Hedge Fund Performance and the U.S.-China Tension

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Abstract

This paper investigates whether hedge funds are systematically rewarded for their exposure to U.S.–China tensions. We construct a return-based measure of fund-level exposure ("tension beta") using a novel news-based index of U.S.–China tension orthogonalized to macroeconomic and policy uncertainty. We find that funds with higher tension betas earn significantly higher out-of-sample excess returns and risk-adjusted alphas. This positive relation cannot be explained by conventional risk factors or fund characteristics. Form 13F holdings show that manager families with more hedge-like fund-return exposure also hold long-equity portfolios with more favorable sensitivity to rising tension. We further show that a subset of directional and semi-directional funds actively time U.S.–China tension: they maintain higher exposure in normal periods but strategically reduce exposure during high-tension episodes. In contrast, non-directional funds show no evidence of tension timing.

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1 Introduction

Geopolitical risk has emerged as a central driver of financial market dynamics, reflecting escalating strategic tensions between major global powers. The U.S.-China rivalry, in particular, has evolved into a sustained and multidimensional source of uncertainty, spanning trade, investment, technology, and national security domains. Unlike other short-lived geopolitical shocks, this bilateral conflict is characterized by repeated retaliatory measures and institutionalized decoupling efforts, creating persistent policy uncertainty. Such tensions have the potential to shape firm behavior, disrupt capital flows, and alter asset pricing. For sophisticated institutional investors, especially hedge funds, accounting for these risks may be increasingly integral to return generation and risk management.

A growing body of research has documented that policy and geopolitical uncertainties affect financial markets. Pástor and Veronesi (2012, 2013) develop theoretical models linking political risk to time-varying discount rates and expected returns. Baker, Bloom, and Davis (2016) introduce the Economic Policy Uncertainty (EPU) index and show that elevated policy uncertainty depresses investment and asset prices. Similarly, Caldara and Iacoviello (2022) construct a Geopolitical Risk (GPR) index and find that geopolitical threats reduce firm investment and cross-border M&A activity. More recent work demonstrates that firms more exposed to geopolitical risk earn higher expected returns, suggesting that such uncertainty may represent a priced risk factor (Sheng, Sun, & Wang, 2025).

While prior studies have established the relevance of political and geopolitical risk at the stock level, relatively little is known about how institutional investors, especially hedge funds, respond to sustained geopolitical tensions. Hedge funds are uniquely positioned to dynamically manage macro risk exposures due to their flexible mandates and timing capabilities (Agarwal, Daniel, & Naik, 2009; Fung & Hsieh, 1997). More related to this paper, Liang, Wang, and Zhou (2020) and Chen et al. (2022) find empirical evidence that hedge funds adjust exposures to economic policy uncertainty and electoral cycles, respectively. However, most of this literature focuses on the general policy uncertainty or one-off events, leaving open the question of how hedge funds navigate bilateral, structural geopolitical conflicts such as the U.S.-China tension.

This paper addresses that gap by examining whether hedge funds are exposed to the U.S.-China tension and how they dynamically manage the associated risk. We construct a novel return-based measure of fund-level exposure, tension beta, and test whether it is associated with fund performance and timing ability. Specifically, we address three research questions. First and most importantly, do hedge fund returns exhibit systematic exposure to U.S.-China tension? Second, is this exposure priced in the cross-section of hedge fund returns? Third, do hedge funds demonstrate skill in dynamically adjusting their exposures to U.S.-China tension developments—i.e., do they time the risk?

To answer these questions, we estimate fund-specific exposure to bilateral tensions using the U.S.–China Tension (UCT) index developed by Rogers, Sun, and Sun (2024). The index quantifies the intensity of bilateral conflict by measuring the share of articles in major U.S. newspapers that reference both countries alongside contentious issues and tension-related terms. The keyword set is derived from a combination of human-labeled samples and machine-learning techniques, ensuring coverage of domains such as trade, technology, human rights, and security. The index isolates U.S.-China–specific tensions and exhibits limited correlation with the broader geopolitical measure of Caldara and Iacoviello (2022). This design provides a directional, time-varying indicator of geopolitical risk that is specific to U.S.-China relations.

By construction, the raw UCT Index remains correlated with broader macroeconomic fundamentals, which are known to affect the cross-section of hedge fund returns (Bali, Brown, & Caglayan, 2014). Moreover, as the raw UCT index captures policy-related elements such as tariffs, export controls, and sanctions, it is also positively correlated with the EPU index of (Baker, Bloom, & Davis, 2016), especially when U.S.-China tension is the root cause of policy uncertainty (Davis, 2019). To isolate variation in the UCT index that is not driven by broader macroeconomic or economic policies, we orthogonalize the index with respect to the EPU index and a set of macroeconomic variables shown to influence hedge fund returns (see Section 2.2). The orthogonalized index offers a cleaner measure of U.S.-China tension not confounded by business cycle and economic policy effects.

We then estimate fund-level tension exposure ("tension beta") by regressing fund excess returns on the first difference of the orthogonalized UCT index using rolling-window regressions. This approach captures each fund's dynamic sensitivity to innovations in U.S.-China tension, reflecting how hedge funds adjust to new information or shocks from the bilateral relationship. The empirical results reveal two key findings. First, there is substantial cross-sectional variation in hedge funds' tension exposures. Estimated tension betas differ meaningfully across funds, indicating that geopolitical risk is not a uniform or passively borne factor. Second, funds with higher tension beta earn significantly higher excess returns and risk-adjusted returns, even after controlling for common fund-level characteristics and fixed effects.

The hedge-like sensitivity observed in fund returns has a counterpart in disclosed equity portfolios. Using SEC Form 13F filings, we construct a portfolio-based measure of tension exposure from the securities held by each manager family. Manager families with higher return-based tension betas also hold long-equity portfolios with more positive tension exposure. This correspondence appears both in exposure levels and in quarter-to-quarter changes in exposure rankings. The holdings evidence thus connects funds' differing responses to geopolitical escalation to observable portfolio positions.

Next, we explore whether hedge funds can time the U.S.-China tensions. Following the pioneering work of Treynor and Mazuy (1966) and the more recent works discussing the timing ability of hedge funds (Cao et al., 2013; Chen, Han, & Pan, 2021; Liang, Wang, & Zhou, 2020), we estimate fund-level timing coefficients, which capture their timing ability with respect to the U.S.-China tensions. Specifically, we test whether hedge funds adjust their market exposure in response to tension shocks. We find that hedge funds increase market exposure during periods of heightened tension, consistent with proactive timing skill. Similar to Cao et al. (2013), we examine the cross-sectional distribution of timing coefficients and implement a bootstrap procedure to test whether observed timing ability could arise by chance. The analysis confirms that the estimated timing coefficients are unlikely to be driven by luck, as their empirical distribution significantly deviates from the bootstrapped null of static exposures. Notably, the evidence of timing skill is concentrated among directional and semi-directional hedge funds.

We further investigate whether hedge funds actively time their exposure to U.S.–China tension. Funds with stronger timing ability maintain higher exposure in normal periods but strategically reduce exposure when tensions escalate, suggesting an attempt to harvest premia in tranquil times while avoiding downside risks during high-tension episodes. This dynamic is concentrated among directional and semi-directional funds, which appear to tactically manage exposures in response to changing geopolitical conditions. In contrast, non-directional funds reduce exposure more uniformly regardless of the tension environment, reflecting a more defensive orientation rather than active timing. These findings underscore that the U.S.-China tension is not only priced in the cross-section of hedge fund returns but also strategically timed by a subset of hedge funds with directional mandates.

This paper contributes to several strands of literature. First, it adds to the growing body of research on geopolitical risk and asset pricing by introducing a bilateral, directionally disaggregated measure of geopolitical risk into the hedge fund domain.

While prior studies have documented that economic policy uncertainty (Baker, Bloom, and Davis, 2016) and global geopolitical risk (Caldara and Iacoviello, 2022; Sheng, Sun, and Wang, 2025) influence asset returns, this paper shows that U.S.-China tension, orthogonal to those aggregate measures, is also a priced source of risk. Second, this study extends the literature on hedge fund performance by presenting more evidence on cross-sectional determinants of hedge fund returns. Prior literature has documented hedge fund returns are cross-sectionally related to fund-level characteristics, such as manager incentives (Agarwal, Daniel, & Naik, 2009; Gupta & Sachdeva, 2025), distinctiveness of investment strategy (Sun, Wang, & Zheng, 2012), share restrictions (Aragon, 2007) and systematic risks such as liquidity risk (Sadka, 2010) and volatility of aggregated volatility (Agarwal, Arisoy, & Naik, 2017), etc. This paper shows that hedge funds exhibit economically meaningful heterogeneity in how their exposure to U.S.-China tension relates to returns. Third, this paper contributes to the literature on the timing ability of hedge funds. Chen and Liang (2007) find evidence of hedge funds' market timing ability at both the aggregate and fund levels. Similarly, other studies find evidence of hedge funds' timing ability with respect to liquidity (Cao et al., 2013), sentiment (Chen, Han, & Pan, 2021), and economic policy uncertainty (Liang, Wang, & Zhou, 2020). Moreover, Osinga, Schauten, and Zwinkels (2021) document that one-third of hedge funds have factor timing ability on at least one of the Fung and Hsieh (2004) seven factors. This paper adds to the literature of the timing skill of the asset management industry by showing hedge funds' timing ability on the U.S.-China tension. Finally, the paper complements its return-based analysis with holdings-based evidence on geopolitical exposure. The analysis brings together two perspectives on hedge fund exposure: how fund returns respond to tension and how the securities in managers' disclosed long-equity portfolios are exposed to it. Their positive correspondence provides portfolio-based support for the exposure measure underlying the performance results. Taken together, the results highlight the importance of U.S.-China tension as a persistent, institutionalized source of priced risk and suggest that hedge funds act as an active channel through which such risks are priced and timed in financial markets.

The remainder of the paper is organized as follows. Section 2 describes the data and variable construction. Section 3 presents the empirical results on fund performance to geopolitical tension. Section 4 examines the fund-level timing ability and determinants of tension exposure. Section 5 concludes.

