Between Scylla and Charybdis: U.S. Trade Policy Uncertainty and the Equity Risk Premium Across Sectors

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Abstract

Trade policy uncertainty does not price equity risk the way conventional wisdom suggests. Using daily data for 18 major U.S. sectors over 2014–2025, a sample spanning two full cycles of tariff escalation, we construct a multidimensional equity risk premium integrating rolling CAPM decomposition, habit-based time-varying risk aversion, and sector-specific loss aversion, and isolate trade-specific uncertainty through a VIX-orthogonalised index. This design allows us to separate what trade policy uncertainty actually does to equity risk pricing from what general market fear makes it appear to do. The results reveal a clear pattern. Combining event-study analysis, Forbes-Rigobon heteroskedasticity correction, EGARCH-X estimation, and linear and nonlinear Granger causality, we show that the apparent co-movement between trade policy uncertainty and sectoral premia is genuine for only four sectors – Technology, TMT, Health Care, and Aerospace, and reflects volatility artefacts for the rest. Cumulative abnormal premia following uncertainty spikes are significant only in discount-rate-sensitive sectors, dissipate within a week, and virtually disappear from conditional mean and variance specifications once the VIX component is removed. The results challenge the conventional view of trade policy uncertainty as a persistent priced factor. We show that its effects are short-lived, sectorally heterogeneous, and transmitted through a directional supply-chain structure. Trade policy uncertainty operates as a high-frequency discount-rate shock that is rapidly incorporated and largely invisible once market fear is stripped out. Transmission across sectors follows supply-chain logic. Eight upstream and technology-oriented sectors embed trade risk information before it appears in the uncertainty index, acting as net transmitters. Five financially constrained sectors: Financials, Health Care, Basic Materials, Real Estate, and Banks absorb subsequent discount-rate adjustments as net receivers. All significant impulse responses peak within two to three trading days. The practical implication is direct: the two-step transmission chain from upstream sector premia to financial sector stress provides macroprudential authorities with an early warning signal that VIX-based surveillance cannot deliver.

Keywords:

equity risk premium; trade policy uncertainty; sectoral heterogeneity; supply-chain transmission; habit formation.

JEL Classification:G12, G15, F13, F14, E44, C32

1. Introduction

Trade policy uncertainty is widely believed to be a priced source of risk in equity markets, yet the mechanism through which it is incorporated into prices remains unclear. When the Trump administration imposed broad-based import tariffs on April 2, 2025, raising the effective U.S. tariff rate from 2.5% to an estimated 27% in a single quarter, the highest level since 1935, equity markets reacted immediately but unevenly. Financial intermediaries repriced risk within hours as funding conditions tightened; upstream manufacturers in chemicals and basic materials registered muted or even positive abnormal returns as domestic pricing power expectations improved; technology firms with globally diversified revenues barely moved. These divergent reactions are not noise. They reflect systematic differences in how trade policy uncertainty enters the pricing kernel of equity markets, differences that aggregate market indices conceal, that standard asset-pricing models do not accommodate, and that this paper sets out to explain.

The equity risk premium, the excess return investors require for holding equities over risk-free assets, is the primary market-based measure of how risk is priced (Lucas, 1978). A substantial literature, dating to the equity premium puzzle of Mehra and Prescott (1985), has established that observed premia are too large and too variable to be explained by standard consumption-based models alone. Subsequent work has shown that political and policy uncertainty contributes meaningfully to this variability: Pastor and Veronesi (2012) demonstrate that government policy uncertainty shifts discount rates and elevates required returns; Bekaert et al. (2014) establish that political risk spreads explain equity returns across developed and emerging markets; Baker et al. (2016) show that policy uncertainty spikes depress investment and raise market volatility. More recently, evidence from the first wave of U.S.-China trade tensions confirms that tariff announcements generate large and immediate valuation effects (Amiti et al., 2020; He et al., 2021; Huang et al., 2023), with consequences propagating through global production networks to firms not directly targeted by the measures (Egger & Zhu, 2020). Yet this literature has focused predominantly on aggregate market indices or firm-level event windows. The sector level, the granularity at which supply-chain exposure, regulatory constraints, and balance-sheet structures actually differ, has received far less systematic attention.

A second gap concerns the nature of trade policy uncertainty as a priced risk. The literature implicitly treats trade policy uncertainty as a persistent risk factor affecting expected returns. We show that this interpretation is misleading. However, it remains unclear whether trade policy uncertainty generates sustained changes in required risk premia, or whether its effects are instead short-lived, event-driven, and absorbed rapidly by financial markets. Distinguishing between these possibilities is crucial for understanding whether trade policy uncertainty should be interpreted as a structural pricing factor or as a transient shock to the pricing kernel. A related gap concerns the propagation of trade policy risk across sectors. Financial markets are interconnected systems in which shocks travel through supply chains, balance sheets, and investor rebalancing. The position of a sector in the global value chain plausibly determines whether it originates or absorbs trade-policy-induced risk: upstream producers whose input costs and order books embed early signals of trade frictions may incorporate information about trade risk before it becomes reflected in policy uncertainty measures. Conversely, financially constrained and regulated sectors, sensitive to discount-rate shifts and macroeconomic expectations, may primarily absorb these shocks, with their required returns adjusting in response to prior movements in uncertainty. Empirical evidence on these directional relationships, using measures of risk compensation rather than raw returns, remains scarce.

This paper addresses these gaps. Using daily data for 18 major U.S. sectors over 2014–2025, i.e., a sample encompassing the first U.S.-China trade conflict, the COVID-19 shock, and the full cycle of tariff escalation and reversal under the second Trump administration, we construct a multidimensional sector-level equity risk premium and examine how it responds to and transmits trade policy uncertainty. Our measure integrates three components: rolling CAPM regressions that isolate sectoral excess returns from abnormal performance and market exposure (Duarte & Rosa, 2015); a habit-formation adjustment for time-varying risk aversion (Campbell & Cochrane, 1999; Jordà et al., 2019), producing a risk aversion parameter that rises in adverse states; and a sector-specific loss-aversion correction from a TGARCH(1,1) model that captures asymmetric downside volatility responses (Barberis et al., 2001). Trade policy uncertainty is measured using a VIX-neutralized index that isolates trade-specific policy risk from general market fear.

We address two questions. First, does trade policy uncertainty generate persistent pricing adjustments in sectoral equity risk premia, or are its responses transitory and concentrated around uncertainty shocks? Second, does trade policy uncertainty propagate directionally across sectors in a manner consistent with supply-chain structure, with upstream sectors embedding information earlier and downstream sectors absorbing discount-rate adjustments?

The empirical analysis proceeds in two stages. In the first stage, we examine the short-run response of sectoral ERP to extreme trade policy uncertainty events using an event-study framework with GARCH-adjusted abnormal returns, and distinguish genuine pricing adjustments from volatility artefacts using the Forbes-Rigobon (2002) heteroskedasticity correction. In the second stage, we analyze the direction and persistence of uncertainty transmission using bivariate Granger causality tests, a loss-aversion-adjusted vector autoregressive neural network (LA-VARNN) that accommodates nonlinear dependencies, and orthogonalized impulse response functions with bootstrap confidence bands.

Our results qualify the conventional view of trade policy uncertainty as a priced factor. We find no evidence of persistent responses in conditional mean specifications of sectoral premia. Instead, pricing adjustments are short-lived and heterogeneous: financially constrained and regulated industries experience negative abnormal premia following uncertainty spikes, while upstream tradeables display neutral or mildly positive adjustments. Much of the apparent co-movement between uncertainty and premia reflects volatility-driven artefacts, while the remaining responses are concentrated in a subset of sectors and operate through short-term discount-rate adjustments. At the same time, we document a clear directional structure in the transmission of trade policy uncertainty. Upstream and technology-adjacent sectors embed information about trade-related risks earlier, while financially constrained sectors are systematically preceded by prior movements in uncertainty, absorbing policy-driven discount-rate shocks.

Our findings challenge the standard interpretation of trade policy uncertainty in asset pricing and suggest that it should be modelled as a high-frequency, state-dependent shock rather than a persistent risk factor. This reinterpretation has implications both for empirical asset pricing and for real-time monitoring of financial stability. Trade policy uncertainty should be understood not as a persistent pricing factor, but as a high-frequency, sectorally transmitted shock to the pricing kernel.

This paper makes three contributions to the existing literature. First, we provide a comprehensive analysis of sector-level ERP dynamics under trade policy uncertainty, documenting a cross-sectional structure of risk pricing that aggregate market measures cannot reveal. Second, we introduce a multidimensional ERP construction combining habit-based time-varying risk aversion, rolling CAPM decomposition, and behavioral loss aversion, that enables cleaner identification of trade-specific risk pricing than raw return measures allow. Third, we document directional transmission mechanisms that map onto supply-chain position, providing a tractable framework for macroprudential surveillance: elevated ERP movements in upstream sectors may serve as early warning signals for subsequent stress in financial intermediaries.

This paper shows that trade policy uncertainty is a priced, sector-specific and state-dependent source of equity risk premia that operates through both volatility asymmetry and cross-sector transmission channels. The remainder of the paper is structured as follows. Section 2 reviews the related literature and develops the research hypotheses. Section 3 describes the data and methodological framework. Section 4 presents the empirical results and reports robustness checks. Section 5 discusses the findings, and Section 6 concludes.

2. Theoretical framework and hypothesis development

This section develops the conceptual framework for understanding trade policy uncertainty as a source of variation in sectoral risk premia and its propagation across sectors. We distinguish between pricing mechanisms operating through the discount-rate channel and transmission mechanisms driven by supply-chain structure and financial intermediation. These distinctions motivate the two research hypotheses tested in the empirical analysis.

2.1 The Equity Risk Premium Under Policy Uncertainty

The equity risk premium has occupied a central place in asset pricing since Mehra and Prescott (1985) documented that observed excess returns on U.S. equities are an order of magnitude larger than standard consumption-based models with power utility function. Two broad classes of solution have been proposed. The first modifies investor preferences to generate time-varying risk aversion that rises precisely when the economy deteriorates. Campbell and Cochrane (1999) show that a slow-moving external habit, captured by the surplus consumption ratio $S_t = \frac{C_t - H_t}{C_t}$, produces countercyclical risk aversion and replicates the history of U.S. stock prices without sacrificing a plausible risk-free rate. Barberis, Huang, and Santos (2001) introduce loss aversion into the pricing kernel, showing that investors' asymmetric sensitivity to gains and losses — more painful in bad states than gratifying in good ones — generates a substantial and state-dependent equity premium. The second class modifies the information structure to allow for regime-dependent discount rates. Duarte and Rosa (2015) survey nineteen alternative ERP measures and find that their common factor is driven primarily by variation in discount rates rather than cash-flow expectations, establishing the discount-rate channel as the primary short-run vehicle through which macroeconomic uncertainty enters required returns.

The specific role of policy uncertainty in shaping the equity risk premium has been formalized by Pastor and Veronesi (2012, 2013) and Kelly, Pastor & Veronesi (2016). In their general equilibrium model, government policy uncertainty reduces the value of the implicit put protection that the government provides to the market, raises required returns, and increases both stock volatility and cross-sectional correlations — particularly in weak economic conditions. The key finding is that political risk commands a time-varying premium whose magnitude is inversely related to the state of the economy: when fundamentals are poor, policy changes are more likely, their consequences are more uncertain, and markets demand higher compensation. Brogaard and Detzel (2015) provide cross-sectional and time-series evidence that the Baker-Bloom-Davis (2016) economic policy uncertainty index is associated with time-varying expected returns, although the persistence and economic interpretation of this effect remain debated: portfolios with higher EPU exposure earn higher average returns, and EPU innovations command a negative price of risk consistent with an investor preference for certainty. Bekaert, Hoerova, and Lo Duca (2013) decompose VIX into risk aversion and uncertainty components, finding that risk aversion is the primary channel through which economic policy uncertainty affects equity pricing.

Within this general literature, trade policy uncertainty has emerged as a distinct and quantitatively significant source of equity risk. Baker et al. (2016) construct a text-based Trade Policy Uncertainty index that spikes around tariff escalation episodes and co-moves with equity volatility at short horizons. Caldara et al. (2020) document, using both firm-level earnings call data and aggregate newspaper coverage, that trade policy uncertainty reduced U.S. business investment by approximately 1.5 percent in 2018 alone, with the effect operating primarily through the precautionary savings and option value of waiting channels rather than through cash-flow revisions. Handley and Limao (2022) provide a broader theoretical framework showing that trade policy uncertainty acts as an implicit tax on trade by raising the option value of deferring market entry decisions, with the magnitude of this implicit tax varying with tariff binding commitments across industries. Amiti, Kong, and Weinstein (2020) extend this evidence to equity markets directly: by estimating the response of aggregate and firm-level stock returns to U.S.-

China tariff announcements during 2018-2019, they show that the cumulative equity market loss attributable to the trade war substantially exceeded the findings of conventional trade models that abstract from investment channel effects and uncertainty costs. Amiti et al. (2024) subsequently confirm that these stock price declines were persistent and correlated with lower subsequent TFP and investment, ruling out the interpretation that markets overreacted to temporary tariff news.

A key limitation of this literature, however, is its focus on aggregate market indices or firm-level outcomes around specific event windows. The sector level — where supply-chain exposure, regulatory constraints, and balance-sheet structures differ systematically — has received comparatively little attention. Caldara et al. (2020) and Guo and Shi (2024) document that trade uncertainty exhibits stronger sectoral variation than aggregate uncertainty, and that industries with higher import penetration mention trade policy more frequently in earnings calls, but they do not examine how these sectoral differences translate into heterogeneous equity risk premia. The event study of Huang, Lin, and Liu (2023) documents heterogeneous stock return responses to tariff announcements across U.S. industries and finds that firms deeply embedded in global value chains suffer disproportionately, but uses raw returns rather than risk-adjusted premia and does not correct for co-movement induced by heteroskedasticity during uncertainty episodes. More recently, Amiti et al. (2025) study global equity price reactions to the April 2025 tariff announcements across 11 major industries in 67 countries, finding that energy, basic materials, and technology sectors experienced the steepest losses, with the cross-country variation driven by tariff exposure, technological competitiveness, and sector-specific valuation profiles. This recent evidence reinforces the relevance of sector-level analysis but still relies on raw price changes rather than risk-adjusted required returns, and does not distinguish genuine co-movement from volatility artefacts.

Against this background, the first research question we address is how trade policy uncertainty is priced in sector-level equity risk premia i.e not in raw returns but in the risk compensation required by investors after controlling for abnormal performance, systematic market exposure, time-varying habit-based risk aversion, and sector-specific loss aversion. If trade policy uncertainty operates primarily through the discount-rate and funding conditions channel, we expect sectors with balance-sheet constraints and regulated cash flows to exhibit significant negative abnormal premia following uncertainty spikes, while upstream tradeables benefit from domestic pricing power adjustments. If it operates through a cost pass-through channel, we expect sectors with limited pricing flexibility and high imported input dependence to be most affected. The Forbes-Rigobbon (2002) correction allows us to separate these genuine economic linkages from the mechanical co-movement that arises because uncertainty spikes are themselves periods of elevated heteroskedasticity. Importantly, the existing literature does not distinguish clearly between persistent pricing responses and short-lived adjustments concentrated around uncertainty shocks. As a result, the interpretation of policy uncertainty as a priced factor may conflate sustained risk compensation with high-frequency discount-rate adjustments that are rapidly incorporated into asset prices (Bouras et al. 2019). This motivates our first hypothesis:

> **H1 — Heterogeneous and Asymmetric Pricing Hypothesis —** *Trade policy uncertainty shocks affect sectoral equity risk premia, but the magnitude, sign, and persistence of the response differ systematically across sectors as a function of their regulatory exposure, balance-sheet constraints, and sensitivity to import cost pass-through* and are concentrated in short-lived, state-dependent adjustments rather than persistent pricing responses.

2.2 Supply-Chain Position, Sectoral Heterogeneity, and Directional Transmission

A large body of research documents that trade policy shocks propagate through supply chains in ways that are not captured by direct tariff exposure. Barrot and Sauvagnat (2016) provide foundational evidence that input-supply disruptions transmit downstream through production networks, with firms that are more central in the input-output network acting as amplifiers rather than absorbers of shocks. Carvalho et al. (2021) extend this framework to show that network structure determines the persistence and direction of shock propagation: sectors with many downstream customers and few upstream suppliers are natural transmitters, while sectors with many suppliers and few customers tend to absorb and attenuate shocks. Applied to trade policy, Egger and Zhu (2020) show that the U.S.-China trade conflict affected third-country firms through global value chain linkages, with upstream exposure being the primary transmission channel. Benguria et al. (2022) document that Chinese firms exposed to tariff uncertainty reduced capital expenditures and employment, and that these adjustments were concentrated in intermediate-goods sectors that are upstream in the value chain, i.e., precisely the sectors that would act as transmitters in our framework.

The role of financial intermediaries as absorbers of trade policy risk deserves particular attention, as it connects the supply-chain transmission literature with the asset-pricing literature. He and Krishnamurthy (2013) show that the financial sector's equity capital is the key state variable governing the aggregate risk premium in intermediary-based models: when financial intermediaries are constrained, risk premia rise across all asset classes through a discount-rate channel that is independent of direct exposure to the underlying shock. Adrian, Etula, and Muir (2014) provide empirical evidence that broker-dealer leverage is a priced risk factor, confirming that changes in financial intermediary balance sheets transmit to equity premia. In the context of trade policy, this mechanism implies that tariff uncertainty. Even when it primarily affects non-financial sectors through input cost and demand channels, should eventually raise the financial sector's required equity return through the balance-sheet and collateral channels, with the timing depending on how quickly trade frictions translate into credit risk and funding conditions.

