Collaborative Innovation: A Strategic Pathway to Higher Domestic Value-added in Manufacturing Exports

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Abstract: *International trade research has long sought to investigate how manufacturers can upgrade within global value chains and escape the "low-end trap". This paper examines how collaborative innovation can facilitate this ascent, using an undirected weighted network of joint patent applications and firm-level data. By analyzing the network's structural characteristics and its evolution, we explore the mechanisms through which collaboration drives the rise of manufacturing enterprises within global value chains. Our findings show that: (1) China's rapidly expanding collaborative innovation network features a distinct "core-periphery" structure, with leading firms, universities, and government research institutions at its center. (2) By strengthening market power and enabling firms to take on more advanced production, collaborative innovation contributes to a higher domestic value-added rate in exports. (3) Heterogeneity analysis reveals that the impact of collaborative innovation on moving up the value chain is particularly evident for firms with strong production and technology absorption capabilities, those positioned lower in the value chain, and those facing fewer trade barriers.*

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1. Introduction

As the cost advantage of "Made in China" gradually erodes and new dynamics emerge—such as the dual pressures of "high-end reshoring" back to developed countries and "low-end offshoring" to developing nations (Liu & Wu, 2018)—there is an increasing urgency to identify new drivers for transforming "Made in China" into "Created in China". For Chinese manufacturers, this transition represents not just a challenge but a significant opportunity to redefine their position in the global economy. A crucial question is how these manufacturers can successfully ascend the global value chain (GVC).

Technological collaboration has emerged as a key strategy, enabling firms to pool R&D resources and strengthen their competitive edge (Li & Yu, 2016). Through collaborative innovation networks, firms can facilitate patent cooperation, technology transfer, and resource flows—key mechanisms that

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open pathways for deeper integration into GVCs. A prime example is the partnership between CRRC Zhuzhou Electric Locomotive Co., Ltd. and Zhuzhou Jiufang Equipment Co., Ltd. In June 2020, these companies leveraged joint innovation to develop an elastic wheel that reduces noise by 20 decibels for the Mexico City subway renovation project[1]. This breakthrough not only enhanced the project's quality but also eliminated China's reliance on imported components, underscoring the power of collaboration in advancing technological independence and integration within global supply chains.

Building on theoretical foundations, we analyze how collaborative innovation enables firms to climb the GVC ladder, formulating hypotheses about the specific mechanisms at play. We begin by constructing an undirected weighted collaborative innovation network using joint patent data from the China National Intellectual Property Administration (CNPA). Nodes in this network represent innovation actors (firms, universities, research institutes, government bodies, etc.), and edges represent collaborative patenting activity. Analysis of this network reveals its structural evolution and key characteristics, notably a rapid expansion and a distinct "core-periphery" structure, with leading industrial firms, prominent universities, and government research institutions at central positions.

Next, using the domestic value-added share of exports as a proxy for firms' GVC position and trade gains, we empirically assess the impact of collaborative innovation, finding that network participation enhances firms' domestic value-added. Furthermore, firms at the network's core are more likely to transition to higher-value-added activities. We then delve into the mechanisms driving this effect, examining both cost and technology channels. Our findings suggest that collaborative innovation networks enhance firms' export performance by strengthening their market power and enabling them to engage in more technologically sophisticated production processes.

Finally, we conduct a battery of robustness tests, employing multi-dimensional fixed effects, the Heckman two-stage model, and instrumental variables to address potential endogeneity concerns. Heterogeneity analysis across firm production capacity, technology absorption capacity, industry value chain position, and trade barrier risk reveals that the positive impact of collaborative innovation on GVC upgrading is particularly significant for firms with high levels of production and technology absorption capacity, initially in lower GVC positions, and facing lower trade barrier risks.

The literature relevant to this paper can be broadly divided into two main strands. The first focuses on the drivers of global value chain (GVC) upgrading and the barriers firms encounter in this process. GVC upgrading refers to the shift of economic actors from lower-value to higher-value activities within the international division of labor. Research has identified various factors influencing this transition, including institutional elements such as the business environment and property rights protection (Peng & Wu, 2022), as well as economic variables like factor endowments, technological capabilities, and trade liberalization, all of which shape national or regional GVC positioning (Tang & Zhang, 2018; Mao & Xu, 2019; Liu et al., 2021). Within the GVC framework, developed economies tend to capitalize on their technological advantages to dominate higher-value segments, while developing economies usually follow a path of "process upgrading → product upgrading → functional upgrading → chain upgrading". However, this progression is often hindered by several challenges, such as limited access to advanced knowledge, difficulties in enhancing competitive capabilities, and the strategic disadvantages posed by more advanced nations. These constraints can trap domestic firms in low-value-added activities and create technological path dependence. From the perspective of development economics, some scholars argue that technological revolutions and innovation represent a key pathway for developing countries to break free from these barriers and achieve GVC upgrading in manufacturing (Oliveira et al., 2021).

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[1] This research was also informed by the "Strengthening the Chain: The Backbone of the Industrial Chain" series report launched by the "China Economic Forum" program of CCTV2 Finance Channel, China Central Television.

The second strand of literature explores the concept and impact of collaborative innovation. Unlike traditional models of independent R&D, where risks and rewards are borne solely by individual firms, collaborative innovation adopts an open innovation approach. It is rooted in social network embedding, knowledge transfer, and resource integration (Wang et al., 2021). This innovation typically manifests through networks formed by joint patent applications during cooperative efforts. With growing market competition and increasing technological complexity, few firms can monopolize innovation resources or possess comprehensive innovation capabilities. As a result, collaborative innovation has emerged as a key avenue for inter-firm learning and technological complementarity. By fostering the exchange of both domestic and international ideas, it facilitates the flow of tacit knowledge and the integration of diverse technologies (Hervas-Oliver et al., 2021). This collaborative process helps firms break free from technological lock-in and rigid innovation patterns, driving substantial advancements in their technological capabilities. The existing literature not only underscores the pivotal role of collaborative innovation in technology diffusion but also highlights the positive impact of specific innovation models—such as industry-university-research partnerships, R&D alliances between firms, and transnational patent cooperation—on both financial performance and technological innovation outcomes (Wei & Yuan, 2018; Zhao et al., 2020; Kai et al., 2022).

Prior research has underscored the critical role of technological innovation in global value chain (GVC) upgrading and has provided valuable insights into the spillover and cost-sharing benefits of collaborative innovation. However, several important gaps remain. For instance, existing literature on the impact of technological innovation on GVC upgrading has not sufficiently differentiated between the effects of enterprise collaborative innovation and independent R&D. Further research is needed to systematically explore the relationship between collaborative innovation and GVC upgrading, as current theoretical and empirical studies on this subject are limited. Additionally, unlike independent R&D, collaborative innovation involves a complex network of interacting actors, which requires a network-based approach to accurately measure its effects.

