Trade War and Technology Rivalry*

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Abstract

We develop a trade model with endogenous innovation and trade-facilitated technology diffusion to quantify the impacts of trade wars on global technology rivalry. In the model, trade policy shapes technological progress through (i) knowledge embodied in trade flows and (ii) firms' market size, which determines returns to innovation. We validate the model in the context of US export controls on China and calibrate it to match trade flows and patent citations across major economies. Counterfactual analysis yields three main results. First, U.S. export controls on China reduce technological progress in both countries: China experiences a sharp contraction in knowledge inflows, while the U.S. faces weakened incentives for R&D. Second, endogenous innovation and trade-facilitated diffusion substantially amplify the technological and welfare losses from the U.S. Liberation Day tariffs in China and other major economies. Third, optimal U.S. tariffs on China reflect a trade-off between curbing technology spillovers to China and sustaining domestic innovation incentives.

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Keywords: trade-facilitated technology diffusion; innovation; endogenous growth model; trade war; optimal tariffs

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1 Introduction

Technology rivalry lies at the center of recent trade wars. Governments increasingly deploy trade policies to curb cross-border technology spillovers, restrict technological progress in rival economies, and preserve their own technological advantage.[1] While some measures effectively limit technology diffusion to rivals,[2] leading innovators caution that such policies may also erode innovation capacity at home,[3] thereby questioning their overall effectiveness: *What are the effects of trade policy on technological progress in the home country and its rivals? How do trade wars reshape technology rivalry across major economies? And how should trade policy be designed once its impacts on technological progress are taken into account?* Yet, the literature lacks tools to conduct quantitative analysis of trade wars and technology rivalry in the global economy. This paper aims to fill this gap.

We develop a dynamic trade model with endogenous innovation and trade-facilitated technology diffusion. In the model, trade policy shapes global technology progress through two channels. First, it affects firms' market size and thus their incentives to innovate, in line with the trade-and-endogenous-growth literature.[4] Second, knowledge is embodied in international trade flows, following recent work on trade-facilitated technology diffusion,[5] so that trade policy also affects the cross-border technology diffusion.

In particular, our model nests a static trade model within a dynamic growth model of innovation and knowledge diffusion. In the static model, firms produce and trade given their productivities, earning profits under Bertrand competition. These profits incentivize

[1] For example, the U.S. has explicitly framed its export controls on China as a strategy to impede Chinese advancement in strategic sectors such as semiconductors and artificial intelligence (`https://www.congress.gov/crs-product/R48642`). Moreover, Ju, Ma, Wang, and Zhu (2024) have documented that the initial Trump's tariffs in 2018 targeted high-tech industries supported by the "Made-in-China 2025" initiative.

[2] For example, Shen, Gao, Cheng, and Wang (2024) find that U.S. export controls on China significantly reduce Chinese firms' reliance on U.S. technologies.

[3] For example, Jensen Huang, CEO of Nvidia, noted that the firm's market share in China collapsed from 95% to zero following U.S. export controls, warning of adverse implications for innovation (`https://fortune.com/2025/10/19/jensen-huang-nvidia-china-market-share-ai-chips-trump-trade-war`).

[4] See, for example, Eaton and Kortum (2001), Aghion, Bergeaud, Lequien, and Melitz (2024b), Cai, Li, and Santacreu (2022), and Bai, Jin, and Lu (2025a).

[5] See, for example, Buera and Oberfield (2020) and Bai, Jin, Lu, and Wang (2025b)

firms to hire researchers and generate new ideas. Ideas then diffuse across countries and sectors, subject to frictions, shaping the *dynamics* of productivities. We model diffusion frictions as comprising (i) an endogenous component that declines with bilateral trade flows and (ii) an exogenous component capturing all other channels of technology transmission. By jointly determining firm profits and diffusion frictions, the static trade equilibrium pins down the growth path of all countries and sectors. Despite allowing for rich trade, production, and knowledge networks across countries and sectors, the model remains tractable and readily disciplined by data on trade, output, and patents.

The model implies that trade restrictions, such as U.S. export controls against China, are a double-edged sword for technological progress in both home and rival countries. On the one hand, they curb knowledge diffusion to the rival, hindering its technological advancement in ways that increased domestic R&D cannot offset. On the other hand, they may weaken innovation incentives at home, reducing R&D in exposed industries. These effects are not confined to directly affected sectors but propagate to other industries through intersectoral knowledge networks.

We then test these double-edged effects in the context of U.S. export controls against China. Combining data on patents, firm-level R&D expenditures, and sectoral measures of export control intensity, we document three findings. First, following the post-2018 tightening, Chinese firms in more exposed industries sharply reduce citations to U.S. patents relative to less exposed industries. Second, these firms increase patenting and R&D spending. Third, U.S. firms in more exposed industries experience a decline in patenting. These descriptive patterns validate our key mechanisms through which trade policies affect technology progress, suggesting that both endogenous innovation and trade-facilitated technology diffusion are essential.

We calibrate the model to a world economy with 18 economies and 23 sectors. The model delivers a structural mapping from bilateral trade to knowledge flows, which allows us to estimate the elasticity of knowledge diffusion with respect to trade using data on trade (UN COMTRADE) and patent citations (PATSTAT). Following Autor, Dorn, and

Hanson (2013), we construct a Bartik instrument for bilateral trade flows by interacting initial export structures with growth in aggregate exports to specific destinations. Our instrumental-variable estimates imply an elasticity of knowledge diffusion with respect to trade of approximately 0.3–0.5, consistent with prior work, for example, the value of 0.4 in Buera and Oberfield (2020). The estimates are robust across specifications and to an alternative instrument exploiting gradual improvements in aircraft technology. In addition, we recover the rich trade, input–output, and knowledge networks required for counterfactual analysis directly from OECD ICIO and PATSTAT.

Armed with the calibrated model, we conduct four sets of counterfactual exercises:

First, we examine the interactions between trade and technological progress through the lens of our model. In particular, we introduce observed changes in tariffs and non-tariff trade costs over 1996–2007 into the model and compute counterfactual changes in R&D and technological progress for 18 economies and 23 sectors. In China, which experienced substantial trade liberalization during this period, sectors more exposed to import competition exhibit slower growth in R&D inputs, consistent with Liu, Lu, Lu, and Luong (2021), but faster technological advancement, in line with Brandt, Van Biesebroeck, Wang, and Zhang (2017). These patterns arise only when both endogenous innovation and trade-facilitated technology diffusion are incorporated into the model.

Second, we quantify the effects of U.S. export controls on China since 2018. Export controls reduce technological capacity in both the U.S. and China: the U.S. experiences a decline in R&D, while China faces a reduction in knowledge inflows that is not offset by increased R&D. These negative effects are not confined to sectors directly subject to export controls but propagate across most sectors through knowledge networks. As a result, export controls generate a lose-lose outcome: China's real income falls by 0.267%, while U.S. real income declines by 0.034%. Accounting for technological responses is critical: China incurs larger losses when its R&D does not respond, while U.S. losses shrink to 0.016% in a model without endogenous innovation. If technology is exogenous, export controls reduce China's real income by only 0.03% and slightly increase U.S. real

income by 0.002%.

Third, we quantify the effects of U.S. Liberation Day tariffs on major economies starting in 2025, together with China's retaliatory tariffs. These tariffs increase U.S. R&D by 0.70% and technological capacity by 1.24%, raising U.S. real income by 0.02%, while generating substantial welfare losses in China (-1.26%), the European Union (-0.28%), Japan (-0.36%), and India (-0.46%). China's welfare loss shrinks to -0.30% when innovation is exogenous and further to -0.22% when technology is exogenous. Similar patterns hold for the European Union, Japan, and India.

Finally, we quantify the U.S. optimal tariffs on China. The U.S. welfare-maximizing policy features substantial export subsidies and import tariffs in high-tech sectors such as "Computer&Electronic," "Electrical Equipment," and "Pharmaceuticals," aimed at promoting U.S. innovation in these sectors. The role of export subsidies is much weaker when innovation is exogenous or when the U.S. can rely on industrial subsidies instead. These optimal policies not only increase U.S. real income by 3.95% but also raise China's real income by 6.49%. However, if the U.S. pursues not only higher domestic welfare but also the objective of reducing China's welfare, the optimal policy shifts toward prohibitive export tariffs that restrict trade-facilitated technology diffusion, resulting in smaller gains for the U.S. (1.43%) and welfare losses for China (-1.05%).

Related Literature. This paper contributes to the quantitative analysis of the impact of trade policies on global technological progress. Bai et al. (2025b) develop a trade model with trade-facilitated technology diffusion, following Buera and Oberfield (2020), and characterize optimal trade policies, highlighting the incentives to use tariffs to shape technology flows toward targeted countries. This paper complements their work by emphasizing the costs of such policies for innovation in the home country, in line with the trade and endogenous growth literature that studies how trade policies affect market size and, in turn, innovation and technology (*e.g.*, Bai et al., 2025a; Bartelme, Costinot, Donaldson, and Rodriguez-Clare, 2021; Lashkaripour and Lugovskyy, 2023). This paper

further shows that both trade-facilitated technology diffusion and endogenous innovation are essential for explaining the relationship between U.S. exports to China and R&D and patenting in both China and the U.S., with important implications for evaluating the recent trade wars initiated by the Trump administration.

This paper also relates to broader discussions on the effects of trade on innovation and growth. A large literature emphasizes how trade shapes market size and innovation incentives (*e.g.,* Eaton and Kortum, 2001; Autor et al., 2013; Grossman and Helpman, 2015; Perla, Tonetti, and Waugh, 2021; Aghion et al., 2024b; Cai et al., 2022; Chen, Fan, and Luo, 2025; Hemous, Lepot, Ossa, and Sampson, 2025), while more recent work highlights the role of trade in facilitating technology diffusion (*e.g.,* Grossman and Helpman (1991); Buera and Oberfield, 2020; Aghion, Bergeaud, Gigout-Magiorani, Lequien, and Melitz, 2024a; Bai et al., 2025b; Cai, Caliendo, Parro, and Xiang, 2025; Keller, 2021). Melitz and Redding (2021) provide a comprehensive survey of these channels. This paper contributes to this literature by integrating both mechanisms into a unified framework to quantify the effects of trade wars.

Finally, this paper contributes to the quantitative literature on recent trade conflicts (*e.g.,* Fajgelbaum, Goldberg, Kennedy, and Khandelwal, 2020; Lashkaripour and Lugovskyy, 2023; Bonadio, Huo, Kang, Levchenko, Pandalai-Nayar, Toma, and Topalova, 2024; Ju et al., 2024; Alessandria, Khan, Khederlarian, Ruhl, and Steinberg, 2025; Ignatenko, Lashkaripour, Macedoni, and Simonovska, 2025), as surveyed by Fajgelbaum and Khandelwal (2022). It complements this literature by highlighting the role of technology responses in shaping the consequences of trade wars.

The rest of the paper is arranged as follows. Section 2 builds and characterizes the model. Section 3 validates and calibrates the model. Section 4 conducts counterfactual exercises. Section 5 concludes.

2 Model

We build a multi-country-multi-sector quantitative trade model with endogenous innovation, trade-facilitated technology diffusion, and import and export tariffs. Tariffs shape technologies in two ways. First, tariffs affect trade and thereby technology diffusion. Second, tariffs affect market size, profits, and thereby the incentives for innovation.

2.1 Environment and Dynamic Equilibrium

Time is continuous and goes to infinity. Consider N countries and J sectors. Countries are indexed by i and n and sectors are indexed by j and k. Each country $i = 1, \ldots, N$ has a measure L_{it} of representative households that each supplies one unit of labor to either the production or the research sector. Labor is immobile across countries.

Preferences. The representative household in country n has the following linear lifetime utility:

$$U_{nt} = \int_0^\infty e^{-\rho_n t} C_{nt} dt, \tag{1}$$

where C_{nt} is the consumption of final goods and ρ_n is the discounting factor.

Technologies and Market Structure. Final goods are non-tradable across countries and are produced under perfect competition by aggregating J intermediate goods:

$$Q_{nt} = \prod_{j=1}^{J} \left(Q_{nt}^j \right)^{\alpha_n^j}, \tag{2}$$

where Q_{nt} is the quantity of final goods and Q_{nt}^j is the quantity of intermediate good j.

In each sector j, there is a continuum of intermediate producers indexed by $\omega \in [0, 1]$. Varieties are aggregated into composite sectoral good j through a CES function with the

elasticity of substitution $\sigma_j > 1$. The unit cost of producing ω of sector j in country n is:

$$uc_{nt}^{j}(\omega) = \frac{c_{nt}^{j}}{z_{nt}^{j}(\omega)}, \quad c_{nt}^{j} = w_{nt}^{\gamma_n^j} \prod_{k=1}^{J} \left(P_{nt}^{k}\right)^{\gamma_n^{kj}}, \tag{3}$$

where w_{nt} is the wage and P_{nt}^{j} is the price index.

Productivity $z_{it}^{j}(\omega)$ is drawn from a Frechet distribution:

$$Pr\left[z_{it}^{j}(\omega) \leq z\right] = \exp\left[-T_{it}^{j} z^{-\theta_j}\right], \quad \theta_j \geq \max\left\{1, \sigma_j - 1\right\}. \tag{4}$$

We assume that intermediate producers in each ω face a Bertrand competition: the lowest-cost producer occupies the market, pricing in the level of the second-lowest cost. Therefore, the markup in each ω is the difference between the second-lowest and the lowest costs. Intermediate producers are owned by households, and their technologies build on the households' cumulative innovation activities from the past up to the present as well as diffused technology from other country-sector pairs.

Trade Frictions and Policies. Exporting good j from country i to n is subject to an iceberg trade cost $\tau_{int}^{j} \geq 1$ with $\tau_{iit}^{j} = 1$, an import tariff $t_{int}^{j} \geq 0$, and an export tariff $e_{int}^{j} \geq 0$. We denote $\kappa_{int}^{j} \equiv \tau_{int}^{j}\left(1 + t_{int}^{j}\right)\left(1 + e_{int}^{j}\right)$.

Then the price index of good j in country n can be expressed as

$$P_{nt}^{j} = \left(\sum_{i=1}^{J} T_{it}^{j}\left(c_{it}^{j}\kappa_{int}^{j}\right)^{-\theta_j}\right)^{-\frac{1}{\theta_j}}. \tag{5}$$

The price index of final goods in country n is thus

$$P_{nt} = \prod_{j=1}^{J}\left(P_{nt}^{j}\right)^{\alpha_n^j}. \tag{6}$$

Let X_{nt}^j be the total expenditure on j in country n and X_{int}^j be the sales of good j from country i to n. Then

$$\lambda_{int}^j \equiv \frac{X_{int}^j}{X_{nt}^j} = \frac{T_{it}^j \left(c_{it}^j \kappa_{int}^j\right)^{-\theta_j}}{\sum_{i'=1}^N T_{i't}^j \left(c_{i't}^j \kappa_{i'nt}^j\right)^{-\theta_j}}. \tag{7}$$

Under the Bertrand competition, the profit of producing j in country i is

$$\Pi_{it}^j = \sum_{n=1}^N \frac{1}{1+\theta_j} \frac{\lambda_{int}^j X_{nt}^j}{\left(1+e_{int}^j\right)\left(1+t_{int}^j\right)}. \tag{8}$$

Total expenditure is the sum of final and intermediate expenditure:

$$X_{nt}^j = \alpha_n^j Y_{nt} + \sum_{k=1}^J \gamma_n^{jk} \left(1 - \frac{1}{1+\theta_k}\right) \sum_{i=1}^N \frac{\lambda_{nit}^k X_{it}^k}{\left(1+e_{nit}^k\right)\left(1+t_{nit}^k\right)}, \tag{9}$$

where Y_{nt} represents the total nominal income of the household in country n.

Labor market clearing for workers:

$$w_{it} L_{it}^P = \sum_{j=1}^J \gamma_i^j \left(1 - \frac{1}{1+\theta_j}\right) \sum_{i=1}^N \frac{\lambda_{int}^j X_{nt}^j}{\left(1+e_{int}^j\right)\left(1+t_{int}^j\right)}, \tag{10}$$

where L_{it}^P is the production labor in country i.

Total nominal income is the sum of wage income, tariff revenues and net profits:

$$Y_{nt} = w_{nt} L_{nt} + \sum_{j=1}^J \sum_{i=1}^N \frac{e_{nit}^j}{1+e_{nit}^j} \lambda_{nit}^j X_{it}^j + \sum_{j=1}^J \sum_{i=1}^N \frac{t_{int}^j \lambda_{int}^j X_{nt}^j}{\left(1+e_{int}^j\right)\left(1+t_{int}^j\right)} + \Pi_{nt}. \tag{11}$$

where $\Pi_{nt} = \sum_{j=1}^J \Pi_{nt}^j - \sum_j w_{nt} R_{nt}^j$ incorporates the profits from current producers (owned by households) net of costs on producing new innovations.

Innovation and Technology Diffusion. In each sector j and country n, there is a continuum of entrepreneurs who employ researchers to develop new knowledge. Let R_{it}^j be the number of researchers in sector j of country i. We assume that knowledge is created through the Poisson process with the arrival rate:

$$A_{it}^j R_{it}^j$$

where $A_{it}^j = \bar{A}_{it}^j \left(R_{it}^j / L_{it} \right)^{\xi - 1}$ is the research productivity per R&D worker. Here, $\bar{A}_{it}^j$ is the fundamental innovation efficiency in sector i of country j, and $\xi < 1$ captures the diminishing returns of innovation, as more R&D workers may lead to fewer discoveries per worker. We scale by total employment to ensure a balanced growth path.

