

Digital Goods Trade and National Innovation: A dual-mediation Perspective

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Abstract

This study investigates how digital goods trade affects national innovation capacity through dual mediating channels. Using panel data from 69 countries over 2011-2020, we construct a multiple mediation model to test the parallel mediating roles of domestic research and development (DRD) and international technology cooperation (ITC). Results show that digital goods imports significantly enhance innovation through both DRD and ITC, with the ITC channel exhibiting a substantially larger mediation effect. However, digital goods exports show no significant mediating effects through either channel. Heterogeneity analysis across five digital goods categories reveals that the positive effects of imports are concentrated in communication equipment and electronic components, while exports of computer peripherals exhibit a significant direct effect. These findings extend the trade-innovation nexus to the digital goods context, reveal asymmetric mediating mechanisms between imports and exports.

Keywords: Digital goods trade; National innovation capacity; Domestic research and development; International technology cooperation; Multiple mediation effect model.

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1. Introduction

The exponential growth of digital goods trade — encompassing software, databases, cloud services, and ICT equipment — has reshaped global commerce (Brynjolfsson et al., 2025). Unlike conventional goods, digital products are characterized by high knowledge intensity, near-zero marginal replication costs, and the capacity to embody and transmit technological know-how across borders (UNCTAD, 2021). Between 2019 and 2022, while global goods trade contracted by 10.5%, digital goods trade expanded by 4.0%, underscoring its resilience and growing economic significance (UNCTAD, 2021; UNCTAD, 2024). This trend has prompted governments worldwide to prioritize digital trade as a strategic lever for economic transformation (Ma et al., 2019).

A substantial body of research has established that international trade fosters innovation through mechanisms such as market expansion, import competition, and knowledge spillovers (Grossman & Helpman, 1991; Bloom, Draca, & Van Reenen, 2016; Aghion et al., 2018). However, the unique attributes of digital goods suggest that their impact on innovation may extend beyond these conventional channels. Digital goods are not merely traded commodities; they are also carriers of codified knowledge and platforms for cross-border collaboration. This duality implies that digital goods trade could enhance national innovation capacity (NIC) through pathways that are distinct from — or complementary to — those of traditional trade. Prior studies have explored related but distinct questions. Some have examined the innovation effects of high-tech trade (Wu, Ma, & Zhuo, 2017) or ICT diffusion (Nair, Pradhan, & Arvin, 2020). Others have documented the positive correlation between digital exports and international co-invention. Yet, to date, no systematic investigation has explicitly modeled the mediating mechanisms through which digital goods trade — both exports and imports — affects national innovation. This paper addresses this gap by proposing and testing a dual-mediation framework. We argue that digital goods trade enhances NIC through two parallel channels: (1) by stimulating domestic research and development (DRD), driven by intensified competition and expanded market scale; and (2) by fostering international technology cooperation (ITC), facilitated by the knowledge-embedded nature of digital goods and the lower coordination costs of digital platforms.

Using a panel data of 69 countries between 2011 to 2020 and rigorous mediation analysis, we find supporting evidence for both pathways. These findings contribute to the literature in three ways. First, we extend the trade-innovation nexus to the digital goods context, revealing mechanisms that are amplified by digitalization. Second, we provide a unified framework that reconciles the “R&D channel” and the “cooperation channel” as complementary rather than substitute forces. Third, our results offer actionable policy insights for leveraging digital trade to build national innovative capacity.

The paper proceeds as follows. Section 2 develops the theoretical framework and formulates testable hypotheses. Section 3 describes the empirical strategy and presents results. Section 4 concludes with policy implications.

2. Theoretical Framework and Hypotheses

2.1 Direct effect of digital goods trade on NIC

The proposition that trade stimulates innovation is deeply rooted in endogenous growth theory. Grossman and Helpman (1991) formalized how trade expands the stock of accessible knowledge, accelerates technology diffusion, and reallocates resources toward innovative activities. Subsequent empirical work has confirmed that both exports and imports contribute to innovation — exports through learning-by-exporting effects (Salomon & Shaver, 2005; Love & Ganotakis, 2013) and imports through technology spillovers embedded in foreign goods (Connolly, 2003; Liu & Zou, 2008).

Digital goods trade amplifies these effects. On the export side, digital products embody advanced technologies, exposing domestic firms to sophisticated global demand and incentivizing continuous quality upgrading (Teritlak, 2016). On the import side, digital goods serve as direct conduits for foreign technical knowledge; importing countries can decode, adapt, and build upon the technologies embedded in these products (Kubielas & Olender-Skorek, 2014). Consequently, both export and import flows of digital goods are expected to positively influence a nation's innovative capacity. We therefore hypothesize:

H1: Both digital goods exports and imports positively affect NIC.

2.2 The mediating role of DRD

The link between trade and innovation is often mediated by domestic research and development (R&D) efforts. R&D intensity — typically measured by R&D expenditure or personnel — is a proximate driver of innovation outcomes (Keller, 2004; Liu & Buck, 2007; Hammar & Belarbi, 2021). Digital goods trade can stimulate R&D through two well-established economic mechanisms.

