Technology Decoupling along Production Networks: Supply-Side Costs and Demand-Induced Upgrading

Ningjing Li[1]✉, Di Wang[1], Chunding Li[1]*✉, Xiaoying Yang[1]

[1]College of Economics and Management, China Agricultural University, Beijing 100083, China

* *Corresponding author*

✉ e-mail: jennylnj@vip.qq.com; lichd@cau.edu.cn

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Abstract : Technology decoupling is reshaping global production networks by simultaneously disrupting firms' access to foreign technologies and creating incentives for domestic capability building. This paper examines how these opposing forces jointly affect firms' export quality. We develop a production-network framework in which technology decoupling generates two distinct transmission channels: a Supply-Side Cost Effect, arising from restricted access to foreign technologies, and a Demand-Induced Upgrading Effect, driven by domestic substitution opportunities. Guided by the theoretical framework, we construct two theory-guided shift-share exposure measures that translate firm-level U.S. Entity List restrictions into product-year treatment intensity using firms' predetermined product-level trade shares. Combining these measures with Chinese ICT export data, we separately identify the two channels and evaluate their effects on export quality, a direct measure of firms' realized upgrading outcomes. We find that Demand-side Upgrading Exposure increases export quality, whereas Supply-side Cost Exposure reduces it. Mechanism analyses show that the upgrading effect operates primarily through domestic innovation and vertical integration, while stronger production-network connectivity enhances firms' adaptive capacity by mitigating supply-chain adjustment frictions. Our findings highlight that the industrial consequences of technology decoupling depend not only on the intensity of external restrictions but also on how shocks propagate through production networks and on firms' ability to reorganize production and accumulate domestic capabilities.

Keywords: Technology decoupling; Export quality; ICT industry; production networks; China

JEL codes: F14; F51; F61; L15; L63; O14; O33

1. Introduction

The rapid escalation of technology decoupling has become a defining feature of the ongoing reorganization of global production networks. Unlike conventional trade barriers, which primarily increase transaction costs or border prices, technology restrictions directly constrain firms' access to knowledge-intensive intermediate inputs, advanced equipment, software, and technical services that are essential for innovation and production. These constraints are particularly consequential in high-technology industries, where competitiveness depends on specialized intermediate inputs, cumulative technological capabilities, and tightly interconnected cross-border supply chains. Recent evidence suggests that geoeconomic fragmentation and the decoupling of global supply chains can impose substantial output and welfare losses on the global economy (Attinasi et al., 2025). From a theoretical perspective, these costs are amplified when trade barriers distort production networks and firms face limited substitutability across intermediate inputs, leading to sizeable welfare losses through network propagation (Baqaee and Farhi, 2024). Consistent with these predictions, firm-level evidence shows that disruptions to the supply of foreign critical inputs generate substantial short-run losses in value added, particularly for firms that rely heavily on vulnerable suppliers and have limited scope to substitute toward alternative inputs (Panon et al., 2026). At the same time, the production-network literature highlights that firms' exposure to supply disruptions depends critically on their position within supplier–customer networks. Firms that rely on specialized upstream suppliers or have greater exposure to disrupted supply chains experience disproportionately larger production losses following upstream shocks (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). More generally, production-network models show that distortions affecting strategically positioned sectors can accumulate and spread through input–output linkages (Liu, 2019). Taken together, these studies imply that the economic consequences of technology decoupling depend not only on which firms are directly exposed to technology restrictions, but also on how these shocks propagate through production networks.

While these studies have substantially advanced our understanding of the aggregate costs of technological fragmentation, they primarily characterize technology decoupling as a negative supply shock that propagates through production networks. Much less attention has been paid to the possibility that technology decoupling simultaneously reshapes both the supply and demand conditions faced by firms within production networks. Restrictions imposed on producers may disrupt production and increase sourcing costs for downstream products, whereas restrictions imposed on purchasers may redirect demand toward domestic alternatives and create incentives for upgrading among potential suppliers. Technology decoupling may therefore simultaneously generate Supply-Side Costs and Demand-Induced Upgrading within the same production network. Understanding how these two channels interact, and how their relative importance varies across products and stages of production, is essential for evaluating the industrial consequences of technology decoupling.

To address this question, we adopt a production network perspective that explicitly distinguishes the transmission of technology restrictions through firms' purchasing and production activities. We develop a theoretical framework in which technology decoupling affects firms through two opposing channels. On the one hand, restrictions on foreign technologies reduce firms' access to quality-enhancing intermediate inputs, increase sourcing costs, and weaken their ability to upgrade product quality, generating a Supply-Side Cost Effect. On the other hand, reduced access to imported products redirects demand toward domestic suppliers, raises the expected returns to capability accumulation, and creates a Demand-Induced Upgrading Effect. Rather than treating technology decoupling as a single adverse shock, the framework highlights that its economic consequences depend on the interaction of these two channels within production networks. The same technology restriction may therefore generate heterogeneous outcomes across products because firms differ in their positions within production activities and in their exposure to foreign technologies and domestic substitution opportunities.

The theoretical framework not only clarifies the underlying economic mechanisms but also directly disciplines the empirical identification. Guided by the model, we construct two theory-guided shift-share

exposure measures at the product-year level following the logic of Borusyak et al. (2022). Specifically, we use firms' predetermined product-level import and export shares before the shock as exposure weights to translate the firm-level U.S. Entity List shock into heterogeneous product-year treatment intensity. The resulting Demand-Side Upgrading Exposure captures the extent to which products become exposed to domestic substitution opportunities following restrictions on firms that previously relied on imported products, whereas Supply-Side Cost Exposure measures products' exposure to production disruptions associated with restrictions imposed on firms that previously supplied these products. These two exposure measures constitute the empirical counterparts of the Demand-Induced Upgrading Effect and the Supply-Side Cost Effect implied by the theoretical framework. By mapping a firm-level technology restriction into product-level exposure through predetermined trade shares, this theory-guided shift-share design enables us to separately identify the two transmission channels while evaluating their joint effects on export quality.

China’s ICT industry provides a particularly suitable setting for this analysis. First, the industry is deeply embedded in global production networks and relies heavily on imported technology-intensive intermediate inputs, making it particularly vulnerable to technology restrictions. Second, since 2018 the U.S. government has successively added Chinese ICT firms and related institutions to the Entity List, restricting their access to U.S.-origin technologies, software, equipment, and key components. Unlike conventional trade policies that primarily affect products through tariffs or border prices, the Entity List targets firms, while firms differ systematically in the composition of their pre-shock product-level import and export activities. Consequently, the same firm-level technology restriction generates heterogeneous exposure across products, providing a natural setting for translating firm-level shocks into product-year treatment intensity using predetermined trade shares. More importantly, because many developing economies are simultaneously experiencing deeper integration into global production networks and increasing risks of technological fragmentation, the Chinese ICT industry provides a useful laboratory for understanding how firms in developing countries adjust to technology decoupling and for evaluating the

conditions under which domestic capability building can offset the production costs created by restricted access to foreign technologies.

Within this framework, export product quality provides a informative outcome because it captures whether firms ultimately transform innovation, production adjustment, and capability accumulation into internationally competitive products (Verhoogen, 2008; Khandelwal, 2010; Baldwin and Harrigan, 2011; Manova and Yu, 2017; Verhoogen, 2023). A growing literature shows that geopolitical shocks and technology sanctions reshape firms' innovation incentives, domestic capability building, and resource allocation (Han et al., 2024; Li et al., 2025; Lin et al., 2025; Yang et al., 2022). In particular, recent evidence based on the U.S. Entity List indicates that technology restrictions stimulate firms' R&D investment and innovation output (Lin et al., 2025). However, innovation represents only an intermediate stage in firms' adjustment process. Whether these adaptive responses are sufficiently strong to compensate for the production costs created by disrupted access to foreign technologies and intermediate inputs—and ultimately translate into higher-quality products—remains largely unknown. Export quality therefore provides a direct measure of firms' realized upgrading outcomes, allowing us to evaluate whether domestic capability building induced by technology decoupling is sufficient to overcome the production constraints created by restricted access to foreign technologies.

The framework predicts that technology decoupling simultaneously generates a Demand-Induced Upgrading Effect and a Supply-Side Cost Effect, with their relative importance varying across products according to firms' exposure to domestic substitution opportunities and foreign technology dependence. The negative channel reflects disruptions in access to quality-enhancing intermediate inputs, costly supplier substitution, and adjustment frictions within global production networks, consistent with theories emphasizing sticky supplier relationships and the propagation of shocks through complementary production linkages (Antràs and De Gortari, 2020; Grossman and Helpman, 2021; Handley et al., 2024; Baqaee and Farhi, 2024; Elliott and Golub, 2022; Acemoglu and Tahbaz-Salehi, 2025). The positive channel reflects firms' incentives to strengthen domestic innovation, expand internal production capacity through vertical

integration, diversify suppliers, and reorganize production activities in response to heightened supply-chain risks (Oriani and Sobrero, 2008; Ross et al., 2018; Grossman et al., 2023; Ersahin et al., 2024; Sadiah et al., 2025). Consequently, the overall effect of technology decoupling on export quality is theoretically ambiguous, and the empirical question is not whether one channel exists in isolation, but how the two channels jointly determine firms' realized upgrading outcomes.

Our empirical design is built around the two transmission channels implied by the theoretical framework. A key identification challenge is that products historically connected to firms subsequently placed on the Entity List may differ systematically in technological sophistication, market conditions, or pre-existing quality trends. To address this concern, both exposure measures are constructed exclusively from predetermined firm-product trade shares before the Entity List shock. The baseline specification includes product and year fixed effects while controlling product- and destination-specific characteristics, so that identification comes from differences in products' historical exposure to subsequently sanctioned firms rather than contemporaneous changes in trade patterns or export quality. We further examine the robustness of the estimates using alternative pre-shock exposure weights, tests for the correlation between exposure and pre-shock market characteristics, controls for other major contemporaneous shocks—including the Belt and Road Initiative, RCEP, CPTPP, and the COVID-19 pandemic—and an instrumental-variable strategy based on third-country market exposure. Together, these exercises strengthen the interpretation that the estimated coefficients separately identify the Demand-Induced Upgrading Effect and the Supply-Side Cost Effect, while recognizing that both channels may simultaneously influence the same product.

The empirical results strongly support the theoretical framework. Products with greater Demand-Side Upgrading Exposure exhibit significantly higher export quality, indicating that technology restrictions create domestic substitution opportunities and strengthen firms' incentives to upgrade. By contrast, products with greater Supply-Side Cost Exposure experience significantly lower export quality, suggesting that disruptions in access to foreign technologies and intermediate inputs increase production costs and weaken

firms' upgrading capacity. On average, the estimated Supply-Side Cost Effect outweighs the Demand-Induced Upgrading Effect, implying that technology decoupling imposes substantial production costs even though it simultaneously creates incentives for domestic capability building.

Mechanism analyses further show that the Demand-Induced Upgrading Effect operates primarily through domestic innovation and vertical integration, as firms strengthen technological capabilities and expand internal production capacity following reduced access to foreign technologies. In addition, improvements in production-network connectivity enhance firms' adaptive capacity by facilitating access to alternative production resources and mitigating supply-chain adjustment frictions, thereby reinforcing firms' upgrading responses. Taken together, these findings suggest that the industrial consequences of technology decoupling are shaped not only by the intensity of external restrictions but also by firms' capacity to reorganize production activities and accumulate domestic capabilities.

