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Keywords: trade-driven technology diffusion, innovation, endogenous growth model, trade war, optimal tariffs
JEL Classification: F12, F13, F14, O31, O33

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Trade War and Technology Rivalry

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Abstract

We develop a dynamic quantitative trade model featuring endogenous innovation and trade-driven technology diffusion. In the model, tariffs shape global technological progress by (i) altering knowledge flows embodied in trade and (ii) changing market sizes and thus innovation incentives. We estimate the model's key parameter—the elasticity of international knowledge diffusion, proxied by patent citations, with respect to trade flows—using quasi-experimental shocks to global trade patterns. With the estimated model in hand, we quantify the effects of recent trade wars and show that endogenous innovation and trade-driven technology diffusion substantially amplify the technological and welfare losses from rising trade barriers. Finally, we characterize the unilaterally optimal U.S. tariffs on China, highlighting a trade-off between limiting China's technological advance and fostering U.S. innovation.

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1 Introduction

Trade policy is increasingly used to hinder technological progress in targeted countries, thereby securing an advantage in global technological rivalry.[1] On the one hand, measures such as export controls are used to restrict the diffusion of knowledge to rival countries;[2] on the other, leading innovators worry that such measures may reduce their global market shares and, in turn, their returns to innovation.[3] Yet we lack a quantitative framework to assess how these impacts of trade policy on technological progress shape the motives and consequences of recent trade wars[4]—a gap this paper fills.

In this paper, we develop a quantifiable multi-country-multi-sector trade model with endogenous innovation and trade-driven technology diffusion. In the model, trade policy can shape firms' market size and, in turn, their incentives to innovate—a mechanism well established in the trade and endogenous growth literature.[5] We also allow technology to diffuse through trade flows, following Buera and Oberfield (2020), so that trade policies affect the knowledge spillovers received by rival countries. We show analytically that in our model export controls have a double-edged effect: they reduce technology diffusion to rival countries but also depress domestic R&D investment, generating a lose–lose

[1]For example, the USTR's 2018 Section 301 report—and the subsequent tariffs—explicitly targeted China's "Made in China 2025" initiative, aiming to curb China's acquisition of U.S. core technologies and preserve the United States' long-run technological edge. For a detailed discussion, see Matt Sheehan, "Trump's Trade War Isn't About Trade, It's About Technology," available at: https://archivemacropolo.org/analysis/trumps-trade-war-isnt-about-trade-its-about-technology.

[2]The U.S. explicitly states that its export controls on China are intended to slow Chinese technological progress in strategic fields such as semiconductors and AI. See the official documentation at https://www.congress.gov/crs-product/R48642

[3]For example, Jensen Huang, the CEO of Nvidia, noted that the company's market share in China fell from 95% to zero and warned of the adverse innovation effects (https://fortune.com/2025/10/19/jensen-huang-nvidia-china-market-share-ai-chips-trump-trade-war/).

[4]The quantitative frameworks in the literature have separately considered the impacts of trade shocks on innovation (e.g., Eaton and Kortum, 2001; Autor, Dorn, Hanson, Pisano, and Shu, 2020; Grossman and Helpman, 2015; Perla, Tonetti, and Waugh, 2021; Aghion, Bergeaud, Lequien, and Melitz, 2024b) and on trade-driven technology diffusion (e.g., Buera and Oberfield, 2020; Aghion, Bergeaud, Gigout-Magiorani, Lequien, and Melitz, 2024a; Bai, Jin, Lu, and Wang, 2025b; Cai, Caliendo, Parro, and Xiang, 2025). However, there is no unified framework that incorporates both mechanisms simultaneously.

[5]See, for example, Aghion et al. (2024b), Autor et al. (2020), Grossman and Helpman (2015), and Perla et al., 2021.

outcome.

Our quantitative model produces a tractable mapping from bilateral trade flows to knowledge spillovers, allowing the mechanism to be disciplined by observed trade and patent citation data. However, estimating the elasticity of knowledge spillovers with respect to trade flows is challenging because factors that affect trade may also affect knowledge diffusion. To address this challenge, we exploit two alternative quasi-random shocks to bilateral trade flows. The first is a Bartik instrument, constructed following Autor, Dorn, and Hanson (2013) by interacting initial bilateral trade flows with the growth of aggregate imports in destination countries, where identification arises from the quasi-random "shifts" in import growth across destinations. The second leverages gradual improvements in aircraft technology that disproportionately reduce transportation costs for country pairs with longer sea distances and for sectors with higher value-to-weight ratios (Feyrer, 2019). These exogenous cost shifters are orthogonal to other determinants of bilateral trade flows.

We estimate the elasticity of knowledge spillovers with respect to trade flows using the two instruments described above and patent citations across all countries and sectors from the PATSTAT database over 1996–2019 as a proxy for international knowledge diffusion. The estimated elasticities obtained using both instruments range from approximately 0.3 to 0.5, consistent with prior empirical findings—for instance, the elasticity of knowledge flows with respect to trade shares of 0.4 used in Buera and Oberfield (2020).

Armed with the estimated elasticity of knowledge diffusion with respect to trade flows, we bring the model to bilateral trade and knowledge flow data over 1996–2019. We then conduct a series of counterfactual exercises to quantify how trade shocks and policies shape technological rivalry among major economies.

First, we quantify how changes in tariffs and non-tariff trade costs over 1996–2007 affected innovation and technological progress across major economies. Using the observed changes in trade barriers, we compute counterfactual changes in R&D investment and technology. We find that Chinese sectors more exposed to import competition experienced slower growth in R&D investment but faster technological advancement. This pattern, consistent with empirical evidence in Brandt, Van Biesebroeck, Wang, and Zhang (2017), Liu, Lu, Lu, and Luong (2021), Autor et al. (2020), and Aghion et al. (2024a), arises only when both endogenous innovation and trade-driven technology diffusion are present in the model. This finding highlights the importance of incorporating both mechanisms.

Second, we quantify the effects of U.S. unilateral export controls on China. Starting from the calibrated economy over 2015–2019, we insert the increase in U.S. export costs of dual-use goods to China into the model and compute counterfactual changes in R&D, technology, and real income across major economies. We find that the export controls stimulate R&D investment in China's dual-use sectors, but this response is insufficient to offset the negative technology effects from reduced trade-driven diffusion, leading to a decline in Chinese technological capabilities in these sectors. At the same time, the export controls lower R&D and technological progress in the corresponding U.S. sectors. These results reflect the double-edged effect of export controls in our model, yielding a lose–lose outcome: China's real income falls by 0.39% and the U.S.'s by 0.06%.

Third, we quantify the effects of the U.S. reciprocal tariffs initiated on Liberian Day 2025, along with China's retaliatory tariffs, on all major economies. We find that incorporating both endogenous innovation and trade-driven technology diffusion substantially amplifies the welfare losses from the trade war. In our full model, China's real income falls by 1.34%, compared with declines of 0.28% in the model without technology diffusion and 0.22% in the model with exogenous technology. Similar amplification effects arise in other major economies, including the EU, Switzerland, India, Indonesia, and Japan.

Finally, we quantify the unilaterally optimal U.S. tariffs on China. We find that the United States has an incentive to subsidize exports to China in sectors such as ICT, pharmaceuticals, and machinery in order to stimulate domestic innovation. This incentive is much weaker in the model without endogenous innovation or when the United States can employ industrial subsidies. The resulting optimal tariffs generate a win–win outcome, raising U.S. real income by 3.95% and China's by 6.49%. However, when the United States pursues not only higher domestic welfare but also the objective of lowering China's real income, its optimal tariffs feature prohibitive export tariffs against China to restrict trade-driven technology diffusion. These tariffs increase U.S. real income by 1.43% while reducing China's by 1.05%.