This paper makes three key contributions. First, it clarifies the unique characteristics of collaborative innovation compared to independent R&D, emphasizing its advantages in reducing R&D costs and improving innovation quality. It also provides a theoretical framework to explain the factors driving the positive influence of collaborative innovation on firms' GVC upgrading, setting the stage for future research in this area. Second, from a network perspective, this paper quantitatively assesses the effects and mechanisms by which collaborative innovation impacts firms' domestic value-added share of exports. Based on these findings, it offers policy recommendations aimed at leveraging collaborative innovation to address challenges and promote high-quality development in the manufacturing sector, thereby expanding the research on GVC upgrading.Third, this paper constructs a collaborative innovation network using social network analysis methods to evaluate the level of firms' collaborative innovation. By analyzing the network's topological features and structural evolution, this approach provides a more scientifically rigorous and reliable measure than traditional methods. It enables a more accurate identification of collaborative innovation activities while reducing potential biases, such as double counting and over-dispersion.

2. Theoretical Analysis and Research Hypotheses

In recent years, market dynamics and the evolving innovation landscape have intensified the pressures on technological innovation, driven by factors such as shorter product life cycles, faster knowledge iteration, and the growing complexity of technological advancements. These pressures have begun to erode the "virtuous cycle" of independent R&D that many enterprises once relied upon[2].

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[2] The "virtuous cycle" of independent R&D refers to: increased investment in R&D → fundamental technological breakthroughs → development of new products or new performance features → achieving higher sales and profits through existing business models → further investment in R&D.

To mitigate the uncertainties associated with R&D and overcome limitations in their own resources, companies are increasingly turning to external technical collaborations. Collaborative innovation has thus become a crucial strategy for achieving technological progress.

According to the framework of Belso-Martinez & Diez-Vial (2018), companies face decisions about whether to establish innovative partnerships with other entities, such as other companies, universities, research institutions, and government organizations. These partnerships collectively form a collaborative innovation network. The more innovative partnerships an enterprise has, the more central its position is within the network, which in turn enhances its ability to leverage, integrate, and share diverse resources, such as knowledge and technology (Wang & Hu, 2020).

Unlike traditional independent R&D models, where firms bear the full risk and reward, collaborative innovation emphasizes the synergistic combination of internal and external innovation resources. It essentially constitutes an innovation network built upon technological partnerships, facilitating the sharing of R&D resources and the distribution of R&D risks. Collaborative innovation offers two primary advantages: reduced R&D costs and enhanced innovation quality.

First, existing research suggests that collaborative innovation serves as an effective mechanism for addressing insufficient internal R&D investment (Kafouros et al., 2015). By transcending the boundaries of internal and external innovation resources, collaborative innovation enables firms to integrate complementary resources from within the network, alleviate R&D investment pressures, and accelerate the technology innovation cycle (Yan & Dooley, 2014). This effectively lowers R&D costs, thereby maximizing firms' innovation benefits.

Second, some literature argues that collaborative innovation promotes knowledge openness and helps firms overcome technological lock-in (Beers & Zand, 2014), leading to increased innovation success rates and broader technical knowledge (Li et al., 2022). These factors can directly or indirectly influence firms' global value chain (GVC) strategic choices.

Therefore, building on existing research on the concept and effects of collaborative innovation, this paper analyzes the impact and mechanisms of collaborative innovation networks on firms' domestic value-added share of exports from the perspectives of cost effects and technology effects. Based on this analysis, we develop research hypotheses to provide a theoretical basis for the subsequent empirical analysis.

The cost-effectiveness channel suggests that collaborative innovation plays a key role in facilitating the sharing of innovation resources and complementary strengths among partners, which can significantly lower unit R&D costs and, in turn, drive the growth of the domestic value-added rate of exports. Specifically, collaborative innovation fosters a strong integration of innovation resources. Through international scientific and technological cooperation, shared research facilities, academic exchanges, and other collaborative efforts, partners can pool their complementary resources for joint research and value co-creation. This not only enhances the efficiency of resource utilization in enterprises, but also mitigates R&D risks, shortens innovation cycles, and lowers unit R&D costs (Cen et al., 2022).

From a theoretical perspective, a reduction in R&D costs incentivizes firms to engage more in innovation activities (Zhu et al., 2017), thereby improving their production efficiency. This, in turn, influences their market power and cost markup. According to the framework established by Kee & Tang (2016), there is a significant positive relationship between the domestic value-added rate of exports and both enterprise cost markup and the relative price of intermediate inputs. With input prices held constant, manufacturing firms with higher cost markups possess greater pricing and market power, which helps increase the domestic value-added component of their exports.

Thus, this paper posits that enterprises participating in collaborative innovation networks can leverage, integrate, and share heterogeneous innovation resources to reduce R&D costs and enhance production efficiency. In doing so, they can boost their cost markup and market power, ultimately raising the domestic value-added rate in manufacturing exports.

The "technology effect" channel suggests that collaborative innovation enhances firms' technological capabilities and knowledge base, enabling them to engage in or take on more advanced production segments. This, in turn, leads to a significant increase in the domestic value added to manufacturing export products. Late-industrializing countries, aiming to climb the global value chain, often face challenges like the "low-end trap" and path dependence (Lyu et al., 2018). Research indicates that collaborative innovation fosters knowledge openness, helping firms overcome technological lock-in (Beers & Zand, 2014), which improves innovation success rates and broadens their technological expertise.

First, the exchange of advanced innovation ideas and creative problem-solving among partners in collaborative innovation helps firms overcome existing technological paradigms, enabling breakthroughs in critical core technologies (Walsh et al., 2016). This drives technological progress by leveraging collective knowledge.

Second, participation in collaborative innovation networks accelerates technology spillovers between partners and facilitates the integration of technologies from different knowledge domains. This can significantly enhance the quality and breadth of firms' innovations (Nieto et al., 2007).

As a result, by expanding their technological capabilities and knowledge, firms embedded in collaborative innovation networks can take on more high-tech production segments, leading to an increase in the domestic value added in their export products. This, in turn, raises the domestic value-added ratio for manufacturing enterprises.

In conclusion, manufacturing firms involved in collaborative innovation networks can influence the domestic value-added rate of exports through two primary channels: the "cost effect" and the "technology effect". Building on this, this paper proposes:

Hypothesis 1: Collaborative innovation contributes to a higher domestic value-added rate of exports for firms.

Hypothesis 2: Collaborative innovation affects firms' domestic value-added rate of exports through both cost effect and technology effect channels.

