Knowledge Spillovers, Market Power and Innovation under Trade Shocks

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Abstract

This paper examines how international trade shocks affect firm innovation when knowledge spillovers interact with market power. Using matched firm–patent data from China and the United States, I compare two opposite trade episodes—China's WTO accession and the 2018 U.S. trade war. I find that tariff reductions during liberalization increased innovation, whereas tariff increases under protection reduced it. The direction of these effects depends systematically on pre-existing spillover intensity: in China, sectors with stronger spillovers responded less to liberalization, while in the United States they experienced larger declines during protection. Firms with greater market share consistently exhibited stronger innovation responses in both settings. To explain these patterns, I develop a dynamic two-country model in which oligopolistic firms invest in R&D while knowledge flows among incumbents and to a competitive fringe. Calibrated counterfactuals show that modest, sector-specific R&D subsidies or competition-policy interventions can offset welfare losses at minimal fiscal cost.

Keywords: Knowledge spillovers; Market power; Diffusion; Endogenous growth

JEL codes: F12, F43, O31, O33

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1 Introduction

Understanding how international trade shapes innovation and growth is a central question in modern economics and policy-making. A key mechanism is knowledge spillover—the idea that cross-border exchange facilitates access to new ideas, technologies, and production methods. Recent quantitative trade models have formalized this channel: Buera and Oberfield (2020) show that international knowledge diffusion accelerates TFP growth, while Cai et al. (2022) find that sectoral knowledge flows from trade boost gains from trade liberalization. At the micro level, studies such as Sampson (2016) and Perla et al. (2021) emphasize that greater export opportunities and foreign competition can induce dynamic selection toward more productive and innovative firms.

While these studies underscore the importance of knowledge spillovers, they largely abstract from market structure and firms' strategic interaction. However, a complementary literature—pioneered by Aghion et al. (2005)—shows that the relationship between competition and innovation is non-monotonic: moderate competition encourages innovation as firms attempt to "escape" rivals, whereas too little or too much competition weakens incentives. These insights help explain why the effects of trade on innovation vary across contexts. For instance, Bloom et al. (2016) find that Chinese import competition boosted innovation in Europe, whereas Autor et al. (2020b) document that similar shocks depressed innovation in the United States.

Together, these two strands of literature suggest that trade's impact on innovation may depend crucially on how knowledge spillovers interact with market power and competitive pressure. This paper bridges these two literatures by asking: *How do trade shocks influence firms' incentives to innovate when knowledge spillovers interact with market power? And how should policy be designed when these effects vary systematically across sectors?*

To answer these questions, I combine new firm-level evidence from two major trade episodes—China's WTO accession and the 2018 U.S. trade war—with a dynamic model of oligopolistic innovation and knowledge spillover. The paper thus contributes along three dimensions. Empirically, it provides the first comparative evidence linking the direction of trade shocks to heterogeneous innovation responses across sectors that differ in spillover intensity and market power. Theoretically, it develops a tractable two-country model in which variable markups and knowledge spillover jointly determine R&D incentives, rationalizing the contrasting empirical patterns. Quantitatively, it shows that modest, sector-specific interventions—such as targeted R&D subsidies or competition-policy adjustments—can offset welfare losses at minimal fiscal cost. Together, the results highlight that understanding the innovation effects of trade requires accounting for both strategic behavior and the diffusion of knowledge across firms.

The empirical analysis focuses on two natural experiments that move trade costs in opposite directions: China's WTO accession in 2001, a major liberalization, and the 2018 U.S. trade war, a sharp protectionist reversal. Using matched firm–patent data—China's Annual Survey of Industrial Firms (ASIF) linked to State Intellectual Property Office (SIPO) and U.S. Compustat firms linked to USPTO patents—I document three main findings. First, tariff reductions during China's WTO accession significantly increased firm innovation, whereas higher import tariffs in the U.S. trade war reduced it; retaliatory tariffs partially offset these declines. Second, the role of knowledge spillovers differs sharply across episodes: in China, spillover-intensive sectors innovated less from liberalization; in the United States, the high-spillover sectors suffered larger innovation declines under protection. Third, firms with larger market shares within each sector exhibited stronger innovation responses in both settings. These facts suggest that the aggregate innovation effects of trade cannot be understood without considering both knowledge spillover across firms and the market structure within which firms compete.

To interpret these patterns, I develop a dynamic two-country model in which innovation interacts with two forms of knowledge externalities. The first is *spillover* — knowledge sharing among innovators that reduces their individual R&D costs by allowing each firm to build on others' research efforts. The second is *diffusion* — the transfer of knowledge from innovators to non-innovators, enabling imitation and entry by firms that do not invest in R&D themselves. Spillovers thus lower the private cost of innovation, while diffusion expands the competitive fringe and erodes incumbents' rents. The equilibrium rate of innovation balances these opposing forces.

Within this environment, there are two types of firms. Innovative firms invest in R&D to lower marginal costs and compete oligopolistically, internalizing their impact on aggregate prices and markups. Non-innovators operate for a single period under zero-profit entry conditions (Atkeson and Burstein, 2008; Shimomura and Thisse, 2012; Helpman, 2024). Because diffusion raises the productivity of non-innovators, it intensifies competition and alters the incentives for innovators. The interaction between spillovers and diffusion therefore determines how trade shocks affect aggregate innovation. The model embeds firm heterogeneity in market share. Larger firms—those that contribute more to the aggregate price index and rely more heavily on foreign markets—adjust innovation more sharply when trade costs change, so market power amplifies the innovation response to trade shocks.

Three predictions follow: (i) when spillover effects dominate diffusion, sectors with higher spillover intensity respond less to trade liberalization, as knowledge sharing dilutes incentives; (ii) when diffusion dominates, the same sectors respond more strongly to protectionist shocks, as diffusion erodes rents and induces defensive innovation; and (iii) firms with larger market shares respond more strongly in both cases. These mechanisms reproduce the heterogeneous responses observed empirically and help reconcile contrasting results across studies.

Finally, because trade shocks affect firms asymmetrically across spillover intensities, I estimate key structural parameters—spillover intensity, the ratio of knowledge to R&D intensity, and diffusion rates—using firm-level regressions, and use the calibrated model to conduct counterfactual policy experiments. Motivated by current industrial-policy debates—such as the U.S. CHIPS Act, the EU's strategic subsidies, and ongoing WTO disputes—I compare three policy instruments: monetary transfers, R&D subsidies, and changes in market concentration. The results show that uniform subsidies or transfers are inefficient, whereas modest, sector-specific interventions—such as targeted R&D support in high-spillover sectors or antitrust measures in concentrated industries—can offset heterogeneous welfare losses at minimal fiscal cost.

Overall, the findings emphasize that the long-run innovation consequences of trade policy depend not only on the direction of tariff changes but also on the structure of knowledge spillovers and market power. Policies that ignore these interactions risk misallocating resources and amplifying inequality across sectors.

Relation to the literature. This paper connects to three strands of literature. First, it relates to the theoretical literature on international trade and innovation under imperfect competition. Melitz and Ottaviano (2008) shows opening to trade compresses markups by reallocating market shares toward more productive firms, thereby reducing market power. Van Long et al. (2011) develop a static oligopoly model with heterogeneous firms and endogenous R&D, showing how trade affects innovation through markups and market size. Impullitti and Licandro (2018); Impullitti et al. (2022) embed endogenous growth into trade models with oligopolistic competition, highlighting that variable markups and entry dynamics can generate large welfare gains from trade. Recent contributions by Helpman and Niswonger (2022, 2023); Helpman (2024) incorporate dynamic product-span innovation and foreign competition, emphasizing how trade liberalization reallocates innovation across firms and varieties. These studies establish that market structure and selection matter for trade-induced innovation, but they typically treat knowledge spillovers as exogenous or do not distinguish them from diffusion to non-innovators. My model extends this literature by explicitly separating spillovers among innovators from diffusion to followers, showing that the balance between the two determines whether trade shocks amplify or dampen innovation incentives.

Second, the paper contributes to the growth literature on knowledge externalities. A large body of work emphasizes diffusion as a driver of long-run growth and convergence through trade and cross-sector linkages (Akcigit et al., 2018; Buera and Oberfield, 2020; Cai et al., 2022; Lind and Ramondo, 2023a,b; Zhang, 2024). Within closed economies, Sampson (2016) and Perla et al. (2021) show that domestic spillovers sustain innovation and productivity growth. My framework is closest to the second branch but departs by focusing on how trade shocks shift firms' incentives to innovate through the joint evolution of spillovers and diffusion, rather than treating these forces as exogenous spillover coefficients.

Third, there is a large empirical literature on trade and innovation. For example, Bloom et al. (2016) show that Chinese import competition spurred innovation in European firms, while Autor et al. (2020b) document negative innovation responses among U.S. firms. In China, Liu and Ma (2020); Liu et al. (2021) find heterogeneous innovation effects following WTO accession. More recently, studies of the U.S.–China trade war have focused primarily on trade volumes and supply chains (e.g., Fajgelbaum et al. 2020; Jiao et al. 2024), paying less attention to innovation outcomes. Regarding knowledge diffusion, Bilir and Morales (2020) show that innovation investments by U.S. parents raise the performance and innovation of foreign affiliates, quantifying intra-firm knowledge flows across borders. This paper complements these studies by emphasizing how the direction and magnitude of innovation responses depend jointly on inter-firm spillover intensity and market power, and by developing a unified framework that rationalizes these heterogeneous empirical findings.

The rest of the paper is structured as follows. Section 2 presents empirical results; Section 3 lays out the model and its key predictions; Section 4 calibrates parameters; Section 5 analyzes optimal policies. Section 6 concludes.

2 Empirical findings

In this section, I use comprehensive firm-level data from China and the United States to examine how two major trade events—China's WTO accession and the U.S. trade wars—affect firms' innovation responses, depending on sector-level knowledge spillovers and pre-shock market shares. In both cases, treatment variation comes from sector-level tariff changes. For China, I define the tariff gap as the reduction in applied tariffs between 2001 and 2002 at the 4-digit CIC level, while for the U.S. I use the 2018 sector-level tariff increases aggregated to NAICS industries. In both cases, the treatment variable is a continuous measure of tariff change at the industry level, interacted with post-event dummies. This harmonization ensures that results are directly comparable across the two episodes. I find that knowledge spillovers dampen innovation in response to trade liberalization but amplify innovation in the context of trade conflict. However, in both cases, firms with higher market shares exhibit stronger innovation responses.

2.1 The WTO accession

China's accession to the WTO provides a natural experiment in large-scale trade liberalization. China formally applied for membership in 1995 and, after 25 rounds of negotiations with major trading partners, reached a final agreement in September 2001. On November 10, 2001, China was approved for accession by consensus. As shown by Lu and Yu (2015), applied tariffs were stable between 1997 and 2001 but began to fall sharply in early 2002, with most reductions completed by 2004. This liberalization led to a rapid expansion in trade and a surge in innovative activity. For instance, Liu and Ma (2020) document a sharp post-accession rise in patenting, while Liu and Qiu (2016) find that input tariff cuts sometimes depressed firm-level innovation, pointing to heterogeneous effects.

Building on these insights, I examine how pre-accession knowledge-spillover intensity shaped the innovation response to tariff reductions. The analysis uses China's *Annual Survey of Industrial Firms* (ASIF, 1998–2007), which covers nearly all manufacturing firms with annual sales above five million RMB and provides detailed balance-sheet and export information (Brandt et al., 2012). Only firms with positive total assets are retained. Patent data are merged from He et al. (2018), which link firm names in ASIF to applications recorded by China's State Intellectual Property Office (SIPO). Following He et al. (2018), I restrict to patents assigned to Chinese firms, excluding individual and foreign assignees. The merged dataset allows firm-level tracking of patent applications before and after accession.

Knowledge spillover is measured through firm-to-firm patent citations, following Griffith et al. (2011), Bloom et al. (2013), and Cai et al. (2022). Citation data for Chinese patents are collected from Google Patents, including patent IDs, IPC codes, and citation links. Using the concordance of Lybbert and Zolas (2014), IPC codes are mapped to ISIC sectors to construct annual and cumulative citations per patent from 1985 to 2007. Appendix Table A.1 reports summary statistics.

Identification exploits cross-sector variation in tariff reductions from Lu and Yu (2015). Tariff schedules were negotiated multilaterally and predetermined at the HS product level before being aggregated to 4-digit CIC sectors. Because these commitments were finalized in 2001 and implemented in 2002, they are plausibly exogenous to firms' short-run innovation decisions. Firms that switched sectors after 2001 are excluded. Spillover intensity, measured by accumulated citations per patent before the shock (from 1985), serves as a pre-determined indicator of technological connectedness shaping sectoral responses to tariff changes. While sectors with stronger citation networks may differ in unobserved characteristics such as R&D culture or global integration, the analysis focuses on systematic heterogeneity rather than causal identification.

The baseline specification is:

$$y_{ist} = \exp(\alpha_0 + \alpha_1 TG_s \times Post01 + \alpha_2 TG_s \times Post01 \times HighS_{s,2001} + \mu_i + \mu_t + \mathbf{X}) + \varepsilon_{it}, \tag{1}$$

where y_{ist} is firm i's number of new patent applications in sector s and year t, TG_s is the tariff gap between 2001 and 2002, and $Post01$ equals one after 2001. $HighS_{s,2001}$ is a dummy for sectors with above-median cumulative citations per patent in 2001; continuous measures yield similar results. Firm fixed effects μ_i and year effects μ_t absorb time-invariant and aggregate shocks. The control vector $\mathbf{X}$ includes pre-determined sectoral variables—patent stock, trade-policy uncertainty, HHI, capital, and employment—measured before the reform to account for baseline differences in innovation capacity and market structure.

