Geopolitics Meets AI War: Stock Market Evidence from China*

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Abstract

We develop a model in which heterogeneous firms—state-owned enterprises (SOEs) and privately owned enterprises (POEs)—choose among U.S. high-tech inputs, U.S. low-tech inputs, and domestic inputs. High-tech imports enable AI innovation through learning, but require costly external financing. Geopolitical risk (GPR) raises the effective cost of U.S.-origin inputs, while financially constrained POEs face tighter collateral constraints, leading them to reallocate more sharply away from AI-embedded imports than SOEs. Using a continuous difference-in-differences design around the 2018 U.S.–China trade war and LLM-based measures of firm-level geopolitical exposure, we show that higher geopolitical risk reduces high-tech imports, AI innovation, product diversification, and firm fundamentals, with significantly larger effects among POEs. Financial markets also price this risk: higher GPR exposure predicts positive abnormal returns, reduced debt issuance, and negative cumulative returns around tariff events. The differential financial-friction channel explains why POEs bear disproportionately larger losses, revealing AI learning through imports as a novel mechanism linking geopolitical shocks to real outcomes and asset prices.

JEL classification: F14, G32, O31, O33

Keywords: Geopolitical risk, AI import learning, product innovation, financial frictions, SOE, POE, high-tech imports

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1 Introduction

Geopolitical tensions between the United States and China have intensified markedly in recent years, as evidenced by escalating export controls, technology decoupling, and investment restrictions. Since 2022, the U.S. government has progressively expanded its entity list to include leading Chinese high-tech firms, curbing their access to advanced semiconductors, artificial intelligence (AI) software, and precision manufacturing equipment. China has responded with export curbs on critical minerals and heightened regulatory scrutiny over foreign operations. These developments have disrupted cross-border innovation supply chains and elevated policy uncertainty for globally exposed corporations. Motivated by these events, this paper investigates whether geopolitical risk (GPR) negatively affects corporate valuation in the stock market. More fundamentally, we ask how geoeconomic pressure influences corporate decisions and perceptions of financial markets.

This question is puzzling for several reasons. First, standard real options theory (Dixit, 1994) suggests that uncertainty raises the value of waiting, thereby delaying irreversible investment. Yet recent work shows that firms respond asymmetrically to uncertainty shocks, with downward adjustments in employment and capital occurring much more rapidly than upward adjustments (Bloom, 2009). Whether geopolitical risk operates through similar real-options channels remains an open question. Second, the distinction between geopolitical threats and realized events is crucial. Using a novel text-based measure, Caldara and Iacoviello (2022) document that geopolitical threats, rather than actual conflicts, are the primary drivers of economic downturns. Third, the macro-finance literature shows that global political uncertainty leads to equity market declines and capital outflows from exposed countries (Kelly et al., 2016). Yet these studies typically treat geopolitical shocks as having symmetric effects on instantaneous cash flows (Crosignani et al., 2026; Huang et al., 2023), potentially missing how the nature of exposure—through technology supply chains as a real-options channel rather than through trade flows—shapes valuation consequences. A large international finance and trade literature documents related phenomena at the macro or welfare level (Buera and Oberfield, 2020a; Bai et al., 2025; Gavazzoni and Santacreu, 2020), but it does not explicitly identify the effect of technology supply chains through the real-options channel.

The Chinese setting renders this problem particularly distinct and underexplored. Unlike prior episodes of geopolitical tension (e.g., the Cold War or the 2014 Russia sanctions), U.S.–China decoupling directly targets cutting-edge technology sectors in which innovation depends on global knowledge spillovers (Song et al., 2011; Allen et al., 2024, 2005). China's institutional environment also introduces distinctive mechanisms. State-owned enterprises

(SOEs) benefit from implicit government guarantees and preferential credit access, which potentially insulate them from valuation shocks. By contrast, non-SOEs, which drive much of China's technological innovation, lack such protection. How do Chinese firms make import decisions conditional on their state ownership status? How do these import decisions transmit through technology supply chains to affect real options? These questions remain challenging and important in this setting.

We develop a two-period model in which heterogeneous firms, including both state-owned enterprises (SOEs) and privately owned enterprises (POEs), choose among U.S. high-tech inputs, U.S. low-tech inputs, and domestic inputs to produce differentiated goods. High-tech inputs, such as advanced semiconductors and AI-embedded capital goods, drive AI innovation through an import-learning channel: firms that absorb these frontier goods develop the capability to apply AI to their own products and operations. These inputs, however, typically require costly upfront financing. Geopolitical risk raises the effective costs of all U.S.-origin inputs, making high-tech imports less attractive. Furthermore, compared to SOEs, POEs face higher borrowing rates and tighter collateral constraints, leading to reallocation away from AI-embedded inputs. The model predicts that this differential response widens the innovation gap between POEs and SOEs and makes geopolitical risk a priced factor, because high-geopolitical-pressure states are precisely those in which the marginal utility of consumption is high.

Our model delivers four key predictions. First, when geopolitical risk rises, all firms reduce their use of U.S. high-tech inputs and increase their use of domestic inputs, but POEs do so to a significantly larger degree because their higher financing costs magnify every margin of adjustment. Second, the net effect on total AI innovation is theoretically ambiguous: geopolitical risk simultaneously weakens import-based learning and stimulates domestic innovation. When the negative import-based effect dominates, however, innovation declines, and the decline is strictly larger for POEs, provided that the import-learning curve is sufficiently concave relative to the domestic-innovation curve. Third, in value terms, the decline in U.S. high-tech imports exceeds that in U.S. low-tech imports under a condition that essentially requires high-tech goods to be sufficiently expensive relative to low-tech goods, which holds for AI hardware and advanced semiconductors. Fourth, because geopolitical risk reduces aggregate consumption, high-risk states are bad times in which households value payoffs more. Firms whose dividends are more sensitive to geopolitical risk (that is, those with greater U.S. input exposure) therefore have returns that covary negatively with the pricing kernel and command larger risk premia. Thus, POEs face a strictly larger premium than comparable SOEs when the direct amplification effect from their higher borrowing costs dominates the indirect offset from their reduced U.S. input base.

Our identification strategy exploits the exogenous variation generated by the 2018 U.S.–China tariff war in a difference-in-differences design. We construct firm-level geopolitical risk exposure from MD&A texts using a large language model (DeepSeek-v4-flash), measuring exposure to tariffs, sanctions, and export controls. Interacting pre-shock baseline exposure (2014–2015) with aggregate U.S.–China conflict intensity as an aggregate geopolitical risk shock from Clayton et al. (2025) or exact events during 2018, we trace causal effects from geopolitical shocks to real outcomes and asset prices. We find three results consistent with the model. First, higher geopolitical risk reduces high-tech and AI-related imports, with POEs exhibiting significantly larger declines than SOEs. Second, these import reductions translate into lower AI innovation (a 23% decline in three-year AI patents for POEs), reduced product diversification (19.8% fewer trademarks for POEs), and weaker fundamentals (8.34% lower sales growth for POEs). Third, financial markets price this risk: higher exposure predicts positive abnormal returns in Fama-MacBeth regressions (up to 6% monthly), reduced debt issuance (8.93% lower probability), and negative cumulative returns around tariff events. Our framework bridges structural cross-partials to reduced-form estimates and transforms the measurement of geopolitical risk from a macro-only construct into a firm-level, causally identified treatment.

A central contribution of this paper is to demonstrate that state ownership fundamentally shapes how geopolitical risk transmits to firm outcomes, a dimension largely overlooked in existing work on trade policy uncertainty and geoeconomic shocks. While prior literature conceptually treats firms as homogeneous in their exposure to trade frictions through technology supply chains and real options (Gavazzoni and Santacreu, 2020; Bai et al., 2025; Buera and Oberfield, 2020a) even without clear identification, we show that China's two-tier ownership structure generates starkly heterogeneous responses. State-owned enterprises benefit from implicit government guarantees, preferential credit access, and looser collateral constraints, which insulate them from the full force of geopolitical shocks. By contrast, privately owned enterprises face higher borrowing rates and tighter financing constraints, which amplify every margin of adjustment. Our findings reveal novel heterogeneity along three dimensions. First, POEs reduce high-tech and AI-related imports significantly more than SOEs when geopolitical risk rises, because their higher financing costs magnify the impact of rising input prices. Second, the innovation gap widens markedly: POEs experience large and statistically significant declines in AI patents over three-year horizons, while SOEs show no meaningful change, implying that state backing preserves innovative capacity during geoeconomic crises. Third, financial markets penalize POEs disproportionately—the geopolitical risk premium is roughly twice as large for POEs as for SOEs, and only POEs generate significant abnormal returns in long-short portfolio strategies. These results establish that

state ownership acts as a buffer against geoeconomic pressure, while private ownership amplifies vulnerability—a novel mechanism with direct policy implications for understanding how institutional frictions mediate the transmission of global shocks.

We make four contributions. We first develop a granular, firm-level measure of geopolitical risk exposure for Chinese public firms. Existing work relies on aggregate indices that cannot capture heterogeneous firm vulnerability. We address this gap by applying a large language model (DeepSeek-v4-flash) to the MD&A sections of annual reports from 2010 to 2024, identifying discussions of tariffs, financial sanctions, export controls, and integrated geoeconomic pressure. The prompt is designed to capture only ex ante uncertainty, distinguishing geopolitical risk from business cycle fluctuations. The resulting measure exhibits substantial cross-sectional variation—POEs face higher exposure than SOEs, and tariff pressure dominates the time-series trend. This transforms geopolitical risk from a macro-only aggregate into a firm-level, causally identifiable treatment, providing the foundation for our quasi-experimental design.

We next identify the "learning by importing" channel through which firms acquire AI capabilities from foreign suppliers. Using LLM-based classification of customs product descriptions, we construct firm-level measures of high-tech and AI-related imports, with AI products (GPUs, chips, deep-learning hardware) classified by the LLM as high-AI relevance and cross-validated against China's official patent classification. This allows us to trace how geopolitical shocks disrupt import learning separately from domestic AI substitution. We find that geopolitical risk reduces precisely those imports that embed frontier AI capabilities, and this reduction translates directly into lower AI innovation and product diversification. By isolating the learning-by-importing mechanism, our framework moves beyond aggregate import measures to identify the specific technological content that drives real outcomes.

We then show that high-tech import learning drives creative innovation—product-scope expansion and appeal enhancement—rather than merely process efficiency. In a multi-product firm framework, we show that U.S. high-tech inputs raise product appeal, while domestic AI provides only an imperfect substitute. Linking this mechanism to corporate fundamentals, we find that geopolitical risk reduces trademarks by 20% and product patents by 13%, indicating lost product diversification. These innovation losses translate into real underperformance: sales growth falls by 5.11% (8.34% for POEs), the investment ratio drops by 0.67% (1.14% for POEs), and the probability of debt issuance declines by 5.36% (8.93% for POEs). Geopolitical shocks thus disrupt import learning, depressing innovation, fundamentals, and financing access, with POEs bearing larger losses across every margin.

Finally, we show that geopolitical risk is priced in both debt and equity markets. Firms with higher exposure face tighter credit access: debt issuance falls by 5.36% overall and by

8.93% for POEs, while SOEs show no significant change. In equity markets, a long-short portfolio of high- versus low-GPR firms earns 2.5–2.6% annualized abnormal returns. Fama-MacBeth regressions confirm that a one-standard-deviation increase in exposure predicts 6.0% higher monthly returns—6.3% for POEs versus 3.4% for SOEs. Event studies around tariff announcements show that high-GPR portfolios underperform by 0.54–1.73% within short windows. Geopolitical risk thus commands a significant premium, driven almost entirely by POEs, which face both higher equity costs and restricted debt access—a double penalty in their cost of capital.

This paper relates to several strands of the literature. First, within the international trade literature, most studies focus on how geopolitical tensions or trade policy uncertainty instantaneously affect firm cash flows. Crosignani et al. (2026) documents how U.S. companies taking a stance on tech leadership experience market devaluations following U.S. geopolitical tensions over export controls. Huang et al. (2023) characterizes the trade-network effect in propagating trade policy uncertainty and how such uncertainty deteriorates firm value in financial markets. The work most closely related to ours is Waugh (2026), which documents AI adoption from an international trade perspective. However, that paper focuses on AI trade primarily in Mexico and estimates its fiscal sustainability implications for the United States arising from tax exemptions. By contrast, our paper contributes to the emerging literature on geopolitical risk and examines how it propagates through international trade as a real-options channel. Rather than focusing solely on real options through trade policy, we embed our analysis within the framework of the Chinese economy, highlighting cross-sectional differences across distinct types of state ownership.

Second, our paper contributes to the emerging literature on AI in finance. Most frontier papers study AI within domestic economies and measure AI exposure using either textual data or labor-market proxies. Babina et al. (2024) show that AI adoption has a positive effect on gaining market power through product innovation. Eisfeldt et al. (2023) identify firm-level exposure to generative AI and examine its implications for market valuation, confirming a labor-technology substitution effect for U.S. corporations. Acemoglu et al. (2022) first show that AI adoption displaces routine labor, with sizable substitutability at the aggregate level. Babina et al. (2025) documents a new role for AI in stabilizing corporate performance by reducing profitability volatility. Our paper documents a distinct pattern of AI adoption through international trade. Using exogenous variation from geopolitical conflicts, we show how cross-country conflicts drive AI adoption and AI capital accumulation.

Third, our paper contributes to the asset pricing literature, particularly to the asset pricing framework in the Chinese economy. Relatively few papers investigate the cross-section of stock returns in Chinese financial markets, and most are empirically motivated.

Geng and Pan (2024) examine China's credit market and government debt using a structural estimation that incorporates credit and liquidity factors. Allen et al. (2024) summarize the long-run underperformance of Chinese stocks relative to alternative equity markets and rationalize it within a behavioral framework. Liu et al. (2019) document the factor structure in the Chinese stock market and evaluate its efficiency in explaining cross-sectional stock performance. The framework closest to ours is Belo et al. (2026), who build a structural asset pricing model to explain the asymmetric cross-sectional performance of Chinese stock returns arising from state-ownership exposure to Chinese monetary policy. Our setting also starts from the underlying assumption of heterogeneous state ownership in financial accessibility. However, we focus on the intensive margin of state ownership with respect to financial frictions and explore its implications for geopolitical risk in asset pricing through the international trade channel.

The remainder of the paper proceeds as follows. Section II develops a two-period model of input choice under geopolitical risk, highlighting how financial frictions amplify POE losses relative to SOE losses. Section III describes our LLM-based measurement of firm-level geopolitical exposure and high-tech import classification. Section IV presents the data and summary statistics. Section V reports the causal effects of geopolitical risk on imports, innovation, and product diversification. Section VI documents financial market consequences, including event studies, fundamentals, and the cost of capital. Section VII concludes.

2 Theoretical Framework

Environment. Consider a two-period economy ($t = 0, 1$) populated by a representative household and a continuum of firms. Firms are of two ownership types $j \in \{SOE, POE\}$. There is no labor; production follows an AK technology where productivity depends on the composition of intermediate inputs. The economy is subject to geopolitical risk, which raises the effective cost of sourcing U.S.-origin inputs.

Timeline. The sequence of events is as follows:

1. At $t = 0$: The household observes the distribution of τ and prices equity claims to SOE and POE firms. The household chooses consumption C_0.

2. At $t = 1$: The geopolitical risk shock τ is realized. Firms observe τ and choose their input composition $\omega_f^j(\tau)$. Firms finance input purchases using internal cash and bank borrowing. Production occurs and dividends $D_1^j(\tau)$ are paid. The household consumes $C_1(\tau)$.

This timing is important: equity claims are priced *ex ante* (before τ is realized), while firms' import decisions are made *ex post* (after τ is observed). The comparative statics in Section 5 characterize firms' optimal responses to realized τ, while the asset pricing results in Section 6.3 concern the *ex ante* risk premium arising from uncertainty over τ.

2.1 Representative Household and Stochastic Discount Factor

The representative household has CRRA preferences over consumption in the two periods:

$$U = u(C_0) + \beta\,\mathbb{E}[u(C_1)], \quad u(C) = \frac{C^{1-\gamma}}{1-\gamma}$$

where $\beta \in (0,1)$ is the subjective discount factor and $\gamma > 0$ is the coefficient of relative risk aversion. The household's period-t consumption C_t is a real consumption index that aggregates over all differentiated products and varieties produced by SOE and POE firms. As detailed in Appendix A, within each period consumers have nested CES preferences across products (elasticity ν) and across firm varieties within each product (elasticity $\sigma > \nu$). This within-period CES structure determines relative demand for individual varieties and generates the product-level revenues and price indices that underpin the micro-foundation for AI import learning. The CRRA specification over the CES aggregate governs intertemporal allocation and determines the stochastic discount factor used to price assets.

The household owns all firms in the economy. At $t = 0$, the household is endowed with wealth W_0 and chooses consumption C_0. At $t = 1$, aggregate real income equals aggregate dividends from all firms. Since the CES consumption index is monotonically increasing in real income (for a given aggregate price index, which is determined by firms' pricing and product scope decisions), we can express the household's period-1 consumption in terms of aggregate dividends:

$$C_1 = \alpha\, D_1^{SOE} + (1-\alpha)\, D_1^{POE}$$

where $\alpha \in (0,1)$ is the share of SOE firms in the economy and D_1^j denotes the aggregate real payout from type-j firms. This formulation is without loss of generality for the comparative statics: any monotone transformation of income preserves the signs of all derivatives with respect to τ.

The household's Euler equation determines the risk-free rate r_f on financial assets:

$$u'(C_0) = \beta(1+r_f)\,\mathbb{E}[u'(C_1)] \tag{1}$$

The stochastic discount factor (SDF), derived from the household's first-order condition,

is:

$$M = \beta \frac{u'(C_1)}{u'(C_0)} = \beta \left(\frac{C_1}{C_0} \right)^{-\gamma} \tag{2}$$

The SDF prices all assets in the economy. For any asset with gross return R:

$$\mathbb{E}[M \cdot R] = 1$$

which implies:

$$\mathbb{E}[R] - (1 + r_f) = -\frac{\text{Cov}(R, M)}{\mathbb{E}[M]} \tag{3}$$

Assets whose returns covary negatively with M—i.e., that pay off poorly when consumption is low—command a positive risk premium.

An important distinction in this economy is that the risk-free rate r_f determined by the Euler equation (1) is the return on *financial assets*, not the cost of bank credit that firms face. As we discuss in Section 2.2.4, the borrowing rates r^j for SOEs and POEs are determined by the banking system and government policy, and are not tied to r_f. This separation—between the financial market pricing kernel and the administered credit market—is a key feature of the Chinese economy and ensures that changes in r_f do not feed back into firms' import decisions.

2.2 Firms

2.2.1 Production Technology and Import Learning

Each firm f of type j enters period 0 with capital K_f. Production uses an AK technology with three intermediate inputs:

$$Y_f = A(\omega_H, \omega_O)\, K_f$$

where $\omega_H \in [0, 1]$ is the U.S.-origin high-tech input share, $\omega_L \in [0, 1]$ is the U.S.-origin low-tech input share, $\omega_O = 1 - \omega_H - \omega_L \geq 0$ is the domestic input share, and $A(\omega_H, \omega_O)$ is the firm's productivity.

The three input types differ in both cost and productivity contribution. Input prices satisfy:

$$p_H > p_O > p_L > 0$$

U.S.-origin high-tech inputs (p_H) are the most expensive, reflecting the frontier nature of AI-embedded capital goods. Domestic inputs (p_O) are intermediate in cost, reflecting the quality and reliability premium of indigenous production. U.S.-origin low-tech inputs (p_L) are the cheapest — they are commodity-like goods (standardized components, raw materials)

available at competitive world prices below domestic alternatives.

The three inputs differ sharply in their productivity contributions:

- **U.S. high-tech inputs** (ω_H) generate *AI import learning*: firms that absorb AI-embedded intermediate goods develop capabilities to apply AI to their own products and operations, enabling both innovation and efficiency gains. This is the primary mechanism connecting geopolitical risk to firm performance.

- **Domestic inputs** (ω_O) contribute to *domestic AI innovation*: indigenous technology capabilities, state-supported AI programs, and domestically developed AI tools (e.g., large language models, chip architectures) provide a separate but imperfect substitute for frontier AI capabilities. This channel is independent of U.S. sourcing and unaffected by geopolitical risk.

- **U.S. low-tech inputs** (ω_L) contribute *neither* AI import learning nor domestic AI innovation. They are pure cost-minimizing inputs used because $p_L < p_O$—firms prefer them over domestic goods purely for cost reasons, not productivity.

We model productivity as additively separable in the two productive inputs:

$$A(\omega_H, \omega_O) = \underline{A} + \theta\,\omega_H - \frac{\delta}{2}\omega_H^2 + \mu\,\omega_O - \frac{\zeta}{2}\omega_O^2, \quad \theta, \delta, \mu, \zeta > 0$$

The parameters θ and δ govern AI import learning productivity and absorptive capacity. The parameters μ and ζ govern domestic AI innovation productivity and its diminishing returns.

2.2.2 AI Import Learning and Product Innovation

Following Babina, Fedyk, He and Hodson (2024), who show that AI investment drives firm growth primarily through product innovation rather than process innovation, we focus on the AI innovation channel through which high-tech input reliance affects firm performance.

AI innovation: two channels. Total AI innovation combines two independent channels:

$$\text{Innovation}_f = \phi_H(\omega_H) + \phi_O(\omega_O)$$

where $\phi_H' > 0$, $\phi_H'' \leq 0$ captures AI import learning from U.S. high-tech inputs, and $\phi_O' > 0$, $\phi_O'' \leq 0$ captures domestic AI innovation from indigenous inputs. The two channels are *imperfect substitutes*: domestic AI capabilities can partially offset the loss of U.S. import

learning, but cannot fully replicate frontier AI technologies (hardware, training infrastructure, proprietary models) embedded in U.S. high-tech goods.

This two-channel structure reflects an important feature of China's AI landscape. While U.S. export controls and entity list restrictions have curtailed access to advanced semiconductors and AI hardware, Chinese firms and research institutions have responded by accelerating domestic AI development — large language models (DeepSeek, ERNIE), domestic chip architectures (Huawei Ascend), and state-sponsored AI research programs. The model captures both the disruption of the U.S. import learning channel and the countervailing domestic innovation response.

U.S. low-tech inputs. The share ω_L contributes neither AI import learning nor domestic AI innovation. Firms use U.S. low-tech inputs purely for cost reasons: $p_L < p_O$ makes them cheaper than domestic alternatives. As geopolitical risk raises κp_L toward p_O, this cost advantage erodes and firms substitute toward domestic inputs.

Ex-post price ordering. We maintain the condition $\kappa(\tau, \eta_f)\, p_L < p_O$ for all $\tau \in [0, \bar{\tau}]$ and $\eta_f \in [0, \bar{\eta}]$, equivalently $\bar{\tau} < (p_O/p_L - 1)/\bar{\eta}$. This ensures the price ordering $p_H > p_O > \kappa p_L$ holds ex-post throughout the support, so U.S. low-tech imports are never fully wiped out: firms always prefer some U.S. low-tech over domestic on cost grounds.

2.2.3 Input Costs and Geopolitical Risk

Sourcing intermediate inputs requires upfront payment. Let $\eta_f \geq 0$ denote firm f's *geopolitical exposure*. Geopolitical risk raises the cost of *all U.S.-origin inputs* proportionally while leaving domestic input costs unaffected. The total input cost per unit of capital is:

$$p(\omega_H, \omega_L, \tau, \eta_f) = \kappa(\tau, \eta_f)\big[p_H\, \omega_H + p_L\, \omega_L\big] + p_O\, \omega_O$$

where $\kappa(\tau, \eta_f) \equiv 1 + \eta_f \tau$ and prices satisfy $p_H > p_O > p_L > 0$. Total input cost is $\Xi_f = p\, K_f$.

It is convenient to reformulate in terms of (ω_H, ω_O) — the two productive inputs — by substituting $\omega_L = 1 - \omega_H - \omega_O$:

$$p = \kappa p_L + \kappa(p_H - p_L)\, \omega_H + (p_O - \kappa p_L)\, \omega_O \tag{4}$$

The term $\kappa(p_H - p_L)$ is the cost premium of high-tech over low-tech U.S. inputs; $(p_O - \kappa p_L) > 0$ (maintained by Assumption 1) is the cost premium of domestic over U.S. low-tech. As τ rises: the high-tech premium grows (discouraging ω_H); the domestic premium shrinks (making domestic relatively cheaper vs. U.S. low-tech, encouraging substitution from ω_L

toward ω_O). The problem separates cleanly in (ω_H, ω_O), making the comparative statics tractable.

2.2.4 Debt Financing

Firms finance input costs using a combination of internal funds and external borrowing. Let C_f^j denote the internal cash holdings of firm f of type j, and let B_f denote the amount borrowed. The financing constraint is $\Xi_f = C_f^j + B_f$. We define the cash-to-capital ratio $\chi^j \equiv C_f^j / K_f$. Since internal cash C_f^j is predetermined at $t = 0$ and non-stochastic, it does not affect comparative statics with respect to τ; where necessary we compare firms with equal cash-to-capital ratios $\chi^{SOE} = \chi^{POE} \equiv \chi$.

In China, the cost of borrowing is determined by the banking system and government policy, not by a frictionless capital market. The People's Bank of China uses M2 growth as the intermediate monetary policy target and influences credit volumes through the banking system, while state-owned banks—which account for more than half of total banking assets—channel credit preferentially to SOEs (Belo et al., 2026). We therefore specify the borrowing rate as:

$$r^j = \bar{r} + \xi^j, \quad \xi^{SOE} < \xi^{POE}$$

where $\bar{r}$ is the base lending rate set by the banking system and ξ^j is an ownership-specific financing friction wedge. Importantly, r^j is *not* tied to the risk-free rate r_f in the SDF (2). The SDF prices assets in financial markets, while r^j reflects the cost of bank credit, which in China is shaped by government guarantees, directed lending, and regulatory policy rather than by market-clearing conditions.

The financing friction wedge $\xi^{POE} > \xi^{SOE}$ reflects several well-documented channels: SOEs benefit from implicit government guarantees that lower perceived default risk; SOEs have special connections to the government and state-owned banks that facilitate access to credit; and government monetary and credit policies tend to favor SOEs.

For aggregate resource accounting, we interpret $(1 + r^j)B_f$ as a reduced-form financing-inclusive resource cost of funding input purchases. The ownership-specific component r^j captures both the direct cost of external finance and the real intermediation and shadow costs associated with directed credit allocation in China (see, e.g., Song et al., 2011; Hsieh and Klenow, 2009). We abstract from bank profits being rebated to the representative household: the financing-cost term should be read as a reduced-form shadow cost of external finance, not as a pure transfer within the household sector. As a result, the decline in firm dividends from rising τ maps into a decline in aggregate household consumption rather than being offset by recycled bank income.

The firm must also satisfy a collateral constraint:

$$B_f \leq \varphi^j \, K_f, \quad \varphi^{SOE} > \varphi^{POE}$$

where φ^j is the collateralizability of capital for type-j firms.

2.2.5 Firm's Problem

Each firm jointly chooses (ω_H, ω_O) — the two productive input shares — to maximize its dividend, with U.S. low-tech $\omega_L = 1 - \omega_H - \omega_O$ determined residually. The dividend is:

$$D_f^j = A(\omega_H, \omega_O) \, K_f - (1 + r^j) \big[p(\omega_H, \omega_O, \tau, \eta_f) \, K_f - C_f^j \big]$$

Using (4) and suppressing the constant κp_L term, the firm's problem is:

$$\max_{\omega_H, \omega_O \geq 0, \, \omega_H + \omega_O \leq 1} \Bigg[\underline{A} + \theta \omega_H - \frac{\delta}{2} \omega_H^2 + \mu \omega_O - \frac{\zeta}{2} \omega_O^2 \\ - (1 + r^j) \big(\kappa (p_H - p_L) \omega_H + (p_O - \kappa p_L) \omega_O \big) \Bigg] K_f + (1 + r^j) C_f^j$$

subject to the collateral constraint $[\kappa p_L + \kappa(p_H - p_L)\omega_H + (p_O - \kappa p_L)\omega_O] K_f - C_f^j \leq \varphi^j K_f$.

The objective is *additively separable* in (ω_H, ω_O): optimizing over ω_H depends only on θ, δ, $\kappa(p_H - p_L)$; optimizing over ω_O depends only on μ, ζ, $(p_O - \kappa p_L)$. The two FOCs are independent in the unconstrained interior.

2.3 Optimal Input Choice

Interior Solution. The first-order conditions with respect to ω_H and ω_O yield:

$$\theta - \delta \, \omega_H = (1 + r^j) \, \kappa(\tau, \eta_f) \, (p_H - p_L)$$
$$\mu - \zeta \, \omega_O = (1 + r^j) \, (p_O - \kappa(\tau, \eta_f) \, p_L)$$

Solving for the optimal shares:

$$\omega_H^{*j} = \frac{\theta - (1 + r^j) \, \kappa(\tau, \eta_f) \, (p_H - p_L)}{\delta} \tag{5}$$
$$\omega_O^{*j} = \frac{\mu - (1 + r^j) \, (p_O - \kappa(\tau, \eta_f) \, p_L)}{\zeta} \tag{6}$$

and $\omega_L^{*j} = 1 - \omega_H^{*j} - \omega_O^{*j}$.