3. Variables, Data, and Model Specification

3.1 Domestic Value Added Ratio of Exports

Upward et al. (2013) were the first to use the Domestic Value Added Ratio (DVAR) of exports to measure a firm's competitiveness and position in the global production division of labor. However, their calculation method has certain limitations, as it assumes that all imports are used as intermediate inputs and does not consider issues such as trade intermediaries, the types of imported products, and the overseas components of domestic intermediate inputs. With the continuous deepening of related research, Zhang et al. (2013) and Lyu et al. (2018) have made improvements in terms of trade intermediaries, product classification, and firms' indirect imports.

Existing literature often assumes a uniform 5% foreign value-added content in firms' domestic intermediate inputs when calculating DVAR (Koopman et al., 2012). However, this assumption overlooks significant inter-industry variations in the proportion of indirect imports and fails to account for the returned value-added from inter-firm product transactions—that is, the domestic value-added embedded in imported products that are subsequently returned to and absorbed by the home country. In addition to the potential overseas components in domestic intermediate products used by firms, imported intermediate products may also contain domestic value-added. The former should not be included in DVAR, while the latter should (Su et al., 2020). To address these issues, this paper improves the DVAR calculation by incorporating a more nuanced approach. Specifically, it uses the World Input-Output Database (WIOD) to determine the proportion of indirect imports and the proportion of returned value-added within the industry to which a firm belongs. The calculation is further refined by classifying data based on the enterprise's trade type, as shown in Equation (1):

$$DVAR=\begin{cases} DVAR^{p}=1-\dfrac{M_{A}^{p}+\theta_{j}^{1}DII-\theta_{j}^{2}M_{A}^{p}}{X} \\ DVAR^{o}=1-\dfrac{M_{A,BEC}^{o}\cdot(X^{o}/(D+X^{o}))+\theta_{j}^{1}DII-\theta_{j}^{2}M_{A,BEC}^{o}}{X} \\ DVAR^{m}=1-\dfrac{X_{A,BEC}^{p}+X_{A,BEC}^{o}\cdot[X^{o}/(D+X^{o})]+\theta_{j}^{1}DII-\theta_{j}^{2}(M_{A,BEC}^{p}+M_{A,BEC}^{o}(X^{o}/(D+X^{o})))}{X} \end{cases} \tag{1}$$

In Equation (1), the superscript p denotes processing trade, o denotes ordinary trade, and m denotes mixed trade; the subscripts A and BEC respectively indicate intermediate products indirectly adjusted through trade intermediaries and identified by Broad Economic Categories (BEC) coding; θ_j^1 and θ_j^2 respectively represent the proportion of indirect imports and the proportion of returned value-added in the industry j where the enterprise is located; M, X, and D respectively represent the enterprise's import value, export value, and domestic sales value; DII represents the total domestic intermediate inputs used by the enterprise. The variable symbol settings are consistent with the existing literature. For example, M_A^p represents the import value of processing trade enterprises indirectly adjusted through trade intermediaries, and the remaining variables are similarly defined.

3.2 Collaborative Innovation Network

It is crucial to accurately measure and effectively identify collaborative innovation behavior. To achieve this, this paper utilizes the patent search system of the State Intellectual Property Office to create a collaborative innovation database. It then combines web crawlers and big data text analysis techniques to collect and organize joint patent application information. Drawing on social network analysis methods from Wang & Hu (2020) and Yang & Wang (2020), we construct an undirected weighted collaborative innovation network based on innovation entities and their patent cooperation relationships. This network consists of nodes and edges, where nodes represent innovation entities (such as enterprises, universities, research institutes, and government organizations), and edges represent patent cooperation relationships. For example, if applicants A, B, and C jointly apply for the same patent, it is considered that there is a patent cooperation relationship between A and B, A and C, and B and C. The cooperation relationships for other patents are confirmed using similar principles.

Liu & Ma (2021) developed a global innovation network based on patent citations to explore the optimal inter-sectoral allocation of R&D resources. They argued that more R&D funding should be directed towards departmental nodes with high centrality in the innovation network in order to achieve potentially optimal welfare gains from R&D. Building on this concept, the current paper extends the idea by using the weighted degree centrality (WDC) of firms in the collaborative innovation network to measure the strength of their collaborative innovation ties with other entities. Drawing on the work of Wang & Hu (2020), the weighted degree centrality of firm i in year t can be expressed by Equation (2):

$$WDC_{it}=\sum\nolimits_{i\neq j}^{n}\delta_{ijt} \tag{2}$$

In Equation (2), δ_{ijt} represents the patent cooperation relationship established between enterprise i and innovation entity j in the collaborative innovation network in year t. In an undirected weighted collaborative innovation network, weighted degree centrality is an indicator for measuring the level of collaborative innovation of innovation entities. It can reflect the breadth and strength of collaborative innovation between enterprise i and other entities, and can measure the network entity's ability to integrate and share innovation resources, the learning, absorption, transformation, and dissemination capabilities of knowledge and technology, as well as the network position and influence in the collaborative innovation network (Wang et al., 2023).

3.3 Data Description

This study constructs a firm-level collaborative innovation database by integrating patent data from the State Intellectual Property Office's patent search system with web scraping and big data text analysis techniques. The data sources include the firm collaborative innovation database, the China Industrial Enterprise Database, and the China Customs Import and Export Database. A panel data structure is created by matching patent, product, and firm-level data annually, covering the period from 2000 to 2015. The key steps are as follows:

First, identification of collaborative innovation: Patents with two or more applicants are classified as collaborative innovation patents. To focus on meaningful technological innovation, only invention patents are considered, excluding design and utility model patents due to their lower technical value. Additionally, patents co-applied by individuals as the primary applicant are excluded from the sample.

Second, data matching: Data from the China Industrial Enterprise Database, the firm collaborative innovation database, and the China Customs Import and Export Database are linked annually using firm names and patent applicant identifiers.

Third, indicator processing: Trade intermediaries or agents are identified and removed from the dataset. Firms that have not filed patents during the sample period are excluded to ensure that comparisons between collaborative innovation and independent R&D are based on firms actively involved in technological innovation. All continuous economic variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers.

Ultimately, the dataset includes 197,171 "firm-year" observations, covering 38,804 firms across 30 two-digit manufacturing industries.