Inspired by Buera and Oberfield (2020), we assume that knowledge can also diffuse across countries and sectors. Thus, the evolution of technology in country n and sector j can be written as:

$$\dot{T}_{nt}^j = \sum_{i=1}^{N} \sum_{k=1}^{J} \underbrace{\bar{\epsilon}_{int}^{kj} \left(\eta_{int}^{kj} \right)^{\nu}}_{\equiv \epsilon_{int}^{kj} \text{(diffusion strength)}} \times \underbrace{A_{it}^k R_{it}^k}_{\text{innovation in country } i \text{ and sector } k}, \tag{12}$$

where

$$\eta_{int}^{kj} \equiv \frac{X_{int}^{kj}}{\sum_{i'=1}^{N} \sum_{k'=1}^{J} X_{i'nt}^{k'j}}, \quad X_{int}^{kj} \equiv \begin{cases} \gamma_n^{kj} \lambda_{int}^k X_{nt}^k & \text{if } k \neq j \\ \lambda_{int}^k X_{nt}^k & \text{otherwise} \end{cases}. \tag{13}$$

We assume that researchers receive the entire stream of current and future profits generated by their country–sector's increment of knowledge, which encompasses both their own innovations and the diffused knowledge. This assumption reflects the idea that diffused knowledge is often embodied in improvement of domestic innovations (Liu and Ma, 2023).[6] The value of knowledge increment in sector j of country i is equal to its dis-

[6] Alternatively, Holmes, McGrattan, and Prescott (2015) introduce country-specific appropriators who capture the profits from transferred technologies.

counted expected utility for households:

$$V_{it}^{j} = \dot{T}_{it}^{j} \int_{t}^{\infty} e^{-\rho_i s} \frac{P_{it}}{P_{is}} \frac{\Pi_{is}^{j}}{T_{is}^{j}} ds. \tag{14}$$

$1/T_{is}^{j}$ determines the probability that an idea succeeds in sector j of country i at time s, so Π_{is}^{j}/T_{is}^{j} represents the expected profit from that idea in period s. The term $e^{-\rho s} P_{it}/P_{is}$ serves as the discount factor for future nominal incomes, expressed relative to nominal income in period t. We assume that households can freely choose whether to allocate labor to the research sector. Therefore, we have

$$\underbrace{V_{it}^{j}}_{\text{total value of research}} = \underbrace{w_{it} R_{it}^{j}}_{\text{total costs of research}}, \tag{15}$$

Given the diminishing returns of innovation, this equation pins down the size of the research sector in country i and sector j.

Finally, wage is determined by labor market clearing in each country:

$$L_{nt} = L_{nt}^{P} + \sum_{j=1}^{J} R_{nt}^{j}. \tag{16}$$

Definition 1 (Dynamic Equilibrium) *Given the initial technology* $\left(T_{i0}^{j}\right)$*, our dynamic equilibrium consists of* $\left(w_{it}, L_{it}^{P}, R_{it}^{j}, T_{it}^{j}, X_{it}^{j}, P_{it}^{j}\right)$ *such that*

i.) Production workers $\left(L_{it}^{P}\right)$ *satisfy labor market clearing in Equation* (10)

ii.) Researchers $\left(R_{it}^{j}\right)$ *are determined by the value of ideas in Equation* (14) *and* (15)

iii.) Technologies $\left(T_{it}^{j}\right)$ *are progressed via the dynamics described by Equation* (12)

iv.) Expenditures $\left(X_{it}^{j}\right)$ *satisfy Equation* (9) *and* (11)

v.) Price indices $\left(P_{it}^{j}\right)$ *satisfy Equation* (5)

vi.) Wages (w_{it}) *are determined by Equation* (16)

2.2 Balanced-Growth-Path Equilibrium and Gains from Trade

We consider semi-endogenous growth in the BGP. In particular, we assume that L_{nt} grows at the rate $g > 0$ for all (n, t) and all other exogenous shocks are constant over time. We treat a benchmark country's wage as numeraire in each period. In this setting, we have

$$\frac{\dot{T}_{nt}^j}{T_{nt}^j} = \sum_{i=1}^{N}\sum_{k=1}^{J} \bar{A}_{it}^k \epsilon_{int}^{kj} \left(\frac{R_{it}^k}{L_{it}}\right)^{\xi} \frac{L_{it}}{T_{nt}^j}. \tag{17}$$

It is straightforward to show that the growth rate of T_{nt}^j is g for all (n, j, t).

For variable Z_t, we detrend it by its BGP growth rate g_Z and denote $Z = Z_t e^{-g_z t}$. Then in the BGP we have

$$T_n^j = \frac{1}{g}\sum_{i=1}^{N}\sum_{k=1}^{J} \bar{A}_i^k \underbrace{\bar{\epsilon}_{in}^{kj}\left(\eta_{in}^{kj}\right)^{\nu}}_{\epsilon_{in}^{kj}} \left(\frac{R_i^k}{L_i}\right)^{\xi} L_i, \tag{18}$$

where

$$\eta_{in}^{kj} \equiv \frac{X_{in}^{kj}}{\sum_{i'=1}^{N}\sum_{k'=1}^{J} X_{i'n}^{k'j}}, \quad X_{in}^{kj} \equiv \begin{cases} \gamma_n^{kj}\lambda_{in}^k X_n^k & \text{if } k \neq j \\ \lambda_{in}^k X_n^k & \text{otherwise} \end{cases}. \tag{19}$$

In the BGP, researchers' wage income is equal to the de-trended profits:

$$V_i^j = w_i R_i^j, \quad V_i^j = \frac{g}{\rho - \frac{1}{\bar{\theta}_i}g}\sum_{n=1}^{N}\frac{1}{1+\theta_j}\frac{\lambda_{in}^j X_n^j}{\left(1+e_{in}^j\right)\left(1+t_{in}^j\right)}, \tag{20}$$

where $\bar{\theta}_i = \frac{1}{\sum_j \alpha_i^j \frac{1}{\theta_j}}$ is the weighted trade elasticity across sectors. We assume that discount rate $\rho_i = \frac{\bar{\theta}_i+1}{\bar{\theta}_i}g$, which ensures that the net profit $\Pi_i = 0$ in the BGP.

Trade shares and price indices along the BGP satisfy:

$$\lambda_{in}^j \equiv \frac{X_{in}^j}{X_n^j} = \frac{T_i^j\left(c_i^j\kappa_{in}^j\right)^{-\theta_j}}{\sum_{i'=1}^{N} T_{i'}^j\left(c_{i'}^j\kappa_{i'n}^j\right)^{-\theta_j}}, \quad P_n^j = \left(\sum_{i=1}^{N} T_i^j\left(c_i^j\kappa_{in}^j\right)^{-\theta_j}\right)^{-\frac{1}{\theta_j}}, \tag{21}$$

where $c_i^j = w_i^{\gamma_i^j} \prod_{k=1}^{J} \left(P_i^k\right)^{\gamma_i^{kj}}$.

Labor market clearing along the BGP:

$$w_i L_i = \sum_{j=1}^{J} \left[\frac{1}{1+\theta_j} + \gamma_i^j \left(1 - \frac{1}{1+\theta_j} \right) \right] \sum_{n=1}^{N} \frac{\lambda_{in}^j X_n^j}{\left(1+e_{in}^j\right)\left(1+t_{in}^j\right)}. \tag{22}$$

Total expenditure along the BGP:

$$X_n^j = \alpha_n^j Y_n + \sum_{k=1}^{J} \gamma_n^{jk} \left(1 - \frac{1}{1+\theta_k} \right) \sum_{i=1}^{N} \frac{\lambda_{ni}^k X_i^k}{\left(1+e_{ni}^k\right)\left(1+t_{ni}^k\right)}, \tag{23}$$

where

$$Y_n = w_n L_n + \sum_{j=1}^{J} \sum_{i=1}^{N} \frac{e_{ni}^j}{1+e_{ni}^j} \lambda_{ni}^j X_i^j + \sum_{j=1}^{J} \sum_{i=1}^{N} \frac{t_{in}^j \lambda_{in}^j X_n^j}{\left(1+e_{in}^j\right)\left(1+t_{in}^j\right)} + \Pi_n. \tag{24}$$

where $\Pi_n = \sum_j \sum_{i=1}^{N} \frac{1}{1+\theta_j} \frac{\lambda_{ni}^j X_i^j}{\left(1+e_{ni}^j\right)\left(1+t_{ni}^j\right)} - \sum_j w_n R_n^j$, which equals zero in the BGP.

Definition 2 (BGP Equilibrium) *Given the population growth rate g, our BGP equilibrium consists of $\left(w_{it}, R_{it}^j, T_{it}^j, X_{it}^j, P_{it}^j\right)$ such that*

i.) Researchers $\left(R_{it}^j\right)$ are determined by Equation (20)

ii.) Technologies $\left(T_{it}^j\right)$ are determined by Equation (18)

iii.) Expenditures $\left(X_{it}^j\right)$ satisfy Equation (23) and (24)

iv.) Price indices $\left(P_{it}^j\right)$ satisfy Equation (21)

v.) Wages (w_{it}) are determined by Equation (22)

Since the BGP growth rate of technology always equals the population growth rate (g),

welfare along the BGP in each country n is proportional to its per-period real income:[7]

$$W_n = \frac{Y_n}{P_n}, \quad P_n = \prod_{j=1}^{J} \left(P_n^j\right)^{\alpha_n^j}. \tag{25}$$

For country n, let GT_n represent the ratio of welfare in the observed equilibrium to that in autarky, where bilateral trade costs are infinite ($\kappa_{in}^j \to \infty \; \forall \; i \neq n$). We use the superscript A to denote variables in autarky.

Proposition 1 (Gains from Trade) *The gains from trade in country i in the BGP are:*

$$GT_n = \underbrace{\prod_j \prod_k \left(\lambda_{nn}^k\right)^{-\frac{\alpha_n^j \beta_n^{kj}}{\theta_k}}}_{\text{(i) ACR formula}} \times \underbrace{\prod_j \prod_k \left(\frac{R_n^k}{R_n^{k,A}}\right)^{\frac{\xi \alpha_n^j \beta_n^{kj}}{\theta_k}}}_{\text{(ii) endogenous innovation}} \times \underbrace{\prod_j \prod_k \left(\frac{\epsilon_{nn}^{kk}/\delta_{nn}^{kk}}{\epsilon_{nn}^{kk,A}/\delta_{nn}^{kk,A}}\right)^{\frac{\alpha_n^j \beta_n^{kj}}{\theta_k}}}_{\text{(iii) trade-facilitated knowledge diffusion}} \times \underbrace{\frac{Y_n}{w_n L_n}}_{\text{(iv) tariff revenue}}. \tag{26}$$

β_n^{kj} is the (j,k) element of the Leontief inverse matrix $(\mathbf{I} - \mathbf{\Gamma}_n)^{-1}$, where $\mathbf{I}$ is a $J \times J$ identity matrix, and $\mathbf{\Gamma}_n$ is a $J \times J$ matrix with the (j,k) element being γ_n^{kj}. $\delta_{nn}^{kk} \equiv \frac{\bar{A}_n^k \epsilon_{nn}^{kk} \left(R_n^k\right)^{\xi} L_n^{1-\xi}}{\sum_{i'=1}^{N} \sum_{k'=1}^{N} \bar{A}_{i'}^{k'} \epsilon_{i'n}^{k'k} \left(R_{i'}^k\right)^{\xi} L_{i'}^{1-\xi}}$ is the share of knowledge generated from the own sector and country.

Term (i) on the right-hand side of equation (26) represents the multisector extension (with input–output linkages) of the canonical ACR formula (Arkolakis, Costinot, and Rodriguez-Clare, 2012). It reflects the gains arising from changes in wages and prices following trade liberalization, holding technology constant and considering zero tariff revenues in our model.

Term (ii) and (iii) capture the two primary channels through which trade influences technology. First, increased trade openness alters the returns to innovation, thereby affecting the allocation of R&D labor across sectors (R_n^j). Second, for a given level of do-

[7] For example, consider the economy is on the BGP in period 0. For each household in country n, its utility is given by $\int_0^\infty e^{-\rho_n t} \frac{Y_{n,t}}{L_{n,t} P_{n,t}} dt = \frac{Y_n}{P_n L_n (\rho_n - \frac{1}{\theta_n} g)} = \frac{Y_n}{P_n L_n g}$. Thus, the total welfare for all households in country n in period 0 is $\frac{1}{g} \frac{Y_n}{P_n}$.

mestic innovation intensity, openness promotes international knowledge diffusion, potentially expanding the domestic knowledge stock in country n. This effect is represented by $\epsilon_{nn}^{kk}/\delta_{nn}^{kk}$, which measures the share of knowledge originating from the country's own sector—where a lower value indicates stronger cross-country and cross-sector knowledge diffusion.

Term (iv) accounts for changes in tariff revenues associated with import and export tariffs when a country opens to trade.

2.3 Equilibrium in Relative Changes

Our counterfactuals focus on how changes in trade frictions, including iceberg trade costs and tariffs, affect technology, production, trade, and welfare. Therefore, we express our equilibrium in relative terms. For any variable $Z > 0$, we denote Z' as the level after change and $\hat{Z} \equiv Z'/Z$.

2.3.1 "Exact-hat" algebra for the BGP equilibrium

Changes in trade shares:

$$\hat{\lambda}_{in}^{j} = \frac{\hat{T}_i^j \left(\hat{c}_i^j \hat{\kappa}_{in}^j\right)^{-\theta_j}}{\sum_{i'=1}^{N} \lambda_{i'n}^{j} \hat{T}_{i'}^{j} \left(\hat{c}_{i'}^{j} \hat{\kappa}_{i'n}^{j}\right)^{-\theta_j}}, \tag{27}$$

where

$$\hat{\kappa}_{int}^{j} = \hat{\tau}_{int}^{j} \widehat{1 + t_{int}^{j}} \widehat{1 + e_{int}^{j}}, \quad \hat{c}_i^j = \hat{w}_i^{\gamma_i^j} \prod_{k=1}^{J} \left(\hat{P}_i^k\right)^{\gamma_i^{kj}}. \tag{28}$$

Changes in price indices:

$$\hat{P}_n^j = \left(\sum_{i=1}^{J} \lambda_{in}^{j} \hat{T}_i^j \left(\hat{c}_i^j \hat{\kappa}_{in}^j\right)^{-\theta_j}\right)^{-\frac{1}{\theta_j}}. \tag{29}$$

Changes in wages:

$$\hat{w}_i w_i L_i = \sum_{j=1}^{J} \left[\gamma_i^j \left(1 - \frac{1}{1+\theta_j} \right) + \frac{1}{1+\theta_j} \right] \sum_{n=1}^{N} \frac{\hat{\lambda}_{in}^j \hat{X}_n^j}{\widehat{1+e_{in}^j}\,\widehat{1+t_{in}^j}} \frac{\lambda_{in}^j X_n^j}{\left(1+e_{in}^j\right)\left(1+t_{in}^j\right)}. \tag{30}$$

Changes in expenditures:

$$\hat{X}_n^j X_n^j = \alpha_n^j \hat{Y}_n Y_n + \sum_{k=1}^{J} \gamma_n^{jk} \left(1 - \frac{1}{1+\theta_k} \right) \sum_{i=1}^{N} \frac{\hat{\lambda}_{ni}^k \hat{X}_i^k}{\widehat{1+e_{ni}^k}\,\widehat{1+t_{ni}^k}} \frac{\lambda_{ni}^k X_i^k}{\left(1+e_{ni}^k\right)\left(1+t_{ni}^k\right)}, \tag{31}$$

where

$$\hat{Y}_n Y_n = \hat{w}_n w_n L_n + \sum_{j=1}^{J} \sum_{i=1}^{N} \frac{\left(e_{ni}^j\right)'}{\left(1+e_{ni}^j\right)'} \left(\lambda_{ni}^j\right)' \left(X_i^j\right)' + \sum_{j=1}^{J} \sum_{i=1}^{N} \frac{\left(t_{in}^j\right)' \left(\lambda_{in}^j\right)' \left(X_n^j\right)'}{\left(1+e_{in}^j\right)' \left(1+t_{in}^j\right)'}. \tag{32}$$

Changes in researchers:

$$\hat{w}_i w_i R_i^j \widehat{R}_i^j = \sum_{n=1}^{N} \frac{1}{1+\theta_j} \frac{\hat{\lambda}_{in}^j \hat{X}_n^j}{\widehat{1+e_{in}^j}\,\widehat{1+t_{in}^j}} \frac{\lambda_{in}^j X_n^j}{\left(1+e_{in}^j\right)\left(1+t_{in}^j\right)}. \tag{33}$$

Changes in technologies:

$$\hat{T}_n^j = \sum_{i=1}^{N} \sum_{k=1}^{J} \delta_{in}^{kj} \left(\hat{\eta}_{in}^{kj} \right)^{\nu} \left(\hat{R}_i^k \right)^{\xi}, \quad \delta_{in}^{kj} \equiv \frac{\bar{A}_i^k \epsilon_{in}^{kj} \left(R_i^k\right)^{\xi} L_i^{1-\xi}}{\sum_{i'=1}^{N} \sum_{k'=1}^{N} \bar{A}_{i'}^{k'} \epsilon_{i'n}^{k'j} \left(R_{i'}^k\right)^{\xi} L_{i'}^{1-\xi}}, \tag{34}$$

where

$$\hat{\eta}_{in}^{kj} = \frac{\hat{X}_{in}^{kj}}{\sum_{i'=1}^{N} \sum_{k'=1}^{J} \eta_{i'n}^{k'j} \hat{X}_{i'n}^{k'j}}, \quad \hat{X}_{in}^{kj} = \hat{\lambda}_{in}^k \hat{X}_{nt}^k. \tag{35}$$

No Diffusion: Suppose that there are no technology diffusion. Then we have

$$\hat{T}_n^j = \left(\hat{R}_n^j \right)^{\xi}, \quad \forall (n, j). \tag{36}$$

Exogenous R&D: Suppose that country i is exogenously endowed with R_i^j researchers for sector j in the BGP. Then we have

$$\hat{R}_i^j = 1, \quad \forall\,(i,j)\,. \tag{37}$$

Exogenous Technologies: If the technologies are exogenously fixed, then we have

$$\hat{T}_n^j = 1, \quad \forall\,(n,j)\,. \tag{38}$$

Comparing the counterfactuals in our baseline case with those in "no diffusion" and "fixed T" cases, we could quantify the implications of technology diffusion and endogenous innovation for trade wars.