This paper makes three contributions. First, it contributes to the growing literature on geoeconomic fragmentation, technology restrictions, and firms' responses to geopolitical shocks. Existing studies have primarily emphasized the adverse consequences of technological fragmentation, including trade contraction, production losses, higher sourcing costs, sectoral misallocation, and weaker international knowledge diffusion (Cerdeiro et al., 2021; Funke and Wende, 2022; Cai et al., 2022; Baqaee and Farhi, 2024; Attinasi et al., 2025; Panon et al., 2026). A related literature shows that trade policy uncertainty and geopolitical shocks can reshape firms' international activities by altering sourcing decisions, input choices, and investment behavior (Novy and Taylor, 2020; Benguria et al., 2022; Handley et al., 2024). Recent studies further document that technology sanctions affect firms' innovation, production decisions, and performance (Yang et al., 2022; Han et al., 2024; Li et al., 2025; Lin et al., 2025). We advance this literature by showing that technology decoupling generates two distinct transmission channels operating through products rather than a single adverse supply shock. Restrictions imposed on producers reduce access to technology-intensive inputs and generate a Supply-Side Cost Effect, whereas restrictions imposed on major purchasers redirect demand toward domestic alternatives and create a Demand-Induced Upgrading Effect. Estimating

both channels within a unified framework, we show that demand-induced upgrading is robust and economically meaningful, demonstrating that domestic substitution opportunities can translate external restrictions into realized product-quality improvements, even though these gains do not fully offset the supply-side cost pressures associated with restricted access to foreign technologies. Our results further uncover the mechanisms underlying the upgrading effect and the conditions under which the cost effect can be mitigated, offering broader insights into how developing economies can strengthen adaptive capacity in response to adverse external technology shocks.

Second, the paper contributes to the literature on production networks by developing a theoretical framework that incorporates endogenous production-network adjustment in response to technology restrictions. Existing studies show that the propagation of trade and supply-chain shocks depends on input specificity, limited substitutability, and firms' positions within production networks (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021; Dhyne et al., 2021; Elliott and Golub, 2022; Elliott et al., 2022; Baqaee and Farhi, 2024; Acemoglu and Tahbaz-Salehi, 2025). Rather than treating production networks as a fixed environment through which shocks propagate, the framework allows firms to reorganize production linkages in response to technology restrictions. These adjustments reshape firms' effective network positions and generate heterogeneous product-level adjustment capacity. The framework further distinguishes how technology restrictions operate through the demand and supply sides of production networks, providing the theoretical foundation for separately identifying the two transmission channels in the empirical analysis and for deriving testable predictions on the role of network connectivity. Consistent with these predictions, we show that stronger network connectivity facilitates product-quality upgrading by improving access to alternative markets and productive resources while reducing adjustment frictions associated with disrupted sourcing relationships.

Third, the paper contributes to the literature on firm upgrading and export quality in developing economies. Existing studies identify output-market demand, access to high-quality imported inputs, and knowledge or capability accumulation as central drivers of firm upgrading (Verhoogen, 2008, 2023;

Khandelwal, 2010; Baldwin and Harrigan, 2011; Mayer et al., 2014; Manova and Yu, 2017). A large body of evidence also shows that trade liberalization and imported intermediate inputs raise productivity, expand product scope, and facilitate quality upgrading (Amiti and Konings, 2007; Goldberg et al., 2010; Khandelwal et al., 2013; Halpern et al., 2015; Bas and Strauss-Kahn, 2015; Fieler et al., 2018). More recent work finds that geopolitical and technology restrictions may stimulate R&D and domestic innovation (Han et al., 2024; Lin et al., 2025), but whether these adaptive responses ultimately translate into higher-quality products remains less well understood. By focusing on export quality at the product level, we evaluate the realized outcome of firms' optimization decisions rather than adaptation efforts alone. We show that domestic innovation and vertical integration enable products facing stronger demand-induced upgrading incentives to achieve quality improvements, while production-network connectivity determines whether these incentives can be successfully transformed into realized upgrading. These findings identify the conditions under which external technology restrictions induce product upgrading rather than merely stimulating adaptive investment.

The remainder of the paper proceeds as follows. Section 2 provides institutional background on U.S. technology decoupling and China's ICT industry. Section 3 develops the conceptual framework linking technology decoupling to product quality through the quality-upgrading effect and the cost effect. Section 4 presents the empirical strategy, the construction of the two exposure measures. Section 5 reports the baseline results and robustness checks. Section 6 investigates the mechanisms. Section 7 concludes.

2. Background

2.1. U.S. Export Restrictions and the Entity List Shock

Since 2018, the U.S. government has expanded the use of the Entity List to restrict selected Chinese ICT firms and related institutions from accessing U.S.-origin technologies and products. These restrictions affect not only the listed firms themselves, but also their upstream suppliers, downstream customers, and related product markets. In practice, they may disrupt access to semiconductors, electronic components,

design software, production equipment, and other inputs that are difficult to replace quickly. For affected firms, this creates a negative supply shock by raising input costs and increasing uncertainty. At the same time, it may also create domestic substitution opportunities by increasing demand for locally produced inputs and raising the returns to independent R&D and domestic production capacity.

2.2. China's ICT Industry in Global Production Networks

China's ICT industry is a suitable setting for examining these competing forces. ICT products are technology-intensive and require the integration of electronics, communications, computer science, artificial intelligence, and advanced manufacturing capabilities. Product quality is therefore a central dimension of competition in this sector. Firms that compete only on scale or low costs may find it difficult to sustain their market position in high-end ICT markets, whereas quality upgrading allows firms to move into more sophisticated segments of global value chains.

At the same time, China's ICT industry is deeply embedded in global production networks and has historically relied on imported intermediate inputs and foreign technologies. This dependence makes the industry vulnerable to external supply restrictions. However, the industry also has a large domestic market, expanding local supplier networks, and accumulated manufacturing capabilities. These features imply that technology decoupling may generate both cost pressures and adaptive responses. This duality makes China's ICT sector an informative setting for studying whether technology restrictions weaken export quality or induce upgrading through import substitution, domestic R&D, production reorganization, and trade-network adjustment.

2.3. Descriptive Evidence: Competition, Disruption, and Adaptive response

Several descriptive facts motivate the empirical analysis. First, China and the United States have become increasingly close competitors in ICT exports. We measure China–U.S. ICT export similarity by summing, across ICT product categories, the minimum export share of the two countries. A higher value indicates greater overlap in export structure. Figure 1 shows that China–U.S. ICT export similarity increased over time, suggesting that China's ICT exports became increasingly comparable to those of the

United States. After the 2018 Entity List shock, the index declined temporarily and then recovered, displaying a V-shaped pattern. This pattern is consistent with short-run disruption followed by adjustment.

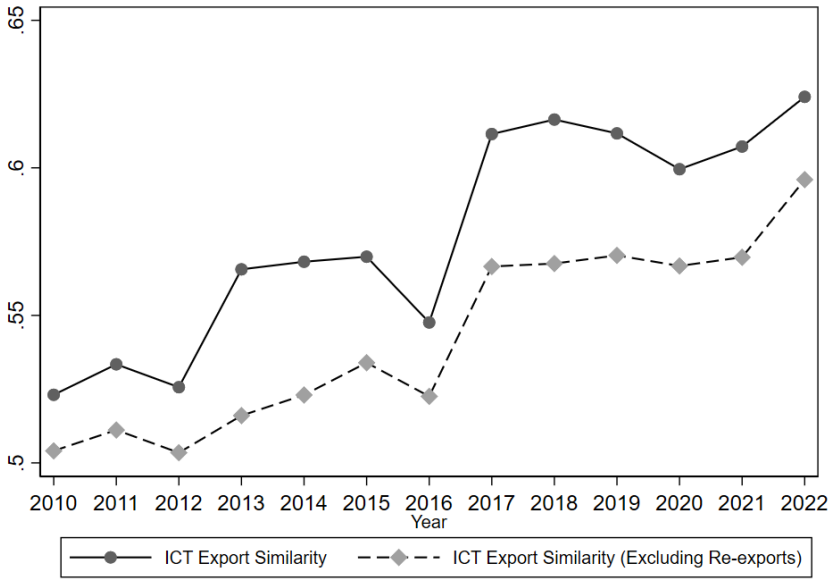


Figure 1 China–U.S. ICT Export Similarity

Notes: This figure reports the similarity between Chinese and U.S. ICT export structures over time. For each year t, we calculate the export similarity index as:$Sim_t = \sum_p \min(u\,s_{pt}, cs_{pt})$where $us_{pt}$and cs_{pt}denote the export shares of ICT product $p$in total ICT exports of the United States and China, respectively. The index ranges between 0 and 1, with higher values indicating greater similarity in export composition between the two countries. The solid line reports the baseline index, while the dashed line excludes re-exported products to better capture similarity in underlying production structures.

Second, China's ICT trade network shows evidence of adjustment. We construct an ICT trade network in which nodes are export destinations for Chinese ICT products and links are formed when bilateral ICT trade exceeds a threshold based on export values. We then calculate network density and degree centralization. Figure 2 shows that both indicators declined in 2018: network density fell from 0.149 in 2017 to 0.143, while degree centralization declined from 0.689 to 0.683. After 2018, both indicators gradually recovered, reaching 0.163 and 0.694 in 2022, respectively. This suggests that the Entity List shock disrupted existing trade relationships but did not permanently sever China's ICT trade network. Instead, the network appears to have adjusted through the formation or strengthening of alternative links.

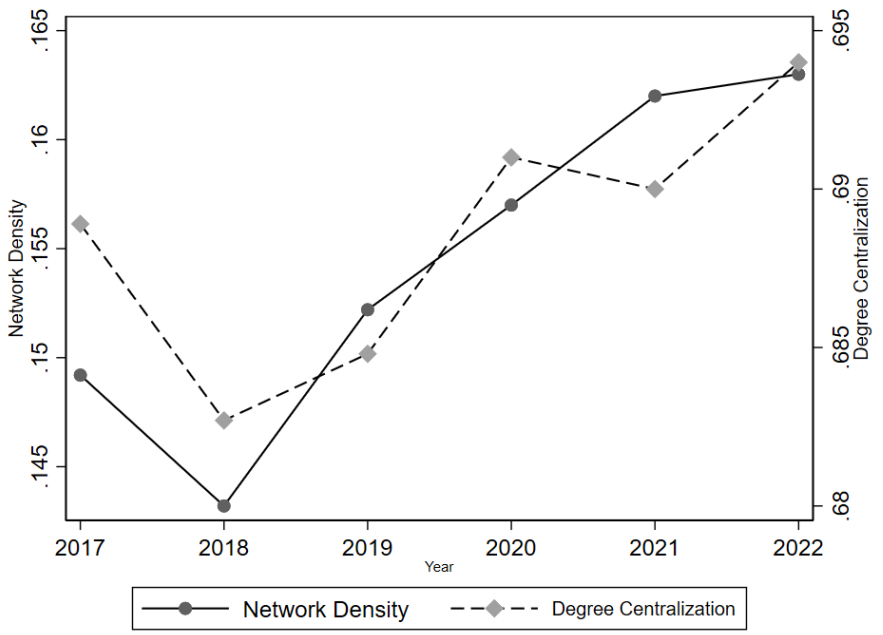


Figure 2 Network Density and Degree Centralization of China's ICT Trade Network

Notes: This figure reports changes in the structure of China's ICT trade network from 2017 to 2022. Network density captures the overall connectedness of the network by measuring the proportion of realized linkages relative to all possible linkages. Degree centralization captures the concentration of network connections by measuring nodes' degrees relative to the maximum possible degree. An increase in these measures indicates stronger network integration and a more concentrated network structure.

Third, firm-level indicators suggest that Chinese ICT firms also adjusted along domestic capability margins. Figure 3 plots R&D intensity and the growth rate of newly added productive fixed assets for Chinese ICT firms. Both indicators increased after 2018, suggesting that firms strengthened innovation efforts and expanded production capacity following the Entity List shock. These patterns are consistent with the idea that external restrictions may raise the returns to independent R&D and domestic production control, although they should be interpreted as descriptive rather than causal evidence.