The question of directional transmission in financial networks has been formalized through Granger causality and related methods. Billio et al. (2012) construct a Granger causality network among hedge funds, banks, broker-dealers, and insurance companies, finding that the financial sector tends to be a net receiver of shocks during stress episodes rather than a transmitter. Diebold and Yilmaz (2014) introduce generalized forecast error variance decompositions to measure directional spillovers in financial networks, and find systematic patterns of transmission from commodity markets to equity markets and from equity markets to bond markets during uncertainty episodes. Oh and Kim (2023) apply a similar framework to sectoral equity returns during the U.S.-China trade conflict, finding that manufacturing sectors transmitted uncertainty to financial markets with a lag of two to five trading days . This pattern is consistent with the price discovery hypothesis that upstream sectors embed trade information before it appears in financial sector valuations.

The evidence on supply-chain transmission through equity risk premia, rather than through returns or investment, is more limited. He, Lucey, and Wang (2021) examine the asymmetric responses of U.S. and Chinese trade policy uncertainty on bilateral equity markets, finding that U.S.-originating TPU has larger and more persistent responses on both markets, consistent with the U.S. being the dominant uncertainty originator. However, their analysis is at the country level and does not address sectoral transmission within the U.S. economy. Poilly and Tripier (2025) use regional variation in U.S. import exposure to identify the causal effect of trade policy uncertainty on economic activity, finding significant negative adjustments that take up to a year to materialize – a timing that suggests a multi-stage transmission process compatible with the upstream-to-downstream propagation mechanism we study. The recent evidence from the 2025 tariff cycle reinforces this mechanism: the CEPR analysis of Adolfsen and Harr (2025) shows that the macroeconomic response to TPU operates primarily through confidence and investment channels, with manufacturing and tradable sectors leading the adjustment, while financial intermediaries absorb the aggregate discount-rate consequences with a lag.

A structural gap in this literature is the absence of evidence on whether sectoral equity risk premia, as opposed to raw returns or aggregate uncertainty indices, exhibit directional Granger causality patterns consistent with supply-chain position. If upstream real sectors act as price discovery nodes for trade-related risk, their ERP movements should precede subsequent readings of trade policy uncertainty indices and subsequent ERP movements in financially constrained sectors. Conversely, if the financial sector is a net receiver, its premia should be preceded by prior movements in trade uncertainty but not the reverse. Testing these directional relationships requires a measure of risk compensation that isolates the trade-specific pricing signal from general market noise, precisely what our multidimensional ERP measure provides. Moreover, given the well-documented nonlinearities in financial network transmission during uncertainty episodes (Billio et al., 2012; Adrian et al., 2014), linear Granger causality tests may understate the true directional dependencies Chen & Sun (2024). The LA-VARNN approach of Barberis-adjusted neural network Granger causality, which we apply alongside standard VAR tests, is designed to capture exactly these nonlinear threshold dependencies in the tails of the distribution. This motivates our second hypothesis:

> **H2 — Supply-Chain Transmission Hypothesis —** *The direction and strength of trade policy uncertainty transmission across sectors depend on their position in the global value chain: upstream real sectors act as net transmitters of risk information whose equity risk premia precede subsequent readings of the trade policy uncertainty index, while downstream and financially constrained sectors act as net receivers whose premia are preceded by prior movements in trade policy uncertainty.*

3. Research design

The empirical design combines multiple complementary methods, each targeting a distinct aspect of risk pricing, rather than relying on a single specification. This layered approach allows us to distinguish persistent pricing responses from short-lived adjustments, separate genuine economic dependence from volatility-induced co-movement, and identify the direction of transmission across sectors. Among these methods, the event study and EGARCH-X specifications provide the primary evidence on pricing, while the causality and impulse response analyses are used to characterise the transmission mechanism.

3.1 Data

The empirical analysis uses daily data for 18 U.S. equity sectors over the period January 2014 to September 2025, yielding 2,794 trading-day observations per series with no missing values after rolling-window initialisation. Sector-level returns are constructed from the corresponding S&P 500 sector indices: Technology (TECH), Telecommunication Services and Media (TMT), Financials (FIN), Energy (ENRG), Insurance (INS), Water Utilities (WATR), Food Producers (FOOD), Health Care (HLTH), Aerospace and Defence (AERO), Banks (BANKS), Construction (CONS), Chemicals (CHEM), Industrials (INDUS), Automobiles (AUTO), Basic Materials (BMAT), Real Estate (RE), Software (SOFT), and Consumer Discretionary (CDIS). The risk-free rate is the daily U.S. three-month Treasury bill yield converted to a daily rate. The market return is the value-weighted CRSP market portfolio return. Consumer Staples sector returns serve as the high-frequency consumption proxy for the habit formation adjustment, following Lettau and Ludvigson (2001).

The sample spans two complete cycles of U.S. trade policy escalation. The first cycle covers 2018 to 2020, encompassing the Section 301 tariff announcements of March-June 2018, the escalation rounds of May and August 2019, and the Phase One agreement of January 2020. The second cycle runs from late 2024 through September 2025, covering the renewed tariff escalation under the second Trump administration, including the April 2, 2025 broad-based import levies and the subsequent partial reversal. The pre-war baseline period of 2014-2017 provides a reference against which both cycles can be benchmarked. Table 1 reports descriptive statistics for all 19 series.

3.2 Construction of the Sectoral Equity Risk Premium

We construct a multidimensional sector-level equity risk premium, denoted $ERP_{i,t}^{adj}$, through three successive layers of adjustment targeting distinct sources of contamination in raw sector returns.

We start with the rolling CAPM decomposition. For each sector i we estimate a bivariate rolling OLS regression over a backward-looking window of W = 30 trading days:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t}$$

where $r_{i,t}$ is the daily log return of sector i, $r_{m,t} - r_{f,t}$ is the market excess return, and $\alpha_{i,t}$ and $\beta_{i,t}$ are the rolling intercept and market loading. The raw sector ERP is the beta-normalized, net-of-alpha excess return:

$$ERP_{i,t}^{raw} = \frac{\left(r_{i,t} - \hat{\alpha}_{i,t-1} - r_{f,t}\right)}{\beta_{i,t-1}}$$

Dividing by the estimated beta converts the raw excess return into a market-risk-equivalent premium; subtracting α removes the component attributable to abnormal performance unrelated to systematic risk. The 30-day window follows Duarte and Rosa (2015) and is short enough to track structural breaks in betas across trade-war regimes.

Next we introduce a habit-based risk aversion scaling. In the habit formation model of Campbell and Cochrane (1999), the representative investor's coefficient of relative risk aversion is $\gamma_t = \frac{\bar{\gamma}}{S_t}$, where the surplus consumption ratio is:

$$S_t = \frac{(C_t - H_t)}{C_t}$$

C_t is aggregate consumption proxied by Consumer Staples returns, and H_t is a slow-moving external habit stock constructed as a geometric average of past consumption following Jordà, Schularick, and Taylor (2019). S_t is bounded below by $S_{min} = 0.01$. We estimate $\bar{\gamma}$ by matching the unconditional equity premium over the full sample via method of moments. The habit-adjusted ERP is:

$$ERP_{i,t}^{hab} = ERP_{i,t}^{raw} \cdot \frac{S_t}{\bar{\gamma}}$$

This adjustment is common to all sectors, so cross-sectional variation in ERP^{hab} reflects sector-specific risk rather than the aggregate risk aversion state.

Finally we define a sector-specific loss-aversion multiplier. We estimate a TGARCH(1,1) model for each sector to identify the leverage parameter η_i measuring the incremental amplification of conditional volatility following losses relative to equal-magnitude gains:

$$h_{i,t} = \omega_i + \alpha_i \, \varepsilon_{i,t-1}^2 + \eta_i \, \varepsilon_{i,t-1}^2 \cdot \mathbb{1}(\varepsilon_{i,t-1} < 0) + \beta_i \, h_{i,t-1}$$

The sector-specific loss-aversion multiplier, following Barberis, Huang, and Santos (2001), is defined as:

$$\lambda_i = \max(1, 1 + \frac{\eta_i}{\bar{\eta}}), \quad \bar{\eta} = N^{-1} \Sigma_i \, \eta_i, \quad N = 18$$

The $\max(1, \cdot)$ operator ensures $\lambda_i \geq 1$ for all sectors, consistent with the theoretical requirement that loss aversion amplifies rather than attenuates required returns. The final adjusted measure is:

$$ERP_{i,t}^{adj} = \lambda_i \cdot ERP_{i,t}^{hab}$$

Where $ERP_{i,t}^{adj}$ is the dependent variable in all subsequent empirical analyses.

3.3 Trade Policy Uncertainty: Measurement and VIX Neutralisation

Our baseline uncertainty measure is the daily Baker-Bloom-Davis (2016) Trade Policy Uncertainty index (TPU_{raw}), constructed from the frequency of joint occurrences of trade policy and uncertainty terms in major U.S. newspapers. Caldara et al. (2020) validate TPU_{raw} as a meaningful precursor of firm-level investment decisions. We standardize TPU_{raw} to zero mean and unit standard deviation over the full sample.

To isolate trade-specific policy risk from aggregate market fear, we regress the standardized daily change in TPU_{raw}on contemporaneous and one-lag changes in VIX:

$$\Delta TPU_{raw,t} = \delta_0 + \delta_1 \Delta VIX_t + \delta_2 \Delta VIX_{t-1} + u_t$$

and define the VIX-neutralized index as the residual: $TPUI_{adj,t} = \hat{u}_t$. By construction, TPU_{adj} is orthogonal to both contemporaneous and lagged VIX.This assures, that the neutralisation removes a substantial shared component while preserving the trade-specific signal. TPU_{adj} is our primary uncertainty measure throughout. Section 5 replaces it with TPU_{raw} and TPU_{std} as robustness checks.

Trade policy uncertainty event dates are days on which $TPUI_{adj}$ exceeds its 95th sample percentile, subject to a minimum inter-event separation of 10 trading days to ensure non-overlapping event windows. The resulting event set concentrates around the 2018 Section 301 announcements, the 2019 escalation rounds, and the 2025 Liberation Day cycle.

3.4 Methods for Testing H1: Heterogeneous and Asymmetric Pricing

H1 is tested through three complementary methods that together document whether trade policy uncertainty is priced in sectoral ERP and whether that pricing is heterogeneous across sectors: an event study, a Forbes-Rigobon co-movement correction, and an EGARCH-X parametric model.

Following Patell (1976) we start with event study. For each sector i and each event date τ, we compute cumulative abnormal returns (CAR) over the window $[-10, +10]$ trading days. Abnormal returns are residuals from a sector-specific GARCH(1,1)-t model estimated on the pre-event window $[-120, -11]$:

$$ERP_{i,t}^{adj} = \mu_i + \varphi_i \, ERP_{i,t-1}^{adj} + \xi_{i,t}, \quad \xi_{i,t} = \sqrt{h_{i,t}} \cdot z_{i,t}$$

$$h_{i,t} = \omega_i + \alpha_i \, \xi_{i,t-1}^2 + \beta_i \, h_{i,t-1}, \quad z_{i,t} \sim t(0,1,\nu_i)$$

Abnormal returns on event-window days are standardized by $\sqrt{\hat{h}_{i,\tau+k}}$. Cumulative abnormal returns are:

$$CAR_i(k_1, k_2) = \Sigma_{k=k_1}^{k_2} AR_{i,\tau+k}$$

Cross-sectional significance uses the standardized test of Boehmer, Musumeci, and Poulsen (1991), robust to event-induced variance increases. We test for heterogeneity across sectors using a chi-squared test of equal CARs and for asymmetry using a t-test of the difference in CAR between the upstream and financial sector groups.

Next we perform a Forbes-Rigobon correction. Positive co-movement between $ERP_{i,t}^{adj}$ and $TPUI_{adj}$ during high-uncertainty periods may reflect genuine pricing or may be a statistical artefact of heteroskedasticity. Forbes and Rigobon (2002) show that the bivariate correlation measured in a high-variance regime ρ^H is a biased estimator of the true correlation ρ, with the bias proportional to the variance ratio. The adjusted correlation is:

$$\rho^{adj} = \frac{\rho^H}{\sqrt{(1 + \delta(1 - (\rho^H)^2))}} \quad , \quad \delta = \left(\frac{\sigma_X^H}{\sigma_X^L}\right)^2 - 1$$

where σ_X^H and σ_X^L are the standard deviations of $TPUI_{adj}$ in the top and bottom quartiles of its distribution. We test H_0: $\rho^{adj} = \rho^L$ using a block bootstrap with 1,000 replications and block length of 22 trading days selected following Patton, Politis, and White (2009). A positive and significant difference indicates genuine economic dependence; failure to reject indicates a heteroskedasticity artefact.

As a third and parametric test of H1, we estimate for each sector i an AR(1)-EGARCH(1,1) model with $TPUI_{adj}$ entering as an exogenous regressor in both the conditional mean and the conditional log-variance equations:

$$ERP_{i,t}^{adj} = \mu_i + \varphi_i \, ERP_{i,t-1}^{adj} + \delta_i \sqrt{h_{i,t}} + \lambda_i^1 \, TPUI_{adj,t} + \varepsilon_{i,t}$$

$$\log h_{it} = \omega_i + \alpha_i \left|z_{i,t-1}\right| + \gamma_i \, z_{i,t-1} + \beta_i \log h_{i,t-1} + \lambda_i^2 \, TPUI_{adj,t}$$

where $z_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{it}}}$ is the standardized innovation and γ_i is the asymmetry parameter of the EGARCH specification. The parameter λ_i^1 measures the direct effect of $TPUI_{adj}$ on the conditional mean of $ERP_{i,t}^{adj}$: a statistically significant positive λ_i^1 indicates that higher trade uncertainty raises the required premium through the pricing-kernel channel, consistent with H1. The parameter λ_i^2 measures the response on conditional ERP volatility: a significant positive λ_i^2 indicates that trade policy uncertainty amplifies return variance, consistent with option value of waiting and precautionary demand mechanisms. The model is estimated by maximum likelihood with t-Student innovations using a hybrid solver. The EGARCH-X results complement the event study by providing a time-series characterisation of the mean and volatility channels through which H1 operates, and they directly motivate the robustness comparison of Section 3.6 between $TPUI_{adj}$ and TPU_{raw} .

3.5 Methods for Testing H2: Directional Transmission

H2 is tested through three complementary methods: linear Granger causality in a bivariate VAR, nonlinear Granger causality through the LA-VARNN, and orthogonalized impulse response functions.

First we test linear Granger causality and use a bivariate VAR. For each sector i we estimate a bivariate VAR(p) system in ERP_{it}^{adj} and $TPUI_{adj,t}$ following the Toda-

Yamamoto (1995) procedure, which augments the selected lag order p with one extra lag $d_{max} = 1$ to ensure valid asymptotic inference without pre-testing for integration:

$$ERP_{i,t}^{adj} = c_1 + \Sigma_{j=1}^{p+1} A_{11,j}\, ERP_{i,t-j}^{adj} + \Sigma_{j=1}^{p+1} A_{12,j}\, TPUI_{adj,t-j} + u_{1,t}.$$

$$TPUI_{adj,t} = c_2 + \Sigma_{j=1}^{p+1} A_{21,j}\, ERP_{i,t-j}^{adj} + \Sigma_{j=1}^{p+1} A_{22,j}\, TPUI_{adj,t-j} + u_{2,t}$$

The lag order p is selected by AIC with a maximum of 10. Granger non-causality X→Y (sector does not precede TPUI) is tested as H_0: $A_{21,1} = \cdots = A_{21,p} = 0$ via Wald test on the first p lags, with HAC standard errors following Newey and West (1987). The analogous test for Y→X applies the restriction to $A_{12,j}$. Sectors with significant X→Y causality are classified as net transmitters; sectors with significant Y→X causality as net receivers.

Next we focus on nonlinear Granger causality using LA-VARNN. We complement the VAR with a loss-aversion-adjusted vector autoregressive neural network that accommodates nonlinear threshold effects and tail dependencies. For each direction, we compare a restricted multilayer perceptron receiving only p lags of the dependent variable against an unrestricted model that additionally receives p lags of the candidate causal variable:

$$\text{Restricted:} \quad ERP_{i,t}^{adj} = f(ERP_{i,t-1}^{adj}, \ldots, ERP_{i,t-p}^{adj}) + \varepsilon_t$$

Unrestricted:

$$ERP_{i,t}^{adj} = g(ERP_{i,t-1}^{adj}, \ldots, ERP_{i,t-p}^{adj}, TPUI_{adj,t-1}, \ldots, TPUI_{adj,t-p}) + \varepsilon_t$$

Both $f(\cdot)$ and $g(\cdot)$ use hidden layer architecture (6, 3), logistic activation, and five random weight initialisations. Inputs are min-max scaled to [0,1]. The test statistic is:

$$F = \frac{\left(\frac{RSS_R - RSS_U}{p}\right)}{\left(\frac{RSS_u}{n - k_U}\right)}$$

When $RSS_U \geq RSS_R$ we set F = 0 and p-value = 1, precluding the numerical artefact of negative F-statistics. Statistical significance is assessed through a permutation test with B = 199 random permutations of the causal variable columns, preserving the temporal structure of the dependent variable. Permutation p-values are our primary inferential criterion throughout. For robustness, we also considered the nonparametric test of Diks and Panchenko (2006)

Finally we focus on impulse response functions. We estimate orthogonalized IRFs from each bivariate VAR(p), placing $TPUI_{adj}$ first in the Cholesky decomposition to identify a one-standard-deviation structural innovation in trade policy uncertainty. The IRF at horizon h is:

$$IRF_{i,h} = \frac{\partial ERP^{adj}_{i,t+h}}{\partial \varepsilon_{TPUI,t}} \ , \quad h = 0, 1, \ldots, 10$$

Confidence bands at 95% are constructed via residual bootstrap with 1,000 replications. The IRFs quantify the magnitude and persistence of the ERP adjustment and provide a cross-sector comparison that maps directly onto the transmitter-receiver classification established by the Granger causality tests.

3.6 Robustness Check Methodology

We implement three robustness checks to verify that the main results are not sensitive to our key modelling choices.