2.3.2 "Exact-hat" algebra for the transitional dynamics

To simulate the counterfactual changes along the transitional path, we discretize the time and, therefore, $\dot{Z} \equiv Z_{t+1} - Z_t$ for any variable Z. Notably, for any $Z_t > 0$ with the BGP level Z and the after-change level Z_t', $\hat{Z}_t \equiv Z_t'/Z$. Suppose that shocks start at period t from the BGP equilibrium. Then $T_{nt}^j = T_n^j$ for all (n,j), *i.e.* $\hat{T}_{nt}^j = 1$. The changes in T_{nt+s+1}^j for $s = 0, 1, \ldots$ can be expressed as

$$\hat{T}_{nt+s+1}^j = \frac{T_{nt+s}^{j'} + \sum_{i=1}^N \sum_{k=1}^J \bar{A}_{it+s}^k \epsilon_{int+s}^{kj'} \left(R_{it+s}^{k'}\right)^{\xi}}{T_n^j + \sum_{i=1}^N \sum_{k=1}^J \bar{A}_i^k \epsilon_{in}^{kj} \left(R_i^k\right)^{\xi}}, \quad s \geq 0, \quad T_{nt}^{j'} = T_n^j, \forall (n,j). \tag{39}$$

Notice that in the BGP, we have $T_{nt+1}^j = (1+g) T_{nt}^j$. Then we approximately have

$$\hat{T}_{nt+s+1}^j = \frac{1}{1+g} \hat{T}_{nt+s}^j + \frac{g}{1+g} \sum_{i=1}^N \sum_{k=1}^J \delta_{in}^{kj} \left(\hat{\eta}_{int+s}^{kj}\right)^{\nu} \left(\hat{R}_{it+s}^k\right)^{\xi}, \quad s \geq 0, \tag{40}$$

where $\hat{T}_{nt}^j = 1$ for all (n,j).

Given technology changes for all $s \geq t$, we can express $\left(\hat{w}_{is}, \hat{P}^j_{is}, \hat{X}^j_{is}, \hat{R}^j_{is}\right)$ as

$$
\begin{aligned}
\hat{w}_{is} w_i L_i &= \sum_{j=1}^{J} \left[\gamma_i^j \left(1 - \frac{1}{1+\theta_j}\right) + \frac{1}{1+\theta_j} \right] \sum_{n=1}^{N} \frac{\hat{\lambda}^j_{ins} \hat{X}^j_{ns}}{\widehat{1+e^j_{in}}\,\widehat{1+t^j_{in}}} \frac{\lambda^j_{in} X^j_n}{\left(1+e^j_{in}\right)\left(1+t^j_{in}\right)} \\
\hat{P}^j_{ns} &= \left(\sum_{i=1}^{J} \lambda^j_{in} \hat{T}^j_{is} \left(\hat{c}^j_{is} \hat{\kappa}^j_{in}\right)^{-\theta_j} \right)^{-\frac{1}{\theta_j}} \\
\hat{X}^j_{ns} X^j_n &= \alpha^j_n \hat{Y}_{ns} Y_n + \sum_{k=1}^{J} \gamma^{jk}_n \left(1 - \frac{1}{1+\theta_k}\right) \sum_{i=1}^{N} \frac{\hat{\lambda}^k_{nis} \hat{X}^k_{is}}{\widehat{1+e^k_{ni}}\,\widehat{1+t^k_{ni}}} \frac{\lambda^k_{ni} X^k_i}{\left(1+e^k_{ni}\right)\left(1+t^k_{ni}\right)} \\
\hat{w}_{is} w_i R^j_i \widehat{R}^j_{is} &= \sum_{n=1}^{N} \frac{1}{1+\theta_j} \frac{\hat{\lambda}^j_{ins} \hat{X}^j_{ns}}{\widehat{1+e^j_{in}}\,\widehat{1+t^j_{in}}} \frac{\lambda^j_{in} X^j_n}{\left(1+e^j_{in}\right)\left(1+t^j_{in}\right)}
\end{aligned}
\tag{41}
$$

2.4 Mechanism: Double-Edged Effects of Export Controls

In this subsection, we analytically examine the effects of unilateral tariffs in the following stylized version of our model:

Remark 1 (A Two-Country-Two-Sector Stylized Model) *Consider $N = J = 2$. There is no intermediate,* i.e. *$\gamma^j_i = 1$ for all (i, j). Sector 1 is homogeneous ($\theta_1 = \infty$), freely traded, has technology $T^1_i = 1$ and thereby $w_i = 1$ for $i = 1, 2$. To simplify notation, we omit the sector subscript j for sector 2 throughout this subsection. There are no tariffs initially. Moreover, countries are initially symmetric: $A_i = \bar{\epsilon}_{in} = L_i = 1$ and $\tau_{in} = \tau \geq 1$ for all $i \neq n$.*

We first investigate the impacts of country 1's export control against country 2, e_{12}, on innovation, technology, and real income in both countries:

Proposition 2 (Export Control as a Double-Edged Sword) *Consider the stylized model in Remark 1. If $\tau = 1$ and $\xi, \nu \in (0, 1)$, then the unilateral export tariff imposed by country 1 has the following first-order effects:*

1. *Innovation effect:* $\frac{\partial \log R_2}{\partial \log(1+e_{12})} > 0 > \frac{\partial \log R_1}{\partial \log(1+e_{12})}$.

2. *Technology effect:* $\frac{\partial \log T_1}{\partial \log(1+e_{12})} < 0, \quad \frac{\partial \log T_2}{\partial \log(1+e_{12})} < 0.$

3. *Real-wage effect:* $\frac{\partial \log(w_1/P_1)}{\partial \log(1+e_{12})} < 0, \quad \frac{\partial \log(w_2/P_2)}{\partial \log(1+e_{12})} < 0.$

4. *Welfare effect:* $\frac{\partial \log W_1}{\partial \log(1+e_{12})} > 0 > \frac{\partial \log W_2}{\partial \log(1+e_{12})}.$

Proposition 2 highlights the double-edged technological effect of export controls in our model. On the one hand, export controls reduce technology in the targeted country by restricting trade-facilitated knowledge diffusion; on the other hand, they lower technology in the implementing country by depressing R&D investment. Meanwhile, export controls stimulate R&D investment in the targeted country as import competition declines, but this surge in innovation is insufficient to offset the negative technology effects of reduced knowledge inflows. This lose–lose technological outcome and the associated real-income losses arise only when both endogenous innovation and trade-facilitated technology diffusion are present—two core elements of our framework.

The welfare effects in Proposition 2 provide a rationale for unilateral export controls: although such controls lower productivity in both countries, the implementing country is compensated by the associated export tariff revenue, resulting in a welfare gain. However, we can show that

$$\frac{\partial \log (W_1 + W_2)}{\partial \log (1 + e_{12})} < 0, \tag{42}$$

indicating that the welfare loss in the targeted country exceeds the gain in the implementing country, leading to an aggregate decline in global welfare from unilateral export controls.

To highlight the role of trade-facilitated technology diffusion in shaping the effects of tariffs, we consider the case without international technology diffusion:

Corollary 1 (No Diffusion) *Consider the stylized model in Remark 1. If* $\tau = 1$, $\xi \in (0,1)$, *and there is no technology diffusion,* i.e. $T_i = R_i^{\xi}$, *then the unilateral export tariff imposed by country* 1 *has the following first-order effects:*

1. *Innovation effects:* $\frac{\partial \log R_2}{\partial \log(1+e_{12})} > 0 > \frac{\partial \log R_1}{\partial \log(1+e_{12})}$.
2. *Technology effects:* $\frac{\partial \log T_2}{\partial \log(1+e_{12})} > 0 > \frac{\partial \log T_1}{\partial \log(1+e_{12})}$.
3. *Welfare effects:* $\frac{\partial \log W_1}{\partial \log(1+e_{12})} > 0 > \frac{\partial \log W_2}{\partial \log(1+e_{12})}$.

Corollary 1 shows that without international knowledge diffusion, the double-edged technological effect of export controls no longer exists: export controls raise productivity in the targeted country by stimulating its innovation. In this case, the rationale for a unilateral export tariff once again lies in the tariff revenue and the resulting welfare gain in the implementing country.

3 Model Calibration

We calibrate the model's balanced growth path to match the world economy averaged over 2015–2019. This section is organized into four parts. First, we introduce the data used for calibration. Second, we document motivating facts about export controls, knowledge diffusion, and innovation. Third, we estimate the elasticity of knowledge diffusion with respect to trade flows using a Bartik instrument. Fourth, we calibrate the remaining parameters by matching moments in trade and patent data and by drawing on existing estimates in the literature.

3.1 Data

We obtain data on patent applications and citations from the PATSTAT Global database (Autumn 2022 edition), which contains approximately 120 million patent applications from 209 national and regional patent offices. It includes detailed information on each patent application and its citation behavior. Since our analysis focuses on cross-country knowledge flows, geographic information for each patent is required. We identify the

patent's location based on the inventors' countries.[8] When inventor address data are unavailable, we use information on the applicants' countries or, if that is also missing, the country of the patent office where the application was filed. For patents filed in multiple jurisdictions, we assign the location according to the first application within the corresponding patent family.[9] By merging the geographic information of patents with bilateral citation data, we construct the number of citations from patents developed by country n in each International Patent Classification (IPC) category j to those developed by country i in each category k. This measure, commonly used in the literature, serves as a proxy for cross-country technology flows (e.g., Liu and Ma, 2023; Akcigit, Ates, Lerner, Townsend, and Zhestkova, 2024; Berkes et al., 2024). The citation year is defined by the publication year of the citing patent's document that contains the citation.

Data on trade, output, and input-output linkages are from UN COMTRADE and OECD ICIO. Bilateral trade flows from UN COMTRADE are used for our empirical estimation. We assemble and clean it using the algorithm in Feenstra and Romalis (2014). OECD ICIO provides bilateral trade flows, output, and input-output linkages for quantification. Because the citation data are organized by IPC categories while the trade data follow the Standard International Trade Classification (SITC) system, we aggregate PATSTAT and UN COMTRADE into the 23 ISIC sectors used in the OECD ICIO Database and in our quantitative analysis. This harmonization relies on two concordances: the IPC-ISIC concordance developed by Lybbert and Zolas (2014), which employs data mining and probabilistic matching to assign each IPC category a likelihood of belonging to a particular ISIC industry,[10] and the SITC–ISIC concordance provided by the World Bank and the United Nations.[11] Our empirical estimates use patent citation and trade data for the 1975–2020 period, whereas our counterfactual analysis use patent citation and trade and

[8] When a patent lists multiple inventors, we assign equal weights to each inventor's country of residence.

[9] The data cleaning procedure closely follows the approach described in Berkes, Manysheva, and Mestieri (2024).

[10] We use these probabilities to weight citation counts, enabling us to estimate the number of citations from patents invented by each country–sector to those invented by other country–sectors.

[11] See `https://wits.worldbank.org/product_concordance.html` and `https://unstats.un.org/unsd/classifications/Econ`.

production data for the 1996-2019 period.

Tariff data is from the WTO Tariff&Trade Data, a standard and widely used source that provides comprehensive, harmonized information on applied tariff rates across countries and products. In addition, we obtain the sectoral measure of US export controls on China using detailed HS product–year–level export control data compiled by Li, Liang, Pan, and Tao (2025) from the annual "Commerce Control List" by the Bureau of Industry and Security. Finally, for the U.S Liberation Day tariffs, we obtain the U.S. reciprocal tariffs from USTR tariff calculator `https://tariffs.inasimonovska.com/`.

3.2 Motivating Facts: Export Controls, Knowledge Diffusion, and Innovation

Policy Background. The United States has a long history of regulating exports of strategically sensitive goods, a regime that was substantially expanded with the passage of the Export Control Reform Act of 2018 (ECRA). ECRA modernized U.S. export controls by extending coverage to so-called "emerging and foundational technologies" and by granting the U.S. Department of Commerce broader authority to restrict exports deemed critical to national security. Technologies explicitly covered under ECRA include advanced computing, artificial intelligence, semiconductor manufacturing technologies, biotechnology, and other enabling inputs essential to technological development across sectors.

Building on this statutory foundation, the Bureau of Industry and Security (BIS) has, since 2018, implemented a sequence of increasingly stringent measures that explicitly target China and aim to curb its access to frontier technologies. These actions include expanded use of the Entity List to restrict transactions with Chinese firms, tightened licensing requirements for advanced semiconductors and semiconductor manufacturing equipment, and sweeping controls on high-performance computing and artificial intelligence chips. The October 2022 and October 2023 rulemakings, in particular, introduced broad restrictions on exports of leading-edge chips, chipmaking equipment, and related

services to China, alongside prohibitions on U.S. persons supporting certain advanced semiconductor activities.

Measure of US export controls on China. Using detailed HS product–year–level export control data compiled by Li et al. (2025) from the annual "Commerce Control List" by the Bureau of Industry and Security, we construct a measure of export restrictiveness from the United States to China:

$$EC_{jt} = \frac{\sum_{p \in j} export_value_{p,14\text{–}16} \times export_control_{pt}}{\sum_{p \in j} export_value_{p,14\text{–}16}}, \tag{43}$$

where $export_value_{p,14\text{–}16}$ denotes the pre–trade war export volume of 6-digit HS product p from the U.S. to China, and $export_control_{pt}$ is an indicator equal to one if product p is subject to any export restriction in year t, as compiled by Li et al. (2025). $p \in j$ denotes the set of 6-digit HS products mapped to each 2-digit ISIC sector, based on concordances provided by the United Nations Statistics Division.[12]

We report $EC_{j,2019}$ in Appendix Table B4, which we use as a policy shock in our counterfactual exercises. Based on $EC_{j,2019}$, we identify five sectors where export controls are in particular restrictive: "Petroleum", "Computer&Electronic", "Electrical equipment", "Machinery nec", and "other mineral". Figure 1 shows that these five sectors account for 54% of China's citations to U.S. patents within the manufacturing sector over our sample period. This pattern indicates that U.S. export controls are strategically targeted at Chinese industries that rely most heavily on U.S. technologies.

Export Controls on Knowledge Diffusion. Did U.S. export controls curb knowledge diffusion? Panel (a) of Figure 2 plots the number of citations by Chinese patents to U.S. patents in the five sectors subject to restrictive export controls. As a control group, we also show citations by Chinese patents to U.S. patents in other manufacturing sectors.

[12]Specifically, we use the HS-to-ISIC Rev. 4 concordance constructed via CPC 2.1 as an intermediate classification.

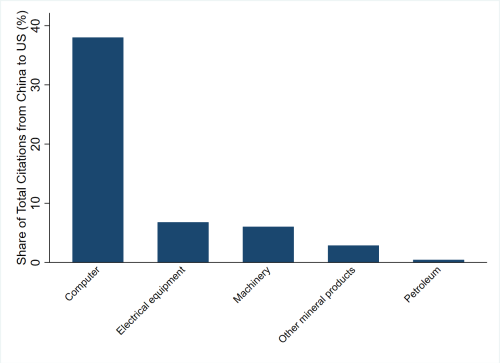
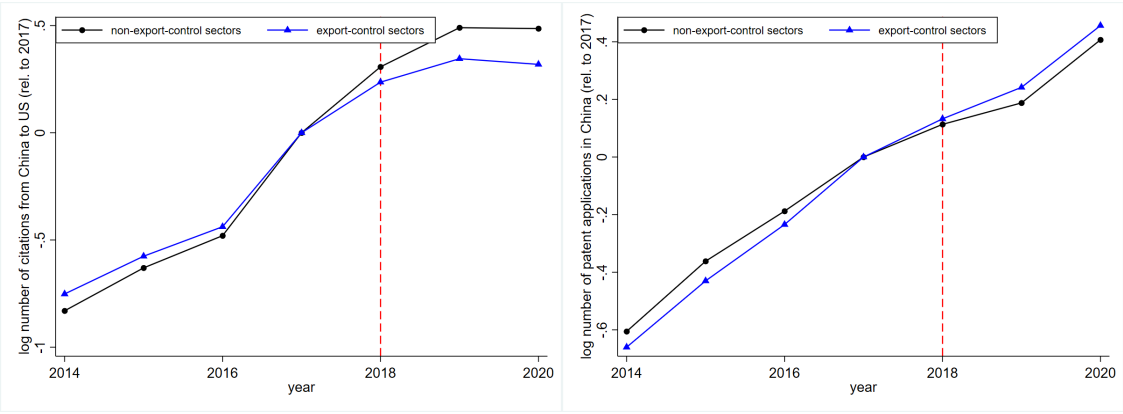


Figure 1: Citation Shares of Major Sectors Subject to Restrictive Export Controls

Note: This table reports the share of citations from China to the U.S. accounted for by five sectors subject to particularly stringent export controls—"Petroleum", "Computer&Electronic", "Electrical equipment", "Machinery nec", and "other mineral"—over the 1975–2020 period.

Both treated and control groups are normalized to their 2017 levels, the year before the passage of the Export Control Reform Act. Despite an overall upward trend in Chinese citations to U.S. patents, citations in the five sectors subject to export restrictions have grown markedly more slowly relative to other manufacturing sectors since the passage of ECRA in 2018, suggesting that U.S. export controls effectively slowed knowledge diffusion in targeted industries.



(a) Citation from China to US (b) Patent Applications in China

Figure 2: US Export Controls and Chinese Patent Citations and Innovation

Note: Panels (a) and (b) of Figure 2 plot, respectively, the number of citations from Chinese patents to U.S. patents and the number of patent applications in China for the five sectors subject to restrictive export controls, compared with other manufacturing sectors (labeled "non-export-control sectors"). Both series are normalized to their 2017 levels. The red dashed line denotes 2018.