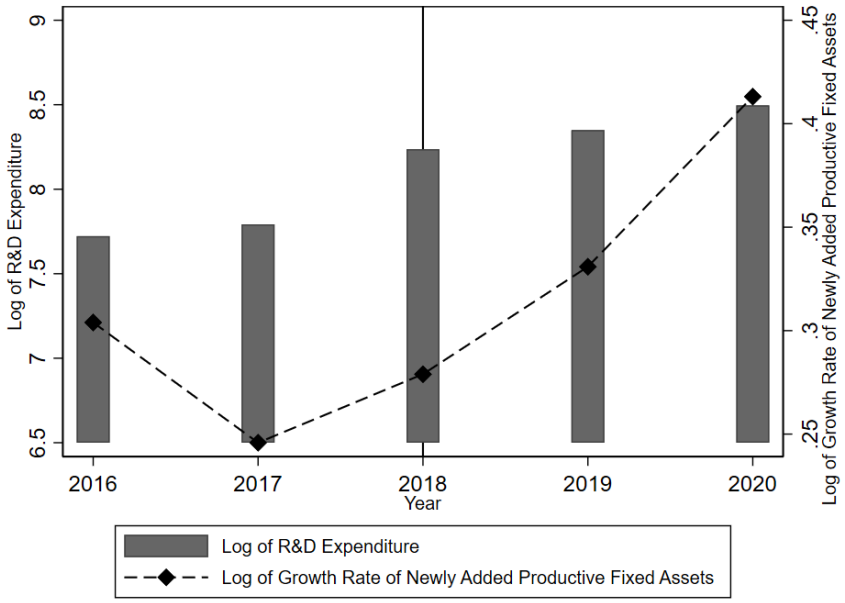


Figure 3 R&D Intensity and New Productive Fixed Assets of Chinese ICT Firms

Notes: The indicators are calculated using data from the National Enterprise Tax Survey Database.

3.Theoretical Framework

To analyze how technology decoupling affects firms' export quality through global production networks, we develop a model of endogenous quality choice with input sourcing and network formation. The central insight of the model is that technology decoupling generates two opposing forces that jointly determine firms' upgrading outcomes. On the one hand, restrictions on foreign intermediate inputs increase sourcing costs, generating a negative cost effect that weakens firms' ability to maintain or upgrade product quality. On the other hand, the loss of foreign inputs creates incentives for domestic substitution, increasing the returns to quality upgrading and encouraging firms to strengthen internal capabilities. A key feature of our framework is that production networks are endogenously formed rather than exogenously given. Building on the preferential attachment mechanism in network formation (Albert and Barabási, 2002), we allow firms' network positions to evolve through the formation of production linkages: firms with stronger connectivity are more likely to attract new relationships and gain access to markets and resources. This feature captures how technology decoupling can reshape firms' positions within global production networks and generate heterogeneous adjustment capacity across firms.

These competing forces are particularly relevant for economies such as China, where firms are deeply embedded in global production networks while possessing substantial domestic production capabilities. Following the Entity List shock, firms may respond by strengthening domestic innovation, expanding internal production through vertical integration, and reorganizing their production networks to mitigate supply-chain disruptions. These responses imply that the effect of technology decoupling

on export quality depends not only on the magnitude of the initial shock, but also on firms' ability to adapt through endogenous changes in production networks.

Our framework incorporates three key ingredients. First, firms source intermediate inputs from external suppliers and sell differentiated products across markets, allowing technology decoupling to affect production costs and market access. Second, network formation follows a preferential attachment process, allowing network connectivity to emerge endogenously and influence firms' access to resources and markets. Third, product quality is an endogenous choice determined by the returns and costs of quality upgrading.

3.1. Demand

Suppose there are *N* regions in the economy. Consumers' utility over product *k* is assumed to take a CES form, yielding the demand function shown in Equation (1). Letλ_{kl}denote the attractiveness of domestic product *k* to consumers in region *l*, which captures the quality level of domestic product $k$in region l. Meanwhile, to characterize the influence of competing foreign products in the global market, let λ_{kl}^{*}denote the attractiveness of foreign product k to consumers in region l.

$$q_{kl}(\omega) = P_l^{\sigma-1} R_l p_{kl}^{-\sigma} \left(\frac{\lambda_{kl}}{\lambda_{kl}^{*}}\right)^{\sigma-1} \quad (1)$$

where $\sigma > 1$denotes the elasticity of substitution across products, $R_l$represents the aggregate income level of region l, p_{kl}denotes the price of product $k$in region l, and $P_l$denotes the aggregate price index in region l.

3.2. Production

Firms are assumed to enter the market with productivity φ after incurring fixed cost f_e. The production function of firms is given by:

$$q(\varphi,k)=\varphi L^{1-\alpha}M^{\alpha} \quad (2)$$

where L and M represent labor input and intermediate input, respectively. Correspondingly, the firm's production cost consists of labor and intermediate input cost. Following Antràs et al. (2024), the cost of intermediate input sourcing is given by $\left(\sum_j\left(\frac{p_{kj}}{z_j}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}}$, where $z_j$and p_{kj}denote the productivity and price of supplier j producing intermediate input for product k, respectively. The elasticity of substitution across intermediate inputs is given by$\rho,\rho>1$. Combining the equation (2), the marginal cost of producing one unit of product k can be derived as $c(\varphi,k)=\frac{Z_a}{\varphi}(c_k)^{1-\alpha}\left(\sum_j\left(\frac{p_{kj}}{z_j}\right)^{1-\rho}\right)^{\frac{\alpha}{1-\rho}}$, where $\left[\frac{1}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}\right]=Z_a$①

For product k, the firm chooses output and quality to maximize profits. The firm may incur a cost $r_k\lambda_{kl}^{2(\sigma-1)}$ to upgrade product quality through the adoption of advanced technologies, where $r_k$represents the cost of adopting advanced technologies. The firm's profit maximization problem can be formulated as follows:

$$\max_{q,\lambda}\ p(\varphi,k)\lambda q(\varphi,k)-c(\varphi,k)q(\varphi,k)-r_k\lambda_{kl}^{2(\sigma-1)}-f \quad (3)$$

Solving the profit maximization problem yields the firm's optimal product quality in region l, which can be expressed as:

$$\lambda_{kl}=(2\sigma)^{\frac{1}{1-\sigma}}\frac{\sigma-1}{\sigma}\frac{\varphi}{Z_a}P_l R_l^{\frac{1}{\sigma-1}}(r_k)^{\frac{1}{1-\sigma}}(c_k)^{\alpha-1}\left(\left(\sum_j\left(\frac{p_{kj}}{z_j}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}}\right)^{-\alpha}\lambda_{kl}^{*-1} \quad (4)$$

where $\left[\frac{1}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}\right]=Z_a$, $r_k$denotes the relative cost of advanced technology required for quality upgrading, andφ denotes the firm's productivity. $P_l$and $R_l$represent the regional price

①The derivations are provided in the Appendix

index and total expenditure in region l, respectively. c_k denotes the local factor input cost used in the production of product k, p_{kj}denotes the price of intermediate input supplied by supplier $j$used in producing product k, and $z_j$denotes the productivity of supplier j.

3.3. Technology Decoupling

Production networks are not randomly formed. Firms with more established linkages are often better positioned to attract new partners, access resources, and expand market opportunities. To capture this endogenous evolution of production networks, we incorporate a preferential attachment assumption into the model (Barabási and Albert, 1999). Specifically, we assume that new production linkages are more likely to form with firms that already occupy more connected positions in the network. This assumption captures the cumulative advantage embedded in production networks: firms with higher connectivity are more likely to attract additional relationships, thereby shaping heterogeneous access to suppliers and markets. Formally, suppose that there are Nnodes in the network and that potential links follow a Bernoulli process with probability p. Under preferential attachment, link formation is not random, the probability that a new node connects to an existing node increases with the existing node's degree d. Therefore, the probability mass function governing link formation can be expressed as:

$$P(X = x) = \begin{cases} pd_k, & x = 1 \\ 1 - pd_k, & x = 0 \end{cases} \quad (5)$$

where $x = 1$denotes a successful link formation, and$pd_k$is the probability of establishing the link. In this case, the quality λ_{kl} is determined according to Equation (4). By contrast, $x = 0$ occurs with probability $1 - pd_k$, in which case the quality of product is normalized to zero.

Combining with the probability mass function in Equation (5), the expected quality of product $k$can be expressed as:

$$\hat{\lambda}_k = \frac{E(\lambda_{kl})}{N} = (2\sigma)^{\frac{1}{1-\sigma}} \frac{\sigma-1}{\sigma} \frac{\varphi}{Z_a} P_l R_l^{\frac{1}{\sigma-1}} (r_k)^{\frac{1}{1-\sigma}} (c_k)^{\alpha-1} \left(\left(\sum_j \left(\frac{p_{kj}}{z_j} \right)^{1-\rho} \right)^{\frac{1}{1-\rho}} \right)^{-\alpha} p d_k \lambda_{kl}^{*-1} \quad (6)$$

We next examine how technology decoupling shocks affect firms' product quality through production networks. As discussed above, the feature of technology decoupling is a reduction in the supply of intermediate inputs, which in turn alters firms' sourcing costs, i.e.,$d\ln p_{kj} \geq 0$.

From the supply side, Technology decoupling generates a direct cost effect. Restrictions on the supply of critical components increase the cost of sourcing intermediate inputs, which is directly reflected in firms' production costs. Specifically, since $\zeta_{kj} \equiv \left(\frac{p_{kj}}{z_j} \right)^{1-\rho}$, it follows that $d\ln \left[\left(\sum_j \zeta_{kj} \right)^{\frac{1}{1-\rho}} \right] = \sum_j w_{kj}\, d\ln p_{kj}$①. An increase in the sourcing cost of intermediate inputs p_{kj}, reduces their attractiveness to firms, as captured by a decline in ζ_{kj}. This, in turn, raises firms' marginal costs, making it more difficult for firms to allocate resources toward quality upgrading.

From the **demand side**, technology decoupling shocks operate through firms' optimal input allocation, giving rise to three distinct but internally consistent adjustment mechanisms: domestic innovation, vertical integration, and network reconfiguration. which lies in the fact that firms jointly choose among three types of inputs: local labor, externally sourced intermediates, and technological investment. These inputs are imperfect substitutes, and their allocation is governed by relative prices. Technology decoupling raises the cost of externally

①$w_{kj}$is the attractiveness share of intermediate input

sourced intermediates, thereby altering the relative price structure across inputs. firms may find domestic innovation and vertical integration increasingly attractive.

A rise in the sourcing cost of intermediates lowers the relative price of advanced technology and local factor input. Therefore, the shock not only encourages firms to invest more in innovation$\chi_k \sum_{j\in m} d\ln p_{kj} \equiv d\ln r_k$,$\chi_k \leq 0$, but also increases the attractiveness of internal production relative to external sourcing $s_k \sum_j d\ln p_{kj} \equiv d\ln c_k$, $s_k \leq 0$①.where $s_k$denotes the internal production parameter. Meanwhile, technology decoupling may induce firms to reconfigure their trading partners, thereby reshaping their connectivity within the global production network. As technological decoupling raises the cost and uncertainty associated with existing trading relationships, firms have incentives to adjust their partner portfolios and form new trade links while potentially terminating or weakening existing ones. This process of trade partner reconfiguration alters the structure of firms' connections within the global production network, leading to changes in their network degree. Formally, $\eta_k \sum_j d\ln p_{kj} \equiv d\ln d_k$.The coefficient on $\eta_k$may be either positive or negative. A positive coefficient suggests that technological decoupling is associated with an increase in the network degree of Chinese firms in the global production network. Substituting the above expressions into Equation (6) yields:

$$d\ln\hat{\lambda}_k = \underbrace{\sum_{j\in m}\left[\frac{\chi_k}{1-\sigma} + (\alpha-1)s_k + \eta_k\right] d\ln p_{kj}}_{\text{Quality-Upgrading Effect}} - \underbrace{\alpha \sum_j w_{kj}\, d\ln p_{kj}}_{\text{Cost Effect}} \qquad (7)$$

①This pattern is illustrated in Figure 3.

Where $\chi_k \leq 0,\ s_k \leq 0,\ w_{kj} > 0$, η_k depends on the network structure. Equation (7) highlights two opposing channels through which technological decoupling affects product quality. The first term represents quality-upgrading effects operating through innovation, integration, and network connectivity. The second term captures a negative cost effect arising from higher intermediate-input sourcing costs. Whether technological decoupling ultimately enhances or reduces product quality depends on the balance between these two channels. This leads to the central hypothesis of the paper:

Hypothesis 1. Technology decoupling affects product quality through two opposing forces. Restrictions on foreign intermediate inputs increase sourcing costs and weaken firms' upgrading capacity, generating a negative cost effect. Meanwhile, technology decoupling creates domestic substitution incentives that raise the returns to capability upgrading, generating a positive quality-upgrading effect. The net effect depends on the relative strength of these two channels.