The two FOCs are independent in the unconstrained interior. The cost wedge driving ω_H^* is $\kappa(p_H - p_L)$: high-tech becomes more expensive relative to U.S. low-tech as τ rises. The cost wedge driving ω_O^* is $(p_O - \kappa p_L)$: domestic becomes relatively cheaper vs. U.S. low-tech as τ rises (the wedge shrinks), inducing substitution from ω_L toward ω_O.

Binding Collateral Constraint. When the collateral constraint binds, a shadow value of funds $\lambda > 0$ augments the effective cost of borrowing. The FOCs become:

$$\frac{\theta - \delta\omega_H}{\kappa(p_H - p_L)} = \frac{\mu - \zeta\omega_O}{p_O - \kappa p_L} = (1 + r^j + \lambda)$$

subject to $[\kappa(p_H - p_L)\omega_H + (p_O - \kappa p_L)\omega_O]K_f = (\chi^j + \varphi^j - \kappa p_L)K_f$. When the collateral constraint binds, the shadow value of funds reduces input use relative to the unconstrained optimum at a given κ. It unambiguously makes U.S. high-tech inputs less attractive; the net effect on domestic inputs as κ rises depends on the balance between tighter financing and the relative-price substitution toward domestic inputs.

Away from the unconstrained interior, the optimal shares are determined by the feasible simplex $\{\omega_H, \omega_O \geq 0,\ \omega_H + \omega_O \leq 1\}$ and the collateral constraint. Since the main propositions focus on the slack-collateral interior region (Assumption 1), we do not use the full constrained solution below.

We derive comparative statics for the unconstrained interior case. We restrict the geopolitical risk shock to a bounded support $\tau \in [0, \bar{\tau}]$ and maintain the following regularity conditions on this support:

Assumption 1. Parameters satisfy for all $\tau \in [0, \bar{\tau}]$ and $\eta_f \in [0, \bar{\eta}]$: (i) $\omega_H^{*j}, \omega_O^{*j} \in (0, 1)$ and $\omega_H^{*j} + \omega_O^{*j} < 1$ for both types on the full support. The individual interiority conditions are ensured by $\theta > (1+r^{POE})\kappa(\bar{\tau}, \bar{\eta})(p_H - p_L)$, $\mu > (1+r^{POE})(p_O - p_L)$, $\theta < \delta + (1+r^{SOE})(p_H - p_L)$, and $\mu < \zeta + (1+r^{SOE})(p_O - \kappa(\bar{\tau}, \bar{\eta})p_L)$; the adding-up constraint $\omega_H^* + \omega_O^* < 1$ is imposed separately. (ii) The ex-post price ordering $\kappa(\bar{\tau}, \bar{\eta})\, p_L < p_O$ holds throughout, ensuring U.S. low-tech costs never exceed domestic costs and $\omega_L^* > 0$ always. (iii) All firms borrow positive amounts and the unconstrained choices $(\omega_H^{*j}, \omega_O^{*j})$ satisfy the collateral constraint strictly on the full support, so the propositions below apply with a slack collateral constraint.

Assumption 2 (Domestic Substitution Dominance)**.** $\zeta(p_H - p_L) < \delta\, p_L$, i.e., the domestic absorptive capacity parameter ζ is small relative to $\delta p_L/(p_H - p_L)$. This ensures that the rise in domestic share ω_O^* more than offsets the fall in high-tech share ω_H^* in the budget allocation, so the U.S. low-tech share ω_L^* also falls with τ.

Proposition 1 (Geopolitical Risk Reduces U.S. High-Tech Imports and Raises Domestic

Input Use). *For all firms with $\eta_f > 0$ and $\tau > 0$:*

$$\frac{\partial \omega_H^{*j}}{\partial \tau} = -\frac{(1+r^j)\,\eta_f\,(p_H - p_L)}{\delta} < 0 \tag{7}$$

$$\frac{\partial \omega_O^{*j}}{\partial \tau} = +\frac{(1+r^j)\,\eta_f\,p_L}{\zeta} > 0 \tag{8}$$

$$\frac{\partial \omega_L^{*j}}{\partial \tau} = -\frac{\partial \omega_H^{*j}}{\partial \tau} - \frac{\partial \omega_O^{*j}}{\partial \tau} = (1+r^j)\eta_f \left[\frac{p_H - p_L}{\delta} - \frac{p_L}{\zeta}\right]$$

The U.S. high-tech share always falls and the domestic share always rises. Under Assumption 2, the U.S. low-tech share also falls: the rise in domestic share ω_O^* dominates the fall in high-tech share ω_H^* in the budget allocation, crowding out ω_L^*. All results hold with analogous expressions for $\partial/\partial\eta_f$.

Proof. See Appendix B.1. □

Proposition 1 is the core input-composition result. The mechanism works through relative cost changes: when geopolitical risk τ rises, the cost multiplier $\kappa = 1 + \eta_f\tau$ increases the effective price of *all* U.S.-origin inputs, but the reallocation differs across the three margins. U.S. high-tech inputs become more expensive relative to U.S. low-tech (the cost wedge $\kappa(p_H - p_L)$ grows), so firms reduce ω_H^*. Meanwhile, domestic inputs become cheaper relative to U.S. low-tech (the cost wedge $p_O - \kappa p_L$ shrinks), so firms increase ω_O^*. The U.S. low-tech share ω_L^*—being determined residually—falls only when the domestic substitution effect is strong enough to dominate (Assumption 2).

Two features of this result merit emphasis. First, all three comparative statics are *linear* in τ and η_f, which is a direct consequence of the quadratic productivity specification and the linear cost structure. This linearity makes the model particularly tractable for empirical implementation: the structural derivatives map directly to regression coefficients in a difference-in-differences design. Second, the results depend on the financing cost r^j through the multiplier $(1 + r^j)$, which creates the ownership differential exploited in Proposition 2.

Proposition 2 (Differential Impact Across Ownership Types). *For any given $\eta_f > 0$ and $\tau > 0$, the changes in all three input shares are larger in magnitude for POE firms:*

$$\left|\frac{\partial \omega_H^{*POE}}{\partial \tau}\right| > \left|\frac{\partial \omega_H^{*SOE}}{\partial \tau}\right|, \quad \frac{\partial \omega_O^{*POE}}{\partial \tau} > \frac{\partial \omega_O^{*SOE}}{\partial \tau}, \quad \left|\frac{\partial \omega_L^{*POE}}{\partial \tau}\right| > \left|\frac{\partial \omega_L^{*SOE}}{\partial \tau}\right|$$

The structural DID cross-partials are:

$$\frac{\partial^2 \omega_H^{*j}}{\partial \eta_f \partial \tau} = -\frac{(1+r^j)(p_H - p_L)}{\delta} < 0, \qquad \frac{\partial^2 \omega_O^{*j}}{\partial \eta_f \partial \tau} = +\frac{(1+r^j)p_L}{\zeta} > 0$$

both larger in magnitude for POEs, providing the structural counterpart to Exposure$_i$ × Shock$_t$ on each margin.

Proof. See Appendix B.2. □

Proposition 2 establishes the central empirical prediction: POE firms are more vulnerable to geopolitical risk than SOEs on every input margin. The mechanism is purely a financing-cost amplification—POEs face higher r^j, which scales up every comparative static through $(1 + r^j)$. Economically, this reflects the fact that input purchases must be financed upfront, and geopolitical risk raises the cost of inputs that are already more expensive to finance for POEs. The amplification is proportional, not additive: if a POE's borrowing rate is 15 percentage points above an SOE's, the POE's input reallocation in response to any given τ shock is roughly 15% larger in magnitude.

The structural DID cross-partials $\partial^2\omega^*/\partial\eta_f\partial\tau$ provide the bridge to the empirical design. In the data, the interaction Exposure$_i$ × Shock$_t$ captures the differential response of high-exposure firms to aggregate geopolitical shocks. The model predicts this coefficient is negative for ω_H^* and positive for ω_O^*, with larger magnitudes for POEs. This motivates splitting the sample by ownership type and testing whether the DID coefficient is amplified for POEs.

Proposition 3 (High-Tech Import Share Declines More Than Low-Tech in Value Terms)**.** *Suppose Assumption 2 holds (so ω_L^* falls). The absolute decline in U.S. high-tech import value exceeds the absolute decline in U.S. low-tech import value:*

$$p_H \cdot \left|\frac{\partial\omega_H^*}{\partial\tau}\right| > p_L \cdot \left|\frac{\partial\omega_L^*}{\partial\tau}\right|$$

if and only if

$$\zeta(p_H^2 - p_L^2) > \delta\, p_L^2.$$

This condition is independent of τ, η_f, and r^j.

Proof. See Appendix B.3. □

Proposition 3 provides a cross-margin prediction: geopolitical risk reduces U.S. high-tech import *values* by more than U.S. low-tech import values. The result requires Assumption 2 (so that both margins decline) plus the additional condition $\zeta(p_H^2 - p_L^2) > \delta p_L^2$. This second condition has a natural interpretation. The left-hand side increases in the price gap $p_H^2 - p_L^2$, which reflects the cost premium of AI-embedded high-tech goods; it also increases in ζ, the domestic absorptive capacity parameter that governs how quickly domestic inputs

exhibit diminishing returns. The right-hand side increases in δ (the import learning absorptive capacity) and p_L^2 (the baseline cost of low-tech goods). Intuitively, the condition says that high-tech inputs must be sufficiently expensive relative to low-tech inputs—which is precisely the empirical pattern for AI hardware and advanced semiconductors versus commodity components.

A notable feature is that the condition is *independent of* τ, η_f, *and* r^j: it holds either for all firms and all risk realizations, or for none. This makes it a sharp cross-margin prediction that can be tested by comparing regression coefficients across the high-tech and low-tech import equations. Note that the proposition compares base-price import-value margins $p_H\omega_H^*$ and $p_L\omega_L^*$, which correspond to the input *share* reallocation weighted by pre-shock prices. This is the appropriate comparison when the empirical variables are import proportions or quantity-based shares. Including the geopolitical price multiplier κ would introduce a countervailing price effect—import unit costs rise with τ—that can dominate the quantity reduction, causing effective dollar import values to increase even as input shares fall.

Proposition 4 (Total AI Innovation: Import Learning vs. Domestic Substitution)**.** *Total AI innovation* $\text{Innovation}_f = \phi_H(\omega_H^*) + \phi_O(\omega_O^*)$ *satisfies:*

$$\frac{\partial\, \text{Innovation}_f^j}{\partial \tau} = (1 + r^j)\eta_f \left[\frac{\phi_O'(\omega_O^{*j})\, p_L}{\zeta} - \frac{\phi_H'(\omega_H^{*j})\, (p_H - p_L)}{\delta} \right] \tag{9}$$

Total AI innovation falls if and only if the import learning destruction exceeds the domestic substitution gain:

$$\frac{\phi_H'(\omega_H^{*j})\, (p_H - p_L)}{\delta} > \frac{\phi_O'(\omega_O^{*j})\, p_L}{\zeta} \qquad (\textit{Import Learning Dominance}) \tag{10}$$

Suppose Import Learning Dominance holds for both ownership types. A sufficient condition for the total innovation decline to be strictly larger for POE firms is that the concavity of the import learning function dominates the concavity of the domestic innovation function:

$$|\phi_H''(\xi_H)|\, \frac{\kappa (p_H - p_L)^2}{\delta^2} \;\geq\; |\phi_O''(\xi_O)|\, \frac{(p_O - \kappa\, p_L)\, p_L}{\zeta^2} \tag{11}$$

for all $\xi_H \in [\omega_H^{*POE}, \omega_H^{*SOE}]$ *and* $\xi_O \in [\omega_O^{*POE}, \omega_O^{*SOE}]$*. This is a directly verifiable sufficient condition: it requires the curvature inequality to hold uniformly over the relevant intervals, which guarantees that it holds at the particular intermediate points delivered by the mean*

value theorem in the proof. Under this condition:

$$\left|\frac{\partial\, Innovation^{POE}}{\partial \tau}\right| > \left|\frac{\partial\, Innovation^{SOE}}{\partial \tau}\right|$$

When condition (10) *fails, the domestic substitution channel dominates and total AI innovation rises with* τ*.*

Proof. See Appendix B.4. □

Proposition 4 addresses the central question of how geopolitical risk affects AI innovation. The result has two parts with distinct economic content.

The first part shows that the net effect on total AI innovation is ambiguous in general, because geopolitical risk simultaneously destroys import learning (ϕ_H falls with ω_H^*) and stimulates domestic innovation (ϕ_O rises with ω_O^*). The Import Learning Dominance condition (10) identifies when the first effect dominates. This condition is more likely to hold in sectors where frontier AI capabilities are hard to replicate domestically—for instance, advanced semiconductor fabrication, where U.S. and allied-nation firms control critical technology nodes. It is less likely to hold in AI software and applications, where Chinese firms have demonstrated substantial domestic capability (e.g., large language models, autonomous driving systems). This cross-sectoral heterogeneity generates a testable prediction: firms in hardware-intensive sectors should experience larger net innovation declines from geopolitical shocks.

The second part establishes that the innovation decline is larger for POEs under a curvature condition (11) that compares the concavity of ϕ_H and ϕ_O weighted by cost-sensitivity parameters. The economic intuition is as follows. POEs have lower ω_H^* and ω_O^* than SOEs (because higher borrowing costs reduce both shares). If import learning is concave ($\phi_H'' < 0$), POEs are on a steeper part of the learning curve and therefore lose more marginal innovation per unit of ω_H^* reduction. But if domestic innovation is also concave ($\phi_O'' < 0$), POEs also gain more marginal domestic innovation per unit of ω_O^* increase. The curvature condition requires that the first effect dominates the second. It holds trivially when ϕ_O is linear (so the domestic offset does not accelerate for POEs), and fails only when the domestic innovation function is "more concave" than the import learning function in a cost-weighted sense.

Remark 1 (Interpretation of the Curvature Condition). Condition (11) is stated in terms of exogenous parameters and the curvatures of the innovation functions ϕ_H, ϕ_O. It is evaluated at the relevant (τ, η_f) through κ; if the prediction is intended to hold over the full support, the condition should be imposed uniformly for all $\tau \in [0, \bar{\tau}]$ and $\eta_f \in [0, \bar{\eta}]$. The condition holds trivially when ϕ_O is linear ($\phi_O'' = 0$), since the right-hand side vanishes. When both functions

are linear ($\phi_H'' = \phi_O'' = 0$), $\Delta^{POE} = \Delta^{SOE}$ and the POE innovation decline is still strictly larger because $(1 + r^{POE}) > (1 + r^{SOE})$. The condition can fail only when ϕ_O is sufficiently more concave than ϕ_H—i.e., when the marginal domestic AI innovation gain accelerates faster for POEs than the marginal import learning loss. Equivalently, condition (11) is the primitive-parameter counterpart of the endogenous-variable condition $\Delta^{POE} \geq \Delta^{SOE}$:

$$\frac{\phi_H'(\omega_H^{*POE})\,(p_H - p_L)}{\delta} - \frac{\phi_O'(\omega_O^{*POE})\,p_L}{\zeta} \geq \frac{\phi_H'(\omega_H^{*SOE})\,(p_H - p_L)}{\delta} - \frac{\phi_O'(\omega_O^{*SOE})\,p_L}{\zeta}$$

Remark 2 (Domestic Innovation Substitution). Condition (10) is more likely to hold when: (i) ϕ_H' is large relative to ϕ_O' (frontier AI capabilities embedded in U.S. high-tech are highly productive and hard to replicate domestically); (ii) $p_H - p_L$ is large (high-tech cost premium is large, so a small reduction in ω_H^* has a large impact on learning); and (iii) p_L is small (U.S. low-tech is cheap, so the domestic substitution from ω_L to ω_O is modest). The condition can fail — i.e., domestic innovation substitution dominates — for firms with high initial ω_O^* (already domestic-oriented), in sectors where domestic AI capabilities are strong (software, applications), or for SOEs that benefit from state-sponsored domestic AI programs. This generates testable cross-sectional heterogeneity: we predict that *firms with larger domestic AI capability respond to geopolitical shocks with smaller total innovation declines*, potentially offset by domestic AI patent growth.

Remark 3 (Collateral Constraint Amplification). When the collateral constraint binds, the firm faces a shadow cost of funds $\lambda > 0$ in addition to r^j. The FOCs become $\theta - \delta\omega_H = (1 + r^j + \lambda)\kappa(p_H - p_L)$ and $\mu - \zeta\omega_O = (1 + r^j + \lambda)(p_O - \kappa p_L)$, so λ further reduces both ω_H^* and ω_O^* below their unconstrained optima.

Suppose $\chi^{SOE} = \chi^{POE} \equiv \chi$, $\eta_f = 1$, and $\kappa(\tau) = 1 + \tau$. The unconstrained borrowing per unit of capital is $B_f^{*j}/K_f = \kappa(p_H - p_L)\omega_H^* + (p_O - \kappa p_L)\omega_O^* + \kappa p_L - \chi$, with derivative

$$\frac{\partial B_f^{*j}/K_f}{\partial r^j} = -\frac{\kappa^2(p_H - p_L)^2}{\delta} - \frac{(p_O - \kappa p_L)^2}{\zeta} < 0$$

Since POEs face higher r^j, they borrow less at any given τ, but their tighter collateral limit $\varphi^{POE} < \varphi^{SOE}$ can nonetheless cause the constraint to bind at a lower τ. Specifically, the POE constraint binds first ($\tau_{bind}^{POE} < \tau_{bind}^{SOE}$) if:

$$(\varphi^{SOE} - \varphi^{POE}) > (r^{POE} - r^{SOE}) \left[\frac{\kappa(\tau_{bind}^{POE})^2\,(p_H - p_L)^2}{\delta} + \frac{(p_O - \kappa(\tau_{bind}^{POE})\,p_L)^2}{\zeta}\right]$$

i.e., the collateral gap exceeds the borrowing gap implied by differential rates. Once the constraint binds, the shadow cost of funds further depresses the use of financing-intensive inputs. It unambiguously amplifies the decline in ω_H; its effect on ω_O depends on whether the financing-cost effect dominates the relative-price substitution toward domestic inputs.

Figure 1 illustrates Propositions 1–3: panel (a) plots U.S. high-tech import shares; panel (b) plots U.S. low-tech import shares. Both margins decline with τ, and the decline is steeper for POEs (Proposition 2). Figure 2 shows the total AI innovation comparison across ownership types. Figure 3 summarizes the full causal chain.

2.4 Aggregate Dividends and Consumption

Aggregate period-1 consumption is:

$$C_1(\tau) = \alpha\, D_1^{SOE}(\tau) + (1-\alpha)\, D_1^{POE}(\tau)$$

where aggregate dividends for ownership type j integrate over the cross-sectional distribution F_j of firms:

$$D_1^j(\tau) = \int \left[A(\omega_H^{*j}, \omega_O^{*j}) - (1+r^j)\, p(\omega_H^{*j}, \omega_O^{*j}, \tau, \eta_f)\right] K_f\, dF_j(f) + (1+r^j) \int C_f^j\, dF_j(f)$$

Because C_f^j is predetermined and non-stochastic, the term $(1+r^j)\int C_f^j\, dF_j(f)$ affects dividend levels but not the firm's exposure to τ; all comparative statics with respect to τ operate exclusively through $\omega_H^{*j}(\tau, \eta_f)$ and $\omega_O^{*j}(\tau, \eta_f)$. Furthermore, because $(1+r^j)B_f$ is interpreted as a reduced-form shadow cost of external finance rather than a pure intra-household transfer (as established in Section 2.2.4), debt repayments do not offset the reduction in firm dividends in the household's budget constraint; the decline in D_1^j maps directly to a decline in aggregate consumption C_1.

Since both ω_H^{*j} and ω_O^{*j} are chosen optimally, we apply the envelope theorem firm-by-firm. Using the cost function (4), the direct effect of τ on firm f's dividend (holding ω_H^{*j} and ω_O^{*j} fixed) is:

$$\left.\frac{\partial D_{1f}^j}{\partial \tau}\right|_{\omega^* \text{fixed}} = -(1+r^j)\eta_f \left[(p_H - p_L)\omega_H^{*j} + p_L(1-\omega_O^{*j})\right] K_f < 0$$

and the indirect effects through optimal adjustment are zero. Integrating:

$$\frac{\partial D_1^j}{\partial \tau} = -\int (1+r^j)\, \eta_f \left[(p_H - p_L)\omega_H^{*j} + p_L(1-\omega_O^{*j})\right] K_f\, dF_j(f) < 0$$

and therefore:

$$\frac{\partial C_1}{\partial \tau} < 0$$

Aggregate consumption is unambiguously decreasing in geopolitical risk.

2.5 Marginal Utility and the SDF

Since the SDF is $M = \beta(C_1/C_0)^{-\gamma}$ and C_1 is decreasing in τ, the SDF is increasing in τ:

$$\frac{\partial M}{\partial \tau} = -\gamma\,\beta \left(\frac{C_1}{C_0}\right)^{-\gamma-1} \cdot \frac{1}{C_0} \cdot \frac{\partial C_1}{\partial \tau} > 0$$

since $\partial C_1/\partial \tau < 0$. High geopolitical risk states are high marginal utility states—"bad times" in which the household values payoffs more. Note that this property is derived endogenously from the household's CRRA preferences and the firms' optimal responses, not assumed.

Importantly, the SDF determines the pricing of risk in financial markets through equation (3), while borrowing rates $r^j = \bar{r} + \xi^j$ are determined by the banking sector and government policy as described in Section 2.2.4. These are distinct markets: the risk-free rate r_f from the Euler equation (1) is the return on financial assets held by investors, whereas r^j is the cost of bank credit faced by firms. In China's financial system, where lending rates are administered and state-owned banks dominate credit allocation, there is no arbitrage condition linking r_f to r^j. This separation ensures that changes in the SDF and r_f do not feed back into firms' import decisions, avoiding a general equilibrium loop.

2.6 Geopolitical Risk Premium

Equity claims to individual firms are priced at $t = 0$ before τ is realized. For firm f of type j, the *ex ante* equity price is:

$$P^j_{0f} = \mathbb{E}[M \cdot D^j_{1f}(\tau, \eta_f)]$$

and the gross equity return, realized at $t = 1$ after τ is observed, is:

$$R^j_f(\tau) = \frac{D^j_{1f}(\tau, \eta_f)}{P^j_{0f}}$$

The expected excess return on each firm's equity satisfies equation (3):

$$\mathbb{E}[R^j_f] - (1 + r_f) = -\frac{\mathrm{Cov}(R^j_f, M)}{\mathbb{E}[M]}$$

The aggregate type-j equity price $P_0^j = \mathbb{E}[M \cdot D_1^j(\tau)]$ is the integral of firm-level prices over F_j. Since M is increasing in τ and firm-level dividends D_{1f}^j are decreasing in τ for $\eta_f > 0$, firm returns covary negatively with M. Both types of firms are therefore exposed to geopolitical risk, but the exposure differs across ownership types.

Proposition 5 (Local Geopolitical Risk Premium)**.** *Consider a POE firm f and an SOE firm f' with the same capital ($K_f = K_{f'} = K$), the same firm-level exposure ($\eta_f = \eta_{f'} = \eta > 0$), and comparable dividend levels at the benchmark $\bar{\tau}$ ($\bar{D}_{1f}^{POE} \approx \bar{D}_{1f'}^{SOE}$, so that $P_{0f}^{POE} \approx P_{0f'}^{SOE}$ at first order). Define $\bar{\kappa} \equiv \kappa(\bar{\tau}, \eta)$ and let:*

$$\mathcal{A} \equiv \frac{\theta(p_H - p_L)}{\delta} + \frac{p_L(\zeta - \mu)}{\zeta}, \qquad \mathcal{B} \equiv \frac{p_L(p_O - \bar{\kappa}\, p_L)}{\zeta} - \frac{\bar{\kappa}(p_H - p_L)^2}{\delta}$$

If the following parameter condition holds:

$$\mathcal{A} + (2 + r^{SOE} + r^{POE})\, \mathcal{B} \;>\; 0 \tag{12}$$

then, to first order around $\bar{\tau}$, the POE firm's equity has a larger negative covariance with the SDF than the SOE firm's equity, and therefore commands a larger local geopolitical risk premium:

$$\big[\mathbb{E}[R_f^{POE}] - (1 + r_f)\big] - \big[\mathbb{E}[R_{f'}^{SOE}] - (1 + r_f)\big] > 0$$

and this return differential is locally increasing in $\mathrm{Var}(\tau)$*. If POEs also have higher average firm-level exposure $\bar{\eta}^{POE} > \bar{\eta}^{SOE}$ across the population, the premium gap is further amplified beyond the financing channel alone.*

Proof. See Appendix B.5. □

Proposition 5 connects the real-side input composition results to asset pricing. The logic proceeds in two steps. First, since geopolitical risk reduces aggregate consumption (through input cost increases and the resulting decline in firm dividends), high-τ states are high-marginal-utility states. Firms with greater dividend sensitivity to τ—those with larger U.S. input exposure—therefore have returns that covary more negatively with the SDF, commanding a larger risk premium.

Second, the ownership comparison is governed by condition (12), which is expressed entirely in primitive parameters through $\mathcal{A}$ and $\mathcal{B}$. The term $\mathcal{A}$ captures the *direct amplification*: higher $(1 + r^j)$ mechanically scales up a firm's dividend sensitivity to τ, favoring a larger POE premium. The term $\mathcal{B}$ captures the *indirect offset*: higher borrowing costs also reduce the firm's optimal use of U.S. inputs, which lowers the base exposure that gets amplified. When $\mathcal{B} < 0$—which occurs when high-tech cost sensitivity dominates the

domestic cost offset—these two forces partially counteract each other. Condition (12) requires that the direct amplification is strong enough to dominate. Notably, the factorization $S^{POE} - S^{SOE} = (r^{POE} - r^{SOE})[\mathcal{A} + (2 + r^{SOE} + r^{POE})\mathcal{B}]$ is *exact*, not a local approximation, so the condition can be verified for any parameter calibration.

Remark 4 (Interpretation of the Dividend-Sensitivity Condition). Condition (12) is stated entirely in primitive parameters (evaluated at $\bar{\kappa} = \kappa(\bar{\tau}, \eta)$). The term $\mathcal{A}$ captures the baseline exposure of the input bundle to geopolitical risk; it is positive when the high-tech exposure term dominates the domestic adjustment term. The term $\mathcal{B}$ captures the net effect of borrowing costs on the input bundle's geopolitical exposure: higher r^j reduces both ω_H^* (lowering high-tech exposure) and ω_O^* (raising low-tech exposure through $1-\omega_O^*$). Condition (12) holds when the direct amplification through $(1 + r^j)$ is not fully offset by the indirect reduction in U.S. input use. Equivalently, condition (12) is the primitive-parameter counterpart of the endogenous-variable condition that the POE firm has strictly larger dividend sensitivity:

$$(1 + r^{POE})\big[(p_H - p_L)\omega_H^{*POE}(\bar{\tau}) + p_L(1 - \omega_O^{*POE}(\bar{\tau}))\big] \\ > \ (1 + r^{SOE})\big[(p_H - p_L)\omega_H^{*SOE}(\bar{\tau}) + p_L(1 - \omega_O^{*SOE}(\bar{\tau}))\big]$$

Proposition 5 should be interpreted as a local sufficient-condition result: firms with larger dividend exposure to geopolitical shocks command larger expected returns. The ownership comparison requires condition (12) rather than following mechanically from $r^{POE} > r^{SOE}$, because higher borrowing costs simultaneously reduce the level of U.S. input use, which partially offsets the amplification through $(1 + r^j)$.

3 Measure of Geopolitical Risk and Import

To identify firm-level exposure to geopolitical risk, we employ an LLM-based measurement approach with prompt engineering. Our methodology relies on a single-step, zero-shot prompting strategy, benchmarked against key terms drawn from the academic literature and Chinese government documents. Because all of the assignments are in Chinese, we adopt DeepSeek-v4-flash, an LLM trained on Chinese-language data, to identify the relevant content.

3.1 Geopolitical Risk Exposure

We first measure geopolitical risk exposure across all Chinese publicly listed firms. Our benchmark follows Clayton et al. (2025), who account for a hegemonic economy in the sense

of Clayton et al. (2026). In contrast to Caldara and Iacoviello (2022), who study global geopolitical conflict more broadly, we define geopolitical pressure as the intensifying global conflict between the United States and China. We focus on the enforcement tools through which the United States exercises its global power over China, namely the trade war (tariffs), export controls, and financial sanctions.

Specifically, as shown in Appendix C.1, our geopolitical risk measure follows the spirit of Baker et al. (2016) by capturing the key concepts of tariffs, sanctions, export controls, and geoeconomic pressure in MD&A texts. To ensure that the content reflects uncertainty or risk, the prompt is designed to capture the measure conditional on the contextual presence of risk or uncertainty. The rationale is to ensure that the measure accurately estimates geopolitical uncertainty across listed firms, rather than other forms of uncertainty, in the manner of Baker et al. (2016). Moreover, to ensure that the identified risks are not driven by alternative forces such as rare disasters or business cycles, we emphasize the ex-ante nature of the risk concept within each context. We ultimately generate binary indicators of geopolitical risk along four dimensions: tariffs, financial sanctions, export controls, and integrated geopolitical pressure.

