

# The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

## *Abstract*

This paper examines the impact of trade-related R&D spillovers on medium-high-technology-intensive (MHT) capital goods exports across 29 OECD countries from 2010 to 2017. It argues that capital goods imports facilitate technological diffusion, driving knowledge transfer and innovation that enhance industrial competitiveness. Machinery and equipment, including machinery and equipment n.e.c. that encompass Industry 4.0 capital goods, shape technological capabilities and trade performance. An augmented gravity model is employed, incorporating trade-related R&D spillovers as a key explanatory variable. The ICT Development Index (IDI) assesses digital infrastructure's role in absorptive capacity, while standard gravity variables (GDP, distance, contiguity, and common language) capture general knowledge spillovers. Industrial capabilities are measured through these variables, with industrial drivers shaping technological capacity and infrastructural enablers supporting adoption. To address endogeneity, IV-GMM estimation is applied. Findings confirm that trade-related R&D spillovers positively influence MHT capital goods exports, highlighting R&D investment's role in sustaining industrial competitiveness and innovation-driven trade growth.

*Keywords: Trade, R&D spillovers, Gravity Equation, International Competitiveness, IV-GMM*

## **1 Introduction**

The Fourth Industrial Revolution (4IR), driven by disruptive technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and advanced robotics, is transforming global manufacturing through automation, real-time decision-making, and enhanced connectivity (Schwab, 2016). The convergence of Industry 4.0 (I4.0) technologies is reshaping production structures and I4.0 integrates digital and physical systems to maximize efficiency and industrial competitiveness (UNIDO, 2019). Countries that successfully implement I4.0 technologies gain a competitive advantage by improving production quality, fostering employees development, and driving industrial growth (Alm et al., 2016; Hermann et al., 2015). However, the adoption of I4.0 technologies varies significantly due to disparities in knowledge resources, educational infrastructure, and institutional capacities, leading to an unequal global distribution of technological benefits (UNIDO, 2015).

The successful adoption of I4.0 technologies depends on key factors such as real-time operational monitoring, decentralized decision-making, and substantial investment in research and development (R&D), all of which contribute to productivity growth (Aghion and Howitt, 1992). In the I4.0 era, industrial competitiveness is shaped by industrial capabilities, which consist of industrial drivers (technological capabilities derived from knowledge stock and technology transfer through capital goods imports) and industrial outcomes (export performance). Trade-related R&D spillovers—knowledge transfers occurring through international trade—can play a vital role in fostering innovation and industrial competitiveness (Coe and Helpman, 1995). Investments in innovation and technology are likely to generate substantial R&D spillovers, which in turn can facilitate economic productivity and long-term industrial growth (Giovannetti and Piga, 2017). Increased R&D expenditure strengthens this relationship, supporting the development of more technology-intensive, higher-quality products, which enhance industrial competitiveness and international trade (Coe and Helpman, 1995).

International trade, particularly in high-tech capital goods, serves as a key channel for R&D spillovers, facilitating technological diffusion across countries and enhancing total factor

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

productivity (TFP) (Coe and Helpman, 1995). Global value chains (GVCs) further amplify these spillovers, as the trade of intermediate and capital goods embeds advanced technologies, strengthening industrial capabilities. However, while I4.0 technologies drive technological advancements, they also widen the competitiveness gap between developed and developing countries. Developing economies often lack the necessary infrastructure, human capital, and institutional frameworks to fully adopt and utilize I4.0 technologies, which limits their ability to remain competitive in global trade.

This study examines the impact of trade-related R&D spillovers on MHT capital goods exports across 29 OECD countries from 2010 to 2017. Trade-related R&D spillovers refer to R&D knowledge embedded in capital goods imports, facilitating technological diffusion and innovation. Existing studies highlight the importance of capital goods trade, often using machinery and equipment as a proxy variable, which centralizes this diffusion and improves manufacturing processes (Xu and Wang, 1999). While empirical studies demonstrate that trade is a key channel for international R&D spillovers (Coe and Helpman, 1995; Keller, 1998), the specific role of machinery and equipment n.e.c., which also includes Industry 4.0 capital goods, remains underexplored. Furthermore, prior studies have primarily focused on the impact of trade-related R&D spillovers on productivity, with limited analysis of their effect on trade flows. This study extends the existing literature by:

- Focusing on machinery and equipment n.e.c. as a key category of Industry 4.0 capital goods, essential for technological diffusion and competitiveness.
- Investigating the impact of trade-related R&D spillovers on MHT capital goods exports, providing insights into how technology transfer through trade influences industrial development and global trade dynamics.

Given that capital goods, such as machinery, equipment, and software, are R&D-intensive and embody high levels of technological knowledge, importing these goods allows countries to indirectly acquire embedded R&D knowledge (Xu and Wang, 1999). This transfer significantly enhances the importing country's productivity and innovation capacity. Trade-related R&D spillovers boost firm productivity, foster innovation, drive technological progress, and reduce production costs. Understanding the role of R&D spillovers is therefore critical for examining factors influencing international trade flows and their implications for economic development.

An augmented gravity model is employed, incorporating trade-related R&D spillovers as a key explanatory variable. The ICT Development Index (IDI) is included to assess the role of digital infrastructure in absorptive capacity, while standard gravity variables such as GDP, distance, contiguity, and common language capture general knowledge spillovers. Trade-related R&D spillovers and the IDI are used to assess countries' industrial capabilities, specifically as industrial drivers and infrastructural enablers, while gravity variables capture broader knowledge spillovers. The study tests the following hypotheses:

- *H1: Trade-related R&D spillovers (R&D spillovers embodied in capital goods imports) positively impact MHT capital goods exports.*
  - *H1.1: R&D spillovers embodied in machinery and equipment imports positively impact MHT exports.*
  - *H1.2: R&D spillovers embodied in machinery and equipment n.e.c. imports positively impact MHT exports.*

By focusing on the trade effects of R&D spillovers rather than just their productivity impact, this study provides new empirical insights into how international technology transfer via capital goods imports influences trade flows. It enhances our understanding of the role of

# The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

Industry 4.0 capital goods in driving competitiveness and industrial upgrading in global trade.