3.4 Stylized Facts Analysis

3.4.1 Topological features of the collaborative innovation network

Since 2000, China's collaborative innovation network has experienced rapid growth in both scale and connectivity, as shown in Figure 1. During the sample period, key metrics such as the number of collaborative innovation applications (network edges), the number of entities (network nodes), and the average weighted degree[3] all exhibited significant upward trends. Specifically, the number of collaborative innovation applications increased from 7,484 in 2000 to 105,481 in 2015, reflecting an average annual growth rate of 19.29%. Similarly, the number of collaborative innovation entities grew substantially, from 5,905 in 2000 to 36,459 in 2015, a fivefold increase. In addition, the average weighted degree of the network continued to rise, indicating a steady improvement in both the overall connectivity and the density of the network. These trends collectively highlight the ongoing expansion and strengthening of China's collaborative innovation network over the sample period, underscoring the increasing intensity of collaboration and integration across innovation entities.

3.4.2 Evolution of the collaborative innovation network structure

To examine the dynamic evolution of China's collaborative innovation network structure, this paper divides its development into two distinct stages based on network scale and the number of network relationships. It compares the evolutionary characteristics of the network's spatial structure across different periods[4]. The study reveals the following findings: In the early stage of the collaborative innovation network (2000-2008), both cooperative relationships and network density were relatively

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[3] The average weighted degree is generally used to measure the overall connectivity of a network. It is measured using the average value of the weighted degree centrality of all nodes. The larger the average weighted degree, the higher the overall connectivity and network density.

[4] Due to space constraints, the evolutionary maps of the collaborative innovation network structure for different stages are not reported but are available upon request.

sparse. Key players in the network included foreign enterprises (e.g., Hitachi, Mitsubishi Electric, Panasonic), large state-owned enterprises (e.g., State Grid Corporation of China, Baoshan Iron & Steel Co., China Petrochemical Group), and Sino-foreign joint ventures (e.g., Haier Group), which held central positions within the network. The distribution of innovation entities was relatively balanced, and the network displayed characteristics of evenly distributed connections and strong overall connectivity. In the subsequent stage between 2009 and 2015, the number of nodes in the collaborative innovation network grew significantly, with cooperative relationships becoming closer and knowledge exchange occurring more frequently. This period saw the emergence of a clear "core-periphery" spatial structure, centered around leading enterprises in the industrial chain, science and engineering universities, and government research institutions.

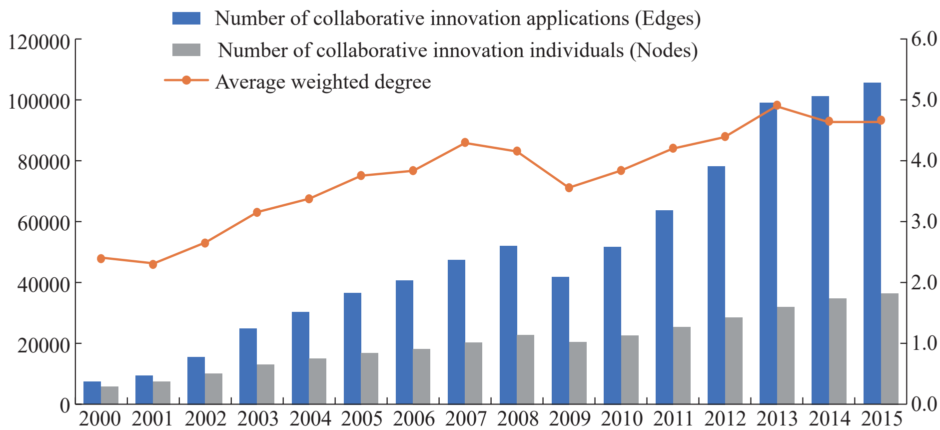

Figure 1: Topological Features of the Collaborative Innovation Network, 2000-2015

Source: Compiled by the authors based on data from the patent search system of the State Intellectual Property Office (SIPO).

3.5 Econometric Model Specification

Based on the theoretical analysis and research hypotheses presented above, this paper focuses on examining the impact and mechanisms of collaborative innovation network embeddedness on firms' domestic value-added share of exports. Therefore, the following baseline regression model is specified:

$$DVAR_{i,t}=\beta_0+\beta_1 Coinno_{i,t-1}+\beta_2 X_{i,t-1}+\mu_{t-1}+\gamma_i+\varepsilon_{i,t} \tag{3}$$

In equation (3), i and t represent the enterprise and year, respectively, and ε is the random error term. $DVAR_{i,t}$ represents the domestic value-added rate of exports of enterprise i in year t, measuring the firm's true trade gains and position in the global value chain. $Coinno_{i,t-1}$ represents the level of collaborative innovation of enterprise i in year $t-1$, measured using the logarithm of the weighted degree centrality of the enterprise in the collaborative innovation network. $X_{i,t-1}$ is a set of control variables that may affect the domestic value-added rate of exports of the enterprise. In order to control the interference of enterprise and time-level influencing factors on the core causal relationship, the baseline model includes time fixed effects μ_{t-1} and enterprise fixed effects γ_i to control potential omitted variable bias, and clusters the standard errors at the enterprise level. All explanatory variables and control variables in this paper are lagged by one period to reduce the endogeneity problem caused by reverse causality.

The control variables ($X_{i,t-1}$) include:

(1) Firm independent R&D level ($Inno_{i,t-1}$): Since technological innovation capability is a key factor for firms to participate in the global value chain, in order to distinguish between firms' collaborative innovation and independent R&D behavior, this paper uses the logarithmic form of the difference between the total number of patent applications and the number of joint patent applications to measure

the firm's independent R&D level.

(2) Firm age ($Age_{i,t-1}$): Firms at different life cycle stages have great differences in trade decision-making and R&D characteristics. Firm age is an important influencing factor of the domestic value-added rate of exports. It is measured by the difference between the firm's start-up time (in years) and the year of the sample, and then logarithmically processed.

(3) Firm size ($Size_{i,t-1}$): It is measured by the logarithm of the firm's total assets at the end of the year. Larger firms may have more production activities, and thus have the need to participate in the global value chain and global production networks.

(4) Productivity ($Labor_{i,t-1}$): After 2007, some key indicators in the China Industrial Enterprise Database are missing, and it is impossible to accurately estimate total factor productivity. This paper uses the firm's labor productivity as a proxy variable for productivity, which is expressed by the logarithm of the firm's per capita industrial output value.

(5) Firm export intensity ($Expint_{i,t-1}$): Export intensity is a key factor for firms to participate in the global value chain division of labor. It is measured by the ratio of the firm's total exports to its total industrial sales output.

(6) Firm external financing constraints ($FC_{i,t-1}$): It is measured by the ratio of the firm's total interest expense to its total fixed assets. The larger the value, the greater the firm's external financing constraints.

(7) Industry concentration ($HHI_{j,t-1}$): It is expressed by the Herfindahl-Hirschman Index at the four-digit code industry level.