Figure 4 plots the aggregate trend in tariff pressure over time. Firm-level tariff risk exposure begins at relatively low levels in 2010. It then intensifies in the form of trade conflict during the first Trump administration, beginning in early 2018.[1] Following the transition to the Biden administration, trade pressure eases somewhat, before rising again toward the end of that administration. We also report granular geopolitical risk exposure across topics and display the integrated measure. Figure 12 in the Appendix presents the aggregate time-varying trends for the alternative dimensions of geoeconomic pressure. Consistently, Panel B (sanctions) and Panel C (export controls) show upward trending gradually。 However, the magnitude of the integrated geoeconomic pressure measure in Panel D indicates that tariff risk accounts for most of the overall variation and magnitude. These results reveal that, over recent years, tariff pressure has been the dominant force shifting geoeconomic political risk in China.

3.2 HighTech/AI Import

We construct measures of firm import behavior in response to the geoeconomic pressure arising from the US trade war. The underlying economic framework follows Bai et al. (2025) and Buera and Oberfield (2020b), in which firms learn from sellers through importing and can attain a long-run endogenous growth path. To identify how firms respond strategically when

[1] US-China first trade war.

importing innovative goods, we propose two ways to quantify innovative imported products. First, we focus on the innovative imports most emphasized by the Chinese government, including semiconductors, aerospace systems, biomedical equipment, and industrial robots. Such innovative imports have consistently played a leading role in confronting and alleviating US geopolitical pressure. Second, given the rising tension of the AI race during the trade-policy period, we follow Waugh (2026) on geoeconomic conflict and examine AI-related imports. AI-related imports are particularly important in light of the fact that AI adoption facilitates product diversification and raises corporate revenues, as documented in Babina et al. (2024).

As shown in Appendix C.2, we use prompt commands to identify the import classification. Our measure is based on the HS code of each product, together with its product description, and assesses whether the product is related to cutting-edge scientific goods. In particular, when interpreting the product description, we guard against the possibility that a product is misclassified as innovative owing to textual complexity. We scale the high-tech intensity scores between 0 and 1, and classify a product as a high-tech import only if its LLM-assigned score is at or above 0.85 (the maximum score cluster). Our AI-import classification follows Waugh (2026). With reference to the "Key Digital Technology Patent Classification System (2023)" published by the China National Intellectual Property Administration, we focus on the key AI-related technologies prioritized by the Chinese government. For example, we examine imported products such as GPUs, chips, deep-learning hardware, and computer vision. Our final measure retains those products the LLM classifies as high-AI relevance. The prompts are detailed in Appendix C.3. Throughout, the procedure combines information from the HS code and the product description.

Table 1 provides illustrative examples of identified high-tech imported products. For instance, our high-tech imports include semiconductors under HS code 848610, semiconductors with electronic materials under HS code 381800, and data storage in the form of solid-state disks. Table 2 presents examples of our AI-related imports. Following the Chinese government's definitions, our AI-related imports concentrate on sensitive technologies, including robots (HS code 847950), electronic circuits (HS code 854231), and miscellaneous chemical products used in disks or chips (HS code 381800).

To assess internal validity, we first design an algorithm that retrieves the rationale for why each imported product is classified as high-tech or AI-related. We then summarize the key tokens of its product description, as displayed in the word clouds. Figure 5 reports the core terms in the HS descriptions of product characteristics after tracing the underlying technology, and shows how the key terms in high-tech import HS descriptions evolve over time. These concepts cluster around state disks, hard disks, computer hardware, and X-ray

equipment. By contrast, the low-tech imported products range from cotton and operating rings to cable operations, which are predominantly manufacturing-related goods. As for AI-related imports in Figure 6, these concentrate on the intense competition in circuits, chips, state disks, and hard disks from 2011 to 2018. These comparisons and stable trends underscore the validity of our proposed measures in capturing high-tech and AI-related imports. They further point to a persistent pattern of geoeconomic pressure, operating through US-China trade tension, in the market for innovative products.

4 Data

4.1 Data Sample

Our full sample integrates multiple data sources. We manually merge data on Chinese imports (Panjiva), corporate fundamentals (CSMAR), stock returns (CSMAR), and Chinese patents (CNRDS). The full sample period, including the cost of capital, spans 2010 to 2025. For the main shock used in our quasi-experimental design, we focus on the 2018 event surrounding the first Trump tariff increase against China, as shown in Figure 4: Trump initiated a series of tariff measures beginning on May 22, 2018, which were gradually resolved by the end of 2020. Cross-sectionally, our sample includes approximately 6,400 firms. After merging with the import data, the matched sample comprises approximately 2,500 firms. Among these, SOEs (state-owned enterprises) account for about one third of the sample, while POEs make up about two thirds.

To capture firm-level geopolitical pressure, we follow the strategy of Clayton et al. (2025) in tracking enterprises, but rely on firm-level disclosures to recover their geopolitical information. The data come from the mandatory public disclosures required by the Chinese exchanges, which are structured similarly to US 10-K filings on EDGAR. Specifically, our analysis focuses on the MD&A sections of listed firms' annual reports. The MD&A (Management's Discussion and Analysis) is a section whose disclosure is mandated by the China Securities Regulatory Commission. As in Buehlmaier and Whited (2018), who exploit the MD&A to capture firm financial constraints, we extract the processed texts from the MD&A of annual reports from 2010 to 2024 and focus on information relevant to geopolitical risk for corporate management. Our definition of geopolitical risk centers on the concepts of tariffs, financial sanctions, and US export controls directed at China.

To highlight the adverse effect of geopolitical risk on cross-border learning (Chang et al., 2023), we draw on the international trade literature on global knowledge diffusion through "learning from sellers" (Bai et al., 2025; Buera and Oberfield, 2020a) and identify the learning

effect using import data from Chinese customs. Specifically, we employ the Panjiva database from S&P, which provides detailed records of imported products sourced from the Chinese customs agency. Each imported product is carefully classified by its 6-digit HS code, and the database also provides a product description documenting its function. Owing to the limited disclosure of imported-product information by Chinese customs, our sample period for imports spans 2011 to 2018. For each imported product, we measure its high-tech (low-tech) intensity and its AI relatedness.

Table 1 presents illustrative examples of imported products of Chinese firms in Panjiva, classified on the basis of their descriptions. For instance, the product with HS code 848610 is identified as high-tech, as it is an automatic temperature control device and constitutes an essential component of semiconductors. Table 2, by contrast, presents examples of AI-related imported products in China. Our examples of AI-related products include, for instance, the AI-technology product with HS code 847950. The rationale for this classification is its close connection to industrial robotics and automation. Following the general definition of AI in Acemoglu et al. (2022), it is regarded as an essential component of automation.

To emphasize the importance of geopolitics for real options, we examine firm innovation performance using patent data from CNRDS, which primarily originate from the China National Intellectual Property Administration (CNIPA). The platform also integrates corporate registration records, annual reports of listed firms, national industry classification standards, and data from the World Intellectual Property Organization (WIPO). Specifically, we follow the Chinese government's definitions of AI innovation (high-tech innovative production) and measure firm real options based on these definitions, focusing on the variables $HighTech_Patent^{3\text{ year}}$, $HighTech_Patent^{5\text{ year}}$, $AI_Patent^{3\text{ year}}$, and $AI_Patent^{5\text{ year}}$. Our emphasis on AI patents follows the Key Digital Technology Patent Classification System (2023), formulated and issued by the China National Intellectual Property Administration (CNIPA) on September 18, 2023 (Document No. CNIPA Office Letter Gui Zi [2023] No. 36), in which the CNIPA officially defines AI as comprising 3 Level-1 branches, 14 Level-2 branches, and 27 Level-3 branches.[2] Our procedure is consistent with Fang et al. (2026), in which AI innovation rises gradually and then declines in recent years owing to heightened geopolitical tension.

We examine the financial market performance of Chinese firms in response to geopolitical risk. Specifically, we carefully match listed firms' corporate balance sheets and stock returns with the Panjiva, CNIPA, and MD&A databases. To connect firm-level financial performance with geopolitics, we exploit corporate balance sheet data and monthly stock return information. Rather than focusing only on a short window around the first Trump

[2] https://www.cnipa.gov.cn/art/2023/9/25/art_75_187769.html

administration (three years before and three years after), we also examine the long-term effect on the cost of capital from 2015 to 2024. With respect to corporate fundamentals, we include standard balance sheet variables in our regressions to control for potential confounding factors. These include market valuation as a proxy for firm size ($Size_{i,t}$), profitability ($ROA_{i,t}$), financial leverage ($Leverage_{i,t}$), defined as outstanding debt divided by total assets, marginal capitalization ($TobinQ_{i,t}$), liquidity relative to total assets ($Cash_Ratio_{i,t}$), and inventory holdings ($Inventory_Ratio_{i,t}$).

Finally, to test the real effect of AI adoption on productivity, we draw on a set of standard external variables to supplement our analysis. We link the trademark database, $Trademarks_{i,t}$ (in logs), in China from CNRDS, which sources the data from the CNIPA. To strengthen the robustness of our product-diversification evidence, we complement the analysis with product patents, $ProductPatent_{i,t}$ (in logs), also from the CNIPA.

4.2 Summary of Statistics

Our full sample exhibits cross-sectional variation around 2018 that allows us to identify the impact of geoeconomic pressure on firms' import decisions, as reported in Table 3. $GPR_{i,t}$ denotes our main measure of firm-level geopolitical risk exposure. As documented in the previous section, our GPR measure is driven primarily by cross-sectional tariff exposure. On average, exposure to geopolitical risk in the full sample is 0.124, with higher GPR for POEs (privately owned enterprises) at 0.125, relative to 0.118 for SOEs (state-owned enterprises), implying that POEs bear greater geopolitical risk exposure than SOEs. Figure 7 displays the most tariff-sensitive industries cross-sectionally, including textiles, rubber & plastics, ferrous metal smelting, automotive, and computer, communication & electronics. The overall pattern of these top industries coincides with the first and second waves of Trump-era geoeconomic friction over trade policy.

We also examine firms' import decisions over high-tech and low-tech products. On average, the full sample shows about 0.062, with SOEs at 0.057 and POEs at 0.071 in high-tech imports. For low-tech imports, there is no significant difference between SOEs and POEs on average. For AI-related imports, POEs consistently exhibit relatively higher AI-related import growth, at -0.007 on average, whereas SOEs exhibit relatively lower growth. By contrast, SOEs' low-AI-related imports are considerably higher, at 0 import growth, than those of POEs at -0.003 on average, indicating that, with respect to import technology, POEs in general concentrate more on high innovation than SOEs.

We also document both the time-varying patterns of innovative imports and the cross-sectional differences in granular import decisions. From the time-series perspective, Figure 8

confirms time variation in firm-level averages at the aggregate level, with high-tech imports declining sharply after 2013. In contrast, low-tech imports increase gradually after 2013. As for total imports, aggregate total imports rise gradually for both high-tech and low-tech imports; only in 2018, following the first Trump administration, do total imports for both high-tech and low-tech products begin to decline. We document similar time-series patterns for AI-related imports in Figure 9, with both high-AI and low-AI aggregate imports rising before the first Trump trade war. From the firm-level average perspective, however, AI-related imports drop sharply after 2013, and the corresponding low-AI imports also decline after 2013. Overall, our summary statistics confirm the stringency of the first Trump administration's trade stance toward China. They further display the relative decline in high-tech and AI imports for Chinese firms, particularly in recent years.

From the cross-sectional perspective, we also highlight our high-tech and AI import rankings across industries. The goal of this visualization is to disentangle the potential rationale for our proposed measure of innovative import decisions. Figure 10 documents the top industries with persistently high-tech import decisions historically. It plots the annual industry-level proportion of high-tech imports for the top ten industries. Overall, we observe a downward trend across all of the top 10 industries, although some of these downward trends are not statistically significant. Among the top industries, software and IT services exhibit the most striking pattern in recent years. Pharmaceutical manufacturing also occupies a prominent position in the cross-sectional comparison over time. We then compare the trends in AI-related imports from the US. Even more strikingly, AI-related imports for the software and IT services industry decline even faster than high-tech products. The next is pharmaceutical manufacturing, followed by electrical machinery and equipment, as shown in Figure 11.

5 Main Findings

Our identification relies on a quasi-experiment that applies a difference-in-differences design to the first Trump tariff increase beginning in January 2018, under the assumption that the tariff measures are not driven by economic forces. The first Trump administration initiated the trade war against China by raising tariffs on solar panels and washing machines. Subsequently, beginning on April 1, China raised tariff rates on pork products and aluminum scrap by 25 percent. Beijing also imposed a 15 percent tariff on 120 other US commodities, ranging from almonds to apples. These repeated trade tensions intensified the geopolitical pressure between the two countries.

Our first strategy for capturing these US-China trade tensions at the firm level is to

use China's tariff measures as a proxy for the global geopolitical risk facing the Chinese market. More specifically, we focus on the days of China's tariff announcements during 2018, following its first response to the US trade-war announcements, as the key event shocks for identifying the effects of the trade war. This strategy applies to a balanced set of financial fundamentals and innovation patents. Firms with greater exposure are defined as the treated group, while the control group comprises firms facing less geoeconomic pressure. A key underlying assumption is that the political shocks are not endogenous to alternative economic forces.

As one of the most important channels operating through internal import decisions, and owing to the limited coverage of Panjiva after March 2018, we adopt a continuous difference-in-differences design to recover the causal effect. To measure geopolitical risk prior to 2018, we construct a granular firm-level index, combining the text-based approach of Caldara and Iacoviello (2022) with the definition of geopolitical risk in Clayton et al. (2025), and aggregate it cross-sectionally over time as a proxy for market-level shocks to US-China geopolitical tension. Similar ideas have been adopted by Baker et al. (2016) in the context of economic policy uncertainty shocks:

$$Y_{i,t} = \beta_0 GPR_i \times Shocks_t + \beta_1 GPR_{i,t} + Control_{i,t-1} + \epsilon_{i,t}$$

where $Y_{i,t}$ denotes the outcomes for granular import decisions and $Shocks_t$ denotes the aggregate time series of US geopolitical pressure against China. To rule out general firm-level confounding factors, we control for firms' market valuation, firm age, profitability, financial leverage, Tobin's Q, corporate liquidity, and inventory for every observation.

5.1 Firm-Level High-Tech/AI Import

In our economy, the theoretical framework establishes that, when facing geopolitical risk in the form of tariff risk, POEs bear more asymmetric political risk exposure due to asymmetric financial frictions, as stated in Proposition 2 of our framework. The asymmetric financial cost operates as a financial friction at the intensive margin, making it more difficult for POEs to import high-tech facilities at large economic cost. This conceptual framework differs from Belo et al. (2026), in which POEs continuously face financial constraints at the extensive margin and are therefore reluctant to earn premiums in the stock market.

Table 4 reports our main results for high-tech imports. Taking 2018 as the onset of US-China geopolitical risk in the form of the trade war, we find that firms with greater geopolitical exposure undertake lower high-tech import decisions. The economic magnitude is sizable for both POEs and SOEs, in columns (1) and (2), respectively. For a one-standard-deviation

change in geopolitical exposure, POE (SOE) high-tech imports decline by 0.0301 (0.027), respectively. Both estimates are strongly statistically significant, implying that POEs contract relatively more in their high-tech import decisions when confronting geopolitical risk. In the face of geopolitical risk, both POEs and SOEs also reduce their low-tech imports correspondingly. The economic magnitudes are both significant and indistinguishable between SOEs and POEs, at 0.102 and 0.10, respectively.

For AI-related import decisions, as reported in Table 5, greater geopolitical tension implies that POEs reduce their high-AI-related imports significantly more than SOEs. For a one-standard-deviation change in cross-sectional geopolitical exposure, POEs' high-AI-related imports decline significantly more than those of SOEs. The relative economic magnitude for POEs (SOEs) in column (1) ((2)) is approximately 6.34% (2.54%), implying that POEs contract more in their high-AI-related import decisions. As for low-AI-related imports, SOEs in column (4) reduce them by a statistically significantly larger amount than POEs in column (3), at 5.6% versus 3.5%.

Overall, our empirical evidence supports the theoretical framework for import decisions across distinct ownership types. Consistent with Belo et al. (2026), differences in state ownership give rise to asymmetric financial frictions at the intensive margin: POEs are more reluctant than SOEs to import high-AI/tech technologies, even though both sectors reduce their AI/high-tech import decisions consistently. In contrast to recent work such as Ayyagari et al. (2026), which finds that financially constrained firms are more likely to take on risk in automation imports that serve as pledgeable collateral for external finance, our evidence shows that, when facing geopolitical risk through tariffs, POEs are more likely to be conservative in their innovative imports, owing to monetary tightening on POEs.

5.2 Economic Channel: Innovation

Given the asymmetric performance of innovative imports across POEs and SOEs, our next question concerns the underlying force that drives the heterogeneity in import decisions. In our hypothesized economy, we consider a setting analogous to the international trade frameworks of Bai et al. (2025) and Buera and Oberfield (2020a), in which firms accumulate real options by learning from the seller. As shown in Proposition 4, firms that import more technical products accumulate relatively better long-run innovative growth than others. In general, comparing POEs with SOEs, the higher financial frictions on high-tech/AI imports lead POEs to attain lower levels of AI/high-tech innovation. This conjectured economy is important because, in its absence, high-quality goods might never appear in the market, as in Akerlof (1978).

Table 6 and Table 7 confirm our conjecture that firms facing greater geopolitical friction experience harm to their long-run growth options. Given the financial frictions between POEs and SOEs in China, this indeed contributes to lower innovation adoption for POEs than for SOEs on average. We first evaluate the real growth option by examining firms' high-tech innovation. Table 6 shows that, three years after the geopolitical events, our geopolitical-risk-exposed treated group reduces high-tech patents by 0.1707 more than the control group on average. This estimate is approximately 22% of the full-sample historical average of 3-year high-tech innovation. POEs experience a smaller decline in high-tech innovation than SOEs over the first three years, but this effect is statistically insignificant. When we consider 5-year cumulative high-tech results, the aggregate decline remains significant and accounts for a large proportion of the historical average (19.6% in column (4)). The decline is concentrated significantly in POEs' high-tech innovation, at more than 23.6%. By contrast, SOEs show a decrease of only 20% relative to the historical high-tech adoption average over five years.

Next, in Table 7, we track Chinese-government-labeled AI-related patents cumulatively from one year to three years. For the full sample of both SOEs and POEs, one-year cumulative AI innovation is significantly reduced by 0.0953 following the geopolitical tariff conflict. This economic magnitude corresponds to a 23% reduction relative to the historical average level of AI_Patent. Although the estimates for POEs and SOEs are not statistically significant, both sectors reduce their AI innovation accordingly, and POEs reduce theirs more than SOEs, by 0.1134, accounting for about 33% of the POE historical average. SOEs, by contrast, exhibit less pronounced responses. This effect is even larger once we account for AI adoption over the subsequent three years. The full-sample 3-year-ahead AI patent count falls by 0.1737, accounting for 20% of the historical average for 3-year cumulative AI adoption. For POEs, the treated group reduces AI_Patent by 0.237, equivalent to 28.2% of the POE historical 3-year AI innovation average. For SOEs, in column (6), however, this effect is less significant and smaller in economic magnitude.

Overall, combining our findings on import decisions above, we conclude that, with fewer high-tech or AI-related imports due to US geopolitical pressure, firms with higher GPR indeed reduce their long-run growth options through innovation. Conceptually, as documented in Proposition 1, even though firms have the option to improve innovation through domestic consumption, the overall effect of geopolitical risk on corporate innovation remains negative. The reduction in high-tech innovation is concentrated mainly in POEs, owing to the higher asymmetric financial frictions facing POEs relative to SOEs in China. More strikingly, the contraction in AI-related innovation is both larger in magnitude and more statistically significant for POEs than for SOEs.

5.3 Economic Channel: Product Diversification

Taking the evidence from the innovation market together, firms under geopolitical pressure tend to cut their high-tech innovation, particularly AI-related innovation. The next question is whether this reduction in AI-related innovation indeed contributes to firm underperformance, and how it maps into market fundamentals. In our theoretical framework, firms incorporate knowledge-intensive imports to realize valuable long-run growth through product diversification. This argument is consistent with Babina et al. (2024), who document the positive role of AI adoption in reshaping firms' product offerings and enhancing the market power of exposed firms. In contrast to this product-innovation channel, in which innovative imports improve firms' market behavior, a competing explanation is that AI-related product learning may instead improve the automation process and lower operating costs, as argued by Ayyagari et al. (2026). If so, we would expect firms with greater exposure to geopolitical tension to bear higher operating expenses.

Table 8 confirms our results on product diversification. We collect market information tracking firm innovation in the Chinese product market, following Babina et al. (2024). Our first regression tests whether geopolitically exposed firms reduce their product innovation as measured by trademark applications. Columns (1)–(3) of Table 8 show that, for the full sample, firms exposed to geopolitical risk forgo 0.206 trademarks, economically equivalent to 12% of the total. Across ownership types, POEs bear a statistically significant loss relative to SOEs, with 0.338 fewer trademarks, accounting for about 19.8% of the historical average, whereas SOEs show a positive and statistically insignificant effect. As a robustness complement, we also examine product patents as a measure of output diversification. The results are consistent with those for trademarks: firms with greater GPR exposure experience lower product-patent output. The corresponding economic magnitude in column (4) for the full sample is 0.136, accounting for about 6.1% of the historical average of patent innovation. For private enterprises, this decline increases to 0.205 for the treated group following the shocks, accounting for about 9% of the historical average of product innovation. SOEs exhibit a consistent pattern, with a mild decrease in new product creation, but this effect is not statistically significant. In sum, our findings provide consistent evidence that firms facing geopolitical risk cut their AI-related and innovative imports, which in turn adversely affects their product performance.

6 Financial Market Reaction

Firms with greater exposure to GPR experience diminished growth options, owing to reduced innovative learning through their import decisions. Given this empirical finding, we next examine whether the financial market reflects these implications. Our framework comprises two parts, corresponding to the cash-flow channel and the discount-rate channel.

First, under greater geopolitical pressure on firm operations and with fewer real options for growth, we expect firms to experience tighter cash flows and weaker fundamentals. Consistent with Babina et al. (2024), as geopolitical risk impairs the growth options of firms with less product diversification, it inevitably depresses corporate cash flows and sales. These effects materialize contemporaneously with the geopolitical conflict between the United States and China, contributing to lower market valuations for exposed firms. Alternatively, innovation may be disconnected from real economic impact, as Haddad et al. (2022) show, particularly during bubbles. We seek to disentangle the one from the other within this economy. The underlying framework is clearly reflected in the dividend response to geopolitical shocks.

Beyond the cash-flow channel through which geopolitical risk affects the real economy, geoeconomic forces may also operate through the discount-rate channel. As aggregate geopolitical risk, in the form of trade-tariff risk, materializes, aggregate consumption falls and the stochastic discount factor rises, implying a risk compensation for holding risky assets. Consequently, at the aggregate level, the price of risk for portfolios in the POE sector tends to be negative, with higher marginal utility, and the cost of capital for firms exposed to persistent geopolitical risk tends to be higher than that of other firms. This implication follows from our Proposition 5, which predicts a higher cost of capital for firms exposed to geopolitical risk. From the perspective of debt investors, the perceived risk is also accompanied by greater financial frictions in debt financing at the extensive margin.

6.1 Event Studies

We first complement our hypothesis on the negative effect of geopolitical risk on cash flows with event studies centered on geopolitical conflict in the form of tariffs. We select the shock events initiated by the Chinese government in response to US tariff threats, and analyze how the market reacts instantaneously to these shocks. Within our framework, firms with greater exposure to geopolitical risk experience negative cash-flow shocks due to the loss of real options for import learning. In contrast to Haddad et al. (2022), in which innovation is disconnected from fundamentals, product patents and diversification generate market share and higher fundamental profitability. Investors perceive these signals and

reduce their holdings of risky assets accordingly.

Table 9 and Table 10 report the financial market results. Table 9 considers China's tariff-increase events only and estimates the market reaction within 3-day and 5-day windows. Panel A presents the results at the portfolio level across portfolio combinations. For the 3-day window, we compute cumulative abnormal returns (CAR) from the market model and form equally weighted portfolios sorted from high to low GPR exposure. Relative to the equally weighted low-GPR portfolio, the high-exposure portfolio realizes 0.539% lower cumulative abnormal returns within the 3-day window for the full sample. Conditional on POEs (SOEs), high-GPR-exposure portfolios realize 0.838% (0.374%) lower returns than low-exposure portfolios. For the one-week window, the realized portfolio returns are larger, at 1.725% on average for the full sample. For POEs (SOEs), the long-short return spread between high- and low-exposure portfolios is 2.11% (1.13%). The portfolio-level evidence confirms sizable abnormal market returns to geopolitical risk under these long-short strategies.

To further strengthen the robustness of the GPR premium and rule out confounding factors, we include controls similar to those in Table 4 and run cross-sectional regressions of the GPR effect in Panel B of Table 9. Whether or not controls are included, the GPR premium over the 3-day (one-week) window ranges from 0.16% (0.46%) to 0.18% (0.57%) per one-standard-deviation change in GPR, as reported in columns (1) and (4). Regarding differences by state ownership, our security-level cross-sectional regressions confirm that the GPR premium is concentrated in POEs, ranging from 0.26% to 0.28% (0.636% to 0.7%) over the 3-day (5-day) window. To further strengthen the robustness of our findings across broad geopolitical events, we also conduct robustness tests over a series of US-China tariff conflicts during 2018 and stack all cross-sectional regressions. Table 10 reports consistent results for firms exposed to GPR and a stable conclusion that POEs bear most of the pressure, reflected in stock-market devaluation.

This paper investigates whether geopolitical risk (GPR) negatively affects corporate valuation in the stock market. In response to the significant market devaluation associated with GPR, we find consistent evidence that firms with greater exposure to geopolitical risk lose more real-option opportunities, driven by disruptions in the external import of AI and high-tech inputs. As a result, the loss of innovative growth potential is closely linked to fundamental performance and is reflected in investor perceptions.

6.2 Corporate Fundamental

Given the stock-market response to geopolitical risk in China, the next question is how corporate fundamentals respond to these negative shocks. Consistent with our framework, in which product innovation derives from import learning, we examine corporate revenue through sales growth. Table 11 presents the response of corporate balance sheets to geopolitical risk. Columns (1)–(3) verify the cash-flow effect through the sales-growth channel. Firms with high geopolitical risk exposure experience a significant reduction in sales growth. In the full sample of both privately owned enterprises (POEs) and state-owned enterprises (SOEs), treated firms reduce their sales growth by 5.11% more than the control group. Consistent with our main finding of asymmetric pressure on POEs, POEs suffer a larger economic loss of 8.34% in sales growth, whereas SOEs exhibit only a 0.94% reduction. Similar results hold for the corporate investment ratio. When exposed to geopolitical risk, the treated group shows a 0.67% decrease in the total investment ratio, representing a 15.6% decline relative to the historical average. For POEs, the decline in the investment ratio is 1.14%, whereas SOEs show no evidence of a significant reduction.

In this economy, POEs follow Belo et al. (2026) in facing asymmetric financial frictions more severe than those of SOEs, owing to the lack of monetary-shock protection. We therefore examine whether geopolitical risk impairs the cost of financing for firms across ownership structures. Overall, for firms exposed to geopolitical risk, the probability of debt issuance decreases by 5.36%, with POEs accounting for a larger share—an 8.93% reduction. SOEs exhibit a 2.05% lower probability of debt issuance, but this effect is not statistically significant. These estimates reflect the differential feasibility, for firms with heterogeneous geopolitical risk exposure, of obtaining financing during periods of geopolitical tension.

In summary, geopolitical risk shocks impair corporate fundamentals through both the sales-growth and investment channels, with POEs bearing disproportionately larger economic losses than SOEs. Moreover, the reduced probability of debt issuance—particularly pronounced and statistically significant for POEs—reveals that financing constraints serve as a key transmission mechanism. We conclude that geopolitical risk materially weakens real corporate performance, and that ownership structure critically shapes firms' resilience through differential access to credit markets. POEs, lacking the implicit guarantees and monetary-shock protection available to SOEs, face asymmetric financial frictions that amplify the real effects of geopolitical shocks.

6.3 Equity Finance

Beyond the financial friction arising from the debt market, we document the extensive margin of financing: greater geopolitical risk makes it more difficult for firms to finance their activities through debt issuance. We next examine firms' strategies for external equity financing on the intensive margin. Our framework predicts that firms exposed to geopolitical risk incur losses from fewer real options, confirming the effect through the cash-flow channel. Moreover, from the aggregate perspective of the discount-rate channel, the stochastic discount factor rises as a negative consequence of geopolitical risk, reflecting higher required risk compensation. Given these mechanisms, we hypothesize that firms with greater exposure to geopolitical risk should bear higher expected returns, and that the geopolitical risk premium is spanned by firms with heterogeneous exposure.