2 Data

2.1 Hedge Fund Data

The hedge fund data used in this study are obtained from the Lipper TASS and HFR databases, both widely used in the hedge fund literature for providing detailed information on fund performance, characteristics, and strategies. We focus on monthly net-of-fee returns and accompanying fund attributes for the period from January 2002 to December 2024, which covers multiple episodes of elevated U.S.-China geopolitical tension. We follow a common filtering procedure consistent with the empirical literature (e.g., Cao et al., 2013; Chen, Han, and Pan, 2021). First, we restrict our analysis to equity-oriented strategies, excluding funds classified under emerging markets, fixed income arbitrage, managed futures, option strategies, and dedicated short bias. To mitigate backfill bias, we exclude the first 12 months of reported returns for each fund. We further require each fund to have a minimum of 24 non-missing monthly return observations, ensuring sufficient time-series variation for exposure estimation. In addition, we retain only USD-denominated funds to avoid currency-driven return heterogeneity, and require that reported assets under management (AUM) exceed $1 million[1]. Table 1 reports summary statistics for hedge fund variables. The average excess return is 0.52% per month, with a standard deviation of 3.88%. Alphas are positive across all factor models, with the mean ranging from 0.22% under the seven-factor

[1]We apply $5 million as an alternative threshold, and the results obtained are similar as our main findings.

model to 0.32% under the eleven-factor model, though they exhibit sizable dispersion. The average AUM is $419 million, with a median of about $102 million, highlighting the skewness in fund size distribution. The statistics also show that the median fund charges a 1.5% management fee and a 20% incentive fee, consistent with the industry norm. About 84% of funds employ a high-water mark provision and 62% report using leverage. The median redemption notice period and lock-up period are 30 days and zero year, respectively.

2.2 U.S.-China Tension

To capture geopolitical risk specific to the U.S.–China bilateral relationship, we employ the U.S.–China Tension (UCT) index developed by Rogers, Sun, and Sun (2024). The index is constructed from leading U.S. newspapers and measures the share of articles that simultaneously reference (i) the United States and China, (ii) contentious bilateral issues such as trade, technology, or security, and (iii) words indicative of tension. The keyword set is derived from a combination of human-labeled articles and machine-learning techniques, ensuring that the index reflects U.S.–China–specific conflicts rather than broader uncertainty. For validation, the index aligns closely with business concerns (e.g., U.S. Chamber of Commerce surveys and earnings-call discussions), policy stances (anti-China legislation in Congress, presidential speeches), and international indicators (U.N. voting disagreement). Economically, higher levels of UCT are associated with significant declines in U.S. firm investment, supply-chain reallocation away from China, and cross-sectional stock return patterns, with effects that are stronger among firms more exposed to China. Compared with broader measures such as the geopolitical risk index of Caldara and Iacoviello (2022) or the economic policy uncertainty index of Baker, Bloom, and Davis (2016), the UCT index provides a more targeted and directional measure of bilateral geopolitical risk, isolating a channel that is distinct from conventional uncertainty proxies.

An important concern with directly using the raw UCT Index is its potential correlation with broader macroeconomic fundamentals, which are known to influence the cross-section of hedge fund returns (Bali, Brown, & Caglayan, 2014). Moreover, because the construction of UCT incorporates elements of economic policy such as tariffs, export controls, and sanctions, it may also be positively correlated with the EPU index, potentially conflating the bilateral tension with broader policy-related uncertainty. As shown in Table 2, UCT is most strongly correlated with the EPU index (0.399), followed by weaker associations with the default spread (DEF; 0.161), dividend yield (DIV; –0.132), real GDP per capita growth (GDPPC; –0.209), real interest rate (RINT; –0.364), and term spread (TERM; –0.332). These correlations suggest that UCT may embed elements of general economic conditions.

To isolate the U.S.-China tension component, we orthogonalize UCT by regressing it on EPU and the macroeconomic variables, namely DEF, DIV, GDPPC, RINT, and TERM, in a similar fashion as Liang, Wang, and Zhou (2020)[2]. The resulting residual from Equation 1 captures variation in U.S.-China tension that is distinct from broader macroeconomic and policy-related factors. This procedure ensures that our measure reflects the risk component stemmed from bilateral tensions rather than movements associated with business cycles or overall economic policy uncertainty.

$$\mathrm{UCT}_t = \alpha + \gamma_1 \mathrm{EPU}_t + \gamma_2 \mathrm{DIV}_t + \gamma_3 \mathrm{DEF}_t + \gamma_4 \mathrm{GDPPC}_t + \gamma_5 \mathrm{RINT}_t + \gamma_6 \mathrm{TERM}_t + \varepsilon_t \quad (1)$$

Figure 1 plots the monthly UCT Index alongside its orthogonalized version from 2000 to 2024. The raw UCT index (solid blue line) captures the intensity of bilateral geopolitical conflict based on the news-based methodology. The time series reveals several notable spikes corresponding to key geopolitical events between the U.S. and China. For instance, the early 2001 surge aligns with the EP-3 spy plane incident [3],

[2]For robustness, in untabulated results, we further include VIX and Geopolitical Risk Index by Caldara and Iacoviello (2022), respectively, as additional dependent variable in the orthogonalization process, and obtain similar results.

[3]https://en.wikipedia.org/wiki/Hainan_Island_incident

while the spike in 2010 reflects tensions in the South China Sea and disputes over one of largest arms sales to Taiwan by the U.S.[4]. The most prominent increase occurs during the U.S.-China trade war that escalated from mid-2018 through 2020, with multiple rounds of tariff impositions and retaliations. A second pronounced peak is observed around the onset of the COVID-19 pandemic in early 2020, driven by accusations over virus origins and rising diplomatic hostility. After peaking above 300, the index remains elevated throughout the 2020–2022 period, reflecting persistent strategic competition. The orthogonalized UCT index ($\text{Tension}^{\perp}$ hereafter) retains the timing of key geopolitical episodes while exhibiting a significantly muted amplitude. This transformation isolates the idiosyncratic component of geopolitical risk specific to U.S.-China relations, enabling cleaner identification of the pricing channel.

We use the first difference of the orthogonalized U.S.-China Tension Index, , $\Delta\text{Tension}^{\perp}$, to capture monthly innovations in bilateral geopolitical tension. To ensure that it captures a novel source of risk distinct from known systematic drivers, we examine its correlation with commonly used risk factors in the hedge fund literature. This validation step is essential for confirming that our geopolitical risk measure does not simply proxy for existing priced factors. Based on the correlation matrix reported in Table 4, $\Delta\text{Tension}^{\perp}$ exhibits minimal correlation with a wide range of standard factors. Specifically, its correlation with the market excess return (MKTRF) is negligible (−0.022), and similarly low with the size (SMB, −0.014), value (HML, −0.002), profitability (RMW, −0.067), investment (CMA, 0.010), momentum (MOM, −0.033), and liquidity (LIQ, −0.007) factors. Moreover, correlations with alternative hedge fund risk factors such as the credit spread factor (BS, 0.054), the bond market factor (BM, 0.078), and the trend-following risk factors (PTFSBD, PTFSFX, PTFSCOM) remain low in magnitude (all below 0.06). These low pairwise correlations confirm that $\Delta\text{Tension}^{\perp}$ is empirically distinct from standard systematic risk factors. This ensures that our measure captures idiosyncratic geopolitical tensions rather than broader business cy-

[4]https://en.wikipedia.org/wiki/List_of_US_arms_sales_to_Taiwan

cle or macroeconomic risks already embedded in common asset pricing models.

Figure 2 plots the monthly changes in the orthogonalized U.S.-China Tension Index, $\Delta\text{Tension}^{\perp}$, from 2000 to 2024. By taking first differences, we focus on innovations in geopolitical tension rather than persistent levels or slow-moving trends. The resulting series is centered around zero but exhibits sharp fluctuations that closely align with major episodes of U.S.-China conflict, such as tariff escalations and diplomatic disputes. This design highlights the arrival of new information, enabling cleaner identification of tension shocks that may drive both financial and real economic outcomes.

3 Empirical Results

3.1 Portfolio Sorting

To examine how hedge fund performance varies with sensitivity to U.S.-China tension, we begin by estimating fund-level exposures to U.S.-China tension. Specifically, for each fund i in each month t, we run the following time-series regression of monthly excess returns, using a 24-month rolling window:

$$r_{i,t} = \alpha_{it} + \beta_{it}^{\text{MKT}} \cdot \text{MKT}_t + \beta_{it}^{\text{Tension}} \cdot \Delta\text{Tension}_t^{\perp} + \varepsilon_{i,t} \tag{2}$$

where $r_{i,t}$ is the the excess return of fund i in month t, MKT_t is the market excess return, and $\Delta\text{Tension}_t^{\perp}$ is the first difference of the orthogonalized UCT index estimated from regression (1). The coefficient β_i^{Tension} captures the fund's exposure to changes in bilateral geopolitical tension, orthogonalized to eliminate common macroeconomic and policy uncertainty factors.

To further explore the economic significance of hedge fund exposure to U.S.-China geopolitical tensions, we sort funds into deciles based on their estimated β^{Tension}, which measures the sensitivity of each fund's return to innovations in the orthogonalized

UCT index. Specifically, decile 1 contains funds with the lowest (most negative) exposures, while decile 10 contains those with the highest (most positive) exposures. This sorting procedure facilitates the exploration of cross-sectional return patterns across the geopolitical sensitivity distribution. For each decile, we compute the average excess return and risk-adjusted alphas using the Fung and Hsieh (2004) seven-factor model (FH7), the nine-factor model (FH9) augmented with momentum (Fama & French, 2012) and liquidity (Pástor & Stambaugh, 2003) factors, and the eleven-factor model (FH11) that further includes investment and profitability factors (Fama & French, 2015). As reported in Table 5, we find a monotonic pattern across deciles. Funds in the top decile—those with the highest exposure to bilateral geopolitical risk—earn an average excess return of 43 basis points per month, whereas funds in the bottom decile earn only 19 basis points. The return spread between decile 10 and decile 1 is economically meaningful at 24 basis points per month. The spread is more pronounced and significant when we examine alpha measures: the 10-1 spread in alpha ranges from 32 to 38 basis points per month across different factor models. Taken together, these results suggest that funds with greater exposure to U.S.-China tension generate higher returns even after controlling for standard risk factors, implying that such exposure captures a unique and rewarded source of systematic risk. Beyond fund excess return and alpha, several fund characteristics exhibit a U-shaped or an inverted U-shaped pattern across the deciles sorted on β^{Tension}. For example, both management fee (MFee) and incentive fee (IFee) are slightly higher at the extreme deciles compared to the middle ones. Similarly, the prevalence of high-water mark provisions and leverage usage is generally higher in the tails, implying that funds with extreme exposure may be structured to offer more upside optionality or take more aggressive positions. These patterns suggest that the U.S.-China tension exposure is not randomly distributed but correlates with distinct fund characteristics.

To visualize the performance dynamics of hedge funds with differing sensitivity to geopolitical risk, we construct equal-weighted portfolios of funds in the top (decile 10) and bottom (decile 1) deciles sorted on β^{Tension}, re-balancing monthly. Figure 3 plots the cumulative returns of these two portfolios over the sample period. Panel A shows that the high-beta portfolio (decile 10) substantially outperforms the low-beta portfolio (decile 1) in terms of cumulative raw returns, with a return multiple exceeding 5.5 by the end of the sample period, compared to less than 3.5 for the low-beta group. Panels B through D show the comparison using out-of-sample alpha estimates obtained under different factor models. Panel B presents alphas based on the Fung and Hsieh (2004) seven-factor model (FH7), which is widely adopted in the hedge fund literature. Panel C augments this specification with momentum (Fama & French, 2012) and liquidity factors (Pástor & Stambaugh, 2003) , while Panel D further adds investment and profitability factors (Fama & French, 2015). Across all models, the cumulative alpha spread between the highest and lowest tension-beta deciles is both economically large and persistent over time. The divergence becomes particularly pronounced during episodes of elevated geopolitical friction.