Related Literature: This paper first relates to the literature on the impacts of trade on innovation and growth. One strand considers the effects of trade on market size and, consequently, on innovation incentives (*e.g.,* Eaton and Kortum, 2001; Autor et al., 2013; Grossman and Helpman, 2015; Perla et al., 2021; Aghion et al., 2024b), reflecting the so-called Schumpeterian effect which suggests that larger profits incentivize innovation (Schumpeter, 1942). Another strand focuses on the role of trade in facilitating knowledge spillovers across borders, which dates back at least to Grossman and Helpman (1991) and is emphasized in the recent literature (*e.g.,* Buera and Oberfield, 2020; Aghion et al., 2024a; Bai et al., 2025b; Cai et al., 2025). We unify these two mechanisms in a dynamic quantitative trade model and show that both are essential for understanding the technological effects of trade.

By quantifying the optimal tariff policies, this paper also relates to the literature on trade policy in quantitative models linking trade and technology. Bai, Jin, and Lu (2025a) characterizes optimal trade policies through which a country influences innovation in other countries across sectors. Bai et al. (2025b), building on the framework of Buera and Oberfield (2020), studies optimal trade policies that affect other countries' knowledge flows. We show that both dimensions matter and that designing optimal trade policies requires balancing the strategic trade-off between curbing rivals' knowledge inflows and fostering domestic innovation.

Finally, this paper contributes to the quantitative literature on recent trade conflicts (*e.g.,* Ignatenko, Lashkaripour, Macedoni, and Simonovska, 2025; Lashkaripour, 2021; Lashkaripour and Lugovskyy, 2023; Alessandria, Khan, Khederlarian, Ruhl, and Steinberg, 2025; Ju, Ma, Wang, and Zhu, 2024). While prior studies often focus on scale economies and innovation effects of trade wars, we are the first to quantify the motives and consequences of recent trade conflicts incorporating both trade-driven technology diffusion and endogenous innovation, mechanisms that are essential for understanding the technological and welfare effects of trade wars.

The rest of the paper is arranged as follows. Section 2 builds and characterizes the model. Section 3 estimates and calibrates the model. Section 4 conducts counterfactual exercises. Section 5 conducts sensitivity exercises for estimation and counterfactuals. Section 6 concludes.

2 Model

We build a multi-country-multi-sector quantitative trade model with endogenous innovation, trade-driven 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. We consider unilaterally optimal tariffs and tariff wars in this setting.

2.1 Environment

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 discounted 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)

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

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

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:

$$V_{i}^{j} = w_{i} R_{i}^{j}, \quad V_{i}^{j} = \frac{g}{\rho - \frac{1}{\theta_{i}} g} \sum_{n=1}^{N} \frac{1}{1+\theta_{j}} \frac{\lambda_{in}^{j} X_{n}^{j}}{\left(1+e_{in}^{j}\right)\left(1+t_{in}^{j}\right)}, \tag{20}$$

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:

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

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:*

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

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.

[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 $\frac{1}{g} \frac{Y_n}{P_n}$.

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 domestic 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 "Exact-hat" Algebra

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 BGP equilibrium in relative terms. For any variable $Z > 0$, we denote Z' as the level after change and $\hat{Z} \equiv Z'/Z$.

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

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

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.

2.4 Tariffs and Technology Rivalry: A Double-Edged Sword

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. $\gamma_i^j = 1$ *for all (i, j). Sector 1 is homogeneous ($\theta_1 = \infty$), freely traded, has technology $T_i^1 = 1$ 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 (Unilateral Export Tariff 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 effects:* $\frac{\partial \log R_2}{\partial \log(1+e_{12})} = \frac{1}{4}(\theta + \alpha) > 0 > \frac{\partial \log R_1}{\partial \log(1+e_{12})} = -\frac{1}{2}\left[1 + \frac{\theta}{2} - \frac{\alpha}{2}\right]$
2. *Technology effects:* $\frac{\partial \log T_1}{\partial \log(1+e_{12})} = \frac{\partial \log T_2}{\partial \log(1+e_{12})} = -\frac{\xi}{4}(1-\alpha) < 0$
3. *Welfare effects:* $\frac{\partial \log W_1}{\partial \log(1+e_{12})} = \frac{\alpha}{2}\left[1 - \frac{\xi}{2\theta}(1-\alpha)\right] > 0 > \frac{\partial \log W_2}{\partial \log(1+e_{12})} = -\alpha\left[\frac{\xi}{4\theta}(1-\alpha) + \frac{1}{2}\right]$

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-driven 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 arises only when both endogenous innovation and trade-driven 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, Proposition 2 also implies that

$$\frac{\partial \log(W_1 + W_2)}{\partial \log(1+e_{12})} = \frac{1}{2}\left[\frac{\partial \log W_1}{\partial \log(1+e_{12})} + \frac{\partial \log W_2}{\partial \log(1+e_{12})}\right] = -\frac{\alpha\xi}{4\theta}(1-\alpha) < 0, \tag{39}$$

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-driven 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:* $\frac{\partial \log R_2}{\partial \log(1+e_{12})} = \frac{\xi+\theta+(1-\xi)\alpha}{4(1-\xi)} > 0 > \frac{\partial \log R_1}{\partial \log(1+e_{12})} = -\frac{\left(1-\frac{\xi}{2}\right)+\frac{\theta}{2}-\frac{1}{2}(1-\xi)\alpha}{2(1-\xi)}$
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.

Finally, we study how the degree of trade-driven technology diffusion, ν, shapes the effects of tariffs. This cannot be addressed in the knife-edge case where $\tau = 1$, because domestic and foreign technologies are initially equally important, so the effects of declining imports are exactly offset by the rise in domestic production. We therefore characterize the technology and innovation effects of tariffs in the stylized model in Remark 1 under $\tau > 1$:

Proposition 3 (The Implications of Trade-Driven Technology Diffusion ν) *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 effects:* $\frac{\partial \log R_2}{\partial (1+e_{12})} > 0 > \frac{\partial \log R_1}{\partial (1+e_{12})}$
2. *Technology effects:* $\frac{\partial \log T_1}{\partial (1+e_{12})} < 0, \quad \frac{\partial \log T_2}{\partial (1+e_{12})} < 0$

Moreover, there exists a $\bar{\xi} \in (0, 1)$ such that if $\xi \in [0, \bar{\xi})$, $\frac{\partial^2 \log(T_1/T_2)}{\partial (1+e_{12})\partial \nu} > 0$ and if $\xi \in (\bar{\xi}, 1)$, $\frac{\partial^2 \log(T_1/T_2)}{\partial (1+e_{12})\partial \nu} < 0$.

Similar to Proposition 2, Proposition 3 shows that export tariffs can stimulate R&D in the targeted country while reducing innovation in the implementing country and lowering productivity in both countries. However, the relative technological effect of export controls depends on the degree of trade-driven diffusion, ν. When ξ is small—so that export tariffs do not substantially promote innovation in the targeted country—export controls inflict larger losses on the targeted country as ν increases. In this case, the primary rationale for export controls is to curb the knowledge spillovers to the targeted country embodied in trade flows, a motive frequently cited in recent U.S. export controls against China.

3 Calibration

In this section, we bring the model to the data. We begin by combining patent and trade data to calibrate the key elasticity in the technology diffusion equation, and then describe the calibration of the remaining parameters.