We first present portfolio-level evidence in Table 12, where we compare portfolio expected returns across levels of geopolitical risk exposure. For the full sample in columns (1) to (3), a trading strategy that goes long high-GPR-exposure firms and short low-GPR-exposure firms generates the portfolios. The long-short hedging portfolio realizes a significant annualized return of 2.57% to 2.62% in the full sample, depending on the benchmark factor model. For POEs, the long-short strategy generates approximately 2.67% abnormal returns under the CAPM. For SOEs, the long-short strategy does not generate statistically significant returns, yielding only 2.05% and 2.14%, although these magnitudes are economically sizable.

To strengthen our conclusion on equity financing and rule out confounding factors, we estimate Fama-French regressions controlling for well-known factors. Table 13 reports the results. For a one-standard-deviation change in geopolitical risk, monthly stock returns are higher by 6.01%, 6.30%, and 3.38% for the full sample, POEs, and SOEs, respectively. The economic magnitude is sizable and consistently concentrated in the POE sector. Overall, these results imply that equity financing also becomes more expensive at the intensive margin, and that POEs disproportionately absorb most of the market's geopolitical pressure.

Finally, to confirm the SDF response to geopolitical risk, we conduct GMM estimation with marginal utility linearized around aggregate geopolitical risk. Our goal is to explain the cross-section of portfolio returns and to estimate whether geopolitical risk is associated with risk compensation in the stochastic discount factor.

$$M_t = 1 - b_{MKT} F_{MKT} - b_{GPR} F_{GPR}$$

Table 14 reports the results for POE-sorted portfolios. The two-factor model that augments the CAPM with the GPR shock substantially improves the fit of the cross-section: relative to the CAPM, R^2 rises and the mean absolute pricing error (MAE) declines. The estimated

price of risk b_{GPR} is negative and statistically significant, confirming our conjecture that that investors demand additional risk compensation for bearing geopolitical risk through the discount-rate channel.

7 Conclusion

We develop a two-period model in which heterogeneous firms (SOEs versus POEs) choose US high-tech, US low-tech, and domestic inputs to produce differentiated products. High-tech inputs drive AI innovation through import learning but require costly financing. Geopolitical risk raises the effective cost of US-origin inputs, reducing optimal high-tech imports. Financially constrained POEs face higher borrowing rates and tighter collateral constraints, which amplify their reallocation away from AI-embedded inputs relative to SOEs. The model predicts that this differential response widens the POE-SOE innovation gap and makes geopolitical risk a priced factor, since high-geopolitical-pressure states are high-marginal-utility states.

Empirically, using a continuous difference-in-differences design around the 2018 US-China trade war and LLM-based measures of firm-level geopolitical exposure, we find three results consistent with the model. First, higher geopolitical risk reduces high-tech and AI-related imports, with POEs exhibiting significantly larger declines. Second, these import reductions translate into lower AI innovation, reduced product diversification, and weaker fundamentals (sales growth and investment) for POEs. Third, financial markets price this risk: greater exposure predicts positive abnormal returns (Fama-MacBeth), reduced debt issuance, and negative cumulative returns around tariff events. The differential financial-friction channel explains why POEs bear disproportionately larger losses across all margins.

Our findings highlight a novel mechanism—AI import learning—through which geopolitical shocks propagate to real outcomes and asset prices. The results inform policy debates on technology decoupling, industrial subsidies, and the role of state ownership in buffering external shocks.

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8 Figure

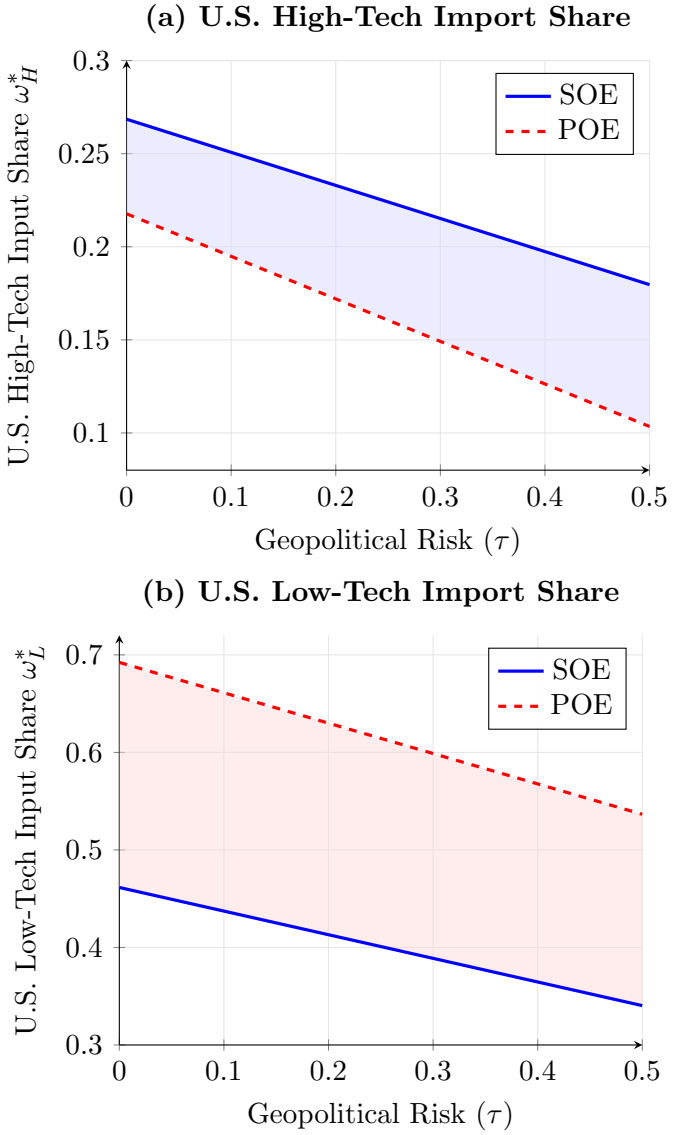


Figure 1: Optimal U.S. import shares as functions of geopolitical risk τ for SOE (solid blue) and POE (dashed red) firms ($\eta_f = 1$). Panel (a): The high-tech input share ω_H^* declines for both types, with the POE decline steeper due to the financing-cost amplification $(1 + r^j)$ (Propositions 1–2). Panel (b): Under Assumption 2, the low-tech input share ω_L^* also declines for both types as rising domestic substitution crowds out U.S. low-tech imports, again with a steeper POE decline. The shaded regions indicate the SOE–POE gap on each margin. Parameters: $\theta = 2.9$, $\delta = 6.5$, $\mu = 0.9$, $\zeta = 1.0$, $p_H = 1.5$, $p_O = 1.0$, $p_L = 0.4$, $r^{SOE} = 0.05$, $r^{POE} = 0.35$.

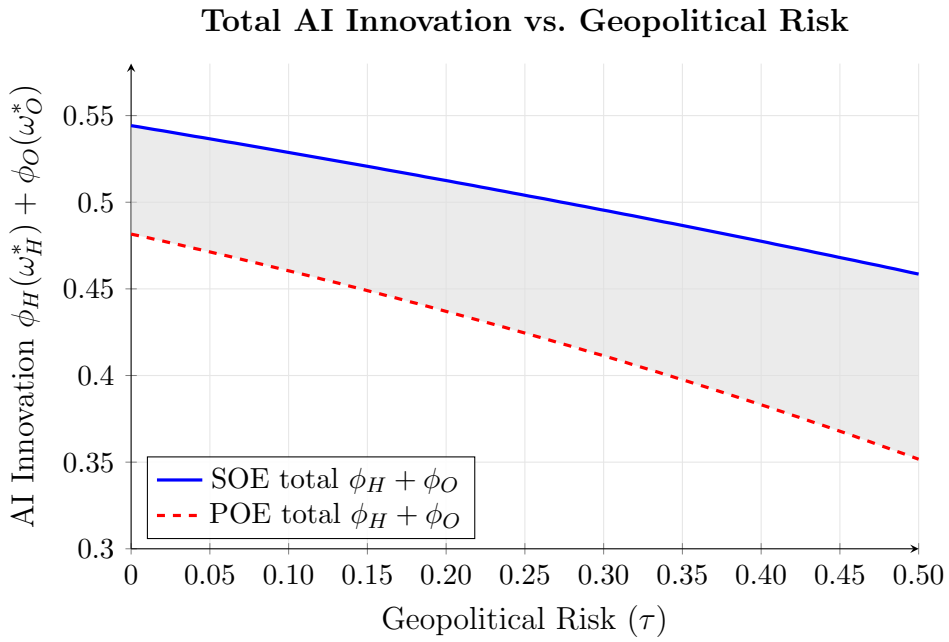


Figure 2: Total AI innovation $\phi_H(\omega_H^*) + \phi_O(\omega_O^*)$ as a function of τ for SOE (solid blue) and POE (dashed red) firms. Under Import Learning Dominance ($\beta = 0.05$, Proposition 4), total innovation declines with geopolitical risk for both ownership types, but the decline is larger for POEs (27.0% vs. 15.7% from $\tau = 0$ to $\tau = 0.5$). The shaded region indicates the SOE–POE innovation gap, which widens with τ. Innovation functions: $\phi_H(\omega) = \omega^{0.5}$, $\phi_O(\omega) = 0.05 \cdot \omega^{0.5}$. Parameters as in Figure 1.

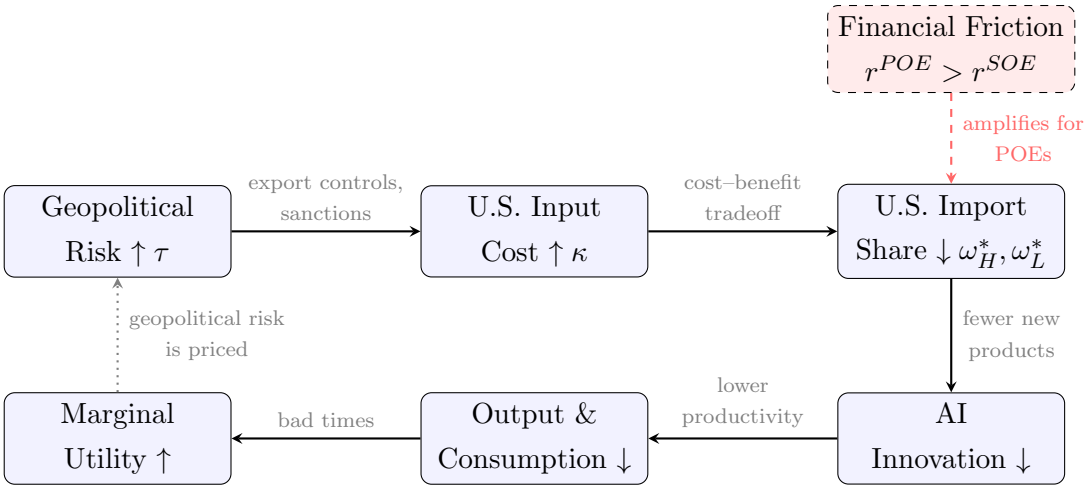


Figure 3: Mechanism diagram. Geopolitical risk increases the effective cost of U.S.-origin inputs ($\kappa \uparrow$), reducing the optimal U.S. high-tech and low-tech import shares ω_H^* and ω_L^*. The loss of AI import learning reduces innovation, lowers output and consumption, and raises the household's marginal utility. The financial friction between SOEs and POEs amplifies all effects for POEs. Because high-τ states are high-marginal-utility states, geopolitical risk is a priced risk factor.

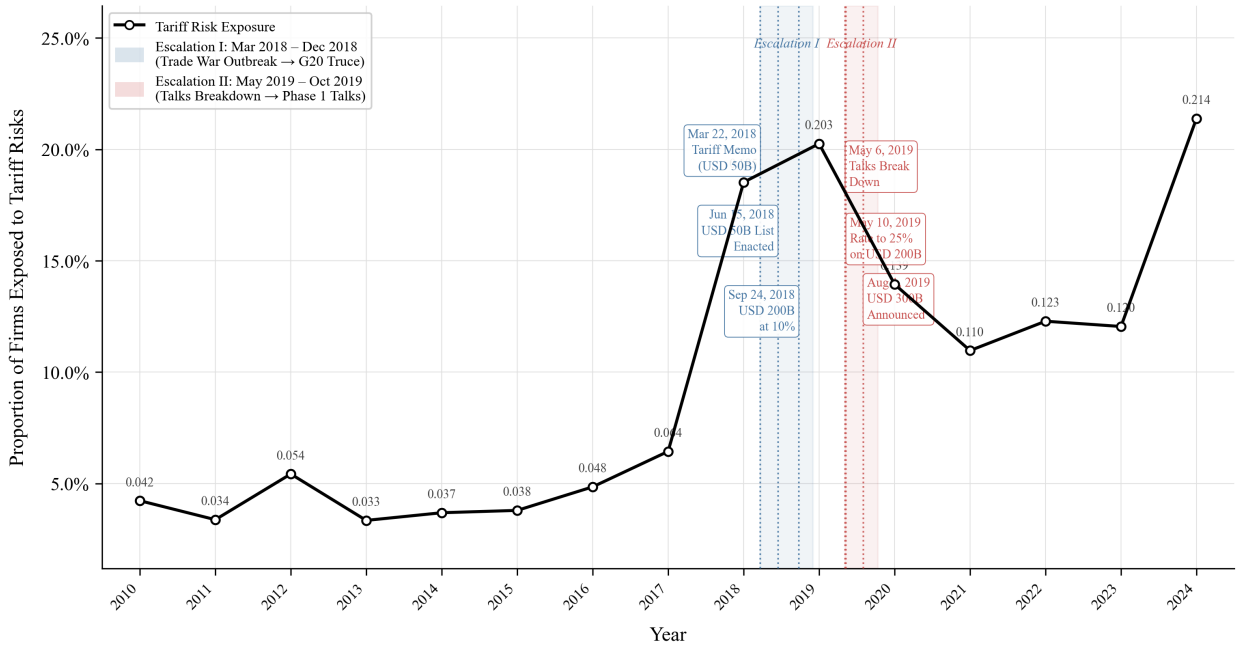


Figure 4: Evolution of Firm-Level Tariff Risk Exposure, 2010–2024.

Notes: The figure plots the annual share of A-share listed firms whose MD&A disclosures are classified as exposed to tariff risk, identified using a large language model (LLM) applied to Chinese-language annual report texts. Vertical dotted lines mark six key escalation events in the US–China trade war: (1) March 22, 2018—announcement of a tariff memorandum targeting USD 50 billion of Chinese goods; (2) June 15, 2018—formal enactment of the USD 50 billion tariff list; (3) September 24, 2018—imposition of a 10% tariff on USD 200 billion of Chinese goods; (4) May 6, 2019—collapse of the eleventh-round negotiations following China's withdrawal of prior commitments; (5) May 10, 2019—rate increase to 25% on the USD 200 billion list; and (6) August 1, 2019—announcement of additional tariffs on the remaining USD 300 billion of Chinese imports. Two shaded regions demarcate the primary escalation windows identified from the diplomatic timeline: *Escalation I* (blue, March 22 – December 1, 2018) spans the outbreak of the trade war to the G20 Buenos Aires truce; *Escalation II* (red, May 6 – October 11, 2019) spans the breakdown of negotiations to the resumption of high-level talks and the announcement of a Phase 1 framework. The y-axis reports the share of firms in the sample with tariff risk disclosure in a given year.



Figure 5: Evolution of U.S. Import Product Descriptions

Notes: The top panel presents the word clouds for *High-Tech* products across different time periods (2011, 2015, and 2017–2018). The bottom panel presents the symmetric word clouds for *Low-Tech* products. Larger font sizes indicate higher frequency of the terms in the raw customs product descriptions.

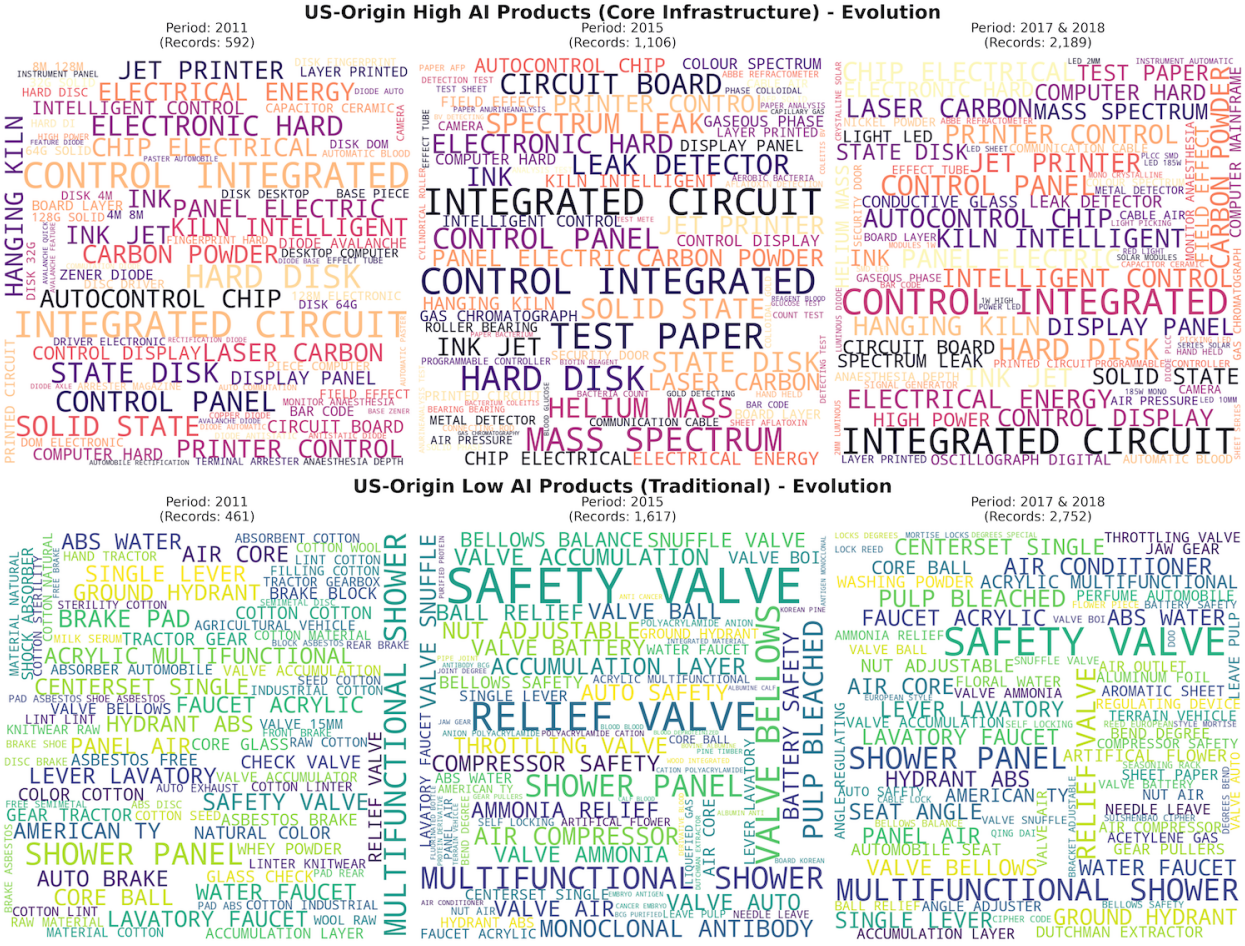


Figure 6: Evolution of U.S. AI Import Product Descriptions

Notes: The top panel presents the word clouds for *High-AI* products across different time periods (2011, 2015, and 2017–2018). The bottom panel presents the symmetric word clouds for *Low-AI* products. Larger font sizes indicate higher frequency of the terms in the raw customs product descriptions.



Figure 7: Industries with the Highest Share of Tariff-Exposed Firms, 2010–2024

Notes: This figure plots, for each year over 2010–2024, the share of firms within an industry that are classified as tariff-exposed, for the ten industries with the highest overall exposure share. To reduce small-sample noise, an industry-year is retained only if it contains at least 10 firms, and an industry is included only if it has at least 50 firm-year observations in total over the sample period and reports a valid value in every year (balanced panel). The ten industries are ranked by their pooled mean across all firm-year observations that pass these filters.

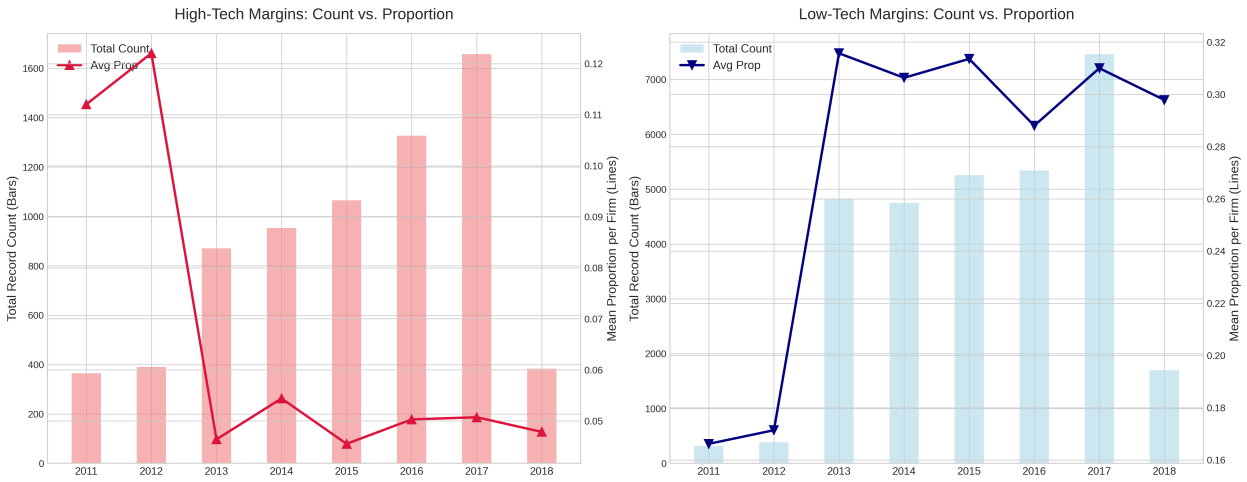


Figure 8: Extensive and Intensive Margins of High- and Low-Tech Imports

Notes: The left panel illustrates the extensive margin (total record count, represented by bars) and the intensive margin (mean proportion per firm, represented by lines) for high-tech imports using the maximum breakpoint of 0.85. The right panel displays the symmetric margins for low-tech imports using the minimum threshold of 0.05.

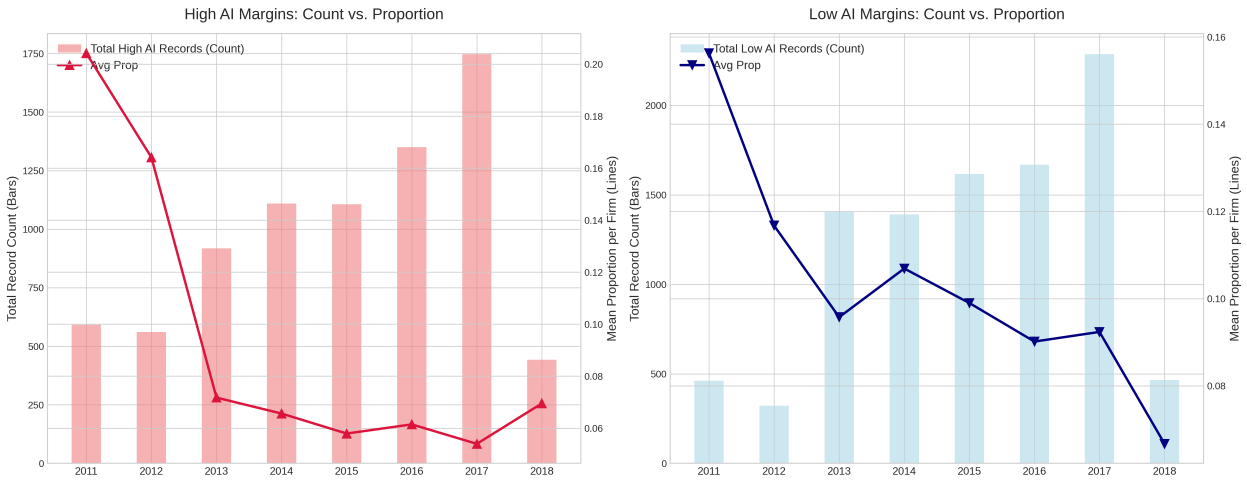


Figure 9: Extensive and Intensive Margins of High- and Low-AI Imports

Notes: The left panel illustrates the extensive margin (total record count, represented by bars) and the intensive margins (mean proportion per firm, represented by lines) for high-AI imports. The right panel displays the symmetric placebo margins for low-AI imports.

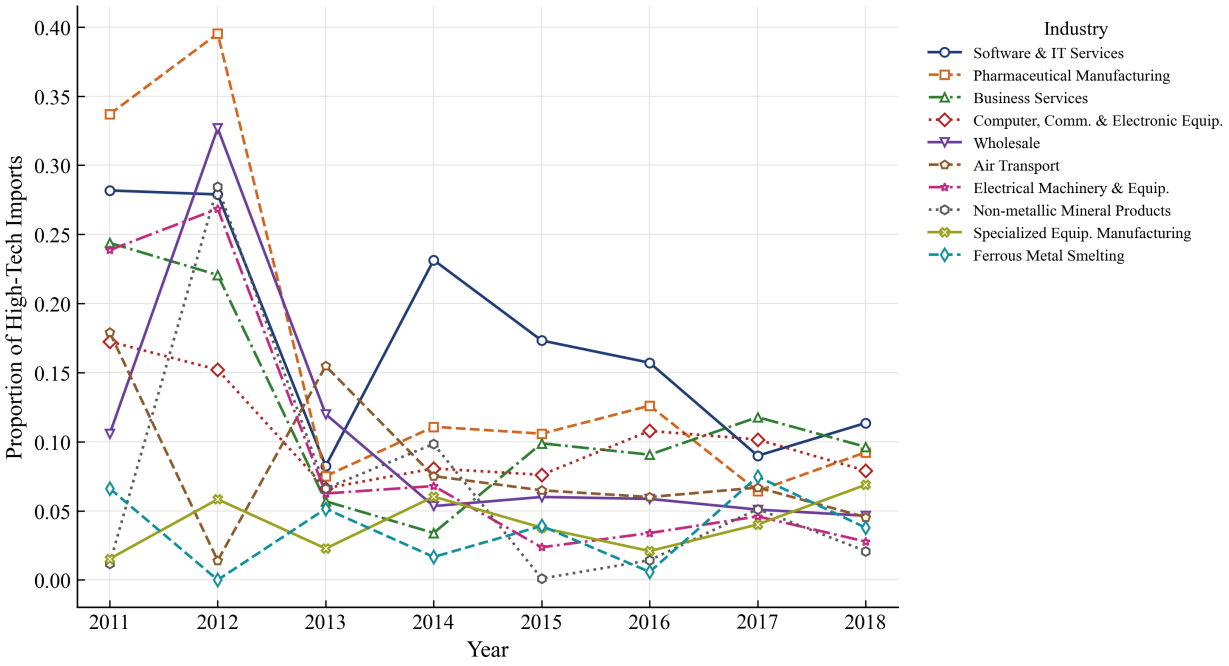


Figure 10: Industries with the Highest Proportion of High-Tech Imports, 2011–2018

Notes: This figure plots the annual industry-level proportion of high-tech imports for the ten industries with the highest overall high-tech import share over 2011–2018. The plotted series is the unweighted mean of the firm-level high-tech proportion across firms within each industry-year. To reduce small-sample noise, an industry-year is retained only if it contains at least 30 import records, and an industry is included only if it has at least 100 import records in total over the sample period and reports a valid value in every year (balanced panel). The ten industries are ranked by their pooled mean across all firm-year observations that pass these filters.