One possible interpretation is that these funds are better positioned to exploit the risk premium associated with geopolitical frictions or have superior information-processing capabilities to navigate such shocks. Alternatively, they may engage in opportunistic strategies that benefit from volatility induced by geopolitical events. Regardless of the mechanism, the monotonic return pattern implies that geopolitical risk exposures are priced in the cross-section of hedge fund returns.

3.2 Long–Short Portfolio Spreads

We then formally assess the statistical significance of the return and alpha differentials between the highest and lowest β^{Tension} deciles using the Newey and West (1987) test with two lags [5]. Each month, we construct equal-weighted portfolios of funds in the top (decile 10) and bottom (decile 1) and calculate the return and risk-adjusted

[5] For robustness, we obtain similar results with more lags.

alpha spread as the difference between the top and the bottom decile. The results in Table 6 indicate that the raw return spread between the highest and lowest β^{Tension} deciles is positive but not statistically significant, whereas the alpha spreads based on risk-adjusted models are significant at conventional levels. The significant alpha spread implies that high-β^{Tension} funds outperform not merely due to risk exposure, but through value-added performance beyond what is explained by known factors, consistent with strategic positioning or skillful timing of geopolitical risks.

3.3 Panel Regression Analysis

To further test the pricing of geopolitical exposure, we estimate panel regressions of fund performance on β^{Tension}, controlling for fund characteristics and fixed effects. As in Regression (3), we regress the fund excess return and risk-adjusted alpha on β^{Tension} and a set of control variables and fixed effects:

$$\text{Performance}_{i,t} = \gamma_0 + \gamma_1 \cdot \beta^{\text{Tension}}_{i,,t-1} + \mathbf{X}'_{i,t}\boldsymbol{\gamma} + \eta_i + \theta_t + \varepsilon_{i,t} \tag{3}$$

where $\text{Performance}_{i,t}$ is either the raw excess return or an out-of-sample alpha (e.g., FH7, FH9, FH11). $\mathbf{X}_{i,t}$ includes controls such as fund size, age, management and incentive fees, high-water mark, leverage, lockup, redemption notice period and payout period, and η_i and θ_t represent fund/style/country-fixed effects and time-fixed effects, respectively. We further include style and country fixed effects to control for unobserved heterogeneity across fund style and domicile country.

Table 7 presents panel regression results with monthly excess return as the dependent variable. Across all specifications, the coefficient on β^{Tension} is positive and statistically significant, even after controlling for fund characteristics and various levels of fixed effects. For example, in the specification with style and time fixed effects (Column 4), the coefficient on β^{Tension} is 1.333 and statistically significant at the 5% level

[6]. This implies that a one-standard-deviation (0.048) increase in β^{Tension} is associated with a 0.064% increase in monthly excess return, or about 0.77% annually. The effect is economically meaningful in the context of typical hedge fund return dispersion and highlights a return premium associated with greater sensitivity to U.S.-China geopolitical risk.

To evaluate whether this performance premium persists after controlling for other systematic risk factors, we re-estimate the regressions using risk-adjusted returns as dependent variables. Table 8 reports the results using alphas estimated from the FH7 model, FH9 model (FH7 augmented with liquidity and momentum), and FH11 model (further augmented with investment and profitability factors), respectively. The coefficient on tension beta remains statistically significant and economically sizable in all cases. For instance, under the FH11 model with style and time fixed effects (Column 4), the coefficient on β^{Tension} is 2.883 and statistically significant at the 1% level. This implies that a one-standard-deviation (0.048) increase in β^{Tension} is associated with a 0.138% increase in monthly alpha, or about 1.66% annually. The result underscores a strong return premium for hedge funds that are more sensitive to U.S.-China tension, even after accounting for a comprehensive set of risk exposures.

These results provide compelling evidence that U.S.-China geopolitical risk represents a priced source of risk in hedge fund returns. The premium persists after controlling for known systematic factors and fund characteristics, and its magnitude is robust to a range of model specifications.

We also examine heterogeneity in the geopolitical return premium across fund strategies by interacting β^{Tension} with style dummies. As shown in Table 9, the return premium is concentrated in styles that are more directional in nature. Specifically, equity market neutral, long/short equity hedge, and multi-strategy funds exhibit the

[6] As a robustness check, we re-estimate the regression with Style × Time fixed effects to absorb style-specific time-varying shocks, and the results remain qualitatively unchanged.

strongest and most significant exposures. In contrast, strategies such as convertible arbitrage or fixed income arbitrage do not appear to load significantly on tension beta.

3.4 Holdings-Based Validation of U.S.–China Tension Exposure

We use quarterly Form 13F holdings to test whether return-based U.S.–China tension (UCT) exposure is reflected in disclosed long-equity portfolios. We construct a holdings-implied UCT beta for each manager family and compare it with the return-based beta of its funds.

3.4.1 Holdings data and exposure construction

We link HFR and TASS management companies to SEC filing entities and combine their quarterly Form 13F positions with CRSP security returns. Form 13F is reported at the management-company level, so the unit of observation is a manager family-quarter. The manager–CIK crosswalk retains deterministically accepted identity links. We route filings by report quarter and use line-level `OTHERMANAGER` information when positions are reported through another filing entity. The sample excludes ambiguous security links and manager-quarters with inadequate coverage. The holdings infrastructure covers 2013Q2–2024Q4; the overlapping regression sample ends in 2023Q4, the final quarter with the required fund-return UCT beta.

Following the portfolio-aggregation logic of Chen et al. (2022) and the stock-level UCT-beta approach of Rogers, Sun, and Sun (2024), we estimate a UCT beta for each CRSP security. For security j and holdings quarter q, the baseline regression is estimated over the preceding 60 months and requires at least 36 monthly observations:

$$r^e_{j,t} = a_{j,q} + \beta^{UCT}_{j,q} UCT^{\perp}_t + \boldsymbol{\beta}^{F\prime}_{j,q} \mathbf{F}_t + \varepsilon_{j,t}, \qquad t < q, \tag{4}$$

where $r^e_{j,t}$ is the security's excess return, $UCT^{\perp}_t$ is the UCT measure used in the main analysis, and $\mathbf{F}_t$ contains the market, size, value, profitability, investment, momentum, and liquidity factors. The estimation window uses monthly observations dated before the calendar-quarter end. We attach the estimated beta to the identical holdings quarter and do not carry an older estimate forward when the quarter-specific beta is missing.

The holdings-implied UCT exposure of manager family i in quarter q is

$$B^{H}_{i,q} = \sum_{j} w_{ij,q} \widehat{\beta}^{UCT}_{j,q}, \tag{5}$$

where $w_{ij,q}$ is security j's share of the market value of the manager's linked long-equity positions. In addition to the raw exposure, we construct 1st/99th-percentile winsorized, standardized, and centered within-quarter rank measures. The centered-rank specification is preferred for changes because it is less sensitive to extreme generated stock betas.

For consecutive quarters, we decompose the change in holdings-implied exposure into security-beta updates, active portfolio reallocation, and passive price drift:

$$\begin{aligned}
\Delta B^{H}_{i,q} = {} & \underbrace{\sum_{j} w_{ij,q} \left(\widehat{\beta}^{UCT}_{j,q} - \widehat{\beta}^{UCT}_{j,q-1} \right)}_{\text{security-beta update}} \\
& + \underbrace{\sum_{j} \left(w_{ij,q} - w^{P}_{ij,q} \right) \widehat{\beta}^{UCT}_{j,q-1}}_{\text{active reallocation}} \\
& + \underbrace{\sum_{j} \left(w^{P}_{ij,q} - w_{ij,q-1} \right) \widehat{\beta}^{UCT}_{j,q-1}}_{\text{passive price drift}},
\end{aligned} \tag{6}$$

where $w^{P}_{ij,q}$ is the counterfactual quarter-q weight obtained by allowing the previous quarter's holdings to evolve only with security returns. This decomposition distinguishes security-beta updates and active reallocation from exposure changes due to relative price movements.

3.4.2 Empirical specification

We aggregate the rolling fund-return UCT beta to the manager-family level using equal fund weights in the baseline and positive AUM weights as a sensitivity test. The level specification is

$$B^F_{i,q} = \alpha_i + \delta_q + \gamma B^H_{i,q} + \boldsymbol{\lambda}'\mathbf{X}_{i,q} + u_{i,q}, \tag{7}$$

where $B^F_{i,q}$ is the return-estimated UCT beta of funds in family i, α_i and δ_q are manager-family and calendar-quarter fixed effects, and $\mathbf{X}_{i,q}$ contains the holdings-implied market beta, the logarithm of reported long-equity value, and security-link coverage. We also estimate first-difference specifications that relate consecutive-quarter changes in the fund-return beta to total and decomposed changes in the holdings-implied beta. Standard errors are two-way clustered by manager family and calendar quarter.

3.4.3 Results

Table **??** reports a positive association between the UCT beta inferred from disclosed holdings and the UCT beta estimated from fund returns. In the equal-weighted level specification, the coefficient on holdings-implied UCT exposure is 17.302 (t = 1.772, p = 0.076). The corresponding AUM-weighted estimate is 17.943 (t = 1.716, p = 0.086). A one-standard-deviation increase in holdings-implied exposure in the equal-weighted specification is associated with a 0.00431 increase in the family fund-return UCT beta, or approximately 16% of the within-sample standard deviation of the fund-return beta.

Consecutive-quarter changes in the centered-rank measures also move together. In column (3), the coefficient relating the total change in holdings-implied exposure to the change in the fund-return UCT beta is 0.433 (t = 2.332, p = 0.020). The Benjamini–Hochberg adjusted q-value is 0.091. A one-standard-deviation change in this holdings measure is associated with a 0.0154 change in the rank of the fund-return beta, approximately 11% of its standard deviation. The AUM-weighted estimate in column (4) is positive and less precise ($\widehat{\gamma} = 0.380$, $p = 0.070$, $q = 0.139$). Replacing the multifactor stock-beta model with a model containing only the market and UCT factors produces nominal p-values of 0.010 and 0.020 for the equal- and AUM-weighted total-rank-change specifications, respectively; both corresponding within-family adjusted q-values are 0.041.