Export Controls on Innovation. How did Chinese innovation respond to the U.S. export controls? Panel (b) of Figure 2 plots the number of patent applications in China for the five sectors subject to restrictive export controls, comparing with those for other manufacturing sectors, with both groups normalized to their 2017 levels. We find that the number of Chinese patent applications in sectors facing restrictive export controls grew faster than those in other manufacturing sectors after 2017. This pattern is consistent with the innovation effect of Proposition 2 where export controls could spur innovation in the targeted country through the decline in import competition and knowledge flows.

Complementing the descriptive evidence in Panel (b) of Figure 2, we regress Chinese firm-level R&D investment, available for listed Chinese firms, on EC_{jt} as defined in Equation (43) and its interaction with a post-2018 dummy. Columns (1) and (2) of Table 1 indicate that Chinese firms exposed to U.S. export controls have increased their R&D investment following the passage of ECRA in 2018.

Table 1: Impacts of US Export Controls on Chinese R&D and US Patenting

Dep var	Chinese R&D		US Patents	
	(1)	(2)	(3)	(4)
US export control	-0.480	-0.639	-0.017	0.020
	(0.872)	(0.873)	(0.101)	(0.101)
US export control		0.076**		-0.062***
× post 2018		(0.031)		(0.010)
Firm FE	✓	✓		
HS FE			✓	✓
Year FE	✓	✓	✓	✓
Controls	✓	✓		
Obs	24,370	24,370	38,713	38,713
R-squared	0.880	0.880	0.988	0.988

Note: Columns (1)–(2) report OLS estimates using the logarithm of the Chinese firm-level R&D investments as the dependent variable. The regressions control for firms' exposure to U.S. tariffs, domestic retaliatory tariffs, sanctions, and the import input effects arising from U.S. export controls, following the construction of these shocks in Ma, Ma, Tao, and Zhang (2025). Columns (3)–(4) report OLS estimates using the logarithm of the US number of patent applications as the dependent variable. Robust standard errors are reported in parentheses. Significance levels: 10% (*), 5% (**), and 1% (***). Additional details are reported in Appendix B.2.

How did U.S. innovation respond to export controls? We regress the log of U.S. patent applications at the HS-6 level on EC_{jt}, as defined in Equation (43), and its interaction with a post-2018 dummy. Columns (3) and (4) of Table 1 indicate that U.S. industries subject to export controls experienced a decline in innovation following the passage of ECRA in

2018.

In sum, the motivating facts above suggest that (i) U.S. export controls on China are associated with a reduction in knowledge diffusion to affected Chinese industries; (ii) exposure to the U.S. export controls is associated with the increase in Chinese patent applications and R&D investment; and (iii) the U.S. patent applications tend to decline in export-control sectors. Taken together, these patterns are consistent with our model predictions, summarized by Proposition 2.

3.3 Estimating the Elasticity of Technology Diffusion with Trade Flows

Correlation between Bilateral Knowledge and Trade Flows. Trade economists have long recognized the role of international trade in facilitating knowledge diffusion, dating back at least to Grossman and Helpman (1991). This channel has been further emphasized in recent contributions (*e.g.*, Buera and Oberfield, 2020; Aghion et al., 2024a; Bai et al., 2025b; Cai et al., 2025), as reviewed by Keller (2021).

Consistent with this literature, Figure 3 illustrates the correlation between bilateral citation counts (PATSTAT) and trade flows (UN COMTRADE), revealing a strong positive association between knowledge diffusion and trade connections.

Estimation Equation. To recover the parameter ν that governs the intensity of trade-facilitated technology diffusion, we approximate knowledge diffusion across countries by the observed patent citations. In particular, we assume that the technology diffusion share, δ_{in}^{kj}, defined in Equation (34) can be approximated by the patent citations of sector j in country n from sector k of country i. Adding the time dimension and taking the

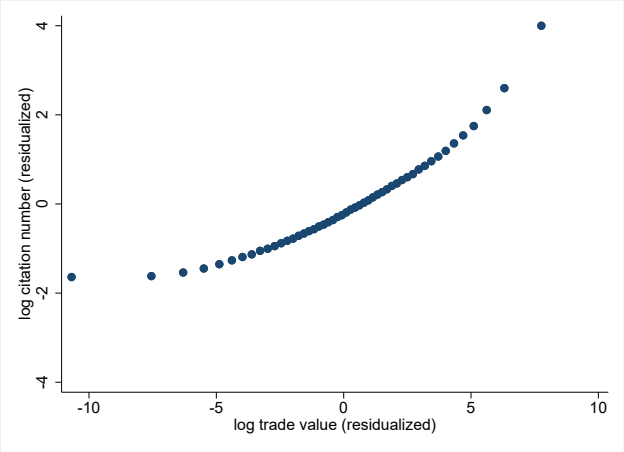


Figure 3: Correlation between Bilateral Citation Counts and Trade Flows

Note: Aligning with gravity equations (7) and (12), citation counts and trade flows are residualized with respect to origin–sector–year and destination–sector–year fixed effects. Because trade flow data do not identify destination sectors, we adjust trade flows using input-output linkages to ensure consistency with our model, as described in equation (13). As there are too many observations, we group observations into 50 bins based on residualized log trade value.

logarithm of equation (34), we obtain the following estimating equation:

$$\log\left(\delta_{int}^{kj}\right) = \nu \log\left(X_{int}^{kj}\right) + \text{fe}_{it}^{k} + \text{fe}_{nt}^{j} + \log\left(\bar{\epsilon}_{int}^{kj}\right), \quad X_{int}^{kj} \equiv \begin{cases} \gamma_{n}^{kj}\lambda_{int}^{k}X_{nt}^{k} & \text{if } k \neq j \\ \lambda_{int}^{k}X_{nt}^{k} & \text{otherwise} \end{cases}, \tag{44}$$

where fe_{it}^{k} and fe_{nt}^{j} are origin-sector-time-specific and destination-sector-time-specific fixed effects, respectively.

Data. As described in Section 3.2, we use patent and trade data covering the period 1975–2020 for the estimation, together with input–output linkages γ_{n}^{kj} from the OECD ICIO Database. To mitigate potential endogeneity arising from the evolution of production networks, we fix the input–output linkages γ_{n}^{kj} at their 2010 values.

Instrument on X_{int}^{k}. The correlation between bilateral citation counts and trade flows, displayed in Figure 3, reveals a positive association between knowledge diffusion and trade. However, when estimating equation (44) to identify the causal effect of trade flows on knowledge diffusion, a key challenge is the potential endogeneity of trade flows X_{int}^{k}.

For instance, a country that enjoys larger knowledge diffusion may thus experience faster productivity growth and larger trade flows with partner countries.

To address endogeneity concerns, we construct a Bartik-type instrument, in the spirit of Autor et al. (2013). Specifically, we construct the instrument as follows:

$$X_{int}^{k,Bartik} = \underbrace{\lambda_{in0}^{k} X_{n0}^{k}}_{\text{exports from } i \text{ to } n \text{ in initial period}} \times \underbrace{\frac{(1-\lambda_{int}^{k})X_{nt}^{k}}{(1-\lambda_{in0}^{k})X_{n0}^{k}}}_{\text{growth in exports to destination } n \text{ by other countries}}, \quad (45)$$

where $\lambda_{in0}^{k} X_{n0}^{k}$ is the export flow from country i to n in sector k in the initial year (1975), and $\frac{(1-\lambda_{int}^{k})X_{nt}^{k}}{(1-\lambda_{in0}^{k})X_{n0}^{k}}$ is growth in the value of exports to destination n (excluding those from country i) from initial year to year t.

Our instrument is designed to capture plausibly exogenous demand shocks in trade flows. Identification of shift–share instruments, as specified in equation (45), relies on the assumption that the shifts—growth in exports to destination n in industry k (excluding those from country i)—are randomly assigned (Borusyak, Hull, and Jaravel, 2022). Notice that our key explanatory variable, $X_{int}^{kj} \equiv \gamma_{n}^{kj} X_{int}^{k}$ for $k \neq j$. Therefore, we multiply our instruments above by γ_{n}^{kj} as an instrument for X_{int}^{kj} where $k \neq j$.

Table 2: Impact of Trade Flows on Number of Citations, Least Squares

Dep var	Log Number of Citations					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all	same ind	diff ind	all	same ind	diff ind
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Log Trade Flow	0.268***	0.128***	0.172***	0.307***	0.230***	0.212***
	(0.00065)	(0.00142)	(0.00067)	(0.00071)	(0.00280)	(0.00086)
Obs	14,231,955	1,219,398	12,989,202	14,231,720	1,219,367	12,989,003
R-squared	0.584	0.738	0.584	0.106	0.004	0.032
First-stage F				2.6e+07	3.8e+05	1.5e+07

Note: Columns (1)–(3) present the OLS results and Columns (4)–(6) display the 2SLS results using the instrument from equation (45). Columns (1) and (4) correspond to the full sample, while Columns (2) and (5) focus on citations within the same industry ($j = k$). Columns (3) and (6) are restricted to citations across different industries ($j \neq k$). We control for origin-sector-year and destination-sector-year fixed effects. Additionally, we report the first-stage F-statistic for the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

Estimation Results. Table 2 presents the estimation results for equation (44). We utilize bootstrap standard errors.[13] Columns (1)–(3) report the OLS results, revealing a positive correlation between trade flows and the number of citations. This positive relationship persists when the sample is restricted to citations within the same industry ($j = k$) in Column (2) or across different industries ($j \neq k$) in Column (3). In Columns (4)–(6), where we use the Batik instruments, we continue to observe that higher trade flows lead to more citations, with coefficients remaining stable across the different specifications.

Robustness. We conduct several robustness exercises on the estimation equation (44). First, because bilateral citation measures are count-based and include zero values, the literature has noted that ordinary least squares estimation can be biased in such settings and therefore recommends the use of Poisson pseudo–maximum-likelihood (PPML) estimation (Silva and Tenreyro, 2006; Cohn, Liu, and Wardlaw, 2022). This concern is mitigated in our context because, when mapping citation data from IPC to ISIC categories, we adopt the probabilistic matching approach of Lybbert and Zolas (2014), which assigns small but positive probabilities to IPC–ISIC pairs and thus avoids zero-value outcomes. Nevertheless, Table 3 reports estimation results obtained using Poisson maximum-likelihood estimation. We continue to find that higher trade flows are associated with more citations, and this relationship is robust across specifications both with and without instrumental variables.

Second, we augment equation (44) by further including origin–destination fixed effects, controlling for (i, n)-pairwise components in the error term $\log\left(\bar{\epsilon}_{int}^{kj}\right)$ of Equation (44). The resulting estimates, reported in Table 4, are similar to our baseline results.

Third, to address concerns about the exclusion restriction of our baseline Bartik instrument, we construct an alternative instrument exploiting improvements in aircraft technol-

[13]Since traditional methods for computing standard errors introduce bias when Bartik instruments are used (Adao, Kolesár, and Morales, 2019; Goldsmith-Pinkham, Sorkin, and Swift, 2020), we follow the approach outlined in Goldsmith-Pinkham et al. (2020) by utilizing bootstrap standard errors. This method accommodates a flexible structure for standard errors, helping to mitigate potential bias.

Table 3: Impact of Trade Flows on Number of Citations, Poisson Maximum Likelihood

Dep var	Number of Citations					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all	same ind	diff ind	all	same ind	diff ind
Method	PPML	PPML	PPML	PPML(Bartik)	PPML(Bartik)	PPML(Bartik)
Log Trade Flow	0.478***	0.249***	0.266***	0.507***	0.274***	0.292***
	(0.00160)	(0.00338)	(0.00225)	(0.00198)	(0.00309)	(0.00268)
Obs	14,231,955	1,219,398	12,989,202	14,231,720	1,219,367	12,989,003
R-squared	0.938	0.987	0.911	0.939	0.987	0.911
First-stage F				2.6e+07	3.8e+05	1.5e+07

Note: Columns (1)–(3) present the PPML results and Columns (4)–(6) display the PPML results using the instrument from equation (45). Columns (1) and (4) correspond to the full sample, while Columns (2) and (5) focus on citations within the same industry ($j = k$). Columns (3) and (6) are restricted to citations across different industries ($j \neq k$). We control for origin-sector-year and destination-sector-year fixed effects. Additionally, we report the first-stage F-statistic for the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

Table 4: Impact of Trade Flows on Number of Citations, with Origin-Dest. Fixed Effects

Dep var	Log Number of Citations					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all	same ind	diff ind	all	same ind	diff ind
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Log Trade Flow	0.300***	-0.00115	0.183***	0.342***	-0.0196*	0.233***
	(0.000223)	(0.00176)	(0.000298)	(0.000267)	(0.0107)	(0.000408)
Obs	14,231,854	1,218,704	12,989,071	14,231,619	1,218,673	12,988,872
R-squared	0.619	0.774	0.620	0.112	0.000	0.027
First-stage F				3.2e+07	3.0e+04	1.5e+07

Note: Columns (1)–(3) present the OLS results and Columns (4)–(6) display the 2SLS results using the instrument from equation (45). Columns (1) and (4) correspond to the full sample, while Columns (2) and (5) focus on citations within the same industry ($j = k$). Columns (3) and (6) are restricted to citations across different industries ($j \neq k$). We control for origin-sector-year, destination-sector-year, and origin-destination fixed effects. Additionally, we report the first-stage F-statistic for the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

ogy (Feyrer, 2019), which have raised the share of trade transported by air and disproportionately benefit country pairs with shorter air distances and sectors more reliant on air transport. Specifically, for each industry, we estimate the following gravity equation:

$$\ln X_{int}^k = \beta_{sea,t}^k \ln(seadist_{in}) + \beta_{air,t}^k \ln(airdist_{in}) + \text{fe}_i^k + \text{fe}_n^k + \text{fe}_t + u_{int}^k \tag{46}$$

where $seadist_{in}$ is the distance by sea between country i and n, and $airdist_{in}$ is the distance by air. fe_i^k, fe_n^k and fe_t are origin-sector-specific, destination-sector-specific, and year fixed effects. We estimate equation (46) by industry and obtain the following instrument:

$$X_{int}^{k,Air} = \exp\left(\hat{\beta}_{sea,t}^k \ln(seadist_{in}) + \hat{\beta}_{air,t}^k \ln(airdist_{in}) + \widehat{\text{fe}}_i^k + \widehat{\text{fe}}_n^k + \widehat{\text{fe}}_t\right), \tag{47}$$

which captures the evolving importance of aircraft and sea transportation for trade flows. The estimates of ν using this alternative instrument are similar to our baseline results. We report the detailed results and various robustness exercises in Appendix B.3.

In our counterfactual exercises, we take $\nu = 0.307$ as our baseline estimate. We set $\nu = 0.507$ as an alternative estimate in our sensitivity analysis. The magnitude of our estimates is consistent with prior empirical findings. For example, the elasticity of knowledge flows with respect to trade shares of 0.4 in Buera and Oberfield (2020), which was estimated based on matching the idea arrival rates in the U.S. in their paper.

3.4 Other Parameters Required by the "Exact-hat" Algebra

In additional to the diffusion intensity ν, the "exact-hat" algebra requires the parameters $\left(\theta_j; \gamma_i^j, \gamma_i^{kj}, \alpha_i^j\right)$ as well as data moments $\left(X_{in}^j, t_{in}^j, e_{in}^j, \delta_{in}^{kj}\right)$. We calibrate these parameters over the period 1996–2019. Specifically, we assume that $\left(\theta_j; \gamma_i^j, \gamma_i^{kj}, \alpha_i^j\right)$ remain constant throughout 1996–2019, while $\left(X_{in}^j, t_{in}^j, e_{in}^j, \delta_{in}^{kj}\right)$ are calibrated separately for four periods: 1996–2000, 2003–2007, 2010–2014, and 2015–2019.

The input–output parameters, $\left(\gamma_i^j, \gamma_i^{kj}, \alpha_i^j\right)$, are obtained from the OECD ICIO Tables. To align with our empirical specification, we use data for the year 2010. Our sample includes 17 major economies and the rest of the world, with European Union (EU) member countries (excluding the United Kingdom) aggregated into a single "EU" economy.

We calibrate the time-invariant trade elasticities, $\left(\theta_j\right)$, using estimates from Fontagne, Martin, and Orefice (2018). We aggregate all service sectors into a single category, "services." This leaves us with 23 sectors in the quantitative analysis.

We take X_{in}^j directly from the OECD ICIO Tables over 1996–2019 and obtain t_{in}^j in the corresponding periods from the WITS. We assume that $e_{in}^j = 0$ for all (i, n, j) in the baseline scenario.

We approximate knowledge flows δ_{in}^{kj} using the PATSTAT Global database and average observations within each period. A well-documented limitation of PATSTAT is that

records from the Japanese Patent Office contain disproportionately more missing values than those from the U.S. Patent and Trademark Office (Kang and Tarasconi, 2016). This discrepancy affects the knowledge diffusion networks in our quantitative framework. To address this issue, we reweight citations from Japanese and U.S. patents—the two largest sources of international citations—according to their shares in OECD triadic patent families.[14] Details of the reweighting procedure are provided in Appendix B.1.

For the return to innovation, ξ, we target $\frac{\xi}{\bar{\theta}} = 0.15$, where $\bar{\theta}$ is the average of θ_j for all manufacturing sectors, following Cai et al. (2022) and Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018). This leads to $\xi = 0.9$.

4 Counterfactuals

We conduct four sets of counterfactual exercises. First, we study how changes in trade barriers over 1996–2019 affect trade, innovation, and technology, further validating the model's core mechanisms. Second, we quantify the technological, innovation, and welfare effects of U.S. export controls on China, illustrating the double-edged effect characterized analytically in Proposition 2. Third, we examine the effects of the Liberation Day tariffs in 2025 on China and other major economies, highlighting how endogenous innovation and trade-facilitated technology diffusion amplify the consequences of trade wars. Finally, we characterize the U.S. optimal tariffs on China, emphasizing the trade-off between restricting China's access to advanced technologies and sustaining U.S. innovation.