Table 1 reports the Poisson Pseudo-Maximum-Likelihood estimates. Columns (1)–(2) show that tariff cuts significantly increased patenting among innovative firms. Columns (3)–(6) introduce spillover heterogeneity: interaction terms with high-spillover indicators or continuous citation measures are negative and significant, implying that liberalization spurred less innovation in knowledge-intensive sectors. For example, the coefficient of -0.086 in column (4) indicates that high-spillover sectors exhibit an 8.2% smaller patenting response to a one-percentage-point tariff cut. A one-unit increase in citations per patent (CpP) reduces the innovation response by 22% in column (5) and by 57% in column (6), conditional on the same tariff reduction.

Table 1: Effect of tariff reduction on innovation (PPML)

	(1)	(2)	(3)	(4)	(5)	(6)
Tariff × Post01	0.109***	0.101**	0.113***	0.107***	0.128***	0.125***
	(0.041)	(0.039)	(0.040)	(0.036)	(0.043)	(0.038)
Tariff × Post01 × High spillover			-0.049*	-0.086**		
			(0.028)	(0.036)		
Tariff × Post01 × Accumulated CpP					-0.224**	
					(0.089)	
Tariff × Post01 × CpP						-0.572***
						(0.215)
Observations	20783	20665	20783	20665	20665	20665
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	Yes	Yes

Notes: This table reports the estimated effects of tariff reductions following China's WTO accession on firm-level innovation outcomes, using Poisson Pseudo Maximum Likelihood (PPML). *Post01* equals one for years after 2001. *High spillover* is an indicator for sectors with above-median accumulated citations per patent in 2001. *CpP* is a continuous measure of current sectoral citations per patent. *Accumulated CpP* is the discounted accumulated citations per patent. All regressions include firm fixed effects and year fixed effects. Additional controls are included where noted. Standard errors are clustered at the 4-digit sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

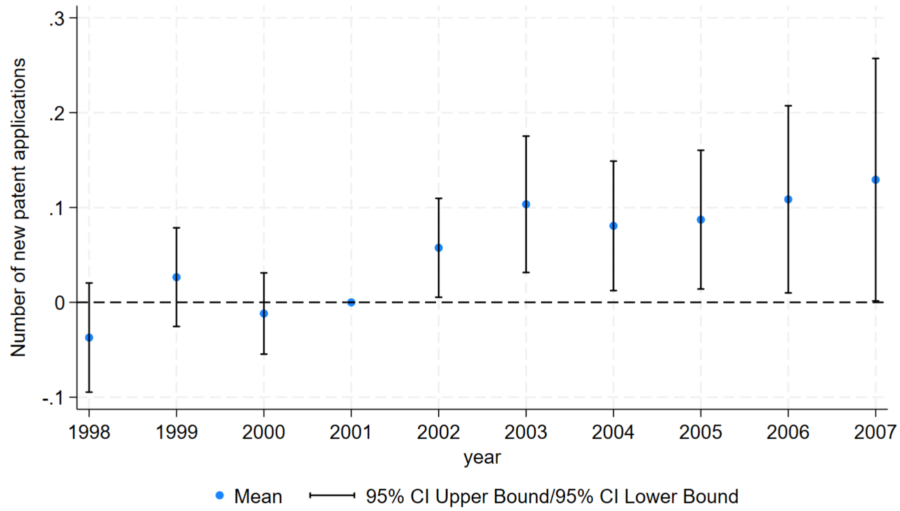

Figure 1: Event-study estimates of tariff reductions

Notes: The figure plots coefficients from event-study regressions of firm-level patenting on sector-level tariff reductions at the 4-digit CIC level, controlling for sector-level pre-shock patent stock, capital, labor, HHI and uncertainty.

To verify identification, I perform event-study analyses. Figure 1 shows that patenting trends across sectors were parallel before accession. Figure A.1 presents placebo estimates using pseudo-treatment years prior to 2001, yielding no effects. Figure 2 further shows that the weaker post-accession response of high-spillover sectors emerges only after 2001. A Wald test cannot reject joint insignificance of pre-shock coefficients. This pattern is consistent with diffusion reducing private returns to R&D in knowledge-intensive sectors. To exclude the possibility that the observed patterns are actually due to higher export intensity of Chinese firms instead of knowledge spillover, I add a high-exporting sector dummy in the robustness check and the result remains consistent in Appendix A.2.

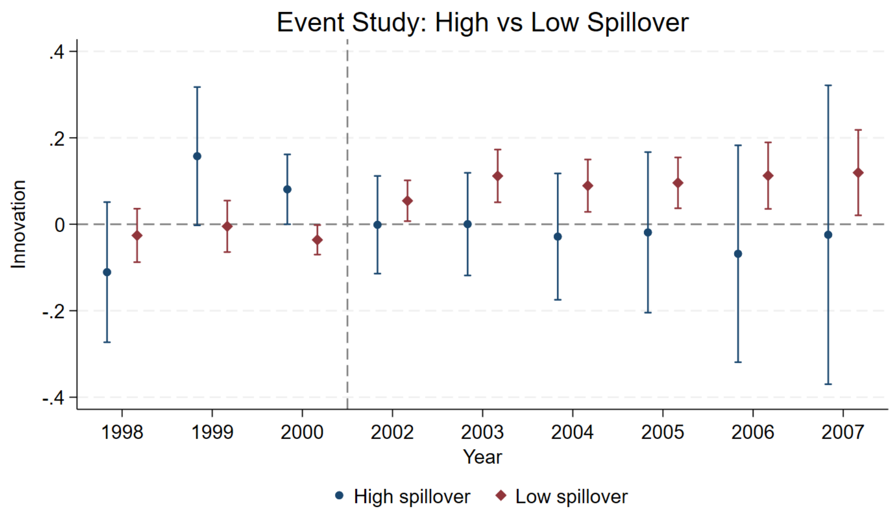

Figure 2: Event-study by spillover intensity

Notes: Event-study estimates comparing firms in high- and low-spillover sectors. Dependent variable: firm-level patent applications. All regressions include firm and year fixed effects and sector-level controls.

Finally, I examine heterogeneity by pre-accession market power. The specification adds an interaction with a high-market-share dummy:

$$\begin{aligned} y_{isdt} = \exp(&\alpha_0 + \alpha_1 TG_s \times Post01 + \alpha_2 TG_s \times Post01 \times HighS_{s,2001} \\ &+ \alpha_3 TG_s \times Post01 \times HighM_{s,2001} + \mathbf{X} + \mu_i + \mu_t) + \varepsilon_{it}, \end{aligned} \tag{2}$$

where $HighM_{s,2001}$ equals one for firms whose average market share in 2001 exceeded the median in the sector they operate. Appendix Table A.3 shows that high-market-share firms experienced significantly larger innovation gains, even after controlling for spillover heterogeneity. Figure 3 confirms parallel pre-trends: after 2001, patenting rises sharply for high-share sectors but not for low-share ones. This pattern aligns with the model's prediction that firms with greater market power respond more strongly to trade shocks.

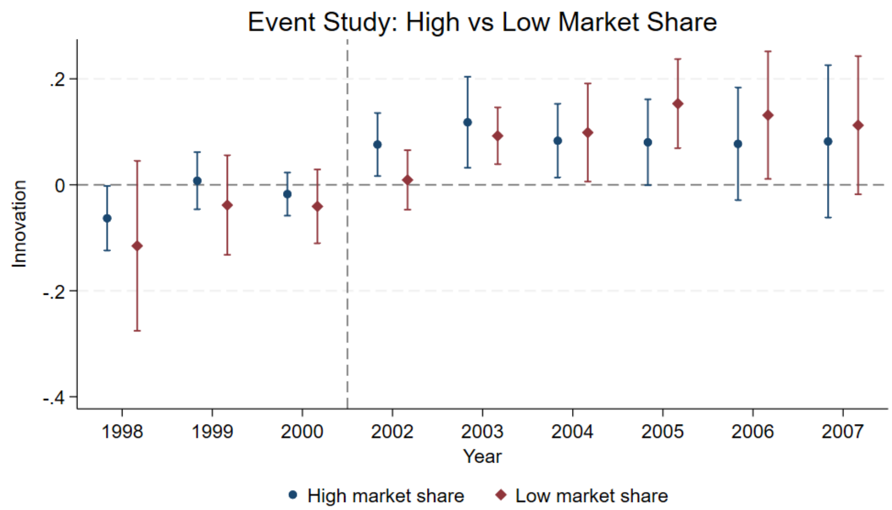

Figure 3: Event-study by market-share intensity

Notes: Event-study estimates comparing firms in high- and low-market-share sectors. Dependent variable: firm-level patent applications. All regressions include firm and year fixed effects and sector- and firm-level covariates.

Summary.— Tariff liberalization under WTO accession significantly boosted innovation overall, but diffusion effects dampened this response in high-spillover sectors. Firms with a higher market share before the shock exhibited stronger post-accession innovation gains.

2.2 The U.S. trade war

The 2018 trade war between the United States and its trading partners offers a contrasting setting of rising trade barriers. Tariffs were introduced in multiple waves. In February 2018, the Trump administration imposed duties on $8 billion of solar panels and washing machines, followed by tariffs on iron, aluminum, and steel. Subsequent measures targeted Chinese imports worth $247 billion, covering 48.8% of traded goods. As documented by Fajgelbaum et al. (2020), these actions provoked widespread retaliation from China, Mexico, Turkey, the European Union, Canada, and Russia, jointly affecting more than 7,000 products. The resulting increases in U.S. import tariffs and foreign retaliatory tariffs provide a natural test of the model's predictions for protectionist shocks.

Firm-level data for 2013–2020 come from Compustat; the main regressions focus on 2013–2019 to avoid distortions from the COVID-19 pandemic. Compustat reports detailed balance-sheet variables such as total assets, employment, capital stock, and

R&D expenditures. The sample is restricted to firms with positive total assets and employment. I augment these data with patent and citation information from the U.S. Patent and Trademark Office (USPTO). Patent assignments and citations are obtained from PatentsView and restricted to patents granted to U.S. firms. Patent assignees are matched to Compustat identifiers using the algorithm of Dyevre (2023).

Knowledge spillovers are measured using accumulated patent citations in each Cooperative Patent Classification (CPC) sector from 1975 to 2017, converted to NAICS sectors using the concordance in Lybbert and Zolas (2014). Summary statistics are reported in Table A.5.

Tariff data are from Fajgelbaum et al. (2020) and aggregated to the 4-digit NAICS level, weighted by import values. The baseline specification is:

$$y_{isdt} = \exp(\alpha_0 + \alpha_1 TG_s \times Post18 + \alpha_2 TC_s \times Post18 + \mathbf{X} + \mu_i + \mu_t) + \varepsilon_{it}, \qquad (3)$$

where y_{isdt} denotes the number of new patent applications by firm i in sector s, state d, and year t. TG_s and TC_s represent the 2018 increases in U.S. import tariffs and foreign retaliatory tariffs, respectively. Both are continuous sector-level measures of tariff changes, analogous to the WTO tariff gaps. $Post18$ equals one for $t \geq 2018$. Firm and year fixed effects, μ_i and μ_t, absorb time-invariant heterogeneity and aggregate shocks. The vector $\mathbf{X}$ includes sector-level controls (pre-shock patent stock, HHI, capital, and employment) and firm-level controls (employment, capital and total assets). Tariff variation arises only across sectors.

Table 2 reports the baseline estimates. Columns (1)–(4) use patent counts as the dependent variable. Across both contemporaneous and one-year-ahead specifications, the coefficient on *Import tariff* $\times$ *Post18* is negative and significant: a one-unit tariff increase reduces patenting by 3–5%. The corresponding coefficients on *Retaliatory tariff* $\times$ *Post18* are small and mostly insignificant, with a mild positive effect in column (2). Columns (5)–(8) use $\log R\&D$ expenditure as the outcome. Import tariffs again exert a negative effect without controls, while retaliatory tariffs show no systematic impact.

These results indicate that higher import tariffs consistently depress innovation, whereas retaliatory tariffs have at best a weakly positive effect. To test the identifying

Table 2: Effect of trade wars on innovation

	Patent		One-year-ahead patent		lnRD		One-year-ahead lnRD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import tariff × Post18	-0.031***	-0.039***	-0.052***	-0.053***	-0.024**	-0.002	-0.013**	-0.004
	(0.009)	(0.009)	(0.015)	(0.011)	(0.009)	(0.005)	(0.006)	(0.004)
Retaliatory tariff × Post18	0.008	0.016**	0.001	0.013	-0.018	-0.005	-0.012*	0.001
	(0.008)	(0.008)	(0.013)	(0.013)	(0.011)	(0.007)	(0.007)	(0.006)
Observations	8756	7987	7405	6678	10593	9604	9207	8144
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table reports the effects of the 2018 U.S. trade war on innovation outcomes for U.S. firms. The dependent variables are the number of new patent applications (Columns 1–4) and log R&D expenditure (*lnRD*, Columns 5–8). Columns 1-4 are estimated using Poisson Pseudo Maximum Likelihood (PPML) and 5-8 using OLS. "Import tariff" denotes the U.S. sector-level tariff increase against other countries in 2018, and "Retaliatory tariff" captures the foreign retaliatory tariffs imposed on U.S. exports in the same year. *Post18* is an indicator equal to one for years after 2017. All regressions include firm fixed effects and year fixed effects. Sector and firm-level controls are included as indicated. All regressions control for firm and year fixed effects. Standard errors are clustered at the 4-digit sector level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

assumption, I estimate an event-study specification:

$$y_{isdt} = \exp\Big(\alpha_0 + \sum_{t=2014, t\neq 2018}^{2020} \big[\alpha_1 TG_s \times 1_{Year=t} + \alpha_2 TC_s \times 1_{Year=t}\big] + \mathbf{X} + \mu_i + \mu_{td}\Big) + \varepsilon_{it}. \tag{4}$$

Figure A.2 shows no significant pre-2018 differences in innovation trends, supporting the parallel-trends assumption.