3.1 Trade-Induced Technology Diffusion

Estimation Equation. To recover the parameter ν that governs the intensity of trade-driven 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 logarithm of equation (34), we obtain the following estimating equation:

$$\log \delta_{int}^{kj} = \nu \log X_{int}^{kj} + \mathrm{fe}_{it}^{k} + \mathrm{fe}_{nt}^{j} + \log \bar{\epsilon}_{int}^{kj}, \quad X_{int}^{kj} \equiv \begin{cases} \gamma_n^{kj} \lambda_{int}^{k} X_{nt}^{k} & \text{if } k \neq j \\ \lambda_{int}^{k} X_{nt}^{k} & \text{otherwise} \end{cases}, \tag{40}$$

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

Data. To estimate equation (40), we rely on three data sources. The first is 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 ϵ_{int}^{kj} (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.

Second, we obtain input-output linkages γ_n^{kj} from the OECD Inter-Country Input-Output (ICIO) Database. We set the input-output linkages γ_n^{kj} to the values from the year 2010 to prevent any potential endogeneity in their evolution. Third, we obtain international trade data from UN Comtrade, which we assemble and clean using the algorithm in Feenstra and Romalis (2014).

Because the citation data are organized by IPC categories while the trade data follow the Standard International Trade Classification (SITC) system, we aggregate both datasets 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

[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).

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 analysis focuses on patent citation and trade data for the 1975–2020 period.

Instrument on X_{int}^{k}. In the estimation of equation (40), one challenge we face is that traded flows X_{nt}^{k} can be endogenous. For instance, a country that enjoys larger knowledge diffusion may thus experience faster productivity growth and larger trade flows with partner countries. To avoid this endogeneity issue, we construct two instruments. The first instrument is a Bartik-type instrument, in the spirit of Autor et al. (2013). Specifically, we construct the instrument as follows:

$$X_{int}^{k,IV1} = \underbrace{\lambda_{in0}^{k} X_{n0}^{k}}_{\text{exports from } i \text{ to } n \text{ in initial period}} \times \underbrace{\frac{(1-\lambda_{int}^{k})X_{nt}^{k}}{(1-\lambda_{in0}^{k})X_{n0}^{k}}}_{\text{growth in exports to destination } n \text{ by other countries}}, \tag{41}$$

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 (41), relies on the assumption that the shifts—growth in exports to destination n in industry k—are randomly assigned (Borusyak, Hull, and Jaravel, 2022). This assumption may be violated if trade growth is influenced by knowledge diffusion, but is likely to hold when changes in trade flows are driven by improvements in transportation infrastructure.

Therefore, in the second instrument, we rely on the time-varying evolution in aircraft transportation technology. As shown by Feyrer (2019), the gradual improvement in aircraft technology have caused the quantity of world trade carried by air to increase over

[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`.

time, benefiting country pairs with relatively shorter air distance and sectors that rely more heavily on aircraft transportation. Specifically, for each industry, we estimate the following gravity equation:

$$\ln X_{int}^{k} = \beta_{sea,t}^{k} \ln(seadist_{in}) + \beta_{air,t}^{k} \ln(airdist_{in}) + \text{fe}_{i}^{k} + \text{fe}_{n}^{k} + \text{fe}_{t} + u_{int}^{k} \tag{42}$$

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. Incorporating these fixed-effects controls follows the standard gravity estimation and will not introduce endogeneity issues when we apply the instrument to estimation (40), where we more stringently control for origin-sector-time-specific and destination-sector-time-specific fixed effects. We estimate equation (42) by industry and obtain the second instrument:

$$X_{int}^{k,IV2} = \exp(\hat{\beta}_{sea,t}^{k} \ln(seadist_{in}) + \hat{\beta}_{air,t}^{k} \ln(airdist_{in}) + \widehat{\text{fe}}_{i}^{k} + \widehat{\text{fe}}_{n}^{k} + \widehat{\text{fe}}_{t}), \tag{43}$$

which captures the evolving importance of aircraft and sea transportation for trade flows.

Table 1: Impact of Trade Flows on Number of Citations, Least Squares

Dep var	Log Number of Citations								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	all	same ind	diff ind	all	same ind	diff ind	all	same ind	diff ind
Method	OLS	OLS	OLS	2SLS(Bartik)	2SLS(Bartik)	2SLS(Bartik)	2SLS(air)	2SLS(air)	2SLS(air)
Log Trade	0.268***	0.128***	0.172***	0.307***	0.230***	0.212***	0.326***	0.232***	0.230***
Flow	(0.00065)	(0.00142)	(0.00067)	(0.00071)	(0.00280)	(0.00086)	(0.00075)	(0.00219)	(0.00057)
Obs	14,231,955	1,219,398	12,989,202	14,231,720	1,219,367	12,989,003	9,999,959	831,556	9,151,581
R-squared	0.584	0.738	0.584	0.106	0.004	0.032	0.103	0.000	0.028
First-stage F				2.6e+07	3.8e+05	1.5e+07	3.2e+07	4.1e+05	1.8e+07

Note: Columns (1)–(3) present the OLS results, while Columns (4)–(6) display the 2SLS results using the instrument from equation (41), and Columns (7)–(9) show the 2SLS results with the instrument from equation (43). Columns (1), (4), and (7) correspond to the full sample, while Columns (2), (5), and (8) focus on citations within the same industry ($j = k$). Columns (3), (6), and (9) are restricted to citations across different industries ($j \neq k$). 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% ***.

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 $k \neq j$.

Estimation Results. Table 1 presents the estimation results for equation (40). We utilize bootstrap standard errors.[12] 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)–(9), where we use the two constructed instruments, we continue to observe that higher trade flows lead to more citations, with coefficients remaining relatively consistent across the different specifications.

Since bilateral citation values are count-based and may include zeros, the literature notes that ordinary least squares estimation may produce biased results, and therefore recommends Poisson pseudo-maximum-likelihood (PPML) estimation (Silva and Tenreyro, 2006; Cohn, Liu, and Wardlaw, 2022). This issue is less concerning in our case, because when converting citation data from IPC to ISIC categories, we employ the probabilistic matching method of Lybbert and Zolas (2014), which assigns very small probabilities to certain IPC–ISIC pairs and avoids zero-value problems. Nevertheless, in Table 2, we present the estimation results using Poisson maximum likelihood estimation. We continue to find that higher trade flows lead to more citations, with this relationship holding consistently across specifications both with and without the use of instruments.

In our counterfactual exercises, we take $\nu = 0.307$ as our baseline estimate. We set $\nu = 0.507$ as an alternative calibration in our sensitivity analysis. The magnitude of our estimates is consistent with prior empirical findings—for instance, 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 US in their paper.

[12]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), and the second instrument is derived from regression coefficients, 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 2: Impact of Trade Flows on Number of Citations, Poisson Maximum Likelihood

Dep var	Number of Citations								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	all	same ind	diff ind	all	same ind	diff ind	all	same ind	diff ind
Method	PPML	PPML	PPML	PPML(Bartik)	PPML(Bartik)	PPML(Bartik)	PPML(air)	PPML(air)	PPML(air)
Log Trade Flow	0.478*** (0.00160)	0.249*** (0.00338)	0.266*** (0.00225)	0.507*** (0.00198)	0.274*** (0.00309)	0.292*** (0.00268)	0.490*** (0.00184)	0.232*** (0.00341)	0.275*** (0.00288)
Obs	14,231,955	1,219,398	12,989,202	14,231,720	1,219,367	12,989,003	9,999,959	831,556	9,151,581
R-squared	0.938	0.987	0.911	0.939	0.987	0.911	0.944	0.990	0.918
First-stage F				2.6e+07	3.8e+05	1.5e+07	3.2e+07	4.1e+05	1.8e+07

Note: Columns (1)–(3) present the OLS results, while Columns (4)–(6) display the 2SLS results using the instrument from equation (41), and Columns (7)–(9) show the 2SLS results with the instrument from equation (43). Columns (1), (4), and (7) correspond to the full sample, while Columns (2), (5), and (8) focus on citations within the same industry ($j = k$). Columns (3), (6), and (9) are restricted to citations across different industries ($j \neq k$). 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% ***.