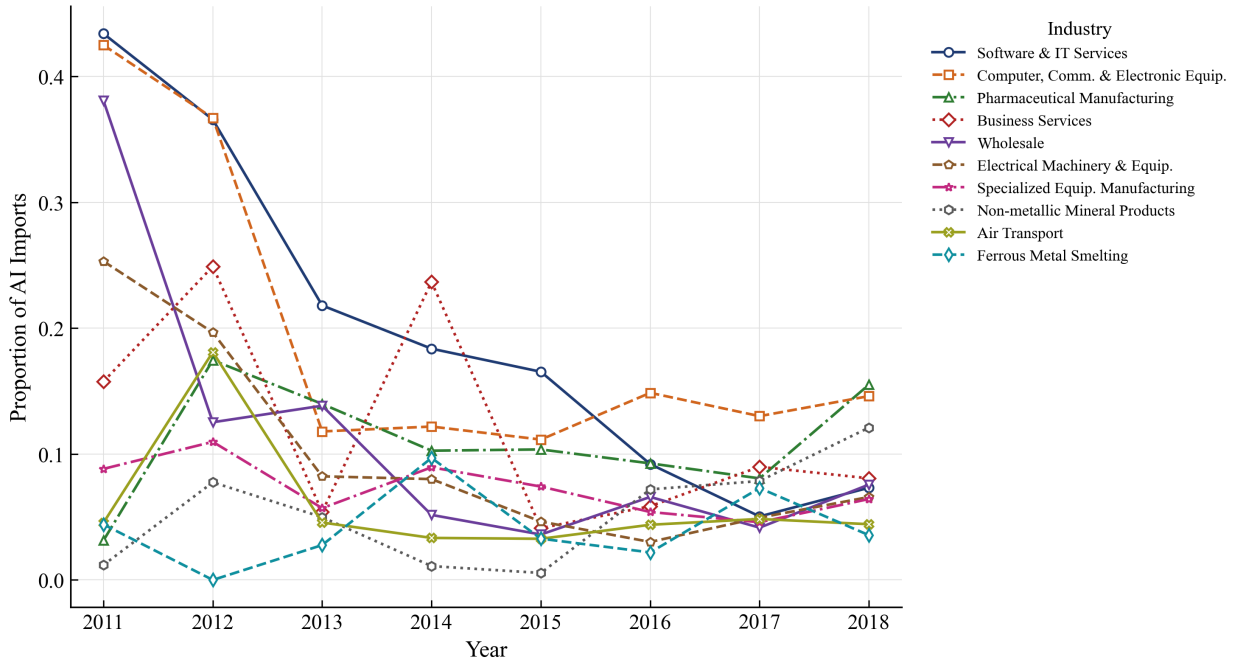


Figure 11: Industries with the Highest Proportion of AI-Related Imports, 2011–2018

Notes: This figure plots the annual industry-level proportion of AI-related imports for the ten industries with the highest overall AI import share over 2011–2018. The plotted series is the unweighted mean of the firm-level AI proportion across firms within each industry-year. To reduce small-sample noise, an industry-year is retained only if it contains at least 30 import records, and an industry is included only if it has at least 100 import records in total over the sample period and reports a valid value in every year (balanced panel). The ten industries are ranked by their pooled mean across all firm-year observations that pass these filters.

9 Table

Table 1: High-tech HS Code Classification and Product Descriptions

Category	**HS Code**	**HS Description**	**Product Description**
Semiconductor Manufacturing Equipment	848610	Machines and apparatus of a kind used solely or principally for the manufacture of semiconductor boules or wafers	AUTOMATIC TEMPERATURE-CONTROL DIFFUSION FURNACE; HIGH TEMPERATURE SCATTERING STOVE; SEMICONDUCTOR ELEMENT FINE CONTROL DIFFUSION FURNACE;
Semiconductor Wafers & Electronic Materials	381800	Chemical elements; doped for use in electronics, in the form of discs, wafers or similar forms; chemical compounds doped for use in electronics	ABRASIVE DISK; CHIP; CRYSTAL MATERIAL; ELECTRONIC CRYSTAL; FREQUENCY SLICES; GALLIUM ARSENIDE WAFER; INTEGRATED CIRCUIT GRADE SILICON POLISHED PIECE; MONOCRYSTALLINE SILICON CHIP; MONOCRYSTALLINE SILICON OPTICAL CHIP; MONOCRYSTALLINE SILICON ROUN
Semiconductor Devices & Chip Components	854190	Electrical apparatus; parts for diodes, transistors and similar semiconductor devices and photosensitive semiconductor devices	ALUMINIUM MAGNETIC CORE; AUTOMOBILE DIODE CHIP; BACKLIGHT SOURCE IRON FRAME; BARE SEMICONDUCTOR CHIP; BIDIRECTIONAL TRIGGER DIODE CMOS CHIPS; BLUE LIGHT-EMITTING DIODE BASE SHEET; CAP; CASE; CASE OF CRYSTAL VIBRATOR; CERAMIC DISCHARGE TRIODE; CE

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Table 1 – continued from previous page

Category	HS Code	HS Description	Product Description
Optoelectronic Devices & LEDs	854140	Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles: Diodes, transistors and similar semiconductor devices; photosensitive semiconductor devices, including photovoltaic cells whether or not assembled in modules or made up into panels; light-emitting diodes (LED); mounted piezoelectric crystals; parts thereof: Photosensitive semiconductor devices, including photovoltaic cells whether or not assembled in modules or made up into panels; light-emitting diodes (LED):	0603 RED-LIGHT PICKING LED; 10MM WHITE LIGHT LED; 160-185W MONO-CRYSTALLINE SOLAR MODULES; 1W HIGH-POWER LED; 2MM LUMINOUS DIODE; 3528 PLCC SMD LED; 36 SHEET SERIES SOLAR PANELS; 360 DEGREE WHITE LIGHT LED; 360??ROTATING COUPLER; 3W HIGH-POWER LE
Data Storage Units	847170	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof: Automatic data processing machines and units thereof; magnetic or optical readers, machines for transcribing data onto data media in coded form and machines for processing such data, not elsewhere specified or included: Storage units:	128G SOLID STATE DISK; 32G SOLID STATE DISK; 4M/8M-128M ELECTRONIC HARD DISK; 64G SOLID STATE DISK; ALUMINIUM BASE PIECE; COMPUTER HARD DISK; DESKTOP COMPUTER HARD DISK; DOM ELECTRONIC HARD DISC; DRIVER; ELECTRONIC HARD DISK; FINGERPRINT HARD DI

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Table 1 – continued from previous page

Category	HS Code	HS Description	Product Description
Data Processing Units	847150	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof: Automatic data processing machines and units thereof; magnetic or optical readers, machines for transcribing data onto data media in coded form and machines for processing such data, not elsewhere specified or included: Other units of automatic data processing machines:	COMPUTER HARD DISK; COMPUTER MAINFRAME; COMPUTER OUTER EQUIPMENT; COMPUTER PERIPHERAL EQUIPMENT; HOST COMPUTER; MAINFRAME; USB SOUND CARD;
AI: Intelligent Navigation & Radar	852691	Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles: Radar apparatus, radio navigational aid apparatus and radio remote control apparatus: -	AUTO NAVIGATION INSTRUMENT; AUTO NAVIGATIONAL SYSTEM; AUTOMOBILE AUTONOMOUS NAVIGATION SYSTEM; AUTOMOBILE GPS NAVIGATOR; AUTOMOBILE GPS POSITIONING NAVIGATION SYSTEM; AUTOMOBILE SATELLITE INTELLIGENT NAVIGATION SYSTEM; AUTOMOTIVE GPS NAVIGATION BOX;
High-End Medical Imaging: MRI	901813	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof: Instruments and appliances used in medical, surgical, dental or veterinary sciences, including scintigraphic apparatus, other electro-medical apparatus and sight-testing instruments; parts and accessories thereof: -	BODY RECEIVING COIL; BONE DENSITY INSTRUMENT; BRAIN RF COIL; DIGITAL ELECTROENCEPHALOGRAPH; DYNAMIC ELECTROENCEPHALOGRAM INSTRUMENT; EEG MACHINE; MAGNETIC RESONANCE IMAGING TECHNIQUE FOR MEDICAL APPLIANCE; MAGNETIC RESONANCE MEDICAL EQUIPMENT; MAM

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Table 1 – continued from previous page

Category	HS Code	HS Description	Product Description
High-End Medical Imaging: Ultrasound	901812	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof: Instruments and appliances used in medical, surgical, dental or veterinary sciences, including scintigraphic apparatus, other electro-medical apparatus and sight-testing instruments; parts and accessories thereof: -	B FORM DIASONOGRAPH FOR KNAPPER POSITIONING; B MODEL MEDICAL ULTRASOUND SCANNER AND PROBES; B TYPE DIASONOGRAPH; B ULTRASONIC DIAGNOSTIC UNIT; B-MODE ULTRASONIC DIAGNOSIS IMAGE WORKSTATION; B-TYPE ULTRASONIC DIAGNOSIS INSTRUMENT WITH ELECTRONIC LINEA
Scientific Analysis Instruments: Chromatography & Spectroscopy	902720	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof: Instruments and apparatus for physical or chemical analysis (for example, polarimeters, refractometers, spectrometers, gas or smoke analysis apparatus); instruments and apparatus for measuring or checking viscosity, porosity, expansion, surface tension or the like; instruments and apparatus for measuring or checking quantities of heat, sound or light (including exposure meters); microtomes; parts and accessories thereof: Chromatographs and electrophoresis instruments:	CAPILLARY GAS CHROMATOGRAPHY INSTRUMENT; COLOUR SPECTRUM GAS LOGGING APPARATUS; COURSE GAS CHROMATOGRAPH; GAS CHROMATOGRAPH; GASEOUS PHASE CHROMATOGRAM MASS SPECTRUM SPECTROMETER; GASEOUS PHASE COLOUR SPECTRUM COMBINATORY INSTRUMENT; GCMS; HIGH STR

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Category	HS Code	HS Description	Product Description
	902730	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof: Instruments and apparatus for physical or chemical analysis (for example, polarimeters, refractometers, spectrometers, gas or smoke analysis apparatus); instruments and apparatus for measuring or checking viscosity, porosity, expansion, surface tension or the like; instruments and apparatus for measuring or checking quantities of heat, sound or light (including exposure meters); microtomes; parts and accessories thereof: Spectrometers, spectrophotometers and spectrographs using optical radiations (ultraviolet, visible, infrared):	ATOM ABSORB SPECTROPHOTOMETER; ATOM FLUORESCENCE SPECTRUM INSTRUMENT; ATOM SPECTROPHOTOMETER; ATOMIC ABSORPTION SPECTROGRAPH; ATOMIC ABSORPTION SPECTROPHOTOMETER; ATOMIC ABSORPTION SPECTROSCOPY; ATOMIC FLUORESCENCE PHOTOMETER; ATOMIC FLUORESCENCE S
High-Energy Lasers	901320	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof: Liquid crystal devices not constituting articles provided for more specifically in other headings; lasers, other than laser diodes; other optical appliances and instruments, not specified or included elsewhere in this chapter; parts and accessories thereof: -	ADJUSTABLE LASER; ARGON ION LASER; BEAM EXPANDER LASER MODULE; BLUE LASER; CARD LASER/LASER CARD; CATV FEEDBACK LASER; CROSS LASER MODULE; CROSSCURRENT CO2 LASER; CROSSWISE ATMOSPHERIC PRESSURE EXCITATION LASER; DOT LASER MODULE; DUAL-IN-LINE TY
Extreme Precision & Particle Physics	854310	Electrical machines and apparatus; particle accelerators	HALL TYPE ELECTRONIC ACCELERATOR;

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Category	HS Code	HS Description	Product Description
	901210	Microscopes (excluding optical microscopes); diffraction apparatus	ATOMIC FORCE MICROSCOPE; CONTINUOUS ZOOM DIGITAL MICROSCOPE; DIGITAL METALLOGRAPHIC MICROSCOPE; DIGITAL MICROSCOPE; ELECTRON MICROSCOPE; FLEXO CONTINUOUS ZOOM DIGITAL MICROSCOPE; GRADING ZOOM STEREO MICROSCOPE; MACHINE TOOL SIZE MICROSCOPE; MICROS
Aerospace & Advanced Navigation	901420	Navigational instruments and appliances; for aeronautical or space navigation (excluding compasses)	AVIATION INSTRUMENT; GLOBAL NAVIGATION INSTRUMENT; POSITIONING NAVIGATOR; SPACEFLIGHT PRODUCT;
Aerospace Components	880330	Aircraft, spacecraft, and parts thereof: Parts of goods of heading 8801 or 8802: Other:	AIRCRAFT BRAKE SYSTEM; AIRCRAFT BRAKE SYSTEM ACCESSORIES; AIRPLANE PART AND ACCESSORY; AIRPLANE STAINLESS STEEL FITTINGS; ALUMINIUM ALLOY HELICOPTER TRANSMISSION GEAR CASE; AVIATION FITTINGS; AVIATION MATERIALS; CRANK SHAFT; FORGING ALUMINUM ALLOY

Table 2: Representative "High AI" Import Records and Product Descriptions

Category	**HS Code**	**HS Description**	**Product Description**
AI Key Technology *(Computer Vision & Robotics)*	847950	Industrial robots, not elsewhere specified or included: Machines and mechanical appliances having individual functions.	DETECTION SPRAYING ROBOT; FULL AUTOMATIC ROTARY BRUSH WASHING ROBOT; INDUSTRIAL ROBOT; MULTIFUNCTIONAL ROBOT; VOICE INTELLIGENT ROBOT
AI Key Technology *(Sensors & Edge AI)*	854231	Electronic integrated circuits; Processors and controllers, whether or not combined with memories, converters, logic circuits.	CAMERA MODULE; CONTROL INTEGRATED CIRCUIT FOR INK BOX; CONTROL PANEL; ELECTRIC IRON AUTOCONTROL CHIP; HANGING KILN INTELLIGENT CONTROL PANEL
AI Hardware Platform *(Semiconductors)*	381800	Miscellaneous chemical products: Chemical elements doped for use in electronics, in the form of discs, wafers or similar forms.	ABRASIVE DISK; CHIP; CRYSTAL MATERIAL; ELECTRONIC CRYSTAL; GALLIUM ARSENIDE WAFER; INTEGRATED CIRCUIT GRADE SILICON POLISHED PIECE; MONOCRYSTALLINE SILICON CHIP
AI Hardware Platform *(Industrial Automation)*	853710	Boards, panels, consoles, desks and other bases; for electric control or the distribution of electricity, for a voltage not exceeding 1000 volts.	10 POINT AC PROGRAMMABLE CONTROLLER; 20 POINT PROGRAMMABLE CONTROLLER; 48-DOT PROGRAMMABLE CONTROLLER; AC SERVO CONTROLLER; AUTOMATIC RECTIFYING SYSTEM
AI Key Technology *(Medical Imaging)*	901813	Instruments and appliances used in medical or surgical sciences, including scintigraphic apparatus, other electro-medical apparatus.	BODY RECEIVING COIL; BONE DENSITY INSTRUMENT; BRAIN RF COIL; DIGITAL ELECTROENCEPHALOGRAPH; DYNAMIC ELECTROENCEPHALOGRAM INSTRUMENT; MAGNETIC RESONANCE MEDICAL EQUIPMENT

Table 3: Summary of Statistics for Firm Characteristics

Variable	Mean	SD	Min	p25	Median	p75	Max	N
Panel A: Full Sample								
$GPR_{i,t}$	0.124	0.329	0.000	0.000	0.000	0.000	1.000	6436
$Import_{i,t}^{High_Tech}$	0.062	0.204	0.000	0.000	0.000	0.000	1.000	3553
$Import_{i,t}^{Low_Tech}$	0.274	0.401	0.000	0.000	0.004	0.577	1.000	3553
$\Delta Import_{i,t}^{High_AI}$	-0.008	0.183	-1.000	0.000	0.000	0.000	1.000	2590
$\Delta Import_{i,t}^{Low_AI}$	-0.002	0.187	-1.000	0.000	0.000	0.000	1.000	2590
$HighTech_Patent^{3\ \text{year}}(ln)$	0.752	1.158	0.000	0.000	0.000	1.099	7.231	6417
$HighTech_Patent^{5\ \text{year}}(ln)$	0.987	1.303	0.000	0.000	0.693	1.609	7.668	6417
$AI_Patent^{1\ \text{year}}(ln)$	0.413	0.792	0.000	0.000	0.000	0.693	5.493	6436
$AI_Patent^{3\ \text{year}}(ln)$	0.872	1.106	0.000	0.000	0.693	1.386	6.400	6436
$Size_{i,t}$	22.565	1.391	19.951	21.577	22.372	23.368	26.659	6436
$FirmAge_{i,t}$	10.627	7.115	1.000	5.000	9.000	16.000	31.000	6436
$ROA_{i,t}$	0.035	0.069	-0.261	0.014	0.038	0.068	0.209	6436
$Leverage_{i,t}$	0.432	0.195	0.046	0.279	0.428	0.577	0.912	6436
$TobinQ_{i,t}$	2.095	1.318	0.840	1.250	1.692	2.425	8.168	6373
$Cash_Ratio_{i,t}$	0.181	0.117	0.017	0.098	0.153	0.233	0.730	6436
$Inventory_Ratio_{i,t}$	0.119	0.088	0.000	0.056	0.104	0.162	0.455	6415
$\Delta ln(Sales)_{i,t}$	0.118	0.249	-0.761	0.001	0.115	0.238	0.952	6436
$Invest_Ratio_{i,t+1}$	0.043	0.040	0.001	0.014	0.031	0.059	0.214	6416
$D(Debt_Issuance > 0)_{i,t+1}$	0.847	0.360	0.000	1.000	1.000	1.000	1.000	6416
$Trademarks(ln)_{i,t}$	1.710	1.546	0.000	0.000	1.386	2.773	7.521	8886
$Product_Patents(ln)_{i,t}$	2.327	1.461	0.000	1.386	2.303	3.219	9.162	11982
Panel B: State-Owned Enterprises (SOE)								
$GPR_{i,t}$	0.118	0.323	0.000	0.000	0.000	0.000	1.000	2237
$Import_{i,t}^{High_Tech}$	0.057	0.188	0.000	0.000	0.000	0.000	1.000	1205
$Import_{i,t}^{Low_Tech}$	0.275	0.401	0.000	0.000	0.011	0.576	1.000	1205
$\Delta Import_{i,t}^{High_AI}$	-0.012	0.181	-1.000	0.000	0.000	0.000	1.000	854
$\Delta Import_{i,t}^{Low_AI}$	0.000	0.199	-1.000	-0.004	0.000	0.000	1.000	854
$HighTech_Patent^{3\ \text{year}}(ln)$	0.845	1.315	0.000	0.000	0.000	1.386	7.231	2233
$HighTech_Patent^{5\ \text{year}}(ln)$	1.120	1.469	0.000	0.000	0.693	1.792	7.668	2233
$AI_Patent^{1\ \text{year}}(ln)$	0.456	0.916	0.000	0.000	0.000	0.693	5.493	2237

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Table 3 – continued from previous page

Variable	Mean	SD	Min	p25	Median	p75	Max	N
$AI_Patent^{3\ year}(ln)$	0.940	1.258	0.000	0.000	0.693	1.386	6.400	2237
$Size_{i,t}$	23.384	1.470	19.951	22.330	23.264	24.369	26.659	2237
$FirmAge_{i,t}$	15.889	6.938	1.000	10.000	17.000	21.000	31.000	2237
$ROA_{i,t}$	0.033	0.057	-0.261	0.012	0.031	0.056	0.209	2237
$Leverage_{i,t}$	0.507	0.194	0.046	0.365	0.522	0.651	0.912	2237
$TobinQ_{i,t}$	1.763	1.186	0.840	1.044	1.331	1.995	8.168	2212
$Cash_Ratio_{i,t}$	0.172	0.115	0.017	0.090	0.145	0.225	0.701	2237
$Inventory_Ratio_{i,t}$	0.121	0.099	0.000	0.044	0.106	0.167	0.455	2236
$\Delta ln(Sales)_{i,t}$	0.098	0.223	-0.761	0.003	0.094	0.198	0.952	2237
$Invest_Ratio_{i,t+1}$	0.038	0.036	0.001	0.013	0.027	0.052	0.214	2233
$D(Debt_Issuance > 0)_{i,t+1}$	0.860	0.347	0.000	1.000	1.000	1.000	1.000	2233
$Trademarks(ln)_{i,t}$	1.679	1.570	0.000	0.000	1.386	2.708	7.521	2348
$Product_Patents(ln)_{i,t}$	2.445	1.618	0.000	1.386	2.303	3.434	9.162	3318
Panel C: Privately-Owned Enterprises (POE)								
$GPR_{i,t}$	0.125	0.331	0.000	0.000	0.000	0.000	1.000	3791
$Import_{i,t}^{High_Tech}$	0.071	0.220	0.000	0.000	0.000	0.000	1.000	2073
$Import_{i,t}^{Low_Tech}$	0.272	0.401	0.000	0.000	0.001	0.575	1.000	2073
$\Delta Import_{i,t}^{High_AI}$	-0.007	0.190	-1.000	0.000	0.000	0.000	1.000	1515
$\Delta Import_{i,t}^{Low_AI}$	-0.003	0.184	-1.000	0.000	0.000	0.000	1.000	1515
$HighTech_Patent^{3\ year}(ln)$	0.702	1.067	0.000	0.000	0.000	1.099	6.105	3778
$HighTech_Patent^{5\ year}(ln)$	0.916	1.205	0.000	0.000	0.693	1.609	6.501	3778
$AI_Patent^{1\ year}(ln)$	0.389	0.714	0.000	0.000	0.000	0.693	5.283	3791
$AI_Patent^{3\ year}(ln)$	0.840	1.012	0.000	0.000	0.693	1.386	6.258	3791
$Size_{i,t}$	22.123	1.107	19.951	21.368	22.004	22.743	26.659	3791
$FirmAge_{i,t}$	7.765	5.216	1.000	4.000	7.000	10.000	28.000	3791
$ROA_{i,t}$	0.035	0.075	-0.261	0.016	0.042	0.071	0.209	3791
$Leverage_{i,t}$	0.395	0.184	0.046	0.247	0.394	0.529	0.912	3791
$TobinQ_{i,t}$	2.258	1.336	0.840	1.414	1.854	2.599	8.168	3755
$Cash_Ratio_{i,t}$	0.184	0.117	0.017	0.102	0.155	0.236	0.730	3791
$Inventory_Ratio_{i,t}$	0.118	0.080	0.000	0.062	0.102	0.158	0.455	3771
$\Delta ln(Sales)_{i,t}$	0.129	0.262	-0.761	0.000	0.134	0.265	0.952	3791
$Invest_Ratio_{i,t+1}$	0.045	0.041	0.001	0.016	0.033	0.062	0.214	3778

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Table 3 – continued from previous page

Variable	Mean	SD	Min	p25	Median	p75	Max	N
$D(Debt_Issuance > 0)_{i,t+1}$	0.844	0.363	0.000	1.000	1.000	1.000	1.000	3778
$Trademarks(ln)_{i,t}$	1.728	1.543	0.000	0.000	1.386	2.833	7.378	5902
$Product_Patents(ln)_{i,t}$	2.281	1.393	0.000	1.386	2.303	3.178	8.225	7843

Notes: This table reports summary statistics for the main variables used in the empirical analysis. Panel A presents the full sample, Panel B state-owned enterprises (SOEs), and Panel C privately owned enterprises (POEs). For each variable, we report the mean, standard deviation, minimum, 25th percentile, median, 75th percentile, maximum, and number of observations. All continuous variables are winsorized at the 1st and 99th percentiles. $GPR_{i,t}$ equals one for firms with above-median exposure to tariff-specific geopolitical risk, and zero otherwise. $Import_{i,t}^{High_Tech}$ and $Import_{i,t}^{Low_Tech}$ are the proportions of firm i's imports classified as high-tech and low-tech, respectively, in year t. $\Delta Import_{i,t}^{High_AI}$ and $\Delta Import_{i,t}^{Low_AI}$ are year-over-year changes in high-AI and low-AI imports. $HighTech_Patent^{3\text{ year}}(ln)$ and $HighTech_Patent^{5\text{ year}}(ln)$ are the natural logarithms of one plus high-tech patent applications over the subsequent three- and five-year horizons. $AI_Patent^{1\text{ year}}(ln)$ and $AI_Patent^{3\text{ year}}(ln)$ are defined analogously over one- and three-year horizons. $Product_Patents(ln)_{i,t}$ and $Trademarks(ln)_{i,t}$ are the natural logarithms of one plus product patents and valid trademark registrations. $Size_{i,t}$ is the natural logarithm of total assets. $FirmAge_{i,t}$ is years since establishment. $ROA_{i,t}$ is net income divided by lagged total assets. $Leverage_{i,t}$ is total debt divided by total assets. $TobinQ_{i,t}$ is the market value of assets divided by their book value. $Cash_Ratio_{i,t}$ is cash and equivalents divided by total assets. $Inventory_Ratio_{i,t}$ is inventory divided by total assets. $\Delta ln(Sales)_{i,t}$ is the year-over-year change in log net sales. $Invest_Ratio_{i,t+1}$ is capital expenditures divided by total assets, measured at $t+1$. $D(Debt_Issuance > 0)_{i,t+1}$ equals one if the firm issues positive new debt in year $t+1$, and zero otherwise.

Table 4: High-Tech Import Response to Geopolitical Risk

	Dependent Variable: Innovative Import			
	$Import_{i,t}^{High_Tech}$		$Import_{i,t}^{Low_Tech}$	
	(1) POE	(2) SOE	(3) POE	(4) SOE
$Exposure_i \times Shock_t$	-1.3937**	-1.2999*	-4.7760***	-4.7784**
	(0.7004)	(0.6964)	(1.5140)	(2.0091)
$Size_{i,t-1}$	0.0096	0.0039	-0.0120	-0.0545***
	(0.0080)	(0.0060)	(0.0167)	(0.0146)
$FirmAge_{i,t-1}$	-0.0002	-0.0013	-0.0011	0.0008
	(0.0014)	(0.0012)	(0.0036)	(0.0030)
$ROA_{i,t-1}$	-0.1064	-0.0139	0.1255	0.4316*
	(0.1573)	(0.1119)	(0.2495)	(0.2520)
$Leverage_{i,t-1}$	-0.0559	-0.0004	0.0946	0.1353
	(0.0389)	(0.0358)	(0.0893)	(0.1021)
$TobinQ_{i,t-1}$	0.0130*	0.0050	-0.0132	-0.0280**
	(0.0069)	(0.0089)	(0.0099)	(0.0130)
$Cash_Ratio_{i,t-1}$	0.0905**	-0.0028	-0.0021	-0.0266
	(0.0460)	(0.0733)	(0.0846)	(0.1261)
$Inventory_Ratio_{i,t-1}$	0.1086	0.0151	0.1408	0.1242
	(0.0887)	(0.0797)	(0.1905)	(0.2450)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.0697	0.1092	0.2885	0.3256
N	2185	1214	2185	1214

Notes: This table reports continuous difference-in-differences estimates of the effect of geopolitical exposure on firm-level imports of high-tech and low-tech products, separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The dependent variable is $Import_{i,t}^{High_Tech}$ in columns (1)–(2) and $Import_{i,t}^{Low_Tech}$ in columns (3)–(4). The variable of interest is the interaction $Exposure_i \times Shock_t$, where $Exposure_i$ is the firm's pre-shock baseline exposure, measured as its average over 2014–2015 using the tariff-specific GPR index, and $Shock_t$ is the yearly prevalence index of US-China conflict discussions extracted from US corporate earnings calls. All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous controls are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: AI Import Response to Geopolitical Risk

	Dependent Variable: AI Import			
	$\Delta Import_{i,t}^{High_AI}$		$\Delta Import_{i,t}^{Low_AI}$	
	(1) POE	(2) SOE	(3) POE	(4) SOE
$Exposure_i \times Shock_t$	-3.0270*	-1.1779	-1.6875	-2.6120**
	(1.5897)	(1.2097)	(1.2209)	(1.2760)
$Size_{i,t-1}$	-0.0027	-0.0017	0.0030	-0.0076
	(0.0054)	(0.0044)	(0.0059)	(0.0062)
$FirmAge_{i,t-1}$	0.0006	-0.0013	0.0015	0.0018
	(0.0010)	(0.0009)	(0.0012)	(0.0011)
$ROA_{i,t-1}$	-0.0053	-0.0011	-0.1919	0.3022**
	(0.1084)	(0.1334)	(0.1363)	(0.1358)
$Leverage_{i,t-1}$	0.0083	-0.0078	-0.0201	0.1217**
	(0.0349)	(0.0350)	(0.0335)	(0.0541)
$TobinQ_{i,t-1}$	-0.0012	-0.0059	0.0024	0.0076
	(0.0056)	(0.0041)	(0.0045)	(0.0071)
$Cash_Ratio_{i,t-1}$	-0.0249	-0.0223	0.0504	-0.0072
	(0.0441)	(0.0571)	(0.0332)	(0.0559)
$Inventory_Ratio_{i,t-1}$	-0.0114	0.0469	-0.0346	-0.0547
	(0.0572)	(0.0451)	(0.0656)	(0.0813)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.0297	0.0476	0.0388	0.0778
N	1514	853	1514	853

Notes: This table reports continuous difference-in-differences estimates of the effect of geopolitical exposure on firm-level imports of high-AI and low-AI products, separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The dependent variable is $\Delta Import_{i,t}^{High_AI}$ in columns (1)–(2) and $\Delta Import_{i,t}^{Low_AI}$ in columns (3)–(4). The variable of interest is the interaction $Exposure_i \times Shock_t$, where $Exposure_i$ is the firm's pre-shock baseline exposure, measured as its average over 2014–2015 using the tariff-specific GPR index, and $Shock_t$ is the yearly prevalence index of US-China conflict discussions extracted from US corporate earnings calls. All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous controls are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Economic Mechanism: High-Tech Innovation in Response to Geopolitical Risk