The remainder of this paper is structured as follows: Section 2 presents the theoretical background and hypotheses, Section 3 outlines the model and data, Section 4 discusses the empirical results, and Section 5 provides concluding remarks.

## 2 Trade-Related R&D Spillovers and Capital Goods Trade

R&D activities are fundamental to knowledge accumulation, directly influencing a country's productivity and global competitiveness (Coe and Helpman, 1995; Griliches, 1988). The cross-border diffusion of technological knowledge—referred to as R&D spillovers—enables firms to benefit from external innovations, advancing the global technology frontier (Griliches, 1979; Keller, 2004). Endogenous growth theories highlight R&D-driven innovation as a key determinant of long-term economic growth (Aghion and Howitt, 1992; Grossman and Helpman, 1991).

International trade serves as a vital channel for R&D spillovers, particularly through capital goods imports. The knowledge embedded in imported capital goods enhances recipients' technological capabilities, fostering production efficiency and innovation (Gong and Keller, 2003; Griliches, 1992). This process, known as embodied R&D spillovers, plays a crucial role in Industry 4.0 (I4.0), where advanced technologies are integrated into capital goods, shaping industrial competitiveness (Los and Verspagen, 2007).

The literature emphasizes the transformative role of technology transfer through capital goods trade, particularly in developing economies. Trade liberalization and tariff reductions facilitate this transfer, enhancing efficiency and reducing the costs of acquiring R&D-intensive capital goods. Xu and Wang (1999) highlight the critical role of machinery and equipment in transmitting R&D spillovers through trade flows. Their study underscores the need to differentiate between various machinery and equipment categories to capture their distinct contributions to technological advancements (Lee, 1995).

However, the benefits of capital goods imports depend on a country's absorptive capacity—its ability to integrate and utilize foreign knowledge effectively. Blyde (2003) argues that nations with higher absorptive capacity experience greater efficiency gains from imported capital goods due to their ability to adapt and apply foreign technology to domestic production processes. Capital goods imports facilitate both vertical and horizontal efficiency gains, improving the quality of domestic products (vertical relation) and expanding the variety of available inputs (horizontal relation). Knowledge spillovers from international trade further enable learning and imitation, a phenomenon historically observed in the industrialization of East Asian economies (Blyde, 2003). Grossman and Helpman (1991) assert that developing economies, often constrained by limited R&D investment, rely on capital goods imports as a critical means of technological catch-up to maintain global competitiveness.

Xu and Wang (1999) reinforce the idea that capital goods serve as the primary vehicles for international R&D spillovers, embedding significantly more technological knowledge than non-capital goods. Their empirical findings suggest that capital goods imports enhance productivity, whereas non-capital goods imports have a negligible impact on technological diffusion. Similarly, Mutreja et al. (2018) emphasize that reducing trade barriers to capital goods enables developing countries to access advanced technologies at lower costs, boosting investment, improving capital-output ratios, and enhancing total factor productivity (TFP). These spillovers help narrow the technological gap between developed and developing nations, fostering innovation-driven economic growth. However, Eaton and Kortum (2001) caution that capital goods production remains highly concentrated, with ten countries accounting for nearly

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

80% of global production. This imbalance forces developing economies to rely on capital goods imports, highlighting the importance of understanding trade-related R&D spillovers in shaping industrial capabilities.

Empirical evidence confirms that imports and foreign direct investment (FDI) are key channels for R&D spillovers in developing economies, facilitating access to foreign technology and improving innovation (Wang and Choi, 2023). Countries with robust human capital and open trade policies experience enhanced spillover effects, leading to increased productivity (Seck, 2012). Both import and export trade play a crucial role in technological diffusion, fostering economic growth. Import trade, in particular, has a pronounced effect on international technology spillovers, improving domestic productivity (Da Silva et al., 2019). These spillovers operate through demonstration effects, competition, and industrial linkages, reinforcing trade's role in knowledge diffusion (Kim et al., 2019).

This research focuses specifically on R&D spillovers embodied in capital goods, as these goods—such as machinery, equipment, and software—are R&D-intensive and embed high levels of technological knowledge and innovation. When a country imports these capital goods, it indirectly acquires the R&D knowledge embedded within them (Xu and Wang, 1999). This knowledge transfer significantly enhances productivity and innovation capacity. Capital goods trade is essential to open-economy innovation-driven growth models, as highlighted by Grossman and Helpman (1991) and Rivera-Batiz and Romer (1991). The R&D spillovers embedded in capital goods imports (trade-related R&D spillovers) can drive firm productivity, stimulate innovation, advance technological progress, and lower production costs. Consequently, understanding R&D spillovers is critical to assessing factors influencing international trade flows and their broader economic implications.

Within capital goods trade, machinery and equipment imports are key carriers of R&D spillovers. Existing studies widely acknowledge that these goods embody advanced technological knowledge, making them a primary means of cross-border technology transfer (Coe and Helpman, 1995; Xu and Wang, 1999). Importing firms gain access to cutting-edge innovations, enhancing production efficiency, improving product quality, and expanding trade opportunities (Wang et al., 2010). However, previous research has largely focused on general capital goods imports, using machinery and equipment as a broad proxy variable (Xu and Wang, 1999). While studies confirm the positive impact of trade-related R&D spillovers on productivity, the role of machinery and equipment trade in influencing export flows remains underexplored. This study addresses this research gap by differentiating between:

- Machinery and equipment imports (general capital goods trade): which includes industries such as the manufacture of computer, electronic and optical products; manufacture of electrical equipment; and manufacture of machinery and equipment n.e.c (not elsewhere classified),
- Machinery and equipment n.e.c, representing Industry 4.0 capital goods: this specifically covers the manufacture of general-purpose machinery; other general-purpose machinery; special-purpose machinery (including robotics and additive manufacturing); agricultural and forestry machinery; and metal forming machinery and machine tools (including CAD-CAM goods), which embed advanced technologies associated with Industry 4.0.