The active-reallocation relation depends on the weighting scheme. The active rank-change coefficient is positive with the equal-weighted fund-beta measure ($\widehat{\gamma} = 0.418$, $p = 0.038$, $q = 0.101$), but small and statistically insignificant under AUM weighting ($\widehat{\gamma} = 0.093$, $p = 0.572$, $q = 0.654$). The positive correspondence is therefore more consistent across weighting schemes for total exposure changes than for active reallocation.

The interaction between the manager timing signal and the subsequent raw return of the disclosed long-equity portfolio is positive but statistically insignificant ($p = 0.192$); the market- and UCT-adjusted return specification is also insignificant ($p = 0.146$).

3.4.4 Interpretation and scope

The holdings and fund-return measures exhibit positive correspondence in levels and total changes. The evidence concerns manager-family disclosed long-equity portfolios, with positions generally not assignable to individual funds. Short positions, derivatives, cash, leverage, many foreign securities, confidential holdings, and within-quarter trading are outside this long-equity measure. The accepted crosswalk covers 36.3% of managers in the return-beta dataset, selecting managers with unambiguous SEC identities and sufficient disclosed U.S. equity positions.

4 Timing the Tension

4.1 Cross-section of the tension timing ability

An important strand of the hedge fund literature examines whether managers possess dynamic market-timing ability, defined as the capacity to adjust exposures in response to changes in risk factors. Among the factors, equity market exposure is the most important for equity-oriented hedge funds. Thus, prior studies test for timing ability by examining the changes in equity market exposure, and we adopt a similar approach in this paper to study timing with respect to geopolitical risk. Building on the framework of Treynor and Mazuy (1966) and its extensions of hedge funds' timing ability with respect to liquidity (Cao et al., 2013) and economic policy uncertainty (Liang, Wang, & Zhou, 2020), we estimate the fund-level tension-timing ability by examining the changes in equity market exposure. To obtain reliable estimates, we require each fund to have at least 24 monthly return observations. We then estimate timing ability for each fund using the following specification:

$$r_{i,t} = \alpha_i + \beta_{i,\text{mkt}}\text{MKT}_t + \theta_i\text{MKT}_t\left(\text{UCT}_t - \overline{\text{UCT}}\right) + \sum_{j=1}^{6}\beta_{i,j}f_{j,t} + \varepsilon_{i,t} \tag{8}$$

where $r_{i,t}$ is the excess return on fund i; MKT_t is the market excess return; $f_{j,t}$, $j = 1, \ldots, 6$ are the non-MKT factors of FH7; UCT_t is the UCT index of Rogers, Sun, and Sun (2024); and $\overline{\text{UCT}}$ is the time-series mean of UCT_t. In the above model, the coefficient θ measures the hedge fund's timing ability of the U.S.-China tension.

The resulting coefficient θ captures the extent to which each fund adjusts its market exposure in response to unanticipated shocks in bilateral geopolitical risk. A significantly positive (negative) θ implies that the fund scales up (down) its exposure to the market when tensions rise. Table 11 presents the cross-sectional distribution of the t-statistics on θ across individual funds. Under the null hypothesis of no timing ability, the share of funds exceeding conventional significance thresholds (e.g., $|t| > 1.96$)

should be close to 5%. Yet we find that 10.5% of funds exhibit t-statistics below -1.96, and 6.83% exceed 1.96, suggesting that both negative and positive timing behavior are more prevalent than would be expected by chance. Moreover, 23.14% of funds have $t < -1.282$, compared to only 14.37% with $t > 1.282$, indicating an asymmetric distribution skewed toward negative timing estimates. This left-skewed pattern suggests that a greater share of funds reduce market exposure to the market during periods of rising U.S.-China tension. In total, nearly 40% of funds exhibit moderate timing coefficients ($|t| > 1.282$), providing suggestive evidence that the tension timing is a non-negligible component of hedge fund behavior.

We further examine the distribution of timing ability across hedge fund investment styles. Following Bali, Brown, and Caglayan (2014), we classify funds into three broader categories based on their investment strategies: directional (global macro), semi-directional (fund of funds, long/short equity, event-driven, and multi-strategy funds), and non-directional (convertible arbitrage and equity market neutral funds). Directional funds exhibit the most pronounced asymmetry, with 26.67% showing $t > 1.282$ compared to 15.34% with $t < -1.282$, suggesting that some managers in this group may actively increase exposure in anticipation of return-enhancing tension shocks. In contrast, semi-directional funds display a left-skewed pattern similar to the full sample, with 24.70% falling below $t = -1.282$ versus only 11.55% above $t = 1.282$, implying more defensive repositioning. Non-directional funds appear less engaged in tension timing, with relatively balanced proportions on both tails and fewer extreme t-values overall.

Taken together, the cross-sectional distribution of timing coefficients and the style-based heterogeneity suggest that some hedge fund managers may possess skill in anticipating and responding to bilateral geopolitical shocks. The significant deviation from the null distribution highlights that timing responses to U.S.-China tension are prevalent and worthy of further investigation.

4.2 Bootstrap Analysis

A potential concern with the inference drawn from the panel regressions in Table 11 is that conventional t-statistics may not provide valid inference in the presence of cross-sectional dependencies and non-normal return distributions. First, hedge fund returns, particularly those employing dynamic trading strategies, are known to exhibit significant deviations from normality (e.g., Fung and Hsieh, 1997; Fung and Hsieh, 2001). Second, evaluating timing ability across a large sample of funds introduces a multiple testing problem—under the null hypothesis of no true timing skill, a non-trivial fraction of funds may appear statistically significant purely by chance. Third, if funds within the same strategy category respond similarly to geopolitical events or macroeconomic shocks, the estimated timing coefficients θ_i and corresponding β_i^{Tension} exposures may be cross-sectionally correlated, violating the assumption of independence across observations. To address these issues, we implement a bootstrap procedure that preserves the time-series dependence of fund returns while resampling at the fund level, thereby generating a more robust distribution of the test statistics under the null.

To evaluate the extent to which significant positive or negative tension timing estimates may arise by chance, we conduct a bootstrap analysis to assess the statistical significance of the tension timing coefficient at the individual fund level. Our bootstrap procedure is similar to Chen and Liang (2007) and Cao et al. (2013) in prior hedge fund literature. The basic concept behind the bootstrap analysis is to generate hypothetical fund return series that preserve each fund's estimated factor exposures but eliminate any potential timing ability. By randomly resampling regression residuals to construct synthetic returns under the null of no timing skill and comparing the distribution of t-statistics from these simulated funds to those of the actual timing coefficients, we can assess whether observed timing performance is significantly different from what would be expected by chance. Specifically, the procedure consists of the following steps.

- **Step 1:** For each fund i, estimate regression (8) and store the estimated coefficients $\hat{\alpha}_i$, $\hat{\beta}_{i,\text{mkt}}$, $\hat{\beta}_{i,j}$, $\hat{\theta}_i$, and residuals $\hat{\varepsilon}_{i,t}$.

- **Step 2:** Under the null hypothesis that fund i has no U.S.-China tension timing ability (i.e., $\hat{\theta}_i = 0$), simulate pseudo excess returns as:

$$r_{i,t}^b = \alpha_i + \hat{\beta}_i^{\text{mkt}}\text{MKT}_t + \sum_{j=1}^{6} \hat{\beta}_{i,j} f_{j,t} + \hat{\varepsilon}_{i,t}^b$$

  where $\hat{\varepsilon}_{i,t}^b$ is drawn with replacement from $\hat{\varepsilon}_{i,t}$ in the b-th bootstrap iteration.

- **Step 3:** Re-estimate the original regression model using the pseudo returns $r_{i,t}^b$ and record the t-statistic for the U.S.-China tension timing coefficient.

- **Step 4:** Repeat Steps 1 to 3 for all funds and collect the cross-sectional distribution of t-statistics for each bootstrap iteration.

- **Step 5:** Repeat Steps 1 to 4 for **B** bootstrap iterations (we use **B** = 1,000) to construct the empirical distribution of the cross-sectional t-statistics. This allows us to evaluate how likely the observed timing performance is to occur under the null of no true timing ability.

Table 12 presents the cross-sectional distribution of t-statistics for the U.S.-China tension timing coefficient and the corresponding empirical p-values based on 1,000 bootstrap iterations. For all the extreme 1%, 3%, 5%, and 10% percentiles of the distribution, the empirical p-values are all close to zero, indicating that these tension-timing funds are unlikely to result from random chance. Similar patterns are observed in the left and right tails for directional and semi-directional funds, where the extreme t-statistics are consistently accompanied by near-zero p-values. In contrast, the top percentiles for non-directional funds are associated with relatively higher p-values.

Specifically, the p-values for top 1%, 3%, 5%, and 10% percentile are 0.141, 0.175, 0.097, and 0.139, respectively. These evidences suggest that their timing abilities are not statistically distinguishable from the null. The absent of timing ability of non-directional funds is consistent with the findings of Cao et al. (2013). Overall, the bootstrap analysis indicates that hedge fund managers with the highest-ranked timing coefficients exhibit statistically significant ability to time the U.S.-China tension.

To provide visual evidence on whether the observed UCT-timing performance is driven by skill rather than chance, we first construct kernel density distributions of t-statistics for the tension-timing coefficient θ_i among pseudo-funds in the top 5th percentile from each of 1,000 bootstrap simulations. We then overlay the actual t-statistics for the corresponding top 5th percentile funds as vertical dashed lines. Figure 4 shows the results for the full sample and for strategy subsamples. Panel A presents the distribution for all funds, while Panels B through D correspond to directional, semi-directional, and non-directional funds, respectively. In all cases except Panel D, the actual t-statistics lie to the right of the bulk of the bootstrap distribution, indicating that the observed timing ability exceeds what would be expected under the null of no skill. The displacement is most pronounced for directional funds (Panel B), whereas for non-directional funds (Panel D), the vertical dashed line exhibits only a marginal rightward shift, suggesting limited evidence of active timing of the U.S.-China tension.

We provide further evidence of the economic value of the tension timing ability. We sort the funds into deciles based on their timing coefficient θ_i estimated from Regression (8). We then form ten equal-weighted portfolios based on deciles and calculate the cumulative return of each decile. Figure 5 plots the cumulative returns of the top-decile portfolio and bottom-decile portfolio, respectively. We focus on the post-GFC period after 2008, when global markets stabilized and geopolitical tensions emerged as an increasingly salient macroeconomic risk. All return series are normalized to one at the beginning of the sample. Panel A shows that funds in the top decile of timing coefficients (decile 10) consistently outperform those in the bottom decile (decile 1), generating materially higher cumulative returns over time. This return spread is especially pronounced for directional and semi-directional funds (Panels B and C), consistent with earlier evidence that timing ability is concentrated in these strategy groups. In contrast, the return difference between the top and bottom deciles is less persistent among non-directional funds (Panel D), aligning with the weaker statistical evidence from the bootstrap analysis. Overall, the portfolio-level results suggest that successful timing of U.S.-China tensions leads to economically meaningful differences in hedge fund performance.