4.1 Trade and Technology Progress: 1996–2019

In the first set of counterfactual exercises, we insert changes in tariffs and non-tariff trade barriers over 1996-2019 into our model and quantify the impacts of these trade shocks on

[14] Data available at `https://www.oecd.org/en/data/indicators/triadic-patent-families.html`.

innovation, technology, and welfare.

First, we compute and decompose welfare gains from trade utilizing Proposition 1. The results are shown in Table 5. We find that the diffusion term dominates the gains from trade in most countries, while the ACR term—representing the gains from trade in static trade models—accounts for only a small fraction of the total gains in our model. Based on our estimate of the elasticity of technology diffusion with respect to trade, the majority of welfare gains stem from trade-facilitated technology diffusion. This finding aligns with the quantitative pattern observed in Figure 4 of Buera and Oberfield (2020). Additionally, the innovation term is slightly negative in most countries, indicating that import competition outweighs export expansion and suppresses innovation in many country-sector pairs.

Table 5: Decomposing Gains from Trade in Period 4 (2015-2019)

	(i) ACR	(ii) Innovation	(iii) Diffusion	(iv) Tariff	GT	GT/ACR
Australia	5.82	-1.79	33.99	0.35	38.37	6.60
European Union	5.45	-1.44	32.77	0.34	37.12	6.81
Brazil	2.94	-0.01	52.38	0.27	55.58	18.93
Canada	7.55	-0.44	30.60	0.28	37.99	5.03
Switzerland	9.88	-1.20	53.08	0.24	61.99	6.28
China	3.55	0.03	16.60	0.30	20.48	5.77
United Kingdom	6.70	-1.28	41.73	0.29	47.44	7.08
Indonesia	5.11	-0.68	65.46	0.43	70.32	13.77
India	8.22	-2.66	81.25	0.68	87.49	10.64
Japan	7.76	-4.08	6.27	0.41	10.36	1.34
Korea	20.20	-10.40	33.78	0.69	44.28	2.19
Mexico	9.00	-0.69	52.50	0.51	61.32	6.81
Norway	9.14	-4.06	35.69	0.26	41.02	4.49
Rest of the World	5.88	-0.55	48.16	0.37	53.86	9.16
Russia	5.27	-1.00	12.57	0.43	17.27	3.27
Turkey	7.20	-1.86	61.00	0.53	66.87	9.28
Taiwan	18.01	-5.16	49.76	1.19	63.81	3.54
United States	3.01	-0.64	11.88	0.27	14.52	4.83

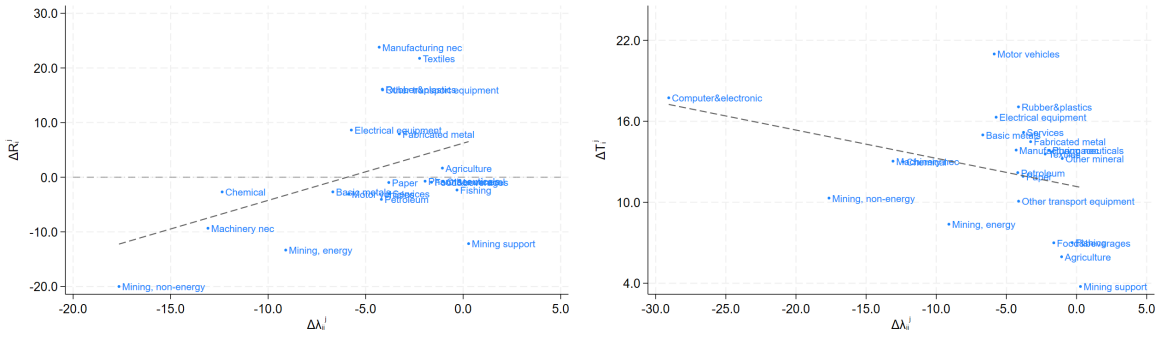
Note: The four terms and GT reported above correspond to those in Proposition 1. Each is expressed in logarithms and multiplied by 100.

Second, we impute changes in iceberg trade costs from the observed trade flows. Under the assumption of symmetric changes in trade costs for all (i, n) pairs, the changes in trade costs can be expressed as:

$$\hat{\tau}_{in}^{j} = \left(\frac{\hat{X}_{in}^{j} \hat{X}_{ni}^{j}}{\hat{X}_{ii}^{j} \hat{X}_{nn}^{j}} \right)^{-\frac{1}{2\theta_j}} \frac{1}{\sqrt{\widehat{1 + t_{in}^{j}}} \sqrt{\widehat{1 + t_{ni}^{j}}}}. \tag{48}$$

Figure 4 presents the quantitative effects of trade liberalization between period 1 (1996–2000) and period 2 (2003–2007) on China's R&D and technology. Panel (a) shows that R&D declines more sharply in sectors more exposed to import competition, reflecting reduced innovation returns in these sectors. This pattern is consistent with Proposition 2 and with empirical evidence on the adverse effects of import competition on Chinese innovation (*e.g.*, Liu et al., 2021). In contrast, Panel (b) shows that productivity rises in sectors facing greater import competition. This finding, again consistent with Proposition 2, suggests that increased import exposure has accelerated the inflow of advanced foreign technologies into China, offsetting the decline in domestic innovation intensity. This result aligns with the literature identifying trade as a major channel of international knowledge diffusion (*e.g.*, Aghion et al., 2024a) and with empirical evidence on the positive productivity impacts of China's WTO accession (Brandt et al., 2017). Taken together, these effects—each supported by the empirical literature—underscore the importance of modeling both trade-induced technology diffusion and endogenous innovation, the two core mechanisms in our model.

Figure 4: Trade Liberalization (1996-2007): Impacts on Technology and R&D in China



(a) R&D (b) Technology

Note: λ_{ii}^{j} denotes the share of domestic production in total expenditure, serving as an inverse measure of import penetration. All values represent percentage changes. Trade liberalization refers to changes in tariffs and iceberg trade costs between Period 1 (1996-2000) and 2 (2003-2007). The fitted line in Panel (a) has the slope coefficient −0.21 with standard error 0.09. The fitted line in Panel (b) has the slope coefficient is 1.05 with standard error 0.43.

Table 6 reports the welfare effects of trade shocks over 1996–2019. It shows that many economies gained substantially from trade liberalization during 1996–2007, with endogenous innovation and trade-facilitated technology diffusion amplifying the gains

Table 6: Welfare Effects of Changes in Trade Barriers, 1996-2019

	Period 1 → 2			Period 2 → 3			Period 3 → 4		
	Full	ND	FT	Full	ND	FT	Full	ND	FT
Australia	-1.5	1.0	0.1	-0.3	-0.0	-0.2	-0.1	0.2	-0.3
European Union	0.4	1.1	0.4	-0.3	0.2	0.1	1.3	0.3	0.2
Brazil	0.3	1.5	1.1	1.8	0.3	0.4	-0.1	-0.0	-0.1
Canada	-1.3	-0.2	-0.3	-0.8	1.0	0.4	0.8	0.4	0.1
Switzerland	1.3	0.8	0.7	1.9	1.2	0.8	2.2	0.8	0.7
China	9.5	5.9	3.4	0.6	0.8	0.3	0.1	0.5	-0.1
United Kingdom	-0.4	0.6	0.2	-1.1	0.5	0.0	0.3	0.2	0.0
Indonesia	-1.6	1.8	0.5	-2.1	1.1	-0.5	-1.9	-0.4	-0.9
India	7.2	2.8	2.6	7.0	2.2	2.2	1.0	0.1	-0.3
Japan	0.0	1.2	0.4	-0.6	0.1	-0.2	0.3	0.3	-0.1
Korea	2.2	5.5	1.7	1.3	2.7	1.3	-0.4	-1.0	-0.2
Mexico	3.3	1.4	1.3	2.4	3.0	1.2	2.7	1.1	1.1
Norway	-0.4	7.5	-0.1	1.1	-0.6	0.7	0.9	-1.4	0.4
Rest of the World	0.8	2.3	0.9	-0.3	0.9	0.2	-0.2	0.4	-0.1
Russia	3.0	1.1	1.1	0.9	0.0	0.2	-0.9	-0.2	-0.4
Turkey	2.3	3.1	1.9	0.6	1.1	0.4	1.7	0.6	0.4
Taiwan	3.4	13.8	2.3	-1.6	-1.9	-1.1	-2.4	15.1	-1.3
United States	-0.7	1.0	0.2	-0.5	1.4	0.3	0.6	0.6	0.0

Note: All values are percentage changes. "Full" denotes the baseline model. "ND" stands for "No Diffusion" ($\hat{T}_i^j = \left(\hat{R}_i^j\right)^{\xi}$). "FT" stands for "Fixed T" ($\hat{T}_i^j = 1$). For each initial period, we incorporate changes in iceberg trade costs and observed tariff changes to compute counterfactual real income changes. Period 1: 1996–2000. Period 2: 2003–2007. Period 3: 2010–2014. Period 4: 2015–2019.

from trade. After 2010, however, the welfare gains from liberalization became minimal—especially for China, whose gain declined from 9.5% in 1996–2007 to only 0.1% in 2010–2019. Meanwhile, advanced economies such as the United States and the European Union experienced greater gains from trade liberalization during the later period, with much of these gains attributable to trade-facilitated technology diffusion in the European Union and endogenous innovation in the United States.

4.2 U.S. Export Controls on China

In this subsection, we quantify the impacts of U.S. export controls against China. In particular, we start from our calibrated economy over the period 2015-2019, assuming no export controls at the initial equilibrium. We then convert the export control measure defined in Equation (43) into an export-tariff equivalent:

$$e^j_{US,CN} = \frac{0.355 \times EC_j}{\theta_j / 3}, \tag{49}$$

where EC_j takes the values in 2019, and 0.355 represents the elasticity of U.S. exports of HS-6 product p to China, $X^p_{US,CN,t}$, with respect to the export control dummy, $export_control_{pt}$. Notably, we interpret 0.355 as the short-run elasticity of trade under export controls. To align long-run trade elasticities θ_j with this horizon, we divide them by 3, converting them into short-run elasticities, following the estimates in Boehm, Levchenko, and Pandalai-Nayar (2020).

Table 7: U.S. Export Controls against China: Impacts on Technology and R&D

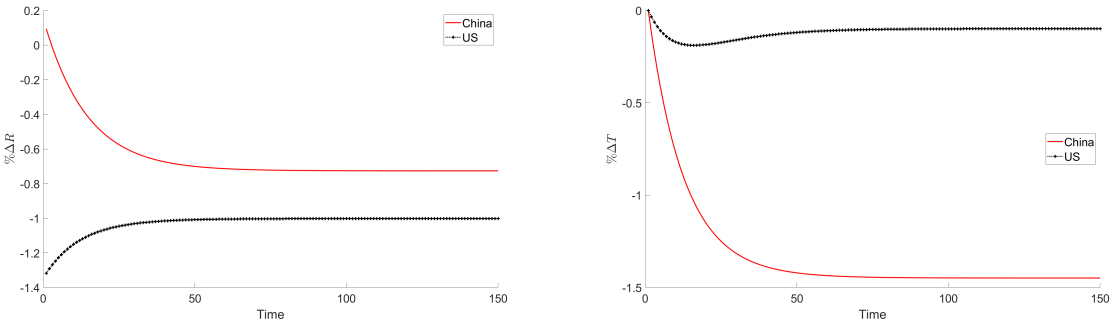
Sector	Tax Equiv.	China		U.S.	
		$\%\Delta T$	$\%\Delta R$	$\%\Delta T$	$\%\Delta R$
Agriculture	0.00	-0.14	-0.01	-0.08	0.11
Fishing	0.00	-0.07	0.00	0.14	0.93
Mining, energy	0.05	-0.20	0.19	-0.20	-0.12
Mining, non-energy	0.00	-0.07	0.23	-0.29	-0.19
Mining support	0.00	-0.60	0.08	-0.24	0.04
Food&Beverages	0.00	-0.12	-0.00	-0.07	0.08
Textiles	0.01	-0.27	-0.06	0.01	0.42
Wood	0.00	-0.26	-0.08	-0.21	0.17
Paper	0.00	-0.28	-0.06	-0.14	0.13
Petroleum	0.20	-0.74	0.22	-0.22	-0.16
Chemical	0.04	-0.28	0.20	-0.17	-0.48
Pharmaceuticals	0.00	-0.32	-0.01	-0.03	0.48
Rubber&Plastics	0.07	-0.51	-0.01	-0.14	-0.17
Other mineral	0.12	-0.39	-0.01	-0.17	-0.22
Basic metals	0.05	-0.24	0.26	-0.29	-1.73
Fabricated metal	0.10	-0.49	-0.01	-0.15	-0.14
Computer&Electronic	0.17	-1.45	-0.73	-0.10	-1.00
Electrical equipment	0.14	-0.67	-0.05	-0.13	-0.68
Machinery nec	0.18	-0.46	0.30	-0.29	-1.58
Motor vehicles	0.00	-0.40	-0.11	-0.14	0.29
Other transport equipment	0.05	0.15	2.27	-0.36	-1.27
Manufacturing nec	0.05	-0.62	-0.20	-0.06	0.13
Services	0.00	-0.69	-0.03	-0.10	0.06

Note: We start from the world economy in period 4 (2015-2019). Tax equiv. refers to the export-tariff equivalent of export controls constructed by Equation (49).

Table 7 reports the effects of U.S. export controls on R&D and technology outcomes in both China and the United States. Consistent with Proposition 2 and motivating facts in Table 1, export controls reduce R&D investment and, consequently, the level of BGP technologies in the affected U.S. sectors, particularly in "Computer&Electronic", "Electrical equipment", and "Machinery nec." Importantly, U.S. technology losses are not confined

to the sectors directly subject to export restrictions but propagate across most sectors. In other words, export controls targeting a few strategic sectors–critical to national security and central within knowledge networks–can generate broader technological losses across the aggregate economy.

Export controls also reduce the level of BGP technologies in the affected Chinese sectors, consistent with Proposition 2. This effect is primarily driven by a decline in technology diffusion from the U.S., consistent with the patterns shown in Panel (a) of Figure 2. The impacts on Chinese R&D are heterogeneous: among affected industries, R&D increases in "Petroleum" and "Machinery nec" but declines in "Computer& Electronic" and "Electrical Equipment." Intuitively, U.S. export controls reduce import competition faced by Chinese firms, which tends to stimulate innovation, but they also limit technology inflows from the U.S., which suppresses innovation by reducing firms' effective market size. For Chinese sectors that rely heavily on U.S. technologies, such as "Computer&Electronic" and "Electrical Equipment," the negative effect of reduced technology diffusion dominates, resulting in a net decline in R&D.



(a) $\%\Delta R$ (b) $\%\Delta T$

Figure 5: U.S. Export Controls against China: Dynamic impacts on Technology and R&D of Computer&Electronic

Note: All changes are relative to the BGP levels. We set the BGP growth rate $g = 0.1$.

Figure 5 illustrates the counterfactual trajectory of technology and R&D in the "Computer&Electronic" sector under U.S. export controls. It highlights the opposing forces shaping changes in R&D and technology. Notably, export controls initially boost R&D

in China due to reduced import competition, but R&D subsequently declines as China's technology base shrinks. In contrast, U.S. experiences a sharp initial decline in R&D, followed by partial recovery as the contraction of China's technology reduces competitive pressure abroad.

Table 8: U.S. Export Controls against China: Impacts on Real Income

	Full	FR	FT
Australia	0.023	0.032	0.004
European Union	0.018	0.014	-0.000
Brazil	-0.001	0.013	-0.000
Canada	-0.000	0.003	-0.004
Switzerland	0.021	0.019	0.001
China	-0.267	-0.268	-0.030
United Kingdom	0.012	0.013	-0.001
Indonesia	0.015	0.023	-0.001
India	0.009	0.030	-0.005
Japan	0.044	0.011	0.000
Korea	0.068	0.036	0.009
Mexico	-0.024	-0.008	-0.009
Norway	0.007	0.016	-0.002
Rest of the World	0.024	0.029	0.000
Russia	0.022	0.011	-0.002
Turkey	0.012	0.018	-0.002
Taiwan	0.065	0.054	0.020
United States	-0.034	-0.016	0.002

Note: All values are percentage changes. "Full" denotes the baseline model. "FR" stands for "Fixed R" ($\hat{R}_i^j = 1$). "FT" stands for "Fixed T" ($\hat{T}_i^j = 1$).

Table 8 reports the welfare effects of U.S. export controls against China. In our baseline model, real income declines by 0.034% in the U.S. and by 0.267% in China. Notably, in a model without endogenous innovation, the U.S. real income declines by only 0.016%. In other words, models with trade-facilitated diffusion but exogenous innovation (e.g., Buera and Oberfield, 2020 and Bai et al., 2025b) tend to underestimate welfare losses in the home country by ignoring the impact of export controls on R&D incentives, while they tend to overestimate welfare losses in the targeted country by ignoring the compensating effects of R&D responses.

Table 8 also shows that endogenous innovation and trade-facilitated technology diffusion substantially amplify welfare losses from export controls. In a model with exogenous

technology, Chinese real income declines by only 0.03% while U.S. real income slightly increases by 0.002%. This result highlights the importance of accounting for technological responses when evaluating the effects of export controls.

4.3 The U.S. Liberation Day Tariffs in 2025

In this subsection, we quantify the effects of the U.S. Liberation Day tariffs in 2025. The U.S. unilaterally imposes a 10% baseline tariff increase, with higher rates for selected economies in our calibrated model: 34% for China, 20% for EU countries, 27% for India, 32% for Indonesia, 24% for Japan, 26% for Korea, 16% for Norway, 31% for Switzerland, and 32% for Taiwan.[15] In response, China raises tariffs by 10% on all tradable goods imported from the United States.