Given the crucial role of machinery and equipment in technology transfer and export performance, this study builds on these insights to propose hypotheses H1.1 and H1.2, and, more generally, H1, as presented in the Introduction.

### 3 Methodology

This study examines the impact of R&D spillovers embodied in capital goods imports on capital goods exports at an aggregated level. These R&D spillovers, referred to as trade-related R&D spillovers, are analysed using gravity models. Gravity models are a widely employed approach in international trade literature for studying bilateral trade flows (Yotov et al., 2016). These models integrate multiple data sources to how technological advancements and trade interactions influence exports, including non-directional general spillovers. This relationship has not been extensively studied in gravity models. To bridge this research gap, the study applies panel gravity models to examine the effect of trade-related R&D spillovers on medium-high-technology (MHT) exports among OECD countries.

Our model consists of three key components that capture essential aspects of trade-related R&D spillovers: (1) technological advancements, (2) geographic factors influencing local spillovers, and (3) trade in goods to analyse high-quality product flows. Trade-related R&D spillovers embodied in capital goods imports are used as a proxy for technological innovation, while the International Telecommunication Union's ICT Development Index (IDI) represents a country's digital infrastructure. Gravity model variables are incorporated to capture general knowledge spillovers that are not tied to specific transmission channels.

To ensure robust and policy-relevant findings, the study focuses on OECD countries for three primary reasons:

- Most prior research on the link between R&D spillovers and total factor productivity (TFP) has concentrated on OECD countries.
- OECD countries exhibit higher R&D expenditures due to the elevated costs of innovation.
- OECD countries provide more comprehensive and reliable data.

The dataset covers 29 OECD countries from 2010 to 2017, aligning with the first wave of Industry 4.0 (I4.0) technologies influencing trade patterns. The analysis is conducted in two stages: first, using the full sample of 29 OECD countries, and second, focusing on a subset of 18 OECD countries classified as innovation leaders and strong innovators. This segmentation helps clarify differential trade flows between countries. To evaluate the impact of early I4.0 technologies, the study emphasizes MHT sectors.

#### 3.1 Model Specification

This research employs panel gravity models to analyse the effects of trade-related R&D spillovers on exports at an aggregated level. The gravity dataset is structured in a square matrix format, where each observation represents a country pair's yearly data, providing insights into country characteristics and trade relationships (Head et al., 2010). The gravity model incorporates variables measuring trade determinants, such as trade facilitation policies, geographic distance, and cultural similarities influencing trade patterns (Gurevich and Herman, 2018; Head et al., 2010). Each observation in the gravity dataset is uniquely identified by a combination of country pairs, with variables that can be either unilateral (e.g., each country's GDP and population) or bilateral (e.g., geographic distances and trade flows) (Mayer and Zignago, 2011).

An extended gravity model is employed to capture essential linkages between R&D spillovers, geographic factors, digital performance, and trade in goods. The dependent variable is capital goods exports, specifically MHT exports, to evaluate high-quality or diverse product exports among OECD countries. The analysis distinguishes different country groups to assess trade competitiveness.

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

The explanatory variables include trade-related R&D spillovers, the ICT Development Index (IDI), and gravity model variables:

- Trade-related R&D spillovers embodied in capital goods imports serve as a proxy for technological innovation, a crucial driver of international trade. These spillovers capture the diffusion of knowledge and technology across borders, enhancing productivity and economic growth.
- The ICT Development Index (IDI) is included as a proxy for a country's digital performance, encompassing factors such as infrastructure, accessibility, affordability, digital skills, and usage. These elements are vital for absorptive capacity and reducing trade costs.
- Gravity model variables such as common language, shared borders, and colonial ties are included to capture general knowledge spillovers beyond specific transmission channels.

This structured approach ensures a comprehensive analysis of how trade-related R&D spillovers influence MHT exports and their broader implications for international trade and technological diffusion.

### *Measurement of R&D spillovers*

The measurement of R&D spillovers in this study follows well-established approaches in the literature. Trade-related R&D spillovers are quantified using a modified version of the gravity model framework. Specifically, R&D spillovers are estimated by incorporating R&D expenditures and trade flows of capital goods across countries. The spillover effect is captured through bilateral trade in R&D-intensive goods, where capital goods imports serve as a conduit for technology diffusion.

The trade channel is recognized as one of the most effective means of acquiring foreign knowledge stocks. Numerous studies have identified a statistically significant positive relationship between trade-related R&D spillovers and productivity. A seminal study by Coe and Helpman (1995, hereafter CH) analysed the effects of domestic and foreign R&D capital stocks on total factor productivity (TFP) through trade channels. However, subsequent critiques by Keller (1998) and Lichtenberg and van Pottelsberghe (1998, hereafter LP) raised concerns regarding CH's weighting formula, citing potential aggregation bias. In response, Coe, Helpman, and Hoffmaister (1998) refined their methodology using alternative weighting criteria, reaffirming that imports serve as a key conduit for R&D spillovers with a statistically significant effect on productivity. LP (1998) further supported these findings using a modified weighting formula, which has since been widely adopted in the literature.