3.2 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 BGP subperiods: 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). To reduce the dimensionality of the parameter space, 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 in the 1995–2020 period and obtain t_{in}^j in the corresponding periods from the WITS. These observations are averaged within each BGP subperiod. We assume that $e_{in}^j = 0$ for all (i, n, j).

For the return to innovation, ξ, we set $\xi = 0.9$, following Cai, Li, and Santacreu (2022) and Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018). While their estimates of ξ

Table 3: Calibrated Values of (θ_j)

Index	ICIO Code	Industry	θ_j
1	D01T02	Agriculture, hunting, forestry	3.19
2	D03	Fishing and aquaculture	6.99
3	D05T06	Mining and quarrying, energy producing products	3.16
4	D07T08	Mining and quarrying, non-energy producing products	8.31
5	D09	Mining support service activities	6.16
6	D10T12	Food products, beverages and tobacco	4.09
7	D13T15	Textiles, textile products, leather and footwear	4.71
8	D16	Wood and products of wood and cork	8.68
9	D17T18	Paper products and printing	7.98
10	D19	Coke and refined petroleum products	4.51
11	D20	Chemical and chemical products	8.25
12	D21	Pharmaceuticals, medicinal chemical and botanical products	8.54
13	D22	Rubber and plastics products	6.86
14	D23	Other non-metallic mineral products	4.81
15	D24	Basic metals	7.12
16	D25	Fabricated metal products	4.33
17	D26	Computer, electronic and optical equipment	5.38
18	D27	Electrical equipment	4.74
19	D28	Machinery and equipment, nec	4.38
20	D29	Motor vehicles, trailers and semi-trailers	8.66
21	D30	Other transport equipment	8.93
22	D31T33	Manufacturing nec	4.57
23	S	Services	6

are around 0.5–0.6, their trade elasticity is roughly 4—considerably lower than our value, which exceeds 6. To align the product $\xi\theta$ with previous studies, we set ξ to 0.9.

4 Counterfactuals

We conduct three sets of counterfactual exercises. First, we quantify the effects of trade shocks, including changes in tariffs and non-tariff trade barriers, over 1996–2019. This exercise aims to understand and validate the linkages between trade and technological rivalry characterized analytically in Section 2.4. Second, we quantify the effects of Trump's Trade War 2.0, starting from Liberation Day 2025, including U.S. export controls against China and reciprocal tariffs on China and other major economies. Third, we quantify the unilaterally optimal U.S. tariffs on China, highlighting the role of endogenous innovation and trade-driven technology diffusion in shaping these optimal tariffs.

4.1 Gains from Trade and Gains from Trade Liberalization

Our first set of counterfactual exercises aims to quantify the gains from trade and gains from trade liberalization. First, we decompose gains from trade in Period 4 (2015-2019) utilizing Proposition 1.

Table 4: 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.

Table 4 presents the decomposition results. It reveals 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-driven 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.

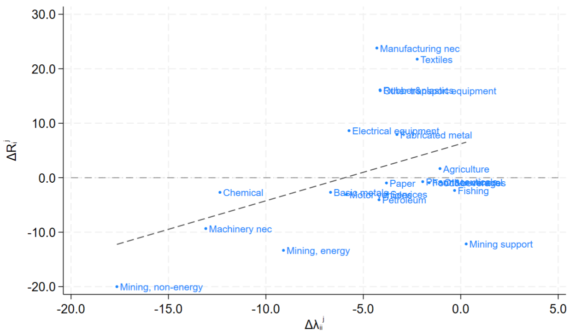
To quantify the impacts of real-world trade liberalization, we incorporate observed trade shocks across periods, including changes in iceberg trade costs and tariffs, into our model to quantify their effects on real incomes. To compute changes in τ^j_{in} across periods, we assume symmetric changes for all (i, n) pairs. Thus, we express the change in trade costs as:

$$\hat{\tau}^j_{in} = \left(\frac{\hat{X}^j_{in} \hat{X}^j_{ni}}{\hat{X}^j_{ii} \hat{X}^j_{nn}} \right)^{-\frac{1}{2\theta_j}} \frac{1}{\sqrt{\widehat{1 + t^j_{in}}} \sqrt{\widehat{1 + t^j_{ni}}}}. \tag{44}$$

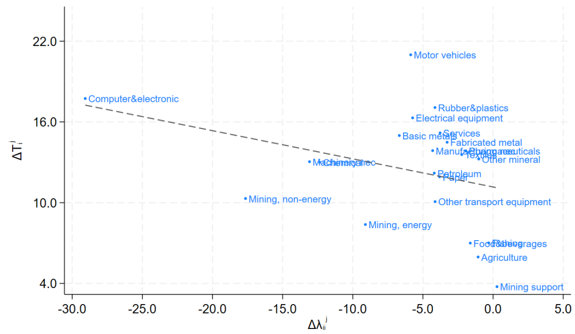
Figure 1 presents the quantitative effects of trade liberalization between period 1 (1996–2000) and period 2 (2003–2007) on China's R&D and technology. Panel (a) shows that R&D declines more sharply in sectors more exposed to import competition, reflecting reduced innovation returns in these sectors. 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.

Table 5 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-driven technology diffusion amplifying the gains 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

Figure 1: 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.

gains attributable to trade-driven technology diffusion in the European Union and endogenous innovation in the United States.

4.2 Quantifying Trump's Trade War 2.0

The trade war launched during the second term of the Trump administration—often dubbed Trump's Trade War 2.0—is marked by two defining features: (i) a sweeping escalation of export controls targeting China, particularly in dual-use high-technology sectors, and (ii) the imposition of extensive "reciprocal tariffs" on nearly all major economies since Labor Day 2025, with rates varying sharply across countries.

We first quantify the U.S. export controls against China. As outlined by the U.S. Department of Commerce, these export controls aim "to protect national security interests and promote foreign policy objectives related to dual-use items and less-sensitive military items."[13] Following the discussion on dual-use goods in Alekseev and Lin (2025), we identify the dual-use sectors in our calibrated economy as follows: 11 "Chemical and chemical products"; 13 "Rubber and plastic products"; 17 "Computer, electronic and optical equipment"; 18 "Electrical equipment"; 19 "Machinery and equipment, nec"; and 21

[13]See `https://www.trade.gov/country-commercial-guides/china-us-export-controls`

Table 5: Observed Trade Shocks over 1996-2019: Impacts on Real Income

	Period 1 $\rightarrow$ 2			Period 2 $\rightarrow$ 3			Period 3 $\rightarrow$ 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.

"Other transport equipment". We consider two levels of the U.S export controls against China: a 30% and a 100% export tariff on each of these sectors. We start from our calibrated economy over the period 2015-2019.

Table 6 reports the impacts of U.S. export controls against China on R&D and technology in both countries. Consistent with Proposition 2, the export controls stimulate R&D in most of China's dual-use sectors while reducing R&D in the corresponding U.S. sectors. At the same time, the controls lower dual-use technologies in both countries, reflecting the double-edged effect highlighted in Proposition 2. In addition, technological declines also appear in many sectors beyond the dual-use ones, emphasizing the central role of dual-use industries in intersectoral knowledge diffusion. In other words, technology rivalry in a few strategic sectors—critical to national security and central to global technology networks—can generate broader technological losses across the entire economy.