4.3 Dynamics of the Tension Beta

To better understand which hedge funds are exposed to U.S.-China geopolitical tension and how they dynamically adjust this exposure, we examine the cross-sectional determinants of β^{Tension} using the regression below:

$$\beta_{i,t}^{\text{Tension}} = \alpha + \gamma_1 \theta_i + \gamma_2 \theta_i \cdot \text{High Tension}_t + \mathbf{X}_{i,t}' \boldsymbol{\gamma} + \eta_i + \iota_t + \varepsilon_{i,t} \tag{9}$$

where $\beta_{i,t}^{\text{Tension}}$ is the tension beta of fund i in month t estimated from Equation (8). θ_i is the timing ability of fund i estimated from equation (8). HighTension_t is an indicator equal to one when the UCT index is above its time-series average and zero otherwise. $\mathbf{X}_{i,t}$ is a vector of fund characteristics, including size, age, management and incentive fees, high-water mark provision, leverage, redemption notice period, and payout period. η_i and ι_t represent style fixed effects and time fixed effects, respectively.

Column (1) of Table 13 presents baseline panel regression results of fund-level tension betas on fund characteristics, controlling for style and time fixed effects. Several characteristics are systematically related to geopolitical exposure: funds with shorter lockup periods, lower management and incentive fees, and high-water mark provisions tend to exhibit higher tension betas. These results suggest that funds offering more investor-friendly liquidity terms or compensation structures are more inclined to take directional positions on geopolitical risk.

To explicitly capture the dynamic adjustment of a fund's exposure to U.S.-China geopolitical tensions, we extend the model in Column (1) by incorporating each fund's estimated timing ability θ_i and its interaction with a high-tension regime indicator. The high-tension indicator equals one when the UCT index is above its time-series average and zero otherwise. In Column (2), the coefficient on θ_i is 0.0070 and statistically significant at the 5% level, indicating that funds with stronger timing ability tend to maintain higher average tension betas. Economically, a one-standard-deviation (0.542) increase in θ_i is associated with a 0.0038 increase in β^{Tension}. However, the negative and significant interaction term of -0.0088 suggests that these same funds strategically scale back their exposure during periods of elevated geopolitical tension, reducing β^{Tension} by roughly 0.0048 per standard deviation increase in θ_i. Together, these results emphasize that geopolitical risk exposure is actively managed, varying with both fund-specific timing skill and the prevailing risk environment.

Columns (3) through (5) explore heterogeneity in timing behavior across fund styles. Among directional and semi-directional funds, higher timing coefficients are associated with greater exposure during normal periods, but with reduced exposure during high-tension episodes—consistent with a tactical adjustment to perceived geopolitical risks. Semi-directional funds, in particular, appear to follow this pattern closely. In contrast, non-directional funds exhibit a distinct response. As shown in Column (5), the coefficient on θ_i is significantly negative and the interaction term is insignificant, indicating that these funds reduce their tension exposure as their timing coefficient increases, regardless of the tension regime. This behavior likely reflects a more risk-averse or volatility-sensitive strategy, consistent with a mandate that emphasizes market-neutral positioning.

Overall, the results highlight that dynamic exposure to the U.S.-China tension varies substantially across hedge fund categories. Directional and semi-directional funds actively adjust their positions based on perceived timing ability and tension regimes, whereas non-directional funds appear more conservative in their approach.

5 Conclusion

This paper examines how hedge funds respond to sustained bilateral geopolitical risk. Using a novel index of U.S.-China tension, we show that higher exposure to the tension is associated with higher excess returns and risk-adjusted returns. These results are robust across factor models and persist after controlling for fund characteristics and fixed effects. Moreover, hedge funds with directional mandates exhibit timing ability of the tension as they dynamically increase their tension exposure in normal periods and reduce the exposure in high-tension episodes. In contrast, non-directional funds show no tension-timing abilities. The findings suggest that hedge funds' performance differential reflects skill rather than compensation for passive systematic risk exposure. Overall, this study highlights geopolitical tension as a meaningful source of return heterogeneity in hedge fund strategies.

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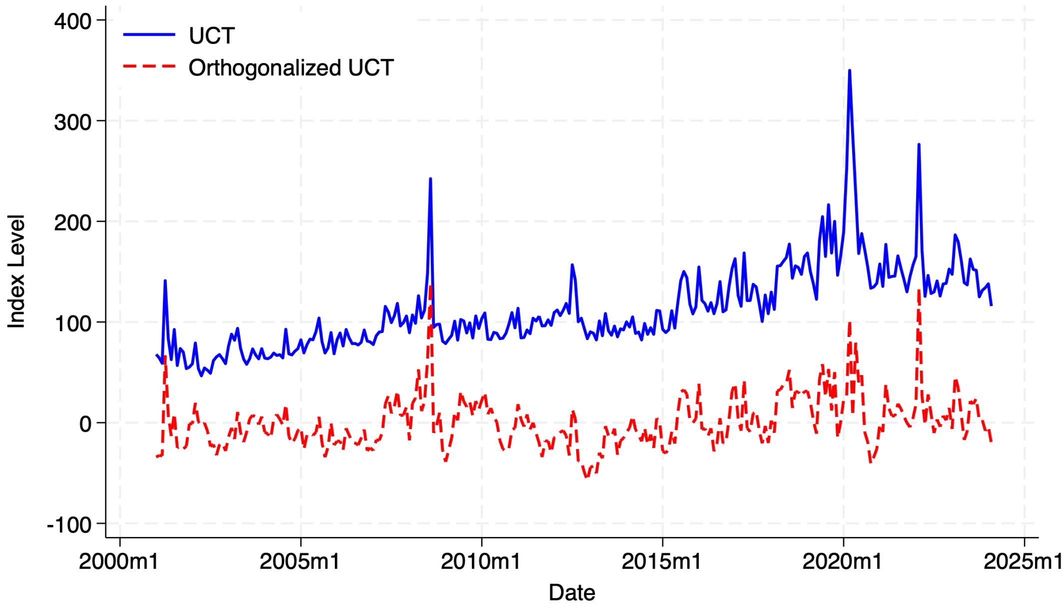
Figure 1: The U.S.-China Tension Index

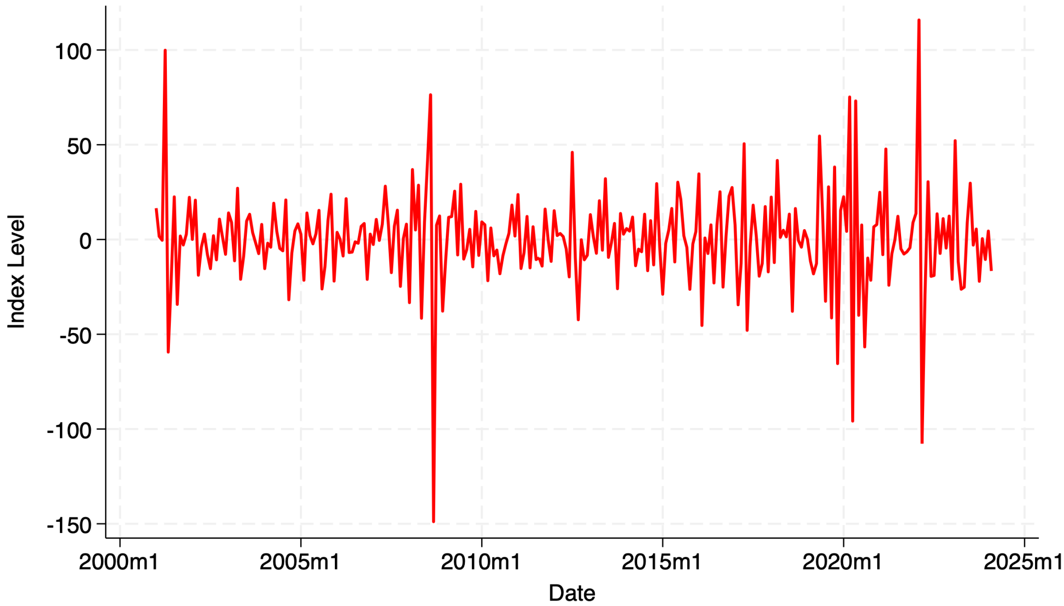


Note: This figure plots the monthly U.S.-China Tension (UCT, Rogers, Sun, and Sun, 2024) index and its orthogonalized counterpart from January 2002 to December 2024. The orthogonalized UCT index is the residual from a regression of the raw UCT index on macroeconomic controls and the Economic Policy Uncertainty Index (EPU, Baker, Bloom, and Davis, 2016). Specifically, we regress the UCT index on Economic Policy Uncertainty (EPU), dividend yield (DIV), default spread (DEF), the growth in real GDP per capita (GDPPC), real interest rate (RINT), and the term spread (TERM), as shown in the equation:

$$\mathrm{UCT}_t = \alpha + \gamma_1 \mathrm{EPU}_t + \gamma_2 \mathrm{DIV}_t + \gamma_3 \mathrm{DEF}_t + \gamma_4 \mathrm{GDPPC}_t + \gamma_5 \mathrm{RINT}_t + \gamma_6 \mathrm{TERM}_t + \varepsilon_t$$

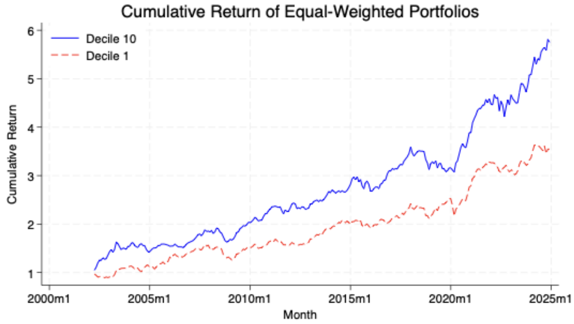
The residual ε_t from this regression is used as the orthogonalized UCT index.

Figure 2: The Innovation of Tension$^{\perp}$

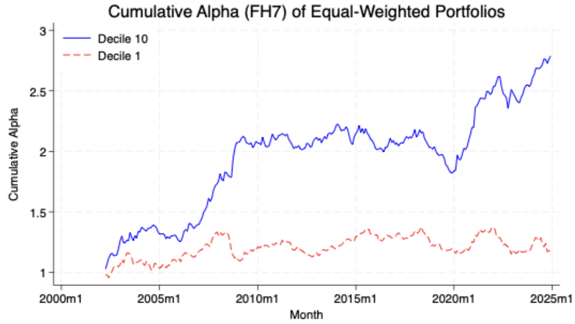


Note: This figure plots monthly changes in the orthogonalized UCT index over the period from 2000 to 2024. The orthogonalized UCT index is the estimated residual of regression (1).