Building on this framework, the present study employs the LP (1998) weighting scheme to analyse trade-related R&D spillovers within the context of the gravity model. The LP method was selected due to its reduced sensitivity to data aggregation bias, ensuring greater reliability in the measurement of spillover effects. The foreign R&D capital stock is computed as follows:

$$S_i^{f-LP}(M) = \sum_{j \neq i} \left( \frac{m_{ij}}{Y_j} * S_j^d \right) \quad (1)$$

In accordance with this weighting scheme, a fraction  $m_{ij}/Y_j$  of country  $j$ 's domestic R&D stock spillovers flows to country  $i$  through bilateral trade, and  $Y_j$  is country  $j$ 's output (Lichtenberg and Van Pottelsberghe De La Potterie, 1998). Therefore, R&D spillovers  $S_i^{f-LP}$  are computed for the receiver country (country  $i$ ) as a weighted sum of (cumulative) domestic R&D capital stocks in the manufacturing industry  $S_j^d$  which originates from the

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

sending countries (country  $j$ ).  $S_j^d$  refers to foreign R&D capital stocks.

This study specifically measures R&D spillovers embodied in capital goods imports by categorizing them into machinery and equipment (ME\_KM) and machinery and equipment not elsewhere classified (ME\_KM)<sup>1</sup>, which includes I4.0-ready capital goods such as additive manufacturing, robotics, and CAD-CAM technologies. The mathematical representation is as follows:

$$FRD\_ME_{it} = \sum_{j \neq i} \left( \frac{ME\_KM_{ijt}}{Y_{jkt}} * S_{jkt}^d \right) \quad (2)$$

and

$$FRD\_MEN_{it} = \sum_{j \neq i} \left( \frac{MEN\_KM_{ijt}}{Y_{jkt}} * S_{jkt}^d \right) \quad (3)$$

They measures that country  $i$  gains from international R&D spillover through imports from their trade partners in year  $t$ ; where imports are machinery and equipment, and machinery and equipment n.e.c.  $Y_{jkt}$  represents country  $j$ 's real GDP in manufacturing sector in time  $t$ .  $S_{jkt}^d$  denotes country  $j$ 's domestic R&D capital stocks. That is, this variable shows the accumulated domestic R&D capital stocks from country  $i$ 's trading partners<sup>2</sup> for each year  $t$ .  $ME\_KM_{ijt}$  is bilateral capital goods imports of country  $i$  from country  $j$ , where machinery and equipment are used as a proxy for capital goods.  $MEN\_KM_{ijt}$  is bilateral capital goods imports of country  $i$  from country  $j$ , where machinery and equipment n.e.c are used as a proxy for capital goods. Machinery and equipment n.e.c also represents medium-high digital intensive goods (Calvino et al., 2018).

As countries invest in R&D, new knowledge accumulates over time, forming a nation's knowledge stock. This accumulated knowledge, commonly referred to as the domestic R&D capital stock, plays a crucial role in economic growth. However, one of the primary challenges in empirical studies is the lack of globally comparable capital stock data. R&D capital stock is not directly observable, necessitating the use of estimation techniques to measure its impact effectively.

To address this issue, various proxies for capital accumulation have been employed in the literature. One widely accepted approach is the Perpetual Inventory Method (PIM), which has been frequently utilized in studies on R&D spillovers (Benhabib and Spiegel, 1994; Berlemann and Wesselhöft, 2016). This study adopts a variation of PIM to compute R&D capital stock variables, ensuring consistency with prior research methodologies (Coe and Helpman, 1995; Xu and Wang, 1999). By leveraging these advanced estimation techniques, this research aims to provide a robust and comprehensive analysis of trade-related R&D spillovers and their implications for international trade flows.

This structured approach ensures a comprehensive analysis of how trade-related R&D spillovers influence MHT exports and their broader implications for international trade and technological diffusion.

### *Absorptive capacity and digital infrastructure*

The ICT Development Index (IDI) serves as a crucial indicator of a country's digital

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<sup>1</sup> Machinery and equipment (ME) industries includes machinery and equipment n.e.c (MEN); Electrical equipment; computer, electronic and optical. These are also referred to as medium-high digital intensive sectors.

<sup>2</sup> Our sample consists of 29 countries, and Foreign R&D capital stocks for each country are calculated as the sum of their trade partners' domestic R&D capital stocks (28 countries).

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

performance, significantly enhancing absorptive capacity and reducing trade costs. Developed by the International Telecommunication Union (ITU), the IDI is a composite index that compares and explains ICT advancements across countries, providing valuable insights into ICT development levels, digital disparities, and growth potential (ITU, 2017). Given its comprehensive approach, the IDI considers factors such as infrastructure, access, affordability, skills, and usage, making it an appropriate proxy for assessing a country's digital performance in this research. The primary objective is to evaluate the role of reducing barriers to technology transfer through capital goods imports by integrating the IDI into the gravity model.

Supporting this approach, prior studies emphasize the positive impact of input liberalization in the ICT industry on firm productivity, whereas output liberalization has been found to have a negative effect (Zhang, Wei, and Ma, 2021). The increasing prevalence of emerging technologies and plurilateral agreements has significantly boosted trade in ICT goods (Ghods, 2021). Moreover, the role of technical IT skills in fostering organizational capabilities, including absorptive capacity, has been widely recognized (Bolívar-Ramos, García-Morales, and Martín-Rojas, 2013). These skills enable firms to access and share external knowledge effectively, further reducing trade costs. Recent empirical evidence from Mehmood, Arif Malik, and Khalid (2021), using the IDI within a gravity model, confirms that ICT development positively influences trade flows. Therefore, by incorporating the IDI into this research, the study aims to assess the impact of ICT in facilitating technology transfer, increasing absorptive capacity, and enhancing the effectiveness of capturing technological innovation in capital goods imports.

### *General knowledge spillovers channel in the gravity model*

The gravity model, incorporating key variables such as language, border, or colonial ties, facilitates the capture of general knowledge spillovers, unrestricted by specific transmission channels. This approach acknowledges the role of geography in shaping trade-related R&D spillovers, recognizing that capital goods used in production embed technologies and knowledge that can disseminate across firms and industries when imported. This diffusion leads to productivity gains and innovation, highlighting the importance of geographic factors in capturing local spillovers. To account for general knowledge spillovers, this research incorporates essential gravity variables such as distance, contiguity, and common language.

