but their pricing effects are weaker and noisier than those based on GPFS.

A.5 GPFS Exposure, Investment, and Operating Performance

This section examines whether GPFS exposure is associated with subsequent firm-level real outcomes. Table A.6 studies future investment, while Table A.7 studies future earnings and cash flow. Investment is constructed from Compustat quarterly capital expenditures, computed from year-to-date `CAPXY` within a firm's fiscal year, and measured as 100 times the log of quarterly capital expenditures scaled by beginning-of-period property, plant, and equipment, measured by lagged `PPENTQ`. Earnings are measured by ROA. Cash flow is measured as cash and short-term investments, `CHEQ`, scaled by lagged `PPENTQ`. The main regressor is the interaction between quarterly GPFS and firm-level GPFS beta. The regressions include firm and quarter fixed effects and are estimated separately for the 2001–2016 and 2017–2024 samples.

Table A.6 shows that the investment response is concentrated in the post-2017 period. In the 2001–2016 sample, the interaction between GPFS and firm-level GPFS beta is not robustly negative. The coefficients are close to zero at short horizons and become only weakly negative at $h = 4$. In contrast, in the 2017–2024 sample, the interaction is negative and statistically significant at horizons of two to four quarters. The coefficients are -0.017, -0.014, and -0.012 for $h = 2$, $h = 3$, and $h = 4$, with t-statistics of -2.87, -2.17, and -2.32, respectively. These estimates indicate that when GPFS is high, firms with higher GPFS beta subsequently reduce investment relative to firms with lower GPFS beta.

Table A.7 shows little evidence that the same exposure predicts a persistent decline in operating performance. For earnings, the interaction is positive and marginally significant contemporaneously in both subsamples, but the effect disappears at longer horizons. For cash flow, the interaction coefficients are small and statistically insignificant across all horizons in both the pre-2017 and post-2017 samples.

Taken together, Tables A.6 and A.7 suggest that GPFS exposure is associated with firms' real investment decisions in the recent period, but not with realized short-run declines in earnings or cash flow. This distinction helps interpret the pricing results: the GPFS premium appears less related to contemporaneous operating losses and more consistent with compensation for exposure to adverse geopolitical states. High-beta firms reduce investment when this risk becomes salient, even though their contemporaneous operating performance does not deteriorate systematically.

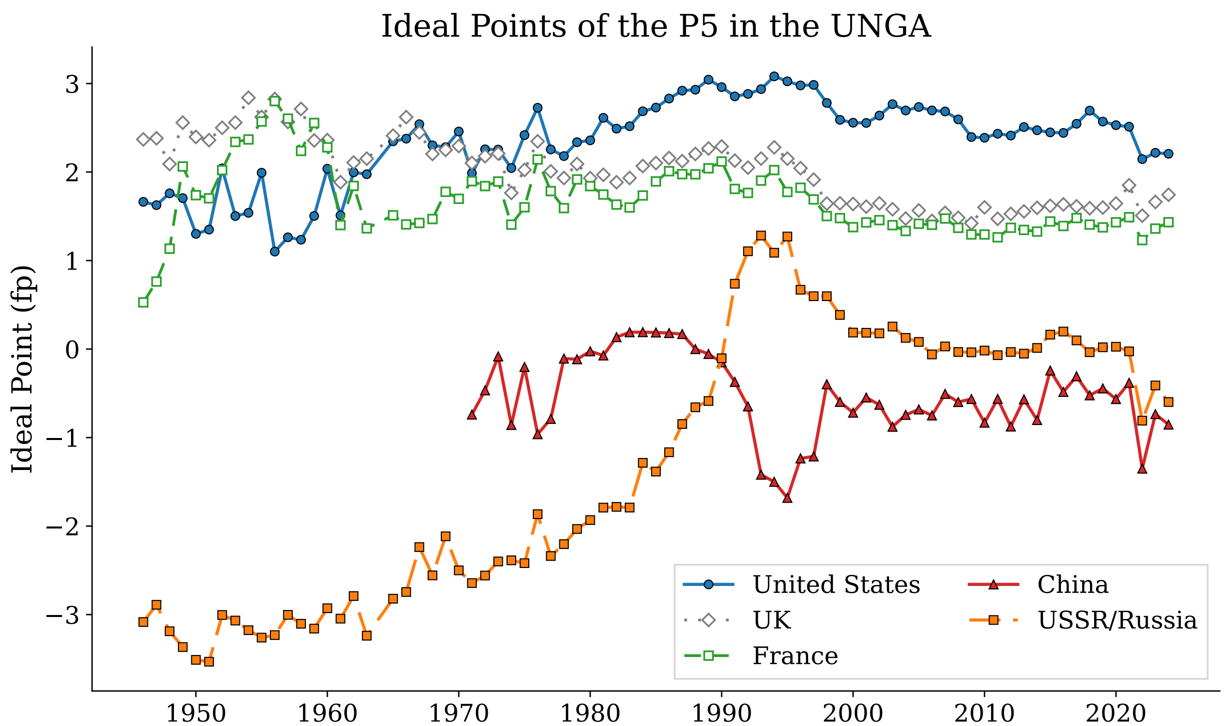

Figure A.1: UN General Assembly Ideal Points of the Permanent Five Members. This figure plots annual ideal point estimates for the permanent five members of the United Nations Security Council. Idealpoint estimates are based on votes on the final passage of General Assembly resolutions, including failed 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.