4. Empirical Results and Analysis

4.1 Baseline Estimation Results

The research hypothesis suggests that collaborative innovation enhances firms' true trade gains and their position within the global value chain, as measured by the domestic value-added rate of exports. Table 1 presents the baseline regression results. Column (1) controls for fixed effects and examines the impact of the collaborative innovation network on firms' domestic value-added rate of exports. The results show a significant positive coefficient for $Coinno_{i,t-1}$, indicating that collaborative innovation notably improves firms' domestic value-added exports, enabling Chinese manufacturing firms to move from low-value-added to higher-value-added stages in the global value chain.

Column (2) presents results after including control variables, time effects, and firm-specific fixed effects. The coefficient for the main explanatory variable $Coinno_{i,t-1}$ remains positive and highly significant (at the 1% level), confirming the robustness of the results even after accounting for firm and industry-level factors and unobserved fixed effects. This further substantiates the role of collaborative innovation in facilitating value chain advancement.

Column (3) additionally controls for firms' independent R&D activities. The coefficients for both $Coinno_{i,t-1}$ and $Inno_{i,t-1}$ are significantly positive at the 1% level, with the coefficient for collaborative innovation ($Coinno_{i,t-1}$) being larger. These findings suggest that both collaborative innovation and independent R&D significantly contribute to increasing the domestic value-added rate of firms' exports. However, collaborative innovation appears to offer a greater advantage. Firms engaged in cooperative innovation networks are better positioned to enhance their domestic value-added capabilities and global division of labor, providing stronger momentum for Chinese manufacturing to move up the global value chain.

In summary, even after accounting for various influencing factors, collaborative innovation plays a crucial role in boosting the domestic value-added rate of firms' exports.

4.2 Robustness Checks

4.2.1 Using an alternative global value chain indicator

To examine whether the baseline regression results change with adjustments in the variable

Table 1: Baseline Regression Results

Variable	(1)	(2)	(3)
	$DVAR_{i,t}$	$DVAR_{i,t}$	$DVAR_{i,t}$
$Coinno_{i,t-1}$	0.004**	0.004***	0.005***
	(0.002)	(0.001)	(0.001)
$Inno_{i,t-1}$			0.002***
			(0.001)
$Age_{i,t-1}$		-0.006***	-0.006***
		(0.002)	(0.002)
$Size_{i,t-1}$		0.002	0.002
		(0.001)	(0.001)
$Labor_{i,t-1}$		-0.004***	-0.004***
		(0.001)	(0.001)
$Expint_{i,t-1}$		0.100***	0.100***
		(0.003)	(0.003)
$FC_{i,t-1}$		0.014**	0.014**
		(0.006)	(0.006)
$HHI_{j,t-1}$		0.003	0.003
		(0.007)	(0.007)
Fixed effects	Yes	Yes	Yes
Sample size	197 171	197 171	197 171
Within R^2	0.065	0.079	0.079

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed). The values in parentheses are the enterprise-level clustered standard errors of the regression coefficients. Due to space limitations, the results for the constant term are omitted. Fixed effects represent time and enterprise fixed effects. Unless otherwise specified in the following tables, they all have the same settings as this table.

calculation method, this paper uses the Global Value Chain Status Index (*Pos*) calculated by Su et al. (2020) for robustness testing, and the estimation results are shown in column (1) of Table 2. The robustness test shows that after including the control variables and fixed effects, the coefficient of the core explanatory variable is significantly positive, which indicates that embedding in the collaborative innovation network can significantly improve the global value chain division of labor position of enterprises, and the regression results further confirm the robustness of the basic conclusions.

4.2.2 Using alternative collaborative innovation indicators

For robustness, this paper builds on the research of Liang & Liu (2018) and uses two alternative variables—*Betweenness* of the collaborative innovation network and the number of partners (*Partner*)—to serve as substitutes for the core explanatory variables. A corresponding robustness analysis is then conducted to test the validity of the results. The estimation results are shown in columns (2) and (3) of Table 2. The results show that the variable estimation coefficients are significant and positive at the 1% level, indicating that deeper and broader integration into the collaborative innovation network is conducive to the improvement of the domestic value-added rate of enterprise exports.

4.2.3 Replacement of estimation methods

The domestic value-added rate of enterprise exports ranges between 0 and 1, making it a typical restricted dependent variable. Using ordinary least squares (OLS) for estimation in this context can lead to biases and other issues. Therefore, we employ a two-sided censored Tobit model as an alternative. However, in the case of a Tobit model with panel fixed effects, the absence of a sufficient statistic for

Table 2: Robustness Analysis Results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	GVC Position	Betweenness Centrality	Number of Partners	Tobit Model	Exclusion of Developed Cities	Exclusion of Internal R&D
$Coinno_{i,t-1}$	0.005***			0.021***	0.005**	0.004**
	(0.001)			(0.006)	(0.002)	(0.002)
$Betweeness_{i,t-1}$		0.003**				
		(0.001)				
$Partner_{i,t-1}$			0.004***			
			(0.002)			
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	196 669	197 171	197 171	197 171	112 469	196 617
Within R^2	0.180	0.079	0.079	0.304	0.077	0.079

Note: Column (4) includes time, industry, and region fixed effects, and reports Pseudo R2 in the results of the two-sided censored Tobit regression.

individual effects prevents estimation through conditional maximum likelihood estimation (MLE). As a result, this paper does not control for firm-level fixed effects. Instead, we estimate the Tobit model by incorporating control variables along with fixed effects for year, industry, and region, while clustering the standard errors at the firm level. The test results are presented in column (4) of Table 2. The estimated coefficient for *Coinno* remains significantly positive, suggesting that collaborative innovation significantly enhances the domestic value-added rate of enterprise exports. This confirms that the core conclusion of this paper holds.

4.2.4 Sample adjustment

(1) Excluding samples from developed cities. Enterprise collaborative innovation is closely tied to the economic characteristics of the city in which the enterprise is located. Large cities, as primary hubs for innovation resources, offer superior business environments and have a stronger ability to integrate resources, making them ideal platforms for innovation and entrepreneurship. The willingness to engage in collaborative innovation and the foundational conditions for scientific research vary significantly across cities with different levels of economic development. This raises the question of whether the effect of climbing the global value chain through collaborative innovation could lead to statistical distortions due to urban economic disparities. To test this, we exclude samples from municipalities directly under the central government, provincial capitals, and sub-provincial-level cities. This adjustment allows us to assess the robustness of our benchmark results. The findings, presented in column (5) of Table 2, indicate that the coefficient for the core explanatory variable remains significantly positive, thereby further supporting the enabling role of collaborative innovation in helping enterprises ascend the global value chain.