Geographic distance, measured between the capital or most populated cities of two countries, serves as a proxy for trade barriers, including transportation costs, time, and home bias (Mayer and Zignago, 2011). Empirical studies indicate that whether distance is measured from a country's geographic centre or major cities does not significantly impact results in a global sample (Melitz, 2007). Additionally, strong local ties among firms can foster increased trade (Head, 2003). Countries sharing borders tend to trade more due to reduced trade costs (Anderson and Van Wincoop, 2003; Coughlin and Novy, 2012).

Transaction costs and cultural differences arising from communication challenges further impact trade flows. Countries sharing a common language tend to trade more due to lower communication barriers, an assertion supported by empirical evidence indicating that trade significantly increases among countries with a shared language (Melitz, 2008).

This study prioritizes the similarity index over the general GDP variable. R&D accumulation in countries with similar technological capabilities is a key driver of bilateral trade. This aligns with neoclassical and new trade theories (NTTs), which emphasize technology's role in shaping trade patterns (Krugman, 1980; Helpman and Krugman, 1985). NTTs highlight economies of scale, increasing returns to scale (IRS), and product differentiation as key factors in international trade (Kiriya, 2012).

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

To account for product differentiation, this study follows Krugman and Helpman (1985) by incorporating bilateral economic size and a similarity index instead of GDP alone. The similarity index measures relative country size, a frequently used approach in gravity literature (Breuss and Egger, 1999; Egger, 2000, 2002; Baltagi et al., 2003).

This study highlights intra industry trade (specifically focus on Medium-high technology intensive goods in manufacturing industry) role in explaining how R&D-driven innovation shapes product differentiation, thereby increasing trade. The similarity hypothesis asserts that when trading partners share comparable technological capabilities, intra-industry trade intensifies. Wang, Wei, and Liu (2010) used R&D accumulation (domestic R&D capital stock) and technological similarity in an extended gravity model to demonstrate the positive impact on trade. However, this research focuses specifically on trade-related R&D spillovers rather than general R&D accumulation.

The bilateral overall economic size and the similarity size index are calculated using the following equations (Baltagi et al., 2003)

$$GDPT_{ijt} = \ln (RGDP_{it} + RGDP_{jt}) \quad (4)$$

Where  $GDPT_{ijt}$  is the bilateral overall economic size and  $RGDP_{it}$  is real GDP<sup>3</sup> for country  $i$  and  $RGDP_{jt}$  is real GDP for country  $j$  in time  $t$  (Feenstra, 2003, p. 146).

$$SIM = 1 - \left( \frac{RGDP_{it}}{RGDP_{it} + RGDP_{jt}} \right)^2 - \left( \frac{RGDP_{jt}}{RGDP_{it} + RGDP_{jt}} \right)^2 \quad (5)$$

where  $0 < SIM < 0.5$ ;  $SIM = 0$ . If one country produces nothing, the  $SIM_{ij} = 0.5$ , and if the RGDPs of the two countries are equal, trading partners are sharing the market. Then,  $\ln SIM$  refers to Breuss and Egger (1999), Egger (2000, 2002), and Serlenga and Shin (2007), the similarity index is defined as:

$$\ln SIM = \ln \left[ 1 - \left( \frac{RGDP_{it}}{RGDP_{it} + RGDP_{jt}} \right)^2 - \left( \frac{RGDP_{jt}}{RGDP_{it} + RGDP_{jt}} \right)^2 \right] \quad (6)$$

While existing research has explored the impact of trade-related R&D spillovers on productivity, there are limited studies evaluating their influence on trade flows. Notably, a research gap exists at the intersection of gravity theories and R&D spillovers literature, particularly in estimating the impact of R&D spillovers embodied in capital goods imports using gravity models in the context of Industry 4.0 (I4.0) technologies. The current literature lacks a comprehensive analysis of the influence of trade-related R&D spillovers on MHT exports.

Therefore, this research aims to fill this gap by examining the role of R&D spillovers embodied in capital goods imports on MHT exports at an aggregated level, using panel gravity models.

### 3.2 Data

The dataset is constructed from multiple sources, including CEPII, OECD.Stat, and other relevant databases, to develop the gravity model, which assesses the impact of economic factors and trade barriers on bilateral trade. The model integrates proxies for trade costs such as distance, contiguity, and cultural proximity (e.g., common language), which influence trade patterns based on economic sizes and trade costs.

The key dependent variable is MHT capital goods exports, reflecting a country's trade

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<sup>3</sup> Gross Domestic Products (GDP) data were used in real terms (constant 2015 US\$) based on ISIC (Rev. 4). Sectoral GDP data gathered from World Development Indicators (WDI).

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

competitiveness. MHT exports contribute to economic growth by enhancing productivity and efficiency. The bilateral trade dataset is sourced from the CEPII-BACI database, a harmonized, product-level international trade database (Gaulier and Zignago, 2010), which provides a single harmonized bilateral trade flow for each year and country pair, ( $ij$  or  $ji$ ) (exporter ( $i$ ) and importer ( $j$ ) country).

The research primarily focuses on MHT exports in capital goods, evaluating the impact of I4.0 technologies on trade patterns. Technology-intensive exports are identified using six-digit Harmonized System classifications, aggregated from Industry-level (ISIC, Rev.4) to EU-level (NACE, Rev.2) classifications to ensure robust policy analysis.

Explanatory variables include trade-related R&D spillovers, the ICT Development Index (IDI), and gravity variables such as distance, common language, colonial ties, and GDP.

- *Trade-related R&D spillovers*, derived from capital goods imports, serve as a proxy for technological innovation, facilitating knowledge diffusion and economic growth.