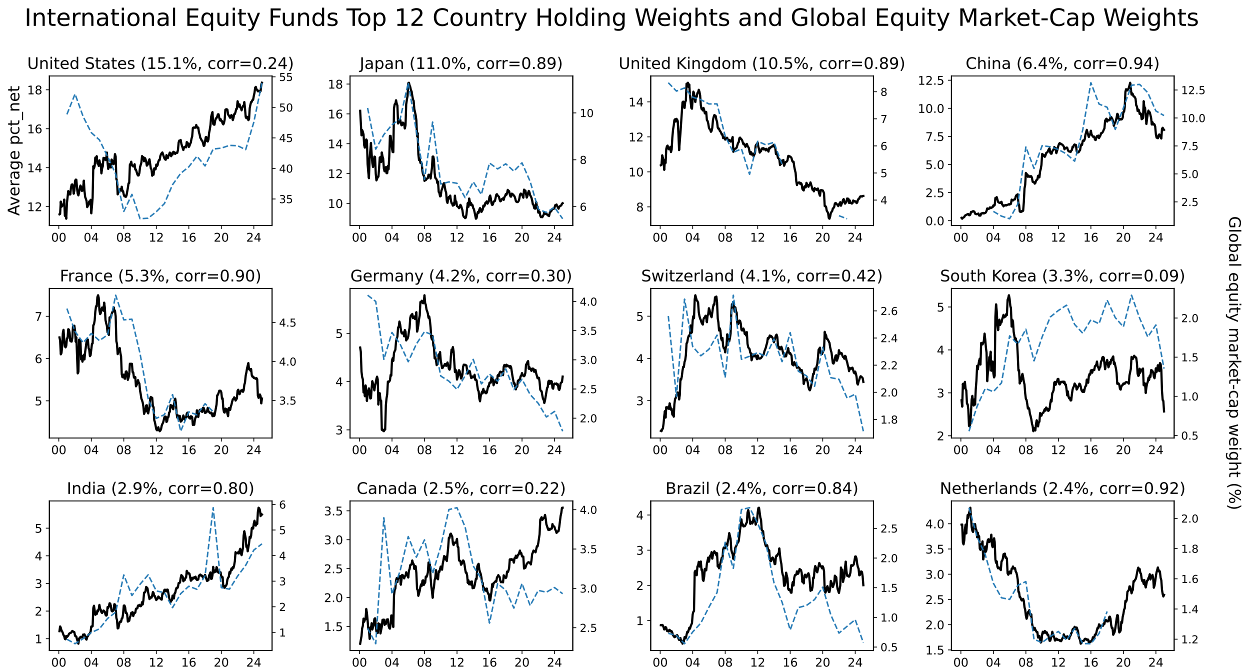

Figure A.2: International Equity Fund Country Exposure and Global Equity Market-Cap Weights. This figure compares international equity funds' country exposure with each country's share of global equity market capitalization from January 2000 to December 2024. The figure displays the 12 countries with the largest average fund exposure over the sample period. The solid black line reports the monthly average portfolio weight invested in equities domiciled in each country, shown on the left axis, while the dashed blue line reports the country's year-end global equity market-cap weight, shown on the right axis. Numbers in parentheses report full-sample average fund portfolio weights, and correlations compare year-end fund exposure with global equity market-cap weights.