Table 6: U.S. Export Controls against China: Impacts on Technology and R&D

Sector	Dual-Use	30% Tariffs on Dual-Use				100% Tariffs on Dual-Use			
		China		U.S.		China		U.S.	
		ΔT	ΔR	ΔT	ΔR	ΔT	ΔR	ΔT	ΔR
Agriculture		-0.2	-0.0	-0.1	0.1	-0.5	0.1	-0.1	0.1
Fishing		-0.1	0.0	0.2	1.4	-0.3	0.1	0.2	1.3
Mining, energy		-0.3	0.1	-0.4	0.1	-0.6	0.3	-0.4	0.2
Mining, non-energy		-0.2	0.2	-0.3	0.2	-0.4	0.6	-0.3	0.2
Mining support		-0.8	0.0	-0.3	0.1	-1.7	0.2	-0.3	0.1
Food&beverages		-0.3	0.0	-0.2	0.1	-0.5	0.1	-0.2	0.1
Textiles		-0.5	-0.1	-0.0	0.7	-0.9	0.1	-0.0	0.7
Wood		-0.3	-0.1	-0.3	0.3	-0.7	0.0	-0.3	0.3
Paper		-0.5	-0.1	-0.3	0.2	-1.2	-0.0	-0.3	0.2
Petroleum		-1.0	0.1	-0.4	0.0	-2.0	0.1	-0.5	0.0
Chemical	✓	-0.9	0.8	-0.4	-2.2	-1.8	1.0	-0.4	-2.3
Pharmaceuticals		-0.8	-0.1	-0.1	0.7	-1.6	0.0	-0.1	0.8
Rubber&plastics	✓	-1.2	0.0	-0.2	-0.5	-2.4	-0.0	-0.2	-0.5
Other mineral		-0.4	-0.1	-0.2	0.2	-0.9	-0.1	-0.1	0.2
Basic metals		-0.3	0.1	-0.3	-0.0	-0.7	0.2	-0.3	-0.1
Fabricated metal		-0.5	-0.0	-0.2	-0.0	-1.1	-0.0	-0.2	-0.0
Computer&electronic	✓	-2.2	-1.2	-0.1	-1.1	-4.6	-2.5	0.3	-1.0
Electrical equipment	✓	-1.1	0.0	-0.2	-1.0	-2.4	-0.1	-0.0	-1.2
Machinery nec	✓	-0.7	0.4	-0.4	-2.0	-1.6	0.6	-0.4	-2.6
Motor vehicles		-0.6	-0.1	-0.2	0.4	-1.4	-0.2	-0.2	0.5
Other transport equipment	✓	0.8	7.2	-0.8	-4.2	-0.7	7.8	-0.8	-4.4
Manufacturing nec		-0.7	-0.3	-0.1	0.3	-1.4	-0.2	-0.0	0.4
Services		-1.0	-0.1	-0.1	0.1	-2.2	-0.1	0.0	0.1

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

Table 7: U.S. Export Controls against China: Impacts on Real Income

	30% Tariffs on Dual-Use			100% Tariffs on Dual-Use		
	Full	FR	FT	Full	FR	FT
Australia	0.04	0.04	0.00	0.07	0.04	0.00
European Union	0.03	0.02	-0.00	0.07	0.03	-0.00
Brazil	0.00	0.02	0.00	0.02	0.02	-0.00
Canada	0.01	0.01	-0.00	0.06	0.02	-0.01
Switzerland	0.04	0.03	0.00	0.08	0.04	0.00
China	-0.39	-0.42	-0.03	-0.82	-0.83	-0.04
United Kingdom	0.02	0.02	-0.00	0.07	0.03	-0.00
Indonesia	0.03	0.03	-0.00	0.05	0.04	-0.00
India	0.02	0.05	-0.01	0.08	0.06	-0.01
Japan	0.07	0.02	0.00	0.12	0.02	0.00
Korea	0.11	0.06	0.01	0.19	0.08	0.02
Mexico	-0.03	-0.01	-0.01	-0.01	-0.01	-0.02
Norway	0.02	0.02	-0.00	0.05	0.03	-0.00
Rest of the World	0.04	0.04	0.00	0.09	0.05	0.00
Russia	0.04	0.02	-0.00	0.08	0.02	-0.00
Turkey	0.02	0.03	-0.00	0.06	0.04	-0.00
Taiwan	0.11	0.08	0.03	0.17	0.12	0.04
United States	-0.06	-0.04	-0.01	-0.05	-0.06	-0.03

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 7 reports the welfare effects of U.S. export controls against China. The results indicate that these measures reduce real income in both China and the United States. Moving from a 30% to a 100% export tariff on dual-use goods leads to substantially larger welfare losses for China but slightly smaller losses for the United States, offering an economic rationale for tightening export restrictions. In response, China raises R&D investment in the targeted sectors, partially offsetting the negative technology effects of reduced knowledge inflows: China's welfare declines by 0.39% in our full model and by 0.42% in the model with trade-driven diffusion but exogenous innovation (*e.g.,* Buera and Oberfield, 2020 and Bai et al., 2025b).

We next quantify the effects of U.S. reciprocal tariffs on China. As specified in U.S. Executive Order 14298, issued on May 12, 2025, the United States raised tariffs on all tradable goods imported from China by 30%.[14] In response, China increased tariffs on all tradable goods imported from the United States by 10%.

The combined effects of these tariffs and the U.S. export controls against China are reported in the first five columns of Table 8. The results show that the U.S.–China trade war under Trump 2.0 substantially harms China in both real income and technology. Although China modestly raises R&D investment, this response cannot offset the losses caused by diminished knowledge inflows. In contrast, the United States experiences sizable gains in real income, R&D, and technology. This asymmetry reflects the greater importance of U.S.-origin knowledge diffusion to China than the reverse, giving the United States leverage to manipulate tariffs in its favor in technological rivalry.

Notably, China's welfare loss and the U.S. welfare gain are both markedly smaller in the absence of trade-driven 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 under-

[14] See https://www.whitehouse.gov/presidential-actions/2025/05/modifying-reciprocal-tariff-rates-to-reflect-discussions-with-the-peoples-republic-of-china/. The U.S. reduces the reciprocal tariff on Chinese goods announced on Liberation Day to 10% while maintaining an additional 20% tariff aimed at pressuring Beijing to curb illegal fentanyl trade.

standing U.S. trade policies toward China.