To calculate R&D spillovers, the study incorporates R&D expenditure, GDP, and bilateral trade data from OECD.Stat:

- Business Enterprise Expenditure on R&D (BERD) is utilized within the manufacturing sector due to its strong spillover effects. Real BERD flows (constant 2015 PPP dollars) are sourced from the OECD's Analytical Business Enterprise Research and Development (ANBERD) database.
- The Perpetual Inventory Method (PIM) (Benhabib and Spiegel, 1994; Berlemann and Wesselhöft, 2017; Coe et al., 1993; Xu and Wang, 1999) is employed to measure accumulated R&D capital stock. The PIM formula from Coe and Helpman (1995) is used to calculate domestic R&D stock (details in the Appendix).
- Gross Value Added (GVA) data at the sectoral level is sourced from the OECD's Structural Analysis (STAN) database.
- Bilateral capital goods imports are gathered from the OECD's STAN Bilateral Trade Database by Industry and End-Use Category (BTDIxE), which is used to weight spillovers.
- *The ICT Development Index (IDI)*, developed by the International Telecommunication Union (ITU), measures digital infrastructure, accessibility, and technological capacity. The IDI is a composite index introduced in the Measuring the Information Society Report (ITU, 2017), encompassing ICT readiness, ICT use, and ICT capability, which together compress infrastructure and access levels, societal ICT utilization, and ICT skill outcomes.
- *Gravity variables*, including distance, common language, and colonial ties, are obtained from the CEPII database (Head et al., 2010). These variables play a key role in quantifying trade patterns. Manufacturing sector GDP data is sourced from the World Bank Development Indicators (WDI).

Both models utilize 6,496 observations for the full sample (29 OECD countries) and 2,448 observations for innovation leaders and strong innovators (18 OECD countries). The models incorporate two binary variables—contiguity and common language—along with two index values—IDI and LSIMR. All other variables are continuous. Descriptive statistics for explanatory variables are presented in Table 1.

# The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

*Table 1: Descriptive statistics of explanatory variables for Models*

|                                                                             | Explanatory Variables | Mean   | Std Dev | Min.   | Max.   |
|-----------------------------------------------------------------------------|-----------------------|--------|---------|--------|--------|
| <b>Full sample</b><br><b>(29 OECD Countries)</b>                            | <i>LFRD_ME</i>        | 25.458 | 1.134   | 22.573 | 27.379 |
|                                                                             | <i>LFRD_MEN</i>       | 24.907 | 1.09    | 22.072 | 26.854 |
|                                                                             | <i>LRGDPT</i>         | 26.157 | 1.121   | 22.814 | 28.764 |
|                                                                             | <i>LSIMR</i>          | -1.52  | .92     | -5.952 | -.693  |
|                                                                             | <i>LDIST</i>          | 7.937  | 1.206   | 4.088  | 9.883  |
|                                                                             | <i>CONTIG</i>         | .079   | .269    | 0      | 1      |
|                                                                             | <i>COMLANG</i>        | .059   | .236    | 0      | 1      |
|                                                                             | <i>IDI_o</i>          | 7.348  | 1.069   | 3.6    | 8.86   |
|                                                                             | <i>IDI_d</i>          | 7.348  | 1.069   | 3.6    | 8.86   |
| <b>Innovation leader and strong innovator</b><br><b>(18 OECD Countries)</b> | <i>LFRD_ME</i>        | 25.629 | 1.087   | 23.222 | 27.298 |
|                                                                             | <i>LFRD_MEN</i>       | 25.032 | 1.056   | 22.781 | 26.752 |
|                                                                             | <i>LRGDPT</i>         | 26.515 | 1.104   | 24.014 | 28.764 |
|                                                                             | <i>LSIMR</i>          | -1.464 | .829    | -4.864 | -.693  |
|                                                                             | <i>LDIST</i>          | 8.127  | 1.282   | 5.156  | 9.866  |
|                                                                             | <i>CONTIG</i>         | .085   | .279    | 0      | 1      |
|                                                                             | <i>COMLANG</i>        | .144   | .351    | 0      | 1      |
|                                                                             | <i>IDI_o</i>          | 7.975  | .551    | 6.54   | 8.86   |
|                                                                             | <i>IDI_d</i>          | 7.975  | .551    | 6.54   | 8.86   |

### 3.3 The Empirical Model

The empirical framework follows econometric specifications established by Baltagi et al. (2003), Egger (2002), and Serlenga and Shin (2007), integrating key gravity model variables such as bilateral economic size, similarity indices, and geographical distance. The extended model includes trade-related R&D spillovers and IDI to assess their influence on exports. The dataset consists of observations from 29 OECD countries between 2010 and 2017. These specifications encompass key variables such as overall bilateral size, similarity index, distance, and others. The framework of the gravity model is established upon on  $t * n * (n - 1)$  matrix (Bacchetta, 2012), where  $t$  is the timeframe and  $n$  is the sample. We extended the established gravity model adding trade-related R&D spillovers and IDI to examine the influence of R&D spillovers embodied in capital goods imports on export. Our analysis focused on a dataset encompassing 29 OECD countries during the period from 2010 to 2017. The model 1 and model 2 can be seen as follow:

**Model 1** The baseline gravity model incorporates machinery and equipment

$$LMHTCG_{ijt}^k = \beta_0 + \beta_1 LFRD\_ME_{i,t} + \beta_2 LRGDPT_{ijt} + \beta_3 LSIM_{ijt} + \beta_4 LDIST_{ij} + \beta_5 CONTIG_{ij} + \beta_6 COMLANG_{ij} + \beta_7 IDI_{it} + \beta_8 IDI_{jt} + \mu_i + \mu_j + \mu_t + e_{ijt} \quad (7)$$

**Model 2** Gravity model incorporates machinery and equipment n.e.c.

$$LMHTCG_{ijt}^k = \beta_0 + \beta_1 LFRD\_MEN_{i,t} + \beta_2 LRGDPT_{ijt} + \beta_3 LSIM_{ijt} + \beta_4 LDIST_{ij} + \beta_5 CONTIG_{ij} + \beta_6 COMLANG_{ij} + \beta_7 IDI_{it} + \beta_8 IDI_{jt} + \mu_i + \mu_j + \mu_t + e_{ijt} \quad (8)$$

The variables of the model can be seen as follows:

- $X_{ijt}^k$  is based on Medium-high-technology-intensive (MHT) exports, which denotes the bilateral export flows from origin country  $i$  to destination country  $j$  for timeframe  $t$  in

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

manufacturing industry.