Next, I examine heterogeneity by spillover intensity. Extending equation (3) gives:

$$\begin{aligned} y_{isdt} = \exp(&\alpha_0 + \alpha_1 TG_s \times Post18 + \alpha_2 TG_s \times Post18 \times HighS_{s,2017} + \alpha_3 TC_s \times Post18 \\ &+ \alpha_4 TC_s \times Post18 \times HighS_{s,2017} + \mathbf{X} + \mu_i + \mu_t) + \varepsilon_{it}. \end{aligned} \tag{5}$$

Table 3 shows that spillover heterogeneity is highly significant. Firms in high-spillover sectors experience an additional 5.7–5.8% decline in patenting in response to import tariffs, and a 5.7–6.0% larger increase under retaliatory tariffs. Columns (3)–(6) replace the dummy with continuous citation measures. A one-unit rise in citation intensity amplifies the negative import-tariff effect by roughly 1.3%, and the positive retaliation effect by about 1.1–1.3%, though the latter is marginally significant.

Table 3: Differential Innovation Responses by Knowledge Spillover

	(1)	(2)	(3)	(4)	(5)	(6)
Import tariff × Post18	0.017**	0.013	-0.027***	-0.029***	-0.026***	-0.030***
	(0.008)	(0.013)	(0.006)	(0.010)	(0.007)	(0.010)
Retaliatory tariff × Post18	-0.047**	-0.042*	-0.009	-0.002	-0.009	-0.002
	(0.018)	(0.022)	(0.013)	(0.010)	(0.013)	(0.010)
Import tariff × Post18 × High spillover	-0.058***	-0.057***				
	(0.010)	(0.012)				
Retaliatory tariff × Post18 × High spillover	0.060***	0.057***				
	(0.017)	(0.021)				
Import tariff × Post18 × Accumulated CpP			-0.013***	-0.011*		
			(0.005)	(0.006)		
Retaliatory tariff × Post18 × Accumulated CpP			0.011*	0.013*		
			(0.006)	(0.007)		
Import tariff × Post18 × Citation per patent					-0.013***	-0.011*
					(0.004)	(0.006)
Retaliatory tariff × Post18 × Citation per patent					0.010*	0.010
					(0.005)	(0.006)
Observations	7699	6980	7627	6906	7627	6906
Controls	No	Yes	No	Yes	No	Yes

Notes: This table presents heterogeneous effects of the 2018 U.S. trade war on patenting outcomes, estimated using Poisson Pseudo Maximum Likelihood (PPML). The dependent variable is the number of current-year patent applications. "Import tariff" measures U.S. sector-level tariff increases in 2018, and "Retaliatory tariff" captures foreign retaliatory tariffs targeting U.S. exports. *Post18* is an indicator equal to one for years after 2017. "High spillover" is a dummy equal to one for sectors with above-median pre-shock accumulated citations per patent. "Accumulated CpP" is a continuous measure of accumulated citations per patent, and "CpP" refers to current citations per patent. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered at the 4-digit sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

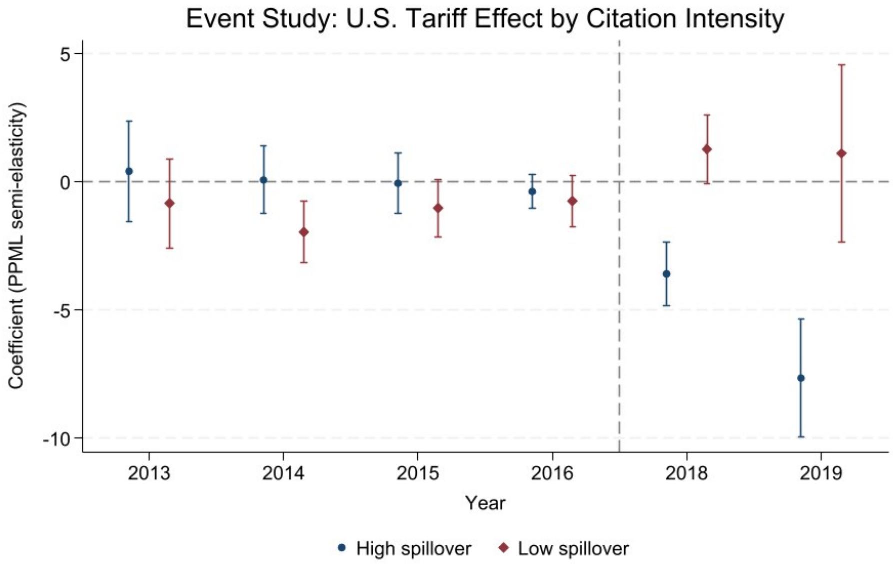

Figure 4: Event-study by spillover intensity

Notes: Event-study estimates of the 2018 U.S. tariff increase, distinguishing high- and low-spillover sectors (citation intensity). Coefficients plot the semi-elasticity of patenting with respect to tariff exposure, estimated via PPML with firm and year fixed effects and sector- and firm-level covariates.

Finally, I analyze heterogeneity by pre-shock market share:

$$\begin{aligned} y_{isdt} = \exp(&\alpha_0 + \alpha_1 TG_s \times Post18 + \alpha_2 TG_s \times Post18 \times HighM_{is,2017} \\ &+ \beta_1 TC_s \times Post18 + \beta_2 TC_s \times Post18 \times HighM_{is,2017} + \mathbf{X} + \mu_i + \mu_t) + \varepsilon_{it}. \end{aligned} \tag{6}$$

Table A.6 demonstrates that market share also shapes innovation responses. Panel A shows positive and significant interactions between retaliatory tariffs and high-share sectors, indicating that firms with more market share experienced stronger innovation increases after foreign retaliation. Interactions with import tariffs are negative but generally insignificant. Panel B replaces the dummy with continuous market-share measures and obtains consistent results. Figure 5 presents placebo tests that reassign the tariff shock to pre-2018 years. Pre-event coefficients are statistically indistinguishable from zero, confirming the absence of pre-trends.

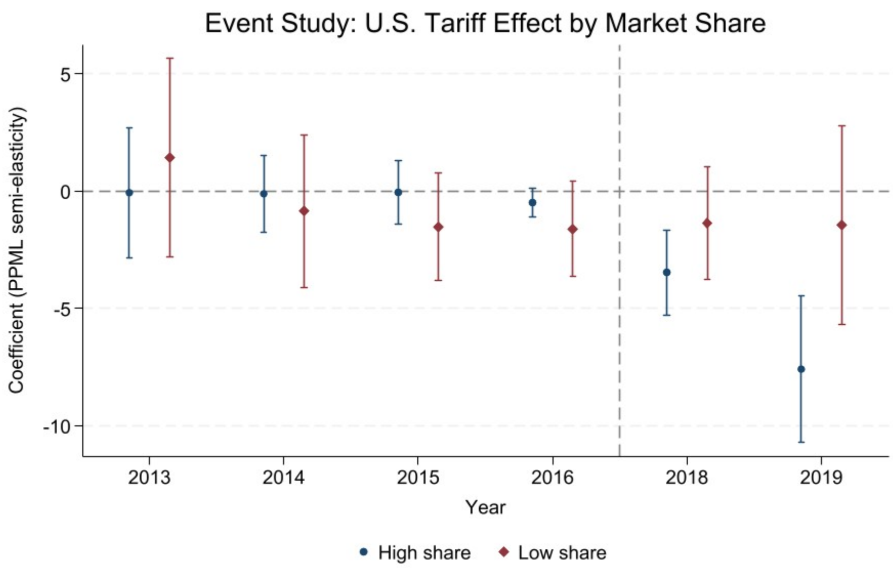

Figure 5: Event-study by market share

Notes: Event-study estimates of the 2018 U.S. tariff increase, comparing firms in high- and low-market-share sectors. Coefficients plot the semi-elasticity of patenting with respect to tariff exposure, estimated via PPML with firm and year fixed effects and sector- and firm-level covariates.

Summary.— Import tariffs reduce innovation among U.S. firms, particularly in knowledge-intensive and highly concentrated sectors. Retaliatory tariffs have a weakly positive effect that is stronger in spillover-rich industries. Relative to the WTO case, knowledge spillovers now amplify rather than dampen responses to trade shocks, underscoring that the distribution of innovation gains depends on both the direction of trade policy and the diffusion environment.

3 Model

The empirical analysis uncovered two robust patterns. First, the role of knowledge spillovers differs sharply across episodes: during China's WTO accession, spillovers dampened the positive innovation response to tariff liberalization, while in the U.S. trade war, spillovers amplified the effects of tariff protection. Second, market share consistently magnified the impact of trade shocks, with larger firms responding more strongly in both settings. The purpose of the theoretical framework that follows is to provide a unified explanation for these findings. In particular, the model shows how the interaction of oligopolistic competition and knowledge diffusion can generate heterogeneous innovation responses, and why the sign of the spillover effect depends on whether trade shocks expand or contract market opportunities.

The model features a two-country, two-sector economy populated by oligopolistic innovators and monopolistically competitive non-innovators. While the empirical analysis focuses on innovating firms, I incorporate non-innovators to reflect the observed firm heterogeneity: many firms in the data do not engage in patenting but remain active producers. This modeling choice follows a growing literature that incorporates both innovating and non-innovating firms to better capture real-world firm distributions (e.g., Atkeson and Burstein (2010), Helpman and Niswonger (2023), Helpman (2024)).

In the model, innovators invest in R&D to reduce marginal costs by combining their own knowledge with spillovers from other innovators.[1] While greater knowledge spillovers lower the private return to innovation—dampening incentives—they also enable non-innovators to free-ride, intensifying competition. This in turn compels innovators to raise their R&D effort to maintain a cost advantage over the monopolistic fringe. The overall effect depends on the relative strength of both effects.

3.1 Market structure

There are two symmetric countries. Each period, households consume a homogeneous good x_o (numeraire, produced one-for-one with labor) and a CES composite $\mathcal{X}$ of differentiated varieties. In each country, the differentiated sector is supplied by (i) a continuum of non-innovators of mass $M > 0$ (monopolistic competition), each active for one period, and (ii) N innovators (oligopolists), each producing one variety and living indefinitely. All firms can export; exporting requires an iceberg trade cost $\tau \geq 1$. Labor is the only primary input and is internationally immobile.

[1] Consistent with process-innovation models (e.g., Aghion et al., 2019; Sampson, 2023; Impullitti et al., 2022), the assumption that $R\&D$ raises productivity is supported by firm-level evidence. In China, regressions of ln(TFP) and $\Delta \ln(\text{TFP})$ on lagged patents or patent growth yield positive and significant coefficients (Appendix Table A.4); TFP is estimated following the Olley–Pakes procedure of Zhang (2024). For U.S. firms, using Compustat data, I construct a cost-based productivity proxy as the residual from regressing ln(COGS) on labor and equipment inputs. Lagged $R\&D$ levels and growth significantly predict both higher productivity and higher subsequent patenting (Table A.7). These results validate that innovation activity is a monotone proxy for productivity improvements, consistent with process innovation frameworks.

3.2 Preferences and demand

The representative household has period utility

$$u(x_o, \mathcal{X}) \;=\; x_o \;+\; \frac{\gamma}{\gamma - 1}\, \mathcal{X}^{\frac{\gamma-1}{\gamma}}, \qquad \gamma > 1, \tag{7}$$

and faces the budget constraint $x_o + P\,\mathcal{X} = w\ell + y$, with w the wage (numeraire), ℓ labor supply, and y non-labor income.

The differentiated composite is CES across varieties with elasticity $\sigma > 1$:

$$\mathcal{X} = \left(\int_0^M q_i^{\frac{\sigma}{\sigma-1}}\, di \;+\; \sum_{j=1}^{N} Q_j^{\frac{\sigma}{\sigma-1}} \right)^{\frac{\sigma-1}{\sigma}}, \tag{8}$$

$$P = \left(\int_0^M p_i^{1-\sigma}\, di \;+\; \sum_{j=1}^{N} p_j^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{9}$$

Let $\delta \equiv \sigma - \gamma > 0$; we assume $\sigma > \gamma > 1$ so that differentiated demand loads on the price index P with positive weight. Standard aggregation implies variety-level demand

$$Q(\omega) \;=\; P^{\delta}\, p(\omega)^{-\sigma}, \tag{10}$$

for any variety ω in the differentiated set. Throughout, we will use the market share of an individual variety j at home,

$$s_j \;\equiv\; \frac{p_j^{1-\sigma}}{P^{1-\sigma}} \in (0,1), \tag{11}$$

to express pricing and markup formulas compactly.

3.3 Non-innovative firms

A non-innovative firm produces a single differentiated variety under monopolistic competition. Each firm pays a fixed entry cost f_e in units of labor and has marginal cost $\bar{a}$ (one unit of output requires $\bar{a}$ units of labor). Firms can export subject to the iceberg trade cost $\tau \geq 1$.

Given CES demand with elasticity $\sigma > 1$, a non-innovative firm charges a constant markup over marginal cost:

$$p_d = \frac{\sigma}{\sigma - 1}\bar{a} \quad \text{domestically,} \qquad p_x = \frac{\sigma}{\sigma - 1}\tau\, \bar{a} \quad \text{abroad.}$$

The two destinations generate operating revenue proportional to $P^{\delta}p^{-\sigma}(1+\tau^{1-\sigma})$, where $\delta \equiv \sigma - \gamma > 0$ originates from the nested CES aggregator. Free entry implies that expected profits are zero, which determines $\bar{a}$ as a function of the aggregate price index:

$$P^{\delta}\left(\frac{\sigma}{\sigma-1}\bar{a}\right)^{1-\sigma}(1+\tau^{1-\sigma}) = \sigma f_e. \tag{12}$$

Equation (12) pins down the equilibrium relationship between $\bar{a}$, P and τ.