First, the competition channel. According to Schumpeterian growth models, import competition pressures domestic firms to innovate defensively—the “escape-competition” effect (Aghion et al., 2005). When foreign digital goods enter the domestic market, they raise the technological bar, compelling local firms to increase R&D investment to differentiate their products and maintain market share (Seker et al., 2024). This effect is particularly pronounced for digital goods, given their rapid obsolescence and steep learning curves (Bloom et al., 2016).

Second, the market size channel. Exporting to global digital markets dramatically expands the potential customer base. Endogenous growth theory predicts that larger markets increase the expected returns to innovation, thereby incentivizing firms to boost R&D spending. For digital goods exporters, the scalability of digital products means that successful innovations can be deployed globally at minimal additional cost, magnifying the market size incentive (Nair, Pradhan, & Arvin, 2020).

Thus, digital goods trade intensifies both the necessity (competition) and the reward (market size) for domestic R&D, which in turn fuels national innovation. This yields:

H2: DRD mediates the effect of digital goods trade on NIC.

2.3 The mediating role of ITC

Beyond stimulating in-house R&D, digital goods trade facilitates cross-border knowledge exchange and joint innovation. International technology cooperation (ITC) — manifested in co-patenting, co-authorship, and strategic R&D alliances — has been shown to enhance innovation outcomes by pooling complementary expertise and sharing risks (Bae & Chang, 2012).

Digital goods trade promotes ITC through two distinct mechanisms. First, digital goods are embodied knowledge repositories. Importing sophisticated digital products enables reverse engineering, adaptation, and subsequent collaboration with foreign technology providers (Lee, 2009). The knowledge embedded in these goods serves as a common ground for initiating joint projects (Belitz & Mölders, 2016; Kim & Wilson, 2019). Second, digital trade reduces coordination costs. The platforms and protocols that facilitate digital goods transactions also lower the barriers to international communication, project management, and data sharing. This “digital infrastructure effect” makes it easier for firms and researchers to form transnational innovation networks, engage in co-development, and sustain long-term technology partnerships.

As these cooperative linkages deepen, countries gain access to external knowledge bases, accelerate learning curves, and enhance their innovative capacity beyond what domestic efforts alone could achieve (Iino et al., 2021). We therefore hypothesize:

H3: ITC mediates the effect of digital goods trade on NIC.

Figure 1 presents the dual-mediation framework, illustrating how digital goods trade affects NIC through DRD and ITC.

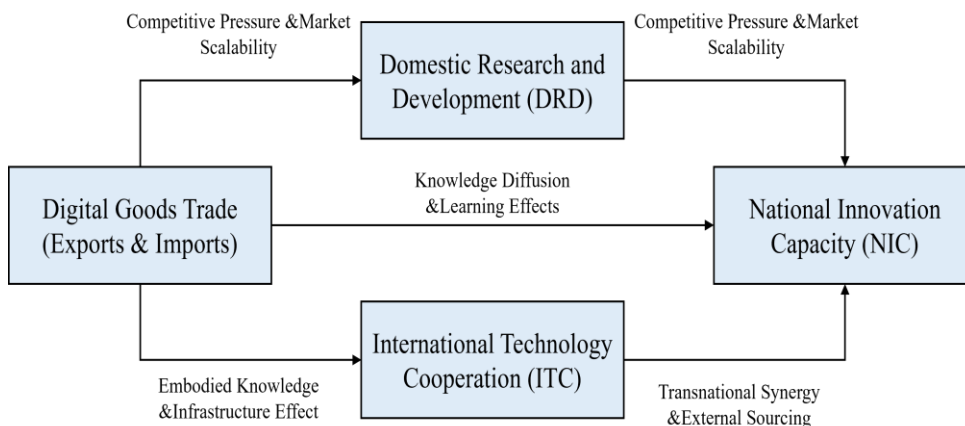


Figure 1: Theoretical mechanism of dual-mediation

3. Model Construction and Variables Illustration

3.1 Model construction

3.1.1 Baseline model

To test the direct effect of digital goods trade on national innovation capacity, we estimate the following fixed-effects model:

$$NIC_{it} = \alpha_0 + \alpha_1 EXdig_{it} + \alpha_2 IMdig_{it} + \gamma Controls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

where i and t denote country and year, respectively.

The dependent variable NIC is proxied by patent-based knowledge flows (KN_{in} and KN_{out}). $EXdig$ and $IMdig$ represent digital goods exports and imports. $Controls$ is a vector of country-level control variables. μ_i and ν_t are country and year fixed effects, and ε_{it} is the error term.

3.1.2 Mediation models

To further examine the mediating roles of domestic R&D intensity and international technology cooperation as proposed in H2 and H3, we adopt the stepwise mediation approach proposed by Baron and Kenny (1986). The system of equations is specified as follows:

$$M_{it} = \beta_0 + \beta_1 EXdig_{it} + \beta_2 IMdig_{it} + \gamma Controls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (2)$$

$$NIC_{it} = \theta_0 + \theta_1 EXdig_{it} + \theta_2 IMdig_{it} + \theta_3 M_{it} + \gamma Controls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

where M denotes the mediating variables, namely DRD and ITC . Equation (2) tests the effect of digital goods trade on the mediator, while Equation (3) tests the effect of the mediator on NIC while controlling for digital goods trade.