	Dependent Variable: High-Tech Innovation					
	$HighTech_Patent^{3\ year}(ln)$			$HighTech_Patent^{5\ year}(ln)$		
	(1) Full	(2) POE	(3) SOE	(4) Full	(5) POE	(6) SOE
$Treat_i \times After_t$	-0.1707**	-0.1012	-0.2357	-0.2243**	-0.2167**	-0.2323
	(0.0833)	(0.0964)	(0.1536)	(0.0875)	(0.0966)	(0.1606)
$Size_{i,t-1}$	0.4073***	0.3420***	0.4913***	0.4675***	0.3707***	0.5727***
	(0.0409)	(0.0551)	(0.0663)	(0.0445)	(0.0611)	(0.0719)
$FirmAge_{i,t-1}$	-0.0136***	-0.0111	-0.0235***	-0.0150**	-0.0122	-0.0271***
	(0.0049)	(0.0088)	(0.0073)	(0.0058)	(0.0105)	(0.0086)
$ROA_{i,t-1}$	1.1238***	1.4042***	0.9865	1.4782***	1.8781***	1.3551
	(0.3193)	(0.3637)	(0.7678)	(0.3642)	(0.4169)	(0.8348)
$Leverage_{i,t-1}$	-0.4000**	-0.2848	-0.6218*	-0.4497**	-0.3253	-0.6905*
	(0.1778)	(0.1941)	(0.3525)	(0.2065)	(0.2294)	(0.3975)
$TobinQ_{i,t-1}$	0.1467***	0.1573***	0.1434***	0.1653***	0.1721***	0.1732***
	(0.0224)	(0.0285)	(0.0425)	(0.0242)	(0.0304)	(0.0471)
$Cash_Ratio_{i,t-1}$	0.4312**	0.2934	0.2326	0.4937**	0.2809	0.3090
	(0.2022)	(0.2173)	(0.4289)	(0.2346)	(0.2543)	(0.4859)
$Inventory_Ratio_{i,t-1}$	0.6173*	0.5529	0.6746	0.7442*	0.6289	0.7881
	(0.3443)	(0.3911)	(0.6504)	(0.4025)	(0.4605)	(0.7375)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2471	0.2299	0.3347	0.2562	0.2395	0.3556
N	6417	3778	2233	6417	3778	2233

Notes: This table reports difference-in-differences estimates of the effect of treatment on firm-level high-tech patent outcomes. The dependent variable is $HighTech_Patent^{3\ year}(ln)$ in columns (1)–(3), measuring high-tech patent applications over a three-year horizon, and $HighTech_Patent^{5\ year}(ln)$ in columns (4)–(6), over a five-year horizon. Regressions are estimated for the full sample and separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The variable of interest is $Treat_i \times After_t$, where $Treat_i$ equals 1 for the treatment group (the firm's tariff-specific GPR exposure exceeds 0 in the pre-shock baseline year 2017), and $After_t$ equals 1 for the post-treatment period (the event year 2018 and the subsequent three years). All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Economic Mechanism: AI Innovation in Response to Geopolitical Risk

	Dependent Variable: AI Innovation					
	$AI_Patent^{1\ year}(ln)$			$AI_Patent^{3\ year}(ln)$		
	(1) Full	(2) POE	(3) SOE	(4) Full	(5) POE	(6) SOE
$Treat_i \times After_t$	-0.0953*	-0.1134	-0.0376	-0.1737**	-0.2367**	-0.0465
	(0.0505)	(0.0762)	(0.0765)	(0.0782)	(0.1068)	(0.1269)
$Size_{i,t-1}$	0.2276***	0.1849***	0.2972***	0.3246***	0.2616***	0.4213***
	(0.0289)	(0.0389)	(0.0469)	(0.0378)	(0.0518)	(0.0603)
$FirmAge_{i,t-1}$	-0.0058*	-0.0099**	-0.0065	-0.0097**	-0.0198***	-0.0081
	(0.0032)	(0.0049)	(0.0053)	(0.0048)	(0.0075)	(0.0075)
$ROA_{i,t-1}$	0.7543***	0.8162***	0.7160	1.5673***	1.6256***	1.6028**
	(0.2195)	(0.2459)	(0.5322)	(0.3160)	(0.3723)	(0.7033)
$Leverage_{i,t-1}$	-0.2601**	-0.2406**	-0.2342	-0.3154*	-0.3005	-0.2981
	(0.1067)	(0.1154)	(0.2215)	(0.1618)	(0.1908)	(0.3094)
$TobinQ_{i,t-1}$	0.0334***	0.0342**	0.0605*	0.0550***	0.0591***	0.0886**
	(0.0126)	(0.0141)	(0.0309)	(0.0178)	(0.0201)	(0.0422)
$Cash_Ratio_{i,t-1}$	0.3650**	0.2914**	0.3104	0.6590***	0.5668**	0.5889
	(0.1589)	(0.1483)	(0.3736)	(0.2211)	(0.2246)	(0.4784)
$Inventory_Ratio_{i,t-1}$	0.3727*	0.4042*	0.5440	0.4577	0.5933	0.5902
	(0.2205)	(0.2421)	(0.4621)	(0.3223)	(0.3754)	(0.6554)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1913	0.1432	0.3014	0.2325	0.1887	0.3505
N	6436	3791	2237	6436	3791	2237

Notes: This table reports difference-in-differences estimates of the effect of treatment on firm-level AI innovation. The dependent variable is $AI_Patent^{1\ year}(ln)$ in columns (1)–(3), measuring AI patent applications over a one-year horizon, and $AI_Patent^{3\ year}(ln)$ in columns (4)–(6), over a three-year horizon. Regressions are estimated for the full sample and separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The variable of interest is $Treat_i \times After_t$, where $Treat_i$ equals 1 for the treatment group (the firm's tariff-specific GPR exposure exceeds 0 in the pre-shock baseline year 2017), and $After_t$ equals 1 for the post-treatment period (the event year 2018 and the subsequent three years). All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Economic Mechanism: Product Diversification

	Trademarks(ln)			Product Patents(ln)		
	(1) Full	(2) POE	(3) SOE	(4) Full	(5) POE	(6) SOE
$Treat_i \times After_t$	-0.2058*	-0.3381**	0.0402	-0.1361*	-0.2048**	-0.0388
	(0.1098)	(0.1411)	(0.1946)	(0.0808)	(0.1027)	(0.1390)
$Size_{i,t-1}$	0.3752***	0.4098***	0.3599***	0.4465***	0.4719***	0.4758***
	(0.0296)	(0.0407)	(0.0491)	(0.0329)	(0.0383)	(0.0553)
$FirmAge_{i,t-1}$	-0.0205***	-0.0320***	-0.0000	-0.0136***	-0.0275***	-0.0050
	(0.0039)	(0.0056)	(0.0069)	(0.0041)	(0.0060)	(0.0065)
$ROA_{i,t-1}$	0.6178**	0.6315**	0.4268	1.3335***	1.4201***	0.4804
	(0.2399)	(0.2682)	(0.6395)	(0.3047)	(0.3179)	(0.6763)
$Leverage_{i,t-1}$	-0.2681*	-0.1883	-0.2441	-0.1372	-0.0494	-0.6618**
	(0.1381)	(0.1634)	(0.2620)	(0.1353)	(0.1549)	(0.2707)
$TobinQ_{i,t-1}$	0.0444***	0.0505***	0.0401*	0.0409***	0.0490***	0.0604**
	(0.0103)	(0.0143)	(0.0209)	(0.0133)	(0.0182)	(0.0289)
$Cash_Ratio_{i,t-1}$	1.1701***	1.5194***	0.5576	0.8032***	0.7507***	0.7183*
	(0.2084)	(0.2369)	(0.4109)	(0.1795)	(0.1929)	(0.4216)
$Inventory_Ratio_{i,t-1}$	0.2663	0.2499	0.3179	0.3681	0.6059**	0.4987
	(0.2411)	(0.2974)	(0.4236)	(0.2461)	(0.2873)	(0.5285)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1450	0.1612	0.1706	0.2521	0.2406	0.3464
N	8886	5902	2348	11982	7843	3318

Notes: This table reports difference-in-differences estimates of the effect of treatment on firm-level trademarks and product patents. The dependent variable is $Trademarks(ln)_{i,t}$ in columns (1)–(3) and $Product_Patents(ln)_{i,t}$ in columns (4)–(6). Regressions are estimated for the full sample and separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The variable of interest is $Treat_i \times After_t$, where $Treat_i$ equals 1 for the treatment group (the firm's tariff-specific GPR exposure exceeds 0 in the pre-shock baseline year 2017), and $After_t$ equals 1 for the post-treatment period (the event year 2018 and the subsequent three years). All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Event Study Analysis and Market Valuation over Main Tarriff Events

	CAR[-1,+1]			CAR[-1,+3]		
	FULL	POE	SOE	FULL	POE	SOE
A. Average CARs per portfolio						
Low GPR risk	-0.272	-0.869	1.067	2.962	2.950	3.207
High GPR risk	-0.811	-1.708	0.693	1.237	0.842	2.077
High-Low	-0.539	-0.838	-0.374	-1.725	-2.109	-1.130
t-test [p-value]	[0.090]*	[0.038]**	[0.499]	[0.000]***	[0.000]***	[0.086]*
B. Regression analysis						
GPR only	-0.5390*	-0.8384**	-0.3738	-1.7251***	-2.1086***	-1.1301*
	(-1.71)	(-2.10)	(-0.68)	(-4.91)	(-4.75)	(-1.75)
GPR + controls	-0.4777	-0.7878**	0.0460	-1.4056***	-1.9187***	-0.3810
	(-1.53)	(-1.99)	(0.09)	(-4.09)	(-4.49)	(-0.65)
Number of observations	2739	1662	902	2724	1653	896

Notes: This table reports event study estimates of cumulative abnormal returns (CARs) around major tariff announcement events (March 22, 2018), separately for the full sample, privately owned enterprises (POEs), and state-owned enterprises (SOEs). CARs are computed over two windows: [-1,+1] (three-day window) and [-1,+3] (five-day window), expressed in percentage points. Panel A presents portfolio-level analysis of abnormal returns. Firms are sorted into portfolios based on their tariff specific geopolitical risk (GPR) exposure. "Low GPR risk" and "High GPR risk" correspond to the tariff specific GPR dummy variable taking the value of 0 and 1, respectively. "High-Low" represents the return spread between the high and low GPR portfolios. The t-test reports the statistical significance of the High-Low spread, with p-values in brackets. Panel B reports the coefficient estimates from cross-sectional regressions of CARs on GPR risk, with and without control variables. The dependent variable is CAR[-1,+1] in columns (1)–(3) and CAR[-1,+3] in columns (4)–(6). The variable of interest is an indicator for high GPR risk. Control variables include firm size, firm age, return on assets (ROA), leverage and BM ratio (all lagged one period). Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Table 10: Robustness: Pooled Event Study Analysis and Market Valuation over Large Tariff Events

	CAR[-1,+1]			CAR[-1,+3]		
	FULL	POE	SOE	FULL	POE	SOE
A. Average CARs per portfolio						
Low GPR risk	-0.178	-0.382	0.289	-0.247	-0.437	0.179
High GPR risk	-0.534	-0.804	0.164	-1.082	-1.410	-0.270
High-Low (diff)	-0.356	-0.422	-0.125	-0.836	-0.972	-0.450
t-test [p-value] (Cluster Robust)	[0.002]***	[0.009]***	[0.360]	[0.000]***	[0.000]***	[0.010]**
B. Pooled Regression analysis						
GPR only	-0.3557***	-0.4221***	-0.1252	-0.8358***	-0.9722***	-0.4497**
	(-3.11)	(-2.61)	(-0.91)	(-5.20)	(-4.21)	(-2.56)
GPR + controls + Event FE	-0.7265***	-0.8262***	-0.3613***	-0.9935***	-1.1320***	-0.5200***
	(-6.44)	(-5.15)	(-2.65)	(-6.22)	(-4.90)	(-2.94)
Number of observations	32949	20974	10074	32919	20953	10066

Notes: This table reports robustness checks for the event study estimates presented in the previous table, using a stacked event study design that incorporates a larger set of major tariff announcement events (include 2018-2019 and 2025 period). The methodology and variable definitions follow the main analysis. Cumulative abnormal returns (CARs) are computed over two windows: [-1,+1] (three-day window) and [-1,+3] (five-day window), expressed in percentage points. Results are presented separately for the full sample, privately owned enterprises (POEs), and state-owned enterprises (SOEs). Panel A presents portfolio-level analysis of abnormal returns. Firms are sorted into portfolios based on their tariff specific geopolitical risk (GPR) exposure. "Low GPR risk" and "High GPR risk" correspond to the tariff specific GPR dummy variable taking the value of 0 and 1, respectively. "High-Low (diff)" represents the return spread between the high and low GPR portfolios. The t-test reports cluster-robust p-values (in brackets) for the High-Low spread, with standard errors clustered by event date to account for cross-sectional correlation across firms within the same event. Panel B reports coefficient estimates from pooled cross-sectional regressions of CARs on an indicator for high GPR risk. Two specifications are presented: (1) "GPR only" includes only the high GPR risk indicator, and (2) "GPR + controls + Event FE" adds firm-level controls and event fixed effects. Control variables include firm size, firm age, return on assets (ROA), leverage and BM ratio (all lagged one period). Standard errors (reported in parentheses below coefficient estimates) are clustered at the firm level. This stacked design, which pools observations across multiple event dates, serves as a robustness check complementing the main table by increasing statistical power and reducing event-specific idiosyncrasies. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Table 11: Corporate Fundamental and Geopolitical Pressure

	Dependent Var: Corporate Fundamentals								
	$\Delta ln(Sales)_{i,t}$			$Invest_Ratio_{i,t+1}$			$D(Debt_Issuance > 0)_{i,t+1}$		
	(1) Full	(2) POE	(3) SOE	(4) Full	(5) POE	(6) SOE	(7) Full	(8) POE	(9) SOE
$Treat_i \times After_t$	-0.0511**	-0.0834***	-0.0094	-0.0067*	-0.0114**	-0.0006	-0.0536*	-0.0893*	-0.0205
	(0.0228)	(0.0317)	(0.0325)	(0.0039)	(0.0054)	(0.0062)	(0.0316)	(0.0519)	(0.0255)
$Size_{i,t-1}$	0.0048	0.0192**	0.0047	0.0021**	0.0036**	0.0011	0.0265***	0.0387***	0.0289***
	(0.0047)	(0.0080)	(0.0065)	(0.0010)	(0.0015)	(0.0014)	(0.0065)	(0.0101)	(0.0106)
$FirmAge_{i,t-1}$	-0.0032***	-0.0074***	0.0006	-0.0011***	-0.0013***	-0.0003	-0.0032**	-0.0031	-0.0008
	(0.0008)	(0.0014)	(0.0011)	(0.0002)	(0.0003)	(0.0002)	(0.0012)	(0.0021)	(0.0020)
$ROA_{i,t-1}$	0.2821***	0.2938**	-0.2970	0.0899***	0.0755***	0.0943***	0.1290	-0.0414	0.2249
	(0.1080)	(0.1200)	(0.2452)	(0.0117)	(0.0147)	(0.0247)	(0.1148)	(0.1367)	(0.2009)
$Leverage_{i,t-1}$	-0.0386	-0.0571	-0.1041**	0.0122**	0.0207***	-0.0010	0.4371***	0.4462***	0.4727***
	(0.0339)	(0.0499)	(0.0491)	(0.0057)	(0.0073)	(0.0096)	(0.0499)	(0.0692)	(0.0838)
$TobinQ_{i,t-1}$	0.0182***	0.0126**	0.0283***	0.0009	0.0020***	-0.0008	-0.0183***	-0.0257***	-0.0048
	(0.0043)	(0.0052)	(0.0079)	(0.0006)	(0.0008)	(0.0010)	(0.0062)	(0.0073)	(0.0135)
$Cash_Ratio_{i,t-1}$	0.0056	0.0164	0.0373	-0.0268***	-0.0197**	-0.0283**	-0.5246***	-0.4414***	-0.4333***
	(0.0355)	(0.0486)	(0.0593)	(0.0062)	(0.0078)	(0.0110)	(0.0714)	(0.0872)	(0.1369)
$Inventory_Ratio_{i,t-1}$	0.1694***	0.2479***	0.1280	-0.0483***	-0.0468***	-0.0537***	0.0770	0.1235	0.0246
	(0.0543)	(0.0741)	(0.0863)	(0.0099)	(0.0137)	(0.0148)	(0.0855)	(0.1047)	(0.1590)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0501	0.0687	0.0556	0.1740	0.2060	0.2342	0.1782	0.1750	0.2430
N	6436	3791	2237	6416	3778	2233	6416	3778	2233

Notes: This table reports difference-in-differences estimates of the effect of treatment on firm-level sales, investment, and debt issuance. The dependent variables are $\Delta ln(Sales)_{i,t}$ in columns (1)–(3), $Invest_Ratio_{i,t+1}$ in columns (4)–(6), and $D(Debt_Issuance > 0)_{i,t+1}$ in columns (7)–(9). Regressions are estimated for the full sample and separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The variable of interest is $Treat_i \times After_t$, where $Treat_i$ equals 1 for the treatment group (the firm's tariff-specific GPR exposure exceeds 0 in the pre-shock baseline year 2017), and $After_t$ equals 1 for the post-treatment period (the event year 2018 and the subsequent three years). All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Portfolio-Level Evidence on Cost of Capital

	Full Sample			POE Only			SOE Only		
	Low	High	H-L	Low	High	H-L	Low	High	H-L
Excess Return	-1.11	1.46	2.57*	-1.07	1.60	2.67**	-0.58	1.47	2.05
	(-0.18)	(0.24)	(1.93)	(-0.16)	(0.24)	(2.25)	(-0.10)	(0.25)	(1.04)
CAPM Alpha	0.49	3.11	2.62**	0.60	3.27	2.67**	0.93	3.07	2.14
	(0.11)	(0.76)	(2.01)	(0.11)	(0.64)	(2.25)	(0.23)	(0.87)	(1.11)

Notes: This table reports portfolio-level returns for firms sorted on tariff-specific geopolitical risk (GPR). "Low" and "High" correspond to the GPR dummy taking values of 0 and 1, respectively; "H-L" is the return spread between the high and low portfolios. *Excess Return* is the portfolio return in excess of the risk-free rate; *CAPM Alpha* is the intercept from regressing portfolio excess returns on the market excess return. Both are reported in annualized percentage points ($\times 1200$). t-statistics (in parentheses) are based on Newey-West standard errors. Results are reported separately for the full sample, privately owned enterprises (POEs), and state-owned enterprises (SOEs). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Fama-MacBeth Cross-Sectional Regressions

	Dependent Variable: $Stock_Return_{t+1}$		
	Full Sample	POE Only	SOE Only
$GPR_{i,t}$	0.1804**	0.1889**	0.1015
	(2.33)	(2.03)	(0.73)
$Beta_{i,t}$	-0.1538	-0.1012	-0.2549
	(-1.08)	(-0.67)	(-1.51)
$MarketValue_{i,t}$	-0.1902	-0.2693	-0.1063
	(-0.69)	(-0.78)	(-0.50)
$BM_{i,t}$	0.3115	0.2334	0.1507
	(0.70)	(0.53)	(0.31)
$MOM_{i,t}$	0.1223	0.2270	-0.0672
	(0.45)	(0.90)	(-0.20)
$Reversal_{i,t}$	-1.2869*	-1.0138	-1.8846**
	(-1.67)	(-1.43)	(-2.21)
$Illiquidity_{i,t}$	0.0010***	0.0009**	0.0014***
	(3.13)	(2.54)	(3.28)
$R\&D/Asset_{i,t}$	11.8967*	12.4638*	14.9661
	(1.84)	(1.91)	(1.59)
$FirmAge_{i,t}$	-0.0987	-0.1073	0.0135
	(-0.91)	(-0.96)	(0.19)
$Subsidy_{i,t}$	3.7968**	5.0058*	1.3548
	(1.98)	(1.93)	(0.82)
$TobinQ_{i,t}$	-0.0698*	-0.0789*	-0.0626
	(-1.93)	(-1.81)	(-1.44)
Constant	4.5676	6.3929	2.5618
	(0.70)	(0.80)	(0.51)
R^2	0.0800	0.0733	0.0942
Observations	295,606	188,258	107,348

Notes: This table reports Fama-MacBeth (1973) cross-sectional regressions of one-month-ahead stock returns on firm characteristics. The dependent variable is $Stock_Return_{t+1}$, the stock return in month $t+1$ in percentage points ($\times 100$). Coefficients represent the time-series average of monthly cross-sectional regression coefficients; t-statistics (in parentheses) are based on Newey-West standard errors. The independent variables are tariff-specific geopolitical risk (GPR), market beta ($Beta$), market value (log of market capitalization), book-to-market ratio (BM), momentum (MOM), short-term reversal ($Reversal$), Amihud illiquidity ($Illiquidity$), R&D intensity ($R\&D/Asset$), firm age ($FirmAge$), government subsidy intensity ($Subsidy$), and Tobin's Q ($TobinQ$). Regressions are estimated separately for the full sample, privately owned enterprises (POEs), and state-owned enterprises (SOEs). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 14: The Price of Risk of GPR Shocks

	POE Only	
	CAPM	2-Factor
b_{MKT}	0.032	-0.129
	(0.02)	(-0.08)
b_{GPR}		-1.091*
		(-1.85)
R^2 (%)	0.00	43.71
MAE (%)	3.16	2.27

Notes: This table reports the GMM asset pricing tests of the following two-factor model $E[r^e_{i,t}] = \alpha_i + b_{MKT}\,\mathrm{Cov}(MKT_t, r^e_{i,t}) + b_{GPR}\,\mathrm{Cov}(GPR_t, r^e_{i,t})$, in which MKT is the market factor, and GPR is the geopolitical risk shock (the CAPM model is the restricted case in which $b_{GPR} = 0$). b_{MKT} denotes the price of risk of the market factor, and b_{GPR} denotes the price of risk of the tariff-specific geopolitical risk shock. The GPR factor is the same aggregate US–China geopolitical risk shock used in our continuous difference-in-differences analysis of firm imports, here aggregated at the quarterly (rather than annual) frequency. We use the (demeaned) level of the quarterly series as the factor. The factor is standardized to zero mean and unit variance, so that b_{GPR} is the price of risk per one-standard-deviation shock. The test assets are the GPR-by-size and GPR-by-book-to-market double-sorted portfolios, 12 portfolios formed by independently double-sorting privately owned enterprises (POEs) on their GPR exposure (low/high) and the respective firm characteristic (three groups). Results are reported for privately owned enterprises (POEs). MAE denotes the mean absolute error of the pricing errors. All portfolio returns are quarterly excess returns; quarterly returns are obtained by compounding the underlying monthly returns within each quarter. The MAE is annualized and expressed in percent by multiplying the quarterly pricing errors by 400. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey–West with 4 lags). R^2 is the unadjusted regression R-squared. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

A Micro-Foundation for Import Learning

This appendix provides a micro-foundation for the *import learning channel*: the productivity function $A(\omega_H)$ and the product innovation function $\phi_H(\omega_H)$ used in Section 2.2.2. We show that both arise from a single mechanism—AI import learning that raises product appeal—within a multi-product firm model extending Bernard et al. (2010) and Melitz and Redding (2014), following the approach in Babina et al. (2024). The domestic AI innovation channel $\phi_O(\omega_O)$ is modeled in reduced form in the main text and is not micro-founded here; it captures indigenous AI capabilities (e.g., state-sponsored programs, domestic chip architectures) that operate through a parallel but distinct mechanism.

A.1 Multi-Product Firm Environment

Consider a continuum of products $i \in [0, 1]$, with the representative consumer's preferences taking the CES form:

$$U = \left[\int_0^1 (a_i \, C_i)^{(\nu-1)/\nu} \, di \right]^{\nu/(\nu-1)}, \quad \nu > 1$$

where C_i is consumption of product i and a_i captures the relative importance of product i. For each product i, there is a set of horizontally differentiated varieties produced by different firms, with preferences across varieties also taking the CES form:

$$C_i = \left[\int_{f \in F_i} (\lambda_{i,f} \, c_{i,f})^{(\sigma-1)/\sigma} \, df \right]^{\sigma/(\sigma-1)}, \quad \sigma > \nu > 1$$

where $\lambda_{i,f}$ determines the product appeal (demand) for firm f's variety of product i, and F_i is the set of all firms producing varieties of product i.

Each firm draws product-specific productivity $\varphi_{i,f}$ and product appeal $\lambda_{i,f}$. Under monopolistic competition, the equilibrium price for each variety is a constant markup over marginal cost:

$$p_{i,f} = \frac{\sigma}{\sigma - 1} \frac{w}{\varphi_{i,f}}$$

Firm profits from product i are:

$$\pi_{i,f}(\varphi_{i,f}, \lambda_{i,f}) = \frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} \, R_i \left(\frac{\varphi_{i,f} \, \lambda_{i,f} \, P_i}{w} \right)^{\sigma-1} - w \, M_i$$

where R_i is an index of market demand, P_i is the product-level price index, and M_i is a fixed cost per product. A firm produces product i if and only if $\pi_{i,f} > 0$, and the set of actively

produced products is $\Phi_f = \{i : \pi_{i,f} > 0\}$.

A.2 AI Import Learning and Product Appeal

When a firm increases its U.S.-origin high-tech input share ω_f, it sources AI-embedded intermediate goods that generate learning spillovers. Through this AI import learning, a fraction ω_f of all products are randomly drawn to receive an upgrade: the firm's existing product appeal $\lambda_{i,f}$ is multiplied by $\kappa > 1$:

$$\lambda'_{i,f} = \kappa\, \lambda_{i,f}, \quad \text{with probability } \omega_f$$

The multiplier κ captures the learning channel: by using AI-powered inputs in production, the firm learns to apply AI capabilities to enhance its own products—improving quality, enabling customization, or adding AI-powered features. This is the central mechanism through which AI import learning simultaneously drives both productivity and product innovation.

A.3 Derivation of $\phi(\omega_f)$: Product Innovation

Product innovation is the expected expansion of the firm's product scope:

$$\phi(\omega_f) \equiv \mathbb{E}\left[|\Phi'_f| - |\Phi_f|\right] = \omega_f \cdot \Pr\Big(\pi_{i,f}(\varphi_{i,f}, \kappa\, \lambda_{i,f}) > 0 \;\Big|\; \pi_{i,f}(\varphi_{i,f}, \lambda_{i,f}) \leq 0\Big)$$

This function satisfies the key properties assumed in Section 2.2.2:

- $\phi(0) = 0$: without AI imports, no products receive the appeal upgrade and no new products are introduced.
- $\phi'(\omega_f) > 0$: a higher U.S.-origin high-tech input share means more products are drawn for the appeal upgrade, increasing the expected number of new product introductions.

In the basic formulation with independent random draws, ϕ is linear in ω_f (i.e., $\phi'' = 0$). The weak concavity $\phi'' \leq 0$ assumed in the main text can be obtained by enriching the model: (i) draws without replacement, so that later draws are less likely to reach products near the profitability threshold; (ii) decreasing returns to managing a larger product portfolio; or (iii) the appeal multiplier κ itself decreasing in ω_f, reflecting absorptive capacity constraints in AI adoption. The linear case is a special case that delivers all the comparative statics in the main text.

More broadly, $\phi(\omega_f)$ can also include improvements in the appeal of existing products (the intensive margin), capturing total AI innovation as a function of the U.S.-origin high-tech input share.

A.4 Derivation of $A(\omega_f)$: Measured Productivity

We now show that the same AI import learning mechanism that generates $\phi(\omega_f)$ also generates an aggregate productivity function $A(\omega_f)$ that is increasing in ω_f, as assumed in the main text.

The firm's total profit across all actively produced products (before fixed headquarters costs) is:

$$\Pi_f = \int_{i \in \Phi'_f} \pi_{i,f}(\varphi_{i,f}, \lambda'_{i,f})\, di$$
$$= \int_{i \in \Phi'_f} \left[\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} R_i \left(\frac{\varphi_{i,f}\, \lambda'_{i,f}\, P_i}{w} \right)^{\sigma-1} - w M_i \right] di$$

where Φ'_f is the product set after AI import learning and $\lambda'_{i,f}$ is the (potentially upgraded) product appeal.

AI import learning raises total profit through two channels:

Intensive margin. For products already in Φ_f, the appeal upgrade from $\lambda_{i,f}$ to $\kappa\lambda_{i,f}$ increases the variable profit component by a factor of $\kappa^{\sigma-1} > 1$. In expectation, a fraction ω_f of existing products receive this upgrade.

Extensive margin. New products enter Φ'_f (those for which $\pi_{i,f}(\varphi_{i,f}, \kappa\lambda_{i,f}) > 0$ but $\pi_{i,f}(\varphi_{i,f}, \lambda_{i,f}) \leq 0$), each contributing positive profit. The expected number of new products is $\phi(\omega_f)$.

Measured productivity in the AK framework is total output per unit of capital, $A = Y_f/K_f$. Since total profit is increasing in ω_H through both margins, and output is monotonically related to profit in the CES framework (higher product appeal raises both revenue and profit), measured productivity $A(\omega_H)$ is increasing in ω_H. The concavity of A in ω_H arises from the same absorptive capacity constraints that generate the concavity of ϕ_H: diminishing returns to AI adoption, coordination costs of managing a larger product portfolio, and the exhaustion of easy-to-exploit AI applications.

Thus, both $A(\omega_H)$ and $\phi_H(\omega_H)$ are increasing and (weakly) concave in ω_H, and both arise from the same micro-level mechanism—AI import learning that raises product appeal $\lambda_{i,f}$.

The micro-foundation motivates the monotonicity and concavity properties of the import learning component. The main text specifies the full productivity function as $A(\omega_H, \omega_O) = \underline{A} + \theta\omega_H - \frac{\delta}{2}\omega_H^2 + \mu\omega_O - \frac{\zeta}{2}\omega_O^2$: the first two terms correspond to the import learning channel micro-founded here, while the domestic component $\mu\omega_O - \frac{\zeta}{2}\omega_O^2$ is introduced in reduced form to capture indigenous AI capabilities that operate through a parallel mechanism.