(2) Excluding internal collaborative innovation within enterprise groups. Helble & Chong (2004) highlighted that R&D cooperation between parent and subsidiary companies within a corporate group is a key form of collaborative innovation. Internal collaboration within a group reflects a specialized division of labor among its subsidiaries, which differs from R&D cooperation between independent innovation entities. To address this distinction, we follow the approach of Sun & Cheng (2020) by excluding samples where a significant number of patents are jointly held within the same enterprise group. The results after this adjustment are presented in column (6) of Table 2. These findings demonstrate that, even after excluding internal collaborative innovation within enterprise groups, the core explanatory variable's coefficient remains significantly positive. This reinforces the robustness of

the observed relationship between the level of collaborative innovation and the domestic value-added rate of exports.

4.3 Endogeneity Problems and Solutions

4.3.1 Omitted variable

Although the baseline regression accounts for control variables and fixed effects at various levels, data limitations prevent the inclusion of certain unobservable, time-varying industry-level factors, such as market conditions, technological changes, and shifts in industry structure. These omitted variables could introduce bias into the estimated results. To address the potential endogeneity problem arising from these omissions, existing studies typically apply cross-fixed effects methods for control. In response, we incorporate "industry-year" level fixed effects into the benchmark model to better account for the influence of unobservable, time-varying industry factors on the domestic value-added rate of enterprise exports. The estimation results, presented in column (1) of Table 3, show that the coefficient of the core explanatory variable is significantly positive at the 1% level, reinforcing the conclusions drawn from the initial analysis.

4.3.2 Sample selection bias

Enterprise export decision-making is an endogenous process driven by internal factors unique to each firm. Typically, only a small subset of high-productivity enterprises can overcome trade barriers and successfully enter international markets. Additionally, the decision to export impacts the domestic value-added rate of a firm's exports. Given the large number of export firms in the matched sample from the China Industrial Enterprise Database and the Customs Database, there may be concerns about potential endogeneity arising from sample selection bias. To address this, this paper employs the Heckman two-step method to control for endogeneity caused by sample selection bias. It constructs a Probit model to estimate the probability of a firm exporting, using variables such as firm size, years of operation, and ownership structure. The inverse Mills ratio (*IMR*) is then calculated and included as a control variable. The results, presented in column (2) of Table 3, show that the coefficients for *Coinno* and *IMR* are both statistically significant, confirming that after accounting for sample selection bias, the core findings of this paper remain robust.

4.3.3 Reverse causality

Firms endogenously choose collaborative innovation (Calcagnini et al., 2016). Firms with strong competitiveness in the global value chain may attract other partners, fostering active collaboration. However, this can lead to reverse causality, where the observed relationship between collaborative innovation and firm performance may be influenced by unobserved factors, raising concerns of endogeneity.

To address potential reverse causality in the baseline regression, we mitigate this issue by lagging all explanatory and control variables by one period. Despite this, residual endogeneity bias may still persist. To further reduce the influence of reverse causality, this study employs an instrumental variable approach (IV-2SLS). Specifically, we use two instrumental variables: the number of national science and technology business incubators (*TBI*, IV I) and the national innovative city pilot policy (*City*, IV II). These variables serve as instruments for enterprise-level collaborative innovation, and we estimate the model using the two-stage least squares (2SLS) method.

The choice of instrumental variables is based on two key considerations. First, national science and technology business incubators, along with innovative city pilots, are strategic initiatives to foster innovation in China. They offer incentives such as office space, shared R&D facilities, and tax reductions to technology firms, encouraging domestic and international collaboration, industry-university-research partnerships, and other forms of cooperation (Kang et al., 2022). This aligns with the instrumental variables' relevance assumption. Second, these incubators and pilot cities are evaluated annually by the Ministry of Science and Technology and are not directly influenced by firm-level actions. The policy measures target R&D and innovation, not firms' trade decisions, thus meeting the "exclusion restriction" and satisfying the exogeneity assumption for instrumental variables.

The number of national science and technology business incubators in each city each year comes from the *China Torch Statistical Yearbook*. This paper manually collects the cities where national science and technology business incubators are located and their evaluation time, and cumulatively aggregates them at the "city-year" level. The national innovative city pilot information comes from the List of Innovative City Pilot Projects of the Ministry of Science and Technology. This paper introduces the above two instrumental variables for two-stage regression separately, and the estimation results are shown in columns (3) through(6) of Table 3. It can be seen that after considering control variables, fixed effects, and endogenous factors, the estimated coefficient of the core explanatory variable $Coinno_{i,t-1}$ is still significantly positive, indicating that embedding in the collaborative innovation network can significantly improve the domestic value added rate of enterprise export, which helps Chinese manufacturing enterprises to leap to the high-end of the global value chain. In addition, each instrumental variable has passed the under-identification test and the weak instrumental variable test, indicating that the instrumental variables selected in this paper have validity and rationality.

Table 3: Results of Endogeneity Analysis

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Industry-Year Fixed Effects	Heckman two-step estimation	Instrumental Variable I		Instrumental Variable II	
			Stage 1	Stage 2	Stage 1	Stage 2
Coinno	0.004^{***}	0.005^{***}		0.208^{***}		0.196^{***}
	(0.001)	(0.001)		(0.051)		(0.036)
IMR		0.006^{***}				
		(0.001)				
TBI			0.011^{***}			
			(0.001)			
City					0.072^{***}	
					(0.005)	
Under-identification test	—		107.380^{***}		195.493^{***}	
Weak identification test	—		107.187^{***}		199.503^{***}	
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	197 171	196 908	197 171	192 307	197 171	192 307
Within R^2	0.082	0.079	0.023	—	0.024	—

Note: Column (1) additionally includes industry-year level fixed effects; the Kleibergen-Paap rk LM and Kleibergen-Paap rk Wald F statistics are used for the under-identification and weak identification tests, respectively, and the standard errors of the instrumental variables are clustered at the city level.

5. Mechanism Test and Heterogeneity Analysis

5.1 Mechanism Test

A clear understanding of the influencing channels is crucial for deciphering the internal dynamics between a collaborative innovation network and the global value chain position of enterprises. Based on theoretical analysis and research hypotheses, it is suggested that collaborative innovation primarily impacts the domestic value-added rate of enterprise exports through two key channels: the cost effect channel and the technology effect channel. Drawing on causal inference research by Jiang (2022), this paper aims to examine the causal relationship between the core explanatory variable and the mechanism variable. The mechanism test model is formulated as follows:

$$M_{i,t}=\alpha_0+\alpha_1 Coinno_{i,t}+\alpha_2 X_{i,t}+\mu_t+\gamma_i+\varepsilon_{i,t} \tag{4}$$

In equation (4), $M_{i,t}$ represents the mechanism variable to be tested, μ_t is the time fixed effect, γ_i is the firm individual fixed effect, $\varepsilon_{i,t}$ is the random error term, and the control variable ($X_{i,t}$) is consistent with the baseline regression.