3.2 Variables definition and measurements

3.2.1 Dependent variable: National innovation capacity (NIC)

Measuring NIC poses empirical challenges. While patent counts are widely used as a proxy for innovation (Chen, 2013; Bosetti et al., 2015; Su & Moaniba, 2017; Jung & Kwak, 2018), this approach has well-documented limitations. As Archibugi (1992) notes, patents fail to capture innovations protected as industrial secrets and may include dormant patents that never translate into economic value. To overcome these limitations, we follow Liu et al. (2022) and measure NIC using patent-based knowledge flows, which capture both explicit and tacit knowledge transfer. Specifically, we construct two indicators based on the distinction between patent inventors and holders:

KN_{in} : Patents owned by residents but invented by foreign residents (inward knowledge flows)

KN_{out} : Patents invented by residents but owned by foreign residents (outward knowledge flows)

These variables capture the bidirectional nature of knowledge flows and serve as the empirical counterparts of NIC in our estimation. Following the theoretical premise that digital goods trade affects both inflow and outflow of knowledge through identical mechanisms, we also construct a composite indicator $KN = KN_{in} + KN_{out}$ to measure overall NIC.

3.2.2 Independent variables: Digital goods trade (EXdig and IMdig)

Given the absence of harmonized statistical standards for digital goods trade, we follow common practice in the literature by using ICT goods trade as a proxy (Khan et al., 2023; Shahbaz et al., 2022). Accordingly, EXdig and IMdig are defined as the volumes of ICT goods exports and imports, respectively, obtained from the OECD Statistics on International Trade (Ferracane et al., 2025).

3.2.3 Mediating variables: DRD and ITC

Domestic R&D intensity (DRD) is proxied by the number of researchers (NOR), a standard measure of a country's human capital investment in innovation activities. Data are sourced from the World Bank. International technology cooperation (ITC) is proxied by the number of patent co-inventions involving inventors (PCI) from different countries. This indicator captures the extent to which a country engages in cross-border collaborative innovation and is extracted from the OECD Statistics on International Trade.

3.2.4 Control variables

To account for other factors influencing NIC, we include a set of control variables informed by prior literature (Zhu et al., 2016; Gnanon, 2018; Njangang et al., 2020; Mahanty et al., 2022), economic development level (GDP per capital), government size, income growth, population, and foreign direct investment (both inflows and outflows). These variables capture a country's scale, economic structure, and openness — all potentially correlated with innovation outcomes.

3.3 Data sources and sample

Our panel datasets covers 69 countries over the period 2011-2020. The sample period is determined by data availability for key variables. Data for digital goods trade (EXdig, IMdig) and knowledge flows (KN_{in}, KN_{out}, PCI) are obtained from the OECD Statistics on International Trade. Data for all control variables and the number of researchers (NOR) are sourced from the World Bank. Table 1 provides detailed variable definitions, measurements, and corresponding data sources.

Table 1: Variable definitions and measurements

Variable	Name	Symbol	Definition
Dependent variable	National innovation capacity (NIC)	KN _{in}	Patents owned by residents but invented by foreign residents knowledge flows). Log-transformed.
		KN _{out}	Patents invented by residents but owned by foreign residents (outward knowledge flows). Log-transformed.
		KN	Composite indicator of national innovation capacity. KN=KN _{in} + KN _{out} . Log-transformed.
Independent variables	Digital goods exports	EX _{dig}	Volume of ICT goods exports. Log-transformed. Unit: Millions of US\$.
	Digital goods imports	IM _{dig}	Volume of ICT goods imports. Log-transformed.
Mediating variables	Domestic R&D intensity	DRD	Proxied by the number of researchers in R&D per million people (NOR). Log-transformed.
	International technology cooperation	ITC	Proxied by the number of patent co-inventions involving inventors from different countries (PCI). Log-transformed.
Controls variables	Economic development level	GDP _{pc}	GDP per capita. Log-transformed. Unit: Current US\$.
	Government size	Gov	General government final consumption expenditure. Unit: % of GDP.
	Income growth	Income	GDP per capita growth. Unit: Annual %.
	Population	Pop	Total population. Log-transformed.
	FDI inflow	FDI _{in}	Net inflow of foreign direct investment. Unit: % of GDP.
	FDI outflow	FDI _{out}	Net outflow of foreign direct investment. Unit: % of GDP.

4. Empirical Results

4.1 Descriptive statistics analysis

Table 2 reports the descriptive statistics for the main variables. The mean values of IMdig and EXdig are 8.452 and 6.889, with standard deviations of 1.757 and 3.306, indicating that imports generally exceed exports and that cross-country variation is more pronounced for exports. For innovation capacity, KNout, (mean=4.303) slightly exceed KNin (mean=3.684), and the large ranges of all knowledge flow indicators suggest substantial disparities in innovation capacity across countries. Among control variables, FDI inflows and outflows exhibit the largest variations (SD of 28.414 and 27.296, respectively), reflecting considerable heterogeneity in countries' engagement with global capital markets.