Table 8: 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	0.71	0.32	0.14	0.02	-0.02	0.40	0.39	-0.05	-0.08	-0.06
European Union	0.70	0.02	0.23	0.02	0.01	-0.16	0.01	-0.20	-0.18	-0.09
Brazil	0.78	0.08	0.20	0.03	-0.00	0.18	0.14	-0.08	-0.13	-0.06
Canada	1.55	0.11	0.45	-0.76	0.02	1.00	0.63	-0.29	-0.89	-0.47
Switzerland	0.94	-0.02	0.32	-0.10	0.01	-0.59	0.41	-0.48	-0.25	-0.24
China	-2.48	0.04	-1.26	-0.21	-0.23	-2.67	0.05	-1.34	-0.28	-0.22
United Kingdom	0.98	0.01	0.29	0.02	0.01	0.43	-0.03	0.06	-0.09	-0.02
Indonesia	0.63	0.14	0.21	-0.00	0.03	-0.49	0.11	-0.38	-0.18	-0.10
India	1.32	0.02	0.45	0.00	0.05	-0.00	0.23	-0.42	-0.35	-0.13
Japan	0.35	0.01	0.09	0.03	0.01	-0.28	0.05	-0.23	-0.16	-0.10
Korea	0.47	0.01	0.14	-0.08	0.01	-0.19	0.16	-0.39	-0.39	-0.23
Mexico	1.61	0.12	0.56	-0.22	0.14	0.13	0.04	-0.55	-0.81	-0.52
Norway	0.74	-0.00	0.23	-0.32	0.01	-0.03	0.34	-0.19	-0.51	-0.11
Rest of the World	0.98	0.14	0.30	0.04	0.02	0.34	0.31	-0.10	-0.17	-0.09
Russia	0.49	0.02	0.14	-0.03	0.01	0.21	0.12	-0.01	-0.08	-0.03
Turkey	0.89	0.02	0.30	-0.01	0.02	0.15	0.04	-0.05	-0.14	-0.04
Taiwan	0.43	0.00	0.14	-1.59	-0.01	-0.48	0.24	-0.58	-2.08	-0.37
United States	2.87	0.27	0.62	0.29	-0.15	2.20	0.62	0.37	-0.06	-0.12

Note: All values are percentage changes. Full: the baseline model. ND: No Diffusion ($\hat{T}_i^j = \left(\hat{R}_i^j\right)^{\xi}$). 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": 30% tariff on dual-use exports to China. "US Reciprocal Tariffs on China": 30% 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: 15% for the EU, 25% for India, 19% for Indonesia, 15% for Japan, 15% for Korea, 15% for Norway, 39% for Switzerland, 20% for Taiwan, and 15% for Turkey. ΔT_i^j and ΔR_i^j are weighted by α_i^j in each economy.

Finally, we quantify the effects of U.S. reciprocal tariffs on all trading partners. The United States imposes a 10% baseline tariff increase, with higher rates for several economies in our calibrated model: 15% for EU countries, 25% for India, 19% for Indonesia, 15% for Japan, 15% for Korea, 15% for Norway, 39% for Switzerland, 20% for Taiwan, and 15% for Turkey.[15] The combined effects of these tariffs and the U.S.–China trade war described above are reported in the last five columns of Table 8. The results indicate that most major economies incur losses from the reciprocal tariffs, with losses amplified by trade-driven technology diffusion and endogenous innovation. Relative to the welfare effects of the U.S.–China trade war, the United States suffers substantially from extending tariffs to all other major economies. In other words, escalating a bilateral trade conflict into a global one reduces U.S. gains.

[15] See https://www.whitehouse.gov/presidential-actions/2025/07/further-modifying-the-reciprocal-tariff-rates/.

4.3 Optimal Tariffs with Endogenous Innovation and Trade-Driven Technology Diffusion

In this section, 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 9 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 9: U.S. Optimal Export and Import Tariffs on China

Sector	Full						FR			
	Optimal Tariffs		China		U.S.		Optimal Tariffs		China	U.S.
	$e^*_{US,CN}$	$t^*_{CN,US}$	ΔT	ΔR	ΔT	ΔR	$e^*_{US,CN}$	$t^*_{CN,US}$	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 10 reports these optimal policies. Compared with Table 9, 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 10: 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

$$\hat{W}_{US} + \chi \hat{W}_{CN}. \tag{45}$$

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 11 reports the resulting optimal tariffs. In stark contrast to Table 9, 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%.

Table 11: 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%.

5 Sensitivity

5.1 Heterogeneous Diffusion Elasticities

In this section, 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:

$$\log \delta^{kj}_{int} = \nu_k \log X^{kj}_{int} + \mathrm{fe}^k_{it} + \mathrm{fe}^j_{nt} + \log \bar{\epsilon}^{kj}_{int}. \tag{46}$$

We summarize the estimates of ν_k in Appendix Table A1. 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 A1, remain broadly consistent with those under a uniform ν

shown in Table 6, confirming the robustness of our main findings to allowing for heterogeneous diffusion elasticities.

5.2 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 then 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 A1, are very similar to our baseline results in Figure 1, confirming that the main findings are robust to this alternative assumption.

6 Conclusion

In this paper, we show that trade policies can profoundly reshape global technological progress by affecting both knowledge diffusion across borders and firms' incentives to innovate. When innovation is endogenous, trade restrictions—such as the recent U.S. export controls against China—have a double-edged effect: they slow knowledge spillovers abroad while also dampening innovation incentives at home, ultimately reducing productivity in both countries.

Quantitatively, the model demonstrates that Trump's trade war 2.0—including export controls against China and reciprocal tariffs on nearly all major economies—induces substantial technological and welfare losses once endogenous innovation and trade-driven diffusion are accounted for. These losses are far larger than those predicted by standard trade models.

The analysis also reveals a strategic tension in designing optimal tariffs. While the United States can use trade measures to constrain China's technological advance, the same policies weaken the forces that sustain U.S. innovation and long-run growth. In a world where major economies are tightly connected through technology diffusion and innovation returns depend on global market size, trade conflicts can be highly damaging, producing lose-lose outcomes for all participants.

A key takeaway is that understanding the motives and consequences of trade conflicts requires explicitly considering their effects on technological progress, beyond traditional terms-of-trade concerns or domestic market effects. It is crucial to incorporate multiple mechanisms through which trade barriers reshape global technological advancement. This area remains under-explored in the literature, leaving important questions for future research, including how trade policies affect multinational firms' innovation across countries and how these effects reshape our understanding of trade conflicts.

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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:

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

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:

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

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:

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

[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

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

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

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

A.4 Proof to Proposition 3

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

$$\begin{aligned}
T_n &= \sum_{i=1}^{N} \lambda_{in}^{\nu} R_i^{\xi}, \quad \lambda_{in} = T_i \tau_{in}^{-\theta} \left(1+e_{in}\right)^{-\theta} P_n^{\theta} \\
R_i &= \sum_{n=1}^{N} \frac{1}{1+\theta} \frac{\lambda_{in} X_n}{1+e_{in}} \\
P_n &= \left(\sum_{i=1}^{N} T_i \tau_{in}^{-\theta} \left(1+e_{in}\right)^{-\theta} \right)^{-\frac{1}{\theta}} \\
X_n &= \alpha Y_n, \quad Y_n = 1 + \sum_{i=1}^{N} \frac{e_{ni}}{1+e_{ni}} \lambda_{ni} X_i
\end{aligned} . \tag{A9}$$

We denote $\lambda_{ii} = \frac{1}{1+\tau^{-\theta}}$ at $e_{in} = 0$ as $\lambda > \frac{1}{2}$; therefore, $\lambda_{in} = 1 - \lambda = \frac{\tau^{-\theta}}{1+\tau^{-\theta}} < \frac{1}{2}$ for all $i \neq n$ at $e_{in} = 0$. Then at $e_{in} = 0$, we have

1. $Y_n = 1$, $X_n = \alpha$
2. $R_i = R = \frac{\alpha}{1+\theta}$, $T_i = T = \left[\lambda^{\nu} + (1-\lambda)^{\nu}\right] \left(\frac{\alpha}{1+\theta}\right)^{\xi}$
3. $P_i = P = \left\{ \left(1+\tau^{-\theta}\right) \left[\lambda^{\nu} + (1-\lambda)^{\nu}\right] \left(\frac{\alpha}{1+\theta}\right)^{\xi} \right\}^{-\frac{1}{\theta}}$
4. Welfare $W_n = \frac{Y_n}{P_n^{\alpha}} = \left\{ \left(1+\tau^{-\theta}\right) \left[\lambda^{\nu} + (1-\lambda)^{\nu}\right] \left(\frac{\alpha}{1+\theta}\right)^{\xi} \right\}^{\frac{\alpha}{\theta}}$