5.1.1 Cost effect mechanism

Our theoretical analysis suggests that collaborative innovation facilitates resource sharing and complements partners' strengths. This can significantly reduce unit R&D costs and increase enterprise cost markup, which, in turn, boosts the domestic value-added rate of manufacturing exports. To verify this mechanism, we examine the effect of involvement in a collaborative innovation network on both unit R&D costs and enterprise cost markup rates.

In this study, we use the ratio of research and development expenses to the number of patents filed by enterprise *i* in year *t* as a proxy for the enterprise's unit R&D cost. Following the production function approach of De Loecker & Warzynski (DLW, 2012), we calculate the cost markup rate at the enterprise-year level. The results of the cost effect mechanism test are presented in Table 4.

Column (1) reports the impact of collaborative innovation on the unit R&D costs of enterprises. The coefficient for *Coinno* is significantly negative at the 1% level, indicating that collaborative innovation allows firms to integrate complementary resources within the network, improving the efficiency of innovation resource use and reducing R&D costs. This reduction in costs encourages firms to engage in more innovation activities, ultimately improving production efficiency.

Additionally, we explore the impact of collaborative innovation networks on enterprise cost markup rates. The results, presented in Column (2) of Table 4, show a significantly positive coefficient for the core explanatory variable. This suggests that participation in collaborative innovation networks significantly increases the cost markup rate of firms. According to the export domestic value-added rate model developed by Kee & Tang (2016), a higher cost markup is positively associated with an increase in the export domestic value-added rate. This finding implies that collaborative innovation can enhance the real trade income and improve the international division of labor for manufacturing enterprises engaged in the global value chain through the cost effect channel.

Table 4: Mechanism Test Results

Variable	(1)	(2)	(3)	(4)
	Unit R&D Cost	Cost Markup	Knowledge Breadth	Export Technology Sophistication
Coinno	-0.068***	0.021***	0.036***	0.024***
	(0.012)	(0.007)	(0.002)	(0.006)
Control variable	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Sample size	45199	285532	285699	260104
Within R^2	0.035	0.153	0.336	0.092

Note: Column (1) omits some years due to the unavailability of R&D expense data in the China Industrial Enterprise Database after 2007.

5.1.2 Cost effect mechanism

Theoretical analysis and research hypotheses suggest that collaborative innovation helps companies expand their technical scope and knowledge breadth, allowing them to engage in higher-tech production processes and increase the domestic value added to their export products. Here, we will test this impact channel. Based on existing literature, this paper measures the technical effect mechanism of manufacturing enterprises in China from the following two aspects: First, knowledge breadth, which directly reflects innovation quality and the expansion of technical knowledge. This paper uses the logarithmic form of the patent knowledge breadth of enterprise i in year t for measurement. Second, the technical complexity of export products increases when firms participate in or undertake more high-tech production. Therefore, this paper selects the technical complexity index of export products of enterprise i in year t for verification.

Table 4 presents the results of the mechanism tests for the technical effect channel. Column (3) shows that the estimated coefficient for *Coinno* is significantly positive. This indicates that participation in the collaborative innovation network notably expands the technical knowledge base of manufacturing firms, which in turn facilitates the adoption of more advanced production processes for high-tech intermediate goods. In column (4), the results reveal a positive relationship between collaborative innovation and the technical complexity of enterprise exports. This suggests that as firms increasingly engage in the collaborative innovation network, the exchange of advanced innovation ideas and approaches among partners helps overcome conventional thinking and business models. This process enables firms to achieve breakthroughs in core technological areas, addressing the low-end lock-in issue that often hampers manufacturing enterprises. Ultimately, this creates conditions conducive to raising the domestic value-added content of their exports. In summary, both the cost and technical effect channels represent key mechanisms through which the collaborative innovation network supports the global value chain ascent of manufacturing enterprises.

5.2 Heterogeneity Analysis

5.2.1 Firm endowment characteristics: production capacity and technology absorption capacity

To investigate whether the "value chain climbing effect" of the collaborative innovation network differs based on firms' production capacity, this paper constructs a dummy variable for small and micro enterprises (SME_{it}) based on the *Classification of Large, Medium, Small and Micro Enterprises in Statistics* by the National Bureau of Statistics. The dummy variable takes a value of 1 if the enterprise qualifies as small or micro, and 0 otherwise. We include the interaction term ($Coinno \times SME$) between the core explanatory variable and the small and micro enterprise dummy in the baseline regression model. The regression results are presented in column (1) of Table 5.

The coefficient of the interaction term is significantly negative, indicating that the global value chain climbing effect of the collaborative innovation network is weaker for small and micro enterprises. This can be attributed to several factors: Small and micro enterprises often face constraints in market competition and knowledge complexity. While they may use collaborative innovation to integrate technical resources within the network and enhance technological capabilities, they typically lack the strong technical foundation and reserves necessary for effective technology absorption. Their capacity to absorb new technologies and knowledge is often limited, making it challenging to implement and transform scientific achievements into practical outcomes.

In contrast, large enterprises, with abundant resources (such as funding, technology, and talent) and robust production capacities, are better positioned to benefit from collaborative innovation. They not only gain more technical benefits but also possess the scale to quickly translate technological advancements into products, which helps them achieve economies of scale, reduce production costs, and increase profit margins. Small and micro enterprises, lacking both the technical depth and sufficient production capacity, face greater difficulty in reaping the full benefits of collaborative innovation.

Table 5: Heterogeneity Analysis Results

	Firm endowments		Industry heterogeneity	
Variable	(1)	(2)	(3)	(4)
	Production Capacity	Technology Absorption	Value Chain Position	Trade Barrier Risk
Coinno	0.007***	0.010***	0.009***	0.010***
	(0.002)	(0.003)	(0.003)	(0.002)
Coinno×SME	-0.007***			
	(0.002)			
Coinno×Absorb		0.002***		
		(0.001)		
Coinno×GVC_Pos			-0.006**	
			(0.003)	
Coinno×TBTRisk				-0.008***
				(0.003)
Control variable	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Sample size	197 171	44 910	197 171	197 171
Within R^2	0.079	0.141	0.079	0.079

From the perspective of a firm's internal capabilities, its ability to identify, absorb, and apply external technical knowledge is critical for advancing in the global value chain through collaborative innovation networks. A firm's capacity for technology absorption is closely linked to its existing knowledge base, which plays a pivotal role in determining how effectively it can process, absorb, and innovate with new knowledge (Fleming, 2001). This capacity largely dictates a firm's ability to leverage collaborative networks, integrate complementary innovation resources, and overcome technological lock-ins.