Determination of M. The mass of non-innovators adjusts endogenously through free entry and aggregate labor supply. Equation (12) pins down the cutoff productivity $\bar{a}(P,\tau)$ that yields zero expected profits. Given $\bar{a}$, each non-innovator employs $\ell_M(\bar{a},P,\tau)$ units of labor for production and the fixed entry cost f_e. Let L denote the total labor endowment (normalized to one). Labor-market clearing requires

$$L = N(1+l^R) + M\,\ell_M(\bar{a},P,\tau), \tag{13}$$

where the first term is innovators' production and R&D labor and the second is employment by the monopolistic fringe. Given L, P, and τ, this condition determines the equilibrium mass M.[2]

3.4 Innovative firms

There are N symmetric innovative firms, each producing one variety j. Innovators have productivity z_j^{-1}, use one unit of labor per unit of output, and can export at cost τ. Unlike non-innovators, each innovator recognizes its effect on the aggregate price index and therefore internalizes the demand curvature.

The firm's profit-maximization problem can be separated for domestic and foreign markets. An innovator chooses its domestic price p_j to maximize static profits:

$$\max_{p_j}\; P^{\delta}p_j^{-\sigma}(p_j - z_j^{-1}), \tag{14}$$

taking P as a function of all prices. The first-order condition yields:

$$\delta s_j(p_j - z_j^{-1}) - \sigma(p_j - z_j^{-1}) + p_j = 0, \tag{15}$$

[2] In comparative statics below, L is held constant, so trade shocks alter M only through their effects on P and $\bar{a}$.

where $s_j \equiv p_j^{1-\sigma}/P^{1-\sigma}$ is the firm's domestic market share. Solving for the optimal price gives

$$p_j = \frac{\sigma - \delta s_j}{\sigma - \delta s_j - 1} \frac{1}{z_j} \equiv \theta_j z_j^{-1}, \tag{16}$$

where θ_j is the endogenous markup index. Hence, the price of an innovative firm depends on its productivity z_j, the elasticity of substitution σ, and its market share s_j. When $s_j \to 0$ (a negligible firm), $\theta_j \to \frac{\sigma}{\sigma-1}$, reproducing the monopolistic-competition markup. Similarly, the price $p_{j,x} = \theta_x \tau z_j^{-1}$ will be charged in the foreign market.

3.5 Instantaneous equilibrium

Static equilibrium in each period proceeds in two stages. In the second stage, given the number of non-innovators M, innovators choose prices according to (16), determining P and market shares s_j. In the first stage, non-innovators anticipate this pricing rule and enter until the zero-profit condition (12) holds. Because fixed export costs are normalized to zero, all active firms sell domestically and abroad. In the Appendix A.4, I extend the model to incorporate firm heterogeneity, where the non-innovators draw productivity from a Pareto distribution and pay fixed costs to export, the main results remain unchanged.

This static block determines P, $\bar{a}$, and markups θ_j for given (z_j, M, τ). Dynamic $R\&D$ decisions of innovators, described below, then determine how z_j evolves over time.

3.6 Dynamic decisions

Non-innovative firms operate for a single period and do not engage in innovation, whereas innovative firms remain in the market indefinitely and face a dynamic optimization problem. Each innovator invests in cost-reducing $R\&D$ by employing l_j^R units of labor. Knowledge accumulates according to

$$\dot{z}_j = z_j^{1-\alpha} S^{\alpha} (l_j^R)^{\beta} - \delta_z z_j, \qquad \alpha, \beta \in (0, 1), \tag{17}$$

where S aggregates diffusion from other innovators and δ_z is the depreciation rate. Higher own effort l_j^R and greater spillovers S raise productivity growth.

Dynamic optimization. Each innovator chooses a time path $\{l_j^R(t)\}$ to maximize discounted profits

$$\max_{\{l_j^R(t)\}} \int_0^{\infty} e^{-rt} \Big[P^{\delta} \big(p_j^{-\sigma}(p_j - z_j^{-1}) + p_{x,j}^{-\sigma}(p_{x,j} - \tau z_j^{-1}) \big) - l_j^R \Big] dt, \tag{18}$$

subject to (17). The associated current-value Hamiltonian and first-order conditions are presented in Appendix A.2.1. On a balanced-growth path (BGP) with constant (z_j, l_j^R), they imply a stationary relationship between $R\&D$ effort and profits,

$$\frac{l_j^R}{\beta} \left(\frac{\rho}{\delta_z} + \alpha \right) = (\sigma - 1)\pi_j, \tag{19}$$

where π_j is the firm's static profit. Equation (19) shows that higher markups or profits induce greater $R\&D$ effort.

Knowledge spillover. Each innovator contributes spillover $S_j = z_j^{\rho}$, $\rho \in [0, 1]$, so that in a symmetric equilibrium

$$S = N z^{\rho}.$$

Innovators take S as given when solving (19). Empirically, knowledge diffusion is largely local and decays with distance (Keller, 2002); allowing for foreign spillovers leaves the symmetric-equilibrium logic unchanged in this symmetric setting. Using (17) and the symmetry condition yields

$$l^{R*} = N^{-\frac{\alpha}{\beta}} z^{(1-\rho)\frac{\alpha}{\beta}} \delta_z^{\frac{1}{\beta}}. \tag{20}$$

Equilibrium profits and innovation. Substituting (20) into (19) gives the link between innovation and profits,

$$N^{-\frac{\alpha}{\beta}} z^{(1-\rho)\frac{\alpha}{\beta}} \delta_z^{\frac{1}{\beta}} \left(\frac{\rho}{\delta_z \beta} + \frac{\alpha}{\beta} \right) = (\sigma - 1)\pi_j, \tag{21}$$

where $\pi_j = P^{\delta} \theta z^{\sigma - 1}$ and $\theta = \theta_d^{-\sigma}(\theta_d - 1) + (\tau\theta_x)^{-\sigma}(\tau\theta_x - 1)$.

Equilibrium closure. The zero-profit condition of the non-innovators, equation (12), implies

$$P^{\delta} = \frac{\sigma f_e}{1 + \tau^{1-\sigma}} \left(\frac{\sigma}{\sigma - 1} \bar{a} \right)^{\sigma - 1}. \tag{22}$$

To sustain coexistence of both firm types, the fringe productivity depends on aggregate knowledge,

$$\bar{a} = (Nz^{-\nu\rho}), \qquad \nu \in (0,1), \tag{23}$$

capturing diffusion from innovators to small firms.

Combining (21)–(23) yields the steady-state innovation condition,

$$N^{-\frac{\alpha}{\beta}} z^{(1-\rho)\frac{\alpha}{\beta}} \delta_z^{\frac{1}{\beta}} \left(\frac{\rho}{\delta_z \beta} + \frac{\alpha}{\beta} \right) = (\sigma - 1) \frac{\sigma f_e}{1 + \tau^{1-\sigma}} \left(\frac{\sigma}{\sigma - 1} \right)^{\sigma - 1} (Nz)^{-\nu\rho(\sigma-1)} \theta z^{\sigma - 1}. \tag{24}$$

Equation (24) determines equilibrium innovation z^* as a function of trade cost τ, number of innovators N, and spillover parameters (ρ, ν). When $N \to \infty$, $s_j \to 0$ and $\theta_j \to \frac{\sigma}{\sigma-1}$, reducing the model to the monopolistic-competition benchmark in which innovation vanishes.

3.7 Trade shocks and innovation

I now analyze how changes in trade costs τ affect the steady-state level of innovation z. For tractability, consider a symmetric and simultaneous change in τ across countries. While Segerstrom and Sugita (2015) shows that multilateral and unilateral tariff adjustments can differ in magnitude, the symmetric case here aligns closely with the empirical context of the 2018–19 U.S. trade wars.

Differentiating the steady-state condition (24) with respect to τ gives the log-linearized comparative-static relationship:

$$\underbrace{\frac{(1-\sigma)\tau^{1-\sigma}}{1+\tau^{1-\sigma}}\hat{\tau}}_{\text{direct trade effect}} - \underbrace{\hat{\theta}}_{\text{markup channel}} + \underbrace{\tfrac{\alpha}{\beta}(1-\rho)\hat{z}}_{\text{spillover channel}} = (\sigma-1)\hat{z} - \underbrace{(\sigma-1)\nu\rho\,\hat{z}}_{\text{diffusion channel}}. \tag{25}$$

The four terms respectively capture: (i) the direct effect of τ on the mass of small firms, (ii) the general-equilibrium markup effect, (iii) the dampening role of intra-innovator spillovers, and (iv) the amplification from diffusion to the fringe.

Proposition 1 (Spillover vs. Diffusion Threshold)**.** *Let $\kappa^\star \equiv \nu(\sigma - 1)$. In the comparative static of* (25)*:*

$$\underbrace{\frac{\partial \hat{z}}{\partial \rho}}_{\textit{innovation response to spillover rate}} \begin{cases} < 0 & \textit{if } \alpha/\beta > \kappa^\star \quad \textit{(spillover-dominant/dampening)} \\ > 0 & \textit{if } \alpha/\beta < \kappa^\star \quad \textit{(diffusion-dominant/amplifying).} \end{cases}$$

Proof. From (25), collecting the ρ terms gives

$$\Big[(\sigma-1)(1-\nu\rho)-\tfrac{\alpha}{\beta}(1-\rho)\Big]\widehat{z} \;=\; -\widehat{\theta}.$$

Differentiating w.r.t. ρ and evaluating the sign yields $\operatorname{sign}\big(\partial\widehat{z}/\partial\rho\big)=\operatorname{sign}\big(\tfrac{\alpha}{\beta}-\nu(\sigma-1)\big)$, so the threshold is exactly $\kappa^{\star}=\nu(\sigma-1)$. □

A higher ρ strengthens (i) intra-innovator knowledge sharing, which lowers the private marginal cost of R&D (coefficient α/β), and (ii) diffusion to the fringe via $\nu\rho$, which compresses markups (coefficient $(\sigma-1)$). Which force dominates is pinned down by the comparison α/β vs. $\nu(\sigma-1)$.

Intuitively, trade liberalization raises overall incentives to innovate but also expands knowledge exchange. If spillovers dominate (high ρ), firms can achieve efficiency gains with less own effort, reducing $R\&D$. If diffusion dominates (high ν), stronger competition compresses markups and encourages defensive innovation. This mechanism explains the contrasting empirical patterns. During China's WTO accession, spillover effects among large innovators dominated: greater cross-firm knowledge sharing eroded the private returns to $R\&D$, so innovation rose less in high-spillover sectors. During the U.S. trade wars, diffusion effects to smaller non-innovators dominated: knowledge spread intensified domestic competition, prompting large firms in knowledge-intensive sectors to innovate more aggressively to defend their market position. The estimated parameters provide support in section 5.

Proposition 2 (General-equilibrium markup effect)**.** *Accounting for the feedback through equilibrium markups, lower trade costs increase innovation if and only if*

$$\frac{\frac{(1-\sigma)\tau^{1-\sigma}}{1+\tau^{1-\sigma}}+\frac{1}{\theta}(A_{\tau}+A_{d\tau}+A_{x\tau})}{(\sigma-1)(1-\nu\rho)-\frac{\alpha}{\beta}(1-\rho)-\frac{1}{\theta}(A_d+A_x)}<0,$$

where A_{τ} and A_d, A_x denote the sensitivities of markups to trade costs in domestic and export markets, respectively.

Proof. See Appendix A.2.2. □

Proposition 2 highlights that trade shocks can have ambiguous effects on innovation, consistent with the mixed empirical evidence (Bloom et al., 2016; Impullitti and Licandro, 2018; Autor et al., 2020a). The numerator reflects direct trade and markup adjustments, while the denominator collects the opposing forces of spillover externalities and competition-induced markup erosion.

Proposition 3 (Market-Power Amplification)**.** *Let $\varepsilon_{z,\tau} \equiv \partial\widehat{z}/\partial\widehat{\tau}$ denote the elasticity of innovation w.r.t. a trade-cost change. Under small cross-price feedbacks (so that $\partial\theta/\partial\theta_d > 0$), the elasticity $\varepsilon_{z,\tau}$ is* increasing *in the pre-shock domestic markup θ_d:*

$$\frac{\partial\varepsilon_{z,\tau}}{\partial\theta_d} \; > \; 0.$$

Proof. See Appendix A.2.2. □

Intuitively, a higher domestic markup implies greater exposure to foreign demand: the foreign component $(\tau\theta_x)^{-\sigma}(\tau\theta_x - 1)$ rises with θ_d, so any trade-cost change affecting exports has a larger overall effect on firms with stronger domestic positions.

Discussion. Together, Propositions 1–3 summarize how trade shocks generate heterogeneous innovation responses. Higher spillovers may either attenuate or amplify innovation depending on the relative strength of diffusion and spillover channels, while market power amplifies these responses through the markup mechanism. The model thus rationalizes the empirical patterns in Section 2: during China's WTO accession, spillover effects dominated and muted the innovation boom, whereas during the U.S. trade war, diffusion and market-power effects prevailed, intensifying the contraction among knowledge-intensive and large-share firms.

4 Parameter Calibration

To conduct counterfactual exercises, I calibrate the parameters $\{\alpha, \beta, \rho, \nu, \delta_z, \sigma, \gamma\}$ using firm-level data for China and the United States. Whenever possible, parameters are externally calibrated; the remainder are estimated directly from the data using the model's structural relationships.

Externally calibrated parameters. For China, the elasticity of substitution σ is inferred from the mean cost-to-output ratio of non-innovators. The average ratio is 1.93, which satisfies $\frac{\sigma}{\sigma-1} = 1.93$, implying $\sigma = 2.08$. For the United States, the corresponding mean ratio is 1.86, yielding $\sigma = 2.16$. Following Edmond et al. (2015), I set the demand curvature parameter to $\gamma = 1.25$. The knowledge depreciation rate δ_z is normalized to match the observed average annual decline of patent citations.

Estimated parameters. The remaining parameters $\{\rho,\, \alpha/\beta,\, \nu\}$ are estimated using firm-level and sector-level data as follows.