Alternative uncertainty measures. As the first check, we re-estimate the AR(1)-EGARCH(1,1)-X model for all 18 sectors using TPU_{raw} and TPU_{std} – a z-score standardized version of the daily change in TPU_{raw} in place of $TPUI_{adj}$. We compare the resulting λ_i^1 and λ_i^2 estimates across specifications using Spearman rank correlations across sectors and report the number of sectors for which λ_i^2 is significant at the 10% level under each specification. The contrast between $TPUI_{adj}$ and TPU_{raw} directly quantifies the fraction of apparent trade policy volatility adjustments that operate through the VIX channel.

Alternative rolling window lengths. As the second check, we repeat the full analysis using 20-day and 60-day rolling windows for the CAPM beta estimation. Consistency of sector classifications across window lengths establishes that the transmitter-receiver distinction is not an artefact of the specific window choice.

Alternative event threshold. As the third check, we repeat the event study using the 90th and 99th percentile thresholds of $TPUI_{adj}$ in place of the 95th percentile. Consistency of the sign and relative magnitude of CARs across thresholds confirms that the heterogeneous pricing pattern is not driven by a specific set of extreme events or by the inclusion of moderate-uncertainty days.

4. Empirical Results

This section presents the empirical results in a structured sequence designed to distinguish short-lived pricing adjustments from persistent responses. We begin with event-study evidence to capture high-frequency responses of sectoral risk premia to trade policy uncertainty shocks. We then assess whether these responses translate into persistent changes in conditional mean or volatility, and finally examine the direction and timing of transmission across sectors.

4.1 Data Properties and ERP Characteristics

[Table 1 here — Descriptive statistics: N, mean, median, SD, skewness, kurtosis for all 18 sectors + $TPUI_{adj}$]

Table 1 reports descriptive statistics for the 18 sector-level adjusted equity risk premia and the VIX-neutralized trade policy uncertainty index over the full 2014-2025 sample. Each series contains 2,794 daily observations with no missing values. The data are decisively non-Gaussian across all sectors: kurtosis ranges from 7.94 (CHEM) to 2,538 (INS), and skewness exhibits large departures from symmetry in both directions. This distributional evidence validates three methodological choices: the use of GARCH-adjusted abnormal returns in the event study, which absorbs the volatility clustering responsible for fat tails; the habit-based scaling of ERP, which captures time-variation in the price of risk; and the permutation-based inference in the LA-VARNN, which does not assume normality.

Medians cluster tightly across sectors in the range 0.001 to 0.002 per day, indicating that on a typical day the ERP measure is near zero once market exposure, risk aversion, and loss aversion are accounted for. Means diverge more substantially: Technology, TMT, Software, Aerospace, and Consumer Discretionary record small positive daily premia, while Energy, Banks, Construction, and Real Estate are negative on average. The divergence between mean and median implies that the sign of the mean is driven by a small number of large-realisation days, consistent with the interpretation that trade-policy risk compensation is earned episodically during uncertainty spikes rather than accruing smoothly.

[Table 2 here — Estimated $\bar{\gamma}$ and λ_i per sector, with TGARCH η_i]

Table 2 reports the long-run risk aversion parameter $\bar{\gamma} = 4.22$, common to all sectors, and the sector-specific loss-aversion multipliers λ_i. The cross-sectional variation in λ_i is economically meaningful. Water Utilities ($\lambda = 1.00$) and Food Producers ($\lambda = 1.23$) sit at the low end, reflecting low leverage effects in their TGARCH specifications and suggesting that investors in regulated, low-volatility sectors do not differentially penalize downside outcomes. Technology ($\lambda = 2.00$) and TMT ($\lambda = 2.00$) sit at the high end, with Software ($\lambda = 1.93$) and Consumer Discretionary ($\lambda = 1.74$) close behind; sectors whose valuations are driven heavily by growth options and whose return distributions exhibit the most pronounced downside asymmetry. Chemicals ($\lambda = 1.53$), Industrials

($\lambda = 1.67$), and Basic Materials ($\lambda = 1.52$) occupy intermediate positions consistent with their mixed exposure to import cost volatility and domestic demand cycles.

4.2 Heterogeneous and Asymmetric Pricing of Trade Policy Uncertainty (H1)

We next assess whether the short-run pricing responses documented in the event-study analysis translate into persistent changes in sectoral equity risk premia. The key question is whether trade policy uncertainty operates as a stable pricing factor, or instead as a transient, state-dependent shock that is not captured by standard conditional mean specifications. We test H1 through three methods in sequence: the event study documents the short-run ERP response across sectors; the Forbes-Rigobon correction distinguishes genuine pricing from volatility artefacts; and the EGARCH-X model identifies the channels through which trade policy uncertainty enters sectoral premia.

Figures 1 and 2 display the average cumulative abnormal returns (CAR) for the adjusted ERP across sectors over the 21-day window [−10, +10] around $TPUI_{adj}$ spikes, with bootstrap confidence bands. Three patterns emerge clearly from the figures.

[Figure 1 here — CAR paths: Panel A (TECH, TMT, FIN, ENRG, INS, WATR, FOOD, HLTH, AERO), 3×3 grid, grey CI bands]

[Figure 2 here — CAR paths: Panel B (BANKS, CONS, CHEM, INDUS, AUTO, BMAT, RE, SOFT, CDIS), 3×3 grid, grey CI bands]

First, most sectors exhibit CARs that are statistically indistinguishable from zero throughout the event window, with confidence intervals that are wide relative to the point estimates. This is the case for Technology, TMT, Financials, Health Care, Aerospace, Chemicals, Industrials, Autos, Basic Materials, Software, and Consumer Discretionary, i.e., eleven of eighteen sectors. For these sectors, trade policy uncertainty spikes do not generate a reliable short-run pricing response in the adjusted ERP measure, consistent with either rapid market incorporation of the trade signal or offsetting adjustments across sub-period episodes.

Second, a distinct subset of sectors with regulated cash flows or balance-sheet constraints exhibits a visible negative drift in CAR following the event date. Real Estate shows the most pronounced and visually consistent downward pattern post-event, with the CAR path declining monotonically from day 0 through day +5 before partially stabilising, consistent with the discount-rate channel: tariff uncertainty compresses expected growth, raises required returns, and depresses real estate valuations through their sensitivity to the long end of the yield curve. Water Utilities displays a similar but less pronounced negative pattern, consistent with regulatory cash-flow constraints that limit pricing flexibility in response to rising input cost uncertainty. Banks exhibits a mildly negative post-event path with wide confidence intervals, suggesting that the financial sector absorbs trade policy shocks through the balance-sheet and funding conditions channel with heterogeneous magnitude across episodes.

Third, two sectors exhibit notably anomalous scales. Insurance displays an extreme CAR range of approximately ±30 units, an order of magnitude larger than the other sectors, with very wide and irregular confidence bands. Construction similarly shows a range of approximately ±60 units. These extreme scales reflect the high unconditional variance of ERP^adj for these sectors documented in Table 1 (SD = 1.91 for INS, SD = 0.59 for CONS), combined with a small number of highly influential event observations. The event study evidence for these two sectors should be interpreted with caution; we treat their results as inconclusive and focus the H1 interpretation on the remaining sixteen sectors.

Taken together, the event study evidence provides qualified support for H1. The pricing of trade policy uncertainty is heterogeneous across sectors: the discount- rate-sensitive group (Real Estate, Water, Banks) exhibits a directionally consistent negative CAR response, while the upstream tradables group and technology-adjacent sectors exhibit responses not significantly different from zero. The absence of a large positive CAR for upstream tradables, which could in principle benefit from domestic pricing power under tariff protection, suggests that the trade-specific pricing component is dominated by the discount-rate and uncertainty-amplification channels rather than by cash-flow revision adjustments.

Table 3 reports the AR(1)-EGARCH(1,1)-X estimates for the conditional mean coefficient λ_i^1 and the conditional variance coefficient λ_i^2 for all 18 sectors with $TPUI_{adj}$ as the exogenous regressor. Three findings stand out. First, λ_i^1 is statistically insignificant for 17 of 18 sectors at conventional levels, with Health Care being the sole exception ($\lambda^1 = 0.0004, p = 0.019$). This near-universal absence of significant mean effects should not be interpreted as evidence that trade policy uncertainty is unpriced. Rather, it indicates that its impact does not operate through persistent shifts in expected returns. Instead, pricing responses are concentrated around short-lived, event-driven adjustments in discount rates that are not captured by standard conditional mean specifications. Second, λ_i^2 is statistically insignificant for nearly all sectors, with Software ($\lambda^2 = 0.026, p = 0.031$) as the only sector where volatility responses remain significant after VIX orthogonalization. Third, and crucially, the robustness comparison with TPU_{raw} reveals that λ_i^2 becomes significant for 13 of 18 sectors when VIX-neutralisation is removed confirming that the near-zero λ_i^2 estimates under $TPUI_{adj}$ reflect genuine isolation of the trade-specific channel rather than a model specification failure. The EGARCH-X results provide parametric confirmation that trade-policy-specific uncertainty operates primarily through episodic discount-rate adjustments rather than through persistent shifts in conditional mean or variance, and that Health Care and Software are the sectors where the trade-specific volatility signal survives VIX orthogonalisation.

[Table 3 here — EGARCH-X results: $\lambda^1{}_i$, p-value, $\lambda^2{}_i$, p-value for all 18 sectors with $TPUI_{adj}$]

Table 4 reports the Forbes-Rigobon t-statistics and p-values comparing the adjusted and raw rolling correlations between $ERP_{i,t}^{adj}$ and $TPUI_{adj}$. The results identify two structurally distinct groups. The reinforced dependence group, comprising Technology (t = 5.35, p ≈ 1.00), TMT (t = 4.90, p ≈ 1.00), Health Care (t = 8.29, p ≈ 1.00), Aerospace (t = 5.09, p ≈ 1.00), and Insurance (t = 3.25, p = 0.999) , shows positive t-statistics with p-values at or near unity, indicating that co-movement with $TPUI_{adj}$ survives the heteroskedasticity correction and reflects genuine structural linkages. For technology-adjacent sectors, this genuine co-movement is consistent with the interpretation that trade policy uncertainty is informative about the pricing kernel, particularly discount rates and aggregate risk aversion, rather than about direct tariff exposure. Health Care's persistence is consistent with genuine supply-chain coupling through pharmaceutical import dependencies.

The attenuated dependence group of Water (t = −5.19), Food Producers (t = −3.96), Chemicals (t = −5.09), Autos (t = −10.17), Real Estate (t = −5.79), Basic Materials (t = −2.69), and Software (t = −1.43) exhibits significantly negative t-statistics, implying that the observed raw correlation for these sectors is largely driven by heteroskedasticity during $TPUI_{adj}$ spikes rather than by structural economic linkages. The block bootstrap results of Table 5 are broadly consistent with this parametric evidence. Notably, Autos exhibits the most extreme attenuation (t = −10.17), suggesting that the apparent co-movement of auto sector ERP with trade uncertainty is almost entirely a volatility artefact, i.e a finding that tempers the intuitive expectation that the auto sector would be a primary victim of trade policy shocks through its global value chain exposure. These findings imply that a substantial portion of the apparent relationship between trade policy uncertainty and sectoral premia in existing studies may reflect volatility-induced co-movement rather than genuine economic dependence. This distinction is critical for correct identification of pricing channels and suggests that empirical results based on raw correlations may overstate the role of trade policy risk.

[Table 4 here — Forbes-Rigobon t-statistics and p-values, 18 sectors]

[Table 5 here — Forbes-Rigobon block bootstrap: obs_diff, p_boot, p_ttest, 18 sectors]

The results suggest that trade policy uncertainty is consistent with the interpretation that trade policy uncertainty operates as a high-frequency, sector-specific discount-rate shock rather than a persistent pricing factor. If this is the case, the key issue is not whether such shocks are priced, but how they propagate across sectors and through which channels they are transmitted. We therefore turn to the analysis of directional transmission, focusing on the timing of information incorporation across sectors and the structure of lead–lag relationships in sectoral risk premia.

4.3 Directional Transmission Along the Supply Chain (H2)

To examine how trade policy uncertainty propagates across sectors, we focus on the direction and timing of transmission in sectoral equity risk premia. The objective is not to establish structural causality, but to identify how information related to trade policy risk is incorporated across sectors and how this generates systematic lead–lag relationships. We test H2 through three complementary methods: linear Granger causality, nonlinear LA-VARNN causality, and impulse response functions. Together they establish both the direction and the temporal structure of trade policy risk transmission across sectors. The causality results should be interpreted as reflecting differences in the timing of information incorporation rather than structural causality. In particular, sectoral premia may embed information about trade-related risks before it becomes reflected in the trade policy uncertainty index.

Table 6 reports Wald test statistics and p-values for both directions of Granger causality from the bivariate VAR specifications. In the direction X→Y (sector ERP precede $TPUI_{adj}$ movements (i.e., premia contain leading information about TPU)), eight sectors are significant at conventional levels: Technology (p = 0.013), TMT (p = 0.007), Financials (p = 0.005), Chemicals (p = 0.012), Industrials (p = 0.005), Basic Materials (p = 0.032), Software (p = 0.028), and Consumer Discretionary (p = 0.004). In the direction Y→X ($TPUI_{adj}$ precede sector ERP), only two sectors are significant: Water (p = 0.029) and Real Estate (p = 0.030).

[Table 6 here — Granger VAR: Instant.Stat, Instant.p, X.Stat, X.p, Y.Stat, Y.p for all 18 sectors]

The linear VAR results provide initial support for the supply-chain transmission hypothesis: technology-adjacent and upstream sectors (Technology, TMT, Chemicals, Industrials, Basic Materials, Software, Consumer Discretionary) act as Granger- causal precursors of trade policy uncertainty, while the financial sector and real estate are instead preceded by it. The bidirectional result for Water Utilities is noteworthy. It is both a precursor of $TPUI_{adj}$ (through input cost dynamics that embed early signals of trade friction) and preceded by it (through regulatory cash-flow constraints that amplify the discount-rate channel). However, the linear VAR may understate the true directional dependencies if they operate primarily through nonlinear threshold effects in the tails of the distribution.

Table 7 reports the F-statistics and permutation p-values from the LA-VARNN for both directions. We treat permutation p-values as the primary inferential criterion given their distribution-free properties. The results substantially extend and refine the linear VAR evidence.

[Table 7 here — LA-VARNN: F_x2y, pPerm_x2y, F_y2x, pPerm_y2x for all 18 sectors]

In the direction X→Y, the LA-VARNN identifies eight sectors with permutation p-values at or near zero: Technology (pPerm = 0.00), TMT (0.00), Energy (0.00), Water (0.00), Food Producers (0.00), Chemicals (0.00), Software (0.00), and Consumer Discretionary (0.00). These sectors act as net transmitters: price discovery in their equity risk premia systematically anticipates subsequent readings of $TPUI_{adj}$. The nonlinear specification additionally identifies Energy and Food Producers as transmitters, i.e., sectors that the linear VAR missed, likely because their causal relationship with trade uncertainty operates through commodity price and import cost threshold effects rather than through linear mean dynamics.

In the direction Y→X, the LA-VARNN identifies five sectors with permutation p-values at or near zero: Financials (pPerm = 0.00), Water (0.00), Health Care (0.00), Basic Materials (0.00), and Real Estate (0.00). Industrials and Banks are borderline significant (pPerm = 0.10). These sectors act as net receivers: their adjusted equity risk premia are systematically preceded by prior movements in $TPUI_{adj}$, consistent with a discount-rate and regulatory cash-flow transmission mechanism. For Financials and Banks, the direction Y→X without significant X→Y is particularly informative: the financial sector absorbs trade policy risk through the balance-sheet and funding conditions channel but does not itself generate early signals of trade friction — a finding directly consistent with H2's implication that financially constrained sectors act as net receivers.

Water Utilities exhibits significant causality in both directions (pPerm = 0.00 for both X→Y and Y→X), confirming the bidirectional feedback loop suggested by the linear VAR. This reflects the dual position of the water sector: it acts as a transmitter through its sensitivity to imported infrastructure inputs and energy costs, and as a receiver through the regulatory discount-rate channel that makes its cash flows sensitive to interest rate movements driven by trade policy shocks.

The cross-method comparison strengthens the H2 interpretation. The transmitter classification is consistent between the linear VAR (Technology, TMT, Chemicals, Industrials, Software, Consumer Discretionary) and the LA-VARNN (which additionally identifies Energy and Food Producers). The receiver classification is broadly consistent, with the LA-VARNN identifying Financials, Health Care, Basic Materials, and Real Estate as receivers — all four of which are economically interpretable through the discount-rate, regulatory, and supply-chain absorption mechanisms described in Section 2.2. The consistency across linear and nonlinear specifications suggests that the transmitter-receiver asymmetry is a robust structural feature of trade policy risk propagation rather than a specification-dependent artefact.

Figures 3 and 4 display the orthogonalized impulse response functions of $ERP_{i,t}^{adj}$ to a one-standard-deviation innovation in $TPUI_{adj}$ over a 10-trading-day horizon, with 95% bootstrap confidence intervals. Three features of the IRF evidence are particularly informative for H2.

[Figure 3 here — IRF Panel A (TECH, TMT, FIN, ENRG, INS, WATR, FOOD, HLTH, AERO): dark blue line, grey CI band, 3×3 grid]

[Figure 4 here — IRF Panel B (BANKS, CONS, CHEM, INDUS, AUTO, BMAT, RE, SOFT, CDIS): dark blue line, grey CI band, 3×3 grid]

First, all significant responses peak within two to three trading days and revert to baseline by day seven or eight. This rapid mean reversion is consistent with markets pricing trade uncertainty as a transitory adjustment in the state variable governing risk compensation rather than as a persistent revision to long-run sectoral growth expectations. The short adjustment horizon also implies that the macroprudential window for monitoring upstream ERP movements as early warning signals is narrow, i.e., reinforcing the practical relevance of real-time surveillance of upstream sector premia. The rapid dissipation of impulse responses provides additional evidence that trade policy uncertainty appears to operate as a transient shock rather than a persistent driver of risk premia. This short adjustment horizon is consistent with high-frequency information processing in financial markets.