Table 2: Descriptive statistics

Variable	Obs	Mean	Standard	Median	Min	Max
KNin	690	3.684	2.446	3.295	0.000	9.300
KNout	690	4.303	2.114	4.191	0.000	8.973
KN	690	4.821	2.221	4.571	0.693	9.842
EXdig	690	6.889	3.306	7.068	0.002	13.305
IMdig	690	8.452	1.757	8.372	4.500	12.698
PCI	690	4.295	2.091	4.192	0.695	9.103
NOR	690	7.315	1.228	7.556	2.714	8.978
GDPpc	690	9.667	1.061	9.663	6.716	11.723
Gov	690	17.253	4.248	17.789	7.774	27.933
Income	690	1.830	3.716	1.887	-14.701	23.997
Pop	690	16.535	1.647	16.319	12.638	21.055
FDI in	690	8.634	28.414	2.689	-57.504	449.079
FDI out	690	6.344	27.296	1.487	-87.231	301.247

4.2 Benchmark regression results

Table 3 reports the benchmark regression results for the effect of digital goods trade on national innovation capacity, measured by knowledge inflows (KNin) and knowledge outflows (KNout). For each dependent variable, we present pooled OLS (POOL), fixed effects (FE), and random effects (RE) estimates. The F-test for individual effects and the Breusch-Pagan test both reject pooled OLS in favor of panel models. The Hausman test ($\chi^2(9)=118.678$ for KNin; $\chi^2(9)=2288.439$ for KNout, both $p<0.001$) strongly rejects the random effects model, indicating that the fixed effects specification is the most appropriate. Therefore, our discussion focuses on the FE results in columns (1-b) and (2-b).

The FE estimates show that IMdig have a positive and significant effect on both knowledge inflows ($\beta=0.188$, $p<0.05$) and knowledge outflows ($\beta=0.155$, $p<0.05$). However, EXdig do not exhibit a statistically significant effect in the FE specifications, suggesting that the positive impact of digital goods trade on

innovation capacity is primarily driven by imports. This finding provides partial support for H1, which posited positive effects for both exports and imports. The limited role of exports may reflect the nature of digital goods trade, where imports serve as a more direct channel for technology transfer and knowledge absorption.

Table 3: Benchmark regression results

Variables	KNin (1)			KNout (2)		
	POOL-(a)	FE-(b)	RE-(c)	POOL-(a)	FE-(b)	RE-(c)
EXdig	0.082*** (3.421)	0.017 (1.146)	0.032* (1.912)	0.100**** (6.249)	0.005 (0.189)	0.026** (1.965)
IMdig	0.421*** (6.115)	0.188** (2.558)	0.276*** (3.965)	0.321*** (6.622)	0.155** (2.408)	0.237**** (3.863)
Population	3.799*** (2.830)	-3.238 (-0.835)	2.802 (1.080)	-1.170 (-1.249)	-0.095 (-0.024)	-0.399 (-0.191)
FDI inflow	0.007*** (3.662)	0.001 (-0.210)	0.001 (0.550)	0.002 (0.377)	0.002 (1.473)	0.003 (1.496)
FDI outflow	-0.003 (-1.615)	-0.002 (-0.682)	-0.002 (-0.383)	-0.001 (0.165)	-0.002 (-0.466)	-0.001 (-0.372)
Income growth	0.042*** (3.645)	-0.001 (-0.090)	0.002 (0.205)	0.028*** (3.387)	0.003 (0.528)	0.007 (1.275)
Government size	0.089*** (8.141)	0.017 (1.031)	0.045*** (3.489)	0.107*** (13.390)	-0.005 (-0.309)	0.046*** (3.909)
Development level	4.705*** (3.502)	-3.139 (-0.818)	3.380 (1.308)	-0.924 (-0.986)	-1.052 (-0.311)	-0.276 (-0.133)
Constant	-20.461*** (-19.355)	-2.912 (-0.384)	-13.328*** (-6.958)	-18.708*** (-25.353)	-12.865* (-1.897)	-15.387**** (-9.742)
Observations	690	690	690	690	690	690
Time period	2011-2020	2011-	2011-2020	2011-2020	2011-	2011-2020
R ²	0.625	0.375	0.518	0.685	0.478	0.509
Overall significance	F(9,680)= 360.800***	F(9,601)= 4.146***	$\chi^2(9)=$ 265.130***	F(9,680)= 592.626***	F(9,601)= 3.166***	$\chi^2(9)=$ 357.550***
F-test	F(79,601)=50.969***			F(79,601)=28.387***		
Breusch-	$\chi^2(1)=1873.300***$			$\chi^2(1)=1138.142***$		
Hausman	$\chi^2(9)=118.678***$			$\chi^2(9)=2288.439***$		

Notes: T-values in parentheses. ****, ***, **, and * indicate significance at the 0.1%, 1%, 5%, and 10% levels, respectively.

4.3 Robustness tests

Digital goods trade may suffer from endogeneity due to reverse causality and omitted variable bias. To address these concerns and assess the robustness of our benchmark findings, we conduct two sets of robustness tests: instrumental variable (IV) estimations using lagged explanatory variables, and quantile regressions.