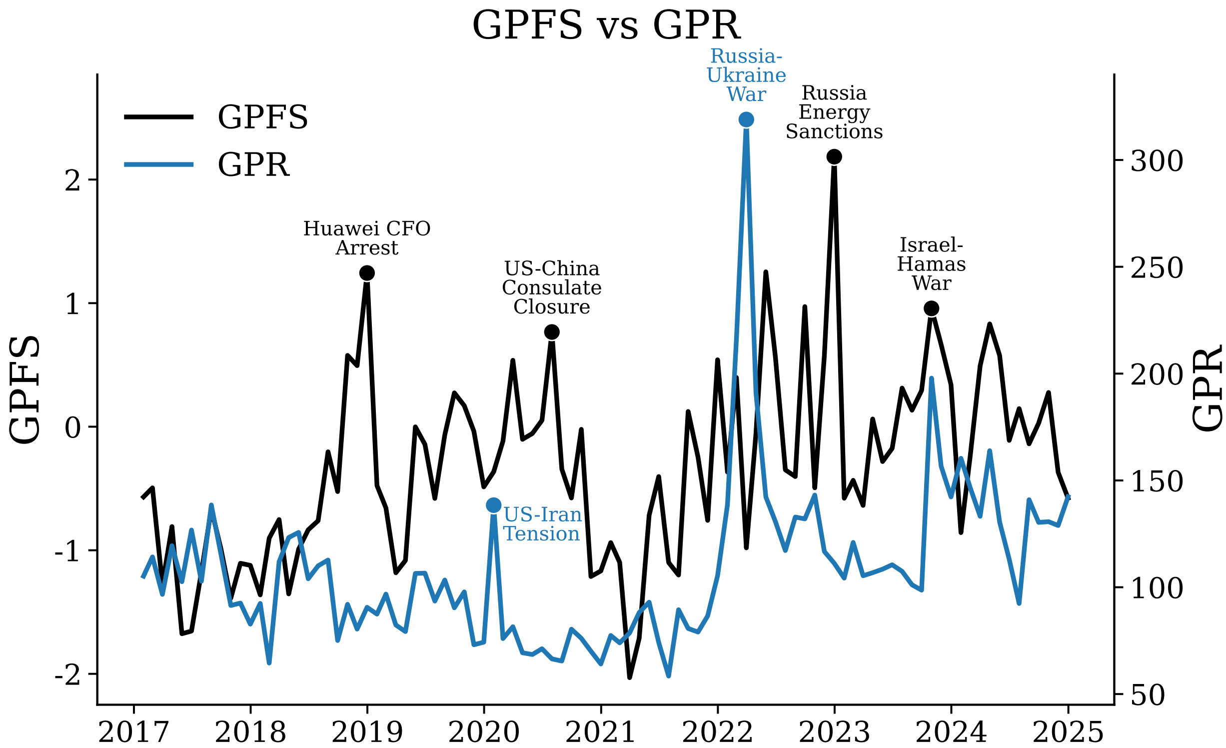

Figure A.3: GPFS versus GPR. This figure compares monthly GPFS with the geopolitical risk index of Caldara and Iacoviello (2022) from January 2017 to December 2024. The black line plots GPFS on the left axis, and the blue line plots GPR on the right axis. Markers on the GPFS series label the Huawei CFO arrest in December 2018, the U.S.–China consulate closure in July 2020, Russia energy sanctions in December 2022, and the Israel–Hamas war in October 2023. Markers on the GPR series label U.S.–Iran tensions in January 2020 and the Russia–Ukraine war in March 2022.

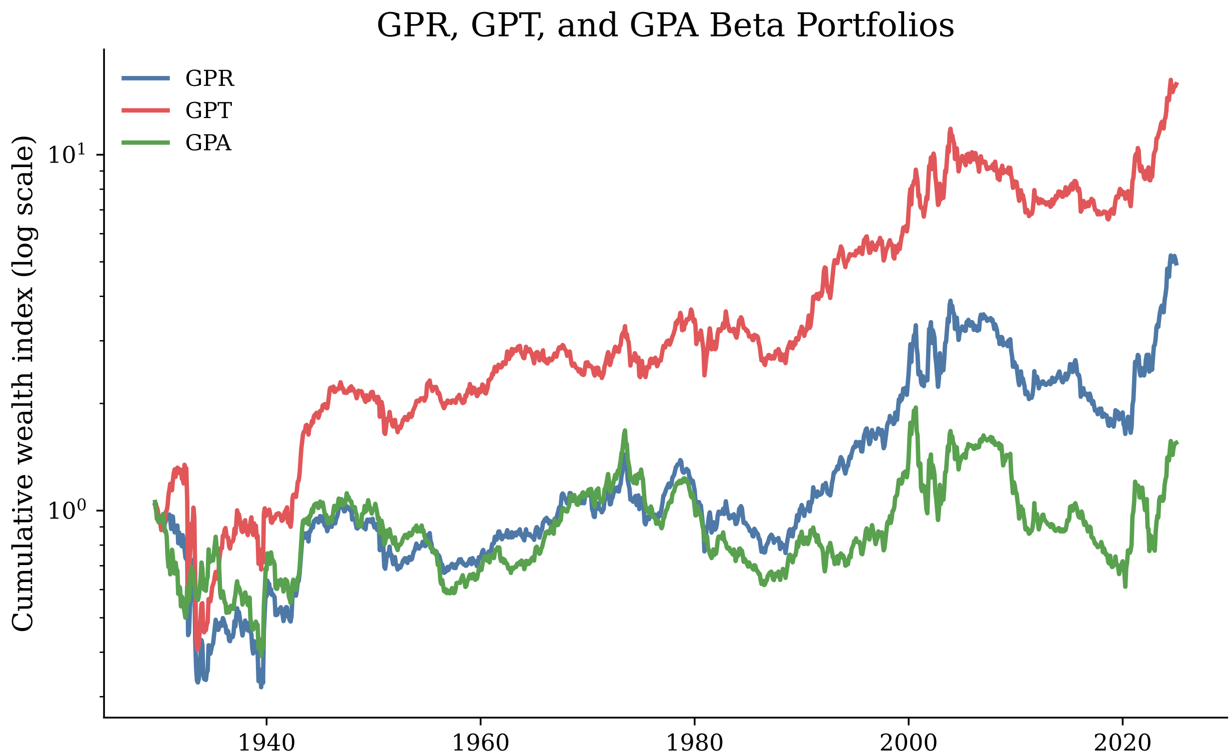

Figure A.4: GPR, GPT, and GPA Beta Portfolios. This figure plots cumulative wealth indices on a log scale from Janurary 1930 to December 2024 for value-weighted high-minus-low portfolios sorted on stock-level betas with respect to the historical GPR, GPT, and GPA indices of Caldara and Iacoviello (2022). Betas are estimated from 36-month rolling regressions of monthly excess stock returns on the negative growth rate of each index. The stock universe consists of CRSP U.S. common stocks listed on NYSE, AMEX, or Nasdaq, excluding financial and utility firms. Stocks are sorted into quintiles each month using NYSE breakpoints, and portfolio returns are value-weighted excess returns of the high-beta quintile minus the low-beta quintile.