This round of the US-China tariff war, together with U.S. export controls on China, is evaluated in the first five columns of Table 9. The results show that the US-China trade war starting from 2025 significantly harms China in both real income and technology. Although China slightly increases R&D investment, this response cannot fully offset the losses caused by reduced knowledge inflows. In contrast, the United States experiences substantial gains in real income, R&D, and technology. Unlike export controls alone, U.S. import tariffs lead to a marked increase in domestic R&D investment, which contributes to the overall welfare gain. These findings provide a rational for combining export controls with import tariffs in U.S. policy toward China.

Notably, China's welfare loss and the U.S. welfare gain are both markedly smaller in the absence of trade-facilitated technology diffusion. Moreover, in a model with exogenous technology, both countries lose from the trade war. These results highlight that the effects of trade on technology—via knowledge diffusion and innovation—are central to evaluating US-China trade wars.

[15] U.S. reciprocal tariffs are obtained from the USTR tariff calculator: `https://tariffs.inasimonovska.com/`.

Table 9: Trump's Trade War 2.0: Impacts on Technology, R&D, and Real Income

	(I) US EC&RT on China+China's Ret.					(I)+US RT on others				
	Full			ND	FT	Full			ND	FT
	ΔT	ΔR	ΔW	ΔW	ΔW	ΔT	ΔR	ΔW	ΔW	ΔW
Australia	0.72	0.31	0.14	0.04	-0.02	0.38	0.41	-0.06	-0.09	-0.07
European Union	0.70	0.02	0.23	0.31	0.01	-0.31	0.00	-0.28	-0.20	-0.11
Brazil	0.82	0.08	0.22	0.01	0.00	0.19	0.14	-0.08	-0.13	-0.06
Canada	1.59	0.12	0.47	-0.39	0.03	1.33	0.67	-0.19	-0.86	-0.46
Switzerland	0.96	-0.02	0.33	-0.32	0.01	-0.56	0.39	-0.46	-0.24	-0.22
China	-2.23	0.03	-1.16	-0.18	-0.23	-2.45	0.05	-1.26	-0.30	-0.22
United Kingdom	1.00	0.01	0.30	-0.03	0.01	0.43	-0.03	0.06	-0.09	-0.02
Indonesia	0.64	0.14	0.22	-0.01	0.03	-0.79	0.08	-0.55	-0.24	-0.14
India	1.35	0.01	0.47	0.01	0.05	-0.05	0.23	-0.46	-0.36	-0.13
Japan	0.28	0.01	0.07	-0.01	0.01	-0.56	0.06	-0.36	-0.21	-0.14
Korea	0.41	0.03	0.12	0.05	0.01	-0.52	0.23	-0.63	-0.50	-0.33
Mexico	1.70	0.13	0.60	-0.14	0.15	0.55	0.07	-0.38	-0.78	-0.46
Norway	0.75	-0.01	0.23	6.32	0.01	-0.09	0.34	-0.21	-0.52	-0.11
Rest of the World	1.00	0.14	0.31	0.04	0.02	0.33	0.32	-0.11	-0.17	-0.09
Russia	0.46	0.01	0.13	0.02	0.01	0.16	0.10	-0.02	-0.08	-0.02
Turkey	0.91	0.01	0.31	-0.08	0.02	0.19	0.02	-0.02	-0.11	-0.02
Taiwan	0.40	0.04	0.12	-1.58	-0.02	-0.76	0.33	-0.80	-2.21	-0.48
United States	3.05	0.29	0.66	0.34	-0.17	1.24	0.70	0.02	-0.10	-0.17

Note: All values are percentage changes. Full: the baseline model. ND: No Diffusion ($\hat{T}_i^j = \left(\hat{R}_i^j\right)^{\hat{\xi}}$). FT: Fixed T ($\hat{T}_i^j = 1$). We start from the world economy in period 4 (2015-2019). EC: Export Controls. RT: Reciprocal Tariffs. Ret.: Retaliatory Tariffs. "US Export Controls on China": measured in Table 7. "US Reciprocal Tariffs on China": 34% tariff increase on U.S. imports from China. "China's Retaliation Tariffs": 10% tariff increase on China's imports from the U.S. "US Reciprocal Tariffs on Others": 10% baseline import tariff increase for all trading partners, with higher increases for specific regions: 20% for the EU, 27% for India, 32% for Indonesia, 24% for Japan, 26% for Korea, 16% for Norway, 31% for Switzerland, and 32% for Taiwan. These tariff rates are from USTR tariff calculator `https://tariffs.inasimonovska.com/`. ΔT_i^j and ΔR_i^j are weighted by α_i^j in each economy.

The U.S. reciprocal tariffs on all trading partners, together with China's retaliatory tariffs and U.S. export controls on China, are evaluated in the last five columns of Table 9. The results indicate that most major economies incur losses from the reciprocal tariffs: China (-1.26%), the European Union (-0.28%), Japan (-0.36%), and India (-0.46%). These losses shrink substantially without trade-facilitated technology diffusion (China -0.30%, the European Union -0.20%, Japan -0.21%, and India -0.36%) and decline further if technology is exogenous (China -0.22%, the European Union -0.11%, Japan -0.14%, and India -0.13%).

Compared with the welfare effects of the bilateral U.S.-China trade war, U.S. real income decreases significantly when tariffs are extended to all major economies. In other words, escalating a bilateral trade conflict into a global one does not serve U.S. interests.

4.4 Optimal Tariffs with Endogenous Innovation and trade-facilitated Technology Diffusion

In this subsection, we characterize the U.S. unilaterally optimal tariffs on China within our model. Given the model's multiple sectors, endogenous innovation, and complex input-output and knowledge diffusion networks, analytical solutions are infeasible. We therefore rely on numerical methods to characterize the optimal tariffs.

Table 10 reports the optimal export and import tariffs and their effects on R&D, technology, and real income in China and the United States. In our full model, the U.S. optimal export tariffs on China are negative, reflecting an export subsidy. This result is intuitive in the presence of endogenous innovation: export subsidies expand the market size of U.S. firms, thereby promoting their innovation. A striking example is the "Computer & electronic" sector. By subsidizing exports in this sector by 65.4%, U.S. R&D rises by 374.7%, raising sectoral productivity by 104.8%. The resulting innovation and technological progress spill over to other sectors, generating a 3.95% increase in overall U.S. real income.

Interestingly, the U.S. optimal tariffs on China, which include substantial export subsidies to strategic sectors, also benefit China. These subsidies promote knowledge diffusion from the United States to China through trade, raising China's real income by 6.49%. In other words, when U.S. optimal tariffs primarily aim to enhance domestic innovation, they are less effective at limiting knowledge spillovers to China.

To assess the role of endogenous innovation, we set $\xi = 0$ and recompute the optimal tariffs. Without endogenous innovation, the U.S. has weaker incentives to subsidize exports and instead relies on tariffs to influence China's technological progress. In this scenario, the optimal tariffs raise U.S. real income by 0.35% while reducing China's real income by 0.12%. This pattern aligns with the optimal tariffs in the framework developed by Bai et al. (2025b): absent the need to stimulate domestic innovation, U.S. tariffs are more effective at curbing knowledge flows to China, resulting in welfare losses there.

Table 10: U.S. Optimal Export and Import Tariffs on China

Sector	Full						FR			
	Optimal Tariffs		China		U.S.		Optimal Tariffs		China	U.S.
	$\epsilon^*_{US,CN}$	$t^*_{CN,US}$	ΔT	ΔR	ΔT	ΔR	$\epsilon^*_{US,CN}$	$t^*_{CN,US}$	ΔT	ΔT
Agriculture	20.3	0.0	3.3	0.8	20.5	-8.6	3.7	0.0	-0.1	1.2
Fishing	-31.7	5.0	2.4	-3.0	16.7	62.7	-8.5	6.8	-0.1	0.8
Mining, energy	29.9	0.0	1.9	4.0	4.7	-11.8	5.9	0.0	0.1	1.1
Mining, non-energy	3.7	0.0	3.7	7.8	16.3	-13.5	-11.2	0.0	-0.1	1.5
Mining support	-8.1	0.0	5.6	3.3	9.5	-7.4	-9.6	0.0	0.7	1.0
Food&beverages	12.3	0.0	1.4	0.8	7.9	-7.0	-1.7	0.0	0.1	0.9
Textiles	-37.3	30.3	3.8	-3.5	14.1	11.8	-16.4	26.7	0.6	1.8
Wood	7.6	2.0	2.8	10.9	8.6	-26.3	3.6	22.4	-0.4	1.4
Paper	1.3	7.3	3.9	1.7	13.2	-10.1	-10.2	17.7	-0.1	1.7
Petroleum	15.1	0.0	1.2	1.6	6.3	-7.9	4.3	0.0	0.1	1.2
Chemical	-19.9	10.2	2.0	-3.1	12.0	-1.6	-14.6	5.9	0.5	1.4
Pharmaceuticals	-29.6	8.6	5.2	-7.4	7.8	-14.6	-12.4	2.8	1.8	1.3
Rubber&plastics	-13.5	23.3	3.9	-3.0	12.4	-3.0	-14.1	24.5	0.3	1.4
Other mineral	-18.5	26.2	3.5	-0.0	20.5	-2.4	-7.8	21.4	-0.2	1.6
Basic metals	1.0	0.0	1.9	1.5	15.6	-4.7	-9.7	5.0	-0.2	1.6
Fabricated metal	-4.3	14.0	5.2	0.3	17.0	-0.6	-4.3	18.0	-0.2	1.4
Computer&electronic	-65.4	165.9	48.7	-30.1	104.8	374.7	-10.4	55.9	0.4	1.3
Electrical equipment	-26.9	44.7	7.8	0.1	32.2	13.6	-7.6	35.3	-0.1	1.6
Machinery nec	-14.1	25.5	3.2	1.1	16.9	-5.7	-5.3	24.9	-0.2	1.3
Motor vehicles	-4.2	3.5	7.1	3.5	19.3	-12.1	-13.8	11.1	0.2	1.6
Other transport equipment	2.8	0.0	15.6	22.5	30.7	-23.9	-11.0	2.6	-0.1	1.7
Manufacturing nec	-53.2	94.0	8.6	-17.1	19.6	22.4	-6.7	48.0	0.2	1.3
Services	0.0	0.0	18.2	1.4	45.3	-6.1	0.0	0.0	-0.2	2.0

Note: All values are in percentage. We start from the world economy in period 4 (2015-2019). Full: baseline model. FR: Fixed R ($\hat{R}^j_i = 1$). Welfare changes under optimal tariffs: Full: U.S. 3.95%, China 6.49%; FR: U.S. 0.35%, China -0.12%.

In practice, the most direct way to promote domestic innovation is through industrial policies rather than export subsidies. We therefore consider a scenario in which the United States optimally chooses both its tariffs on China and its domestic production subsidies. Table 11 reports these optimal policies. Compared with Table 10, the U.S. has much weaker incentives to subsidize exports when domestic production subsidies are available. The resulting U.S. welfare gain rises to 11.58%, substantially higher than relying solely on trade policies against China. China also benefits from these policies, particularly from the spillovers of U.S. industrial subsidies.

Recent discussions of the U.S.–China trade war suggest that the United States cares not only about its own economic gains but also about relative outcomes vis-à-vis China. In particular, the U.S. may be willing to forego some gains, or even accept losses, to amplify China's losses. This zero-sum geopolitical motive can substantially alter the U.S. optimal

Table 11: U.S. Optimal Tariffs on China and Domestic Production Subsidies

Sector	Optimal Tariffs and Subsidies			China		U.S.	
	$e^*_{US,CN}$	$t^*_{CN,US}$	s^*_{US}	ΔT	ΔR	ΔT	ΔR
Agriculture	15.5	0.0	-11.1	6.1	0.5	61.2	-6.5
Fishing	3.3	29.0	-49.5	26.1	-8.1	310.8	1210.5
Mining, energy	23.5	0.0	-14.4	8.3	16.8	15.0	-4.4
Mining, non-energy	-0.6	0.0	-11.3	11.7	27.9	44.4	-2.8
Mining support	-7.7	0.0	-8.3	9.1	12.5	25.4	-19.2
Food&beverages	10.1	0.0	-9.1	3.4	0.5	29.4	-13.6
Textiles	2.4	25.4	-36.8	11.8	-6.9	85.8	254.8
Wood	9.9	12.1	-6.2	4.7	13.0	32.0	-18.2
Paper	-2.3	15.9	-6.6	5.7	2.4	41.2	-14.3
Petroleum	9.0	0.0	0.0	3.3	6.8	16.3	-22.5
Chemical	-18.4	18.5	-5.2	5.8	5.1	35.1	-12.4
Pharmaceuticals	-4.1	1.2	-29.5	10.6	2.9	29.4	58.2
Rubber&plastics	-3.6	20.5	-15.1	6.2	-1.8	38.7	22.5
Other mineral	-11.7	29.1	-9.5	5.3	0.3	52.1	-0.0
Basic metals	0.9	6.9	-8.2	3.2	2.5	40.8	31.9
Fabricated metal	-4.3	25.1	-6.3	7.5	0.3	46.8	10.2
Computer&electronic	-0.1	59.9	-59.5	62.3	-54.9	226.2	715.2
Electrical equipment	-0.6	28.9	-26.9	10.8	-3.2	75.4	76.6
Machinery nec	-0.2	20.6	-17.2	4.5	1.7	41.6	13.7
Motor vehicles	2.5	3.7	-12.4	8.8	2.4	44.1	15.0
Other transport equipment	1.2	1.3	-12.2	19.2	25.2	72.3	-24.7
Manufacturing nec	0.2	34.7	-40.6	12.2	-12.8	55.3	100.5
Services	0.0	0.0	-9.1	23.4	1.4	106.0	-16.0

Note: All values are in percentage. We start from the world economy in period 4 (2015-2019). Welfare changes under optimal policies: U.S. 11.58%, China 6.97%.

tariffs. To capture this preference, we assume that the U.S. maximizes

$$\hat{W}_{US} + \chi \hat{W}_{CN}. \tag{50}$$

We set $\chi = -0.1$, consistent with Thoenig (2024) where a country is willing to sacrifice 8–10% of GDP to engage in a conflict. Table 12 reports the resulting optimal tariffs. In stark contrast to Table 10, the U.S. imposes prohibitive export tariffs on many strategic sectors to curb knowledge diffusion to China. This policy leads to a modest U.S. welfare gain of 1.43% and a substantial loss for China of 1.05%.

In sum, with endogenous innovation and trade-facilitated technology diffusion, the U.S. optimal tariffs on China reflect a trade-off between restricting technology diffusion to China and sustaining U.S. innovation. If the U.S. aims not only to promote its own welfare but also to reduce China's welfare, it would impose highly restrictive export controls on China, sharply limiting technology flows, but this would also dampen U.S. innovation.

Table 12: U.S. Optimal Tariffs on China under Geopolitical Preferences

Sector	Optimal Tariffs		China		U.S.	
	$e^*_{US,CN}$	$t^*_{CN,US}$	ΔT	ΔR	ΔT	ΔR
Agriculture	28.1	0.0	-2.4	-0.4	7.1	-4.0
Fishing	-37.9	23.1	4.9	-9.6	50.7	283.1
Mining, energy	43.1	0.0	0.3	4.3	6.2	-2.6
Mining, non-energy	383.3	0.0	1.0	11.2	5.6	-5.8
Mining support	339.4	0.0	-2.8	3.9	4.1	-2.3
Food&beverages	500.0	0.0	-2.3	0.7	8.5	-2.2
Textiles	500.0	49.1	-5.2	-7.2	18.0	28.8
Wood	247.6	7.9	-2.8	3.5	6.1	-9.3
Paper	430.0	12.8	-4.2	1.9	8.8	-2.2
Petroleum	500.0	0.0	-1.6	1.6	6.5	-1.2
Chemical	-27.7	13.7	-2.6	-7.9	11.1	30.5
Pharmaceuticals	-39.4	17.7	1.3	-31.4	15.3	36.7
Rubber&plastics	499.4	32.5	-2.2	-0.4	11.3	4.1
Other mineral	500.0	34.9	-2.9	0.9	6.4	1.2
Basic metals	1.5	0.0	-1.5	2.9	6.0	-2.5
Fabricated metal	500.0	21.1	-1.8	0.9	10.0	1.1
Computer&electronic	500.0	107.4	-7.5	-5.5	7.1	6.6
Electrical equipment	500.0	60.9	-4.5	-0.2	7.4	8.9
Machinery nec	-20.0	36.6	-1.3	0.6	6.7	4.1
Motor vehicles	-8.1	7.2	-0.8	2.4	5.2	-4.5
Other transport equipment	-7.2	2.1	0.4	9.5	4.7	-10.6
Manufacturing nec	-67.4	150.7	5.8	-39.2	22.5	116.5
Services	0.0	0.0	-2.6	1.3	10.9	-1.9

Note: All values are in percentage. We start from the world economy in period 4 (2015-2019). The U.S. maximizes $\hat{W}_{US} + \chi \hat{W}_{CN}$ where $\chi = -0.1$. The upper bound of tariffs is set to be 500%. Welfare changes under optimal policies: U.S. 1.43%, China -1.05%.

4.5 Sensitivity Analysis

In this subsection, we conduct sensitivity analysis to show how sensitive our counterfactual results are with respect to key model parameters.

Heterogeneous Diffusion Elasticities. We consider the case where the elasticity of knowledge diffusion with respect to trade, ν, could vary across sectors. In particular, we run the following regression separately for each source sector k:

$$\log \delta^{kj}_{int} = \nu_k \log X^{kj}_{int} + \text{fe}^k_{it} + \text{fe}^j_{nt} + \log \bar{\epsilon}^{kj}_{int}. \tag{51}$$

We summarize the estimates of ν_k in Appendix Table B5. The estimates vary considerably across sectors, indicating heterogeneous elasticities of technology diffusion. We then incorporate the estimated ν_k into our model to conduct a counterfactual in which the United States imposes a 30% export tariff on dual-use goods to China. The results,

reported in Appendix Table B5, remain broadly consistent with those under a uniform ν shown in Table 7, confirming the robustness of our main findings to allowing for heterogeneous diffusion elasticities.