4.3.1 Instrumental variable estimations

Following Smith (2014), we employ one-year lagged values of digital goods exports and imports (L.EXdig and L.IMdig) as IVs and perform 2SLS and GMM estimations. Columns (1) and (2) of Tables 4 and 5 report the results for KNin and KNout, respectively. The coefficients of L.IMdig remain positive and statistically significant across both dependent variables (for KNin: $\beta=0.419$, $p<0.001$ in 2SLS; for KNout: $\beta=0.459$, $p<0.001$ in 2SLS), while L.EXdig shows no significant effect. Column (3) presents instrumental variable robust estimations, which further corroborate these findings. The diagnostic tests support the validity of our IV approach. The Durbin test ($\chi^2(2)=5.04$ for KNin; $\chi^2(2)=14.24$ for KNout) and Wu-Hausman test ($F(2,615)=2.49$ for KNin; $F(2,615)=7.15$ for KNout) reject the exogeneity of EXdig and IMdig, confirming the necessity of using instrumental variables. With the number of endogenous variables equal to the number of instruments, the models are exactly identified.

4.3.2 Quantile regressions

To examine whether the effects vary across different levels of innovation capacity, we employ quantile regressions at the 0.25, 0.50, and 0.75 quantiles. Columns (4)–(6) of Tables 4 and 5 present the results. For KNin, L.IMdig is positive and significant at the 0.50 ($\beta=0.261$, $p<0.001$) and 0.75 quantiles ($\beta=0.276$, $p<0.001$). For KNout, L.IMdig is significant at the 0.25 ($\beta=0.153$, $p<0.05$) and 0.50 quantiles ($\beta=0.196$, $p<0.001$). L.EXdig remains insignificant across all quantiles for both dependent variables. These results suggest that the positive effect of digital goods imports on innovation capacity holds across different segments of the conditional distribution, with some heterogeneity in the pattern across knowledge inflow and outflow.

Collectively, the instrumental variable and quantile regression estimations demonstrate that our main findings are robust to alternative estimation methods and to potential endogeneity concerns. The consistently significant positive effect of digital goods imports, coupled with the insignificant effect of exports, confirms the validity and reliability of the benchmark regression results.

Table 4: Robustness test results: dependent variable of KNin

Variables	2SLS - (1)	GMM - (2)	IV - (3)	0.25Q - (4)	0.5 Q - (5)	0.75Q - (6)
L.EXdig	-0.005 (-0.171)	-0.007 (-0.148)	0.029* (1.781)	0.006 (0.229)	0.023 (1.436)	0.062** (2.524)
L.IMdig	0.419*** (3.161)	0.413*** (2.758)	0.204*** (3.261)	0.140 (1.482)	0.261**** (4.335)	0.276*** (3.259)
Population	3.289 (0.816)	3.294 (0.936)	0.977 (0.308)	-0.622 (-0.119)	1.057 (0.345)	0.104 (0.030)
FDI inflow	0.003 (1.188)	0.003 (1.583)	0.003 (1.494)	0.004 (1.385)	0.003 (1.618)	0.001 (0.714)
FDI outflow	-0.002 (-0.929)	-0.002 (-1.211)	-0.002 (-1.445)	-0.004 (-1.486)	-0.003* (-1.868)	-0.000 (-0.055)
Income growth	-0.004 (-0.689)	-0.004 (-0.735)	0.001 (0.158)	0.004 (0.581)	0.003 (0.774)	-0.003 (-0.618)
Government size	0.019 (1.323)	0.019 (1.173)	0.031** (2.428)	0.057*** (3.069)	0.034*** (2.801)	0.008 (0.446)
Development level	3.147 (0.788)	3.151 (0.904)	0.531 (0.171)	-1.375 (-0.271)	0.017 (0.009)	0.398 (0.102)
Constant	0.009 (0.628)	0.009 (0.609)	0.011 (0.854)	-0.173**** (-9.749)	0.003 (0.267)	0.196**** (11.307)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time period	2011-2020	2011-2020	2011-2020	2011-2020	2011-2020	2011-2020
Observations	627	627	627	627	627	627
R ²	0.045	0.043	0.062	0.056	0.058	0.060
Adjusted R ²	0.031	0.029	0.048			
Wald test / F-test	$\chi^2(9) = 33.72^{***}$	$\chi^2(9) = 29.34^{***}$	$F(9,617) = 3.71^{***}$			
Durbin-Watson test	1.889	1.722				
Durbin test	$\chi^2(2)=5.04^*$					
Wu-Hausman test	$F(2,615)=2.49^*$					

Notes: T-values in parentheses. ****, ***, **, and * indicate significance at the 0.1%, 1%, 5%, and 10% levels, respectively.