Step 1. Estimating ρ: Knowledge spillover intensity

The sector-level spillover elasticity ρ is estimated from the log-linearized relationship implied by the model,

$$\ln S_{st} = \rho\, \ln\left(\sum_{s'=1}^{S} w_{ss'} \sum_{j=1}^{N} z_{js'}\right) + \mathrm{FE}_s + \mathrm{FE}_t + \varepsilon_{st},$$

where S_{st} denotes cumulative sectoral patent citations, z_{js} the patent stock of firm j in sector s, and $w_{ss'}$ fixed weights capturing cross-sector citation patterns. Although this relationship is not strictly causal—since diffusion and accumulation are jointly determined—it provides an informative measure of knowledge-flow intensity.

For China, the OLS estimate is $\rho = 0.319$ (Table A.8). To address endogeneity, I construct a shift–share instrument using U.S. patent stocks in the same technology sector:

$$IV_{st} = \sum_{k \neq s} w_{sk,1998} \sum_{j=1}^{N} z^{US}_{jk,t},$$

where $w_{sk,1998}$ is the 1998 citation share from sector s to k. This instrument captures exogenous variation in global knowledge flows unrelated to contemporaneous Chinese productivity shocks. The IV estimate is slightly lower ($\rho = 0.295$) but robust. Subsample estimates yield $\rho = 0.249$ for high-spillover and $\rho = 0.218$ for low-spillover sectors.

For the United States, using foreign patent data from the EPO (via the World Bank), the baseline estimate is $\rho = 0.359$ (Table A.9). The IV estimate, while less precise, is larger and statistically significant at the 10% level when using lagged patent stocks. Subsample estimates yield $\rho = 0.448$ for high- and $\rho = 0.299$ for low-spillover sectors.

Step 2. Estimating α/β: Elasticity of R&D efficiency

Given ρ, I use the model-implied relationship between profits and productivity,

$$\ln \pi_j = (1-\rho)\frac{\alpha}{\beta} \ln z_j - \frac{\alpha}{\beta} \ln N + \varepsilon_j,$$

to estimate α/β. Both profits π_j and productivity z_j are observed at the firm level, while sector-level fixed effects absorb the endogenous number of innovators N and any sector-specific market conditions. The identifying variation therefore comes from within-sector heterogeneity across firms rather than cross-sector differences. Estimating the equation by OLS yields the slope coefficient $(1-\rho)\alpha/\beta$; given the calibrated spillover rate ρ, this provides a direct estimate of α/β. For China, $(1-\rho)\alpha/\beta = 0.075\,(0.018)$, yielding $\alpha/\beta = 0.106$. For the United States, the estimate is $0.085\,(0.021)$, implying $\alpha/\beta = 0.133$. Although α and β cannot be separately identified, their ratio governs the elasticity of innovation to productivity and suffices for counterfactual analysis.

Step 3. Estimating ν: Diffusion to non-innovators

The diffusion parameter ν measures how aggregate knowledge affects the productivity of non-innovating firms. Chinese firms' TFP is estimated using the Olley–Pakes (1996) approach, following the implementation in Zhang (2024). For U.S. firms, using Compustat data, I construct a cost-based productivity proxy as the residual from regressing ln(COGS) on labor and equipment inputs. Then I regress non-innovators' TFP on sectoral citations per patent. The resulting coefficient identifies $\nu\rho$, from which ν follows given ρ. The point estimates are $\nu\rho = 0.020$ for China and $\nu\rho = 0.073$ for the United States, consistent with stronger diffusion effects in advanced economies.

4.1 Model Fit

Using Section 4 estimates, China has $\alpha/\beta \simeq 0.106$, $\sigma \simeq 2.08$, and $\nu\rho \simeq 0.020$ with $\rho \simeq 0.295$, so $\nu \simeq 0.020/0.295 \approx 0.068$ and $\kappa^\star = \nu(\sigma-1) \approx 0.068 \times 1.08 \approx 0.073 < \alpha/\beta$ (spillover-dominant $\Rightarrow$ dampening). For the United States, $\alpha/\beta \simeq 0.133$, $\sigma \simeq 2.16$, $\nu\rho \simeq 0.073$ with $\rho \simeq 0.359$, so $\nu \approx 0.073/0.359 \approx 0.203$ and $\kappa^\star \approx 0.203 \times 1.16 \approx 0.236 > \alpha/\beta$ (diffusion-dominant $\Rightarrow$ amplifying). This exactly matches the empirical patterns in Section 2.

To assess quantitative fit, I compare the model-implied innovation response $\hat{z}$ with the observed change in firm patenting. Since foreign market shares are unobserved, I compute $\hat{z}$ from the simplified domestic version of the GE formula in Proposition 2, omitting the A-terms related to foreign markups. In the two-country setting, the foreign market represents the rest of the world, whose size relative to domestic output is small. The domestic markup term A_d is computed directly from firms' observed market shares.

For each firm, conditional on its sector's spillover group, I calculate predicted $\hat{z}$ using the estimated parameters and the realized sectoral tariff changes in each year. Table 4 compares the predicted and observed changes in innovation (measured by patent applications). While the model, by design, abstracts from other determinants of innovation and therefore cannot fully match total variation, it captures the key cross-sectoral pattern: in China, the low-spillover sectors' innovation changes are closely aligned with predictions, whereas in the U.S., the high-spillover sectors' responses are better matched.

Table 4: Observed vs. model-predicted innovation (%)

	Low spillover	High spillover
Panel A: China		
Empirics	7.219	13.333
Model	7.359	3.597
Panel B: US		
Empirics	23.928	27.951
Model (simple avg.)	7.502	12.641
Model (weighted avg.)	14.926	25.304
Model (export tariffs)	5.229	8.181
Model (import tariffs)	9.697	17.123

Notes: This table shows the model-predicted change in innovation $\hat{z}$ and the empirical change in patent application numbers. For the US case, the simple average is the overall effect by adding import tariffs and retaliatory tariffs together and computing the total change, while the weighted average uses the weights of pre-shock tariff levels.

5 Policy Experiments

This section evaluates alternative policy tools for mitigating the uneven welfare effects of trade shocks across sectors with different spillover intensities. I consider three interventions: (i) monetary transfers, (ii) R&D subsidies, and (iii) adjustments in market structure through changes in the number of innovators. Each policy is designed to equalize real profits between high- and low-spillover sectors following a trade shock. Tables A.10 and A.11 summarize the values used in the counterfactuals.

Welfare in country n can be expressed as real income $\mathbf{W_n} = I_n/P_n$, where $I_n = w_n L_n + \sum_{j=1}^{N_s} \pi_j$. Because wages are normalized to one and non-innovators earn zero profits under free entry, welfare changes are driven entirely by the profits of innovators and the aggregate price level. Equation (21) shows that changes in total profits depend on both the number of innovators N and the level of innovation z:

$$\hat{\pi}_j = -\frac{\alpha}{\beta}\hat{N} + (1-\rho)\frac{\alpha}{\beta}\hat{z}.$$

Since innovation responses differ systematically between high- and low-spillover sectors, I use this structure to design compensating policies.

Before turning to specific interventions, it is useful to establish the condition under which innovation raises aggregate welfare.

Corollary 1 (Innovation and Welfare)**.** *Welfare increases with innovation if*

$$\frac{\alpha}{\beta}(1-\rho) + \frac{(1-\sigma)\nu\rho}{\delta_z} > 0,$$

and decreases otherwise.

Proof. From the definition of real profits, $\frac{\partial(\hat{\pi}-\hat{P})}{\partial\hat{z}} = (1-\rho)\frac{\alpha}{\beta} + \frac{\nu\rho(1-\sigma)}{\delta_z}$. Hence, real profits—and therefore welfare—increase with $\hat{z}$ if and only if this derivative is positive. □

The first term captures the private return to innovation net of intra-industry spillovers, while the second term represents the diffusion-driven welfare gain through lower prices P. When spillover effects among innovators dominate diffusion to non-innovators (high ρ, low ν), additional innovation reallocates resources toward *R&D* without increasing aggregate welfare. Conversely, when diffusion is relatively strong, innovation enhances welfare.

5.1 Monetary transfers

The first policy is a pure redistribution mechanism that does not alter innovation incentives. I compute the transfer T required to equalize changes in *real profits*—defined as $\hat{\pi} - \hat{P}$—across high- and low-spillover sectors:

$$\hat{\pi}^h + \frac{T}{\pi_t^h} - \hat{P}^h = \hat{\pi}^l - \hat{P}^l.$$

The closed-form expression for T is derived in the Appendix A.3. Intuitively, the transfer compensates sectors that lose relatively more innovation rents due to strong spillovers, ensuring comparable welfare impacts across groups.

5.2 R&D subsidies

An alternative is to subsidize innovation directly. I introduce a subsidy rate s that lowers the effective cost of R&D, $(1-s)w$. The subsidy is chosen such that real profits are equalized across sectors. In practice, this means adjusting innovation in the high-spillover sector so that $\hat{z}_h(s) = \hat{z}_h^{\text{required}}$, where the right-hand side is the level that equalizes welfare with the low-spillover sector. The necessary subsidy rate is obtained from the implied change in R&D labor, given normalized wages (see Appendix A.3 for details). Unlike transfers, this policy operates on the incentive margin and increases innovation directly.

5.3 Market structure (antitrust) intervention

Finally, I examine how changes in market concentration affect the distribution of profits. Specifically, I ask: by how much would the number of innovators in the high-spillover sector need to change to restore parity in real profits? From equation (21), this condition implies $\frac{\alpha}{\beta}\hat{N}^h = \frac{(\sigma-1)}{\delta}\left(\frac{\tau_h{}^{1-\sigma}}{1+\tau_h{}^{1-\sigma}}\hat{\tau}_h - \frac{\tau_l{}^{1-\sigma}}{1+\tau_l{}^{1-\sigma}}\hat{\tau}_l\right) + \left[\frac{\alpha}{\beta}(1-\rho_l) + \frac{\nu\rho_l(1-\sigma)}{\delta}\right]\hat{z}_l - \left[\frac{\alpha}{\beta}(1-\rho_h) + \frac{\nu\rho_h(1-\sigma)}{\delta}\right]\hat{z}_h$. This counterfactual can be interpreted as a stylized antitrust or competition policy: reducing concentration in high-spillover sectors relaxes competitive pressure and raises profits for remaining innovators.

5.4 Results

Table 5 summarizes the effects of the three policy instruments for China and the United States, while Table 6 decomposes the U.S. case into import and retaliatory tariff shocks. The baseline cases use the empirically observed change in tariffs, while the same shock scenarios deliberately assume high and low-spillover sectors have the same trade shock. The welfare condition in Corollary 1 provides the benchmark: policies are calibrated to equalize real profits—and hence welfare—between high- and low-spillover sectors following a trade shock.

China. The required adjustments are modest. After WTO accession, equalizing welfare between high- and low-spillover sectors entails a transfer of only 0.2–0.3% of pre-shock average profits (about 38–45 thousand RMB) to the high-spillover sector, or equivalently, a reduction of roughly 2% (13–15 firms) in the number of innovators in high-spillover industries. The implied R&D subsidy is small and positive, around

2.8–3.3% (435–504 RMB per worker). These magnitudes are consistent with the model's prediction that, in a spillover-dominant environment, innovation is privately less rewarding but socially beneficial, so only minor fiscal adjustments are required to restore welfare parity.

United States. For the trade-war episode, the signs reverse. Equalizing profits requires a transfer of –0.7 to –0.8% of pre-shock profits (about –10 to –11 million USD) to low-spillover sectors, an increase of roughly 4–4.5% (33–36 firms) in the number of innovators, and a negative R&D subsidy of –11 to –12%. This pattern reflects a diffusion-dominant environment, in which innovation rents are relatively higher and transfers to low-spillover sectors would overcompensate firms that already benefit from protection.

Decomposition. Table 6 separates the U.S. results into import and retaliatory tariff components. Retaliatory tariffs require a positive transfer of 0.5% to the high-spillover sector, a reduction in innovators (–3.1%), and a required subsidy of 8.5%. Import tariffs work in the opposite direction, implying a –1.1% transfer, a 6.4% expansion in innovators, and a –17.5% subsidy. Combined, the two shocks offset: the net transfer is –0.8%, the number of innovators increases by 4.5%, and the implied subsidy is –12.3%.

Table 5: Effects of Trade Shocks: China vs. US

	Transfer		Firm number		R&D subsidy	
	Baseline	Same shock	Baseline	Same shock	Baseline	Same shock
China (%)	0.23	0.26	-2.13	-2.47	2.83	3.28
Values	38,433	44,542	-12.98	-15.04	434.58	503.66
US (%)	-0.78	-0.71	4.49	4.08	-12.30	-11.19
Values	-10,985,000	-9,990,100	36.18	32.90	5,890,900	5,357,300

Notes: This table reports the counterfactual policy interventions needed to equalize real profits between high- and low-spillover sectors following the WTO accession (China) and the 2018 trade war (U.S.). "Transfer" denotes the required monetary transfer as a share of pre-shock profits. "Firm number" reports the percentage change in the number of innovators in high-spillover sectors consistent with equalizing real profits, holding low-spillover sectors constant. "R&D subsidy" gives the subsidy rate on R&D costs that would restore parity in innovation responses. "Baseline" uses the observed tariff shocks; "Same shock" assumes identical tariff changes across high- and low-spillover sectors, so that differences arise purely from spillover intensity. All values are expressed as percentages.

Table 6: US: Separate Cases

	Transfer	Firm number	R&D subsidy
Retaliatory tariff	0.54	-3.12	8.54
Import tariff	-1.11	6.40	-17.53
Combined weighted tariffs	-0.78	4.49	-12.30

Notes: This table decomposes the U.S. results in Table 5 into separate cases for retaliatory tariffs, import tariffs, and their weighted combination. "Transfer," "Firm number," and "R&D subsidy" are defined as in Table 5. Positive values for transfers and subsidies indicate compensation or support to high-spillover sectors; negative values indicate support to low-spillover sectors. "Same shock sum" assumes identical tariff changes across spillover groups, isolating the pure effect of spillover heterogeneity and adding the effects from two types of shocks together.