Second, the magnitude and direction of IRF responses align closely with the Granger causality classifications. Net receiver sectors, Banks, Real Estate, Water, and Financials, exhibit the sharpest initial responses with confidence intervals that exclude zero at short horizons, consistent with the discount-rate and regulatory cash-flow channels identified in the Granger analysis. Banks shows a positive initial spike followed by rapid reversion, reflecting the short-term tightening of funding conditions that a trade policy shock induces in the banking sector. Real Estate and Water exhibit more persistent downward responses, consistent with their sensitivity to the long end of the yield curve and to input cost dynamics. Net transmitter sectors, Technology, TMT, Chemicals, Software, and

Consumer Discretionary, show responses that are small in magnitude and statistically indistinguishable from zero, consistent with the interpretation that these sectors generate rather than absorb trade policy information.

Third, the IRF evidence for Insurance and Construction should be interpreted with caution given the extreme variance scales documented in the event study and Table 1. Insurance shows a large initial spike with very wide confidence bands, while Construction exhibits an implausibly large scale (±0.03 on the adjusted ERP) that likely reflects the influence of a small number of outlier observations during the most extreme trade policy episodes. For these two sectors we treat the Granger causality evidence as primary and the IRF as indicative only. The evidence points to a structured transmission mechanism in which trade policy uncertainty is not directly priced as a persistent factor, but is instead processed and propagated across sectors through lead–lag relationships in risk premia, with upstream sectors acting as early information carriers and financially constrained sectors absorbing subsequent discount-rate adjustments.

4.4. Robustness Checks

We implement three robustness checks addressing, in turn, the choice of uncertainty measure, the CAPM rolling window length for ERP construction, and the event threshold for identifying trade policy uncertainty spikes.

The main analysis uses $TPUI_{adj}$, the VIX-orthogonalised Baker-Bloom-Davis index. We re-estimate the AR(1)-EGARCH(1,1)-X model for all 18 sectors using TPU_{raw} (raw standardised Baker-Bloom-Davis series) and TPU_{std} (z-score of daily changes in TPU_{raw}). Table 8 presents the conditional variance coefficient λ_i^2 side by side for $TPUI_{adj}$ and TPU_{raw}. Table 9 summarises the count of significant sectors and Spearman rank correlations across all three variants. Full λ^1 and λ^2 estimates for TPU_{raw} and TPU_{std} are in Tables 10 and 11. Pairwise Spearman correlations are in Table 12.

[Table 8 — λ² comparison TPUI_adj vs TPU_raw, 18 sectors]

[Table 9 — summary: N significant sectors + Spearman ρ]

The results reveal a striking pattern. Under $TPUI_{adj}$, λ_i^2 is significant at the 10% level for only 2 of 18 sectors : SOFT ($\lambda^2 = 0.0260, p = 0.031$) and TECH at the margin ($\lambda^2 = 0.0192, p = 0.092$). Under TPU_{raw}, 16 of 18 sectors become significant, with the sole exceptions being TECH (p = 0.378) and BMAT (p = 0.151). Under TPU_{std}, 4 sectors are significant: INS, RE, SOFT, and ENRG at the margin. This collapse from 16 to 2 significant sectors when VIX is orthogonalised out confirms that the bulk of the apparent response of trade policy uncertainty on conditional ERP volatility operates through the general market fear channel captured by VIX.

The Spearman rank correlations in Table 12 provide additional diagnostic evidence. For λ_i^2, the rank correlation between $TPUI_{adj}$ and TPU_{raw} is −0.018, i.e., near zero and negative. This indicates that the cross-sectional ordering of sectors by volatility sensitivity is essentially reversed once VIX is removed: the sectors most sensitive to TPU_{raw} are not the same sectors most sensitive to $TPUI_{adj}$. The rank correlation between $TPUI_{adj}$ and TPU_{std} is positive (0.408), suggesting partial ordering preservation relative to the raw index, but the Spearman ρ between TPU_{raw} and $TPU_{std}$is −0.271, i.e., negative, indicating that the z-score transformation itself substantially changes the sensitivity ordering relative to the raw level series. For λ_i^1, rank correlations are positive across all pairs (0.536, 0.424, 0.201), consistent with moderate stability of the mean effect ordering across specifications, but the absolute significance count falls from 5 under TPU_{raw} to 1 under TPU_{std}. Together these results validate the identification strategy: $TPUI_{adj}$, TPU_{raw}, and TPU_{std} are measuring meaningfully different aspects of the TPU signal, and only $TPUI_{adj}$ isolates the trade-specific component free of aggregate fear.

[Table 10 — full EGARCH-X estimates with TPU_raw]

[Table 11 — full EGARCH-X estimates with TPU_std]

[Table 12 — Spearman rank correlations pairwise]

We repeat the LA-VARNN causality analysis using 20-day and 60-day rolling windows for the CAPM beta estimation in place of the baseline 30-day window, and reconstruct ERP^adj accordingly. Table 13 reports the transmitter (X→Y significant, pPerm ≤ 0.10) and receiver (Y→X significant) classification under all three window lengths side by side.

[Table 13 — transmitter/receiver classification per window (LA-VARNN)]

The most robust finding across all three windows is INDUS: Industrials is classified as a net transmitter (X→Y significant) under the 20-day, 30-day, and 60-day windows, i.e., the only sector to achieve this consistency. This three-window stability is strong evidence that the Industrials sector embeds trade policy information systematically ahead of the uncertainty index, independent of how the CAPM beta is estimated. Under the 20-day window, additional transmitters emerge, TMT, AERO, and AUTO, consistent with the main LA-VARNN classification for TMT and directionally consistent for the others. CONSTR is classified as a receiver at the 20-day window, and BMAT at the 20-day window, both consistent with the main H2 evidence for financially constrained and upstream material sectors. Under the 60-day window, FIN emerges as a transmitter, i.e., an unexpected result not present in the main analysis, which likely reflects the slower-moving risk dynamics at longer horizons. The results are directionally consistent with the main LA-VARNN classification while reflecting the lower statistical power of the linear robustness check relative to the full nonlinear specification.

The main event study identifies uncertainty spikes at the 95th percentile of $TPUI_{adj}$. We repeat the analysis at the 90th percentile (larger, more heterogeneous event set) and the 99th percentile (smallest set, most extreme episodes only, concentrated around March-June 2018, May 2019, and April 2025). Figures 5 through 10 present the cumulative abnormal ERP paths for all 18 sectors under each threshold, in Panels A and B.

[Figure 5 — RC3 Event Study, 90th percentile, Panel A]

[Figure 6 — RC3 Event Study, 90th percentile, Panel B]

[Figure 7 — RC3 Event Study, 95th percentile, Panel A]

[Figure 8 — RC3 Event Study, 95th percentile, Panel B]

[Figure 9 — RC3 Event Study, 99th percentile, Panel A]

[Figure 10 — RC3 Event Study, 99th percentile, Panel B]

The qualitative pattern is consistent across all three thresholds, with several sector-specific observations. Real Estate exhibits a negative post-event drift across all six panels, i.e., the most consistent pattern in the robustness analysis. The drift is visible at 90% (Panel B: scale ±0.4), clear at 95% (Panel B: scale ±0.4, monotonic decline through day +5), and most pronounced at 99% (Panel B: scale ±1.0, sharp decline from day 0). This cross-threshold consistency is the strongest visual evidence that the RE discount-rate channel is not driven by any specific subset of events.

Banks exhibits a negative drift at the 90th percentile (Panel B: scale ±0.3, visible post-event decline) and at the 95th percentile (Panel B: scale ±0.4, wider CI but directionally consistent). At the 99th percentile, the Banks pattern attenuates and becomes noisy (Panel B: scale ±0.04, effectively flat) , which is consistent with the interpretation that Banks' sensitivity operates through moderate but sustained uncertainty rather than isolated extreme events. Technology, TMT, Financials, Aerospace, Chemicals, Industrials, Autos, Basic Materials, Software, and Consumer Discretionary remain statistically indistinguishable from zero across all three thresholds and both panels confirming the stability of the null result for these sectors.

Insurance and Construction exhibit anomalously wide scales at all thresholds (INS: ±4 to ±15 across panels; CONSTR: ±0.4 to ±2.0), consistent with their high unconditional ERP variance documented in Table 1 and the outlier interpretation established in Section 4.2. Their patterns are inconclusive across all thresholds. The sign and relative ordering of CARs for the remaining sixteen sectors are stable across all three thresholds, confirming that the heterogeneous pricing pattern of Section 4.2 is not an artefact of the specific threshold chosen.

The three robustness checks reinforce the main conclusions. The collapse from 16 to 2 significant sectors in λ_i^2 when VIX is orthogonalised out (RC1) directly supports the paper's central identification claim. The Industrials sector is a robust transmitter across all three window lengths in RC2. The event study heterogeneous pricing pattern, anchored by Real Estate and Banks as receivers, is stable across all three event thresholds in RC3.

The robustness evidence reinforces the central interpretation of the paper: once general market fear is removed, trade policy uncertainty has limited and highly selective effects on sectoral risk premia, consistent with a transient discount-rate shock rather than a persistent pricing factor.

5. Discussion

The results suggest a reinterpretation of the role of trade policy uncertainty in asset pricing. Rather than acting as a continuous source of risk compensation, it functions as a high-frequency informational shock that is rapidly incorporated into prices and transmitted across sectors through financial and production networks. More broadly, these findings suggest that policy-related uncertainty may often operate through short-lived discount-rate adjustments rather than persistent risk premia, particularly in high-frequency financial data. This raises the possibility that similar reinterpretations may apply to other forms of macroeconomic and geopolitical uncertainty.

5.1 Confronting the Literature

Our results engage with three distinct strands of the existing literature, and in each case they both confirm and materially qualify the received evidence.

On the pricing of political and policy uncertainty, Pastor and Veronesi (2012, 2013) and Kelly, Pastor & Veronesi (2016) establish theoretically that uncertainty about government policy commands a risk premium that rises in bad economic states and increases stock volatility and cross-sectional correlations. Brogaard and Detzel (2015) provide evidence that economic policy uncertainty is associated with time-varying expected returns, although the persistence and economic interpretation of this effect remain subject to debate. Our EGARCH-X results qualify both contributions in an important way. The near-universal absence of significant conditional mean effects λ_i^1 at the sector level, with Health Care as the sole exception, suggests that the aggregate equity risk premium response to trade policy uncertainty is not driven by broad sectoral repricing but by the averaging of large discount-rate responses in a small number of sensitive sectors against near-zero responses in the majority. The aggregate market result documented by Brogaard and Detzel emerges from this cross-sectional averaging, but it conceals a structure in which most of the pricing action is concentrated in sectors with balance-sheet and regulatory cash-flow sensitivity. This finding has a direct methodological implication: aggregate ERP measures are a noisy proxy for trade-policy risk pricing, and sector-level analysis is necessary to identify the economic channels at work.

Our Forbes-Rigobon results further qualify the policy uncertainty pricing literature by showing that the apparent correlation between sector ERP and $TPUI_{adj}$ is itself heterogeneous in its nature. For technology-adjacent sectors, Technology, TMT, Health Care, Aerospace, the co-movement survives the heteroskedasticity correction and reflects genuine structural linkages consistent with Pastor and Veronesi's (2013) finding that policy uncertainty is priced through the discount-rate channel. For upstream tradables, Chemicals, Autos, Basic Materials, Real Estate, the raw correlation is largely a statistical artefact of the volatility spikes that characterise uncertainty episodes. The extreme attenuation for Autos ($t = -10.17$) is particularly striking: it suggests that the intuitive expectation that the auto sector is among the most trade-exposed, confirmed by its frequent mention in tariff announcements and political discourse, does not translate into genuine equity risk premium repricing once heteroskedasticity is accounted for. Raw return studies that do not apply the Forbes-Rigobon (2002) correction risk attributing volatility co-movement to structural economic linkages that do not exist.

On the real adjustments of trade policy uncertainty, Caldara et al. (2020) document that trade uncertainty reduces U.S. business investment by approximately 1.5 percent in 2018, with the response concentrated in exporting sectors through the option value of waiting mechanism. Our findings extend this evidence to the equity risk premium channel and reveal a complementary propagation mechanism. The sectors that Caldara et al.(2022) identify as most exposed to trade uncertainty through their investment responses, upstream tradables with high import penetration, are precisely the sectors that act as net transmitters in our Granger causality framework. This consistency across two very different empirical approaches and two different outcome variables (capital expenditure versus equity risk premium) provides convergent validity for the supply-chain transmission mechanism. The timing implication is also complementary: our IRF evidence shows that ERP adjustments peak within two to three trading days and revert within a week, suggesting that equity market repricing precedes the investment reductions documented by Caldara et al. (2022) at quarterly frequency. This is consistent with the Tobin's q channel: falling equity valuations in upstream sectors reduce the incentive to invest before the capital expenditure data registers the decline. Our LA-VARNN finding that Energy and Food Producers are transmitters in the nonlinear but not in the linear specification further corroborates Caldara et al.'s (2022) observation that trade uncertainty operates through threshold effects that are invisible to linear models.

On the equity market response of tariff announcements specifically, Amiti et al. (2020) show that U.S.-China tariff announcements generated cumulative equity market losses substantially larger than conventional trade models explain, with the excess attributable to uncertainty costs and investment channel effects. Amiti et al. (2025) extend this evidence to the April 2025 Liberation Day episode, documenting that energy, basic materials, and technology sectors experienced the steepest cross-country losses. Our findings qualify both contributions by distinguishing genuine risk premium repricing from heteroskedasticity-induced co-movement. The Forbes-Rigobon (2002) evidence shows that for Basic Materials — a sector prominently featured in both Amiti studies — the raw correlation with $TPUI_{adj}$ is substantially attenuated once heteroskedasticity is controlled for. This does not invalidate the Amiti et al. findings on aggregate stock price declines, which are based on announcement-day returns rather than rolling correlations. But it does suggest that the cross-sectional distribution of genuine risk premium adjustment is narrower than cross-sectional return distributions imply, and that the sectors whose equity valuations fall most sharply in announcement windows are not necessarily those whose required returns are most structurally sensitive to trade policy uncertainty.

On the transmission of trade policy risk through financial networks, our results connect with and extend the directional spillover literature initiated by Billio et al. (2012) and Diebold and Yilmaz (2014). Billio et al. (2012) find that the financial sector tends to be a net receiver of shocks during stress episodes rather than a transmitter. In this sense a finding our results confirm and extend to the trade policy context specifically. The novelty of our contribution relative to this literature lies in the use of risk-adjusted ERP measures rather than raw returns as the network variable, and in the nonlinear LA-VARNN specification that identifies threshold dependencies missed by linear Granger causality. The identification of a two-step transmission chain, where upstream sector ERP movements anticipate $TPUI_{adj}$, which in turn anticipates financial sector ERP movements, is a structural finding that is not visible in aggregate DY-type connectedness measures that collapse the network to a scalar total connectedness index.

5.2 Economic Interpretation of the Transmitter-Receiver Structure

The transmitter-receiver classification that emerges from the Granger causality and LA-VARNN analyses is not random. It maps onto three distinct economic mechanisms that determine a sector's position in the trade policy risk network. Understanding these mechanisms is essential both for interpreting the empirical patterns and for assessing their generalisability beyond the 2014-2025 U.S. sample.

The price discovery mechanism explains the transmitter role of Technology, TMT, Software, and Consumer Discretionary. These sectors are characterised by high intangible capital intensity, globally diversified revenue streams, and valuations that embed expectations about long-run productivity and demand growth. When trade policy uncertainty rises, equity markets in these sectors reprice not only direct tariff exposure, which is modest for software and media, but also the broader implications for global supply chains, export market access, and the discount rate applied to long-duration growth options. Because these sectors are informationally rich and highly liquid, the price discovery process is rapid: the adjusted ERP in Technology and TMT anticipates subsequent readings of $TPUI_{adj}$ with a lead of one to several days, consistent with the interpretation that equity markets in these sectors process trade policy information before it is codified in the text-based uncertainty index. This mechanism is consistent with the theoretical framework of Pastor and Veronesi (2013), in which stock prices respond to political signals before the policy decision is announced, and with the empirical evidence of Amiti et al. (2020, 2024) that equity market declines following tariff announcements are informationally efficient and short-lived or episodic.

The input cost and commodity channel explains the transmitter role of Chemicals, Energy, and Basic Materials. These upstream sectors are directly exposed to import cost changes through their dependence on traded intermediate inputs and global commodity prices. When trade tensions escalate, the adjustment in input cost expectations for upstream sectors is immediate and quantifiable: earnings calls in these industries mention trade policy concerns at nearly three times the rate of downstream sectors, as documented by Caldara et al. (2020). The resulting repricing of their equity risk premia occurs before the trade policy narrative crystallizes in newspaper counts explaining why their ERP movements precede $TPUI_{adj}$ rather than the reverse. The identification of Food Producers as a transmitter in the nonlinear LA-VARNN, but not in the linear VAR, suggests that the food sector's causal relationship with trade uncertainty operates through commodity price threshold effects that are invisible to linear specifications, consistent with the nonlinear dynamics documented by Benguria et al. (2022) for agricultural trade under tariff uncertainty.

The discount-rate and balance-sheet channel explains the receiver role of Financials, Banks, Real Estate, and Health Care. These sectors share a common feature: their valuations are particularly sensitive to changes in the risk-free rate, credit spreads, and funding conditions rather than to direct trade exposure. For financial intermediaries, trade policy uncertainty raises the probability of an economic slowdown, which in turn elevates expected loan losses, tightens collateral valuations, and increases the cost of wholesale funding. These mechanisms take time to materialize in observable financial data explaining why $TPUI_{adj}$ contain leading information about the financial sector ERP with a measurable lag rather than the reverse. Real Estate is sensitive to the long end of the yield curve, which responds to trade policy through its effect on expected growth and inflation; the monotonically declining CAR path for Real Estate in the event study is consistent with this discount-rate transmission. Health Care's receiver status reflects supply-chain dependence on imported active pharmaceutical ingredients and medical devices. This is a structural vulnerability confirmed by the EGARCH-X finding that its conditional ERP volatility is significantly amplified by $TPUI_{adj}$ even after VIX neutralisation. This mechanism aligns with the intermediary asset pricing framework of He and Krishnamurthy (2013), in which the financial sector's equity capital is the key state variable governing aggregate risk premia: trade policy shocks that deplete intermediary balance sheets raise required returns across all asset classes through the discount-rate channel, with the timing determined by how quickly trade frictions translate into credit risk.