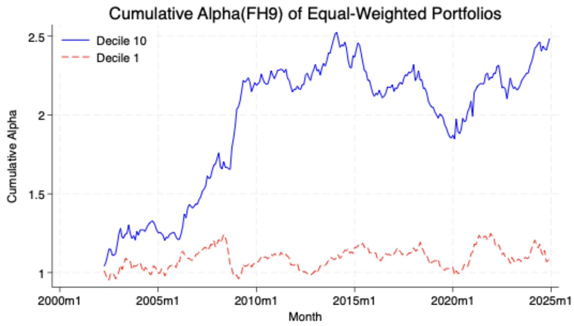
Figure 3: Cumulative Return and Alpha of Equal-Weighted Portfolios: Decile 10 vs. Decile 1



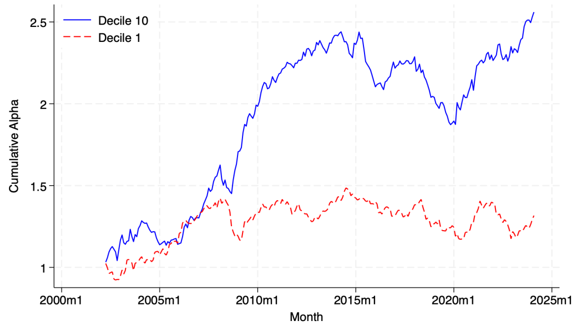
Panel A: Cumulative Raw Return



Panel B: Cumulative Alpha (FH7)



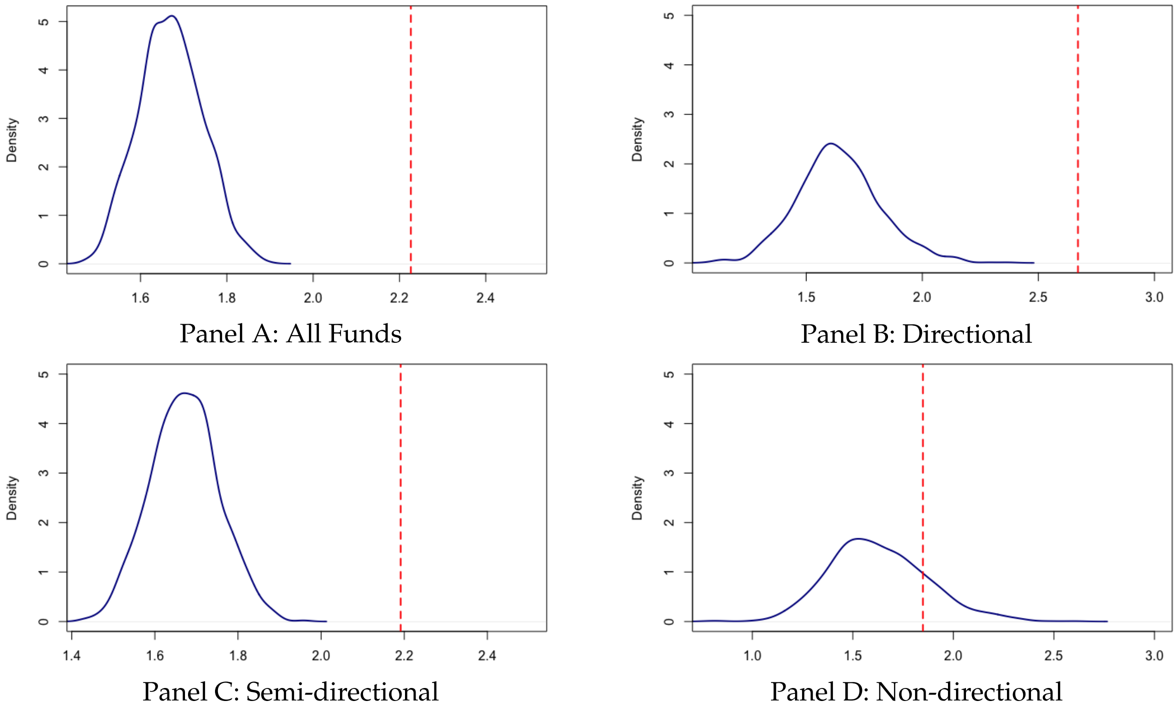
Panel C: Cumulative Alpha (FH9)



Panel D: Cumulative Alpha (FH11)

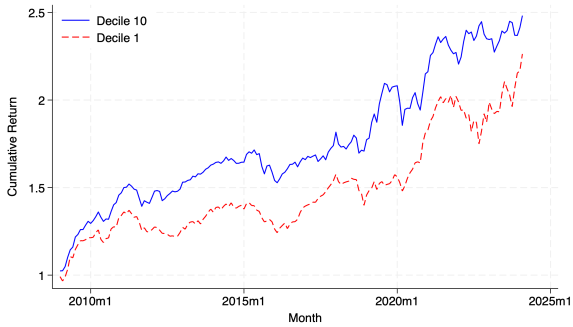
Note: This figure plots cumulative returns and risk-adjusted alphas of equal-weighted portfolios formed from hedge funds in the top and bottom deciles of β_i^{Tension}. All series are normalized to 1 at the start of the sample. The alpha estimates are based on Fama–French factor models with varying degrees of augmentation.

Figure 4: Distribution of t-statistics for the UCT-timing Coefficient

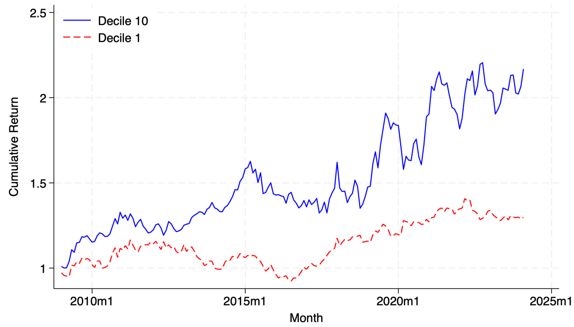


Note: This figure plots the density distribution of the t-statistics of the top 5th percentile tension-timing coefficient θ_i: actual fund verses bootstrapped funds. Panel A presents the distribution for the full sample. Panels B through D show the distribution for the directional, semi-directional, and non-directional subsamples, respectively. The curve represents the density distribution of t-statistics for the tension-timing coefficient among pseudo-funds that fall in the top 5th percentile in each of 1,000 bootstrap simulations for the cross-section of sample funds. The vertical line corresponds to the actual fund value at the top 5th percentile for each strategy category. The sample period is from January 2002 to December 2024.

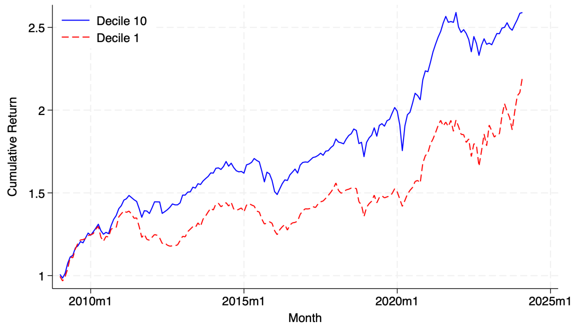
Figure 5: Cumulative Return of θ-sorted Portfolios: Decile 10 vs. Decile 1



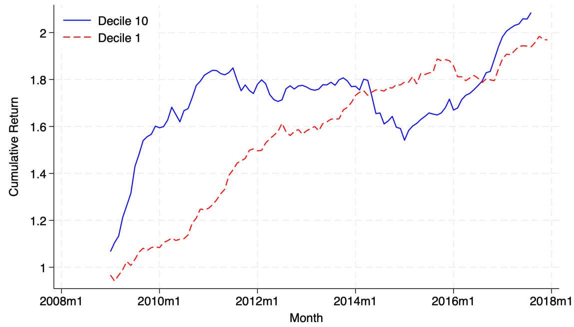
Panel A: All Hedge Funds



Panel B: Directional



Panel C: Semi-directional



Panel D: Non-directional

Note: This figure plots the cumulative returns of equal-weighted portfolios comprising hedge funds in the top and bottom deciles of timing ability (θ_i). Panel A presents results for the full sample. Panels B through D show results for the directional, semi-directional, and non-directional subsamples, respectively. The sample period is from January 2009 to December 2024.

Table 1: Summary Statistics of Hedge Fund Variables

Variable	Mean	SD	p10	p25	p50	p75	p90
Return	0.516	3.878	−3.810	−1.181	0.531	2.270	4.783
Alpha (7-Factor)	0.220	3.788	−3.833	−1.479	0.243	1.875	4.185
Alpha (9-Factor)	0.215	4.016	−4.085	−1.555	0.231	1.940	4.409
Alpha (11-Factor)	0.324	4.407	−4.230	−1.605	0.295	2.169	4.875
AUM ($m)	418.83	960.43	9.40	31.11	101.80	319.40	957.73
Management Fee (%)	1.401	0.496	1.000	1.000	1.500	1.750	2.000
Incentive Fee (%)	16.600	6.998	0.000	15.000	20.000	20.000	20.000
High-Water Mark	0.839	0.368	0.000	1.000	1.000	1.000	1.000
Leverage Dummy	0.617	0.486	0.000	0.000	1.000	1.000	1.000
Redemption Notice (Days)	33.646	27.337	1.000	5.000	30.000	60.000	65.000
Lockup (Years)	1.332	3.403	0.000	0.000	0.000	1.000	3.333

Note: This table reports summary statistics for monthly hedge fund-level variables. All returns and alphas are in percentage terms. *Return* refers to the raw monthly return of the hedge fund. *Alpha (7-Factor)*, *Alpha (9-Factor)*, and *Alpha (11-Factor)* represent hedge fund alphas estimated from regressions using the Fung and Hsieh (2004) seven-factor model, an extended nine-factor model, and an eleven-factor model, respectively. *AUM* denotes assets under management in millions of U.S. dollars. *Management Fee* and *Incentive Fee* are annualized and reported in percentages. *High-Water Mark* is a binary indicator equal to one if the fund employs a high-water mark provision, and zero otherwise. *Leverage Dummy* is an indicator variable equal to one if the fund uses leverage. *Redemption Notice* is the required number of days' notice for redeeming capital. *Lockup* refers to the fund's lock-up period, converted to years. All variables are winsorized at the 1% and 99% levels.