Hypothesis 2. Technology decoupling induces adaptive responses that facilitate quality upgrading, including domestic innovation, vertical integration, and production network adjustment. By increasing the returns to internal capabilities and reducing reliance on external suppliers, technology decoupling encourages firms to strengthen domestic innovation and expand internal production capacity. Meanwhile, disruptions to existing linkages motivate firms to adjust their production networks and seek alternative connections, enhancing their ability to adapt to supply-chain disruptions and sustain quality upgrading.

4.Empirical Strategy

4.1 Measurement of Technological Decoupling

Theoretically, from the supply side, technological decoupling generate a direct cost effect by restricting the supply of critical components. This cost effect reduces firms' marginal flexibility in allocating resources toward quality upgrading. From the demand side, the shocks increase the relative attractiveness of domestic innovation and vertical integration, while also inducing firms to adjust trading relationships, thereby enhancing their capacity for quality upgrading, giving rise to a quality-upgrading effect. Overall, technological decoupling affects product quality through two opposing forces: a negative supply-side cost effect and a positive demand-side quality-upgrading effect.

Therefore, building on Equation (7), we construct measures of the quality-upgrading effect and the cost effect to empirically characterize the impact of technological decoupling on export product quality. Specifically, following Helm (2020), we construct product-year level measures of technology decoupling, namely the cost exposure $cNe_{kt} = \sum_j \frac{\exp_{kj}}{\sum_j \exp_{kj}} Du_{jt}$and the quality-upgrading exposure $qNe_{kt} = \sum_j \frac{imp_{kj}}{\sum_j imp_{kj}} Du_{jt}$.

The quality-upgrading exposure $qNe_{kt}$is constructed as a shift-share measure capturing the impact of technological decoupling through demand-side. Specifically, Du_{jt}takes a value of one to denote that Chinese firm j has been placed on the Entity List in period t. imp_{kj} denotes firm j's imports of product k in the pre-shock period (2016), and $\frac{imp_{kj}}{\sum_j imp_{kj}}$ captures the importance of firm j as a customer of product k. Using pre-shock import shares as weights is motivated by the idea that they capture the ex-ante dependence of demand-side firms on product k. Following the Entity List shock, Chinese firms on the Entity List are no longer able

to access critical foreign intermediate inputs, generating excess demand in affected product markets. This demand–supply imbalance is more pronounced for products that were more heavily sourced by affected firms prior to the shock. By interacting the shock component $Du_{jt}$with pre-determined import shares, we obtain a product-year level measure that captures the extent to which technological decoupling creates quality-upgrading incentives from demand side.

The cost exposure $cNe_{kt}$is constructed as a shift-share measure capturing the impact of technological decoupling through the **supply-side**, exp_{kj}denotes firm j's exports of product k in the pre-shock period (2016). The share $\frac{exp_{kj}}{\sum_j exp_{kj}}$ captures the importance of firm j as a producer of product k. Following the Entity List shock, Chinese firms on the Entity List are no longer able to access critical foreign intermediate inputs, resulting in heightened production cost pressure. Such pressure was particularly severe for products produced by affected firms before the shock. Therefore, the interaction term captures the extent to which technological decoupling generates cost pressures from supply side.

Together, $qNe_{kt}$and cNe_{kt}capture the two opposing channels highlighted in Equation (7). While qNe_{kt}measures the quality-upgrading incentives generated by demand sides following technological decoupling, cNe_{kt} measures the cost pressures arising from supply sides, as shown in Figure 6.

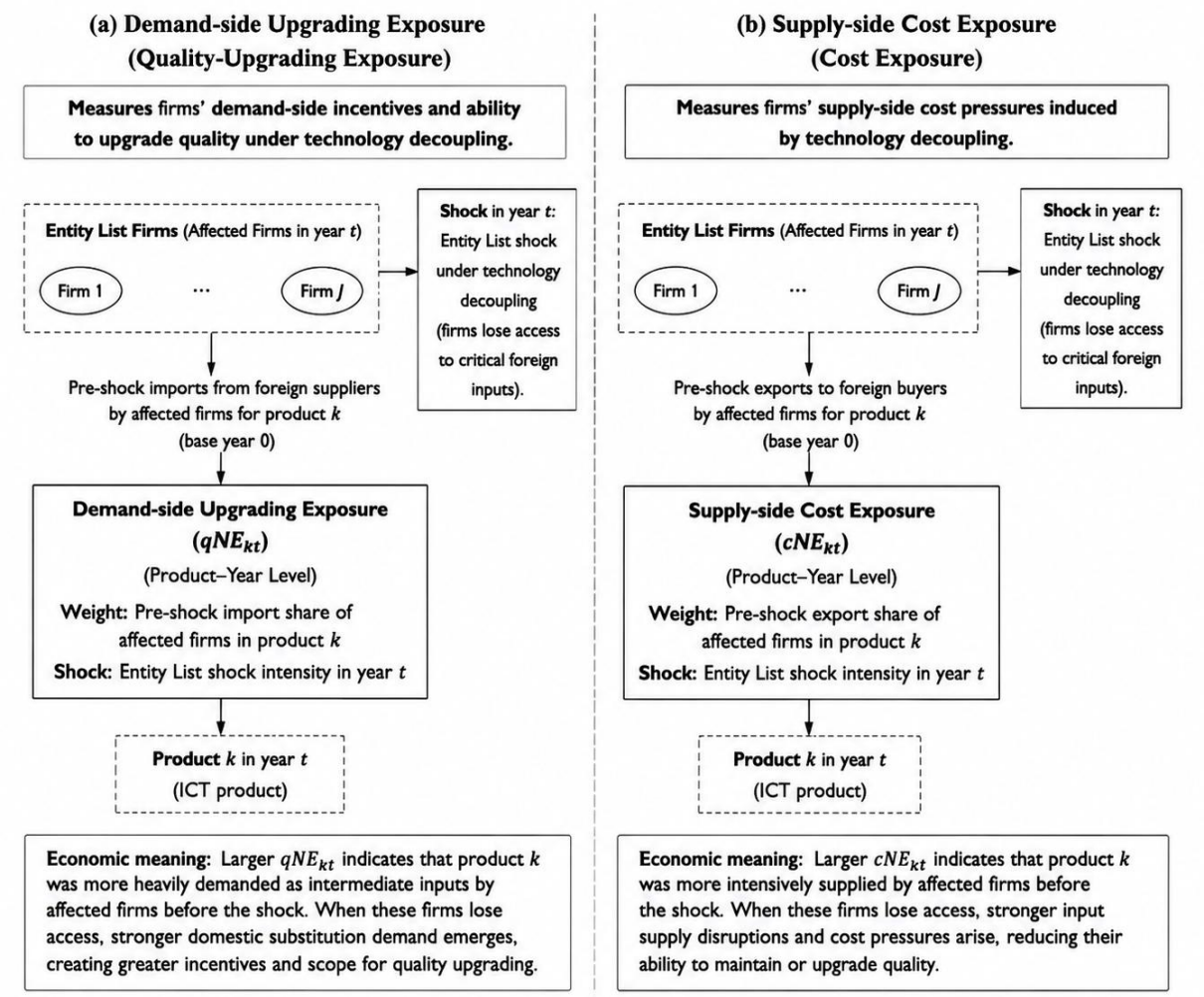


Figure 4 Measuring the Dual Effects of Technology Decoupling

Notes: The two exposure measures are constructed at the product–year level by combining the Entity List shock with firms' pre-shock trade shares (2016) in a shift-share framework. The shock component is a time-varying indicator equal to one if firm *j* is placed on the U.S. Entity List in year *t*. The shift component differs across the two measures. Demand-side Upgrading Exposure uses firm *j*'s pre-shock imports of product *k* as weights, capturing the importance of affected firms as customers of product *k* before the shock. Supply-side Cost Exposure uses firm *j*'s pre-shock exports of product *k* as weights, capturing the importance of affected firms as producers of product *k* before the shock.

4.2 Data and Variable Description

The empirical analysis is conducted at the HS 6-digit product-year level. Table 1 reports summary statistics for the main variables used in the baseline specifications. The sample spans 2016–2022 and combines information from several sources, including the China Customs Database, the CEPII database, the World Bank Open Data platform, and the China Statistical Yearbook.

Table 1. Variable Definitions and Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Log of Export Product Quality	31859	1.181	0.164	-3.835	1.671
Log of Corrected Export Product Quality	31859	1.182	0.169	-7.920	1.681
Quality-Upgrading Exposure	31859	0.023	0.114	0	1
Cost Exposure	31859	0.008	0.040	0	1
domestic factor costs	31859	11.356	0.401	0.148	12.2890
Log of Imported Intermediate Input Quality	31859	1.028	0.059	-2.663	1.617
Log of Export Destination Cargo Throughput	31859	14.505	0.971	9.810	19.577
Log of Export Destination GDP per Capita	31859	8.982	0.366	6.358	11.552
Log of Export Destination Population	31859	16.345	0.677	11.426	21.065
Log of Product Market Concentration	31859	-1.899	0. 581	-3.575	0
Log of Export Scale	31859	6.525	1.957	-5.809	14.090

We construct product-year level quality measures Following Khandelwal（2010）,To mitigate potential endogeneity concerns, we employ the average export price of the same product in alternative destination markets as an instrumental variable and obtain a corrected measure of export quality. we control for a set of destination-specific characteristics, including cargo throughput, GDP per capita, and population, obtained from the World Bank Open Data database for 2016–2022, these variables are aggregated from the country-year level to the product–year level by averaging across all destination countries importing the same HS 6-digit product.

We further control for domestic factor costs by constructing a product-year level measure: $c_{kt} = \sum_c \frac{exp_{ck}}{\sum_c exp_{ck}} w_{ct}$， where $\frac{exp_{ck}}{\sum_c exp_{ck}}$ denotes region c's initial share of China's exports of product k, and $w_{ct}$is the logarithm of wages in the Information Transmission, Software, and Information Technology Services sector in region $c$and year t, obtained from the China Statistical Yearbook. Higher values of c_{kt}indicate greater domestic labor costs embodied in product k.

5. Results

5.1 Baseline Results

Corresponding to Equation (7) in the theoretical framework, we specify the following empirical model:

$$ln\, y_{kt} = a_0 + a_1 cNe_{kt} + a_2 qNe_{kt} + X + \theta_k + \varepsilon_t + v_{kt} \quad (9)$$

where $k$and $t$denote product and year, respectively. The dependent variable, $\ln y_{kt}$, represents either the logarithm of export quality or the logarithm of corrected export quality for product k. cNe_{kt}captures the cost exposure, while qNe_{kt}measures the quality-upgrading exposure. X_{kt}denotes a set of control variables included to account for other factors that may affect export quality. In addition, θ_k and ε_t represent product fixed effects and time fixed effects, respectively.

Table 2 presents the baseline results. Column (1) includes only the quality-upgrading exposure and the cost exposure, together with product and time fixed effects. Column (2) further incorporates the full set of control variables. Columns (3) and (4) report the results using the logarithm of corrected export quality as the dependent variable. Across all specifications, the coefficient on the quality-upgrading exposure is positive and statistically significant at the 1% level, whereas the coefficient on the cost exposure is significantly negative. These findings indicate that although technology decoupling adversely affects export product quality through the supply-side cost channel, it simultaneously promotes export quality through the demand-side upgrading channel.

It is important to note that the estimated effect of Cost Exposure is larger in magnitude than that of Demand-side Upgrading Exposure, indicating that the adverse effects of technology

decoupling outweigh its quality-upgrading benefits on average. The remainder of the paper therefore investigates the mechanisms underlying these two opposing channels. Doing so helps explain how firms adjust to technology decoupling and sheds light on the broader conditions under which developing economies can mitigate the adverse effects of fragmentation in global production networks.