Table 5: Robustness test results: dependent variable of KNout

Variables	2SLS-(1)	GMM-(2)	IV-(3)	0.25Q-(4)	0.5 Q-(5)	0.75Q-(6)
L.EXdig	0.034 (1.023)	0.032 (0.866)	-0.001 (-0.062)	-0.012 (-0.737)	-0.013 (-1.221)	0.020 (1.325)
L.IMdig	0.459*** (3.798)	0.455*** (3.158)	0.155*** (3.209)	0.153** (2.304)	0.196**** (4.108)	0.107 (1.586)
Population	1.699 (0.464)	1.697 (0.389)	2.522 (1.020)	4.943 (1.414)	0.831 (0.341)	0.395 (0.121)
FDI inflow	0.001 (0.664)	0.001 (0.593)	0.001 (0.939)	0.002 (1.318)	0.001 (1.028)	0.000 (0.135)
FDI outflow	0.001 (0.341)	0.001 (0.375)	-0.000 (-0.384)	-0.002 (-1.271)	-0.001 (-0.692)	0.001 (0.447)
Income growth	-0.004 (-0.803)	-0.004 (-0.716)	0.003 (1.027)	0.003 (0.702)	0.003 (0.898)	0.004 (0.921)
Government size	0.001 (0.057)	0.001 (0.045)	0.007 (0.747)	0.019 (1.394)	0.007 (0.709)	-0.014 (-1.073)
Development level	1.107 (0.306)	1.105 (0.255)	1.596 (0.650)	4.369 (1.251)	-0.495 (-0.201)	-1.379 (-0.418)
Constant	-0.012 (-0.854)	-0.012 (-0.847)	0.011 (1.092)	-0.128**** (-9.627)	0.018* (1.790)	0.154**** (11.785)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time period	2011-2020	2011-2020	2011-2020	2011-2020	2011-2020	2011-2020
Observations	627	627	627	627	627	627
R ²	0.043	0.041	0.063	0.055	0.065	0.058
Adjusted R ²	0.029	0.027	0.049			
Wald test / F-test	$\chi^2(9) = 44.51****$	$\chi^2(9) = 37.72****$	$F(9,617) = 3.24****$			
Durbin-Watson test	1.727	1.723				
Durbin test	$\chi^2(2)=14.24****$					
Wu-Hausman test	$F(2,615)=7.15****$					

Notes: T-values in parentheses. ****, ***, **, and* indicate significance at the 0.1%, 1%, 5%, and 10% levels, respectively.

4.4 Multiple mediation effects test

To examine the mediating roles of DRD and ITC as proposed in H2 and H3, we employ the stepwise mediation approach proposed by Baron and Kenny (1986), supplemented by bootstrap tests with 1,000 replications to obtain bias-corrected confidence intervals for the indirect effects. Table 6 reports the stepwise regression results, and Table 7 presents the bootstrap test results.

4.4.1 Mediating effect of domestic R&D intensity (DRD)

Column (1) of Table 6 reports the total effect of digital goods trade on knowledge flow (KN). The results show that IMdig has a positive and significant total effect ($\beta=0.144$, $p<0.001$), while EXdig is insignificant. Column (2) presents the effect of digital goods trade on the mediator DRD. Both EXdig ($\beta=0.017$, $p<0.05$) and IMdig ($\beta=0.141$, $p<0.001$) significantly increase domestic R&D intensity. Column (4) includes both digital goods trade and the mediators. The coefficient of NOR is positive and significant ($\beta=0.136$, $p<0.001$), while the direct effects of EXdig and IMdig become insignificant. The bootstrap results in Table 7 further validate the mediating role of DRD. For IMdig, the mediation effect through DRD is 0.019, with a 95% confidence interval of [0.001, 0.038] excluding zero, confirming significant mediation. For EXdig, the mediation effect through DRD is 0.002 with a confidence interval of [-0.006, 0.028] including zero, indicating no significant mediation. These findings support H2 for digital goods imports but not for exports.

4.4.2 Mediating effect of international technology cooperation (ITC)

Column (3) of Table 6 reports the effect of digital goods trade on the mediator ITC. IMdig has a positive and significant effect ($\beta=0.186$, $p<0.001$), while EXdig is insignificant. In column (4), the coefficient of PCI is positive and highly significant ($\beta=0.681$, $p<0.001$), indicating that increased international technology cooperation strongly enhances knowledge flow. The bootstrap results in Table 7 confirm these patterns. For IMdig, the mediation effect through ITC is 0.127, with a 95% confidence interval of [0.032, 0.197] excluding zero, demonstrating significant mediation. For EXdig, the mediation effect through ITC is 0.005 with a confidence interval of [-0.037, 0.073] including zero, indicating no significant mediation. These results provide support for H3 regarding digital goods imports.

4.4.3 Summary of mediation analysis

The mediation analysis yields three key findings. First, digital goods imports enhance national innovation capacity through both domestic R&D intensity and international technology cooperation, with the ITC channel exhibiting a substantially larger mediation effect (0.127) compared to the DRD channel (0.019). Second, digital goods exports do not exhibit significant mediating effects through either channel, consistent with the benchmark results showing insignificant direct effects of exports. Third, the inclusion of both mediators (DRD and ITC) dramatically improves the model's explanatory power, with the adjusted R^2

increasing from 0.043 in Column (1) to 0.600 in Column (4). This suggests that domestic R&D and international technology cooperation are crucial channels through which digital goods imports influence knowledge flow. These findings confirm H2 and H3 for imports while providing nuanced insights into the differential roles of exports and imports in fostering innovation through distinct pathways.