Water Utilities occupies the unique position of acting as both transmitter and receiver simultaneously. This bidirectionality reflects the sector's dual structural exposure. On one side, water infrastructure depends on imported inputs such as pipes, pumps, and treatment chemicals, which makes its input cost expectations particularly responsive to trade policy signals and allows the sector to act as an early transmitter of trade-related risk information. On the other, water utilities are among the most regulated sectors in the U.S. economy, with revenues set by regulatory commissions based on cost-of-capital benchmarks linked to the risk-free rate and broader capital market conditions, which makes the sector particularly sensitive to discount-rate fluctuations and positions it as a receiver of trade-policy-related shocks. The coexistence of both effects in a single sector is a distinctive precursor of the supply-chain transmission framework that would not emerge from aggregate-level analysis.

5.3 Implications for Macroprudential Policy

Two actionable implications follow from the directional transmission evidence. First, upstream real sectors function as early warning indicators for financial sector stress under trade policy uncertainty. The Granger causality evidence establishes that the adjusted ERP of Technology, TMT, Chemicals, Energy, Food Producers, Software, and Consumer Discretionary systematically precedes subsequent movements in $TPUI_{adj}$, which in turn precedes stress in the financial sector. This two-step transmission chain implies that macroprudential authorities could construct a leading indicator of financial sector vulnerability by monitoring the cross-sectional distribution of ERP movements in upstream sectors in real time. An equal-weighted average of the adjusted ERP in the eight transmitter sectors would have flagged the major trade policy escalation episodes, the 2018 Section 301 announcements, the May 2019 escalation, and the April 2025 Liberation Day cycle, before they registered as significant stress in financial sector valuations. The IRF evidence suggests the available lead time is approximately two to five trading days, which is short but non-negligible for supervisory purposes, particularly for institutions with significant mark-to-market exposure.

Second, the VIX-neutralisation finding has direct implications for the design of stress testing frameworks. The robustness analysis shows that most of TPU's effect on conditional ERP volatility operates through the VIX channel, the general market fear component, rather than through the trade-specific channel isolated by $TPUI_{adj}$. This means that stress tests calibrated on aggregate VIX shocks will overestimate the trade-policy-specific component of financial sector vulnerability while potentially missing the sector-specific transmission patterns documented here. A more targeted approach would use $TPUI_{adj}$, or a similar trade-orthogonalized index, as the conditioning variable for sector-level stress scenarios, with the financial sector ERP response calibrated on the Y→X Granger causality coefficients rather than on aggregate market correlations. The European Central Bank's recent analysis of euro area activity under trade policy uncertainty (Adolfsen and Harr, 2025) similarly distinguishes between adjusted and unadjusted TPU measures, finding that the adjusted measure implies smaller but more precisely identified effects, which is consistent with our identification strategy.

5.4 Limitations and Future Research

Three limitations of the current analysis should be acknowledged. First, the ERP construction relies on Consumer Staples returns as a daily consumption proxy, which introduces measurement error relative to actual consumption expenditure data. The habit-based γ_t is therefore an approximation, and its accuracy depends on the degree to which Consumer Staples returns co-move with non-durable consumption at daily frequency. Future work could refine the consumption proxy using high-frequency retail sales or credit card transaction data, or implement the habit model at weekly frequency where consumption proxies are more reliable.

Second, the bivariate VAR and LA-VARNN specifications do not control for other macroeconomic variables that may jointly drive both sectoral ERP and trade policy uncertainty — including exchange rates, commodity prices, and monetary policy stance. While $TPUI_{adj}$ is orthogonal to VIX by construction, it may still co-move with other financial conditions variables. A multivariate extension that includes the term spread, credit spreads, and dollar index as controls would strengthen the causal interpretation of the Granger causality results, at the cost of reduced statistical power given the short daily horizon.

Third, the analysis covers a single country, the United States, over a specific historical episode dominated by U.S.-China trade tensions. The generalisability of the transmitter-receiver classification to other economies and other types of trade policy shock (export restrictions, investment screening, sanctions) is an open empirical question. A natural extension would apply the same framework to European sector-level ERP data, where the transmission of U.S.-originating trade policy uncertainty to domestic financial sectors operates through a different set of supply-chain linkages and a different regulatory environment for financial intermediaries.

6. Conclusion

This paper re-examines how trade policy uncertainty is incorporated into sectoral equity risk premia and how it propagates across sectors through supply-chain linkages. Using daily data for 18 major U.S. sectors over 2014–2025, a sample that spans two full cycles of tariff escalation under the Trump administrations, we construct a multidimensional sector-level ERP measure that integrates a rolling CAPM decomposition, a habit-based time-varying risk aversion adjustment, and a sector-specific loss-aversion correction. Trade policy uncertainty is measured through a VIX-neutralized index that isolates the trade-specific policy risk component from aggregate market fear.

The results lead to a central conclusion: trade policy uncertainty is not priced as a short lived and episodic factor in sectoral equity risk premia. Instead, it appears to operate as a high-frequency, state-dependent shock to the pricing kernel, whose effects are short-lived, heterogeneous across sectors, and transmitted directionally through the structure of production and financial intermediation. On H1, the Heterogeneous and Asymmetric Pricing Hypothesis, the evidence is nuanced rather than uniform. The event study documents a directionally consistent negative cumulative abnormal return for discount-rate-sensitive sectors, particularly Real Estate, Water Utilities, and Banks, while upstream tradables and technology-adjacent sectors exhibit responses statistically indistinguishable from zero. The Forbes-Rigobon (2002) correction establishes that co-movement with trade policy uncertainty is genuine for Technology, TMT, Health Care, and Aerospace — sectors where structural linkages survive the heteroskedasticity correction — but is largely a volatility artefact for Chemicals, Autos, Basic Materials, and Real Estate. The EGARCH-X results further clarify the mechanism. The near-universal absence of statistically significant effects in the conditional mean of ERP indicates that trade policy uncertainty generate short-lived and episodic shifts in expected returns. Instead, pricing operates through episodic adjustments concentrated around uncertainty shocks. Conditional volatility adjustments that survive VIX orthogonalisation are limited to Health Care and Software, confirming that once general market fear is removed, the trade-specific pricing channel is both selective and short-lived. Taken together, these findings support H1 in its structural dimension, that pricing is heterogeneous and channel-dependent, while fundamentally qualifying its time-series interpretation: trade policy uncertainty is not a stable pricing factor, but a transient shock embedded in discount-rate adjustments.

On H2, the Supply-Chain Transmission Hypothesis, the evidence is consistently strong across both linear and nonlinear specifications. Eight sectors act as net transmitters whose adjusted ERP movements contain leading information about subsequent readings of the trade uncertainty index: Technology, TMT, Energy, Water, Food Producers, Chemicals, Software, and Consumer Discretionary. Five sectors act as net receivers whose premia are systematically preceded by prior movements in trade policy uncertainty: Financials, Health Care, Basic Materials, Real Estate, and, at the margin, Banks. Water Utilities uniquely exhibits bidirectional causality, reflecting simultaneous exposure to input cost dynamics and regulatory cash-flow constraints. Importantly, these causal relationships should be interpreted as differences in the timing of information incorporation rather than structural causality. Upstream sectors appear to embed information about trade-related risks before it becomes reflected in policy uncertainty measures, while financially constrained sectors absorb the resulting discount-rate adjustments with a lag. The impulse response functions confirm that all significant ERP adjustments peak within two to three trading days and dissipate within a week, consistent with markets treating trade uncertainty as a transitory state-variable shock rather than a permanent revision to long-run growth expectations. The consistency of the transmitter–receiver classification across the linear VAR and the nonlinear LA-VARNN , with the latter additionally identifying Energy and Food Producers as transmitters through threshold effects, provides strong support for H2 and highlights the importance of nonlinear transmission mechanisms.

Three contributions to the literature follow from these findings. First, we provide a comprehensive sector-level analysis of equity risk premia under trade policy uncertainty using a multidimensional risk measure that disentangles trade-specific from general market uncertainty. By showing that aggregate ERP responses mask a highly heterogeneous cross-sectional structure, and that much apparent co-movement reflects heteroskedasticity artefacts, we qualify existing aggregate evidence and highlight the limits of inference based on raw return correlations. Second, we document a two-step transmission mechanism in which upstream sector ERP movements precede shifts in measured trade policy uncertainty, which in turn precede adjustments in financially sensitive sectors. This structure is consistent with intermediary asset pricing mechanisms and extends the investment-channel evidence of Caldara et al. (2020) to the equity risk pricing dimension, suggesting that financial market adjustments occur at much higher frequency than real investment responses. Third, the comparison between $TPUI_{adj}$ and TPU_{raw} demonstrates that a substantial portion of the apparent response of trade policy uncertainty operates through general market volatility. By isolating the trade-specific component, we show that the remaining pricing adjustments are more selective, sector-specific, and economically interpretable, thereby validating the identification strategy and clarifying the mechanism through which trade policy risk enters asset prices.

The practical implications are twofold. For investors, the transmitter–receiver classification identifies sectors whose ERP movements embed early information about trade policy developments and sectors whose premia adjust with a lag, providing a framework for sector allocation and hedging strategies during periods of tariff escalation. For macroprudential authorities, the short horizon of impulse responses and the identified transmission chain suggest that monitoring ERP dynamics in upstream sectors may provide a narrow but economically meaningful early-warning signal of financial sector stress. The April 2025 tariff escalation episode, which raised the effective U.S. tariff rate to its highest level since 1935 within a matter of weeks, illustrates the relevance of such high-frequency, sector-based monitoring in an environment of recurrent and rapidly evolving trade policy shocks. More broadly, the results reconcile an apparent tension in the literature: while trade policy uncertainty generates strong event-driven market reactions, it does not behave as a persistent pricing factor in time-series models. This paper shows that these findings are not contradictory. Trade policy uncertainty matters, but it matters as a transient, high-frequency signal that is rapidly incorporated and propagated across sectors, rather than as a continuous source of risk compensation.

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Table 1. Descriptive Statistics

Sector	N	Mean	Median	SD	Skewness	Excess Kurtosis
TECH	2794	0.0012	0.0019	0.0381	-0.511	13.89
TMT	2794	0.0012	0.0017	0.0374	-0.538	14.40
FIN	2794	0.0006	0.0014	0.0311	-0.309	10.01
ENRG	2794	-0.0019	0.0012	0.1557	-16.965	808.57
INS	2794	0.0415	0.0012	1.9120	49.506	2538.04
WATR	2794	0.0048	0.0023	0.3833	4.711	245.73
FOOD	2794	0.0056	0.0014	0.3230	28.173	959.59
HLTH	2794	-0.0005	0.0010	0.0882	-34.197	1586.79
AERO	2794	0.0004	0.0008	0.0397	0.009	35.34
BANKS	2794	-0.0018	0.0006	0.1388	-34.187	1602.18
CONS	2794	-0.0084	0.0009	0.5900	-45.828	2363.11
CHEM	2794	0.0007	0.0013	0.0348	-0.267	7.94
INDUS	2794	0.0009	0.0013	0.0322	-0.502	15.30
AUTO	2794	0.0010	0.0011	0.0342	-0.343	9.66
BMAT	2794	0.0008	0.0014	0.0333	-0.268	8.40
RE	2794	-0.0019	0.0015	0.2884	-2.547	881.10
SOFT	2794	0.0012	0.0015	0.0380	-0.490	12.54
CDIS	2794	0.0010	0.0015	0.0327	-0.772	14.32
TPUI_adj	2794	0.0122	-0.1816	0.9763	1.085	1.50

*Note: Daily adjusted ERP^adj and VIX-neutralized trade policy uncertainty index ($TPUI_{adj}$) over 2014–2025. N = 2,794 observations per series. SD = standard deviation. Excess kurtosis reported. ***, **, * denote significance at 1%, 5%, 10%.*

Table 2. Estimated Risk Aversion and Loss-Aversion Parameters

Sector	$\bar{\gamma}$ (common)	λ_i
TECH	4.2195	2.0000
TMT	4.2195	2.0000
FIN	4.2195	1.4440
ENRG	4.2195	1.1681
INS	4.2195	1.3885
WATR	4.2195	1.0027
FOOD	4.2195	1.2255
HLTH	4.2195	1.3096
AERO	4.2195	1.3205
BANKS	4.2195	1.3023
CONS	4.2195	1.1544

CHEM	4.2195	1.5339
INDUS	4.2195	1.6713
AUTO	4.2195	1.3208
BMAT	4.2195	1.5187
RE	4.2195	1.2330
SOFT	4.2195	1.9293
CDIS	4.2195	1.7389

Note: $\bar{\gamma}$ = 4.2195 is the long-run risk aversion parameter common to all sectors, estimated by method of moments matching the unconditional equity premium over the full sample. λ_i is the sector-specific loss-aversion multiplier derived from TGARCH(1,1) leverage parameters; $\lambda_i = \max(1, 1 + \eta_i/\bar{\eta})$ where $\bar{\eta}$ is the cross-sectional mean leverage effect.

Table 3. AR(1)-EGARCH(1,1)-X Estimates: Effect of $TPUI_{adj}$ on Sectoral ERP

	Conditional mean		Conditional variance	
Sector	**λ^1**	**p-value**	**λ^2**	**p-value**
TECH	0.0002	0.700	**0.0192***	0.092
TMT	0.0001	0.698	0.0169	0.111
FIN	0.0000	0.980	0.0176	0.242
ENRG	-0.0002	0.680	0.0158	0.331
INS	0.0002	0.613	0.0088	0.596
WATR	-0.0003	0.683	0.0292	0.161
FOOD	-0.0006	0.205	0.0011	0.945
HLTH	**0.0004****	0.019	-0.0056	0.713
AERO	-0.0003	0.482	0.0243	0.105
BANKS	0.0001	0.802	0.0198	0.265
CONS	0.0000	0.988	0.0159	0.615
CHEM	-0.0002	0.727	0.0046	0.729
INDUS	-0.0002	0.707	0.0172	0.183
AUTO	-0.0005	0.269	0.0007	0.955
BMAT	-0.0003	0.497	0.0064	0.584
RE	**-0.0007***	0.075	-0.0063	0.692
SOFT	-0.0003	0.480	**0.0260****	0.031
CDIS	-0.0002	0.704	0.0167	0.160

*Note: λ^1 is the conditional mean coefficient and λ^2 is the conditional log-variance coefficient on $TPUI_{adj}$. Estimated by maximum likelihood with t-Student innovations. Bold entries indicate significance at the 10% level. ***, **, * denote significance at 1%, 5%, 10%.*

Table 4. Forbes-Rigobon Heteroskedasticity Correction

Sector	t-statistic	p-value
TECH	**5.3527*****	1.0000
TMT	**4.9020*****	1.0000
FIN	-1.0050	0.1575

ENRG	-0.1351	0.4463
INS	**3.2462*** **	0.9994
WATR	**-5.1899*** **	0.0000
FOOD	**-3.9649*** **	0.0000
HLTH	**8.2898*** **	1.0000
AERO	**5.0881*** **	1.0000
BANKS	-0.0835	0.4667
CONS	**1.4928* **	0.9322
CHEM	**-5.0913*** **	0.0000
INDUS	-0.7265	0.2338
AUTO	**-10.1715*** **	0.0000
BMAT	**-2.6944*** **	0.0035
RE	**-5.7903*** **	0.0000
SOFT	**-1.4321* **	0.0761
CDIS	0.5552	0.7106

Note: t-statistic tests H_0: ρ^adj = ρ^L against the alternative that the Forbes-Rigobon adjusted correlation differs from the low-variance regime correlation. High-variance regime defined as top quartile of $TPUI_{adj}$. p-value reported as the cumulative normal probability; values near 1.000 indicate reinforced dependence (genuine co-movement); values near 0.000 indicate attenuated dependence (heteroskedasticity artefact). Bold entries indicate $|p - 0.5| > 0.45$.