For any variable $Z > 0$, denote $\tilde{Z} = d \log Z$. Then log-linearizing Equation (A9) around $e_{in} = 0$ leads to

$$\tilde{T}_n = \sum_{i=1}^{N} \left[1_{i=n} \frac{\lambda^\nu}{\lambda^\nu + (1-\lambda)^\nu} + 1_{i \neq n} \frac{(1-\lambda)^\nu}{\lambda^\nu + (1-\lambda)^\nu} \right] \left[\nu \tilde{\lambda}_{in} + \xi \tilde{R}_i \right], \quad \tilde{\lambda}_{in} = \tilde{T}_i - \theta \widetilde{1+e_{in}} + \theta \tilde{P}_n$$
$$\tilde{R}_i = \sum_{n=1}^{N} \left[1_{n=i} \lambda + 1_{n \neq i} (1-\lambda) \right] \left[\tilde{\lambda}_{in} + \tilde{X}_n - \widetilde{1+e_{in}} \right]$$
$$-\theta \tilde{P}_n = \sum_{i=1}^{N} \left[1_{i=n} \lambda + 1_{i \neq n} (1-\lambda) \right] \left[\tilde{T}_i - \theta \widetilde{1+e_{in}} \right]$$
$$\tilde{X}_n = \tilde{Y}_n, \quad \tilde{Y}_n = \sum_{i=1}^{N} \alpha \left[1_{i=n} \lambda + 1_{i \neq n} (1-\lambda) \right] \widetilde{1+e_{ni}} \tag{A10}$$

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

Therefore, we have

$$\begin{aligned}
&\tilde{Y}_2 = \tilde{X}_2 = 0, \quad \tilde{Y}_1 = \tilde{X}_1 = \alpha (1-\lambda) \widetilde{1+e_{12}} \\
&-\theta \tilde{P}_1 = \lambda \tilde{T}_1 + (1-\lambda) \tilde{T}_2, \quad -\theta \tilde{P}_2 = \lambda \tilde{T}_2 + (1-\lambda) \tilde{T}_1 - \theta (1-\lambda) \widetilde{1+e_{12}} \\
&\tilde{\lambda}_{11} = (1-\lambda) \left(\tilde{T}_1 - \tilde{T}_2 \right), \quad \tilde{\lambda}_{12} = \lambda \left(\tilde{T}_1 - \tilde{T}_2 \right) - \theta \lambda \widetilde{1+e_{12}} \\
&\tilde{\lambda}_{21} = \lambda \left(\tilde{T}_2 - \tilde{T}_1 \right), \quad \tilde{\lambda}_{22} = (1-\lambda) \left(\tilde{T}_2 - \tilde{T}_1 \right) + \theta (1-\lambda) \widetilde{1+e_{12}}
\end{aligned} \tag{A11}$$

and

$$\begin{aligned}
\tilde{R}_1 &= 2\lambda (1-\lambda) \left[\tilde{T}_1 - \tilde{T}_2 \right] - (1-\lambda) \left[1 + \theta\lambda - \alpha\lambda \right] \widetilde{1+e_{12}} \\
\tilde{R}_2 &= 2\lambda (1-\lambda) \left[\tilde{T}_2 - \tilde{T}_1 \right] + (1-\lambda) \left[\theta\lambda + \alpha (1-\lambda) \right] \widetilde{1+e_{12}}
\end{aligned} \tag{A12}$$

Denote $\Lambda \equiv \frac{\lambda^\nu}{\lambda^\nu + (1-\lambda)^\nu} > \frac{1}{2}$ and $\Omega \equiv [(1-\Lambda)\lambda - \Lambda(1-\lambda)]$. Inserting these expressions into $\tilde{T}_i$, we get

$$\begin{aligned}
[1 + \nu\Omega] \tilde{T}_1 - \nu\Omega \tilde{T}_2 &= \xi \left[\Lambda \tilde{R}_1 + (1-\Lambda) \tilde{R}_2 \right] \\
-\nu\Omega \tilde{T}_1 + [1 + \nu\Omega] \tilde{T}_2 &= \xi \left[\Lambda \tilde{R}_2 + (1-\Lambda) \tilde{R}_1 \right] - \nu\theta\Omega \widetilde{1+e_{ni}}
\end{aligned} \tag{A13}$$

Solving $\left(\tilde{R}_i, \tilde{T}_i\right)$, we have

$$\frac{\partial \log R_1}{\partial\,(1+e_{12})} = \frac{\Lambda F_1(\lambda) + (1-\Lambda)F_2(\lambda)}{\Lambda G_1(\lambda) + (1-\Lambda)G_2(\lambda)}, \tag{A14}$$

where

$$\begin{aligned} G_1(\lambda) &= 1 - 2\nu + 2\lambda\nu - 4\lambda\xi + 4\lambda^2\xi, \\ G_2(\lambda) &= 1 + 2\lambda\nu + 4\lambda\xi - 4\lambda^2\xi, \\ F_1(\lambda) &= -1 + \lambda + 2\nu - 4\lambda\nu - \lambda\theta + 2\lambda\xi - \alpha\lambda^2 + 2\lambda^2\nu + \lambda^2\theta \\ &\quad - 4\lambda^2\xi + 2\lambda^3\xi + 4\alpha\lambda^2\nu - 2\alpha\lambda^3\nu + 4\alpha\lambda^2\xi \\ &\quad - 2\alpha\lambda^3\xi - 2\alpha\lambda\nu - 2\alpha\lambda\xi, \\ F_2(\lambda) &= -1 + \lambda + \alpha\lambda - 2\lambda\nu - \lambda\theta - 2\lambda\xi - \alpha\lambda^2 + 2\lambda^2\nu \\ &\quad + \lambda^2\theta + 4\lambda^2\xi - 2\lambda^3\xi + 2\alpha\lambda\xi + 2\alpha\lambda^2\nu \\ &\quad - 2\alpha\lambda^3\nu - 4\alpha\lambda^2\xi + 2\alpha\lambda^3\xi \end{aligned} \tag{A15}$$

And

$$\frac{\partial \log R_2}{\partial\,(1+e_{12})} = \frac{\Lambda F_3(\lambda) + (1-\Lambda)F_4(\lambda)}{\Lambda G_1(\lambda) + (1-\Lambda)G_2(\lambda)}, \tag{A16}$$

where

$$\begin{aligned} F_3(\lambda) &= \alpha + (-2\alpha + 4\alpha\nu + \theta + 2\xi - 2\alpha\xi)\lambda \\ &\quad + (\alpha - \theta - 4\xi - 6\alpha\nu + 4\alpha\xi)\lambda^2 \\ &\quad + (2\alpha\nu - 2\alpha\xi + 2\xi)\lambda^3, \\ F_4(\lambda) &= \alpha + (-2\alpha + \theta - 2\xi + 2\alpha\nu + 2\alpha\xi)\lambda \\ &\quad + (\alpha - \theta + 4\xi - 4\alpha\nu - 4\alpha\xi)\lambda^2 \\ &\quad + (-2\xi + 2\alpha\nu + 2\alpha\xi)\lambda^3 \end{aligned} \tag{A17}$$