In this context, while firms are often differentiated by production scale, we also examine the heterogeneous effects of their internal technology absorption capacity. To measure this, we use the firm's stock of authorized invention patents over a five-year period (t-1 to t-5) as a proxy for its technology absorption capacity ($Absorb_{it}$). Specifically, we calculate this by summing the number of invention patents granted to the firm during periods t-1 through t-5.

In the baseline regression model, we include an interaction term (*Coinno×Absorb*) between the core explanatory variable and the firm's technology absorption capacity. The estimation results, shown in column (2) of Table 5, indicate that the coefficients for both the core explanatory variable and the interaction term are significantly positive. This suggests that firms with a stronger internal technology base and absorption capacity are better able to absorb knowledge spillovers from collaborative innovation. Consequently, they are more capable of integrating diverse innovation resources from the collaborative network into their own technological development.

5.2.2 Industry heterogeneous characteristics: value chain position and trade barrier risk

The production position of each sub-sector of China's manufacturing industry in the global value chain varies significantly. Referring to the research of Sheng & Wang (2022), this paper sets a group dummy variable (*GVC_Pos*) for whether it is a high-value chain position industry, and includes the interaction term with the core explanatory variable into the regression model. The regression results in column (3) of Table 5 show that the estimated coefficient of the core explanatory variable is significantly positive, while the estimated coefficient of *Coinno×GVC_Pos* is significantly negative, and the regression coefficient of the core explanatory variable is greater than the absolute value of the interaction term coefficient.

Heterogeneity analysis shows that the research conclusion of this paper does not change due to the different value chain positions of the industry. Enterprises in high-value chain position industries can also improve their real trade gains and international division of labor status in the collaborative innovation network, but the positive effect is relatively small compared with low-value chain position industries. The possible reasons are as follows: The global value chain climbing of developing countries has gradually threatened the dominant position of developed countries in the international production division of labor. While collaborative innovation networks offer benefits to firms in high-value chain manufacturing industries in China, this positive effect is partially limited by the increased competitive pressure from developed countries and multinationals as China's industry climbs the value chain.

Technical Barriers to Trade (TBTs) have emerged as a new form of disguised trade protectionism that countries around the world increasingly use. These barriers are shaped by a mix of economic, political, technical, and diplomatic factors, and they reflect competitive conflicts over national interests in specific markets (Zheng et al., 2023). Existing research suggests that TBTs targeting China can hinder the export of affected products by raising compliance costs for Chinese firms. This, in turn, influences firms' global value chain strategies. Specifically, the varying levels of risk associated with facing TBTs across different industries can impact the effectiveness of collaborative innovation in enhancing value chain upgrading.

Building on the work of Zheng et al. (2023), we introduce a dummy variable (*TBTRisk*) to represent industries at high risk of encountering TBTs, based on China's industry-specific exposure to these barriers. We also include an interaction term with the core explanatory variable in our baseline regression model. The results presented in column (4) of Table 5 show that the impact of collaborative innovation networks on value chain upgrading is weaker for firms in industries with a higher risk of facing TBTs.

Combining the results of the heterogeneity analysis, our findings suggest that while collaborative innovation can significantly enhance global value chain upgrading across industries, the industry's position within the value chain and the risk of encountering international trade barriers can partially offset the empowering effects of these innovation networks on upgrading global value chains.

6. Conclusion and Implications

Participation in global value chains is widely regarded as a viable pathway for upgrading developing economies' manufacturing industries, yet whether and how Chinese manufacturing firms can effectively break free from "low-end lock-in" and ascend to higher-value segments remain a subject of considerable debate. This paper empirically investigates the impact and mechanisms of collaborative innovation networks on the export domestic value-added rate of Chinese manufacturing enterprises, drawing on an analysis of network characteristics and the drivers of global value chain participation. Our principal findings are as follows:

(1) Over the sample period, China's collaborative innovation network expanded significantly, exhibiting continuous improvements in connectivity and density. This evolution has fostered a complex network centered on leading industry chain enterprises, specialized science and engineering universities, and government research institutions.

(2) Employing the export domestic value-added rate as a proxy for firms' real trade gains and global value chain position, and utilizing national-level science and technology incubators and innovative city pilots as instrumental variables, we find that integration within collaborative innovation networks facilitates upward movement in the global value chain for Chinese manufacturers.

(3) Mechanism analysis reveals that both a cost-effectiveness channel, enhancing firms' market power, and a technological-effectiveness channel, enabling participation in higher-value production segments, are crucial pathways through which collaborative innovation networks drive value chain upgrading.

(4) The impact of collaborative innovation networks on global value chain ascension is heterogeneous across firms and industries. Specifically, the effect is more significant for firms with greater production capacity and technological absorption capabilities, and for those operating in industries characterized by lower initial value chain positions and reduced trade barrier risks.

The conclusions of this paper offer valuable insights for promoting the advancement of manufacturing enterprises in the global value chain, particularly through the lens of innovation networks. These findings hold significant practical and policy implications.

Firstly, it is crucial to expand intellectual property cooperation and exchanges, while actively integrating into the global innovation network. This integration is a key driver for building competitive advantages and fostering high-quality innovation within the global industrial landscape. Consequently, China must urgently implement institutional and policy reforms, including the establishment of a multilateral intellectual property cooperation framework, a system for preventing and managing intellectual property-related risks abroad, and an intermediary service system for science and technology financing. These measures will help Chinese manufacturing enterprises engage more effectively in the global innovation network and strengthen their technological innovation capabilities through open collaboration.

Secondly, the adoption of a collaborative innovation strategy is essential for overcoming challenges and achieving breakthroughs in critical core technologies. Collaborative innovation facilitates knowledge sharing and helps break technological path dependence, enabling enterprises to both enhance their internal technological innovation and advance their position in the global value chain. Chinese enterprises should seize the opportunity presented by collaborative innovation to overcome key technological barriers, continuously improving their scientific and technological capabilities and boosting their international competitiveness through enhanced cooperation.

Thirdly, it is important to strengthen the organization of scientific research within universities to better support national strategies. Implementing the *Opinions on Strengthening Organized Scientific Research in Universities to Promote High-Level Self-Reliance and Self-Improvement* will help generate significant technological innovations needed for national development. Encouraging the use of national-level projects and university-led initiatives will align collaborative innovation efforts between industry, academia, and research with national priorities and societal needs. This approach ensures that research is strategically focused on areas of critical importance for the country's growth and innovation.

In summary, these recommendations provide a framework for advancing China's manufacturing sector within the global value chain, leveraging innovation networks and strategic collaborations to drive long-term technological progress and competitiveness. CE

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