Table 2. Baseline Regression

Variable	(1) Log Export Product Quality	(2) Log Export Product Quality	(3) Log Corrected Export Product Quality	(4) Log Corrected Export Product Quality
Quality-Upgrading Exposure	0.032***	0.020***	0.032***	0.020***
	(0.009)	(0.005)	(0.010)	(0.007)
Cost Exposure	-0.092***	-0.043***	-0.093***	-0.044**
	(0.026)	(0.015)	(0.029)	(0.020)
Domestic Factor Costs		-0.005***		-0.005**
		(0.001)		(0.002)
Log Quality of Imported Intermediate Inputs		-0.003		-0.005
		(0.004)		(0.006)
Log Cargo Throughput		-0.027***		-0.031***
		(0.002)		(0.002)
Log GDP per Capita		-0.042***		-0.045***
		(0.002)		(0.002)
Log Population		-0.058***		-0.060***
		(0.002)		(0.002)
Log Product Market Concentration		-0.004***		-0.005**
		(0.002)		(0.002)
Log Product Export Scale		0.099***		0.101***
		(0.001)		(0.001)
Constant	1.174***	2.298***	1.174***	2.412***
	(0.000427)	(0.0311)	(0.000480)	(0.0407)
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	34,523	31,859	34,523	31,859
R^2	0.833	0.935	0.801	0.896

Notes: The dependent variable is the logarithm of export product quality in Columns (1)–(2) and the logarithm of corrected export product quality in Columns (3)–(4). Quality-Upgrading Exposure captures the demand-side upgrading incentives induced by technology decoupling, while Cost Exposure measures the supply-side production cost pressures induced by technology decoupling. All specifications include product and year fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2 Robustness Checks

5.2.1 Alternative Parameter Specifications

In the baseline specification, the key explanatory variables are constructed using firms' 2016 import and export shares as weights. Following Borusyak et al. (2022), the exposure shares used in shift-share designs should be predetermined and plausibly exogenous to the subsequent shock, thus, we assess the sensitivity of the results to the choice of exposure shares by replacing the baseline weights with the average import and export shares over the three years preceding the shock. Reconstructing the explanatory variables using these alternative weights yields qualitatively similar results. As reported in Table 3, the coefficient remains statistically significant, confirming the robustness of the baseline estimates.

Table 3. Robustness to Alternative Weighting

Variable	(1) Log Export Product Quality	(2) Log Export Product Quality	(3) Log Corrected Export Product Quality	(4) Log Corrected Export Product Quality
Quality-Upgrading Exposure	0.033***	0.020***	0.033***	0.020***
	(0.009)	(0.005)	(0.010)	(0.007)
Cost Exposure	-0.095***	-0.042***	-0.096***	-0.042**
	(0.026)	(0.015)	(0.029)	(0.020)
Domestic Factor Costs		-0.005***		-0.005**
		(0.001)		(0.002)
Log Quality of Imported Intermediate Inputs		-0.003		-0.005
		(0.004)		(0.006)
Log Cargo Throughput		-0.027***		-0.031***
		(0.002)		(0.002)
Log GDP per Capita		-0.042***		-0.045***
		(0.002)		(0.002)
Log Population		-0.058***		-0.060***
		(0.002)		(0.002)
Log Product Market Concentration		-0.004***		-0.005**
		(0.002)		(0.002)
Log Product Export Scale		0.099***		0.101***
		(0.001)		(0.001)
Constant	1.174***	2.298***	1.174***	2.412***
	(0.000)	(0.031)	(0.000)	(0.041)
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Observations	34,523	31,859	34,523	31,859
R^2	0.833	0.935	0.801	0.896

Notes: This table examines the robustness of the baseline results to alternative exposure weights. Quality-Upgrading Exposure and Cost Exposure are reconstructed using the average pre-shock import and export shares over the three years preceding the Entity List shock. Columns (1)–(2) use the logarithm of export product quality as the dependent variable, while Columns (3)–(4) use the logarithm of corrected export product quality. All specifications include the same control variables, product fixed effects, and year fixed effects as in the baseline regressions. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2.2 Correlation between market characteristics and shocks

The causal interpretation of our baseline estimates relies on the assumption that exposure to the U.S. Entity List shock is not systematically correlated with pre-shock factors that independently affect export quality (Borusyak et al., 2022). Although the Entity List designation itself is not randomly assigned, our identification exploits variation in product-level exposure generated by predetermined firm–product trade patterns before the shock. A potential concern is that firms more likely to be exposed to the Entity List shock may have systematically different market conditions prior to the shock, such as greater demand scale, stronger competitive pressure, or different technological environments, which could independently influence subsequent export quality. In this case, the estimated effects may capture pre-existing differences rather than the causal impact of technology decoupling.

To assess whether exposure to the Entity List shock is systematically related to pre-shock market characteristics, we follow Xu (2022) and examine the relationship between firms' sanction status, Du_j, and destination-market characteristics measured before the shock. Specifically, we construct a firm-level measure of destination-market characteristics as an export-weighted average $X_j = \frac{\sum_c exp_{jc} Cha_c}{\sum_c exp_{jc}}$, where Cha_c denotes a destination-market characteristic measured prior to the shock, including the logarithm of cargo throughput, GDP per capita, population, labor force size, digital development, and aggregate GDP, and

exp_{jc} denotes firm j's exports to destination c. We then estimate Equation (10) using alternative measures of Cha_c. The results, reported in Table 4, show that the coefficients on X_j are statistically insignificant across all specifications. These findings suggest that firms' exposure to the Entity List shock is not systematically predicted by pre-shock destination-market characteristics, supporting the identifying assumption underlying the baseline specification.

$$Du_j = a_0 + a_1 X_j + v_j \quad (10)$$

Table 4 Pre-shock Market Characteristics and Exposure to the Entity List Shock

	Cargo Throughput	GDP per Capita	Population	Labor Force	Digital Development	GDP
Market Characteristic	-0.0002	-0.0002	-0.0002	-0.0002	0.0002	-0.0001
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0001)
Observations	36421	36421	36421	36421	36421	36421

Notes: This table examines whether firms' exposure to the Entity List shock is systematically related to pre-shock destination-market characteristics. The dependent variable is a firm-level indicator equal to one if firm j is placed on the U.S. Entity List and zero otherwise. Market Characteristic denotes the export-weighted average of destination-market characteristics measured prior to the shock, including cargo throughput, GDP per capita, population, labor force size, digital development, and aggregate GDP. Each column reports estimates using one alternative measure of destination-market characteristics. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2.3 Ruling out Concurrent External Shocks

A potential concern is that the estimated effects may capture the influence of other contemporaneous policies or macroeconomic shocks rather than the impact of the Entity List shock itself. To address this concern, we control for several major events that occurred during the sample period (2016–2022), including the Belt and Road Initiative (BRI), the Regional Comprehensive Economic Partnership (RCEP), the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP), and the COVID-19 pandemic.

For the BRI, we construct a product-year level exposure measure, $BRI_{kt} = \sum_c e_{kc} BRI_{ct}$, where e_{kc} denotes product k's pre-shock export share to destination c, and BRI_{ct} equals one if destination c had joined the BRI by year t, and zero otherwise. Thus, BRI_{kt} captures the extent to which product k is exposed to the BRI through its pre-existing

export structure. The exposure measures for the CPTPP ($CPTPP_{kt}$) and the RCEP ($RCEP_{kt}$) are constructed analogously. To account for the potential confounding effects of the COVID-19 pandemic, we use data from Johns Hopkins University to identify destination markets that were more severely affected by the outbreak. We then combine this information with the timing of the pandemic to construct a product-year level exposure measure, COV_{kt}, which captures the extent to which a product's export markets were exposed to COVID-19-related disruptions.

Table 5 reports the results after sequentially controlling for exposure to the BRI, RCEP, CPTPP, and the COVID-19 pandemic. Across all specifications, the estimated coefficients on Quality-Upgrading Exposure and Cost Exposure remain stable in magnitude and statistically significant, providing further evidence that the baseline results are not driven by concurrent external shocks.

Table 5. Robustness to Other External Shocks

Variable	(1) Log Corrected Export Product Quality	(2) Log Corrected Export Product Quality	(3) Log Corrected Export Product Quality	(4) Log Corrected Export Product Quality	（5） Log Corrected Export Product Quality
Quality-Upgrading Exposure	0.020***	0.021***	0.021***	0.031***	0.020***
	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)
Cost Exposure	-0.044**	-0.044**	-0.043**	-0.101***	-0.043**
	(0.020)	(0.020)	(0.020)	(0.029)	(0.020)
BRI	-0.003				-0.003
	(0.004)				(0.004)
RCEP		0.001			0.002
		(0.001)			(0.002)
CPTPP			0.003**		0.003**
			(0.001)		(0.002)
COVID-19				-0.006***	0.002
				(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	31,781	31,859	31,859	34,300	31,781
R^2	0.895	0.896	0.896	0.803	0.895

Notes: This table examines the robustness of the baseline results to concurrent external shocks. Columns (1)–(4) sequentially control for exposure to the Belt and Road Initiative (BRI), the Regional Comprehensive Economic Partnership (RCEP), the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP), and the COVID-19 pandemic, respectively. Column (5) includes all four controls simultaneously. The dependent variable is the logarithm of corrected export product quality. All specifications include the full set of control variables, product fixed effects, and year fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2.3 Third-Country Market Exposure as an Instrument

To further address potential endogeneity concerns, we employ an instrumental-variable (IV) strategy. A key concern is that products more heavily exposed to the Entity List shock may also receive stronger government support, such as industrial subsidies or innovation policies, which could independently affect export quality. In this case, the estimated effects of Quality-Upgrading Exposure and Cost Exposure may partly reflect endogenous policy responses rather than the causal impact of technology decoupling.

To isolate exogenous variation in exposure, we exploit the reallocation of U.S. exports toward third-country markets following the disruption of U.S.–China trade relations. The underlying intuition is that technology decoupling induced U.S. exporters to redirect trade toward alternative destinations. Because the redirection of U.S. exports is driven primarily by U.S. trade restrictions and destination-market conditions, rather than by unobserved characteristics of Chinese firms, it generates exogenous variation in firms' exposure to technology decoupling without directly affecting their export quality.

The instrument is constructed in three steps. First, we identify third-country markets as destinations that experienced an increase in U.S. ICT exports following the onset of technology decoupling. Specifically, we compare U.S. exports before and after the introduction of the Entity List. Between 2017 and 2019, U.S. exports to China declined most sharply in HS Chapter 84 (machinery and mechanical equipment), which contains a number of key products for the ICT industry. We therefore classify a destination as a third-country market if U.S. exports of HS Chapter 84 products to that destination increased during this period.

Second, we construct an indicator of third-country market exposure, T_{jt}. The indicator equals one if firm j's pre-shock export to third-country markets exceeds 50 percent and the observation belongs to the post-decoupling period (2018 onward), and zero otherwise. This indicator identifies firms that had stronger pre-existing links with markets receiving redirected U.S. exports after technology decoupling. Accordingly, T_{jt} captures firms' differential exposure to the U.S.-induced trade reallocation rather than differences in their contemporaneous decisions.

Finally, following the shift-share approach, we interact the predetermined firm-level exposure weights with the time-varying third-country market shock and aggregate the resulting firm-year exposure to the product-year level, yielding two instrumental variables.$ivqNe_{kt} = \sum_j \frac{imp_{kj}}{\sum_j imp_{kj}} T_{jt}$, and $ivcNe_{kt} = \sum_j \frac{exp_{kj}}{\sum_j exp_{kj}} T_{jt}$, which instrument Quality-Upgrading Exposure and Cost Exposure, respectively.

The validity of the instruments rests on two conditions. First, third-country market exposure is closely linked to the trade reallocation induced by technology decoupling and therefore strongly predicts firms' exposure to the Entity List shock. Second, the destination choices of redirected U.S. exports are primarily determined by U.S. policy and market conditions rather than by unobserved factors affecting Chinese firms' export quality. Consequently, third-country market exposure provides plausibly exogenous variation in the two exposure measures.

Table 6 reports the IV estimates. Columns (1)–(4) use the logarithm of export product quality and the logarithm of corrected export product quality as alternative dependent variables, with and without additional controls for concurrent external shocks. Across all specifications, the estimated coefficients on Quality-Upgrading Exposure and Cost Exposure remain statistically

significant and economically similar to the baseline estimates. Moreover, the Cragg–Donald Wald F-statistics exceed the conventional critical values, indicating that weak instruments are unlikely to be a concern. Overall, these results suggest that the baseline findings are robust to potential endogeneity arising from endogenous policy responses and omitted variables.