Table 6: Mediating effect test results

Variables	KN-(1)	NOR (DRD)-(2)	PCI (ITC)-(3)	KN-(4)
EXdig	0.015 (1.280)	0.017** (2.515)	0.008 (0.611)	0.007 (0.953)
IMdig	0.144*** (2.634)	0.141**** (4.411)	0.186*** (3.074)	-0.002 (-0.045)
Population	-1.632 (-0.561)	-0.516 (-0.303)	1.629 (0.507)	-2.671 (-1.420)
FDI inflow	0.001 (0.620)	0.000 (-0.683)	0.001 (0.526)	0.000 (0.431)
FDI outflow	-0.001 (-0.981)	0.000 (-0.352)	-0.001 (-0.538)	-0.001 (-0.848)
Income growth	0.004 (1.053)	0.005** (1.969)	-0.001 (-0.323)	0.004* (1.756)
Government size	0.017 (1.523)	0.018*** (2.867)	-0.008 (-0.638)	0.019*** (2.725)
Development level	-1.829 (-0.634)	-2.019 (-1.196)	1.424 (0.447)	-2.524 (-1.351)
NOR (DRD)				0.136*** (3.199)
PCI (ITC)				0.681**** (30.199)
Constant	0.003 (0.258)	-0.003 (-0.404)	0.000 (0.020)	0.003 (0.425)
Country fixed effects	Yes	Yes	Yes	Yes
Observations	690	690	690	690
Time period	2011-2020	2011-2020	2011-2020	2011-2020
R ²	0.055	0.239	0.037	0.606
Adjusted R ²	0.043	0.229	0.024	0.600
Overall significance	F(9,680) = 4.399***	F(9,680) = 23.674***	F(9,680) = 2.882***	F(11,678) = 94.780****

Notes: T-values in parentheses. ****, ***, **, and* indicate significance at the 0.1%, 1%, 5%, and 10% levels, respectively.

Table 7: Total, direct, and mediating effects with bootstrap tests

Path	Total effect	Direct effect	Mediation effect	Boot LLCI	Boot ULCI	Conclusion
EXdig→DRD→KN	0.015	0.007	0.002	-0.006	0.028	No significant mediation
EXdig→ITC→KN	0.015	0.007	0.005	-0.037	0.073	No significant mediation
IMdig→DRD→KN	0.144***	-0.002	0.019	0.001	0.038	Significant mediation
IMdig→ITC→KN	0.144***	-0.002	0.127	0.032	0.197	Significant mediation

Notes: Bootstrap confidence intervals (95%) are based on 1,000 replications. Mediation is established if the confidence interval for the mediation effect excludes zero. ****, ***, **, * indicate significance at the 0.1%, 1%, 5%, and 10% levels, respectively.

4.5 Heterogeneity test based on products classification

Digital goods exhibit considerable heterogeneity in their technology intensity and functionality, which may lead to differential effects on innovation capacity. Taking this into account, we classify digital goods into five categories based on the OECD HS-2017 six-digit classification: computers and peripheral equipment (DIG-A), communication equipment (DIG-B), consumer electronic equipment (DIG-C), electronic components (DIG-D), and miscellaneous (DIG-E). We then re-estimate the benchmark model separately for each category. Table 8 reports the heterogeneity regression results for overall knowledge flow ($KN = KN_{in} + KN_{out}$).

4.5.1 Heterogeneity in direct effects

For knowledge flow, the results in Table 8 reveal notable heterogeneity across digital goods categories. EXdig exhibits a positive and statistically significant effect only for DIG-A (computers and peripheral equipment) ($\beta=0.028$, $p<0.01$), while remaining insignificant for all other categories. This suggests that the innovation-enhancing potential of digital goods exports, while limited overall, operates through a specific product category characterized by mature technologies and broader user bases. IMdig shows positive and significant effects for DIG-B (communication equipment) ($\beta=0.027$, $p<0.05$) and DIG-D (electronic components) ($\beta=0.072$, $p<0.001$), but insignificant effects for DIG-A, DIG-C, and DIG-E. The magnitude of the effect is substantially larger for electronic components, reflecting their higher technology intensity and greater potential for knowledge spillovers. These findings indicate that the positive impact of digital goods imports on innovation capacity is primarily driven by communication equipment and electronic components.

4.5.2 Patterns across product categories

The heterogeneity analysis yields three important insights. **First**, the positive effects of digital goods imports are concentrated in product categories with higher technology intensity—communication equipment (DIG-B) and electronic components (DIG-D)—both of which embody advanced technologies and facilitate knowledge transfer. Electronic components exhibit the largest effect ($\beta=0.072$), suggesting that products deeper in the value chain generate stronger innovation

spillovers. Second, digital goods exports show limited effects overall, with only computers and peripheral equipment (DIG-A) exhibiting a statistically significant positive effect at the 1% level. This exception may reflect the unique characteristics of this category: computers and peripherals are widely used across industries, involve significant user-producer interactions, and often require ongoing technical support and adaptation, creating channels for knowledge transfer that are less prevalent in other export categories. Third, consumer electronic equipment (DIG-C) and miscellaneous digital goods (DIG-E) show no significant effects on knowledge flow. This suggests that their technology intensity may be insufficient to generate measurable innovation spillovers, or that these products are traded in ways that limit knowledge transfer.