Table 5. Forbes-Rigobon Block Bootstrap

Sector	Obs. diff.	p (bootstrap)	p (t-test)
TECH	0.3034	**0.0280** **	1.0000
TMT	0.2792	**0.0300** **	1.0000
FIN	-0.0818	0.5360	0.1575
ENRG	-0.0018	0.5240	0.4463
INS	0.0038	0.1800	0.9994
WATR	-0.0217	0.9500	0.0000
FOOD	-0.0252	0.8860	0.0000
HLTH	0.2104	**0.0020*** **	1.0000
AERO	0.3193	**0.0340** **	1.0000
BANKS	-0.0014	0.4340	0.4667
CONS	0.0033	0.2700	0.9322
CHEM	-0.3399	0.9460	0.0000
INDUS	-0.0566	0.5220	0.2338
AUTO	-0.7221	1.0000	0.0000
BMAT	-0.1976	0.7540	0.0035
RE	-0.0396	0.9660	0.0000
SOFT	-0.0800	0.6360	0.0761
CDIS	0.0398	0.3160	0.7106

*Note: Obs. diff. = observed difference between high- and low-regime correlations. p (bootstrap) = block bootstrap p-value based on 1,000 replications with block length 22 days. p (t-test) = parametric t-test p-value from Table 4. ***, **, * denote significance at 1%, 5%, 10% for bootstrap p-value.*

Table 6. Bivariate Granger Causality Tests (Linear VAR)

	Instantaneous		X→Y (ERP→TPUI)		Y→X (TPUI→ERP)	
Sector	**Wald**	**p**	**Wald**	**p**	**Wald**	**p**
TECH	0.893	0.345	**6.215****	0.013	0.346	0.556
TMT	0.771	0.380	**7.178*****	0.007	0.466	0.495
FIN	0.063	0.802	**7.734*****	0.005	0.928	0.336
ENRG	0.029	0.865	0.073	0.930	0.636	0.529
INS	1.766	0.184	0.433	0.510	0.240	0.624
WATR	0.368	0.544	0.977	0.323	**4.797****	0.029
FOOD	1.026	0.311	0.160	0.689	0.810	0.368
HLTH	0.771	0.380	0.451	0.502	0.002	0.961
AERO	1.610	0.205	0.079	0.779	0.981	0.322
BANKS	0.074	0.785	0.030	0.970	**2.539***	0.079
CONS	4.844	0.028	0.064	0.800	0.613	0.434
CHEM	0.167	0.683	**6.351****	0.012	0.341	0.560
INDUS	0.007	0.935	**7.920*****	0.005	0.683	0.409
AUTO	0.764	0.382	1.094	0.296	2.174	0.140
BMAT	0.014	0.905	**4.594****	0.032	0.013	0.911
RE	1.441	0.230	0.135	0.714	**4.733****	0.030
SOFT	0.312	0.576	**4.856****	0.028	0.426	0.514
CDIS	0.191	0.662	**8.281*****	0.004	1.187	0.276

*Note: Bivariate VAR estimated following Toda-Yamamoto (1995) with lag order selected by AIC (max 10 lags) plus one augmentation lag. Wald statistics reported for instantaneous causality, X→Y (sector ERP Granger-causes $TPUI_{adj}$), and Y→X ($TPUI_{adj}$ Granger-causes sector ERP). HAC standard errors following Newey-West (1987). Bold entries indicate significance at the 10% level. ***, **, * denote significance at 1%, 5%, 10%.*

Table 7. LA-VARNN Nonlinear Granger Causality Tests

	X→Y (ERP→TPUI)		Y→X (TPUI→ERP)	
Sector	**F**	**p (perm.)**	**F**	**p (perm.)**
TECH	**55.815*****	0.00	1.115	0.90
TMT	**23.790*****	0.00	2.358	0.80
FIN	**12.125**	0.10	**255.435*****	0.00
ENRG	**2.266*****	0.00	0.000	1.00
INS	**2.537**	0.10	12.691	0.20
WATR	**10.302*****	0.00	**21.542*****	0.00
FOOD	**23.299*****	0.00	5.639	0.40

HLTH	**7.490**	0.10	**61.977*** **	0.00
AERO	1.866	0.40	3.463	0.20
BANKS	0.000	1.00	**6.123**	0.10
CONS	3.704	0.20	28.043	0.20
CHEM	**23.945*** **	0.00	0.000	1.00
INDUS	**11.578**	0.10	**11.371**	0.10
AUTO	3.527	0.30	27.710	0.20
BMAT	**11.956**	0.10	**59.154*** **	0.00
RE	2.515	0.50	**27.484*** **	0.00
SOFT	**29.292*** **	0.00	0.560	0.60
CDIS	**26.853*** **	0.00	0.000	1.00

*Note: F-statistic compares RSS of restricted (lagged dependent variable only) vs unrestricted (plus lagged $TPUI_{adj}$ or sector ERP) multilayer perceptron with hidden layers (6,3). Permutation p-value based on B = 199 random permutations of the causal variable columns. When RSS_unrestricted ≥ RSS_restricted, F = 0 and p = 1. Bold entries indicate permutation p-value ≤ 0.10. ***, **, * denote p ≤ 0.01, 0.05, 0.10.*

Table 8. RC1: Conditional Variance Coefficient λ² — $TPUI_{adj}$ vs TPU_{raw}

	$TPUI\_adj$ (main)		TPU_{raw} (robustness)	
Sector	**λ²**	**p-value**	**λ²**	**p-value**
AERO	0.0243	0.1053	**0.0000** **	0.0474
AUTO	0.0007	0.9551	**0.0000** **	0.0433
BANKS	0.0198	0.2649	**0.0000*** **	0.0092
BMAT	0.0064	0.5841	0.0000	0.1513
CDIS	0.0167	0.1600	**0.0000** **	0.0304
CHEM	0.0046	0.7285	**0.0000** **	0.0192
CONSTR	0.0159	0.6147	**0.0002*** **	0.0000
ENRG	0.0158	0.3310	**0.0000** **	0.0100
FIN	0.0176	0.2420	**0.0000** **	0.0145
FOOD	0.0011	0.9453	**0.0002*** **	0.0000
HLTH	-0.0056	0.7133	**0.0000*** **	0.0031
INDUS	0.0172	0.1834	**0.0000** **	0.0174
INS	0.0088	0.5956	**-0.0281*** **	0.0000
RE	-0.0063	0.6923	**0.0000** **	0.0381
SOFT	**0.0260** **	0.0305	**0.0000*** **	0.0019
TECH	**0.0192***	0.0922	0.0000	0.3776
TMT	0.0169	0.1112	**0.0000***	0.0527
WATR	0.0292	0.1613	**0.0001*** **	0.0000

*Note: λ² = conditional log-variance coefficient on the uncertainty measure in AR(1)-EGARCH(1,1)-X. $TPUI_{adj}$ = VIX-neutralised index (main specification). TPU_{raw} = raw standardised Baker-Bloom-Davis TPU index. Sectors sorted alphabetically. Estimated by ML with t-Student innovations. Bold = significant at 10%. ***, **, * = 1%, 5%, 10%.*

Table 9. RC1: Summary — Significant Sectors and Rank Correlations

	$TPUI_{adj}$	TPU_{raw}	TPU_{std}
λ^1 significant ($p < 0.10$)	2	5	1
λ^2 significant ($p < 0.10$)	2	16	4
Spearman ρ λ^1 vs $TPUI_{adj}$	—	0.536	0.424
Spearman ρ λ^2 vs $TPUI_{adj}$	—	−0.018	0.408

Note: Counts of sectors with $p < 0.10$ for λ^1 and λ^2 coefficients. Spearman rank correlations of estimated coefficients across 18 sectors relative to $TPUI_{adj}$ baseline. TPU_{std} = z-score of daily change in TPU_raw. Near-zero or negative Spearman ρ for λ^2 ($TPUI_{adj}$ vs TPU_{raw}) indicates reversal of cross-sectional ordering after VIX orthogonalisation.

Table 10. RC1: Full EGARCH-X Estimates with TPU_{raw}

	Conditional mean		Conditional variance	
Sector	**λ^1**	**p-value**	**λ^2**	**p-value**
TECH	**0.0000*** **	0.0004	0.0000	0.3776
TMT	**0.0000*** **	0.0000	**0.0000***	0.0527
FIN	0.0000	0.9007	**0.0000** **	0.0145
ENRG	**0.0000***	0.0724	**0.0000** **	0.0100
INS	**0.0001*** **	0.0000	**-0.0281*** **	0.0000
WATR	0.0000	0.7821	**0.0001*** **	0.0000
FOOD	0.0000	0.8456	**0.0002*** **	0.0000
HLTH	**0.0000***	0.0672	**0.0000*** **	0.0031
AERO	0.0000	0.9386	**0.0000** **	0.0474
BANKS	0.0000	0.8846	**0.0000*** **	0.0092
CONSTR	0.0000	0.1031	**0.0002*** **	0.0000
CHEM	0.0000	0.8976	**0.0000** **	0.0192
INDUS	0.0000	0.8620	**0.0000** **	0.0174
AUTO	0.0000	0.6025	**0.0000** **	0.0433
BMAT	0.0000	0.8626	0.0000	0.1513
RE	0.0000	0.6971	**0.0000** **	0.0381
SOFT	0.0000	0.7114	**0.0000*** **	0.0019
CDIS	0.0000	0.7491	**0.0000** **	0.0304

*Note: AR(1)-EGARCH(1,1)-X with TPU_{raw} (raw standardised Baker-Bloom-Davis TPU index) as exogenous regressor. λ^1 = conditional mean coefficient; λ^2 = conditional log-variance coefficient. λ^1 values near zero reflect the small scale of the raw index. Estimated by ML with t-Student innovations. Bold = significant at 10%. ***, **, * = 1%, 5%, 10%.*

Table 11. RC1: Full EGARCH-X Estimates with TPU_{std}

	Conditional mean		Conditional variance	
Sector	**λ¹**	**p-value**	**λ²**	**p-value**
TECH	-0.0002	0.6598	0.0566	0.1471
TMT	-0.0004	0.3497	0.0513	0.1819
FIN	-0.0002	0.5952	-0.0127	0.7517
ENRG	-0.0004	0.4738	**0.0863***	0.0535
INS	-0.0002	0.7394	**-0.1469*****	0.0003
WATR	-0.0003	0.6586	0.0254	0.5734
FOOD	-0.0006	0.3632	-0.0083	0.8638
HLTH	0.0004	0.4261	-0.0330	0.4195
AERO	0.0001	0.9041	-0.0629	0.1329
BANKS	-0.0005	0.2827	0.0093	0.8338
CONSTR	0.0000	0.9889	-0.0642	0.1468
CHEM	-0.0001	0.9077	0.0245	0.5090
INDUS	0.0000	0.9451	0.0462	0.2359
AUTO	-0.0002	0.5322	-0.0109	0.7905
BMAT	-0.0004	0.4296	0.0276	0.4822
RE	-0.0005	0.2988	**-0.1502*****	0.0010
SOFT	**-0.0005*****	0.0000	**0.0748***	0.0626
CDIS	0.0000	0.9854	0.0381	0.3090

*Note: AR(1)-EGARCH(1,1)-X with TPU_{std} (z-score of daily change in TPU_{raw}) as exogenous regressor. λ¹ = conditional mean coefficient; λ² = conditional log-variance coefficient. Estimated by ML with t-Student innovations. Bold = significant at 10%. ***, **, * = 1%, 5%, 10%.*

Table 12. RC1: Spearman Rank Correlations of EGARCH-X Estimates Across TPU Variants

	$TPUI_{adj}$ vs TPU_{raw}	$TPUI_{adj}$ vs TPU_{std}	TPU_{raw} vs TPU_{std}
Spearman ρ (λ¹)	0.536	0.424	0.201
Spearman ρ (λ²)	−0.018	0.408	−0.271

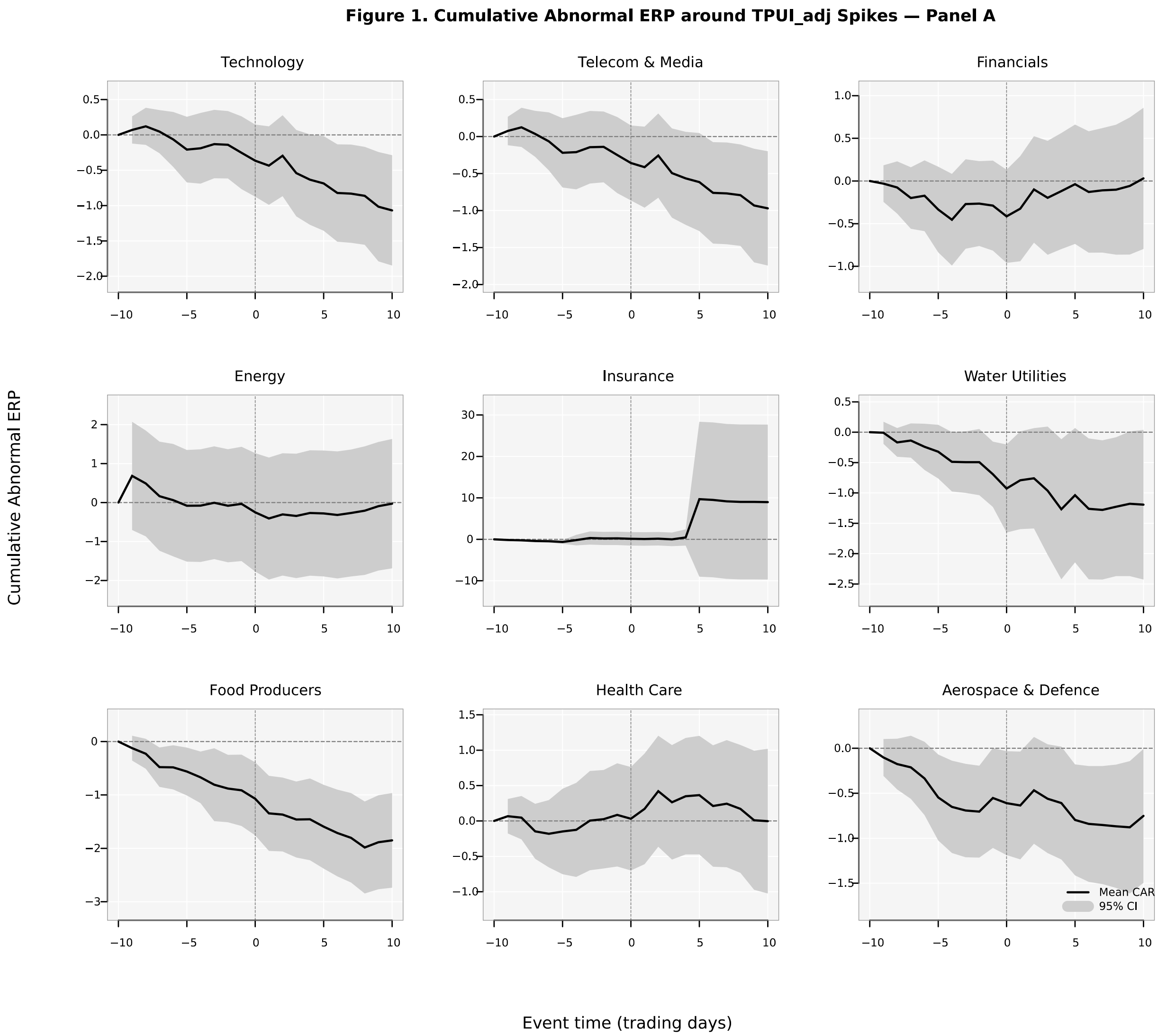
Note: Spearman rank correlations of estimated λ^1_i and λ^2_i across 18 sectors. Near-zero ρ(λ², $TPUI_{adj}$ vs TPU_raw) = −0.018 indicates reversal of cross-sectional ordering after VIX orthogonalisation. Negative ρ(λ², TPU_{raw} vs TPU_{std}) = −0.271 indicates that z-score transformation changes sensitivity ordering relative to the raw level series. High ρ for λ¹ across all pairs indicates partial stability of mean effect ordering.

Table 13. RC2: Transmitter/Receiver Classification by Rolling Window (LA-VARNN)

	20-day		30-day (main)		60-day	
Sector	**X→Y**	**Y→X**	**X→Y**	**Y→X**	**X→Y**	**Y→X**
TECH	—	—	—	—	—	—
TMT	✓	—	—	—	—	—
FIN	—	—	—	—	✓	—
ENRG	—	—	—	—	—	—
INS	—	—	—	—	—	—
WATR	—	—	—	—	—	—
FOOD	—	—	—	—	—	—
HLTH	—	—	—	—	—	—
AERO	✓	—	—	—	—	—
BANKS	—	—	—	—	—	—
CONSTR	—	✓	—	—	—	—
CHEM	—	—	—	—	—	—
INDUS	✓	—	✓	—	✓	—
AUTO	✓	—	—	—	—	—
BMAT	—	✓	—	—	—	—
RE	—	—	—	—	—	—
SOFT	—	—	—	—	—	—
CDIS	—	—	—	—	—	—

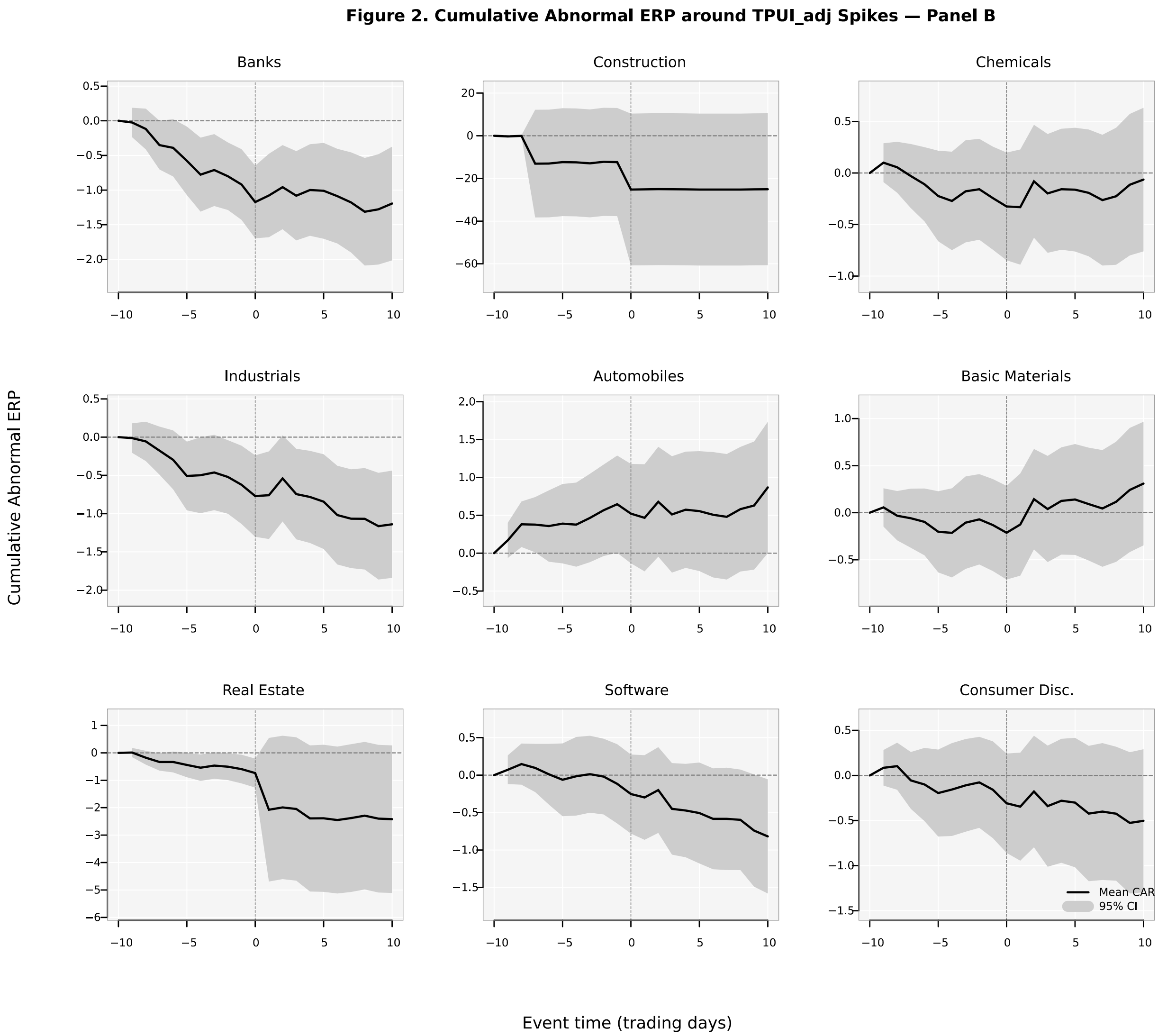
Note: ✓ = classified as net transmitter (X→Y) or net receiver (Y→X) based on LA-VARNN permutation p-value ≤ 0.10 (B = 199 permutations). INDUS is the only sector classified as a transmitter under all three windows. Main 30-day window results reproduced from Section 4.3 for comparison.