- $LMHTCG_{ijt}^k$  is MHT exports in capital goods for the aggregated level analysis, which includes only scientific and technological category of other scientific/technological manufacture economic.
- $LFRD_{it}$  denotes R&D spillovers embodied in bilateral capital goods imports. This variable is used as a proxy variable for technological innovation. Trade-related R&D spillovers increase productivity, and increased productivity can improve product quality. Thus, its impact on export is expected to be significant, with a positive sign. We used two capital goods to see their impact on trade separately.
  - $LFRD_{ME}_{it}$  is R&D spillovers embodied in bilateral capital goods imports in machinery and equipment.
  - $LFRD_{MEN}_{it}$  is R&D spillovers embodied in bilateral capital goods imports in machinery and equipment n.e.c.
- $LRGDP_{ijt}$  refers to overall bilateral economic size and  $LSIM_{ijt}$  is similarity index. GDP is expressed in US dollars at constant prices (2015) in the manufacturing industry.
- $LDIST_{ij}$  refers to the geographical distance between two countries' most populated cities (in km). When the physical distance between countries expands, transactions become more expensive due to higher transportation costs; thus, the distance coefficient is expected to be negative.
- $CONTIG_{ij}$  denotes common border dummy variable, assigned 1 if two countries share a land border and 0 otherwise. This serves as a proxy for natural distance, and its coefficient is expected to be positive.
- $COMLANG_{ij}$  shows common official language dummy variable, taking 1 if both countries share an official language and 0 otherwise. This variable reflects cultural proximity and historical trade ties, which are expected to positively impact trade.
- $IDI_{it}$  and  $IDI_{jt}$  are the ICT development index in country  $i$  and country  $j$  in time  $t$ , respectively. The impact of IDI on trade is expected to be positive because it can improve trade by reducing transaction costs.
- $\alpha_0$  and  $\beta_0$  are constant,  $\mu_i, \mu_j, \mu_t$  dummy for reporter country, destination country and time, respectively, and  $u_{ijt}$  and  $e_{ijt}$  denote the bilateral error term.

### 3.4 Research Method

Endogeneity arises from unobservable variables in the model that violate the Gauss-Markov assumption of zero conditional mean, leading to a correlation between explanatory variables and the error term. To measure the impact of technological innovation, we use a proxy variable (R&D spillovers) due to the unobservable nature of innovation. However, this introduces endogeneity concerns, particularly measurement error in the proxy. The correlation between variables and the error term necessitates caution when interpreting gravity model outcomes (Shepherd, 2013). Ordinary Least Squares (OLS) can produce biased and inconsistent estimates in the presence of endogeneity, leading to misleading hypothesis testing results (Wooldridge, 2009; Shepherd, 2013). Therefore, OLS is not suitable when endogeneity is present. Our proxy variable (R&D spillovers) is imperfect due to its correlation with GDP and the error term, both stemming from theoretical assumptions and calculation processes, introducing measurement error issues.

To address endogeneity, we adopt the Instrumental Variable (IV) technique, a widely used approach for obtaining consistent parameter estimates for endogenous regressors. IV helps

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

mitigate omitted variable bias by using an instrument uncorrelated with the error term but relevant for predicting the explanatory variable. To ensure instrument validity, we verify instrument exogeneity (the instrument is uncorrelated with the error term) and instrument relevance (the instrument is strongly correlated with the endogenous variable). IV models can be either exactly identified or overidentified, with the choice between Two-Stage Least Squares (2SLS) and Generalized Method of Moments (GMM) depending on the characteristics of the error term (Cameron and Trivedi, 2005).

The GMM estimator is particularly useful for addressing endogeneity concerns, especially in the presence of heteroskedasticity, as it efficiently handles unknown forms of heteroskedasticity (Baum, 2006; Baum et al., 2003). GMM incorporates both Instrumental Variable (IV) and Ordinary Least Squares (OLS) estimators (Baum et al., 2010), requiring sufficiently large sample sizes for optimal performance (Baum et al., 2003). Since heteroskedasticity is detected in our model, GMM is selected as the estimation method. Our selection was reinforced through an array of tests encompassing Durbin-Wu-Hausman, overidentifying restrictions, weak instruments, heteroskedasticity, and model specification assessments. These tests confirm the presence of heteroskedasticity, justifying the use of the IV-GMM approach, which outperforms 2SLS in the presence of heteroskedasticity, enhancing estimation efficiency. By applying the IV-GMM estimator, this study ensures robust and reliable parameter estimates while addressing the challenges posed by endogeneity in trade-related R&D spillovers models.

### 4 Empirical Results and Discussion

For hypothesis testing, we utilized data spanning 29 OECD countries from 2010 to 2017. Using a panel gravity model, we applied IV-GMM techniques to analyse aggregated-level data. As discussed in previous sections, our models are based on an augmented gravity model framework, which examines the influence of trade-related R&D spillovers on capital goods exports across OECD countries. Specifically, Models 1 and 2 examine the impact on all 29 OECD countries, while Model 1.1 and 2.1 focus on a subset of 18 OECD countries classified as innovation leaders and strong innovators.