	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.5: U.S. Industry Foreign Production Reliance in 2017. This heatmap reports the source-country composition of upstream production requirements for U.S. industries in 2017. Columns are U.S. industries, rows are input source countries, and each cell gives the percentage of an industry's requirements attributable to that country. The bottom rows summarize foreign and domestic U.S. input reliance, and the rightmost column reports the average across the displayed manufacturing industries. Requirements are computed from the Leontief inverse matrix using the OECD Inter-Country Input–Output (ICIO) tables.

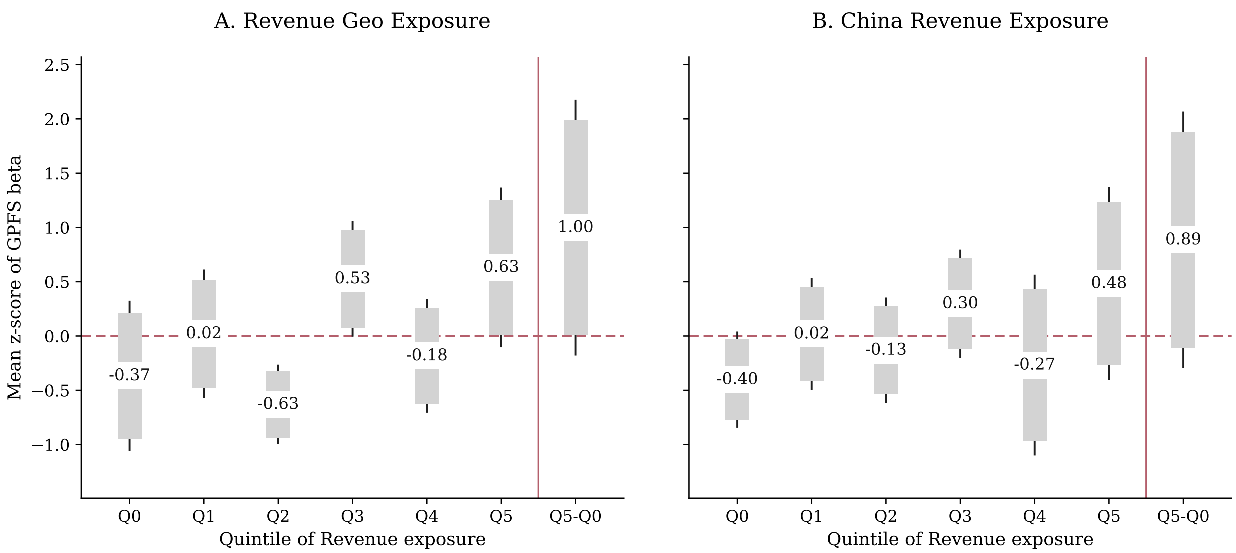

Figure A.6: GPFS Betas by Revenue-Based Geopolitical Exposure. This figure reports mean standardized GPFS betas across revenue-exposure portfolios from 2017 to 2024. Panel A sorts stocks by revenue-based geopolitical exposure, and Panel B sorts stocks by China revenue exposure. Q0 contains firms with zero exposure, while Q1–Q5 sort exposed firms into quintiles using NYSE breakpoints. For each year and portfolio, GPFS beta is averaged using June market-capitalization weights and then standardized within year. The plotted values are time-series means of these standardized portfolio betas. Q5–Q0 reports the difference between the highest-exposure and zero-exposure portfolios. Gray boxes show 90% confidence intervals, and vertical lines show 95% confidence intervals.