B Proofs

B.1 Proof of Proposition 1

Proof. Recall the optimal interior solutions from equations (5)–(6):

$$\omega_H^{*j} = \frac{\theta - (1+r^j)\,\kappa(\tau,\eta_f)\,(p_H - p_L)}{\delta}, \qquad \omega_O^{*j} = \frac{\mu - (1+r^j)\,(p_O - \kappa(\tau,\eta_f)\,p_L)}{\zeta}$$

Since $\kappa(\tau,\eta_f) = 1+\eta_f\tau$, we have $\partial\kappa/\partial\tau = \eta_f$. Differentiating ω_H^{*j} with respect to τ:

$$\frac{\partial\omega_H^{*j}}{\partial\tau} = -\frac{(1+r^j)\,\eta_f\,(p_H - p_L)}{\delta} < 0$$

The numerator is unambiguously negative: all terms are positive. The economic content is that a rise in τ increases the geopolitical cost multiplier κ, which raises the effective price of U.S. high-tech inputs relative to the low-tech alternative. Firms respond by reducing ω_H^*.

For the domestic share, note that $p_O - \kappa p_L$ is decreasing in κ (hence decreasing in τ), so the effective cost of domestic inputs *relative to U.S. low-tech* falls as τ rises. Differentiating:

$$\frac{\partial\omega_O^{*j}}{\partial\tau} = -\frac{(1+r^j)\cdot(-\eta_f p_L)}{\zeta} = +\frac{(1+r^j)\,\eta_f\,p_L}{\zeta} > 0$$

The sign reflects that as U.S. low-tech inputs become more expensive (higher κp_L), domestic inputs become relatively cheaper, inducing substitution from ω_L toward ω_O.

The U.S. low-tech share is residual: $\omega_L^* = 1 - \omega_H^* - \omega_O^*$, so

$$\frac{\partial\omega_L^{*j}}{\partial\tau} = -\frac{\partial\omega_H^{*j}}{\partial\tau} - \frac{\partial\omega_O^{*j}}{\partial\tau} = (1+r^j)\eta_f\left[\frac{p_H - p_L}{\delta} - \frac{p_L}{\zeta}\right]$$

This is negative—meaning ω_L^* also falls—if and only if $\zeta(p_H - p_L) < \delta\,p_L$, which is Assumption 2 (Domestic Substitution Dominance). The condition requires that the domestic absorptive capacity parameter ζ is small enough that the domestic share rises by more than the high-tech share falls, crowding out U.S. low-tech inputs. All expressions for $\partial/\partial\eta_f$ are analogous, with τ replacing η_f in the role of the shock variable. □

B.2 Proof of Proposition 2

Proof. From Proposition 1, each comparative static is proportional to $(1 + r^j)$:

$$\frac{\partial \omega_H^{*j}}{\partial \tau} = -\frac{(1 + r^j)\,\eta_f\,(p_H - p_L)}{\delta}, \qquad \frac{\partial \omega_O^{*j}}{\partial \tau} = +\frac{(1 + r^j)\,\eta_f\,p_L}{\zeta}$$

Since $r^{POE} > r^{SOE}$ by the financing friction specification $r^j = \bar{r} + \xi^j$ with $\xi^{POE} > \xi^{SOE}$, we have $1 + r^{POE} > 1 + r^{SOE}$, and therefore:

$$\left|\frac{\partial \omega_H^{*POE}}{\partial \tau}\right| > \left|\frac{\partial \omega_H^{*SOE}}{\partial \tau}\right|, \qquad \frac{\partial \omega_O^{*POE}}{\partial \tau} > \frac{\partial \omega_O^{*SOE}}{\partial \tau}$$

The economic mechanism is that POEs face a higher effective cost of financing input purchases. When geopolitical risk raises U.S. input prices, the financing-cost amplification—through the $(1 + r^j)$ multiplier in the first-order condition—is stronger for POEs, causing them to reallocate more aggressively away from U.S. inputs.

For U.S. low-tech imports: $\partial \omega_L^{*j}/\partial \tau = -\partial \omega_H^{*j}/\partial \tau - \partial \omega_O^{*j}/\partial \tau$. Both $|\partial \omega_H^{*j}/\partial \tau|$ and $\partial \omega_O^{*j}/\partial \tau$ are larger for POEs, and under Assumption 2 the net effect on ω_L^* is negative for both types. Since the positive term (from $\partial \omega_H^*/\partial \tau$) and the negative term (from $\partial \omega_O^*/\partial \tau$) are both amplified proportionally by $(1+r^j)$, the overall magnitude $|\partial \omega_L^{*j}/\partial \tau|$ is also larger for POEs.

The structural DID cross-partials follow by differentiating the τ-derivatives with respect to η_f:

$$\frac{\partial^2 \omega_H^{*j}}{\partial \eta_f \partial \tau} = -\frac{(1 + r^j)(p_H - p_L)}{\delta} < 0, \qquad \frac{\partial^2 \omega_O^{*j}}{\partial \eta_f \partial \tau} = +\frac{(1 + r^j)p_L}{\zeta} > 0$$

These are the structural analogs of the $\text{Exposure}_i \times \text{Shock}_t$ coefficients in the empirical difference-in-differences design. Both cross-partials are larger in magnitude for POEs, predicting that the interaction effect of firm-level geopolitical exposure and aggregate geopolitical shocks is amplified by financial frictions. □

B.3 Proof of Proposition 3

Proof. The value decline per unit of τ for each U.S. input margin is obtained by multiplying the absolute share derivative by the corresponding price. From Proposition 1, $\partial \omega_H^*/\partial \tau < 0$

and, under Assumption 2, $\partial\omega_L^*/\partial\tau < 0$. The absolute values are:

$$\text{High-tech value decline:} \quad p_H \cdot \left|\frac{\partial\omega_H^*}{\partial\tau}\right| = \frac{(1+r^j)\eta_f\, p_H(p_H - p_L)}{\delta}$$

$$\text{Low-tech value decline:} \quad p_L \cdot \left|\frac{\partial\omega_L^*}{\partial\tau}\right| = (1+r^j)\eta_f\, p_L\left[\frac{p_L}{\zeta} - \frac{p_H - p_L}{\delta}\right]$$

The low-tech expression is positive under Assumption 2, which ensures $p_L/\zeta > (p_H - p_L)/\delta$. Cancelling the common factor $(1+r^j)\eta_f > 0$, the high-tech value decline exceeds the low-tech value decline if and only if:

$$\frac{p_H(p_H - p_L)}{\delta} > p_L\left[\frac{p_L}{\zeta} - \frac{p_H - p_L}{\delta}\right] = \frac{p_L^2}{\zeta} - \frac{p_L(p_H - p_L)}{\delta}$$

Rearranging: $(p_H + p_L)(p_H - p_L)/\delta > p_L^2/\zeta$, which gives $\zeta(p_H^2 - p_L^2) > \delta\, p_L^2$.

The proposition compares base-price import-value margins $p_H\omega_H^*$ and $p_L\omega_L^*$, corresponding to input share reallocations weighted by pre-shock prices. This is the appropriate object when the empirical variables are import proportions. Including the geopolitical price multiplier κ would introduce a countervailing price effect: the effective unit cost κp_k rises with τ, so dollar import values can increase even as input shares fall. This condition has a natural interpretation. The left-hand side, $\zeta(p_H^2 - p_L^2)$, is increasing in ζ (the domestic absorptive capacity parameter) and in the price gap $p_H^2 - p_L^2$ (reflecting the cost premium of high-tech inputs). The right-hand side, δp_L^2, is increasing in δ (the import learning absorptive capacity) and in p_L (the baseline cost of low-tech inputs). The condition holds when high-tech inputs carry a sufficiently large cost premium relative to the parameters governing diminishing returns in both channels. Importantly, the condition is purely a function of structural parameters—it does not depend on τ, η_f, or r^j, so it applies uniformly across all firms and geopolitical risk realizations. □

B.4 Proof of Proposition 4

Proof. **Part 1: Innovation response to τ.** Total AI innovation is $\text{Innovation}_f = \phi_H(\omega_H^*) + \phi_O(\omega_O^*)$. By the chain rule:

$$\frac{\partial\phi_H}{\partial\tau} = \phi'_H(\omega_H^*)\cdot\frac{\partial\omega_H^*}{\partial\tau} < 0, \qquad \frac{\partial\phi_O}{\partial\tau} = \phi'_O(\omega_O^*)\cdot\frac{\partial\omega_O^*}{\partial\tau} > 0$$

The first term captures the destruction of AI import learning as ω_H^* falls; the second captures the domestic innovation offset as ω_O^* rises. Substituting the derivatives from Proposition 1

and factoring $(1 + r^j)\eta_f$:

$$\frac{\partial \,\text{Innovation}_f^j}{\partial \tau} = (1 + r^j)\eta_f \left[\frac{\phi'_O(\omega_O^{*j})\, p_L}{\zeta} - \frac{\phi'_H(\omega_H^{*j})\,(p_H - p_L)}{\delta} \right]$$

Total innovation falls if and only if the import learning destruction exceeds the domestic substitution gain, which is the Import Learning Dominance condition (10). This condition is more likely to hold when frontier AI capabilities embedded in U.S. high-tech are highly productive (ϕ'_H large), hard to replicate domestically (ϕ'_O small), and when the high-tech cost premium $p_H - p_L$ is large relative to the low-tech cost p_L.

Part 2: POE innovation decline is larger (sufficient condition). Write the net innovation decline as $(1 + r^j)\eta_f \cdot \Delta^j$, where

$$\Delta^j \equiv \frac{\phi'_H(\omega_H^{*j})(p_H - p_L)}{\delta} - \frac{\phi'_O(\omega_O^{*j})p_L}{\zeta} > 0$$

under Import Learning Dominance. The POE decline exceeds the SOE decline if $(1 + r^{POE})\Delta^{POE} > (1 + r^{SOE})\Delta^{SOE}$. Since $1 + r^{POE} > 1 + r^{SOE}$, a sufficient condition is $\Delta^{POE} \geq \Delta^{SOE}$.

To express this in primitives, we use the mean value theorem. Since $r^{POE} > r^{SOE}$, the optimal shares satisfy $\omega_H^{*POE} < \omega_H^{*SOE}$ and $\omega_O^{*POE} < \omega_O^{*SOE}$. Specifically:

$$\omega_H^{*SOE} - \omega_H^{*POE} = \frac{(r^{POE} - r^{SOE})\,\kappa(p_H - p_L)}{\delta} > 0$$

$$\omega_O^{*SOE} - \omega_O^{*POE} = \frac{(r^{POE} - r^{SOE})\,(p_O - \kappa p_L)}{\zeta} > 0$$

By the mean value theorem applied to ϕ'_H and ϕ'_O:

$$\phi'_H(\omega_H^{*POE}) - \phi'_H(\omega_H^{*SOE}) = \phi''_H(\xi_H)\,(\omega_H^{*POE} - \omega_H^{*SOE}) = -\phi''_H(\xi_H)\,\frac{(r^{POE} - r^{SOE})\,\kappa(p_H - p_L)}{\delta}$$

$$\phi'_O(\omega_O^{*POE}) - \phi'_O(\omega_O^{*SOE}) = \phi''_O(\xi_O)\,(\omega_O^{*POE} - \omega_O^{*SOE}) = -\phi''_O(\xi_O)\,\frac{(r^{POE} - r^{SOE})\,(p_O - \kappa p_L)}{\zeta}$$

for some $\xi_H \in (\omega_H^{*POE}, \omega_H^{*SOE})$ and $\xi_O \in (\omega_O^{*POE}, \omega_O^{*SOE})$. Since $\phi''_H \leq 0$ and $\phi''_O \leq 0$, the first difference is non-negative (POEs are on a steeper part of the import learning curve) and the second is also non-negative (POEs are on a steeper part of the domestic innovation curve).

Assembling the dominance margin difference:

$$\Delta^{POE} - \Delta^{SOE} = \frac{[\phi'_H(\omega_H^{*POE}) - \phi'_H(\omega_H^{*SOE})](p_H - p_L)}{\delta} - \frac{[\phi'_O(\omega_O^{*POE}) - \phi'_O(\omega_O^{*SOE})]p_L}{\zeta}$$
$$= (r^{POE} - r^{SOE}) \left[\frac{|\phi''_H(\xi_H)|\, \kappa(p_H - p_L)^2}{\delta^2} - \frac{|\phi''_O(\xi_O)|\, (p_O - \kappa p_L)\, p_L}{\zeta^2} \right]$$

Since $r^{POE} > r^{SOE}$, the sign of $\Delta^{POE} - \Delta^{SOE}$ is determined by the bracketed expression. Condition (11) ensures the bracket is non-negative, giving $\Delta^{POE} \geq \Delta^{SOE}$ and hence a strictly larger POE innovation decline.

The economic content of condition (11) is that the concavity of import learning ($|\phi''_H|$), weighted by the squared high-tech cost sensitivity $\kappa(p_H - p_L)^2/\delta^2$, must dominate the concavity of domestic innovation ($|\phi''_O|$), weighted by the domestic cost sensitivity $(p_O - \kappa p_L)p_L/\zeta^2$. When this holds, the fact that POEs operate at lower ω_H^* (and hence face a steeper marginal import learning loss) more than compensates for the fact that they also operate at lower ω_O^* (and hence gain a steeper marginal domestic innovation offset). □

B.5 Proof of Proposition 5

Proof. **Part 1: Geopolitical risk is priced.** From Section 2.3.1, aggregate consumption $C_1(\tau)$ is strictly decreasing in τ, which implies the SDF $M = \beta(C_1/C_0)^{-\gamma}$ is strictly increasing in τ (high-τ states are high-marginal-utility states). For any firm with $\eta_f > 0$, firm-level dividends $D_{1f}^j(\tau)$ are decreasing in τ. Therefore $\text{Cov}(R_f^j, M) < 0$ and the firm's equity earns a positive risk premium:

$$\mathbb{E}[R_f^j] - (1 + r_f) = -\frac{\text{Cov}(R_f^j, M)}{\mathbb{E}[M]} > 0$$

Part 2: POE premium is larger (primitive-parameter condition). Linearize firm-level dividends and the SDF around a benchmark $\bar{\tau}$:

$$D_{1f}^j(\tau) \approx \bar{D}_{1f}^j + D_{\tau f}^j\,(\tau - \bar{\tau}), \qquad M(\tau) \approx \bar{M} + M_\tau\,(\tau - \bar{\tau})$$

where $D_{\tau f}^j = \partial D_{1f}^j/\partial\tau$ and $M_\tau = \partial M/\partial\tau > 0$. By the envelope theorem (holding ω_H^{*j} and ω_O^{*j} fixed at their $\bar{\tau}$-optimal values):

$$D_{\tau f}^j = -(1 + r^j)\,\eta \left[(p_H - p_L)\omega_H^{*j}(\bar{\tau}) + p_L(1 - \omega_O^{*j}(\bar{\tau}))\right] K \equiv -S^j\,\eta\,K < 0$$

where $S^j \equiv (1+r^j)\big[(p_H - p_L)\omega_H^{*j} + p_L(1-\omega_O^{*j})\big]$ is the dividend sensitivity to geopolitical risk. The POE premium is larger if $S^{POE} > S^{SOE}$.

To express $S^{POE} - S^{SOE}$ in primitive parameters, substitute the closed-form solutions (5)–(6). The input-bundle exposure for type j can be written as $B^j \equiv (p_H - p_L)\omega_H^{*j} + p_L(1-\omega_O^{*j}) = \mathcal{A} + (1+r^j)\mathcal{B}$, where

$$\mathcal{A} \equiv \frac{\theta(p_H - p_L)}{\delta} + \frac{p_L(\zeta - \mu)}{\zeta}, \qquad \mathcal{B} \equiv \frac{p_L(p_O - \bar{\kappa}\, p_L)}{\zeta} - \frac{\bar{\kappa}(p_H - p_L)^2}{\delta}$$

are functions of primitive parameters only (evaluated at $\bar{\kappa} = \kappa(\bar{\tau}, \eta)$). Then $S^j = (1+r^j)B^j = (1+r^j)\mathcal{A} + (1+r^j)^2\mathcal{B}$, and:

$$S^{POE} - S^{SOE} = (r^{POE} - r^{SOE})\big[\mathcal{A} + (2 + r^{SOE} + r^{POE})\,\mathcal{B}\big]$$

This factorization is exact (not a local approximation). Since $r^{POE} > r^{SOE}$, the sign is determined by $\mathcal{A} + (2 + r^{SOE} + r^{POE})\mathcal{B}$, which is condition (12).

The term $\mathcal{A}$ captures the direct effect of higher $(1+r^j)$ on dividend sensitivity: all else equal, a higher financing-cost multiplier amplifies the firm's exposure to geopolitical input cost increases. The term $\mathcal{B}$ captures the indirect, countervailing effect: higher r^j also reduces ω_H^* and ω_O^* (the firm uses fewer U.S. inputs), which lowers the base exposure. When $\mathcal{B} < 0$—which occurs when the high-tech cost sensitivity $\bar{\kappa}(p_H - p_L)^2/\delta$ dominates the domestic cost offset $p_L(p_O - \bar{\kappa}p_L)/\zeta$—higher borrowing costs partially offset the direct amplification. Condition (12) requires that this offset is not so large as to reverse the ranking.

Under the maintained condition, the local risk premium for type j is proportional to $S^j \cdot \eta\, K \cdot M_\tau \cdot \mathrm{Var}(\tau)/(P_{0f}^j \cdot \mathbb{E}[M])$. Under comparable ex-ante equity prices ($P_{0f}^{POE} \approx P_{0f'}^{SOE}$), the POE premium exceeds the SOE premium. The return differential scales with $\mathrm{Var}(\tau)$ locally because the covariance terms are proportional to $\mathrm{Var}(\tau)$ at first order. □

C LLM Prompt

C.1 Geopolitical Risk Classification

The following prompt was based on the work of Clayton et al. (2025), used to classify firm-level geopolitical risk exposure from MD&A texts. The prompt was administered in Chinese, consistent with the language of the underlying firm disclosure texts. The original Chinese prompt is presented alongside an English translation for reference.

Original (Chinese):

你是一位资深的金融分析专家。请对以下上市公司 MD&A（管理层讨论与分析）文本进行政策风险识别。
核心维度:
1. 关税风险 (Tariffs): 明确提到「关税」、「加征关税」、「进口税」、「反倾销税」等; 或隐含提到由于贸易壁垒导致的出口成本上升、毛利受压等。
2. 制裁风险 (Sanctions): 明确提到「实体清单」、「制裁」等; 或隐含提到由于地缘政治原因导致的特定市场退出、海外资产冻结、合作受限等。
3. 出口管制 (Export Controls): 明确提到「出口管制」、「出口禁令」、「技术封锁」等; 或隐含提到关键零部件（如芯片、核心软件）的供应稳定性受外部行政干预影响等。
4. 地缘经济压力 (Geoeconomic Pressure): 泛指地缘政治波动, 比如关税、制裁、出口管制、投资审查、鼓励本地化生产的补贴、供应链「去中国化」、外资准入审查趋严、海外业务受到非市场因素干扰等。
审计准则:
- 包含隐含提及: 讨论可以是直接的（如直接提到「关税」、「制裁」、「出口管制」）, 也可以是间接的（如「无法向某国销售」、「因制裁退出某市场」、「面临供应链调整压力」等）。
- 实质重于形式: 请重点关注文本中的「风险因素」、「可能面临的风险」、「不确定性」、「可能影响」等章节或表述。识别文本讨论的实质性风险, 忽略由于表格转换产生的乱码数字或无意义符号。
- 注意: 不要将一般市场波动、经济衰退、自然灾害、汇率波动等与上述政策无关的因素视为地缘经济压力。
输出格式: 必须且仅输出包裹在 <JSON> 和 </JSON> 标签内的 JSON 对象, 严格遵循以下模式:

```
{
  ''llm_tariffs_any'': 0/1,
  ''llm_sanctions_any'': 0/1,
  ''llm_export_controls_any'': 0/1,
  ''llm_geoeconomic_any'': 0/1
```

}
字段说明:
- llm_tariffs_any: 1 表示文本中明确或隐含讨论了关税，0 表示没有。 - llm_sanctions_any: 1 表示文本中明确或隐含讨论了制裁，0 表示没有。 - llm_export_controls_any: 1 表示文本中明确或隐含讨论了出口管制，0 表示没有。 - llm_geoeconomic_any: 1 表示文本中讨论了任何形式的地缘经济压力（如上定义），0 表示没有。

Translation (English):

You are a senior financial analysis expert. Please identify policy-related risks in the following MD&A (Management Discussion and Analysis) text of a listed company.
Core Dimensions:
A. Tariff Risk (Tariffs): Explicit mentions of ‘‘tariffs,’’ ‘‘additional tariffs,’’ ‘‘import taxes,’’ ‘‘anti-dumping duties,’’ etc.; or implicit references to rising export costs or compressed margins due to trade barriers.
B. Sanctions Risk (Sanctions): Explicit mentions of ‘‘entity list,’’ ‘‘sanctions,’’ etc.; or implicit references to market exits, frozen overseas assets, or restricted partnerships due to geopolitical reasons.
C. Export Controls (Export Controls): Explicit mentions of ‘‘export controls,’’ ‘‘export bans,’’ ‘‘technology blockades,’’ etc.; or implicit references to supply stability of key components (e.g., chips, core software) being affected by external administrative intervention.
D. Geoeconomic Pressure (Geoeconomic Pressure): Broadly refers to geopolitical disruptions, including tariffs, sanctions, export controls, investment screening, subsidies encouraging localized production, supply chain ‘‘de-Sinicization,’’ tightened foreign investment reviews, or overseas operations disturbed by non-market factors.
Auditing Criteria:
- Include implicit mentions: Discussion may be direct (e.g., explicitly mentioning ‘‘tariffs,’’ ‘‘sanctions,’’ ‘‘export controls’’) or indirect (e.g., ‘‘unable to sell to a certain country,’’ ‘‘exiting a market due to sanctions,’’ ‘‘facing supply chain restructuring pressure’’).
- Substance over form: Focus on sections or expressions such as ‘‘risk factors,’’ ‘‘potential risks,’’ ‘‘uncertainties,’’ and ‘‘possible impacts.’’

```
Identify substantive risks discussed in the text; ignore garbled numbers or
meaningless symbols resulting from table conversion.
- Note: Do not treat general market fluctuations, economic recessions,
natural disasters, exchange rate volatility, or other factors unrelated to
the above policies as geoeconomic pressure.
Output format: Output must consist solely of a JSON object wrapped in <JSON>
and </JSON> tags, strictly following the schema below:
{
  ‘‘llm_tariffs_any’’: 0/1,
  ‘‘llm_sanctions_any’’: 0/1,
  ‘‘llm_export_controls_any’’: 0/1,
  ‘‘llm_geoeconomic_any’’: 0/1
}
Field descriptions:
- llm_tariffs_any: 1 indicates the text explicitly or implicitly discusses
tariffs, 0 otherwise. - llm_sanctions_any: 1 indicates the text explicitly
or implicitly discusses sanctions, 0 otherwise. - llm_export_controls_any:
1 indicates the text explicitly or implicitly discusses export controls, 0
otherwise. - llm_geoeconomic_any: 1 indicates the text discusses any form of
geoeconomic pressure as defined above, 0 otherwise.
```

C.2 Hightech Import Classification

To systematically identify the technological intensity of imported goods, we employ a Large Language Model utilizing a single-step, zero-shot prompting strategy. Unlike the subsequent AI classification, which requires stringent exclusion criteria to prevent misclassification of general-purpose electronics, evaluating the general "high-tech" nature of a product relies on its position within the global value chain. The prompt is designed to output a continuous score from 0.0 to 1.0, reflecting the upstream knowledge intensity and downstream application sophistication of the declared product.

```
You are a specialized technology analyst. Your task is to evaluate the ‘‘R&D
Intensity’’ and ‘‘Technical Complexity’’ of the following product.
Evaluation Ontology (Guiding Principles):
1. High-Tech (0.8 -- 1.0): Cutting-edge scientific products. E.g.,
advanced semiconductors, aerospace systems, biotechnological equipment, AI
hardware, precision robotics, and other frontier technologies.
```

```
2. Intermediate Tech (0.4 -- 0.7): Specialized industrial machinery,
advanced polymers, precision tools, or sophisticated electronic
sub-assemblies, and products of comparable technical sophistication.
3. Low-Tech / Traditional (0.0 -- 0.3): Raw materials, agriculture,
textiles, wood, simple plastic items, and other products with minimal
technological content.
Note: a long or complex product description does NOT imply high
technological complexity. Complexity of text description ≠ complexity of
technology.
Industry Context (HS Chapter):
- The item belongs to the HS chapter corresponding to the declared product's
trade classification. The chapter heading provides sectoral context for
calibrating the score.
Input Data:
- Declared Product: [product description as declared in customs filing]
Task:
Analyze the product's position in the global value chain. Consider its
upstream knowledge intensity, downstream application sophistication, and the
degree to which its production requires proprietary processes or specialized
human capital. Output ONLY a JSON object with the ''score'' key.
{
  ''score'': [0.00 -- 1.00]
}
```

C.3 AI Import Classification

Identifying imports specifically related to Artificial Intelligence (AI) poses a unique challenge: AI hardware components can easily be conflated with general-purpose electronics or standard industrial automation equipment. To mitigate this risk, the prompt for AI import classification adopts a highly specific, three-step sequential reasoning framework. This framework is grounded in the "Key Digital Technology Patent Classification System (2023)" published by the China National Intellectual Property Administration, which we have adapted for physical traded goods. The design of the input and output specifications follows the LLM-based classification approach developed by Waugh (2026). The multi-step methodology mandates a strict exclusion test before assessing specific AI relevance, ensuring a rigorous differentiation between core AI technologies and standard IT infrastructure.

You are an expert in Artificial Intelligence hardware and international trade. Your task is to classify imported products based on their relevance to the AI industry, using the ‘‘Key Digital Technology Patent Classification System (2023)’’ published by the China National Intellectual Property Administration as the authoritative reference, adapted for physical traded goods.
You will be given: - HS Code: [HS code of the imported product] - HS Description: [official HS chapter/heading description] - Specific Product Description: [product description as declared in customs filing] - Importing Firm’s Industry: [industry classification of the importing firm]

Step 1: Mandatory Exclusion Test (Low Relevance)
First, check if the product falls into any of these inherently non-AI categories. If yes, relevance = ‘‘Low’’, confidence $\geq$ 95. The importing firm’s industry does NOT matter for these categories.
Absolutely Low categories: - Chemicals, plastics, raw materials, metal products (tubes, profiles, bars), textiles, food. - Standard industrial machinery (machine tools, pumps, valves, conveyors). - Industrial automation components (PLCs, PID controllers, generic sensors for pressure, temperature, or flow). - Consumer appliances (washing machines, air conditioners, refrigerators). - Standard IT equipment (CPUs, hard disks, generic memory, generic routers, keyboards, mice, monitors). - Vehicles and parts (except dedicated autonomous driving sensors).
If the product is NOT in the above exclusion list, proceed to Step 2.

Step 2: AI-Specific Identification (High Relevance)
Check if the product’s essential function directly matches one of the three core AI technology categories defined by the official classification.
A product is High relevance if its primary purpose is AI computation, AI-specific sensing, or AI-specific interaction as listed below.
1. AI Hardware Platform: GPU, FPGA (for AI acceleration), ASIC (AI), NPU, TPU, neuromorphic chips, AI-specific DSPs/SoCs, high-bandwidth memory (HBM) specifically designed for AI processors.
2. AI General Technology: Dedicated machine learning training/inference servers, deep learning accelerator hardware (e.g., CNN/RNN accelerators), brain-inspired or quantum computing modules for AI, pattern recognition dedicated processors.

3. AI Key Technology Components: - Computer Vision: LiDAR, TOF depth cameras, stereo vision cameras, machine vision image sensors. - Intelligent Speech: Voice recognition microphone arrays, speech synthesis modules, voiceprint recognition chips. - Natural Language Processing: Semantic analysis dedicated hardware, machine translation modules. - Biometric Recognition: Fingerprint, face, iris, voice, DNA scanners/detectors. - AR/VR: Head-mounted displays, smart glasses, augmented/mixed reality devices. - Human--Computer Interaction: Gesture recognition sensors, brain--machine interfaces, haptic devices for AI.
If the product matches any of these subcategories, relevance = ‘‘High’’, confidence $\geq$ 85, primary_category $\in$ {AI_Hardware_Platform, AI_General_Technology, AI_Key_Technology}.