Table 2: Correlation Matrix: U.S.–China Tension and Macroeconomic Variables

	UCT	EPU	DEF	DIV	GDP	INF	RINT	TERM	UNEMP	VIX
UCT	1.000									
EPU	0.399	1.000								
DEF	0.161	0.230	1.000							
DIV	−0.132	0.107	0.354	1.000						
GDPPC	−0.209	−0.078	−0.205	−0.054	1.000					
INF	0.019	−0.047	−0.216	0.011	0.136	1.000				
RINT	−0.364	−0.109	−0.182	0.456	0.028	0.133	1.000			
TERM	−0.332	−0.005	0.212	0.308	0.003	−0.050	−0.443	1.000		
UNEMP	−0.094	0.317	0.364	0.388	0.077	−0.104	−0.298	0.614	1.000	
VIX	0.117	0.429	0.627	0.029	−0.205	−0.169	−0.090	0.077	0.191	1.000

Note: This table reports the pairwise Pearson correlation coefficients among the U.S.–China Tension Index (UCT), Economic Policy Uncertainty (EPU), and a set of macroeconomic and financial variables. *UCT* is the monthly newspaper-based index of U.S.–China geopolitical tension. *EPU* is the U.S. economic policy uncertainty index from Baker, Bloom, and Davis (2016). *DEF* denotes the default spread, measured as the yield difference between BAA- and AAA-rated corporate bonds. *DIV* represents the dividend yield on the S&P 500. *GDPPC* is the year-over-year percentage change in real U.S. GDP per capita. *INF* refers to the inflation rate, measured as the 12-month change in the Consumer Price Index (CPI). *RINT* is the real interest rate, calculated as the nominal 3-month Treasury bill rate minus the inflation rate. *TERM* is the term spread, defined as the yield difference between 10-year and 3-month U.S. Treasury securities. *UNEMP* is the civilian unemployment rate. *VIX* is the Chicago Board Options Exchange (CBOE) Volatility Index, which proxies for market uncertainty. All variables are measured at the monthly frequency.

Table 3: Orthogonalization of the UCT Index

Variable	Coefficient	t-statistic
EPU	0.131	4.79
DIV	51.199	0.15
DEF	−9.154	−2.24
GDPPC	−22.975	−6.66
RINT	−15.591	−18.66
TERM	−28.021	−19.00
Constant	178.340	23.82
Adj. R^2		0.6506
F-stat		116.76

Note: This table reports the results from a linear regression of the U.S.–China Tension Index (UCT) on the U.S. Economic Policy Uncertainty Index (EPU) and a set of monthly macroeconomic control variables. The dependent variable is the raw UCT index. *EPU* is the economic policy uncertainty index from Baker, Bloom, and Davis (2016). *DIV* is the S&P 500 dividend yield. *DEF* is the default spread, defined as the yield difference between BAA- and AAA-rated corporate bonds. *GDPPC* is the year-over-year percentage change in real GDP per capita. *RINT* is the real interest rate, calculated as the nominal 3-month Treasury bill rate minus CPI inflation. *TERM* is the term spread between the 10-year and 3-month Treasury yields. Coefficients and corresponding t-statistics are reported. Robust standard errors are used to compute t-statistics.

Table 4: Correlation Matrix: Orthogonalized U.S.–China Tension and Risk Factors

	ΔTension$^{\perp}$	MKTRF	SMB	HML	RMW	CMA	MOM	LIQ	BM	BS
MKTRF	-0.022									
SMB	-0.014	0.220***								
HML	-0.002	0.155*	-0.003							
RMW	-0.067	0.279***	-0.437***	0.288***						
CMA	0.010	0.343***	-0.053	0.664***	0.195***					
MOM	-0.033	0.232***	-0.082*	-0.193***	0.061	0.031				
LIQ	-0.007	0.094***	0.035**	-0.130***	-0.071**	-0.163***	0.060			
BM	0.078	0.013**	0.193***	0.085*	-0.149***	0.086	-0.144***	0.069***		
BS	0.054	0.399***	-0.286***	-0.079	0.209***	0.032	0.303***	-0.181***	0.521***	
PTFSBD	0.042	0.292***	-0.093*	-0.091*	0.039	-0.010	0.073	-0.066	0.134***	0.276***
PTFSFX	-0.035	0.247***	-0.045	-0.041	0.042	0.127**	0.160***	-0.140***	0.102***	0.311***
PTFSCOM	0.058	0.206***	-0.084*	-0.123**	0.010	0.008	0.188***	-0.067	0.122**	0.253***

Note: This table presents the pairwise Pearson correlation coefficients between the first-difference of the orthogonalized U.S.–China Tension Index, denoted as ΔTension$^{\perp}$, and a set of standard asset pricing risk factors and characteristic portfolios. ΔTension$^{\perp}$ is the innovation component of the UCT index after controlling for economic policy uncertainty and macroeconomic fundamentals. *MKTRF* is the market excess return. *SMB*, *HML*, *RMW*, and *CMA* are the Fama–French five factors for size, value, profitability, and investment, respectively. *MOM* denotes the Carhart (1997) momentum factor. *LIQ* is the Pastor–Stambaugh (2003) liquidity factor. *BM* and *BS* refer to the returns on high-minus-low book-to-market and size-sorted portfolios, respectively. *PTFSBD*, *PTFSFX*, and *PTFSCOM* are Fung and Hsieh (2004) trend-following risk factors based on bond, currency, and commodity portfolios. All variables are measured at monthly frequency. The sample period spans from 2002 to 2024.

Table 5: Fund Performance and Characteristics by β^{Tension} Decile

Decile	β^{Tension}	Return (%)	Alpha (FH11)	MFee (%)	IFee (%)	HWM (Dummy)	Lockup (Yrs)	Lev. (Dummy)	Redem. (Days)
1	−0.083	0.194	0.154	1.419	16.688	0.842	1.196	0.632	32.622
2	−0.028	0.233	0.175	1.392	16.738	0.826	1.265	0.621	33.985
3	−0.016	0.343	0.203	1.380	16.380	0.818	1.213	0.608	33.623
4	−0.008	0.301	0.218	1.374	16.500	0.832	1.251	0.608	34.527
5	−0.002	0.313	0.348	1.360	16.328	0.820	1.216	0.607	33.710
6	0.003	0.287	0.367	1.367	16.432	0.815	1.186	0.614	33.815
7	0.009	0.304	0.413	1.373	16.679	0.828	1.169	0.616	34.314
8	0.017	0.403	0.469	1.384	16.631	0.824	1.169	0.623	34.117
9	0.030	0.269	0.470	1.397	16.876	0.833	1.236	0.636	34.687
10	0.077	0.430	0.625	1.410	16.420	0.811	1.053	0.639	31.975

Note: This table reports average fund performance and characteristics across deciles sorted by estimated β^{Tension}, which captures a fund's exposure to innovations in the orthogonalized U.S.–China Tension Index. The betas are estimated via time-series regression of monthly hedge fund excess returns on the market factor and first-differences of the orthogonalized UCT index. *Return* is the average monthly return in percentage terms. *Alpha (FH11)* denotes the intercept from the Fung and Hsieh (2004) eleven-factor model regression. *MFee* and *IFee* are the management and incentive fees, respectively, reported in annual percentage terms. *HWM (Dummy)* equals one if the fund employs a high-water mark provision. *Lockup (Yrs)* is the average lock-up period in years. *Lev. (Dummy)* is a binary indicator equal to one if the fund uses leverage. *Redem. (Days)* is the required redemption notice period in days. All statistics are pooled averages over the sample period from January 2002 to December 2024.

Table 6: Newey–West Test of Return and Alpha Spread

	Return	Alpha (FH7)	Alpha (FH9)	Alpha (FH11)
10-1 Spread	0.180	0.320**	0.305*	0.331*
	(0.175)	(0.153)	(0.165)	(0.174)

Note: This table presents the spread in average return and alpha between the highest and lowest deciles sorted by β^{Tension}, which captures hedge fund exposure to innovations in the orthogonalized U.S.–China Tension Index. *Return* is the average raw monthly return. *Alpha (FH7)*, *Alpha (FH9)*, and *Alpha (FH11)* are intercepts from time-series regressions based on the Fung and Hsieh (2004) seven-factor model, an extended nine-factor model, and an eleven-factor model, respectively. All statistics are computed using equal-weighted decile portfolios. Newey–West standard errors with two lags are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Panel Regression of Excess Return

Dependent Variable: Excess Return					
	(1)	(2)	(3)	(4)	(5)
β^{Tension}	1.442*	1.088**	1.337**	1.333**	1.319**
	(1.84)	(2.05)	(2.45)	(2.46)	(2.47)
Size			0.033**	0.035***	0.035**
			(2.28)	(3.00)	(2.58)
Age (Month)			−0.000	−0.000	−0.000
			(-1.03)	(-1.20)	(-1.30)
Lockup (Year)			0.003	0.001	−0.002
			(0.37)	(0.20)	(-0.27)
Management Fee (%)			0.038	0.032	0.035
			(0.77)	(0.63)	(0.69)
Incentive Fee (%)			−0.001	−0.002	−0.001
			(-0.18)	(-0.27)	(-0.12)
High-Water Mark (Dummy)			−0.051	−0.043	−0.053
			(-0.94)	(-0.81)	(-0.99)
Leverage (Dummy)			−0.081	−0.075	−0.076
			(-1.62)	(-1.64)	(-1.44)
Notice Period (Days)			0.000	0.001	0.001
			(0.21)	(0.40)	(0.50)
Redemption Period (Days)			0.002**	0.002**	0.001
			(2.17)	(2.23)	(1.21)
Constant	0.517***	0.517***	0.452***	0.451***	0.466***
	(4.34)	(56.81)	(3.16)	(3.37)	(3.01)
Fixed Effects	Fund	Time	Time	Style & Time	Country & Time
R^2	0.0193	0.2155	0.2237	0.2239	0.2244
Observations	95,555	95,555	58,953	58,953	58,953

Note: This table presents the panel regression results of monthly hedge fund excess return on β^{Tension}, which measures each fund's exposure to innovations in the orthogonalized U.S.–China Tension Index. The dependent variable is fund excess return in percentage terms. Models (1)–(5) incrementally control for fund fixed effects, time fixed effects, and additional fund-level characteristics. Control variables include the natural logarithm of fund size, fund age (in months), lock-up period (in years), management fee (%), incentive fee (%), a dummy for high-water mark provision, a dummy for leverage usage, redemption period (in days), and notice period (in days). Models (4) and (5) further incorporate style and country fixed effects, respectively. t-statistics are reported in parentheses. Standard errors are clustered by fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Panel Regression of Out-of-Sample Alpha on β^{Tension}