Returns to Innovation. Previous studies, such as Buera and Oberfield (2020) and Bai et al. (2025b), impose the restriction $\xi = 1 - \nu$ on the returns to innovation. In our baseline calibration, this restriction implies $\xi = 0.693$. We incorporate $\xi = 0.693$ into our model and simulate trade liberalization between 1996 and 2007 to examine its effects on China's technology and R&D. The results, presented in Appendix Figure B1, are very similar to our baseline results in Figure 4, confirming that the main findings are robust to this alternative assumption.

5 Conclusion

In this paper, we show that the effects of trade policy on technology—both through trade-facilitated technology diffusion and through firms' incentives to innovate—are critical for evaluating the consequences of trade wars. Empirically, we find that both channels are essential for explaining the observed correlation between U.S. exports to China and R&D and patenting in China and the U.S. Quantitatively, we find that U.S. export controls on China have a double-edged effect: they restrict technology diffusion to China while simultaneously reducing U.S. innovation incentives, ultimately lowering productivity and real income in both countries. We also find that the U.S. Liberation Day tariffs in 2025 generate substantial technological and welfare losses once endogenous innovation and trade-facilitated diffusion are taken into account. These losses far exceed the predictions of standard trade models.

Our model further highlights a strategic trade-off in designing optimal tariffs: restricting the diffusion of technology to rival countries versus sustaining incentives for domestic innovation. If the U.S. aims solely to maximize its own welfare, it should consider

substantial export subsidies in strategic sectors to foster domestic innovation, which benefits both the U.S. and China. By contrast, if the U.S. seeks to maximize its own welfare while also reducing Chinese welfare, it would impose prohibitive export restrictions on strategic goods to China—cutting China's access to these technologies but simultaneously eroding U.S. innovation incentives. This latter strategy appears to describe current U.S.–China trade policy.

A key takeaway is that understanding the motivations and consequences of trade conflicts requires explicitly accounting for their effects on technologies, beyond traditional terms-of-trade or home-market effects. It is essential to incorporate the multiple channels through which trade policies shape global technological progress. This area remains under-explored in the literature, leaving important avenues for future research, including how trade policies affect multinational firms' innovation across countries and how these effects reshape our understanding of trade wars.

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A Theory

A.1 Proof to Proposition 1

The unit cost of producing in country n and sector j is (when $z_n^j(\omega) = 1$):

$$c_n^j = w_n^{\gamma_n^j} \prod_{k=1}^{J} \left(P_n^k\right)^{\gamma_n^{kj}}.$$

The self-import share is:

$$\lambda_{nn}^j \equiv \frac{X_{nn}^j}{X_n^j} = \frac{T_n^j \left(c_n^j\right)^{-\theta_j}}{\sum_{i'=1}^{N} T_{i'}^j \left(c_{i'}^j \kappa_{i'n}^j\right)^{-\theta_j}} = \frac{T_n^j \left(c_n^j\right)^{-\theta_j}}{\left(P_n^j\right)^{-\theta_j}}.$$

Let $\tilde{x} = \log(x'/x)$ denote the log change of variable x from the observed equilibrium to the counterfactual case. Taking the log changes of c_n^j and λ_{nn}^j, we can obtain:

$$\tilde{P}_n^j = \frac{\tilde{\lambda}_{nn}^j}{\theta_j} - \frac{\tilde{T}_n^j}{\theta_j} + \gamma_n^j \tilde{w}_n + \sum_k \gamma_n^{kj} \tilde{P}_k^j.$$

Consequently, by performing some matrix calculations, we can derive

$$\tilde{P}_n^j = \sum_k \beta_n^{kj} \left(\frac{\tilde{\lambda}_{nn}^k}{\theta_k} - \frac{\tilde{T}_n^k}{\theta_k} + \gamma_n^k \tilde{w}_n \right),$$

where β_n^{kj} is the (j,k) element of the Leontief inverse matrix $(\mathbf{I} - \mathbf{\Gamma}_n)^{-1}$. Let J be the number of industries. $\mathbf{I}$ is a $J \times J$ identity matrix, and $\mathbf{\Gamma}_n$ is a $J \times J$ matrix with the (j,k) element being γ_n^{kj}. Therefore, according to this formula, the proportional change in prices from the observed equilibrium to autarky is:

$$\frac{P_n^{j,A}}{P_n^j} = \prod_k (\lambda_{nn}^k)^{-\frac{\beta_n^{kj}}{\theta_k}} \times \prod_k \left(\frac{T_n^k}{T_n^{k,A}} \right)^{\frac{\beta_n^{kj}}{\theta_k}} \times \prod_k \left(\frac{w_n^A}{w_n} \right)^{\beta_n^{kj} \gamma_n^k},$$

where $\sum_k \beta_n^{kj}\gamma_n^k = 1$ by the characteristics of the Leontief inverse matrix.[16] Thus, we can obtain $\prod_k \left(\frac{w_n^A}{w_n}\right)^{\beta_n^{kj}\gamma_n^k} = \frac{w_n^A}{w_n}$.

We define W_n as the real consumption in the economy, which is

$$W_n = \frac{Y_n}{P_n} = \frac{Y_n}{w_n L_n}\frac{w_n L_n}{P_n} = \frac{Y_n}{w_n L_n}\frac{w_n L_n}{\prod (P_n^j)^{\alpha_n^j}}.$$

Here $\frac{Y_n}{w_n L_n}$ is 1 in autarky and can be different from 1 in the observed equilibrium due to tariff incomes.

We can then compute the gains from trade as:

$$\begin{aligned}
\text{GT}_n &= \frac{W_n}{W_n^A} \\
&= \frac{Y_n}{w_n L_n}\prod_j \left(\frac{w_n / P_n^j}{w_n^A / P_n^{j,A}}\right)^{\alpha_n^j} \\
&= \frac{Y_n}{w_n L_n} \times \prod_j \prod_k (\lambda_{nn}^k)^{-\frac{\alpha_n^j \beta_n^{kj}}{\theta_k}} \times \prod_j \prod_k \left(\frac{T_n^k}{T_n^{k,A}}\right)^{\frac{\alpha_n^j \beta_n^{kj}}{\theta_k}}.
\end{aligned}$$

It is worth noting that:

$$\frac{T_n^k}{T_n^{k,A}} = \frac{\bar{A}_n^k \epsilon_{nn}^{kk} \left(R_n^k\right)^{\xi} L_n^{1-\xi} / \delta_{nn}^{kk}}{\bar{A}_n^k \epsilon_{nn}^{kk,A} \left(R_n^{k,A}\right)^{\xi} L_n^{1-\xi} / \delta_{nn}^{kk,A}} = \left(\frac{R_n^k}{R_n^{k,A}}\right)^{\xi} \times \frac{\epsilon_{nn}^{kk} / \delta_{nn}^{kk}}{\epsilon_{nn}^{kk,A} / \delta_{nn}^{kk,A}}.$$

Thus, we can write the gains from trade as:

$$\text{GT}_n = \prod_j \prod_k (\lambda_{nn}^k)^{-\frac{\alpha_n^j \beta_n^{kj}}{\theta_k}} \times \prod_j \prod_k \left(\frac{R_n^k}{R_n^{k,A}}\right)^{\frac{\xi \alpha_n^j \beta_n^{kj}}{\theta_k}} \times \prod_j \prod_k \left(\frac{\epsilon_{nn}^{kk} / \delta_{nn}^{kk}}{\epsilon_{nn}^{kk,A} / \delta_{nn}^{kk,A}}\right)^{\frac{\alpha_n^j \beta_n^{kj}}{\theta_k}} \times \frac{Y_n}{w_n L_n}.$$

[16] We have $(\mathbf{I} - \mathbf{\Gamma}_n)^{-1}(\mathbf{I} - \mathbf{\Gamma}_n)\mathbf{e} = \mathbf{e}$, where $\mathbf{e}$ is the $J \times 1$ column with all ones. Thus, we can obtain $\sum_k \beta_n^{kj}\gamma_n^k = 1$ from evaluating each row of this equation.

A.2 Proof to Proposition 2

We consider a first-order change in e_{12}. Then the system can be expressed as

$$\begin{aligned} T_n &= \sum_{i=1}^{N} \lambda_{in}^{\nu} R_i^{\xi}, \quad \lambda_{in} = T_i \left(1+e_{in}\right)^{-\theta} P_n^{\theta} \\ R_i &= \sum_{n=1}^{N} \frac{1}{1+\theta} \frac{\lambda_{in} X_n}{1+e_{in}} \\ P_n &= \left(\sum_{i=1}^{N} T_i \left(1+e_{in}\right)^{-\theta} \right)^{-\frac{1}{\theta}} \\ X_n &= \alpha Y_n, \quad Y_n = 1 + \sum_{i=1}^{N} \frac{e_{ni}}{1+e_{ni}} \lambda_{ni} X_i \end{aligned} \quad . \tag{A1}$$

Notably, if $e_{in} = 0$, then $Y_n = 1$, $X_n = \alpha$, $\lambda_{in} = \frac{1}{2}$, $R_i = \frac{\alpha}{1+\theta}$, $T_n = 2\left(\frac{1}{2}\right)^{\nu} \left(\frac{\alpha}{1+\theta}\right)^{\xi}$, and $P_n = \left(4\left(\frac{1}{2}\right)^{\nu} \left(\frac{\alpha}{1+\theta}\right)^{\xi}\right)^{-\frac{1}{\theta}}$. Welfare $W_n = \frac{Y_n}{P_n^{\alpha}} = \left(4\left(\frac{1}{2}\right)^{\nu} \left(\frac{\alpha}{1+\theta}\right)^{\xi}\right)^{\frac{\alpha}{\theta}}$.

For any variable $Z > 0$, denote $\tilde{Z} = d \log Z$. Then log-linearizing Equation (A1) around $e_{in} = 0$ leads to

$$\begin{aligned} \tilde{T}_n &= \sum_{i=1}^{N} \frac{1}{2} \left[\nu \tilde{\lambda}_{in} + \xi \tilde{R}_i\right], \quad \tilde{\lambda}_{in} = \tilde{T}_i - \theta \widetilde{1+e_{in}} + \theta \tilde{P}_n \\ \tilde{R}_i &= \sum_{n=1}^{N} \frac{1}{2} \left[\tilde{\lambda}_{in} + \tilde{X}_n - \widetilde{1+e_{in}}\right] \\ -\theta \tilde{P}_n &= \sum_{i=1}^{N} \frac{1}{2} \left[\tilde{T}_i - \theta \widetilde{1+e_{in}}\right] \\ \tilde{X}_n &= \tilde{Y}_n, \quad \tilde{Y}_n = \frac{\alpha}{2} \sum_{i=1}^{N} \widetilde{1+e_{ni}} \end{aligned} \tag{A2}$$

The corresponding changes in welfare is $\tilde{W}_n = \tilde{Y}_n - \alpha \tilde{P}_n$.

Therefore, we have

$$
\begin{aligned}
&\tilde{Y}_2 = \tilde{X}_2 = 0, \quad \tilde{Y}_1 = \tilde{X}_1 = \frac{\alpha}{2}\widetilde{1+e_{12}} \\
&-\theta\tilde{P}_1 = \frac{1}{2}\left[\tilde{T}_1 + \tilde{T}_2\right], \quad -\theta\tilde{P}_2 = \frac{1}{2}\left[\tilde{T}_1 + \tilde{T}_2\right] - \frac{\theta}{2}\widetilde{1+e_{12}} \\
&\tilde{\lambda}_{11} = \frac{1}{2}\left[\tilde{T}_1 - \tilde{T}_2\right], \quad \tilde{\lambda}_{12} = \frac{1}{2}\left[\tilde{T}_1 - \tilde{T}_2\right] - \frac{\theta}{2}\widetilde{1+e_{12}} \\
&\tilde{\lambda}_{21} = \frac{1}{2}\left[\tilde{T}_2 - \tilde{T}_1\right], \quad \tilde{\lambda}_{22} = \frac{1}{2}\left[\tilde{T}_2 - \tilde{T}_1\right] + \frac{\theta}{2}\widetilde{1+e_{12}} \\
&\tilde{R}_1 = \frac{1}{2}\left[\tilde{T}_1 - \tilde{T}_2\right] - \frac{1}{2}\left[1 + \frac{\theta}{2} - \frac{\alpha}{2}\right]\widetilde{1+e_{12}} \\
&\tilde{R}_2 = \frac{1}{2}\left[\tilde{T}_2 - \tilde{T}_1\right] + \frac{1}{4}\left[\theta + \alpha\right]\widetilde{1+e_{12}} \\
&\tilde{T}_1 = \tilde{T}_2 = \frac{\xi}{2}\left[\tilde{R}_1 + \tilde{R}_2\right]
\end{aligned}
\tag{A3}
$$

Therefore, we have

$$
\begin{aligned}
&\tilde{R}_1 = -\frac{1}{2}\left[1 + \frac{\theta}{2} - \frac{\alpha}{2}\right]\widetilde{1+e_{12}} \\
&\tilde{R}_2 = \frac{1}{4}\left(\theta + \alpha\right)\widetilde{1+e_{12}} \\
&\tilde{T}_1 = \tilde{T}_2 = -\frac{\xi}{4}\left(1 - \alpha\right)\widetilde{1+e_{12}} \\
&\tilde{P}_1 = \frac{\xi}{4\theta}\left(1 - \alpha\right)\widetilde{1+e_{12}} \quad \tilde{P}_2 = \left[\frac{\xi}{4\theta}\left(1 - \alpha\right) + \frac{1}{2}\right]\widetilde{1+e_{12}} \\
&\tilde{W}_1 = \frac{\alpha}{2}\left[1 - \frac{\xi}{2\theta}\left(1 - \alpha\right)\right]\widetilde{1+e_{12}} \\
&\tilde{W}_2 = -\alpha\left[\frac{\xi}{4\theta}\left(1 - \alpha\right) + \frac{1}{2}\right]\widetilde{1+e_{12}}
\end{aligned}
\tag{A4}
$$

A.3 Proof to Corollary 1

We consider a first-order change in e_{12}. Then the system can be expressed as

$$\begin{aligned}
&T_i = R_i^{\xi}, \quad \lambda_{in} = T_i \left(1+e_{in}\right)^{-\theta} P_n^{\theta} \\
&R_i = \sum_{n=1}^{N} \frac{1}{1+\theta} \frac{\lambda_{in} X_n}{1+e_{in}} \\
&P_n = \left(\sum_{i=1}^{N} T_i \left(1+e_{in}\right)^{-\theta} \right)^{-\frac{1}{\theta}} \\
&X_n = \alpha Y_n, \quad Y_n = 1 + \sum_{i=1}^{N} \frac{e_{ni}}{1+e_{ni}} \lambda_{ni} X_i
\end{aligned} \tag{A5}$$

Notably, if $e_{in} = 0$, then $Y_n = 1$, $X_n = \alpha$, $\lambda_{in} = \frac{1}{2}$, $R_i = \frac{\alpha}{1+\theta}$, $T_i = \left(\frac{\alpha}{1+\theta}\right)^{\xi}$, and $P_i = \left(2\left(\frac{\alpha}{1+\theta}\right)^{\xi}\right)^{-\frac{1}{\theta}}$. Welfare $W_n = \frac{Y_n}{P_n^{\alpha}} = \left(2\left(\frac{\alpha}{1+\theta}\right)^{\xi}\right)^{\frac{\alpha}{\theta}}$.

For any variable $Z > 0$, denote $\tilde{Z} = d \log Z$. We have

$$\begin{aligned}
&\tilde{T}_i = \xi \tilde{R}_i, \quad \tilde{\lambda}_{in} = \tilde{T}_i - \theta \widetilde{1+e_{in}} + \theta \tilde{P}_n \\
&\tilde{R}_i = \sum_{n=1}^{N} \frac{1}{2} \left[\tilde{\lambda}_{in} + \tilde{X}_n - \widetilde{1+e_{in}} \right] \\
&-\theta \tilde{P}_n = \sum_{i=1}^{N} \frac{1}{2} \left[\tilde{T}_i - \theta \widetilde{1+e_{in}} \right] \\
&\tilde{X}_n = \tilde{Y}_n, \quad \tilde{Y}_n = \frac{\alpha}{2} \sum_{i=1}^{N} \widetilde{1+e_{ni}}
\end{aligned} \tag{A6}$$

The corresponding changes in welfare is $\tilde{W}_n = \tilde{Y}_n - \alpha \tilde{P}_n$.