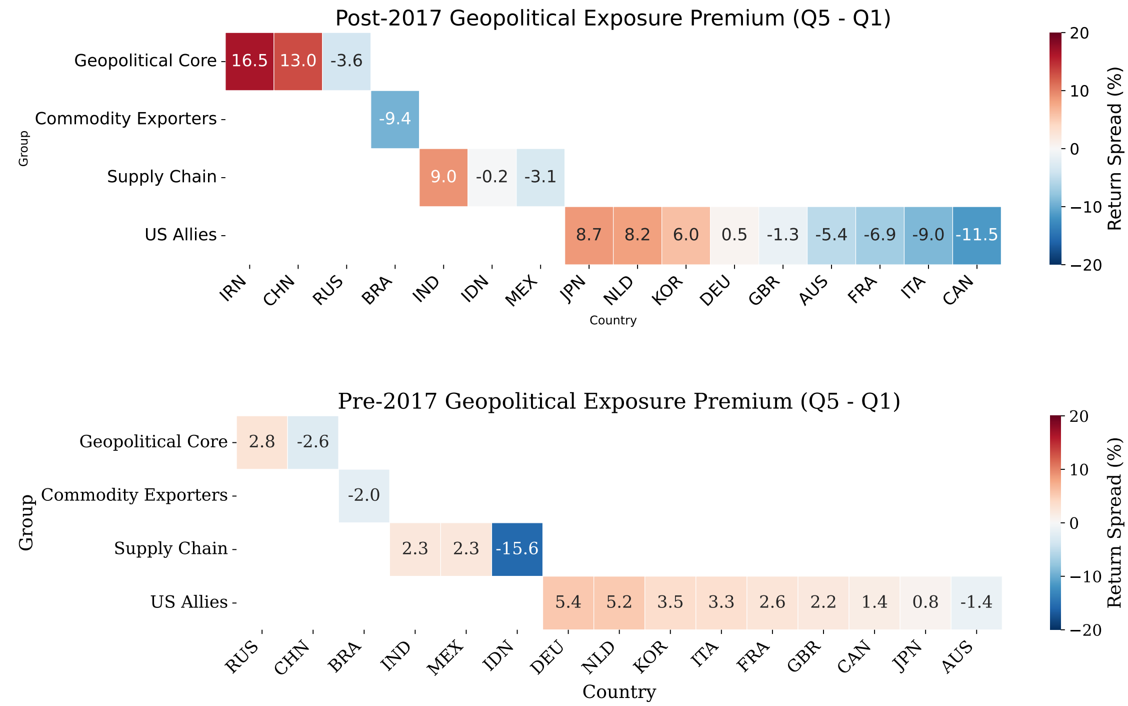

Figure A.7: Geopolitical Exposure Premium by Country. This figure reports the high-minus-low return spread (Q5 minus Q1) for portfolios sorted on country-specific revenue exposure. For each country c, exposure is measured as the share of firm revenue generated from country c, lagged by one year. Each 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.

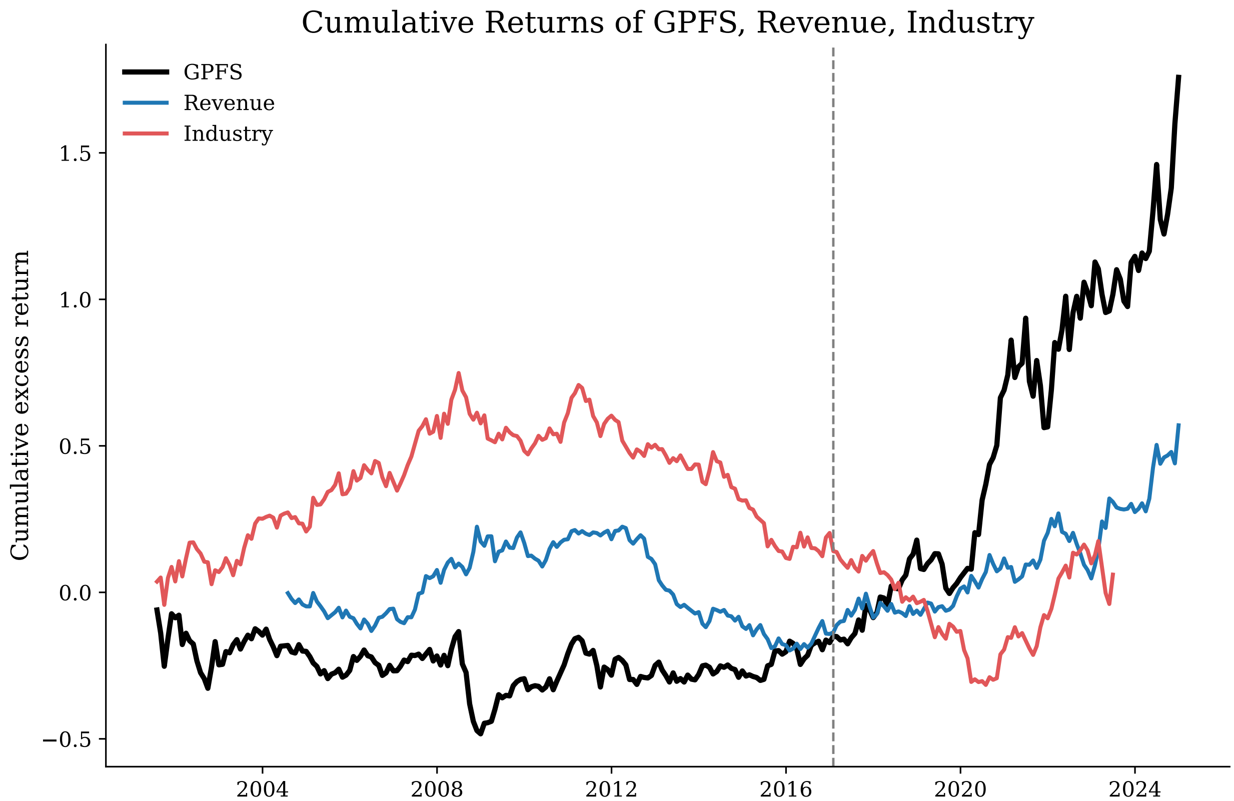

Figure A.8: GPFS, Industry, and Revenue Portfolios. This figure compares cumulative excess returns for three value-weighted high-minus-low portfolios based on GPFS beta, firm-level revenue-based geopolitical exposure, and industry-level geopolitical exposure. The GPFS-beta portfolio sorts stocks on their January–June average GPFS beta; the revenue-exposure portfolio sorts stocks on lagged firm-level revenue-based geopolitical exposure; and the industry-exposure portfolio sorts stocks on industry-level geopolitical exposure. All portfolios are rebalanced each June, use NYSE breakpoints, and hold the $Q5 - Q1$ spread from July of year t to June of year $t + 1$. For the revenue-exposure sort, breakpoints are applied among positive-exposure firms, with zero-exposure firms kept separately. The sample period is July 2001–December 2024 for the GPFS portfolio, July 2004–December 2024 for the revenue portfolio, and July 2001–June 2023 for the industry portfolio. The vertical dashed line marks January 2017.