Discussion. Two points merit emphasis. First, the small differences between the baseline and same-shock scenarios indicate that welfare adjustments arise primarily from heterogeneity in innovation responses rather than from the direct tariff changes themselves. Second, welfare movements need not align with innovation dynamics. For example, in the U.S. case, although innovation declines more sharply in high-spillover sectors (in the empirical section), the welfare-equalizing policy implies a transfer toward low-spillover sectors. This apparent inversion reflects the model's welfare structure: real profits—and thus welfare—depend on both innovation and diffusion effects through aggregate prices. Overall, these results underscore that welfare distortions from trade shocks depend not only on the size or direction of trade protection, but also on how knowledge spillovers and diffusion interact to shape firms' innovation incentives across sectors.

6 Conclusion

This paper studies how trade shocks shape firm innovation through the joint roles of knowledge spillovers and market power. Using firm-level evidence from China's WTO accession and the 2018 U.S. trade war, I show that innovation responses vary systematically with pre-shock spillover intensity and market share: high-spillover sectors react less to liberalization but more to protection, and larger firms adjust more strongly in both episodes.

A two-country dynamic model with oligopolistic innovators and a competitive fringe rationalizes these patterns. Spillovers lower the private return to R&D while diffusion intensifies competition, so the net effect of a trade shock depends on which force dominates. Calibrated counterfactuals imply that uniform policies are inefficient:

modest, targeted instruments—sectoral transfers, R&D subsidies, or competition-policy adjustments—can offset heterogeneous impacts at low fiscal cost.

The analysis abstracts from multinational production, supply chains, and cross-border diffusion. Extending the framework along these dimensions would help quantify global general-equilibrium effects and connect to debates on industrial policy and antitrust. Overall, the results reconcile mixed evidence on trade and innovation by highlighting that long-run effects of trade policy hinge on the interaction between spillovers and market power.

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Appendix A Appendix

A.1 Additional tables and figures

A.1.1 China

Table A.1: Summary Statistics for innovative Chinese firms

	N	Mean	SD	Min	Max
patent number	20783	4.62	39.35	0.00	2255
(log) capital	20734	10.79	1.98	2.41	18.39
(log) employment	20740	6.30	1.46	0.00	12.15
age	20783	19.71	16.31	1.00	57.00
revenue share	20783	2.49	6.29	0.00	97.07
cations per patent	1856	0.12	0.35	0.00	5.00
accumulated cations per patent	1856	0.18	0.41	0.00	6.21

Notes: The sample is restricted to firms that have filed at least one patent application in any two separate years during the sample period. These firms may have zero patent applications in some years, but remain in the sample for all years in which they are active. Only firms observed both before and after the shock are retained, and firms that switch sectors are excluded. Revenue shares of Chinese firms are computed using all firms in the dataset, including those without patents. Sectors for Chinese firms are defined using 4-digit ISIC Rev. 3 codes. Citation statistics are calculated at the sector level.

Table A.2: Robustness check: Spillover and Exports

	(1)	(2)	(3)	(4)
Tariff × Post01	0.090*	0.088*	0.109**	0.104**
	(0.050)	(0.046)	(0.053)	(0.048)
Tariff × Post01 × High spillover	-0.069***	-0.093***		
	(0.023)	(0.034)		
Tariff × Post01 × Accmulated CpP			-0.221**	
			(0.088)	
Tariff × Post01 × CpP				-0.610***
				(0.172)
Tariff × Post01 × High exports	0.076**	0.070**	0.062*	0.072*
	(0.032)	(0.033)	(0.037)	(0.037)
Observations	20783	20665	20665	20665
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Notes: This table reports the estimated effects of tariff reductions following China's WTO accession on firm-level innovation outcomes, using Poisson Pseudo Maximum Likelihood (PPML). *Post01* equals one for years after 2001. *High spillover* is an indicator for sectors with above-median accumulated citations per patent in 2001. *CpP* is a continuous measure of current sectoral citations per patent. *Accumulated CpP* is the discounted accumulated citations per patent. *High exports* is an indicator for sectors with above-median export values in 2001. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered at the 4-digit sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Differential Innovation Responses by Market Share

	(1)	(2)	(3)	(4)	(5)	(6)
Tariff × Post01	0.024	0.021	0.029	0.046	0.073	0.046
	(0.047)	(0.045)	(0.043)	(0.050)	(0.045)	(0.050)
Tariff × Post01 × High share	0.120***	0.118***	0.120***	0.115***		0.115***
	(0.032)	(0.034)	(0.031)	(0.033)		(0.033)
Tariff × Post01 × Firm share					0.021*	
					(0.011)	
Tariff × Post01 × High spillover			-0.085**			
			(0.035)			
Tariff × Post01 × Accumulated CpP				-0.185*		-0.185*
				(0.097)		(0.097)
Observations	14302	14302	14302	14302	14255	14302
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of China's WTO accession in 2001 on firm-level innovation, distinguishing heterogeneity by market structure and knowledge spillovers. *Post01* equals one for years after 2001. *High share* is a dummy for sectors with above-median average market share of innovators in 2001. *High spillover* is a dummy for sectors with above-median accumulated citations per patent in 2001. *Accumulated CpP* is a continuous measure of accumulated citations per patent at the sector level. All regressions include firm fixed effects and year fixed effects. Standard errors are clustered at the 4-digit sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Patent and TFP for Chinese firms

	lnTFP	TFP growth	Production per labor
	(1)	(2)	(3)
Lagged lnN	0.047***		
	(0.009)		
Patent growth (D.lnN)		0.048***	
		(0.014)	
Lagged patent (L.lnN)			0.036**
			(0.014)
Observations	11777	3409	8497
Firm fixed effects	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes

Notes: This table examines the relationship between firm-level innovation proxies (patent counts) and productivity measures for Chinese firms. All regressions include year fixed effects. Columns (1) and (3) include firm fixed effects; Column (2) excludes them due to first-differencing. "Patent growth" (D.lnN) is the first difference in log patent counts, while "Lagged patent" (L.lnN) uses a one-period lag. lnTFP is measured using Olley-Pakes' method with GMM estimation. "Production per labor" is calculated as log output minus costs over total employment. Robust standard errors are reported in parentheses and clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.1.2 US

Table A.5: Summary Statistics for US firms

	N	Mean	SD	Min	Max
(log) R&D	10616	2.72	2.28	-6.91	10.02
patent	13391	19.08	125.58	0.00	3065
sales share	13091	4.26	12.23	0.00	100.00
(log) employments	12020	-0.86	2.69	-6.91	5.81
(log) total assets	13074	5.14	2.92	-6.91	13.39
(log) property, plant and equipment	12551	2.90	3.45	-6.91	12.47
(log) cations per patent	1816	-1.83	3.46	-17.93	8.76
(log) accumulated cations per patent	1816	-2.51	3.16	-14.89	8.57

Notes: The sample is restricted to firms that have filed at least one patent application in any two separate years during the sample period. These firms may have zero patent applications in some years, but remain in the sample for all years in which they are active. Only firms observed both before and after the shock are retained, and firms that switch sectors are excluded. Sales shares are computed using all firms in the dataset, including those without patents. Sectors for the US firms are defined using 4-digit NAICS level. Citation statistics are calculated at the sector level.

Table A.6: Differential Innovation Responses by Market Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Import tariff × Post18	-0.007	-0.019	-0.007	-0.020	0.026*	-0.006	-0.004
	(0.007)	(0.011)	(0.011)	(0.015)	(0.014)	(0.011)	(0.011)
Retaliatory tariff × Post18	0.005	0.006	0.009	0.012	-0.043*	-0.007	-0.009
	(0.013)	(0.014)	(0.011)	(0.010)	(0.023)	(0.010)	(0.010)
Panel A: High Share Index							
Import tariff × Post18 × High share	-0.026**	-0.023**					
	(0.011)	(0.012)					
Retaliatory tariff × Post18 × High share	0.005	0.011					
	(0.011)	(0.011)					
Panel B: Firm Share							
Import tariff × Post18 × Firm share			-0.155***	-0.121***	-0.108**	-0.112***	-0.118***
			(0.047)	(0.047)	(0.043)	(0.042)	(0.039)
Retaliatory tariff × Post18 × Firm share			0.067***	0.053***	0.041*	0.050***	0.053***
			(0.018)	(0.019)	(0.021)	(0.015)	(0.015)
Panel C: Spillover Interaction							
Import tariff × Post18 × High spillover					-0.053***		
					(0.014)		
Retaliatory tariff × Post18 × High spillover					0.056**		
					(0.022)		
Import tariff × Post18 × Accumulated CpP						-0.021***	
						(0.006)	
Retaliatory tariff × Post18 × Accumulated CpP						0.016***	
						(0.006)	
Import tariff × Post18 × Citation per patent							-0.020***
							(0.006)
Retaliatory tariff × Post18 × Citation per patent							0.013**
							(0.006)
Observations	7,699	6,980	7,671	6,974	6,974	6,974	6,974
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	Yes	Yes	Yes

Notes: This table reports the estimated heterogeneous effects of the 2018 trade war on firm patent applications. The dependent variable is the annual number of patent applications by a firm. "Import tariff" denotes the change in U.S. tariffs on imports; "Retaliatory" denotes foreign retaliatory tariffs. "Post18" is a dummy equal to one for years 2018 and after. "High share" is a dummy for firms with above-median pre-shock market share. "Firm share" is the firm's pre-shock revenue share (continuous). "High spillover" is a dummy for sectors with above-median pre-shock citations per patent. "Citation per patent" is the sector's pre-shock citations per patent (continuous), and "Accumulated CpP" is the cumulative version of this measure. All regressions include firm and year fixed effects. Standard errors, clustered at the 4-digit sector level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Patent and proxied TFP for US firms

	Patent		lnTFP	TFP growth
	(1)	(2)	(3)	(4)
Lagged lnR&D	0.188***	0.157**	-0.048	
	(0.070)	(0.076)	(0.035)	
2-year-lagged lnR&D	0.006	0.007	0.073**	
	(0.056)	(0.055)	(0.031)	
Growth of R&D				0.128***
				(0.036)
(log) total assets	0.141	0.061	0.051	
	(0.106)	(0.156)	(0.052)	
(log) employment		0.139		
		(0.114)		
Growth of total assets				-0.019
				(0.041)
Observations	5375	5310	5314	6144
Firm fixed effect	Yes	Yes	Yes	No
Year fixed effect	Yes	Yes	Yes	Yes

Notes: This table examines the relationship between firm-level R&D investment, patenting, and productivity for U.S. firms. The dependent variables are the number of patent applications (Columns 1 and 2), log TFP (Column 3), and TFP growth (Column 4). Lagged log R&D expenditures are used to capture delayed effects on innovation and productivity, while R&D growth is used in the TFP growth specification. Firm-level productivity (lnTFP) is measured as the residual from a regression of log cost of goods sold on log employment and log capital, controlling for firm and year fixed effects; the residual captures efficiency beyond observed inputs. All regressions include year fixed effects; Columns (1) and (2) also include firm fixed effects. Standard errors are reported in parentheses and clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.1.3 Parameters

Table A.8: Estimated ρ for China

	(1) Both	(2) Both	(3) High Spillover	(4) Low Spillover
$\ln \sum_{s=1}^{S} w_{s,t} \sum_{j=1}^{N} z_{j,s}$	0.319***	0.295***	0.249***	0.218***
	(0.0220)	(0.0290)	(0.0433)	(0.0619)
Observations	2377	2377	774	1138
Kleibergen-Paap F		1044.9	559.0	676.4
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
	OLS	IV	IV	IV

Table A.9: Estimated ρ for the US

	(1) Both	(2) Both	(3) High Spillover	(4) Low Spillover
$\ln \sum_{s=1}^{S} w_{s,t} \sum_{j=1}^{N} z_{j,s}$	0.359***	0.511	0.635*	0.476
	(0.0974)	(0.330)	(0.371)	(0.471)
Observations	1418	1418	704	714
First-stage F-stat		21.569	20.349	9.065
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
	OLS	IV	IV	IV

A.1.4 Counterfactual

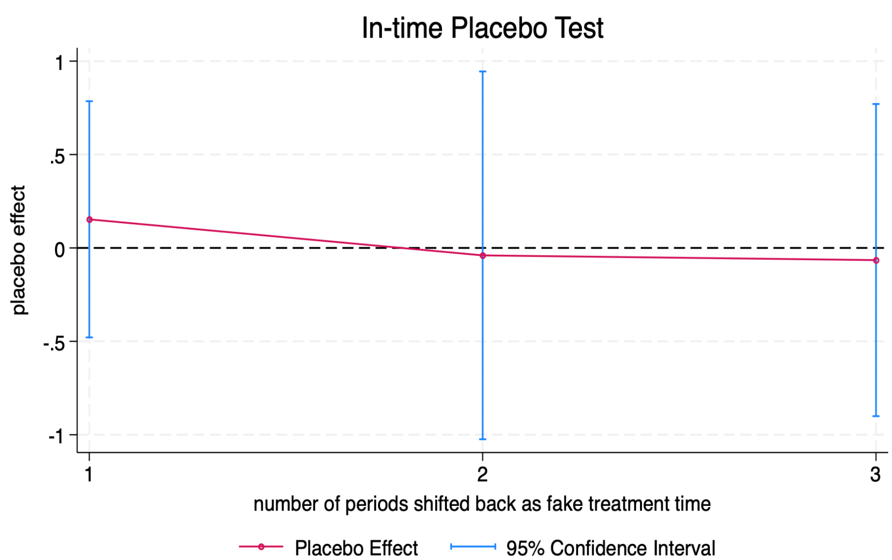
Table A.10: China: Summary Statistics by Spillover Group

Spillover	Firms_{2001}	τ_{2001}	Profit_{2001}	Wage_{2001}	$\hat{z}_{2002}(\%)$	$\Delta\tau_{2002}(\%)$
Low	691	1.107	29,590.86	14980	7.359	-2.438
High	610	1.105	16,980.25	15340	3.597	-2.382