And

$$\frac{\partial \log T_1}{\partial\,(1+e_{12})} = \frac{\Lambda P_1(\lambda) + (1-\Lambda)R_1(\lambda)}{\Lambda G_1(\lambda) + (1-\Lambda)G_2(\lambda)}, \tag{A18}$$

where

$$\begin{aligned} P_1(\lambda) = &-\xi + (-2\xi - \nu\xi)\lambda + (-\nu^2\theta + \nu\xi)\lambda^2 \\ &+ (2\xi^2 + \alpha\nu\xi - 2\nu\theta\xi)\lambda^3 - 2\xi^2\lambda^4, \end{aligned} \tag{A19}$$

and

$$
\begin{aligned}
R_1(\lambda) = & -\alpha\xi + (2\xi + \nu\xi - \theta\xi + 2\xi^2 - \alpha\xi)\lambda \\
& + (-2\xi^2 + \nu^2\theta - \alpha\xi - \nu\xi + \theta\xi + 4\alpha\xi^2)\lambda^2 \\
& + (2\alpha\xi - 2\alpha\xi^2)\lambda^3 + 2\xi^2\lambda^4.
\end{aligned} \tag{A20}
$$

And

$$
\frac{\partial \log T_2}{\partial\,(1+e_{12})} = \frac{\Lambda P_2(\lambda) + (1-\Lambda)R_2(\lambda)}{\Lambda G_1(\lambda) + (1-\Lambda)G_2(\lambda)}, \tag{A21}
$$

where

$$
\begin{aligned}
P_2(\lambda) = & (-\alpha\xi - \nu\theta) + (2\alpha\xi + \nu\theta + 2\nu\xi - \theta\xi)\lambda \\
& + (-\alpha\xi - \nu\xi + \theta\xi - 2\nu^2\theta + 2\xi^2)\lambda^2 \\
& + (-2\nu\theta\xi + 2\alpha\xi^2)\lambda^3 - 2\xi^2\lambda^4,
\end{aligned} \tag{A22}
$$

and

$$
\begin{aligned}
R_2(\lambda) = & (-\xi - \alpha\xi) + (\xi + \nu\theta + \nu\xi + \theta\xi + 2\xi^2 - \alpha\xi)\lambda \\
& + (\alpha\xi - \nu\xi - \theta\xi + \nu^2\theta - 2\xi^2 + 4\alpha\xi^2)\lambda^2 \\
& + (-\alpha\xi + 2\nu\theta\xi - 2\alpha\xi^2)\lambda^3 + 2\xi^2\lambda^4.
\end{aligned} \tag{A23}
$$

Given the expressions above, we can show that if $\nu \in (0,1)$ and $\xi \in (0,1]$, we have

$$
\frac{\partial \log R_2}{\partial\,(1+e_{12})} > 0 > \frac{\partial \log R_1}{\partial\,(1+e_{12})}, \tag{A24}
$$

and

$$
\frac{\partial \log T_1}{\partial\,(1+e_{12})} < 0, \quad \frac{\partial \log T_2}{\partial\,(1+e_{12})} < 0 \tag{A25}
$$

If $\nu \in (0,1)$ and $\xi \in (0,1]$, then $\frac{\partial^2 \log(T_1/T_2)}{\partial(1+e_{12})\partial\xi} < 0$.

If $\nu \in (0,1)$, there exists a $\bar{\bar{\xi}} \in (0,1)$ such that if $\xi \in (0,\bar{\bar{\xi}})$, then $\frac{\partial^2 \log(T_1/T_2)}{\partial(1+e_{12})\partial\nu} > 0$ and if $\xi \in (\bar{\bar{\xi}},1]$, then $\frac{\partial^2 \log(T_1/T_2)}{\partial(1+e_{12})\partial\nu} < 0$.

Exogenous R&D: Suppose that innovation is exogenous, or equivalently, $\xi = 0$. Then we have

$$
\begin{aligned}
[1+\nu\Omega]\,\tilde{T}_1 - \nu\Omega\tilde{T}_2 &= 0 \\
-\nu\Omega\tilde{T}_1 + [1+\nu\Omega]\,\tilde{T}_2 &= -\nu\theta\Omega\widetilde{1+e_{ni}}
\end{aligned} \tag{A26}
$$

Then we have

$$\begin{aligned}\tilde{T}_1 &= -\frac{\theta\nu^2\Omega^2}{1+2\nu\Omega}\widetilde{1+e_{ni}} \\ \tilde{T}_1 &= -\frac{\theta\nu\Omega\left(\nu\Omega+1\right)}{1+2\nu\Omega}\widetilde{1+e_{ni}}\end{aligned} \tag{A27}$$

B Quantification

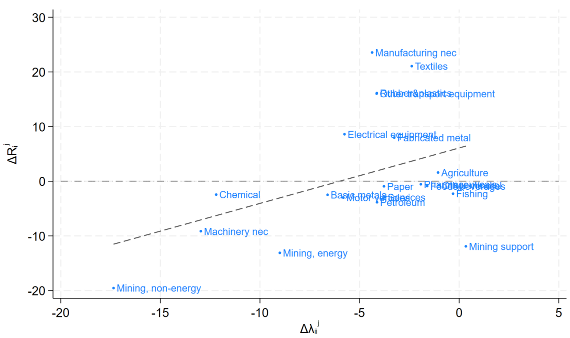
B.1 Sensitivity Results

Table A1: U.S. Export Controls against China: Sector-Specific ν

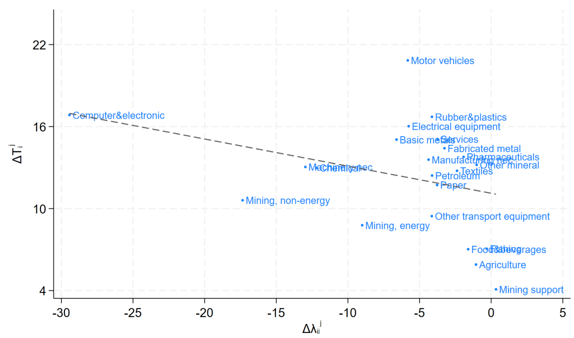
Sector	Dual-Use	ν_k	30% Tariffs on Dual-Use			
			China		U.S.	
			ΔT	ΔR	ΔT	ΔR
Agriculture		0.13	-0.14	-0.03	-0.14	0.14
Fishing		0.13	-0.05	-0.01	0.18	1.42
Mining, energy		0.10	-0.20	0.05	-0.30	0.16
Mining, non-energy		0.08	-0.13	-0.02	-0.28	0.25
Mining support		0.11	-0.65	-0.02	-0.26	0.08
Food&beverages		0.12	-0.19	-0.02	-0.13	0.11
Textiles		0.11	-0.33	-0.18	-0.02	0.71
Wood		0.16	-0.24	-0.18	-0.25	0.29
Paper		0.17	-0.38	-0.12	-0.22	0.20
Petroleum		0.15	-0.66	0.05	-0.40	0.04
Chemical	✓	0.17	-0.50	0.85	-0.35	-2.14
Pharmaceuticals		0.21	-0.58	-0.13	-0.07	0.73
Rubber&plastics	✓	0.20	-0.80	0.08	-0.20	-0.50
Other mineral		0.23	-0.28	-0.09	-0.18	0.17
Basic metals		0.16	-0.19	0.05	-0.23	0.01
Fabricated metal		0.17	-0.34	-0.03	-0.15	-0.01
Computer&electronic	✓	0.20	-1.53	-0.77	-0.18	-1.30
Electrical equipment	✓	0.25	-0.83	0.02	-0.19	-1.03
Machinery nec	✓	0.25	-0.50	0.42	-0.37	-1.97
Motor vehicles		0.22	-0.41	-0.17	-0.20	0.44
Other transport equipment	✓	0.20	0.98	7.14	-0.81	-4.19
Manufacturing nec		0.21	-0.50	-0.37	-0.06	0.34
Services		0.21	-0.72	-0.07	-0.15	0.10

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

Figure A1: 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.