Table 8: Heterogeneity regression results-KN

Variables	DIG-A (1)	DIG-B (2)	DIG-C (3)	DIG-D (4)	DIG-E (5)
EXdig	0.028*** (2.855)	-0.048 (-1.023)	0.006 (0.250)	0.023 (1.134)	-0.016 (-0.722)
IMdig	0.024 (0.927)	0.027** (2.352)	-0.006 (-0.093)	0.072*** (2.960)	-0.073 (-1.507)
Population	-4.431 (-1.146)	-4.832 (-1.242)	-3.375 (-0.864)	-4.472 (-1.171)	-3.122 (-0.802)
FDI inflow	0.000 (0.158)	0.001 (0.433)	0.000 (0.158)	-0.000 (-0.244)	0.000 (0.156)
FDI outflow	-0.001 (-0.795)	-0.001 (-1.022)	-0.001 (-0.720)	-0.000 (-0.319)	-0.001 (-0.767)
Income growth	0.004 (0.822)	0.001 (0.164)	0.003 (0.534)	0.006* (1.763)	0.004 (0.730)
Government size	0.022 (1.434)	0.021 (1.362)	0.021 (1.354)	0.032*** (2.948)	0.018 (1.211)
Development level	-4.443 (-1.161)	0.099** (2.276)	-3.486 (-0.901)	-4.436 (-1.173)	-3.299 (-0.858)
Constant	-12.041** (-2.124)	-7.411 (-1.23)	-13.978** (-2.312)	-10.178* (-1.895)	-14.587** (-2.380)
Model	FE	FE	FE	FE	FE
Observations	690	690	690	690	690
Time period	2011-2020	2011-2020	2011-2020	2011-2020	2011-2020
R ²	0.312	0.347	0.278	0.327	0.251
Overall significance	F(9,601) = 3.576****	F(9,601) = 4.829****	F(9,601) = 3.171****	F(9,601) = 4.948****	F(9,601) = 3.515****
F-test (IE)	F(79,601) = 48.085****	F(79,601) = 54.567****	F(79,601) = 54.697****	F(79,601) = 47.795****	F(79,601) = 50.294****
Breusch-Pagan test	$\chi^2(1)$ = 1847.142****	$\chi^2(1)$ = 1885.586****	$\chi^2(1)$ = 1964.694****	$\chi^2(1)$ = 1762.817****	$\chi^2(1)$ = 1755.409****
Hausman test	$\chi^2(9)$ = 96.559****	$\chi^2(9)$ = 130.264****	$\chi^2(9)$ = 118.587****	$\chi^2(9)$ = 190.579****	$\chi^2(9)$ = 158.078****

Notes: T-values in parentheses. ****, ***, **, * indicate significance at the 0.1%, 1%, 5%, and 10% levels, respectively.

5. Conclusions and policy implications

5.1 Main findings

This study investigates the impact of digital goods trade on national innovation capacity using panel data from 69 countries over 2011-2020. Proposing a dual-mediation framework, we examine two parallel channels—domestic R&D intensity and international technology cooperation—through which digital goods trade affects innovation. The main findings are threefold.

First, digital goods imports have a positive and statistically significant effect on national innovation capacity, while exports show a positive but insignificant effect. The limited role of exports may reflect the nature of digital goods trade, where knowledge spillovers are more readily accessed through imports, whereas exports require stronger domestic absorptive capacity or complementary innovation ecosystems to generate measurable effects.

Second, imports enhance innovation through both domestic R&D intensity and international technology cooperation, with the cooperation channel exhibiting a substantially larger mediation effect. Exports, however, show no significant mediating effects through either channel. This asymmetry reveals that imports and exports operate through distinct mechanisms, and that the innovation-enhancing potential of digital trade is primarily realized through import-driven knowledge acquisition and collaborative networks rather than export activities.

Third, heterogeneity analysis across five digital goods categories shows that the positive effects of imports are concentrated in high-technology products — communication equipment and electronic components — while exports of computer peripherals exhibit a significant direct effect. Other product categories show no significant effects, indicating that the innovation impact of digital goods trade depends critically on product-specific technological intensity and characteristics.

5.2 Policy implications

First, governments should prioritize facilitating imports of high-technology digital goods, particularly communication equipment and electronic components, as these serve as effective conduits for knowledge transfer and innovation spillovers. Trade policies that reduce barriers for these product categories can amplify their innovation benefits.

Second, innovation policies should simultaneously strengthen domestic R&D capacity and foster international research collaboration, recognizing their complementary roles. Investments in R&D infrastructure should be accompanied by initiatives promoting cross-border partnerships, such as joint funding programs and researcher exchanges, given the larger mediation effect of the cooperation channel.

Third, while exports show limited overall effects, the significant impact of computer peripherals suggests that export promotion should adopt a targeted approach, focusing on specific product categories with proven innovation potential rather than undifferentiated export strategies.

5.3 Limitations and future research

This study has several limitations. Using ICT goods as a proxy may not fully capture digital services trade; country-level analysis masks firm-level heterogeneity; and data constraints limit generalizability to developing countries. Future research could refine product classification, explore micro-level mechanisms, and extend analysis to emerging economies.

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