Table A.1: UNGA Resolution Counts and Country Ideal Points. This table reports summary statistics for annual United Nations General Assembly (UNGA) voting data from 2000 to 2024. Panel A reports the number of final-passage resolutions by year, both in total and by issue category. Panel B reports UNGA ideal points. The first row averages the annual cross-sectional distribution of country ideal points. The remaining rows report time-series statistics for the 15 countries with the highest average portfolio exposure among U.S. international equity mutual funds from January 2000 to December 2024. Columns report the mean, standard deviation, 25th percentile, median, and 75th percentile across annual observations.

	Mean	SD	P25	Median	P75
Panel A: Resolution counts					
All final-passage resolutions	82	12	73	78	89
Peace, security, and disarmament	23	7	17	19	30
Israel/Palestine and related regional conflict	20	4	18	20	22
International law, courts, and sovereignty	13	4	11	12	14
Human rights, equality, and democracy	8	4	4	7	11
Transnational governance, cyber, and crime	6	3	4	6	8
Humanitarian protection, migration, and conflict-related rights	3	2	2	3	5
UN institutional affairs	3	3	0	2	5
Development and economic affairs	3	3	1	2	4
Environment, resources, health, and knowledge	1	2	0	1	1
Panel B: Ideal points					
Average annual cross-section	-0.08	0.80	-0.62	-0.33	0.70
United States	2.51	0.16	2.43	2.53	2.64
United Kingdom	1.58	0.09	1.53	1.60	1.63
Canada	1.40	0.24	1.21	1.35	1.50
France	1.38	0.07	1.35	1.39	1.43
Australia	1.25	0.13	1.20	1.25	1.34
Germany	1.08	0.12	0.98	1.14	1.17
Netherlands	1.04	0.07	0.99	1.04	1.09
Italy	0.98	0.09	0.91	0.94	1.06
Sweden	0.86	0.11	0.79	0.85	0.90
Switzerland	0.74	0.10	0.66	0.73	0.78
South Korea	0.73	0.14	0.62	0.71	0.81
Japan	0.69	0.08	0.63	0.69	0.75
Brazil	-0.20	0.26	-0.47	-0.17	-0.02
India	-0.37	0.19	-0.55	-0.34	-0.22
China	-0.65	0.23	-0.75	-0.60	-0.52

Table A.2: Fund Exposure and Future Fund Flows. This table reports panel regressions of monthly share-class flows on the fund's lagged geopolitical exposure and its interaction with geopolitical event indicators. Fund geopolitical exposure is computed by weighting each country-level geopolitical distance by the fund's portfolio weight in that country. For each geopolitical-risk series, $Event_t$ equals one in months when the series is in the top quartile of its 2000–2024 distribution. GPR denotes the Geopolitical Risk Index of Caldara and Iacoviello (2022); GPT and GPA denote its threat and act components; WAR denotes the news-based war discourse risk indicator of Hirshleifer, Mai, and Pukthuanthong (2025b). Panel A reports regression estimates for 2000–2016, and Panel B reports estimates for 2017–2024. WAR estimates are not reported in Panel B because the WAR series is available only through October 2019. Additional controls include lagged flow, current and lagged excess returns, and size, measured by log lagged share-class total net assets. Exposure, lagged flow, and excess-return controls are standardized to have mean zero and standard deviation one over the 2000–2024 full sample. All specifications include share-class and month fixed effects. t-statistics in brackets use two-way clustered standard errors by share class and month.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: 2000–2016				*Panel B: 2017–2024*		
	$Flow_{s,t}$				$Flow_{s,t}$		
	GPR	GPT	GPA	WAR	GPR	GPT	GPA
$Exposure_{s,t-1} \times Event_t$	-0.48***	-0.43**	-0.31*	-0.27**	-0.23***	-0.29***	-0.38***
	[-2.72]	[-2.30]	[-1.68]	[-2.27]	[-2.58]	[-3.42]	[-3.73]
$Exposure_{s,t-1}$	0.50*	0.45*	0.48*	0.48*	-0.27	-0.18	-0.30
	[1.92]	[1.79]	[1.79]	[1.92]	[-1.46]	[-0.97]	[-1.63]
$Flow_{s,t-1}$	-0.19*	-0.19*	-0.19*	-0.19*	0.55	0.55	0.55
	[-1.90]	[-1.90]	[-1.89]	[-1.90]	[1.29]	[1.29]	[1.29]
$ExRet_{s,t}$	0.22	0.21	0.22	0.19	0.04	0.04	0.05
	[1.63]	[1.59]	[1.63]	[1.45]	[0.62]	[0.54]	[0.63]
$ExRet_{s,t-1}$	0.60***	0.60***	0.60***	0.58***	0.28***	0.26***	0.27***
	[7.81]	[7.81]	[7.75]	[7.60]	[3.54]	[3.43]	[3.45]
$Log(TNA_{s,t-1})$	-2.01***	-2.00***	-2.00***	-1.99***	-2.48***	-2.48***	-2.49***
	[-3.20]	[-3.20]	[-3.19]	[-3.20]	[-7.88]	[-7.88]	[-7.90]
Share-class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	249,188	249,188	249,188	249,188	189,893	189,893	189,893
R^2	0.001	0.001	0.001	0.001	0.003	0.003	0.003

Table A.3: FF49–OECD ICIO Industry Mapping. This table maps Fama–French 49 industries to OECD ICIO industries and broad OECD categories. The mapping is constructed manually based on industry descriptions.