Table A.11: US: Summary Statistics by Spillover Group

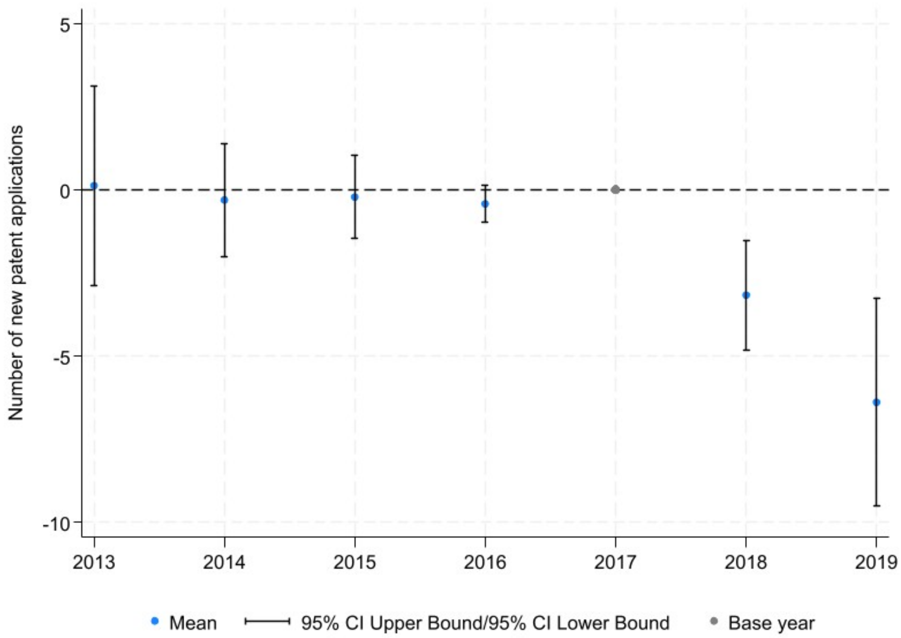
Spillover	Firms_{2017}	τ^x_{2017}	τ^m_{2017}	Profit_{2017}	EBITDA_{2017}	$\text{R\&D}_{2017}$
Low	1030	1.017	1.003	587.975	286.297	389.470
High	806	1.033	1.009	1407.816	727.782	38.820
	$\hat{z}_{2018}(\%)$	$\hat{z}_{w,2018}(\%)$	$\hat{z}^x_{2018}(\%)$	$\hat{z}^m_{2018}(\%)$	$\Delta\tau^x_{2018}(\%)$	$\Delta\tau^m_{2018}(\%)$
Low	7.502	14.926	5.229	9.697	0.073	0.339
High	12.641	25.304	8.181	17.123	0.201	0.575

Figure A.1: Placebo tests for the import tariff reduction



Notes: This figure shows the result of the placebo test for the import tariff reductions of WTO accession with fake treatment years from 1999 to 2001. The specification and treated units are the same as the baseline regression.

Figure A.2: Event study for import tariffs



Notes: This figure plots event study estimates of the 2018 U.S. import tariff increase. The dependent variable is the number of new patent applications. Coefficients are estimated using PPML with firm and year fixed effects, controlling for sector- and firm-level covariates as well as retaliatory tariffs. The 95% confidence intervals are reported.

A.2 Mathematical derivations

A.2.1 Firm's dynamic problem

Assuming the interest rate is constant and equals r, the innovative firms' optimal investment decision is to choose the number of R&D labor input, conditional on their productivity level, to maximize the discounted profits. For exporting firms,

$$\max \int_0^\infty e^{-rt}\pi_j = P^\delta Y p_j^{-\sigma}[p_j - \frac{1}{z_j}] + P^\delta Y p_{x,j}^{-\sigma}[p_{x,j} - \frac{\tau}{z_j}] - l_j^R + \lambda_j(z_j^{1-\alpha} S^\alpha (l_j^R)^\beta - \delta_z z_j) \tag{26}$$

The current-value Hamiltonian can thus be written as

$$\mathcal{H}(z_j, l_j^R, \lambda_j) = P^\delta Y \left(p_j^{-\sigma}[p_j - \frac{1}{z_j}] + p_{x,j}^{-\sigma}[p_{x,j} - \frac{\tau}{z_j}] \right) - l_j^R + \lambda_j(z_j^{1-\alpha} S^\alpha (l_j^R)^\beta - \delta_z z_i) \tag{27}$$

The first-order conditions for l_R^j and z_j are

$$\frac{\partial \mathcal{H}}{\partial l_j^R} = 0 = -1 + \lambda_j z_j^{1-\alpha} S^{\alpha} \beta (l_j^R)^{\beta-1} \tag{28}$$

$$\begin{aligned} \frac{\partial \mathcal{H}}{\partial z_j} =& \rho\lambda_j - \dot{\lambda}_j = P^{\delta} Y(\theta_j)^{-\sigma}(\theta_j - 1)(\sigma - 1) z_j^{\sigma-2} \\ &+ P^{\delta} Y(\tau\theta_{x,j})^{-\sigma}(\tau\theta_{x,j} - 1)(\sigma - 1) z_j^{\sigma-2} \\ &+ \lambda_j[(1-\alpha) z_j^{-\alpha} S^{\alpha}(l_j^R)^{\beta} - \delta_z]. \end{aligned} \tag{29}$$

which can be simplified to

$$\frac{\partial \mathcal{H}}{\partial z_j} =(\sigma - 1)\frac{\pi_j}{z_j} + \lambda_j \left[\frac{(1-\alpha)}{z_j} z_j^{1-\alpha} S^{\alpha}(l_j^R)^{\beta} - \delta_z\right] \tag{30}$$

where $\pi_j = \pi_j^d + \pi_j^x$ is the total profits of domestic and foreign markets.

Finally, the transversality condition implies

$$0 = \lim_{t\to\infty} [e^{-\rho t} \mathcal{H}(z_j, l^R, \lambda_j)] \tag{31}$$

Equation (28) implies that

$$\lambda_j = \frac{1}{z_j^{1-\alpha} S^{\alpha} \beta (l_j^R)^{\beta-1}}$$

and on a balanced growth path we have

$$\dot{\lambda}_j = (1-\alpha)\dot{z}_j - \alpha\dot{S} - (\beta - 1)\dot{l}_j^R.$$

Therefore, substitute for λ and $\dot{\lambda}$ in (29) and using the fact that $\dot{z}_j = \dot{S}$ to get

$$\begin{aligned} &\dot{z}_j + (\beta-1)\dot{l}_j^R = \\ &\qquad (\sigma-1)\frac{\pi_j}{z_j} + \frac{1}{z_j^{1-\alpha} S^{\alpha}\beta(l_j^R)^{\beta-1}}\left(\frac{1-\alpha}{z_j} z_j^{1-\alpha} S^{\alpha}(l_j^R)^{\beta} - (\delta_z + \rho)\right) \end{aligned} \tag{32}$$

Simplify to get

$$\dot{z}_j + (\beta-1)\dot{l}_j^R = (\sigma-1)\frac{\pi_j}{z_j} - \frac{(\delta_z+\rho)}{z_j^{1-\alpha} S^{\alpha}\beta(l_j^R)^{\beta-1}} + \frac{l_j^R}{\beta}\left(\frac{1-\alpha}{z_j}\right) \tag{33}$$

Finally using (17) to get

$$\dot{l}_j^R = \frac{1}{(\beta-1)}\left[(\sigma-1)\frac{\pi_j}{z_j} - \frac{(\delta_z+\rho)}{z_j^{1-\alpha}S^\alpha\beta(l_j^R)^{\beta-1}} + \frac{l_j^R}{\beta}\left(\frac{1-\alpha}{z_j}\right) - \dot{z}_j\right] \tag{34}$$

Therefore, equations (17) and (34) are an autonomous nonlinear system of differential equations in (l^R, z_j). To get the steady-state values (z_j^*, l_j^R), set $\dot{z}_j = \dot{l}_j^R = 0$.

Equation (17) implies

$$z_j^{-\alpha *}S^\alpha(l_j^{R*})^\beta = \delta_z \tag{35}$$

Equation (34) implies

$$\frac{(\delta_z+\rho)}{z_j^{1-\alpha}S^\alpha\beta(l_j^R)^{\beta-1}} = (\sigma-1)\frac{\pi_j}{z_j} + \frac{l_j^R}{\beta}\left(\frac{1-\alpha}{z_j}\right) \tag{36}$$

Simplify to get

$$\frac{(\delta_z+\rho)}{\beta\delta_z}\frac{l_j^R}{z_j} = (\sigma-1)\frac{\pi_j^P}{z_j} + \frac{l_j^R}{\beta}\left(\frac{1-\alpha}{z_j}\right) \tag{37}$$

$$\frac{(\delta_z+\rho)}{\beta\delta_z}l_j^R = (\sigma-1)\pi_j + (1-\alpha)\frac{l_j^R}{\beta} \tag{38}$$

$$\frac{l_j^R}{\beta}\left[\frac{\rho}{\delta_z} + \alpha\right] = (\sigma-1)\pi_j \tag{39}$$

A.2.2 Derivation and proof of proposition

Note that the changes in market share are functions of individual price and aggregate price.

$$\hat{s}_j = -(\sigma-1)\hat{p}_j + (\sigma-1)\hat{P} \tag{40}$$

From equation (12), the changes in price can be written as

$$\hat{P} = \frac{(\sigma-1)\,\tau^{1-\sigma}}{\delta\big(1+\tau^{1-\sigma}\big)}\,\hat{\tau} + \frac{\nu\rho(\sigma-1)}{\delta}\,\hat{z} \tag{41}$$

Moreover, the firm-level price can be written as

$$\hat{p}_j = \frac{\delta s_j}{(\sigma-\delta s_j-1)(\sigma-\delta s_j)}\hat{s}_j - \hat{z}_j \tag{42}$$

Combing equations (40) and (42) to get

$$\hat{p}_j = \frac{-(\sigma-1)\delta s_j}{(\sigma-\delta s_j-1)(\sigma-\delta s_j)}[\hat{p}_j+\hat{P}] - \hat{z}_j \tag{43}$$

which can be simplified to

$$\hat{p}_j = \frac{(\sigma-1)\Theta_j}{1+(\sigma-1)\Theta_j}\hat{P} - \frac{1}{1+(\sigma-1)\Theta_j}\hat{z}_j \tag{44}$$

where $\Theta_j = \frac{\delta s_j}{(\sigma-\delta s_j-1)(\sigma-\delta s_j)}$.

The change in market share is determined by the relative change in p and P. From (44), the domestic price would increase when P decreases and thus a lower τ reduces s_j in the domestic market,

$$\begin{aligned}\hat{s}_j = (\sigma-1)(-\hat{p}_j+\hat{P}) = \frac{(\sigma-1)}{1+(\sigma-1)\Theta_j}(\hat{P}+\hat{z}_j) = \\ \frac{(\sigma-1)}{1+(\sigma-1)\Theta_j}\left(\frac{(\sigma-1)\,\tau^{1-\sigma}}{\delta\big(1+\tau^{1-\sigma}\big)}\hat{\tau} + \frac{\nu(\sigma-1)+\delta}{\delta}\hat{z}_j\right)\end{aligned} \tag{45}$$

Therefore, an increase in z leads to a higher market share at home.

Similarly,

$$\hat{p}_{j,x} = \frac{(\sigma-1)\Theta_{j,x}}{1+(\sigma-1)\Theta_{j,x}}\hat{P} + \frac{1}{1+(\sigma-1)\Theta_{j,x}}\hat{\tau}_j - \frac{1}{1+(\sigma-1)\Theta_{j,x}}\hat{z}_j \tag{46}$$

and

$$\begin{aligned}\hat{s}_{j,x} = (1-\sigma)(\hat{p}_{j,x}-\hat{P}) =& \frac{(\sigma-1)}{1+(\sigma-1)\Theta_{j,x}}\hat{P} + \frac{1-\sigma}{1+(\sigma-1)\Theta_{j,x}}\hat{\tau}_j + \frac{(\sigma-1)}{1+(\sigma-1)\Theta_{j,x}}\hat{z}_j \\ =& \frac{(\sigma-1)}{1+(\sigma-1)\Theta_{j,x}}(\hat{P}+\hat{z}_j-\hat{\tau})\end{aligned} \tag{47}$$

Focusing on the empirically relevant case, we know that trade liberalization increases innovation and trade wars reduce it. So $\hat{\tau}$ goes on the opposite direction of $\hat{z}_j$. Thus, an increase in z also leads to a higher market share in the foreign market. Note that both markups θ_d, θ_x are increasing functions of market shares, so both markups also increase in innovation z. How does θ change? The total derivative implies $-\hat{\theta} = \frac{1}{\theta}\left[\theta_d^{-\sigma}(\theta_d-1)\left(\sigma-\frac{\theta_d}{\theta_d-1}\right)\hat{\theta}_d + (\tau\theta_x)^{-\sigma}(\tau\theta_x-1)\left(\sigma-\frac{\tau\theta_x}{\tau\theta_x-1}\right)(\hat{\tau}+\hat{\theta}_x)\right]$.