	(1)	(2)	(3)	(4)	(5)
Panel A: FH7 — Out-of-Sample Alpha (Fung–Hsieh 7 Factors)					
β^{Tension}	1.619**	1.748***	2.536***	2.551***	2.494***
	(2.19)	(3.06)	(3.94)	(3.95)	(3.84)
Control Variables	×	×	✓	✓	✓
Time Fixed Effects	×	✓	✓	✓	✓
Other Fixed Effects	Fund	×	×	Style	Country
R^2	0.0243	0.0685	0.0700	0.0703	0.0709
Observations	95,555	95,555	58,953	58,953	58,953
Panel B: FH9 — Out-of-Sample Alpha (FH7 + Momentum and Liquidity)					
β^{Tension}	1.836**	1.669***	2.402***	2.403***	2.383***
	(2.52)	(2.89)	(3.87)	(3.85)	(3.84)
Control Variables	×	×	✓	✓	✓
Time Fixed Effects	×	✓	✓	✓	✓
Other Fixed Effects	Fund	×	×	Style	Country
R^2	0.0243	0.0651	0.0665	0.0668	0.0674
Observations	95,555	95,555	58,953	58,953	58,953
Panel C: FH11 — Out-of-Sample Alpha (FH7 + Investment, Profitability, Momentum, Liquidity)					
β^{Tension}	2.007**	1.922***	2.893***	2.883***	2.809***
	(2.54)	(2.93)	(4.01)	(3.97)	(3.87)
Control Variables	×	×	✓	✓	✓
Time Fixed Effects	×	✓	✓	✓	✓
Other Fixed Effects	Fund	×	×	Style	Country
R^2	0.0240	0.0625	0.0645	0.0647	0.0654
Observations	95,555	95,555	58,953	58,953	58,953

Note: This table presents the panel regression results of monthly hedge fund out-of-sample alpha on β^{Tension}, which measures each fund's exposure to innovations in the orthogonalized U.S.–China Tension Index. The dependent variable in Panels A–C is the out-of-sample alpha estimated from the Fung and Hsieh (2004) seven-factor model (FH7), the nine-factor model including momentum and liquidity (FH9), and the eleven-factor model including investment and profitability factors (FH11), respectively. Models (1)–(5) incrementally control for fund fixed effects, time fixed effects, and additional fund-level characteristics. Control variables include the natural logarithm of fund size, fund age (in months), lock-up period (in years), management fee (%), incentive fee (%), a dummy for high-water mark provision, a dummy for leverage usage, redemption period (in days), and notice period (in days). Models (4) and (5) further incorporate style and country fixed effects, respectively. t-statistics are reported in parentheses. Standard errors are clustered by fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Fund Performance by Style

Dependent Variable:	Excess Return	Alpha (FH7)	Alpha (FH9)	Alpha (FH11)
β^{Tension}	0.065	-0.420	-1.467	-0.961
	(0.03)	(-0.30)	(-0.90)	(-0.49)
$\beta \times$ Equity Market Neutral	4.656*	9.747***	9.086***	8.637**
	(1.67)	(4.43)	(3.01)	(2.57)
$\beta \times$ Event Driven	1.353	2.264	3.170	2.272
	(0.68)	(1.20)	(1.59)	(0.97)
$\beta \times$ Fund of Funds	0.521	4.319	4.748	6.474**
	(0.20)	(1.16)	(1.61)	(2.13)
$\beta \times$ Global Macro	-0.794	2.484	3.884**	2.809
	(-0.30)	(1.26)	(2.00)	(1.20)
$\beta \times$ L/S Equity Hedge	1.828	3.161**	3.926**	4.369**
	(0.85)	(2.20)	(2.50)	(2.28)
$\beta \times$ Multi-Strategy	2.460	3.152	5.314*	5.823
	(0.96)	(1.25)	(1.77)	(1.62)
Control Variables	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓
R^2	0.2241	0.0705	0.0669	0.0650
Observations	58,953	58,953	58,953	58,953

Note: This table presents the panel regression results of hedge fund performance on β^{Tension} and its interaction with fund strategy categories. The dependent variables across columns are excess return and out-of-sample alpha estimates from the FH7, FH9, and FH11 models, all expressed in percentage terms. The base group is Convertible Arbitrage; all other strategy dummies are interacted with β^{Tension}. Control variables include the natural logarithm of fund size, fund age (in months), lock-up period (in years), management fee (%), incentive fee (%), a dummy for high-water mark provision, a dummy for leverage usage, redemption period (in days), and notice period (in days). All regressions include time fixed effects. t-statistics are reported in parentheses. Standard errors are clustered by fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Holdings-Based Validation of Return-Estimated UCT Exposure

	Level of UCT beta		Total rank change		Active rank change	
	Equal	AUM	Equal	AUM	Equal	AUM
	(1)	(2)	(3)	(4)	(5)	(6)
Holdings-implied exposure	17.302*	17.943*	0.433**	0.380*	0.418**	0.093
	(1.772)	(1.716)	(2.332)	(1.815)	(2.075)	(0.565)
p-value	0.076	0.086	0.020	0.070	0.038	0.572
Manager-family fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Calendar-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Level controls	Yes	Yes	No	No	No	No
Other decomposition components	—	—	No	No	Yes	Yes
Observations	1,643	1,341	1,075	891	1,075	891
Manager families	109	90	91	76	91	76
Calendar quarters	43	43	42	42	42	42

Notes: The dependent variable in columns (1)–(2) is the manager- family fund-return UCT beta. The regressor is the value-weighted UCT beta of disclosed long-equity holdings. The dependent variable in columns (3)–(6) is the consecutive-quarter change in the centered within-quarter rank of the family fund-return UCT beta. Columns (3)–(4) use the total change in the rank of holdings-implied exposure. Columns (5)–(6) include the ranked security-beta update, active-reallocation, and passive-drift components jointly and report the active-reallocation coefficient. "Equal" aggregates funds equally within a family; "AUM" uses positive AUM weights. Level controls are the holdings-implied market beta, log reported long-equity value, and security-link coverage. All regressions include manager-family and calendar-quarter fixed effects. Parentheses contain t-statistics based on standard errors two-way clustered by manager family and quarter. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on nominal p-values.

Table 11: Cross-Sectional Distribution of UCT-Timing Coefficient

	Percentage of Funds							
Category	$t \leq -2.33$	$t \leq -1.96$	$t \leq -1.65$	$t \leq -1.28$	$t \geq 1.28$	$t \geq 1.65$	$t \geq 1.96$	$t \geq 2.33$
All Hedge Funds	6.22	10.50	15.39	23.14	14.37	9.58	6.83	4.59
Directional	7.33	9.33	12.67	15.34	26.67	13.33	9.33	7.33
Semi-directional	6.24	11.29	16.20	24.70	11.55	8.90	6.64	4.11
Non-Directional	3.85	5.13	12.82	23.08	17.95	8.97	3.85	3.85

Note: This table presents the proportion of hedge funds whose estimated timing coefficients exceed standard t-value thresholds under the null hypothesis that tension-timing ability is zero. Results are based on cross-sectional distributions of fund-level regression t-statistics.

Table 12: Bootstrap Analysis of UCT-timing Coefficient

	Bottom t-statistics for θ				Top t-statistics for θ			
Category	1%	3%	5%	10%	10%	5%	3%	1%
All Hedge Funds	-4.299	-2.996	-2.565	-1.977	1.551	2.226	2.565	3.269
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Directional	-4.224	-3.049	-2.672	-1.862	1.834	2.671	2.794	3.273
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)
Semi-directional	-4.319	-2.934	-2.508	-2.016	1.414	2.191	2.484	3.276
	(0.000)	(0.000)	(0.000)	(0.000)	(0.032)	(0.000)	(0.000)	(0.000)
Non-directional	-3.449	-2.390	-1.967	-1.792	1.462	1.849	2.225	2.622
	(0.005)	(0.047)	(0.108)	(0.009)	(0.141)	(0.175)	(0.097)	(0.139)

Note: This table presents the empirical distribution of the timing coefficient t-statistic under the null, based on 1,000 bootstrap resamples. The test statistic corresponds to the coefficient on the timing term in fund-level regressions. The bootstrap design follows Cao et al. (2013), preserving time-series dependence under the null. Empirical p-values are shown in parentheses.

Table 13: Determinants of the Tension Beta

Dependent Variable: β^{Tension}					
	(1) All HFs	(2) All HFs	(3) Directional	(4) Semi-directional	(5) Non-directional
Timing Ability (θ_i)		0.0070**	0.0084**	0.0086**	−0.0113***
		(1.98)	(2.22)	(2.00)	−3.62
$\theta_i \times$ High Tension		−0.0088**	−0.0104***	−0.0087**	0.0001
		(-2.55)	(-2.76)	(-2.03)	(0.05)
Size	0.0002	0.0002	−0.0001	0.0004	0.0028**
	(0.51)	(0.51)	(-0.30)	(0.97)	(2.20)
Age (Month)	−0.0000	−0.0000	0.0000	−0.0000	−0.0000
	(-0.35)	(-0.30)	(0.17)	(-0.36)	(-0.46)
Lockup Period (Year)	−0.0005*	−0.0005*	−0.0004	−0.0004	−0.0028
	(-1.78)	(-1.83)	(-1.61)	(-1.47)	(-1.10)
Management Fee (%)	−0.0014	−0.0013	−0.0018	0.0003	0.0030
	(-0.95)	(-0.87)	(-1.12)	(0.22)	(0.64)
Incentive Fee (%)	−0.0003**	−0.0003*	−0.0003**	−0.0001	−0.0001
	(-2.00)	(-1.93)	(-2.27)	(-0.59)	(-0.18)
High-Water Mark (Dummy)	0.0054***	0.0052***	0.0049**	0.0041**	0.0032
	(2.86)	(2.73)	(2.27)	(2.13)	(0.75)
Leverage (Dummy)	0.0014	0.0014	0.0009	−0.0007	0.0094
	(1.01)	(1.05)	(0.63)	(-0.48)	(1.65)
Notice Period (Days)	−0.0000	−0.0000	0.0000	−0.0000	−0.0000
	(-0.42)	(-0.45)	(1.13)	(-1.05)	(-0.13)
Redemption Period (Days)	0.0000	0.0000	0.0000	0.0000	0.0001
	(1.49)	(1.52)	(1.55)	(1.36)	(0.44)
Constant	0.0031	0.0029	0.0038	0.0011	−0.0166
	(1.07)	(0.99)	(1.24)	(0.37)	(-1.52)
Time Fixed Effects	✓	✓	✓	✓	✓
Style Fixed Effects	✓	✓	×	×	×
R^2	0.0260	0.0297	0.0221	0.0201	0.2227

Note: This table presents the panel regression results of hedge fund β^{Tension} on the funds' timing ability θ_i. The key explanatory variables include a fund-specific timing coefficient and its interaction with a high-tension dummy, which takes the value of 1 if the U.S.–China Tension index is above its time series average, and zero otherwise. Control variables include the natural logarithm of fund size, fund age (in months), lock-up period (in years), management fee (%), incentive fee (%), a dummy for high-water mark provision, a dummy for leverage usage, redemption period (in days), and notice period (in days). Model (1) includes only fund characteristics. Model (2) adds the timing coefficient θ^i and its interaction with high tension. Models (3)–(5) estimate the same specification across directional, semi-directional, and non-directional hedge fund subsamples, respectively. t-statistics are reported in parentheses. Standard errors are clustered by fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.