FF49 Name	OECD Name	OECD Industry	OECD 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

Table A.4: Mapping CRSP Securities to FactSet Geographic Revenue Shares. This table reports the annual link sequence used to assign FactSet GeoRev country-level revenue shares to CRSP stocks. Links are evaluated as of June 30 of year t, and the final output is a stock-year-country revenue share panel.

Step	Mapping	Source file	Selection rule	Output
1	`permno` → `entity_id`	WRDS CRSP–FactSet linking table	Keep security-level links whose interval [`link_bdate`, `link_edate`] contains June 30 of year t. If multiple links are valid, retain the link with the most recent `link_bdate`.	One `entity_id` per (`permno`, t)
2	`entity_id` → `company_id`	FactSet company file	Keep primary company records with `pri = Y`. Retain records whose interval [`start`, `end`] contains June 30 of year t. If multiple records are valid, retain the one with the most recent `start`.	One `company_id` per (`entity_id`, t)
3	`company_id` → GeoRev report identifier	FactSet GeoRev report file	Keep reports whose reporting period [`period_start_date`, `period_end_date`] contains June 30 of year t. If multiple reports are valid, retain the report with the latest end date.	One report identifier per (`company_id`, t)
4	Report identifier → country revenue shares	FactSet GeoRev report-item and region files	Keep current report items and merge region identifiers to ISO3 country codes. If multiple items exist for the same report-country pair, retain the item with the most recent start date.	Firm-year-country revenue share panel (i, t, c)

Table A.5: GPFS-Mimicking Factor Constructed from Equity Anomaly Portfolios. This table reports annualized risk premia and annualized alphas for SPCA mimicking factors of $-GPFS$, together with their betas estimated from value-weighted high-minus-low quintile portfolios sorted on stock-level GPFS betas. The mimicking factors are constructed from monthly U.S. equity anomaly portfolio returns using supervised principal component analysis (SPCA), following Giglio, Xiu, and Zhang (2025). The test assets include equal- and value-weighted anomaly portfolios from the Open Source Asset Pricing (OSAP) dataset of Chen and Zimmermann (2022) and the factor dataset (JKP) from Jensen, Kelly, and Pedersen (2023). The test assets consist of 3,010 OSAP decile portfolios based on 163 anomaly signals and 306 JKP long-short portfolios based on 153 anomaly signals. For each dataset, we use both value-weighted and equal-weighted portfolios and retain only portfolios with complete monthly returns over January 2000–December 2024. we report four expanding-window out-of-sample SPCA specifications: 4 factors with 10% of test assets, 5 factors with 10%, 5 factors with 20%, and 6 factors with 10%. For each specification, the SPCA weights are estimated using an expanding training window that begins in January 2000. The first out-of-sample mimicking factor return is formed in July 2001 using data through June 2001, and the training window then expands by one month at a time. The weights are rescaled so that the in-sample fitted mimicking factor has an annualized volatility of 20%, close to that of the market factor. Premium and alphas are reported in annualized percentage points. ICAPM alphas are based on the intertemporal factor model of Chabi-Yo, Gonçalves, and Loudis (2025). H-L Ret. β is the slope from regressing the high-minus-low stock GPFS-beta portfolio return on the mimicking factor. Panel A reports results for 2017–2024, and Panel B reports results for 2001–2016. Newey–West t-statistics are reported in brackets.

# of Factors	% of Portfolios	Premium	CAPM α	ICAPM α	FFC α	FF5 α	H-L Ret. β
Panel A: Post period, 2017–2024							
4	10%	20.21***	12.63**	11.29***	11.43**	12.01**	0.383***
		[2.94]	[2.18]	[2.72]	[2.08]	[2.05]	[3.91]
5	10%	20.72***	13.59***	12.84***	13.11***	12.73**	0.374***
		[3.51]	[2.76]	[3.11]	[2.59]	[2.49]	[2.68]
5	20%	19.85***	11.46**	10.73***	8.23*	9.68*	0.330**
		[3.24]	[2.42]	[2.58]	[1.74]	[1.91]	[2.38]
6	10%	15.78***	9.61*	9.46*	11.61**	9.96**	0.258*
		[2.76]	[1.84]	[1.93]	[2.27]	[2.09]	[1.86]
Panel B: Pre period, 2001–2016							
4	10%	1.34	-1.12	-1.19	-0.71	-1.34	0.476***
		[0.29]	[-0.28]	[-0.26]	[-0.18]	[-0.33]	[3.68]
5	10%	4.90	2.21	2.43	1.81	1.36	0.590***
		[1.20]	[0.67]	[0.64]	[0.54]	[0.40]	[5.23]
5	20%	0.45	-2.01	-2.99	-2.58	-3.33	0.476***
		[0.10]	[-0.52]	[-0.68]	[-0.73]	[-0.84]	[3.41]
6	10%	4.64	2.27	3.60	2.13	1.82	0.563***
		[1.22]	[0.74]	[1.05]	[0.67]	[0.59]	[4.77]