Figure 1. ***Cumulative Abnormal Equity Risk Premia Around Trade Policy Uncertainty Spikes: Panel A***



Note: *Cumulative abnormal returns of ERP^adj_{i,t} over the 21-day window [−10, +10] around* $\mathrm{TPUI}_{\mathrm{adj}}$ *spikes (95th percentile threshold, minimum 10-day separation). Shaded band = 95% bootstrap confidence interval. Vertical dashed line marks the event date (day 0). Horizontal dashed line marks zero.*

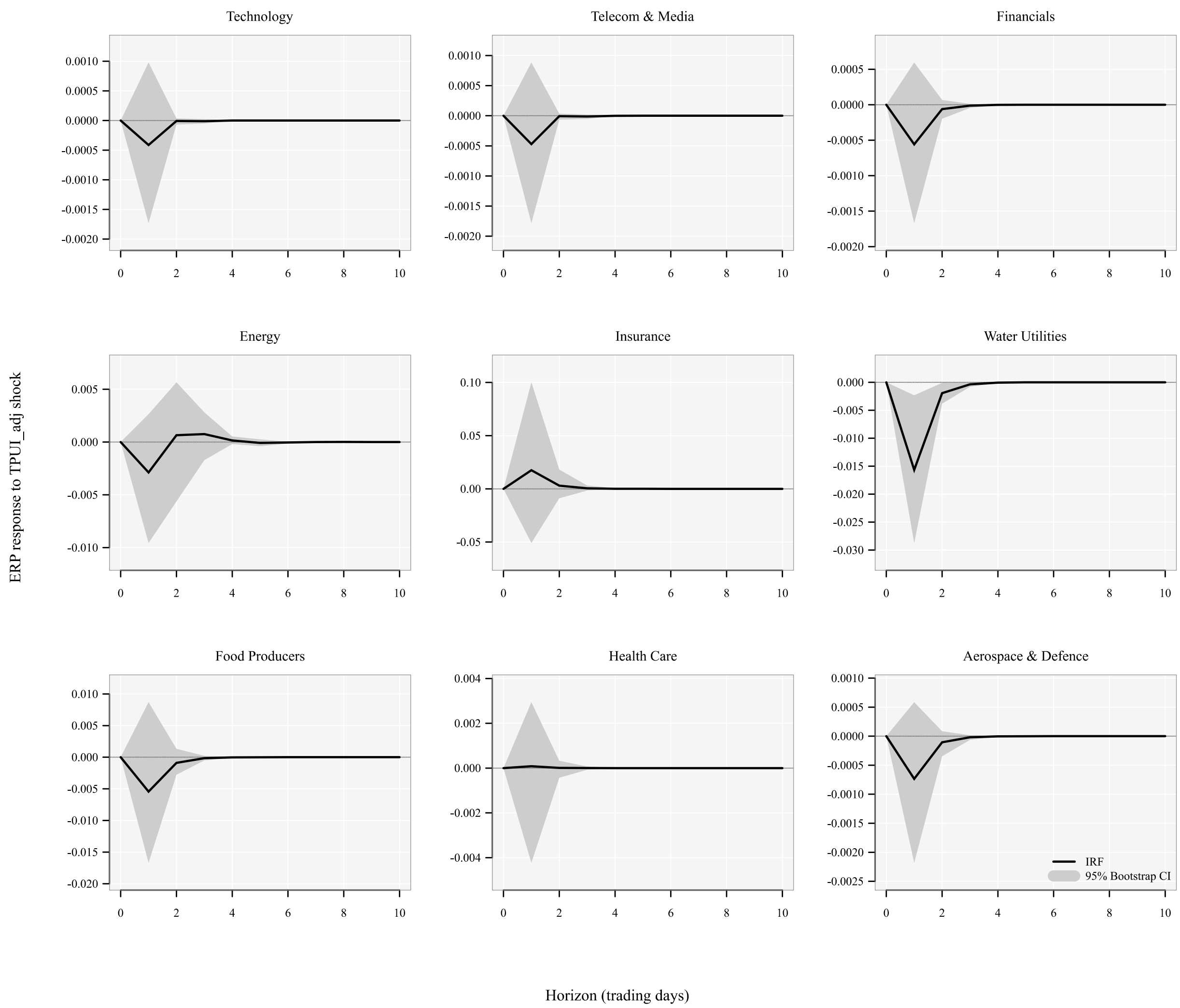
Figure 2. ***Cumulative Abnormal Equity Risk Premia Around Trade Policy Uncertainty Spikes: Panel B***



Note: *Cumulative abnormal returns of ERP^adj_{i,t} over the 21-day window [−10, +10] around* $\mathrm{TPUI}_{\mathrm{adj}}$ *spikes (95th percentile threshold, minimum 10-day separation). Shaded band = 95% bootstrap confidence interval. Vertical dashed line marks the event date (day 0). Horizontal dashed line marks zero.*

Figure 3. ***Impulse Response Functions of Sectoral Equity Risk Premia to a*** $\mathbf{TPUI_{adj}}$ ***Shock: Panel A***

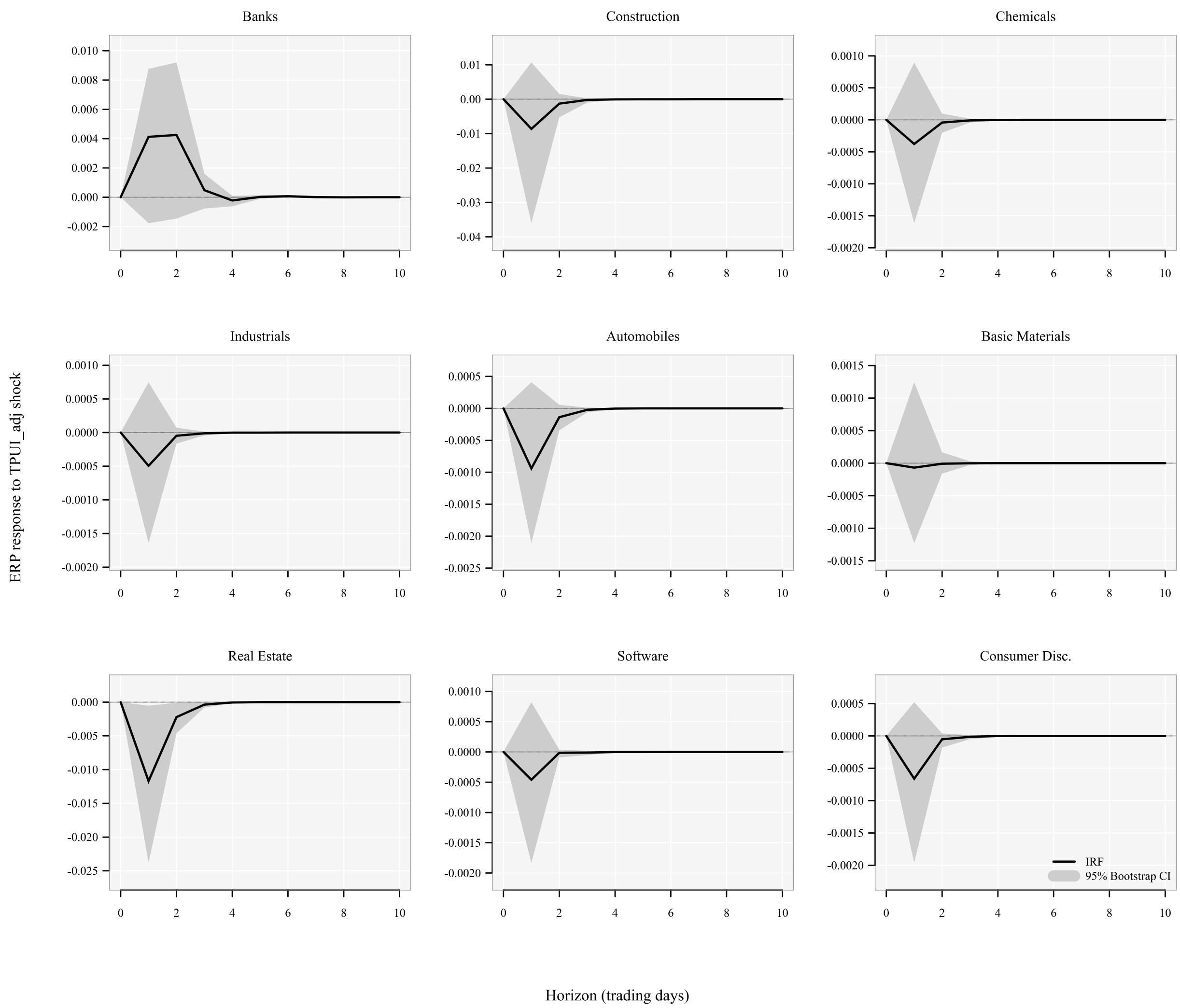
Figure 3. Impulse Response Functions: TPUI_adj → Sectoral ERP — Panel A



Note: *Orthogonalized impulse response of ERP^adj_{i,t} to a one-standard-deviation innovation in* $\mathrm{TPUI}_{\mathrm{adj}}$ *from bivariate VAR(p), Cholesky identification with* $\mathrm{TPUI}_{\mathrm{adj}}$ *ordered first. Shaded band = 95% bootstrap confidence interval (1,000 replications). Horizon in trading days.*

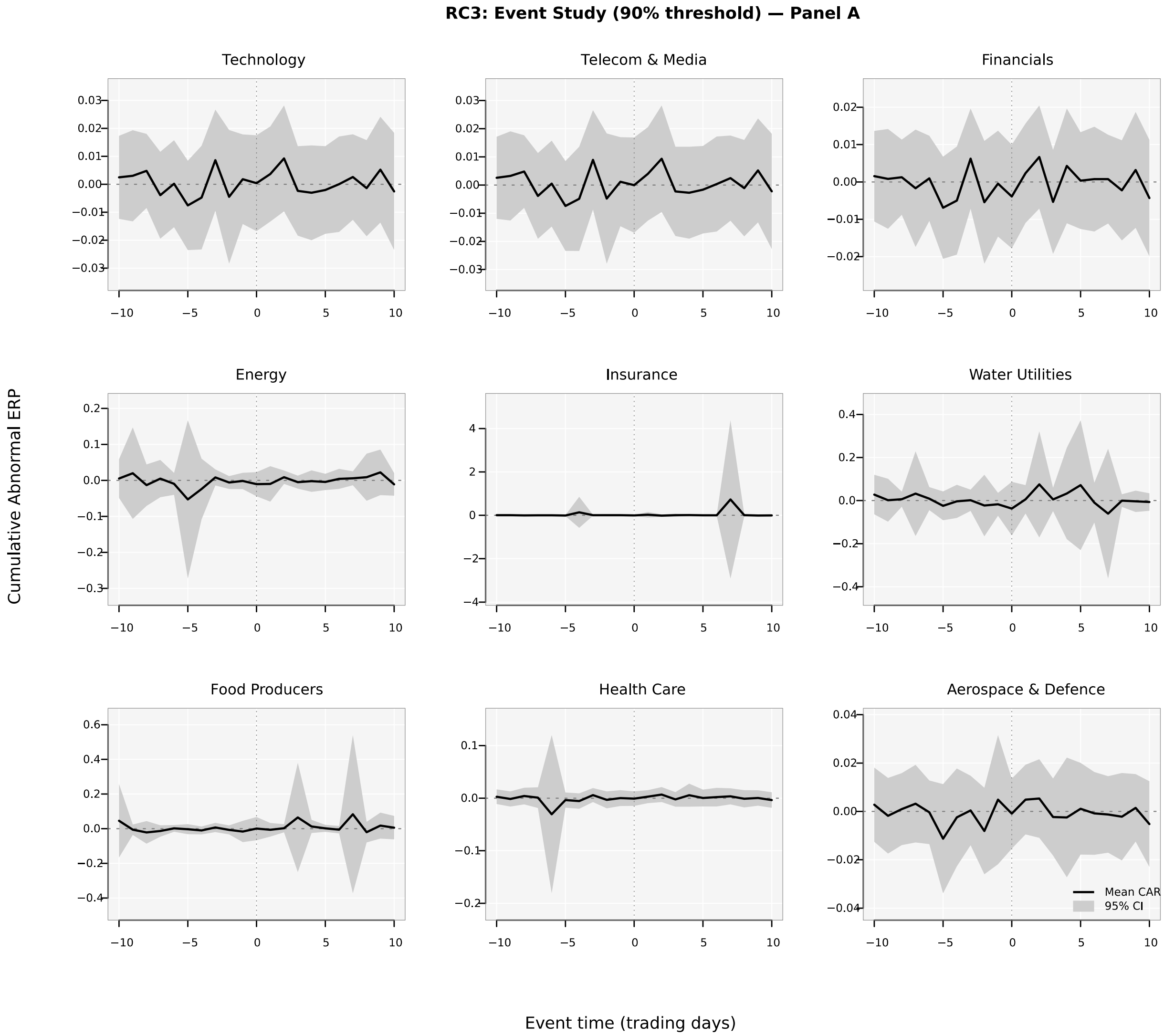
Figure 4. ***Impulse Response Functions of Sectoral Equity Risk Premia to a*** $\mathbf{TPUI}_{\mathbf{adj}}$ ***Shock: Panel B***

Figure 4. Impulse Response Functions: TPUI_adj → Sectoral ERP — Panel B



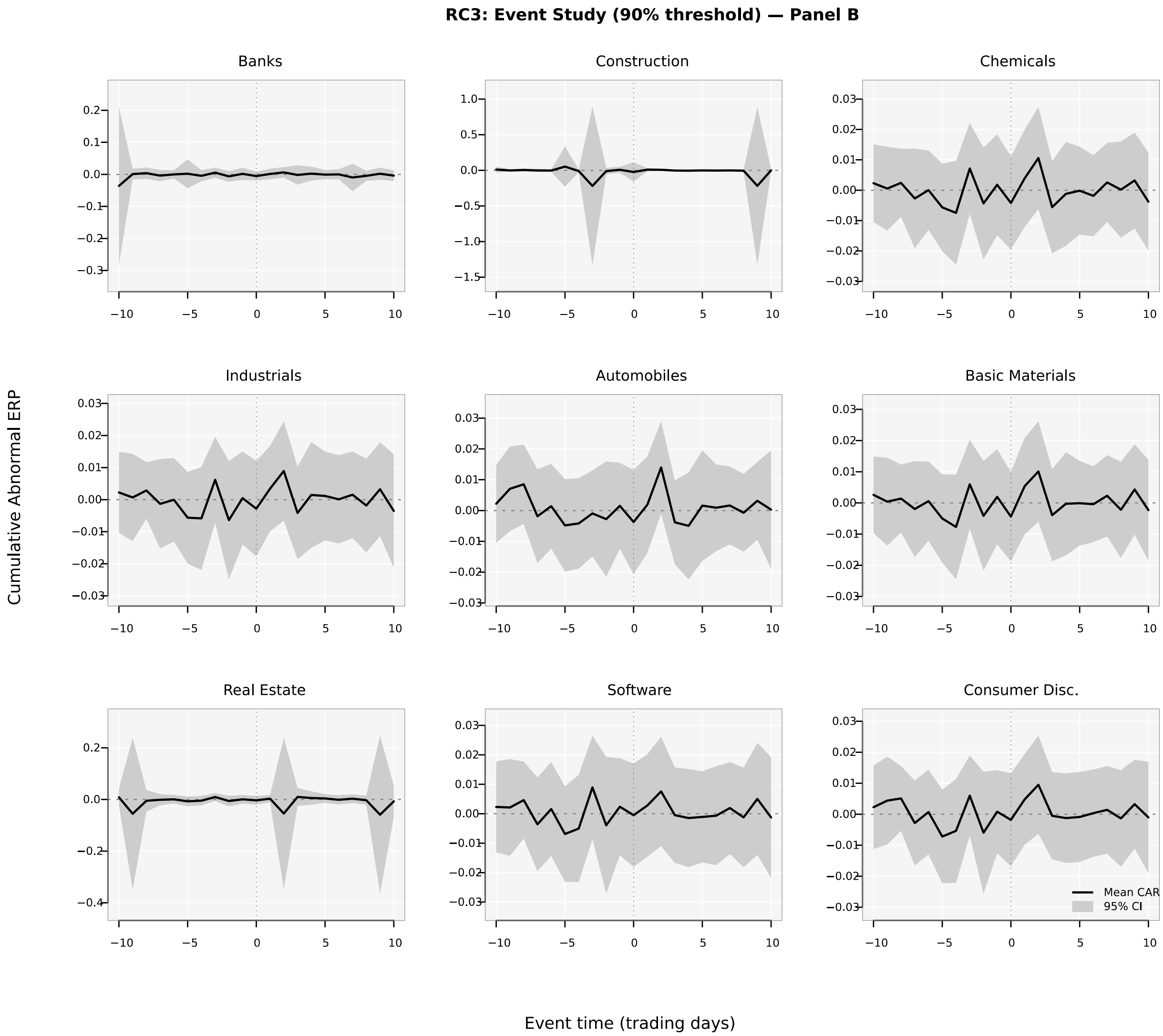
Note: *Orthogonalized impulse response of ERP^adj_{i,t} to a one-standard-deviation innovation in* $\mathrm{TPUI}_{\mathrm{adj}}$ *from bivariate VAR(p), Cholesky identification with* $\mathrm{TPUI}_{\mathrm{adj}}$ *ordered first. Shaded band = 95% bootstrap confidence interval (1,000 replications). Horizon in trading days.*