Table 6 Instrumental Variable Estimates

Variable	(1) Log Export Product Quality	(2) Log Export Product Quality	(3) Log Corrected Export Product Quality	(4) Log Corrected Export Product Quality
Quality-Upgrading Exposure	0.207***	0.206***	0.210***	0.209***
	(0.060)	(0.059)	(0.077)	(0.076)
Cost Exposure	-0.599***	-0.595***	-0.609**	-0.606**
	(0.185)	(0.182)	(0.240)	(0.238)
BRI		-0.003		-0.004
		(0.003)		(0.004)
RCEP		0.002*		0.003*
		(0.001)		(0.002)
CPTPP		0.003**		0.003**
		(0.001)		(0.002)
COVID-19		0.001		0.001
		(0.001)		(0.002)
Controls	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	31,859	31,781	31,859	31,781
Cragg-Donald Wald F	95.213	96.159	95.213	96.159

Notes: This table reports two-stage least squares (2SLS) estimates using third-country market exposure as instruments for Quality-Upgrading Exposure and Cost Exposure. Columns (1)–(2) use the logarithm of export product quality as the dependent variable, and Columns (3)–(4) use the logarithm of corrected export product quality. Columns (2) and (4) additionally control for concurrent external shocks. All specifications include the full set of controls, product fixed effects, and year fixed effects. The Cragg–Donald Wald F-statistic is reported in the last row. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6. Mechanisms

6.1 Quality-Upgrading Effect: Domestic Innovation

Technology decoupling reduces access to critical U.S. intermediate inputs, increasing domestic demand for locally developed substitutes and thereby raising the expected returns to innovation. To examine this domestic innovation channel, we use the logarithm of product-year level R&D expenditure as the dependent variable. R&D expenditure is constructed by

aggregating firm-year level R&D expenditures from China's Tax Survey Database (available through 2020) to the industry-year level based on the National Standard Industrial Classification and then matching them to the product-year sample. The results, reported in Columns (1)–(2) of Table 7, show that Quality-Upgrading Exposure has a positive and statistically significant effect on R&D expenditure, supporting the domestic innovation mechanism. We further split the sample according to the median growth rate of R&D expenditure over the sample period. As reported in Columns (3)–(4), the estimated effect is significantly stronger among products with above-median R&D growth, indicating that technology decoupling induces greater quality upgrading in sectors with stronger innovation responses.

Table7 **Domestic innovation: R&D expenditure**

Variable	(1) logarithm of R&D expenditure	(2) logarithm of R&D expenditure	(3) Log Corrected Export Product Quality (Above-Median R&D Growth)	(4) Log Corrected Export Product Quality (Below-Median R&D Growth)
Quality-Upgrading Exposure	1.406***	1.379***	0.017***	0.019
	(0.422)	(0.423)	(0.005)	(0.023)
Controls	No	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	14,650	13,372	19,406	12,331
R2	0.382	0.378	0.954	0.956

Notes: Columns (1)–(2) examine the domestic innovation channel using the logarithm of product-level R&D expenditure as the dependent variable. Columns (3)–(4) report the baseline specification separately for products with above- and below-median growth in R&D expenditure over the sample period. All specifications include product fixed effects and year fixed effects. Columns (2)–(4) additionally include the full set of control variables. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

In addition to innovation inputs, innovation outputs provide another important dimension of **domestic innovation**. We therefore use data from the *China Patent Database* for 2016–2020 and construct a product-year level measure of patent intensity, denoted by pa_{kt}. The database provides detailed information on each patent application, including application numbers,

publication dates, patent titles, applicant addresses, and IPC classifications. To capture the patent activity associated with product k, we construct pa_{kt}as follows[①]:

$$pa_{kt} = \sum_c \frac{exp_{ck}}{\sum_c exp_{ck}} num_{ct} \quad (12)$$

where $num_{ct}$is the logarithm of ICT-related patents in region $c$and year t, constructed using patents in IPC Sections G and H and assigned according to applicants' registered addresses. The weight $\frac{exp_{ck}}{\sum_c exp_{ck}}$denotes region c's initial export share in product k, which aggregates regional patenting activity into product-level patent intensity. We use patent intensity, pa_{kt}, as a proxy for innovation output. The estimates reported in Table 8 Columns (1)- (2) indicate a positive and statistically significant association between quality upgrading and patent intensity. We further split the sample according to the median increase in patent intensity over the sample period and re-estimate the baseline specification. As reported in Columns (3) and (4), the effect of quality upgrading is substantially stronger among products experiencing larger increases in patent intensity. These findings are consistent with the proposed domestic innovation channel.

Table 8 Domestic innovation: Patents

Variable	(1) logarithm of patents	(2) logarithm of patents	(3) Log Corrected Export Product Quality (Above-Median Patent Growth)	(4) Log Corrected Export Product Quality (Below-Median Patent Growth)
Quality-Upgrading Exposure	0.211***	0.132***	0.012***	0.026
	(0.031)	(0.027)	(0.004)	(0.016)
Controls	No	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	24,741	22,742	18,047	13,734

[①] The empirical analysis is conducted at the HS product level, whereas patent records in the *China Patent Database* cannot be directly linked to HS codes. To bridge this gap, we aggregate regional ICT-related patenting activity using products' initial export shares across regions as weights, thereby constructing a product-year level measure of patent intensity

R2	0.999	0.999	0.970	0.849

Notes: Columns (1)–(2) examine the domestic innovation channel using the logarithm of product-level patent applications as the dependent variable. Columns (3)–(4) report the baseline specification separately for products with above- and below-median growth in patent applications over the sample period. All specifications include product fixed effects and year fixed effects. Columns (2)–(4) additionally include the full set of control variables. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2 Quality-upgrading Effect: Vertical Integration

Technology decoupling may also increase the relative attractiveness of vertical integration by encouraging firms to expand internal production capacity and reduce reliance on external suppliers. To examine this mechanism, we use the logarithm of investment in production-related fixed assets as a proxy for vertical integration. The measure is constructed from the National Tax Survey Database and, following the procedure described above, is aggregated to the product-year level. The results reported in Columns (1)–(2) of Table 9 show that Quality-Upgrading Exposure has a positive and statistically significant effect on investment in production-related fixed assets, consistent with the vertical integration channel.

We further split the sample according to the median growth in production-related fixed assets over the 2016–2020 period and estimate the baseline specification separately for products with above- and below-median asset growth. As shown in Columns (3)–(4), the positive effect of Quality-Upgrading Exposure on export quality is statistically significant only among products with above-median asset growth. This finding suggests that the quality-upgrading channel is stronger in products undergoing greater expansion of internal production capacity, consistent with the view that technology decoupling promotes quality upgrading by encouraging firms to strengthen vertical integration.

Table 9 Vertical Integration

	(1)	(2)	(3)	(4)

Variable	logarithm of production-related fixed assets	logarithm of production-related fixed assets	Log Corrected Export Product Quality (Above-Median Asset Growth)	Log Corrected Export Product Quality (Below-Median Asset Growth)
Quality-Upgrading Exposure	0.949***	0.909***	0.017***	0.028
	(0.278)	(0.273)	(0.005)	(0.030)
Controls	No	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	14,578	13,372	18,623	13,158
R2	0.866	0.864	0.950	0.821

Notes: Columns (1)–(2) examine the vertical integration channel using the logarithm of investment in production-related fixed assets as the dependent variable. Columns (3)–(4) report the baseline specification separately for products with above- and below-median growth in production-related fixed assets over the sample period. All specifications include product fixed effects and year fixed effects. Columns (2)–(4) additionally include the full set of control variables. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.3 Quality-upgrading Effect: Network Position

Facing excess demand and heightened technological decoupling risks, products may adjust their network position by establishing new trade relationships. By expanding their connections within global production networks, firms gain access to a broader pool of resources and knowledge, which can be transformed into improvements in product quality. To examine this channel, we construct the logarithm of import degree, defined as $ln\,D_{kt} = (\sum_c d_{kct})$, where d_{kct} equals one if product k is imported from country c in year t, and zero otherwise. The logarithm of import degree is used as the dependent variable in Columns (1)–(2) of Table 10.

The estimated coefficients on Quality-Upgrading Exposure are statistically insignificant, suggesting that technology decoupling does not systematically increase products' import degree. We next split the sample according to the median growth in import degree over the sample period. Columns (3)–(4) show that the positive effect of Quality-Upgrading Exposure on export quality is concentrated among products with above-median growth in import degree. These findings suggest that network connectivity enhances firms' ability to translate

technology decoupling into quality upgrading, although expanding international sourcing networks is not, on average, the primary adjustment margin.

One possible explanation is that international trade relationships are characterized by substantial search costs, contractual frictions, and path dependence, limiting firms' ability to rapidly establish new foreign sourcing links following technology decoupling. Instead, firms appear to rely more on domestic innovation and expanded internal production capacity, consistent with the evidence presented in the previous sections.

Table 10 **Network Position**

Variable	(1) Log of Import Node Degree	(2) Log of Import Node Degree	(3) Log of Corrected Export Product Quality (High Import Node Degree Growth)	(4) Log of Corrected Export Product Quality (Low Import Node Degree Growth)
Quality-Upgrading Exposure	0.0185	0.0202	0.0307**	0.0105*
	(0.0227)	(0.0214)	(0.0137)	(0.00619)
Controls	No	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	31,322	31,112	14,597	17,184
R2	0.949	0.955	0.847	0.950

Notes: Columns (1)–(2) examine the network position channel using the logarithm of import node degree as the dependent variable. Columns (3)–(4) report the baseline specification separately for products with above- and below-median growth in import node degree over the sample period. All specifications include product fixed effects and year fixed effects. Columns (2)–(4) additionally include the full set of control variables. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.4 Cost Effect vs. Quality-upgrading Effect

The baseline results indicate that technology decoupling affects export quality through two opposing channels. While Quality-Upgrading Exposure promotes export quality by stimulating domestic innovation and production upgrading, Cost Exposure exerts a negative effect by increasing the cost of critical intermediate inputs. Moreover, the estimated cost effect is larger in magnitude than the quality-upgrading effect, suggesting that production-side disruptions

dominate, on average, the upgrading benefits generated by technology decoupling. Understanding where these two channels operate is therefore essential for explaining firms' adjustment patterns, particularly in developing economies that remain dependent on foreign technologies and intermediate inputs.

The two channels are expected to differ systematically across stages of production. The quality-upgrading channel primarily operates upstream, where technology decoupling increases demand for domestically supplied substitutes, then strengthens incentives for innovation and vertical integration. By contrast, the cost channel mainly affects downstream producers, as higher prices of imported intermediate inputs are transmitted through production linkages and reduce the resources available for quality upgrading.

To test this prediction, we classify products into intermediate and final goods using the United Nations Broad Economic Categories (BEC) classification and estimate the baseline specification separately for the two groups. Intermediate goods include primary and processed products (BEC codes 111, 121, 21, 22, 31, 322, 42, and 53), whereas final goods include durable and non-durable consumption goods (BEC codes 61, 62, 63, 112, 122, 522, 41, and 521). This classification distinguishes upstream production stages, where import-substitution incentives are expected to be stronger, from downstream stages, where cost increases are more likely to propagate through production linkages.

The results are reported in Table 11. Cost Exposure has a negative and statistically significant effect only for final goods, while its coefficient is statistically insignificant for intermediate goods. In contrast, Quality-Upgrading Exposure is positive and statistically

significant only for intermediate goods and has no significant effect on final goods. The Chow test rejects the null hypothesis of equal coefficients across the two subsamples ($p<0.001$).

These findings provide strong evidence for the dual-channel mechanism proposed in this paper. The quality-upgrading channel is concentrated in upstream production stages, where import-substitution demand creates stronger incentives for production upgrading. By contrast, the cost channel is concentrated in downstream stages, where higher input costs are transmitted through production networks and constrain firms' upgrading activities. Overall, technology decoupling does not affect products uniformly along the value chain, instead, it generates upstream upgrading but downstream cost burdens. These results underscore the importance of strengthening domestic supply-chain resilience. For developing economies that remain reliant on foreign technologies and critical intermediate inputs, policies that reinforce domestic production linkages and reduce upstream supply constraints can enhance firms' capacity to adjust to external shocks and mitigate the adverse consequences of technology decoupling.