Since $\sigma - \frac{\theta_d}{\theta_d - 1} = \sigma - (\sigma - \delta s_j) > 0$

$$\begin{aligned}
-\hat{\theta} = \frac{1}{\theta} \Bigg[& \underbrace{\theta_d^{-\sigma}(\theta_d - 1)\left(\sigma - \frac{\theta_d}{\theta_d - 1}\right)(1 + \frac{\nu(\sigma-1)}{\delta})\frac{\Theta_j(\sigma-1)}{1+(\sigma-1)\Theta_j}}_{\equiv A_d > 0}\hat{z}_j + \\
& \underbrace{(\tau\theta_x)^{-\sigma}(\tau\theta_x - 1)\left(\sigma - \frac{\tau\theta_x}{\tau\theta_x - 1}\right)\frac{\Theta_{jx}(\sigma-1)}{1+(\sigma-1)\Theta_{jx}}(1 + \frac{\nu(\sigma-1)}{\delta})}_{\equiv A_x}\hat{z}_j + \\
& + \underbrace{\theta_d^{-\sigma}(\theta_d - 1)\left(\sigma - \frac{\theta_d}{\theta_d - 1}\right)\frac{\Theta_j(\sigma-1)}{1+(\sigma-1)\Theta_j}\left(\frac{(\sigma-1)\,\tau^{1-\sigma}}{\delta\big(1+\tau^{1-\sigma}\big)} - 1\right)}_{\equiv A_{d\tau} > 0}\hat{\tau} + \\
& \underbrace{(\tau\theta_x)^{-\sigma}(\tau\theta_x - 1)\left(\sigma - \frac{\tau\theta_x}{\tau\theta_x - 1}\right)\frac{\Theta_{jx}(\sigma-1)}{1+(\sigma-1)\Theta_{jx}}\left(\frac{(\sigma-1)\,\tau^{1-\sigma}}{\delta\big(1+\tau^{1-\sigma}\big)} - 1\right)}_{\equiv A_{x\tau}}\hat{\tau} + \\
& \underbrace{(\tau\theta_x)^{-\sigma}(\tau\theta_x - 1)\left(\sigma - \frac{\tau\theta_x}{\tau\theta_x - 1}\right)}_{\equiv A_\tau}\hat{\tau}\Bigg]
\end{aligned} \tag{48}$$

Therefore, $\hat{z} = \frac{\frac{(1-\sigma)\,\tau^{1-\sigma}}{1+\tau^{1-\sigma}}\hat{\tau} + \frac{1}{\theta}(A_\tau + A_{d\tau} + A_{x\tau})\hat{\tau}}{(\sigma-1)(1-\nu\rho) - \frac{\alpha}{\beta}(1-\rho) - \frac{1}{\theta}(A_d + A_x)}$.

Proof. It is straightforward to see that θ is a decreasing function of θ_d as $\sigma > 1$, given the same τ and θ_x. Moreover, $\frac{\partial\theta_d}{\partial s_j} > 0$, so a higher market share implies a lower θ.

Suppose we are also interested in how $\frac{A_d}{\theta}$ changes with respect to s_j. To do this, we examine the derivative:

$$\frac{\partial}{\partial s_j}\left(\frac{A_d}{\theta}\right).$$

Note that A_d includes the term

$$\frac{\theta_d^{-\sigma}(\theta_d - 1)}{\theta} s_j \cdot \frac{\Theta_j(\sigma-1)}{1+(\sigma-1)\Theta_j},$$

as $\theta_d - 1 = \frac{\sigma-\delta s}{\sigma-1-\delta s} - 1 = \frac{\sigma-\delta s-(\sigma-1-\delta s)}{\sigma-1-\delta s} = \frac{1}{\sigma-1-\delta s}$ and $\frac{\theta_d}{\theta_d-1} = \frac{\frac{\sigma-\delta s}{\sigma-1-\delta s}}{\frac{1}{\sigma-1-\delta s}} = (\sigma - \delta s)$.

Since s_j appears both directly and indirectly (through its effect on θ_j, and hence on Θ_j and θ), we apply the product and chain rules.

Let us denote the full expression as:

$$f(s_j) = \frac{\theta_d^{-\sigma}(\theta_d - 1)}{\theta} s_j \cdot \frac{\Theta_j(\sigma - 1)}{1 + (\sigma - 1)\Theta_j}.$$

Taking the derivative with respect to s_j gives:

$$\frac{df}{ds_j} = \left(\frac{\theta_d^{-\sigma}(\theta_d - 1)}{\theta} \cdot \frac{\Theta_j(\sigma - 1)}{1 + (\sigma - 1)\Theta_j} \right) + s_j \cdot \frac{d}{ds_j} \left[\frac{\theta_d^{-\sigma}(\theta_d - 1)}{\theta} \cdot \frac{\Theta_j(\sigma - 1)}{1 + (\sigma - 1)\Theta_j} \right].$$

The first term is positive by construction, as all components are positive. The sign of the second term depends on the elasticity of θ_d and θ with respect to s_j — that is, how much s_j affects the markup terms via θ_j and how the denominator θ responds.

The second term can be written as $\frac{d}{ds_j}\left[\frac{\theta_d^{-\sigma}(\theta_d-1)}{\theta}\right] \cdot \frac{\Theta_j(\sigma-1)}{1+(\sigma-1)\Theta_j} + \left[\frac{\theta_d^{-\sigma}(\theta_d-1)}{\theta}\right] \cdot \frac{d}{ds_j} \frac{\Theta_j(\sigma-1)}{1+(\sigma-1)\Theta_j}$. Note that $\frac{d}{ds_j} \frac{\Theta_j(\sigma-1)}{1+(\sigma-1)\Theta_j} > 0$ and $\frac{d}{ds_j}\left[\frac{\theta_d^{-\sigma}(\theta_d-1)}{\theta}\right] = \frac{C\left[-\sigma\theta_d^{-\sigma-1}(\theta_d-1)+\theta_d^{-\sigma}\right]}{\left(\theta_d^{-\sigma}(\theta_d-1)+C\right)^2} \cdot \frac{d\theta_d}{ds_j} > 0$ as $\theta_d < \frac{\sigma}{\sigma-1}$. Therefore, we conclude that

$$\frac{\partial}{\partial s_j} \left(\frac{A_d}{\theta} \right) > 0.$$

The same result applies to $A_{d\tau}$.

Nevertheless, whether $\hat{z} = \frac{\frac{(1-\sigma)\,\tau^{1-\sigma}}{1+\tau^{1-\sigma}}\hat{\tau} + \frac{1}{\theta}(A_\tau + A_{d\tau} + A_{x\tau})\hat{\tau}}{(\sigma-1)(1-\nu\rho) - \frac{\alpha}{\beta}(1-\rho) - \frac{1}{\theta}(A_d + A_x)}$ also increases in θ_d is unclear. Although $\frac{A_\tau}{\theta}$ and $\frac{A_x}{\theta}$ both increase in θ_d, the overall effect remains ambiguous. □

A.3 Derivation of optimal policies

A.3.1 Monetary transfer

I design a monetary transfer T such that the change in *real profit*, defined as $\hat{\pi} - \hat{P}$, remains constant across high and low-spillover sectors after a shock. The condition is:

$$\hat{\pi}^h + \frac{T}{\pi_t^h} - \hat{P}^h = \hat{\pi}^l - \hat{P}^l \quad \Rightarrow \quad T = \pi_t^h \left[\left(\hat{\pi}^l - \hat{P}^l \right) - \left(\hat{\pi}^h - \hat{P}^h \right) \right]$$

Substitute:

$$\hat{\pi}^k = -\frac{\alpha}{\beta}\hat{N} + \left(1-\rho^k\right)\frac{\alpha}{\beta}\hat{z}^k$$
$$\hat{P}^k = \frac{(\sigma-1)\,{\tau^k}^{1-\sigma}}{\delta(1+{\tau^k}^{1-\sigma})}\hat{\tau}^k - \frac{\nu\rho^k(1-\sigma)}{\delta}\hat{z}^k$$

Then:

$$\hat{\pi}^k - \hat{P}^k = -\frac{\alpha}{\beta}\hat{N}^k - \frac{(\sigma-1)\,{\tau^k}^{1-\sigma}}{\delta(1+{\tau^k}^{1-\sigma})}\hat{\tau}^k + \left[\frac{\alpha}{\beta}(1-\rho^k) + \frac{\nu\rho^k(1-\sigma)}{\delta}\right]\hat{z}^k$$

Taking the difference:

$$T = \pi_t^h \Bigg\{ \frac{(\sigma-1)}{\delta}\left(\frac{{\tau_h}^{1-\sigma}}{1+{\tau_h}^{1-\sigma}}\hat{\tau}_h - \frac{{\tau_l}^{1-\sigma}}{1+{\tau_l}^{1-\sigma}}\hat{\tau}_l\right)$$
$$+ \left[\frac{\alpha}{\beta}(1-\rho_l) + \frac{\nu\rho_l(1-\sigma)}{\delta}\right]\hat{z}_l - \left[\frac{\alpha}{\beta}(1-\rho_h) + \frac{\nu\rho_h(1-\sigma)}{\delta}\right]\hat{z}_h \Bigg\}$$

A.3.2 Change the number of innovators

Another way to ensure the real profits are constant across groups is to change the number of innovators N. The change in the high-spillover sector's firm number can be calculated by $\frac{\alpha}{\beta}\hat{N}^h = \frac{T}{\pi_t^h}$. Note that I assume the number of low-spillover sector innovators remains constant.

A.3.3 R&D subsidy

Finally, I design a R&D subsidy rate to reach the same goal. The real-profit-equivalent change in innovation can be computed by

$$\hat{z}_h = -\frac{\left\{\frac{(\sigma-1)}{\delta}\left(\frac{{\tau_h}^{1-\sigma}}{1+{\tau_h}^{1-\sigma}}\hat{\tau}_h - \frac{{\tau_l}^{1-\sigma}}{1+{\tau_l}^{1-\sigma}}\hat{\tau}_l\right) \quad + \left[\frac{\alpha}{\beta}(1-\rho_l) + \frac{\nu\rho_l(1-\sigma)}{\delta}\right]\hat{z}_l\right\}}{\left[\frac{\alpha}{\beta}(1-\rho_h) + \frac{\nu\rho_h(1-\sigma)}{\delta}\right]}.$$

Comparing it with the empirically computed real change gives the necessary subsidy rate. To be more specific, the difference between the changes in $\hat{z}$ in both cases equals to the changes in l^R if N does not change (see equation (20)). As the wage is normalized to one, the change in $R\&D$ labor can be treated as the change in each unit's wage for the same number of workers. Therefore, the subsidy rate can be computed using the change in l^R.

A.4 Model with heterogeneous monopolistic firms

In this section, I extend the model to incorporate heterogeneous monopolistic firms. I show that the main results are robust to it, while an additional selection channel affects the equilibrium innovation level.

Non-innovating firms hire f_e workers to pay the fixed cost to enter the market before knowing their productivity level. Then they draw productivity from a Pareto distribution $F(\varphi) = 1 - T\varphi^{-\eta}, \eta > \sigma - 1$ and then decide to exit or not.

If staying in the market, the production function follows Melitz (2003) as $l(\omega) = f + \frac{q(\omega)}{\varphi(\omega)}$. As the small firms take the aggregate price level as given, their price at home is a constant markup over the production cost $p(\omega) = \frac{\sigma}{\sigma-1}\frac{1}{\varphi(\omega)}$.

Since there is free entry, there must exist a survival cutoff productivity φ_d^* at which a firm makes zero profits,

$$0 = P^\delta \varphi_d^{*\sigma-1} - \sigma f.$$

All active firms then make decisions for international trade. An additional fixed cost f_x is required for a firm to export. Due to symmetry, a similar result can be found for trading firms,

$$0 = P^\delta \varphi_x^{*\sigma-1}\tau^{1-\sigma} - \sigma f_x.$$

Therefore,

$$\varphi_x^* = \tau \left(\frac{f_x}{f}\right)^{\frac{1}{\sigma-1}} \varphi_d^* \tag{49}$$

Free entry implies that in equilibrium, this expected measure of ex-ante profits must be equal to zero. Denote $G(\varphi)$ as the cumulative distribution of productivity,

$$f_e = f\int_{\varphi^*}^{\infty} \left(\frac{\varphi}{\varphi^*}\right)^{\sigma-1} - 1 \;\; dG(\varphi) + f_x\int_{\varphi_x^*}^{\infty} \left(\frac{\varphi}{\varphi_x^*}\right)^{\sigma-1} - 1 \;\; dG(\varphi) \tag{50}$$

Using the property of the Pareto distribution, we can solve for φ^* as a function of fixed costs.

$$f_e = Tf\frac{\sigma-1}{\eta-\sigma+1}\varphi_d^{*-\eta} + Tf_x\frac{\sigma-1}{\eta-\sigma+1}\varphi_x^{*-\eta} \tag{51}$$

Substitute φ_x^* by φ_d^* and rearrange to get

$$\frac{\eta-\sigma+1}{\sigma-1}f_e = T\varphi_d^{*-\eta}\left(f+\tau^{-\eta}f^{\frac{\eta}{\sigma-1}}f_x^{\frac{\sigma-1-\eta}{\sigma-1}}\right) \tag{52}$$

Therefore,

$$\left(T\frac{f+\tau^{-\eta}f^{\frac{\eta}{\sigma-1}}f_x^{\frac{\sigma-1-\eta}{\sigma-1}}}{\frac{\eta-\sigma+1}{\sigma-1}f_e}\right)^{\frac{1}{\eta}} = \varphi_d^* \tag{53}$$

Since there is free entry, all small firms make zero profit,

$$P^\delta = (1+\tau^{1-\sigma})^{-1}\sigma f\left(\frac{\sigma}{\sigma-1}\frac{1}{\varphi_d^*}\right)^{\sigma-1} \tag{54}$$

Comparing equation (54) with (12), the only difference is the appearance of φ_d. Therefore, the total derivative of (24) becomes

$$\underbrace{\frac{(1-\sigma)\tau^{-\sigma}}{1+\tau^{1-\sigma}}\hat{\tau}}_{\text{direct effect}} + \underbrace{(\sigma-1)\hat{\varphi}_d}_{\text{selection effect}} - \underbrace{\hat{\theta}}_{\text{markup effect}} + \underbrace{\frac{\alpha}{\beta}(1-\rho)\hat{z}}_{\text{spillover effect}} = (\sigma-1)\hat{z} \tag{55}$$

Note that φ_d^* is a decreasing function of τ. Therefore, the selection effect works in the same direction as the direct effect; thus the only difference is that the magnitude is larger when incorporating firm heterogeneity. If we assume that $\ln T = \nu\rho\sum \ln z$, the results in the main text will also go through, despite some slight modifications, as the elasticity of z w.r.t. τ now also depends on the Pareto distribution's parameter η.