Figure 5. RC3: Cumulative Abnormal ERP — 90th Percentile Threshold, Panel A



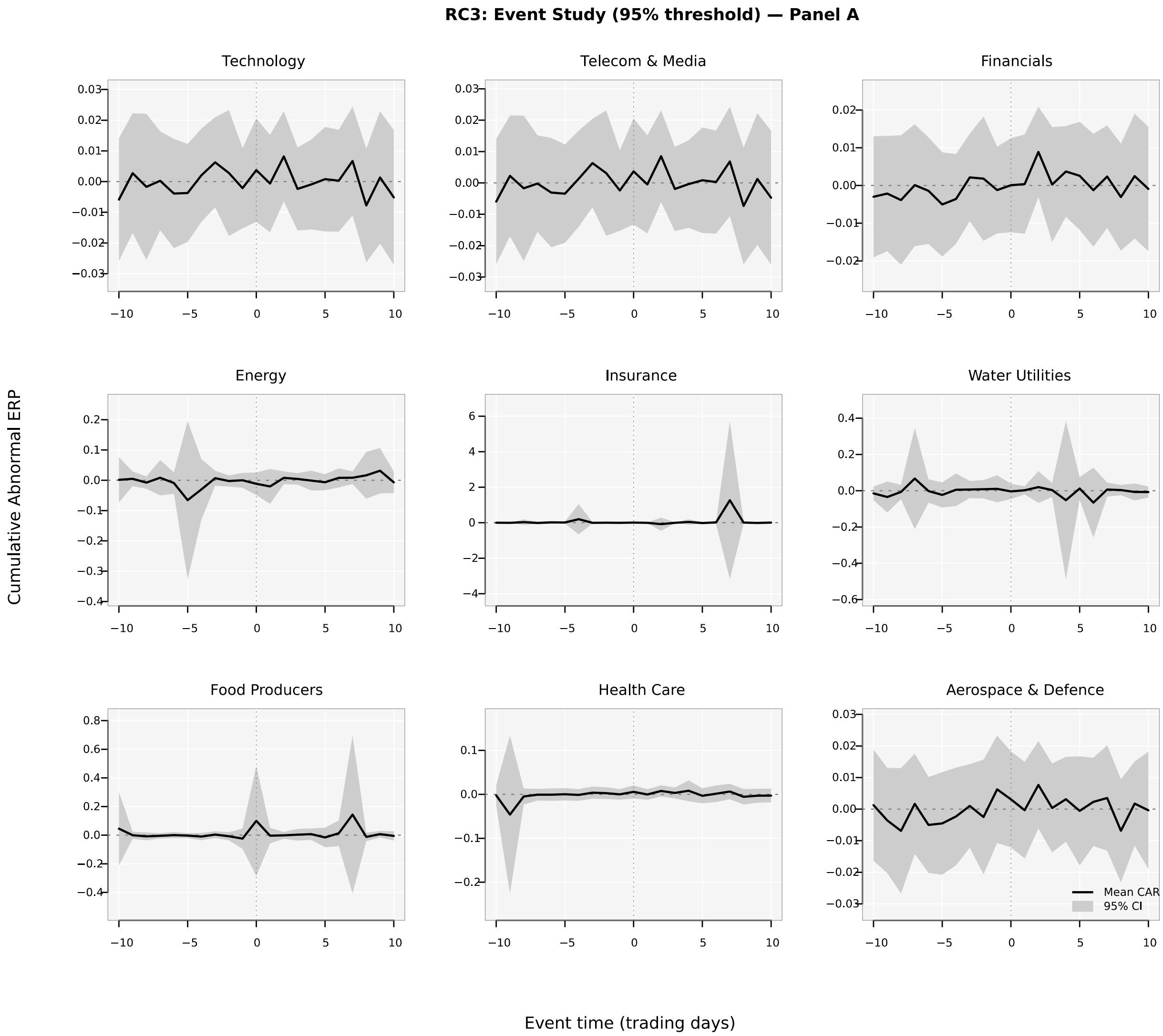
Note: Cumulative abnormal returns of $ERP_{i,t}^{adj}$ over the 21-day window [−10, +10] around $TPUI_{adj}$ spikes at the 90th percentile threshold (minimum 10-day inter-event separation). Shaded band = 95% CI. Vertical dashed line = event date (day 0). Horizontal dashed line = zero. Sectors: Technology, Telecom & Media, Financials, Energy, Insurance, Water Utilities, Food Producers, Health Care, Aerospace & Defence.

Figure 6. RC3: Cumulative Abnormal ERP — 90th Percentile Threshold, Panel B



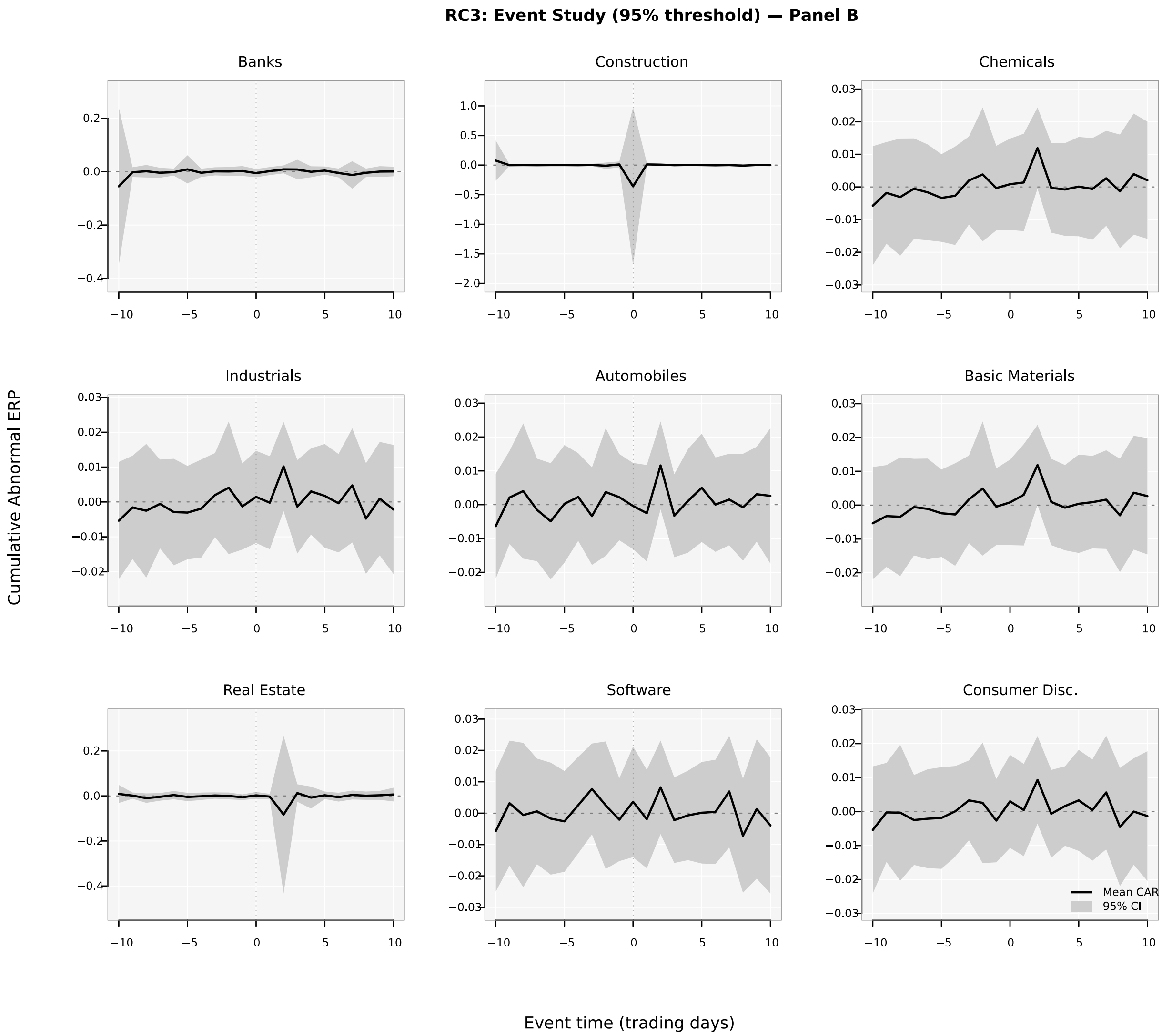
Note: As Figure 5. Sectors: Banks, Construction, Chemicals, Industrials, Automobiles, Basic Materials, Real Estate, Software, Consumer Discretionary.

Figure 7. RC3: Cumulative Abnormal ERP — 95th Percentile Threshold, Panel A



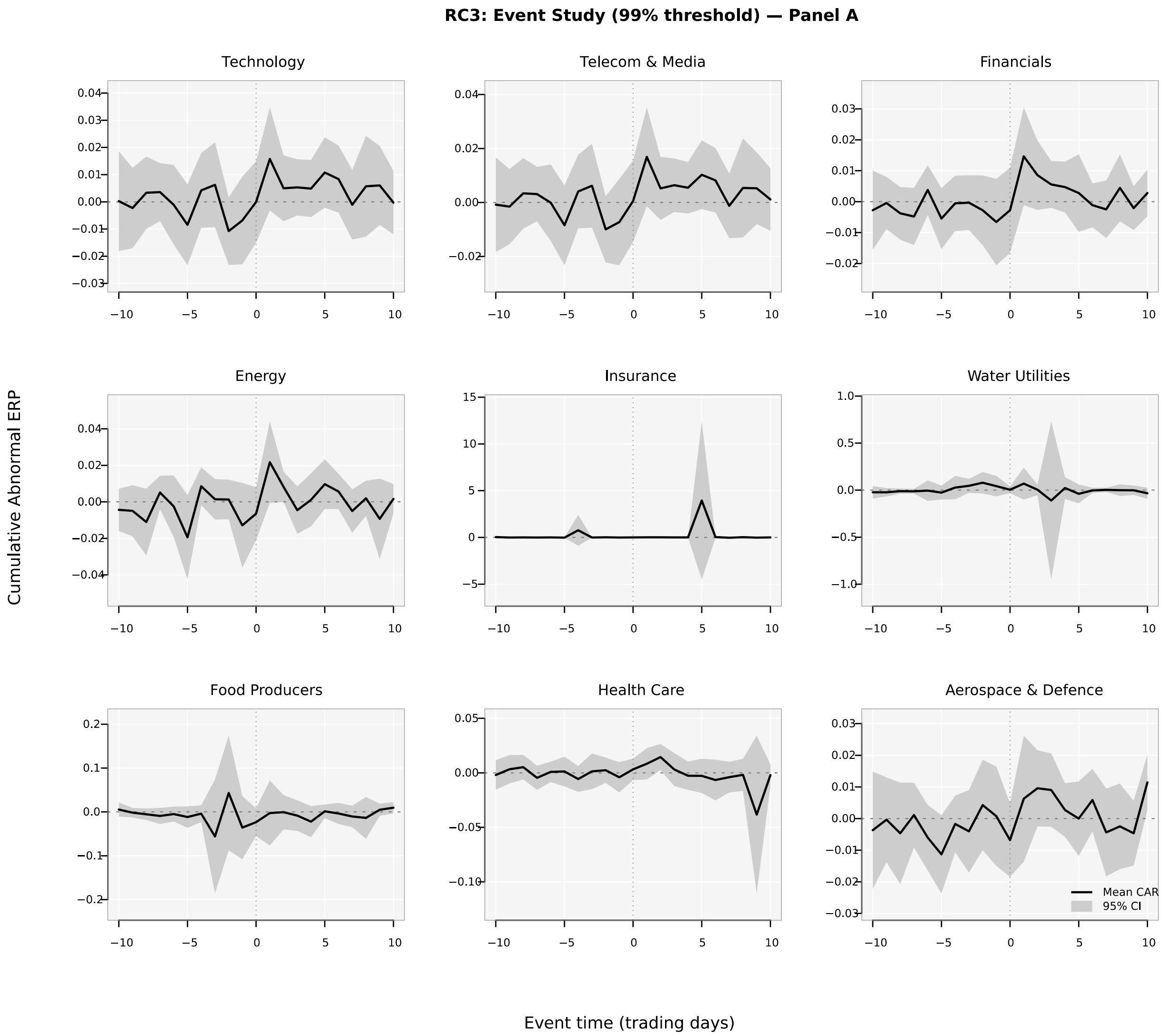
Note: As Figure 5 but with 95th percentile threshold. This is the main analysis threshold, reproduced here for cross-threshold comparison.

Figure 8. RC3: Cumulative Abnormal ERP — 95th Percentile Threshold, Panel B



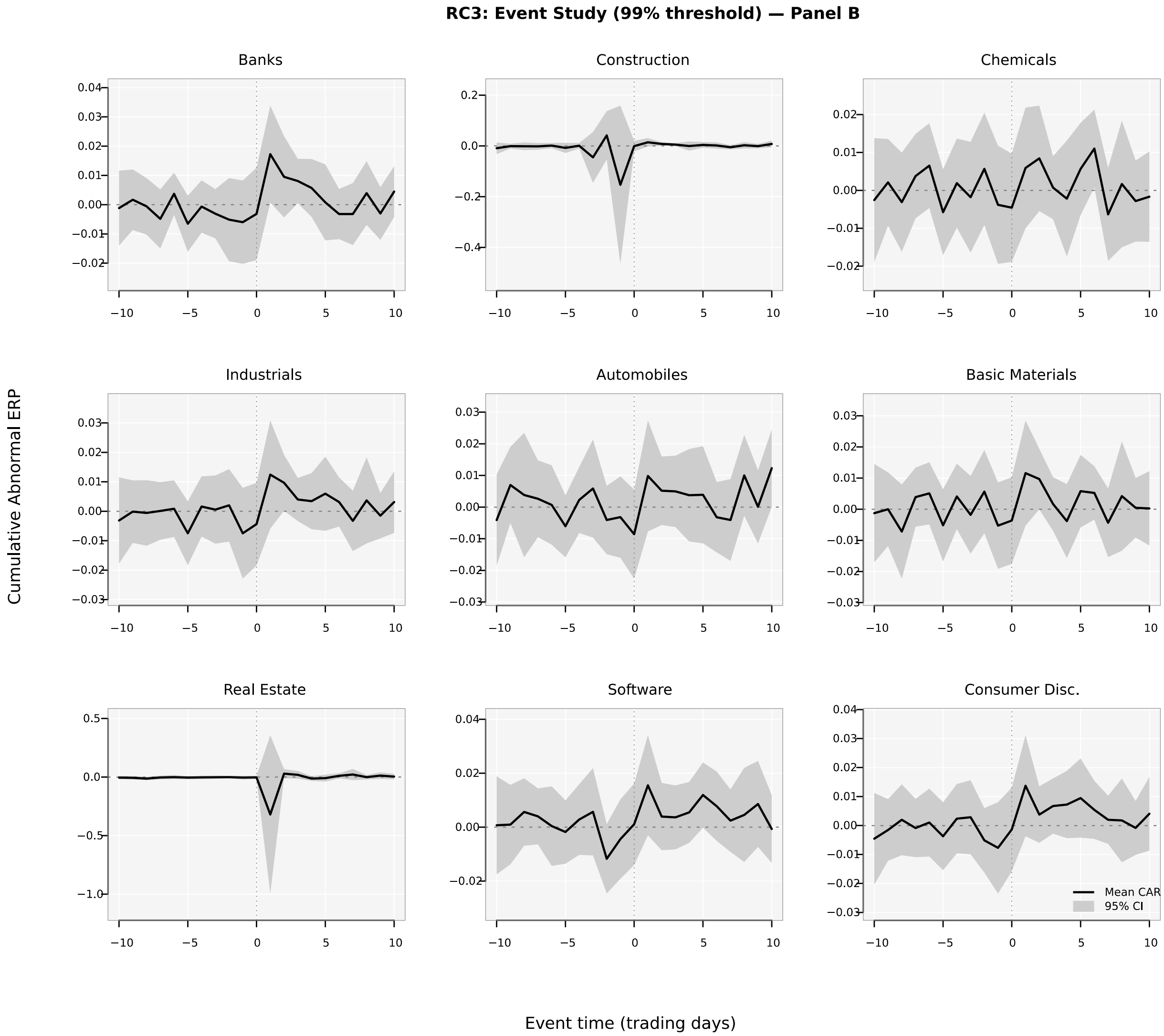
Note: As Figure 7 but with 95th percentile threshold.

Figure 9. RC3: Cumulative Abnormal ERP — 99th Percentile Threshold, Panel A



Note: As Figure 5 but with 99th percentile threshold. Event set concentrated around March-June 2018 (Section 301 announcements), May 2019 (tariff escalation), and April 2025 (Liberation Day cycle).

Figure 10. RC3: Cumulative Abnormal ERP — 99th Percentile Threshold, Panel B



Note: As Figure 9. Note the wider scale for Real Estate (±1.0) relative to the 90th and 95th percentile panels, reflecting sharper responses during the most extreme trade policy episodes.