Table 11 Cost effect vs. Quality-quality-upgrading effect

Variable	(1) Log Export Product Quality (Final goods)	(2) Log Export Product Quality (intermediate gods)	(3) Log Corrected Export Product Quality (Final goods)	(4) Log Corrected Export Product Quality (intermediate gods)
Cost Exposure	-0.125***	-0.016	-0.123***	-0.018
	(0.026)	(0.050)	(0.026)	(0.059)
Quality-Upgrading Exposure	0.015	0.048**	0.015	0.050*
	(0.011)	(0.022)	(0.011)	(0.026)
Controls	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	12,558	21,694	12,558	21,694
R2	0.880	0.826	0.880	0.779
Chow test （P value）	40.75（0.000）***		35.44（0.000）***	

Notes: Columns (1) and (3) report the baseline estimates for final goods, while Columns (2) and (4) report the corresponding estimates for intermediate goods, where product groups are classified according to the United Nations Broad Economic Categories (BEC) classification. Columns (1)–(2) use the logarithm of export product quality as the dependent variable, whereas Columns (3)–(4) use the logarithm of corrected export product quality. All specifications include the full set of control

variables, product fixed effects, and year fixed effects. The last row reports the p-values from Chow tests for the equality of coefficients across the two subsamples. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.5 Cost Effect: Mechanisms

Firms facing higher input costs following technology decoupling may mitigate these disruptions through two main adjustment margins. First, they may substitute disrupted foreign suppliers with alternative domestic suppliers. Second, they may draw on internal resources, such as capital, technology, and organizational capabilities, to absorb higher production costs. The severity of the cost effect therefore depends on the ease of supplier substitution and firms' capacity to mobilize productive resources.

We focus on two factors that are likely to shape these adjustment margins. From the domestic perspective, market fragmentation increases search and matching costs in input markets, making it more difficult for firms to establish new supplier relationships after technology decoupling. From the global production-network perspective, firms occupying more central positions are likely to have better access to suppliers, technology, and complementary resources, enabling them to adapt more effectively to rising input costs. We therefore examine whether domestic market fragmentation amplifies the cost effect, while network position mitigates it.

To examine the role of domestic market fragmentation, we divide sanctioned firms according to the median value of the regional market-fragmentation index. Let I_j equal one if sanctioned firm j is located in a region with above-median market fragmentation and zero otherwise. We then decompose **Cost Exposure** into two components $cNe_{kt}^{H} = \sum_j \frac{exp_{kj}}{\sum_j exp_{kj}} Du_{jt} I_j$ and $cNe_{kt}^{L} = \sum_j \frac{exp_{kj}}{\sum_j exp_{kj}} Du_{jt}(1 - I_j)$, which capture exposure to

supply-side cost shocks originating from sanctioned firms located in regions with high and low levels of domestic market fragmentation, respectively. These two measures are included simultaneously in the baseline specification. The results are reported in Columns (1)–(2) of Table 12. Cost Exposure originating from highly fragmented regions has a negative and statistically significant effect on export quality, whereas the corresponding coefficient for low-fragmentation regions is statistically insignificant. These findings suggest that domestic market fragmentation amplifies the cost effect of technology decoupling by increasing the costs of supplier substitution and slowing the formation of alternative domestic production linkages. In contrast, firms located in more integrated domestic markets appear better able to reorganize their sourcing networks, thereby mitigating the adverse consequences of technology decoupling.

Table 12. Mechanisms of the Cost Effect

Variable	(1) Log Corrected Export Product Quality	(2) Log Corrected Export Product Quality	(3) Log Corrected Export Product Quality	(4) Log Corrected Export Product Quality
Low- Fragmentation Cost Exposure	-0.035	-0.057		
	(0.060)	(0.041)		
High- Fragmentation Cost Exposure	-0.106***	-0.040*		
	(0.031)	(0.021)		
High-Centrality Cost Exposure			0.001	-0.025
			(0.078)	(0.054)
Low-Centrality Cost Exposure.			-0.114***	-0.047**
			(0.033)	(0.023)
Quality-Upgrading Exposure	0.032***	0.020***	0.032***	0.020***
	(0.010)	(0.007)	(0.010)	(0.007)
Controls	No	Yes	No	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	34,523	31,781	34,523	31,781
R2	0.801	0.895	0.801	0.895

Notes: Columns (1)–(2) examine whether the cost effect differs by the degree of regional market fragmentation, while Columns (3)–(4) examine whether it differs by firms' import network centrality. High- Fragmentation Cost Exposure and Low-Fragmentation Cost Exposure denote cost exposure originating from sanctioned firms located in regions with above- and below-median market fragmentation, respectively. High-Centrality Cost Exposure and Low-Centrality Cost Exposure are

defined analogously according to the median level of import network centrality. All specifications include product fixed effects and year fixed effects. Columns (2) and (4) additionally include the full set of control variables. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We next examine the role of firms' positions in global production networks. Using pre-shock import transaction data from the China Customs Database, we construct a firm-level measure of import network centrality, defined as $Cen_j = \frac{n_j}{N-1}$, where n_j denotes the number of source countries from which firm $j$imports and $N$is the total number of potential source countries. A higher value of Cen_jindicates that a firm is connected to a broader set of foreign suppliers and occupies a more central position in the global production network.

Using the median value of import centrality as the threshold, we classify firms into high- and low-centrality groups and decompose the baseline Cost Exposure measure accordingly. Columns (3)–(4) of Table 12 report the corresponding estimates. The results show that the coefficient on Low-Centrality Cost Exposure is negative and statistically significant, whereas the coefficient on High-Centrality Cost Exposure is statistically insignificant. These findings suggest that the adverse cost effect is concentrated among firms located at the periphery of the global production network. Compared with more central firms, peripheral firms have more limited access to alternative suppliers, technologies, and complementary resources, reducing their ability to reconfigure supply chains and absorb increases in input costs following technology decoupling.

6.6 Mitigating the Cost Effect

The preceding analysis shows that the cost effect is weaker for firms occupying more central positions in global production networks, suggesting that access to alternative sourcing relationships plays an important role in mitigating supply-side disruptions. This raises a natural question: which international sourcing markets can most effectively substitute for disrupted technology imports following U.S. technology decoupling?

To address this question, we exploit the community structure of the global production network. As shown in Appendix Figure A1, ICT trade exhibits regional clustering. U.S.-centered communities are concentrated primarily in North and South America, whereas China-centered communities are concentrated mainly in Asia. These network communities imply that Asian economies are more closely integrated into China's production network and are therefore more likely to serve as alternative sourcing markets when access to U.S. suppliers is restricted.

Guided by this network structure, we construct a firm-level indicator using import transactions from the 2016 China Customs Database. The indicator I_j equals one if firm j imported from at least one Asian economy prior to technology decoupling and zero otherwise. We then decompose Cost Exposure into Asia-related Cost Exposure and Non-Asia-related Cost Exposure following the same decomposition strategy as in the previous subsection. Table 13 reports the corresponding estimates.

The results show that the adverse cost effect is concentrated among firms without pre-existing sourcing relationships in Asia. Non-Asia-related Cost Exposure has a negative and statistically significant effect on export quality, whereas the coefficient on Asia-related Cost Exposure is statistically insignificant. These findings suggest that pre-existing sourcing linkages with Asian economies enhance firms' resilience to technology decoupling by facilitating supplier substitution when U.S. technology imports are disrupted. More broadly, the results highlight the importance of regional production networks in strengthening supply-chain resilience and mitigating the production costs associated with technology decoupling.

Table 13 Alternative Sourcing through Asian Production Networks

Variable	(1) Log Export Product Quality	(2) Log Export Product Quality	(3) Log Corrected Export Product Quality	(4) Log Corrected Export Product Quality
Asia-related Cost Exposure	-0.025	-0.011	-0.024	-0.011
	(0.056)	(0.033)	(0.063)	(0.043)
Non-Asia-related Cost Exposure	-0.113***	-0.051***	-0.115***	-0.053**
	(0.030)	(0.018)	(0.034)	(0.023)

Quality-Upgrading Exposure	0.032***	0.020***	0.032***	0.020***
	(0.010)	(0.005)	(0.010)	(0.007)
Controls	No	Yes	No	Yes
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	34,523	31,781	34,523	31,781
R2	0.833	0.935	0.801	0.895

Notes: Asia-related Cost Exposure and Non-Asia-related Cost Exposure denote cost exposure originating from sanctioned firms with and without pre-existing sourcing relationships with Asian economies, respectively. Columns (1)–(2) use the logarithm of export product quality as the dependent variable, while Columns (3)–(4) use the logarithm of corrected export product quality. All specifications include product fixed effects and year fixed effects. Columns (2) and (4) additionally include the full set of control variables. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Taken together, these findings provide a broader understanding of both the origins of the cost effect and the mechanisms through which firms adapt to technology decoupling. The evidence suggests that the severity of the cost effect is shaped by firms' adjustment capacity rather than by technology restrictions alone. Domestically, market fragmentation raises the costs of supplier substitution and weakens production coordination. Internationally, stronger sourcing linkages and more integrated production networks improve firms' access to alternative suppliers and complementary resources when existing supply chains are disrupted. Consequently, the adverse effects of technology decoupling depend not only on the intensity of the external shock but also on the flexibility of domestic and international production networks. These findings underscore the importance of strengthening domestic market integration and deepening regional production networks to enhance supply-chain resilience and reduce the production costs associated with technology decoupling.

7. Conclusion

As technology decoupling reshapes global production networks, a central question is whether restrictions on foreign technologies weaken industrial upgrading or instead induce firms to reorganize production and develop new capabilities. This paper addresses this question by examining how U.S. technology decoupling affects the export quality of Chinese ICT

products. We develop a theoretical framework in which technology decoupling generates two opposing forces: a negative Cost Effect arising from disruptions to foreign intermediate-input sourcing and a positive Quality-Upgrading Effect generated by domestic substitution incentives. Guided by this framework, we construct product-year level measures of Quality-Upgrading Exposure and Cost Exposure using pre-shock firm–product trade relationships and exploit variation induced by the U.S. Entity List to identify their effects on export quality.

Our empirical results show that technology decoupling has heterogeneous effects on export quality. Products with greater demand-side Quality-Upgrading Exposure experience significant improvements in export quality, whereas products with greater supply-side Cost Exposure experience significant declines. These two effects are also unevenly distributed along the production chain. The Quality-Upgrading Effect is concentrated primarily among upstream intermediate goods, where import substitution creates stronger incentives for domestic capability building, while the Cost Effect is concentrated among downstream final goods, where higher input costs are transmitted through production linkages. Although the negative Cost Effect dominates on average, the positive Quality-Upgrading Effect remains economically meaningful, indicating that technology decoupling simultaneously generates production disruptions and industrial adaptation.

Mechanism analysis shows that the Quality-Upgrading Effect is driven primarily by domestic innovation and vertical integration. In addition, firms with stronger production-network connectivity are better able to transform demand-side upgrading opportunities into export quality improvements, highlighting the complementary role of production networks in facilitating industrial adaptation. At the same time, the Cost Effect depends critically on firms'

ability to adjust their sourcing relationships. It is significantly stronger in regions with greater domestic market fragmentation and among firms occupying peripheral positions in global production networks, but substantially weaker for firms with stronger sourcing linkages to Asian economies. These findings suggest that both domestic market integration and diversified international production networks enhance firms' resilience to technology-induced supply disruptions.

Taken together, our findings show that the consequences of technology decoupling are shaped not only by the severity of external technology restrictions but also by how these shocks propagate through production networks and by firms' capacity to reorganize production activities. By identifying both a Demand-Induced Upgrading Effect and a Supply-Side Cost Effect, this paper provides a unified production-network framework for understanding why technology decoupling simultaneously generates incentives for domestic capability building while imposing substantial production costs.

More broadly, our findings suggest that technology decoupling should not be viewed simply as a negative supply shock. Its industrial consequences depend on the interaction between external technology restrictions and firms' adaptive responses through domestic innovation, vertical integration, and production-network adjustment. Ultimately, the consequences of technology decoupling depend not only on the severity of external technology

restrictions but also on whether production networks facilitate or hinder firms' adaptive responses.

Acknowledgement and Disclosure

This research was supported by the National Natural Science Foundation of China. The authors declare that they have no relevant financial interests or other potential conflicts of interest related to this research.