Step 3: Medium Relevance (Bridge Category)
If the product is not excluded in Step 1 but not AI-specific enough for Step 2, it may be Medium. Medium applies to high-performance electronic, optical, or connectivity components commonly used in AI systems but with other high-tech applications. The importing firm's industry serves as supportive evidence here.
Medium if: - The product is a high-end electronic component (e.g., precision analog chips, high-speed ADCs, advanced FPGAs without explicit AI mention, high-density PCBs $\geq$20 layers, high-frequency or low-loss materials for data transmission) AND the importing firm is in a sector clearly related to AI hardware (semiconductors, AI servers, autonomous driving, smart manufacturing). - The product is a precision optical element (e.g., achromatic lens, optical filters, beamsplitters) imported by a firm in machine vision, medical imaging, or instrumentation. - The product is a high-speed connector or cable assembly clearly intended for data centers or high-performance computing, imported by an AI infrastructure firm.
Note: even if the firm is in electronics, a generic capacitor, generic resistor, standard PCB, or standard cable remains Low.
If Medium, confidence is typically 60--75, primary_category $\in$ {High_Performance_Electronics, Optical_Components, Data_Center_Interconnect}.

Output Format:
Output ONLY a valid JSON object with the following keys:
‘‘relevance’’: one of [‘‘High’’, ‘‘Medium’’, ‘‘Low’’]

```
  ‘‘confidence’’: integer 0--100
  ‘‘primary_category’’: one of the categories listed above
  ‘‘specific_use’’: short description, or ‘‘N/A’’
  ‘‘reasoning’’: brief explanation showing how the steps were applied
---
Examples:
Example 1 (Low): HS 845020, industrial washing machine, firm in electrical
machinery. Output: relevance = ‘‘Low’’, confidence = 98, primary_category
= ‘‘Generic_Consumer’’, reasoning: Step 1 Exclusion --- washing machine is a
consumer appliance, not an AI product. Firm industry irrelevant.
Example 2 (High): GPU accelerator card, firm in server manufacturing.
Output: relevance = ‘‘High’’, confidence = 95, primary_category =
‘‘AI_Hardware_Platform’’, specific_use = ‘‘Deep learning training
accelerator’’, reasoning: Step 2 --- GPU matches AI Hardware Platform in
the official classification.
Example 3 (Medium): 24-layer high-density PCB, HS 853400, firm in AI
server manufacturing. Output: relevance = ‘‘Medium’’, confidence = 70,
primary_category = ‘‘High_Performance_Electronics’’, reasoning: Step 1 not
excluded; Step 2 PCB is not AI-specific; Step 3 high layer count and AI
server firm context supports Medium.
Example 4 (Medium): Precision achromatic lens, HS 900190, firm in machine
vision. Output: relevance = ‘‘Medium’’, confidence = 72, primary_category
= ‘‘Optical_Components’’, reasoning: Step 1 not excluded; Step 2 lens is not
AI-specific; Step 3 machine vision firm context supports Medium.
Example 5 (Low): Standard brass capillary tube, HS 741110, firm in
electrical machinery. Output: relevance = ‘‘Low’’, confidence = 90,
primary_category = ‘‘Generic_Metal’’, reasoning: Step 1 Exclusion --- metal
tube is a generic material, not AI.
```

C.4 AI Patent Classification

This subsection documents the rule-based classification system used to identify AI-related patents. Prior to the release of the *Key Digital Technology Patent Classification System (2023)*, identifying AI-related patents was methodologically constrained. Because standard IPC codes do not contain dedicated classes for AI technology, early studies resorted to keyword-based matching against patent abstracts or claims (Yang, 2022). Provincial-level studies alternatively approximated AI innovation through patent counts retrieved via IPC queries in the CNIPA database (Nepal et al., 2025), but without a standardized taxonomy

to anchor the classification.

Our framework draws upon the *Key Digital Technology Patent Classification System (2023)*, formulated and issued by the China National Intellectual Property Administration (CNIPA) on September 18, 2023 (Document No. CNIPA Office Letter Gui Zi [2023] No. 36). This official taxonomy organizes AI patents into three primary branches — hardware platforms, general technologies, and key application technologies — providing a standardized reference that is both authoritative and internationally comparable, given its correspondence with the International Patent Classification (IPC 2022). Following its release, this classification has been operationalized in the literature by combining the official IPC taxonomy with targeted keyword searches (Zhu et al., 2026; Zu et al., 2025), allowing researchers to leverage both the structural coverage of the official taxonomy and the semantic precision of textual filtering.

We adopt this dual-filtering approach. Specifically, a patent is classified as AI-related only if its IPC code matches a prefix in Panel A *and* its title, abstract, or claims contain at least one keyword from Panel B. Requiring both conditions to hold simultaneously reduces false positives that may arise when either criterion is applied in isolation — a common concern when IPC codes are broad or keywords are ambiguous — and ensures that each identified patent reflects genuine AI content as defined by the official classification.

Panel A: IPC Code Prefix Pool

```
G --- Computing, Information, and Control:
  G06N   (Machine learning, neural networks, AI computation)
  G06V   (Image, video, and pattern recognition)
  G06T   (Image data processing and generation)
  G10L   (Speech and audio processing)
  G06Q   (Data processing for administrative and commercial purposes)
  G16B   (Bioinformatics)
  G16C   (Computational chemistry)
  G16H   (Healthcare informatics)
  G05B   (Control systems)
  G05D   (Systems for controlling non-electric variables)
  G01C   (Measuring directions or angles; navigation)
  G01S   (Radio direction-finding; radar; sonar; lidar)
  G08G   (Traffic control systems)
  G06F   (Electric digital data processing)
  G06K   (Graphical data reading and recognition)
```

```
  G11C13   (Digital storage using resistive elements; memristors)
  G02F2   (Optical computing devices)
  G06E1   (Optical computing)


H --- Electronics, Communications, and Semiconductors:
  H01L21, H01L23, H01L25, H01L27, H01L29, H01L33   (Semiconductor devices and
fabrication)
  H03K   (Pulse circuits)
  H05K1, H05K3   (Printed circuits; PCB manufacturing)
  H04B   (Transmission systems)
  H04L   (Transmission of digital information)
  H04N   (Pictorial communication; television)
  H04W   (Wireless communication networks)
  H02J   (Power supply and distribution)


B --- Manufacturing, Robotics, and Autonomous Systems:
  B23P, B23Q   (Precision machining)
  B25J   (Robots and manipulators)
  B60W30, B60W40, B60W50   (Autonomous and intelligent vehicle control)
  B64C, B64D, B64G   (Aircraft, drones, and spacecraft)
  B82Y10   (Nanotechnology for information processing)


A/C --- Biomedical, Interaction, and Recognition:
  A61B5   (Biomedical sensing and brain--computer interfaces)
  A63F13   (Video games)
  A63B71   (Sports and fitness technology)
  G02B27/01   (AR/VR optical systems)
  G07C9   (Access control and biometric recognition)
  G09B5   (Teaching aids)
  G01N33   (Biochemical analysis)
  C07K   (Peptides)
  C12Q   (Measuring or testing processes involving nucleic acids)
```

Panel B: Chinese-Language Keyword Pool

通用与基础类：人工智能、AI、智能系统、智能算法
1. 硬件平台：智能芯片、GPU、FPGA、ASIC、NPU、类脑芯片、神经芯片、神经拟态、忆阻器
2. 通用技术：机器学习、强化学习、深度学习、神经网络、支持向量机、决策树、集成学习、知识图谱、类脑智能、量子算法、模式识别、蚁群算法、粒子群算法
3. 关键技术：
自然语言处理类：自然语言处理、NLP、语义理解、机器翻译
智能语音类：智能语音、语音识别、声纹识别
计算机视觉类：计算机视觉、CV、图像识别、图像生成、图像增强
生物特征识别类：生物特征识别、人脸识别、虹膜识别、动作捕捉
AR/VR 类：增强现实、AR、虚拟现实、VR、混合现实、MR、扩展现实、ER
人机交互类：人机交互、脑机接口

Panel B (Translation): English Equivalents of Chinese Keywords

General and Foundational: artificial intelligence, AI, intelligent system, intelligent algorithm

1. Hardware Platforms: intelligent chip, GPU, FPGA, ASIC, NPU, neuromorphic chip, neural chip, neuromorphic computing, memristor

2. General Technologies: machine learning, reinforcement learning, deep learning, neural network, support vector machine, decision tree, ensemble learning, knowledge graph, brain-inspired intelligence, quantum algorithm, pattern recognition, ant colony algorithm, particle swarm algorithm

3. Key Technologies:
Natural Language Processing: NLP, semantic understanding, machine translation
Intelligent Speech: intelligent speech, speech recognition, voiceprint recognition
Computer Vision: CV, image recognition, image generation, image enhancement
Biometric Recognition: biometric recognition, face recognition, iris recognition, motion capture
AR/VR: augmented reality (AR), virtual reality (VR), mixed reality (MR),

```
extended reality (ER)
  Human--Computer Interaction:  human--computer interaction, brain--computer
interface
```

C.5 Hightech Patent Classification

Unlike AI-related patent identification, which draws on the explicit categorical framework provided by the CNIPA (2023) classification system, no equivalent official taxonomy exists for high-tech patents more broadly. We therefore rely on LLM-based scoring for this classification task. The prompt follows the same evaluative logic as the hightech import classification, adapted for patent texts: the model is provided with the patent title, abstract, and independent claims, and is instructed to assign a continuous score between 0 and 1 reflecting the patent's position in the global technology value chain.

Original (Chinese):

```
你是一位专业的技术评估分析师。你的任务是评估以下专利的「研发强度」与「技术复杂
度」。
评估标准与本体论（指导原则）：
1. 高科技（High-Tech，得分 0.85--1.0）：前沿、突破性的科学技术。例如：先进制程
半导体、航空航天系统、高端生物医药设备、AI 核心算法与底层算力硬件、高精度工业机器
人、尖端新材料等前沿领域。
2. 中等科技（Intermediate Tech，得分 0.4--0.84）：专用的工业机械、进阶的高分子
材料、精密机床加工工具、复杂的电子元器件组装、或者标准的软件系统与商业方法（如常
规 APP、普通信息化系统）等。
3. 低科技/传统（Low-Tech，得分 0.0--0.39）：基础原材料开采加工、农业种植、纺织
品、木材、简单的塑料制品、包装结构、普通日用品、纯外观设计或简单机械结构等传统行
业产品。
极度警告：专利文本描写的字数多、结构长，不代表它就是高科技！使用晦涩的法律或专利
专业术语不等于底层技术复杂。不要被冗长的「权利要求」所误导。
输入专利数据：
- 专利名称：[专利标题] - 专利摘要：[专利摘要文本] - 独立主权项：[独立权利要求文
本]
任务：分析该专利在全球科技价值链中的位置。请且仅请输出一个包含 score 键的 JSON 对
象（分值为 0.0 到 1.0 的浮点数）：
{
  ‘‘score’’:  [0.00 -- 1.00]
}
```

Translation (English):

```
You are a professional technology assessment analyst. Your task is to
evaluate the ‘‘R&D Intensity’’ and ‘‘Technical Complexity’’ of the following
patent.
Evaluation Ontology (Guiding Principles):
1. High-Tech (score 0.85--1.0): Frontier and breakthrough scientific
technologies. E.g., advanced-node semiconductors, aerospace systems,
high-end biomedical equipment, core AI algorithms and underlying computing
hardware, high-precision industrial robots, cutting-edge new materials, and
similar frontier fields.
2. Intermediate Tech (score 0.4--0.84): Specialized industrial machinery,
advanced polymer materials, precision machining tools, complex electronic
component assemblies, or standard software systems and business methods
(e.g., conventional mobile applications, ordinary information systems), and
products of comparable sophistication.
3. Low-Tech / Traditional (score 0.0--0.39): Basic raw material extraction
and processing, agriculture, textiles, timber, simple plastic products,
packaging structures, ordinary consumer goods, pure ornamental designs, or
simple mechanical structures, and other products from traditional industries.
Critical Warning: A patent with a long description and elaborate structure
does NOT imply high-tech content. The use of obscure legal or patent
terminology does not equal underlying technological complexity. Do not be
misled by lengthy claims.
Input Patent Data:
- Patent Title: [title of the patent] - Patent Abstract: [abstract text] -
Independent Claims: [independent claim text]
Task: Analyze the patent’s position in the global technology value chain.
Output ONLY a JSON object containing the ‘‘score’’ key, where the value is a
float between 0.0 and 1.0:
{
  ‘‘score’’: [0.00 -- 1.00]
}
```

D Appendix: Table

Table 15: High-Tech Import Response to General Geopolitical Risk

	Dependent Variable: Innovative Import			
	$Import_{i,t}^{High_Tech}$		$Import_{i,t}^{Low_Tech}$	
	(1) POE	(2) SOE	(3) POE	(4) SOE
$Exposure_i \times Shock_t$	-1.2824**	-1.8581**	-4.4350***	-4.1308**
	(0.6032)	(0.7839)	(1.2620)	(1.7278)
$Size_{i,t-1}$	0.0100	0.0036	-0.0133	-0.0538***
	(0.0080)	(0.0059)	(0.0167)	(0.0148)
$FirmAge_{i,t-1}$	-0.0001	-0.0013	-0.0010	0.0007
	(0.0014)	(0.0012)	(0.0036)	(0.0030)
$ROA_{i,t-1}$	-0.1070	-0.0051	0.1114	0.4321*
	(0.1574)	(0.1093)	(0.2484)	(0.2553)
$Leverage_{i,t-1}$	-0.0560	0.0014	0.0952	0.1386
	(0.0389)	(0.0359)	(0.0895)	(0.1022)
$TobinQ_{i,t-1}$	0.0130*	0.0050	-0.0133	-0.0282**
	(0.0069)	(0.0089)	(0.0099)	(0.0130)
$Cash_Ratio_{i,t-1}$	0.0905**	-0.0019	-0.0064	-0.0330
	(0.0458)	(0.0734)	(0.0849)	(0.1266)
$Inventory_Ratio_{i,t-1}$	0.1100	0.0163	0.1323	0.1275
	(0.0880)	(0.0798)	(0.1909)	(0.2457)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.0701	0.1102	0.2878	0.3254
N	2185	1214	2185	1214

Notes: This table reports continuous difference-in-differences estimates of the effect of geopolitical exposure on firm-level imports of high-tech and low-tech products, separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The dependent variable is $Import_{i,t}^{High_Tech}$ in columns (1)–(2) and $Import_{i,t}^{Low_Tech}$ in columns (3)–(4). The variable of interest is the interaction $Exposure_i \times Shock_t$, where $Exposure_i$ is the firm's pre-shock baseline exposure, measured as its average over 2014–2015 using the general GPR index, and $Shock_t$ is the yearly prevalence index of US-China conflict discussions extracted from US corporate earnings calls. All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous controls are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 16: AI Import Response to General Geopolitical Risk

	Dependent Variable: AI Import			
	$\Delta Import_{i,t}^{High_AI}$		$\Delta Import_{i,t}^{Low_AI}$	
	(1) POE	(2) SOE	(3) POE	(4) SOE
$Exposure_i \times Shock_t$	-2.6654**	-1.9388	-1.8449*	-2.0196*
	(1.2716)	(1.3590)	(1.0713)	(1.0387)
$Size_{i,t-1}$	-0.0021	-0.0016	0.0033	-0.0082
	(0.0054)	(0.0045)	(0.0059)	(0.0062)
$FirmAge_{i,t-1}$	0.0006	-0.0013	0.0016	0.0018
	(0.0010)	(0.0009)	(0.0012)	(0.0011)
$ROA_{i,t-1}$	-0.0085	0.0041	-0.1921	0.3091**
	(0.1082)	(0.1338)	(0.1365)	(0.1375)
$Leverage_{i,t-1}$	0.0076	-0.0048	-0.0205	0.1225**
	(0.0349)	(0.0348)	(0.0335)	(0.0543)
$TobinQ_{i,t-1}$	-0.0012	-0.0059	0.0023	0.0075
	(0.0056)	(0.0041)	(0.0045)	(0.0071)
$Cash_Ratio_{i,t-1}$	-0.0223	-0.0256	0.0518	-0.0029
	(0.0439)	(0.0569)	(0.0331)	(0.0563)
$Inventory_Ratio_{i,t-1}$	-0.0047	0.0471	-0.0312	-0.0508
	(0.0569)	(0.0455)	(0.0653)	(0.0820)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.0296	0.0486	0.0395	0.0779
N	1514	853	1514	853

Notes: This table reports continuous difference-in-differences estimates of the effect of geopolitical exposure on firm-level imports of high-AI and low-AI products, separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The dependent variable is $\Delta Import_{i,t}^{High_AI}$ in columns (1)–(2) and $\Delta Import_{i,t}^{Low_AI}$ in columns (3)–(4). The variable of interest is the interaction $Exposure_i \times Shock_t$, where $Exposure_i$ is the firm's pre-shock baseline exposure, measured as its average over 2014–2015 using the general GPR index, and $Shock_t$ is the yearly prevalence index of US-China conflict discussions extracted from US corporate earnings calls. All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous controls are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 17: Economic Mechanism: High-Tech Innovation in Response to General Geopolitical Risk

	Dependent Variable: High-Tech Innovation					
	$HighTech_Patent^{3\ \text{year}}(ln)$			$HighTech_Patent^{5\ \text{year}}(ln)$		
	(1) Full	(2) POE	(3) SOE	(4) Full	(5) POE	(6) SOE
$Treat_i \times After_t$	-0.1136	-0.1507*	-0.0976	-0.1388*	-0.2390***	-0.0455
	(0.0719)	(0.0856)	(0.1308)	(0.0786)	(0.0903)	(0.1428)
$Size_{i,t-1}$	0.4057***	0.3415***	0.4904***	0.4653***	0.3706***	0.5694***
	(0.0407)	(0.0544)	(0.0671)	(0.0442)	(0.0604)	(0.0722)
$FirmAge_{i,t-1}$	-0.0136***	-0.0112	-0.0234***	-0.0150**	-0.0122	-0.0270***
	(0.0049)	(0.0088)	(0.0073)	(0.0058)	(0.0105)	(0.0086)
$ROA_{i,t-1}$	1.1326***	1.4068***	1.0229	1.4875***	1.8854***	1.3706
	(0.3194)	(0.3645)	(0.7684)	(0.3643)	(0.4175)	(0.8351)
$Lev_{i,t-1}$	-0.4059**	-0.2875	-0.6231*	-0.4543**	-0.3255	-0.6904*
	(0.1779)	(0.1947)	(0.3523)	(0.2065)	(0.2299)	(0.3968)
$TobinQ_{i,t-1}$	0.1463***	0.1578***	0.1407***	0.1650***	0.1725***	0.1701***
	(0.0224)	(0.0285)	(0.0428)	(0.0242)	(0.0304)	(0.0472)
$Cash_Ratio_{i,t-1}$	0.4272**	0.2922	0.2271	0.4898**	0.2802	0.3131
	(0.2019)	(0.2157)	(0.4277)	(0.2345)	(0.2527)	(0.4858)
$Inventory_Ratio_{i,t-1}$	0.6163*	0.5547	0.6651	0.7433*	0.6285	0.7917
	(0.3444)	(0.3909)	(0.6524)	(0.4026)	(0.4602)	(0.7395)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2471	0.2302	0.3339	0.2564	0.2397	0.3556
N	6417	3778	2233	6417	3778	2233

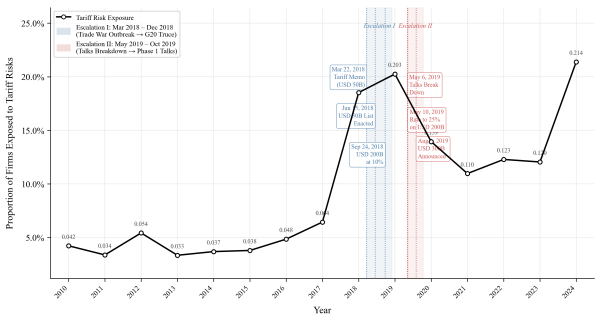
Notes: This table reports difference-in-differences estimates of the effect of treatment on firm-level high-tech patent outcomes. The dependent variable is $HighTech_Patent^{3\ \text{year}}(ln)$ in columns (1)–(3), measuring high-tech patent applications over a three-year horizon, and $HighTech_Patent^{5\ \text{year}}(ln)$ in columns (4)–(6), over a five-year horizon. Regressions are estimated for the full sample and separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The variable of interest is $Treat_i \times After_t$, where $Treat_i$ equals 1 for the treatment group (the firm's general GPR exposure exceeds 0 in the pre-shock baseline year 2017), and $After_t$ equals 1 for the post-treatment period (the event year 2018 and the subsequent three years). All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 18: Economic Mechanism: AI Innovation in Response to General Geopolitical Risk

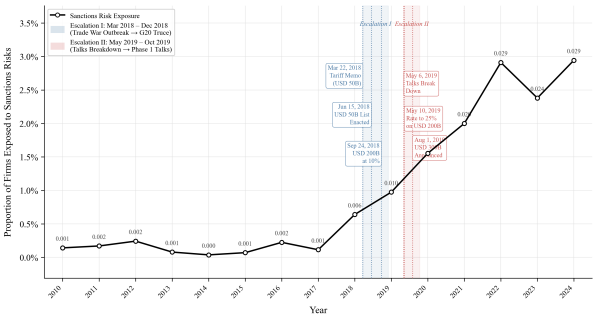
	Dependent Variable: AI Innovation					
	$AI_Patent^{1\ \text{year}}(ln)$			$AI_Patent^{3\ \text{year}}(ln)$		
	(1) Full	(2) POE	(3) SOE	(4) Full	(5) POE	(6) SOE
$Treat_i \times After_t$	-0.0811*	-0.1273*	-0.0183	-0.1443**	-0.2371**	-0.0283
	(0.0487)	(0.0708)	(0.0779)	(0.0728)	(0.1026)	(0.1155)
$Size_{i,t-1}$	0.2266***	0.1839***	0.2980***	0.3245***	0.2614***	0.4233***
	(0.0287)	(0.0377)	(0.0479)	(0.0376)	(0.0508)	(0.0611)
$FirmAge_{i,t-1}$	-0.0058*	-0.0100**	-0.0064	-0.0097**	-0.0198***	-0.0080
	(0.0032)	(0.0049)	(0.0053)	(0.0047)	(0.0075)	(0.0075)
$ROA_{i,t-1}$	0.7617***	0.8193***	0.7855	1.5769***	1.6355***	1.6761**
	(0.2201)	(0.2465)	(0.5442)	(0.3168)	(0.3727)	(0.7166)
$Leverage_{i,t-1}$	-0.2671**	-0.2399**	-0.2442	-0.3199**	-0.2954	-0.3074
	(0.1067)	(0.1158)	(0.2215)	(0.1620)	(0.1912)	(0.3101)
$TobinQ_{i,t-1}$	0.0331***	0.0346**	0.0564*	0.0548***	0.0594***	0.0849**
	(0.0126)	(0.0140)	(0.0314)	(0.0178)	(0.0200)	(0.0426)
$Cash_Ratio_{i,t-1}$	0.3614**	0.2901**	0.2914	0.6560***	0.5675**	0.5668
	(0.1587)	(0.1463)	(0.3723)	(0.2208)	(0.2231)	(0.4770)
$Inventory_Ratio_{i,t-1}$	0.3721*	0.4037*	0.5253	0.4546	0.5900	0.5648
	(0.2210)	(0.2419)	(0.4653)	(0.3226)	(0.3753)	(0.6576)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1912	0.1436	0.2961	0.2322	0.1889	0.3469
N	6436	3791	2237	6436	3791	2237

Notes: This table reports difference-in-differences estimates of the effect of treatment on firm-level AI innovation. The dependent variable is $AI_Patent^{1\ \text{year}}(ln)$ in columns (1)–(3), measuring AI patent applications over a one-year horizon, and $AI_Patent^{3\ \text{year}}(ln)$ in columns (4)–(6), over a three-year horizon. Regressions are estimated for the full sample and separately for privately owned enterprises (POEs) and state-owned enterprises (SOEs). The variable of interest is $Treat_i \times After_t$, where $Treat_i$ equals 1 for the treatment group (the firm's general GPR exposure exceeds 0 in the pre-shock baseline year 2017), and $After_t$ equals 1 for the post-treatment period (the event year 2018 and the subsequent three years). All control variables are lagged one period. Industry and year fixed effects are included in all specifications, and standard errors (in parentheses) are clustered at the firm level. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

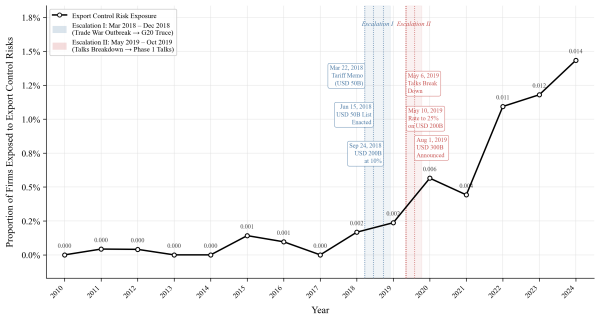
E Appendix: Figures



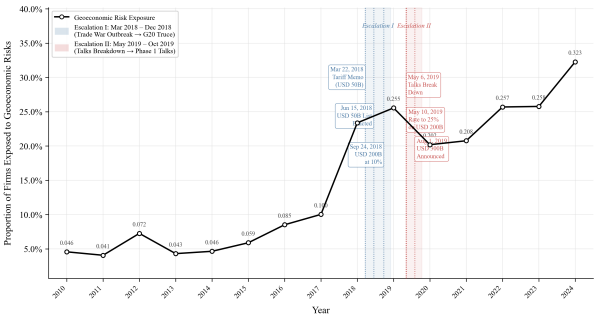
(a) Tariff Exposure



(b) Sanction Exposure



(c) Export Control Exposure



(d) General Geopolitical Risk

Figure 12: **Evolution of Firm-Level Geoeconomic Risk Exposure, 2010–2024.** The figure plots the annual share of A-share listed firms whose MD&A disclosures are classified as exposed to each of four geoeconomic risk dimensions, identified using a large language model (LLM) applied to Chinese-language annual report texts. Panel (a) captures tariff risk, Panel (b) captures sanctions risk, Panel (c) captures export control risk, Panel (d) reports aggregate geoeconomic risk, defined as exposure to any of the three preceding dimensions. Vertical dotted lines mark six key escalation events in the US–China trade war: (1) March 22, 2018—announcement of a tariff memorandum targeting USD 50 billion of Chinese goods; (2) June 15, 2018—formal enactment of the USD 50 billion tariff list; (3) September 24, 2018—imposition of a 10% tariff on USD 200 billion of Chinese goods; (4) May 6, 2019—collapse of the eleventh-round negotiations following China's withdrawal of prior commitments; (5) May 10, 2019—rate increase to 25% on the USD 200 billion list; and (6) August 1, 2019—announcement of additional tariffs on the remaining USD 300 billion of Chinese imports. Two shaded regions demarcate the primary escalation windows identified from the diplomatic timeline: *Escalation I* (blue, March 22 – December 1, 2018) spans the outbreak of the trade war to the G20 Buenos Aires truce; *Escalation II* (red, May 6 – October 11, 2019) spans the breakdown of negotiations to the resumption of high-level talks and the announcement of a Phase 1 framework. The y-axis reports the share of firms in the sample with relevant risk disclosure in a given year.

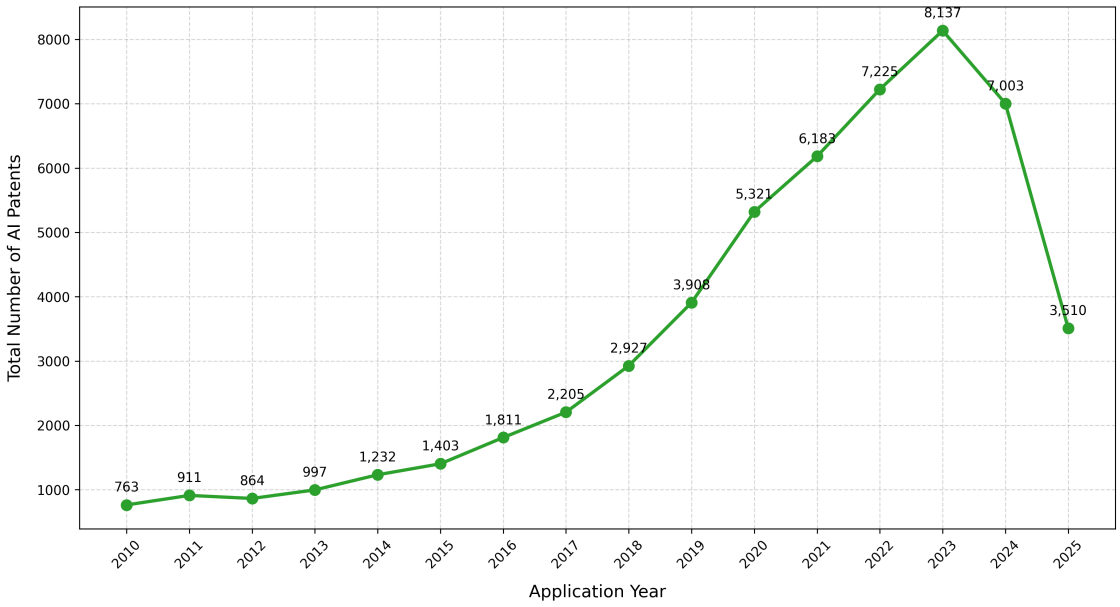


Figure 13: **Annual Trend of AI Patent Applications.** This figure tracks the annual trend of the AI patent applications over the sample from 2010 to 2025.