Therefore, we have

$$
\begin{aligned}
&\tilde{Y}_2 = \tilde{X}_2 = 0, \quad \tilde{Y}_1 = \tilde{X}_1 = \frac{\alpha}{2}\widetilde{1+e_{12}} \\
&-\theta\tilde{P}_1 = \frac{1}{2}\left[\tilde{T}_1 + \tilde{T}_2\right], \quad -\theta\tilde{P}_2 = \frac{1}{2}\left[\tilde{T}_1 + \tilde{T}_2\right] - \frac{\theta}{2}\widetilde{1+e_{12}} \\
&\tilde{\lambda}_{11} = \frac{1}{2}\left[\tilde{T}_1 - \tilde{T}_2\right], \quad \tilde{\lambda}_{12} = \frac{1}{2}\left[\tilde{T}_1 - \tilde{T}_2\right] - \frac{\theta}{2}\widetilde{1+e_{12}} \\
&\tilde{\lambda}_{21} = \frac{1}{2}\left[\tilde{T}_2 - \tilde{T}_1\right], \quad \tilde{\lambda}_{22} = \frac{1}{2}\left[\tilde{T}_2 - \tilde{T}_1\right] + \frac{\theta}{2}\widetilde{1+e_{12}} \\
&\tilde{R}_1 = \frac{1}{2}\left[\tilde{T}_1 - \tilde{T}_2\right] - \frac{1}{2}\left[1 + \frac{\theta}{2} - \frac{\alpha}{2}\right]\widetilde{1+e_{12}} \\
&\tilde{R}_2 = \frac{1}{2}\left[\tilde{T}_2 - \tilde{T}_1\right] + \frac{1}{4}\left[\theta + \alpha\right]\widetilde{1+e_{12}} \\
&\tilde{T}_1 = \xi\tilde{R}_1, \quad \tilde{T}_2 = \xi\tilde{R}_2
\end{aligned}
\tag{A7}
$$

Therefore, we have

$$
\begin{aligned}
&\tilde{R}_1 = -\frac{1}{2\left(1-\xi\right)}\left[\left(1 - \frac{\xi}{2}\right) + \frac{\theta}{2} - \frac{1}{2}\left(1-\xi\right)\alpha\right]\widetilde{1+e_{12}} \\
&\tilde{R}_2 = \frac{1}{4\left(1-\xi\right)}\left[\xi + \theta + \left(1-\xi\right)\alpha\right]\widetilde{1+e_{12}} \\
&\tilde{T}_1 = -\frac{\xi}{2\left(1-\xi\right)}\left[\left(1 - \frac{\xi}{2}\right) + \frac{\theta}{2} - \frac{1}{2}\left(1-\xi\right)\alpha\right]\widetilde{1+e_{12}} \\
&\tilde{T}_2 = \frac{\xi}{4\left(1-\xi\right)}\left[\xi + \theta + \left(1-\xi\right)\alpha\right]\widetilde{1+e_{12}} \\
&\tilde{P}_1 = \frac{\xi}{4\theta}\left(1-\alpha\right)\widetilde{1+e_{12}} \quad \tilde{P}_2 = \left[\frac{\xi}{4\theta}\left(1-\alpha\right) + \frac{1}{2}\right]\widetilde{1+e_{12}} \\
&\tilde{W}_1 = \frac{\alpha}{2}\left[1 - \frac{\xi}{2\theta}\left(1-\alpha\right)\right]\widetilde{1+e_{12}} \\
&\tilde{W}_2 = -\alpha\left[\frac{\xi}{4\theta}\left(1-\alpha\right) + \frac{1}{2}\right]\widetilde{1+e_{12}}
\end{aligned}
\tag{A8}
$$

B Quantification

B.1 The PATSTAT Global Database

The PATSTAT Global database—compiled by the European Patent Office—is the most widely used international patent dataset in empirical economics. It provides harmonized bibliographic information on more than 100 million patent applications filed across major patent offices worldwide, including inventor and applicant identifiers, priority links, patent families, technology classifications, and citation records. Unlike national patent datasets, PATSTAT offers a unified structure that enables researchers to trace inventions across countries, construct international patent families, measure cross-border knowledge flows, and study innovation at the inventor, firm, sector, or country level. Although originally designed for patent examination rather than academic research, PATSTAT has become the standard data infrastructure for quantitative work on technological innovation, global knowledge diffusion, and R&D productivity, and can be linked to numerous auxiliary databases for richer economic analysis.

A well-documented limitation of PATSTAT is that records from the Japanese Patent Office contain disproportionately more missing values than those from the U.S. Patent and Trademark Office. Because this issue primarily affects the magnitudes used in our quantitative exercises, we reweight citations from Japanese and U.S. patents—the two largest sources of international citations—according to their shares in OECD triadic patent families. We implement this adjustment in a simple, time-invariant manner: we aggregate all international patent citations in PATSTAT by their source offices over 1996–2019 and compare these shares to the corresponding shares in the OECD triadic patent families. As expected, the relative share of U.S. citations in PATSTAT is substantially larger than in the OECD triadic patent families, while the opposite is true for Japan. Based on this comparison, we apply a multiplicative weight of 1.45 to citations from Japanese patents and a weight of 0.6 to citations from U.S. patents in constructing our knowledge-flow measures.

B.2 Additional Details for Motivating Facts

Our model predicts that export controls may increase Chinese firms' R&D investment while reducing innovation efforts by U.S. firms, driven by changes in effective market size following the imposition of export restrictions. To examine this prediction, we use detailed export control measures compiled by Li et al. (2025). Specifically, they collect the annual "Commerce Control List" (CCL) from the Bureau of Industry and Security (BIS) for the period 2014–2022 and identify the corresponding 6-digit HS codes for restricted products under each Export Control Classification Number (ECCN).[17]

Chinese Firms' R&D and Export Controls. Due to the lack of economy-wide firm-level R&D data, we test this prediction using a sample of Chinese listed firms from the CSMAR database over the period 2014–2021, which provides information on firms' R&D investments. We construct a measure of each firm's exposure to export controls based on its affiliated industry. Since the industry classification in the CSMAR database differs from the ISIC classification used in the main text, we use a merged dataset combining CSMAR with the Chinese Customs Transactions Database to obtain export values of HS products by industry during the pre–trade war period (2014–2016). We use export values as weights to obtain a mapping from HS products to each industry in CSMAR. Using this concordance together with HS product–year export control indicators, we then construct annual measures of export control exposure at the industry level, as in Equation (43).

US Patent Applications and Export Controls. We next examine whether export controls affected the innovation efforts of U.S. firms. As we do not have access to firm-level export data by product for U.S. firms,[18] we instead use the domestic number of U.S. patent ap-

[17] A key component of the U.S. export control system is the Commerce Control List (CCL), maintained by the Bureau of Industry and Security (BIS) under the Department of Commerce. Each controlled item is assigned an Export Control Classification Number (ECCN), a five-character code that describes the nature of the item and the reasons for its control.

[18] While Compustat provides firm-level financial data for U.S. firms, we do not observe each firm's exports at the HS product level.

plications from the PATSTAT Global database. Specifically, we obtain the annual number of patent applications in each IPC category and use the IPC–HS concordance developed by Lybbert and Zolas (2014) to map patents to 6-digit HS products. This allows us to compute the number of patent applications associated with each 6-digit HS product in each year. We then merge these data with the export control measures constructed at the HS product level.

B.3 Estimating the Elasticity of Technology Diffusion with Trade Flows: Alternative Instrument

Table B1 reports estimation results of the elasticity of technology diffusion with trade flows using the instrument constructed by Equation (47). The results are close to our baseline results in Table 2 and 3.

Table B1: Impact of Trade Flows on Number of Citations, Alternative Instrument

Dep var	Number of Citations					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all	same ind	diff ind	all	same ind	diff ind
Method	2SLS(air)	2SLS(air)	2SLS(air)	PPML(air)	PPML(air)	PPML(air)
Log Trade	0.326***	0.232***	0.230***	0.490***	0.232***	0.275***
Flow	(0.00075)	(0.00219)	(0.00057)	(0.00184)	(0.00341)	(0.00288)
Obs	9,999,959	831,556	9,151,581	9,999,959	831,556	9,151,581
R-squared	0.103	0.000	0.028	0.944	0.990	0.918
First-stage F	3.2e+07	4.1e+05	1.8e+07	3.2e+07	4.1e+05	1.8e+07

Note: Columns (1)–(3) display the 2SLS results using the instrument from equation (47), and Columns (4)–(6) show the PPML results with the instrument from equation (47). Columns (1) and (4) correspond to the full sample, while Columns (2) and (5) focus on citations within the same industry ($j = k$). Columns (3) and (6) are restricted to citations across different industries ($j \neq k$). We control for origin-sector-year and destination-sector-year fixed effects. Additionally, we report the first-stage F-statistic for the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

We also report additional robustness checks for instruments. A potential concern with constructing the instrument in equation (46) using sea and air distances is that sea distance is undefined for trade flows involving landlocked countries, leading to the exclusion of these observations from the estimation. To address this issue, we set the contribution of sea distance to zero for trade flows involving landlocked countries, rather than treating these observations as missing, and allow air distance to have a differential impact

for such trade flows.[19] Under this specification, we reconstruct the instrument for trade flows. As shown in Table B2, the IV estimates remain largely unchanged relative to the baseline results, even when the sample is restricted to trade pairs involving landlocked countries.

Table B2: Impact of Trade Flows on Number of Citations, Considering Landlocked Countries

Dep var	Log Number of Citations					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all	same ind	diff ind	landlocked	landlocked, same ind	landlocked, diff ind
Method	2SLS(air)	2SLS(air)	2SLS(air)	2SLS(air)	2SLS(air)	2SLS(air)
Log Trade	0.325***	0.242***	0.231***	0.366***	0.270***	0.273***
	(0.000256)	(0.00212)	(0.000342)	(0.000647)	(0.0100)	(0.000962)
Obs	12,159,355	1,025,720	11,111,880	2,158,445	174,402	1,957,902
R-squared	0.106	0.000	0.030	0.120	0.000	0.033
First-stage F	3.8e+07	5.2e+05	2.1e+07	7.9e+06	2.5e+04	3.5e+06

Note: Columns (1)–(6) report the 2SLS estimates using the instrument obtained from the following first-stage specification: $\ln X^k_{int} = \beta^k_{sea,t} \ln(seadist_{in}) + \beta^k_{air,t} \ln(airdist_{in}) + \gamma^k_{air,t}\, landlocked_{in} \times \ln(airdist_{in}) + \text{fe}^k_i + \text{fe}^k_n + \text{fe}_t + u^k_{int}$, where $landlocked_{in}$ is an indicator equal to one if either country i or country n is landlocked. When $\ln(seadist_{in})$ is missing (i.e., when either country i or n is landlocked), we set its contribution to zero for those observations. Columns (1)–(3) consider all bilateral flows, bilateral flows within the same industry, and bilateral flows across different industries, respectively. Columns (4)–(6) restrict the sample to observations in which either country i or country n is landlocked. We control for origin-sector-year and destination-sector-year fixed effects. Additionally, we report the first-stage F-statistic for the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

Another concern of using air distance to instrument for trade flows is that advances in aircraft technology over time may also facilitate knowledge diffusion by increasing passenger traffic across regions. To address this issue, we compile flight-level data from the Official Airline Guide (OAG), which reports each flight's departure and arrival airports as well as total seat capacity. Based on these records, we construct annual bilateral passenger counts for each country pair from 2007 to 2020 and include this measure as a control in the IV regressions that use air distance as an instrument. As reported in Table B3, the IV coefficients in Columns (1)–(3) of Table B1 are essentially unchanged when restricting the sample to 2007–2020 and controlling for bilateral passenger flows.

[19] Specifically, we replace equation (46) with the following first-stage specification:

$$\ln X^k_{int} = \beta^k_{sea,t} \ln(seadist_{in}) + \beta^k_{air,t} \ln(airdist_{in}) + \gamma^k_{air,t}\, landlocked_{in} \times \ln(airdist_{in}) + \text{fe}^k_i + \text{fe}^k_n + \text{fe}_t + u^k_{int},$$

where $landlocked_{in}$ is an indicator equal to one if either country i or country n is landlocked. When $\ln(seadist_{in})$ is missing (i.e., when either country i or n is landlocked), we set its contribution to zero for those observations.

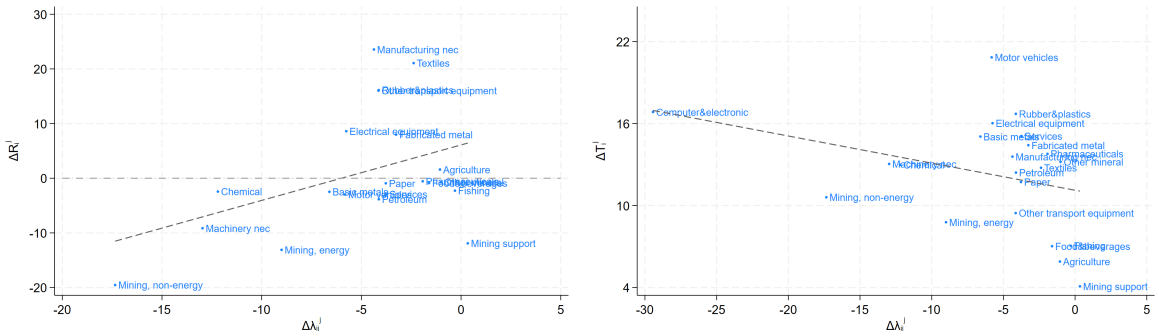
Table B3: Impact of Trade Flows on Number of Citations, Controlling for Passenger Flights

Dep var	Log Number of Citations					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all, 07–20	all, 07–20	same ind, 07–20	same ind, 07–20	diff ind, 07–20	diff ind, 07–20
Method	2SLS(air)	2SLS(air)	2SLS(air)	2SLS(air)	2SLS(air)	2SLS(air)
Log Trade	0.326***	0.340***	0.240***	0.232***	0.235***	0.242***
	(0.00104)	(0.00111)	(0.00446)	(0.00549)	(0.00139)	(0.00159)
Log Number of Flight Passengers		-0.0198***		0.00243***		-0.00627***
		(0.000443)		(0.000800)		(0.000415)
Obs	5,609,811	5,609,811	461,765	461,765	5,142,418	5,142,418
R-squared	0.097	0.096	-0.007	-0.006	0.027	0.026
First-stage F	1.6e+07	1.4e+07	2.1e+05	9.7e+04	8.8e+06	7.3e+06

Note: Columns (1)–(6) report the 2SLS estimates using the instrument defined in equation (47). Columns (2), (4), and (6) further include a control for the annual volume of passengers traveling between each origin–destination pair, as recorded in the OAG data. Since the OAG data are available only from 2007 onward, all regressions are limited to the 2007–2020 period. We use the logarithm of one plus the passenger volume to accommodate zero flows for some country pairs; the regression results are quantitatively unchanged when instead using the logarithm of passenger volume and excluding zero observations. We control for origin-sector-year and destination-sector-year fixed effects. Additionally, we report the first-stage F-statistic for the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

B.4 Additional Results for Calibration and Counterfactuals

Figure B1: Trade Liberalization (1996-2007): under $\xi = 1 - \nu$



(a) R&D (b) Technology

Note: λ_{ii}^j denotes the share of domestic production in total expenditure, serving as an inverse measure of import penetration. All values represent percentage changes. Trade liberalization refers to changes in tariffs and iceberg trade costs between Period 1 (1996-2000) and 2 (2003-2007). The fitted line in Panel (a) has the slope coefficient -0.20 with standard error 0.09. The fitted line in Panel (b) has the slope coefficient is 1.01 with standard error 0.43.

Table B4: Calibrating the Sector-Specific Parameters

Index	ICIO Code	Industry	θ_j	$EC_{j,2019}$
1	D01T02	Agriculture	3.19	0
2	D03	Fishing	6.99	0
3	D05T06	Mining, energy	3.16	0.143
4	D07T08	Mining, non-energy	8.31	0
5	D09	Mining support	6.16	0
6	D10T12	Food&Beverages	4.09	0
7	D13T15	Textiles	4.71	0.060
8	D16	Wood	8.68	0
9	D17T18	Paper	7.98	0
10	D19	Petroleum	4.51	0.855
11	D20	Chemical	8.25	0.280
12	D21	Pharmaceuticals	8.54	0.017
13	D22	Rubber&Plastics	6.86	0.433
14	D23	Other mineral	4.81	0.564
15	D24	Basic metals	7.12	0.363
16	D25	Fabricated metal	4.33	0.402
17	D26	Computer&Electronic	5.38	0.865
18	D27	Electrical equipment	4.74	0.605
19	D28	Machinery nec	4.38	0.760
20	D29	Motor vehicles	8.66	0.003
21	D30	Other transport equipment	8.93	0.392
22	D31T33	Manufacturing nec	4.57	0.207
23	S	Services	6	0.017

Note: θ_j are calibrated from Fontagne et al. (2018). $EC_{j,2019}$ are calibrated from Li et al. (2025).

Table B5: U.S. Export Controls against China: Sector-Specific ν

Sector	ν_k	China		U.S.	
		ΔT	ΔR	ΔT	ΔR
Agriculture	0.13	-0.10	-0.02	-0.08	0.12
Fishing	0.13	-0.05	-0.01	0.13	0.97
Mining, energy	0.10	-0.11	0.16	-0.16	-0.10
Mining, non-energy	0.08	-0.04	0.11	-0.24	-0.17
Mining support	0.11	-0.46	0.06	-0.22	0.04
Food&beverages	0.12	-0.09	-0.02	-0.05	0.09
Textiles	0.11	-0.19	-0.11	0.02	0.45
Wood	0.16	-0.19	-0.11	-0.19	0.19
Paper	0.17	-0.19	-0.08	-0.11	0.14
Petroleum	0.15	-0.42	0.23	-0.19	-0.16
Chemical	0.17	-0.17	0.18	-0.14	-0.46
Pharmaceuticals	0.21	-0.21	-0.05	-0.01	0.49
Rubber&plastics	0.20	-0.34	-0.00	-0.12	-0.16
Other mineral	0.23	-0.27	-0.01	-0.16	-0.22
Basic metals	0.16	-0.14	0.25	-0.26	-1.71
Fabricated metal	0.17	-0.31	0.00	-0.14	-0.14
Computer&electronic	0.20	-0.98	-0.44	-0.19	-1.12
Electrical equipment	0.25	-0.50	-0.04	-0.15	-0.70
Machinery nec	0.25	-0.34	0.29	-0.29	-1.58
Motor vehicles	0.22	-0.29	-0.12	-0.13	0.29
Other transport equipment	0.20	0.24	2.21	-0.36	-1.26
Manufacturing nec	0.21	-0.44	-0.22	-0.06	0.13
Services	0.21	-0.47	-0.03	-0.12	0.06

Note: All values represent percentage changes. We start from the world economy in period 4 (2015-2019).