Table A.6: GPFS Exposure and Future Firm Investment. This table reports firm-quarter panel regressions of future investment, $\text{Investment}_{i,q+h}$, on the interaction between quarterly GPFS and firm-level GPFS beta. Quarterly GPFS is the three-month average of monthly GPFS, and $\beta^{\text{GPFS}}_{i,q}$ is the firm-level average of monthly stock GPFS betas over quarter q. Controls include $\beta^{\text{GPFS}}_{i,q}$, cash flow, Tobin's Q, and lagged investment. All Variables are standardized within each estimation sample before forming the interaction term. Regressions include firm and quarter fixed effects. Panel A reports 2001–2016 results, and Panel B reports 2017–2024 results. t-statistics in brackets are two-way clustered by firm and quarter.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: 2001–2016					*Panel B: 2017–2024*				
	$\text{Investment}_{i,q+h}$					$\text{Investment}_{i,q+h}$				
	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
$\text{GPFS}_q \times \beta^{\text{GPFS}}_{i,q}$	0.007	0.007*	0.001	-0.006	-0.009*	-0.001	-0.008	-0.017***	-0.014**	-0.012**
	[1.48]	[1.69]	[0.27]	[-1.61]	[-1.92]	[-0.13]	[-1.45]	[-2.87]	[-2.17]	[-2.32]
$\beta^{\text{GPFS}}_{i,q}$	0.003	0.006	0.010**	0.012**	0.013**	-0.018**	-0.018**	-0.013	-0.008	0.002
	[0.78]	[1.44]	[2.00]	[2.13]	[2.07]	[-2.43]	[-2.33]	[-1.52]	[-1.00]	[0.24]
$\text{Cash flow}_{i,q}$	0.061***	0.100***	0.106***	0.082***	0.075***	0.065***	0.056***	0.042**	0.026*	0.025
	[4.90]	[4.19]	[4.71]	[3.89]	[3.73]	[3.81]	[3.16]	[2.00]	[1.79]	[1.57]
Tobin's $Q_{i,q}$	0.082***	0.131***	0.144***	0.146***	0.141***	0.081***	0.128***	0.143***	0.125***	0.126***
	[10.16]	[11.29]	[11.17]	[12.28]	[12.42]	[6.92]	[6.02]	[6.54]	[6.25]	[6.32]
$\text{Investment}_{i,q-1}$	0.440***	0.298***	0.217***	0.184***	0.103***	0.432***	0.292***	0.206***	0.161***	0.085***
	[58.65]	[46.04]	[31.82]	[27.89]	[15.09]	[36.76]	[24.58]	[14.73]	[10.35]	[4.91]
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	184,199	180,049	176,227	172,555	168,896	80,744	79,063	77,533	76,053	74,600
R^2	0.220	0.123	0.080	0.065	0.033	0.232	0.128	0.076	0.052	0.024

Table A.7: GPFS Exposure, Future Earnings, and Cash Flow. This table reports firm-quarter panel regressions of future earnings and cash flow on the interaction between quarterly GPFS and firm-level GPFS beta. Panel A uses future earnings $\text{Earnings}_{i,q+h}$, measured by ROA, as the dependent variable, and Panel B uses future cash flow, $\text{CashFlow}_{i,q+h}$. Quarterly GPFS is the three-month average of monthly GPFS, and $\beta_{i,q}^{\text{GPFS}}$ is the firm-level average of monthly stock GPFS betas over quarter q. The main regressor is $\text{GPFS}_q \times \beta_{i,q}^{\text{GPFS}}$, and regressions control for $\beta_{i,q}^{\text{GPFS}}$. All variables are standardized within each estimation sample before forming the interaction term. Regressions include firm and quarter fixed effects. Columns report horizons $h = 0, \ldots, 4$ separately for the 2001–2016 and 2017–2024 samples. t-statistics in brackets are two-way clustered by firm and quarter.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			2001–2016					*2017–2024*		
	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
Panel A: $\text{Earnings}_{i,q+h}$										
$\text{GPFS}_q \times \beta_{i,q}^{\text{GPFS}}$	0.010*	0.007	0.003	0.001	0.001	0.011**	0.007	0.005	0.003	0.003
	[1.75]	[1.40]	[0.69]	[0.33]	[0.23]	[2.24]	[1.35]	[1.31]	[0.84]	[0.79]
$\beta_{i,q}^{\text{GPFS}}$	0.001	0.004	0.008	0.011*	0.011**	0.005	0.001	-0.003	-0.002	0.001
	[0.17]	[0.74]	[1.39]	[1.93]	[2.10]	[0.64]	[0.12]	[-0.36]	[-0.21]	[0.10]
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196,663	196,047	192,067	187,981	183,942	91,781	91,780	90,452	89,018	87,541
R^2	0.000	0.000	0.000	0.001	0.001	0.000	-0.000	-0.000	-0.000	-0.000
Panel B: $\text{CashFlow}_{i,q+h}$										
$\text{GPFS}_q \times \beta_{i,q}^{\text{GPFS}}$	-0.000	-0.003	-0.003	-0.001	0.002	0.004	0.011	0.007	0.007	-0.000
	[-0.07]	[-1.53]	[-1.20]	[-0.23]	[0.49]	[0.85]	[0.98]	[0.62]	[0.59]	[-0.03]
$\beta_{i,q}^{\text{GPFS}}$	-0.008	-0.007	-0.003	-0.002	-0.004	-0.000	0.002	0.014	0.022	0.021
	[-1.08]	[-1.08]	[-0.42]	[-0.44]	[-0.69]	[-0.02]	[0.24]	[1.15]	[1.38]	[1.39]
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	195,988	192,170	187,988	184,008	180,093	90,632	89,477	88,061	86,617	85,195
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000