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Appendix

1. marginal cost

firms solve the following problem:

$$\min \mathrm{p}\mathrm{M} + \mathrm{c}_\mathrm{k}\mathrm{L}$$

$$\mathrm{s.t.}\, \mathrm{q}(\varphi, \mathrm{k}) = \varphi \mathrm{L}^{1-\alpha}\mathrm{M}^{\alpha}$$

where $\mathrm{p}, \mathrm{c}_\mathrm{k}$ denotes the price of intermediate inputs and the relative price of local labor. The first-order condition is as follows:

$$\mathrm{L} = \frac{1-\alpha}{(\alpha)}\frac{\mathrm{p}}{\mathrm{c}_\mathrm{k}}\mathrm{M} \tag{A1.1}$$

Substituting into the cost-minimization problem yields the factor demand functions:

$$L = (1-\alpha)\frac{cq(\varphi,k)}{c_k} \tag{A1.2}$$

$$M = \alpha\frac{cq(\varphi,k)}{p} \tag{A1.3}$$

Substituting Equations (A1.2) and (A1.3) into the production function gives

$$q(\varphi,k) = \varphi((1-\alpha)\frac{cq}{c_k})^{1-\alpha}(\alpha\frac{cq}{p})^{\alpha} \tag{A1.4}$$

Rearranging yields:

$$c(\varphi,k) = \frac{1}{\varphi}(c_k)^{1-\alpha}(p)^{\alpha}[\frac{1}{(\alpha)^{\alpha}(1-\alpha)^{1-\alpha}}] \tag{A1.5}$$

the marginal cost of producing product can be written as:

$$c(\varphi,k) = \frac{1}{\varphi}(c_k)^{1-\alpha}((\sum_j(\frac{p_{kj}}{z_j})^{1-\rho})^{\frac{1}{1-\rho}})^{\alpha}[\frac{1}{(\alpha)^{\alpha}(1-\alpha)^{1-\alpha}}] \tag{A1.6}$$

Define $[\frac{1}{(\alpha)^{\alpha}(1-\alpha)^{1-\alpha}}] \equiv Z_a$, The marginal cost of producing product k is given by $c(\varphi,k) = \frac{Z_a}{\varphi}(c_k)^{1-\alpha}(\sum_j(\frac{p_{kj}}{z_j})^{1-\rho})^{\frac{1}{1-\rho}})^{\alpha}$。

2. Product quality

We assume a monopolistically competitive market structure. The demand for product k in region l is given by:

$$q_{kl}(\omega) = P_l^{\sigma-1}R_l p_{kl}^{-\sigma}(\frac{\lambda_{kl}}{\lambda_{kl}^*})^{\sigma-1} \tag{A2.1}$$

Firms choose the output and quality of product kto maximize profits. The firm's optimization problem is given by

$$\max_{q,\lambda} p(\varphi,k)q(\varphi,k) - c(\varphi,k)q(\varphi,k) - r_k\lambda_{kl}^{2(\sigma-1)} - f$$

where $r_k$represents the relative cost of advanced technology required for quality upgrading. The first-order condition with respect to output is given by

$$\frac{\partial\pi}{\partial q} = \frac{\partial p}{\partial q}q(\varphi,k) + p(\varphi,k) - c(\varphi,k) = 0 \tag{A2.2}$$

marginal revenue can be expressed as:

$$MR = \frac{\partial p}{\partial q}q(\varphi,k) + p(\varphi,k) = (\frac{\sigma-1}{\sigma})p(\varphi,k) \tag{A2.3}$$

Therefore, the profit function can be rewritten as:

$$\pi = \frac{1}{\sigma} pq(\varphi, k) - r_k \lambda_{kl}^{2(\sigma-1)} - f \tag{A2.4}$$

Substituting the demand function $q_{kl}(\omega) = P_l^{\sigma-1} R_l p_{kl}^{-\sigma} (\frac{\lambda_{kl}}{\lambda_{kl}^*})^{\sigma-1}$ into the above expression yields:

$$\pi = \frac{1}{\sigma} P_l^{\sigma-1} R_l p_{kl}^{1-\sigma} (\frac{\lambda_{kl}}{\lambda_{kl}^*})^{\sigma-1} - r_k \lambda_{kl}^{2(\sigma-1)} - f \tag{A2.5}$$

The first-order condition with respect to quality is:

$$\frac{\partial \pi}{\partial \lambda_{kl}} = \frac{\sigma-1}{\sigma} P_l^{\sigma-1} R_l p_{kl}(\omega)^{1-\sigma} \lambda_{kl}(\omega)^{\sigma-2} \lambda_{kl}^{*(1-\sigma)} - 2(\sigma-1) r_k \lambda_{kl}^{2\sigma-3} = 0 \tag{A2.6}$$

It follows that

$$\frac{1}{2\sigma r_k} P_l^{\sigma-1} R_l p_{kl}(\omega)^{1-\sigma} \lambda_{kl}^{*(1-\sigma)} = \lambda_{kl}^{\sigma-1} \tag{A2.7}$$

Rearranging yields:

$$\lambda_{kl} = （2\sigma r_k）^{\frac{1}{1-\sigma}} P_l R_l^{\frac{1}{\sigma-1}} p_{kl}(\omega)^{-1} \lambda_{kl}^{*-1} \tag{A2.8}$$

Since $p_{kl} = \frac{\sigma}{\sigma-1} c(\varphi, k) = \frac{\sigma}{\sigma-1} \frac{Z_a}{\varphi} (c_k)^{1-\alpha} ((\sum_j (\frac{p_{kj}}{z_j})^{1-\rho})^{\frac{1}{1-\rho}})^{\alpha}$， we have：

$$\lambda_{kl} = （2\sigma）^{\frac{1}{1-\sigma}} \frac{\sigma-1}{\sigma} \frac{\varphi}{Z_a} P_l R_l^{\frac{1}{\sigma-1}} (r_k)^{\frac{1}{1-\sigma}} (c_k)^{\alpha-1} ((\sum_j (\frac{p_{kj}}{z_j})^{1-\rho})^{\frac{1}{1-\rho}})^{-\alpha} \lambda_{kl}^{*-1} \tag{A2.9}$$

Taking logarithms and differentiating yields

$$d \ln \lambda_{kl} = -\frac{1}{\sigma-1} d \ln r_k - (1-\alpha) d \ln c_k + \frac{\alpha}{\rho-1} d \ln (\sum_j (\frac{p_{kj}}{z_j})^{1-\rho}) - d \ln \lambda_{kl}^* \tag{A2.10}$$

3. Derivation of the Effect of Technological Decoupling on Product Quality

Combining $d \ln (\sum_j \zeta_{kj}) = (1-\rho) \sum_j w_{kj} d \ln p_{kj}$、$\chi_k \sum_j d \ln p_{kj} \equiv d \ln r_k$、$s_k \sum_j d \ln p_{kj} \equiv d \ln c_k$， we have：

$$d \ln \lambda_{kl} = -\frac{1}{\sigma-1} \chi_k \sum_j d \ln p_{kj} - (1-\alpha) s_k \sum_j d \ln p_{kj} - \alpha \sum_j w_{kj} d \ln p_{kj} \tag{A3.1}$$

Since $\lambda_k = \frac{E(\lambda_{kl})}{N} = （2\sigma）^{\frac{1}{1-\sigma}} \frac{\sigma-1}{\sigma} \frac{\varphi}{Z_a} P_l R_l^{\frac{1}{\sigma-1}} (r_k)^{\frac{1}{1-\sigma}} (c_k)^{\alpha-1} ((\sum_j (\frac{p_{kj}}{z_j})^{1-\rho})^{\frac{1}{1-\rho}})^{-\alpha} p d_k \lambda_{kl}^*$， It follows that：

$$d \ln \lambda_k = -\frac{1}{\sigma-1} \chi_k \sum_j d \ln p_{kj} - (1-\alpha) s_k \sum_j d \ln p_{kj} - \alpha \sum_j w_{kj} d \ln p_{kj} + d \ln d_k \tag{A3.2}$$

Using $\eta_k \sum_j d\ln p_{kj} \equiv d\ln d_k$ and rearranging terms, we obtain:

$$d\ln\hat{\lambda}_k = \underbrace{\sum_{j\in m}\left[\frac{\chi_k}{1-\sigma} + (\alpha-1)s_k + \eta_k\right] d\ln p_{kj}}_{\text{Quality-Upgrading Effect}} - \underbrace{\alpha\sum_j w_{kj}\, d\ln p_{kj}}_{\text{Cost Effect}} \quad \text{(A3.3)}$$

4. Trade Communities

We identify trade communities based on the global ICT trade network. Specifically, we employ the Blondel community detection algorithm (Blondel et al., 2008) to identify the community structure of the global ICT trade network in 2016 and 2020. The algorithm detects communities and their constituent members by maximizing the modularity function (Q). The clustering results for 2016 and 2020 are presented in the figure below. The results indicate that the global ICT trade network is primarily composed of three major trade communities.

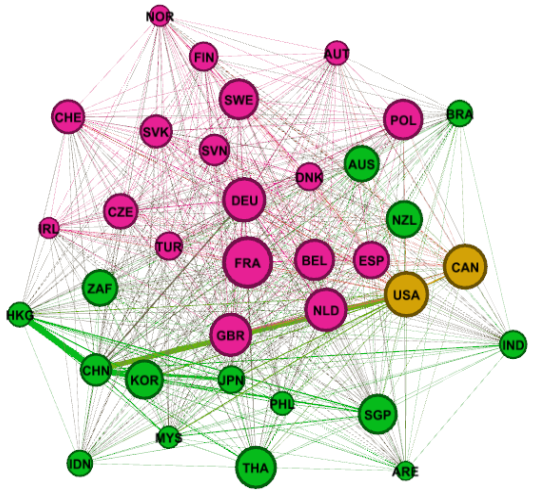


Figure A1. 2016ICT Trade Network

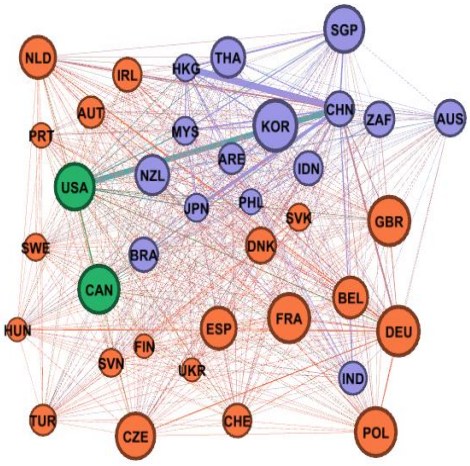


Figure A.2 2020ICT Trade Network

Table A.1 reports the degree centrality of the node, the number of community members, the betweenness centrality of the node, and the clustering coefficient for each trade community across different years. The results reveal a pronounced geographic pattern in the structure of ICT trade communities. The U.S.-centered trade community is primarily concentrated in North and South America. A comparison

between 2016 and 2020 further shows that the China-centered trade community experienced growth in both network size, as measured by the number of community members, and network density, as measured by the clustering coefficient.

Table A.1 Characteristics of ICT Trade Communities

Year	Community	Degree Centrality of Leading Nodes	Number of Members	Betweenness Centrality of Leading Nodes	Clustering Coefficient
2016	1	Singapore (SGP, 214); China (CHN, 209)	103	Singapore (SGP, 253); China (CHN, 205)	0.829
	2	France (FRA, 221); United Kingdom (GBR, 218)	76	France (FRA, 325); United Kingdom (GBR, 273)	0.787
	3	Canada (CAN, 217); United States (USA, 216)	44	Canada (CAN, 283); United States (USA, 287)	0.859
2020	1	Singapore (SGP, 214); China (CHN, 208)	112	Singapore (SGP, 285); China (CHN, 213)	0.840
	2	France (FRA, 218); United Kingdom (GBR, 217)	72	France (FRA, 300); United Kingdom (GBR, 301)	0.783
	3	Canada (CAN, 216); United States (USA, 214)	39	Canada (CAN, 294); United States (USA, 285)	0.858

Notes: Trade communities are identified using the Blondel algorithm (Blondel et al., 2008). Degree centrality counts direct trade links of the leading node. Betweenness centrality measures the node's role in mediating trade flows. The clustering coefficient captures the density of connections among community members. Higher values indicate stronger community cohesion.