Both models were estimated using IV-GMM applied to fixed-effects panel data, leveraging a strongly balanced panel structure. The objective was to gain insights into the distinct impact of trade-related R&D spillovers on overall capital goods exports while separately analyzing the effects of machinery and equipment (ME) and machinery and equipment not elsewhere classified (MEN). Pairwise correlations for Models 1 and 2 are presented in Table 2, summarizing the correlation matrix of explanatory variables. Correlations exceeding 50% are generally considered high (reference). In our case, the correlation between R&D spillovers linked to bilateral capital goods imports—particularly in machinery and equipment n.e.c. industries—was 48%.

Notably, total GDP and both trade-related R&D spillovers variables exhibited strong correlations exceeding 50%, confirming their endogeneity within our model. Endogeneity tests further validated this concern. Additionally, trade agreement variables demonstrated substantial correlation with distance, a common observation in gravity literature (Yotov et al., 2016). To mitigate additional endogenous factors, trade agreement variables were excluded from the model.

# The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

*Table 2: Correlation matrix of explanatory variables<sup>4</sup>*

|                                           | <i>Explanatory Variables</i>          | (1)    | (2)    | (3)     | (4)     | (5)     | (6)    | (7)     | (8)    | (9) |
|-------------------------------------------|---------------------------------------|--------|--------|---------|---------|---------|--------|---------|--------|-----|
| <b>29 OECD Countries</b><br>(Full sample) | <i>LFRD_ME</i> (1)                    | 1      |        |         |         |         |        |         |        |     |
|                                           | <i>LFRD_MEN</i> (2)                   | 0.993* | 1      |         |         |         |        |         |        |     |
|                                           | <i>RGDPT</i> (3)                      | 0.537* | 0.522* | 1       |         |         |        |         |        |     |
|                                           | <i>LSIMR</i> (4)                      | 0.090* | 0.092* | -0.411* | 1       |         |        |         |        |     |
|                                           | <i>LDIST</i> (5)                      | 0.139* | 0.150* | 0.307*  | -0.124* | 1       |        |         |        |     |
|                                           | <i>CONTIG</i> (6)                     | 0.030  | 0.032* | -0.018  | 0.079*  | -0.436* | 1      |         |        |     |
|                                           | <i>COMLANG</i> (7)                    | 0.110* | 0.114* | 0.131*  | 0.040*  | 0.055*  | 0.237* | 1       |        |     |
|                                           | <i>IDI_o</i> (8)                      | 0.135* | 0.106* | 0.148*  | 0.001   | 0.000   | -0.010 | 0.088*  | 1      |     |
|                                           | <i>IDI_d</i> (9)                      | -0.011 | -0.006 | 0.148*  | 0.001   | 0.000   | -0.010 | 0.088*  | 0.081* | 1   |
| <b>18 OECD Countries</b>                  | <i>LFRD_ME</i> (1)                    | 1      |        |         |         |         |        |         |        |     |
|                                           | <i>LFRD_MEN</i> (2)                   | 0.991* | 1      |         |         |         |        |         |        |     |
|                                           | <i>RGDPT</i> (3)                      | 0.496* | 0.477* | 1       |         |         |        |         |        |     |
|                                           | <i>LSIMR</i> (4)                      | 0.020  | 0.021  | -0.533* | 1       |         |        |         |        |     |
|                                           | <i>LDIST</i> (5)                      | 0.025  | 0.050  | 0.181*  | -0.157* | 1       |        |         |        |     |
|                                           | <i>CONTIG</i> (6)                     | 0.046  | 0.044  | 0.006   | 0.060*  | -0.472* | 1      |         |        |     |
|                                           | <i>COMLANG</i> (7)                    | 0.093* | 0.109* | 0.090*  | 0.019   | 0.035   | 0.343* | 1       |        |     |
|                                           | <i>IDI_o</i> (8)                      | 0.185* | 0.163* | 0.093*  | 0.102*  | -0.021  | -0.021 | -0.112* | 1      |     |
|                                           | <i>IDI_d</i> (9)                      | -0.035 | -0.025 | 0.093*  | 0.102*  | -0.021  | -0.021 | -0.112* | 0.286* | 1   |
|                                           | * Shows significance at the .01 level |        |        |         |         |         |        |         |        |     |

## Model Diagnostics and Model Selection

To test Hypothesis 1, which posits that R&D spillovers embodied in bilateral capital goods imports positively impact MHT capital goods exports, we developed two models based on machinery and equipment (ME) (Model 1) and machinery and equipment n.e.c. (MEN) industries (Model 2).

Before estimation, we conducted diagnostic tests to assess model assumptions: Breusch-Pagan/Cook-Weisberg test detected heteroskedasticity, confirming that error variance was not constant. Variance Inflation Factor (VIF) confirmed that multicollinearity was not a concern. Ramsey RESET test rejected the null hypothesis of no omitted variables, indicating model misspecification and further justifying the use of IV techniques.

Given the presence of endogenous variables, we applied IV-GMM techniques. Lagged endogenous variables were used as instruments, following common practices in the productivity literature (Xu and Wang, 1999). IV-GMM was employed to estimate Models 1 and 2, with additional analysis on 18 OECD countries (Models 1.1 and 2.1), categorized as innovation leaders and strong innovators, providing further insights. To validate model correctness, we conducted: Ramsey/Pesaran-Taylor RESET test, confirming correct specification for both equations. Durbin-Wu-Hausman test, rejecting the null hypothesis of exogeneity and confirming the need for IV techniques. IV heteroskedasticity test (Pagan-Hall general test), which further confirmed heteroskedasticity, supporting the selection of the GMM model for efficiency.

To assess the reliability of our approach, we conducted two key tests: the Hansen test for instrument validity and an endogeneity test. The Hansen test confirmed instrument validity, while the endogeneity test demonstrated that the issue was successfully addressed, ensuring

<sup>4</sup> 29 OECD countries show full sample, and 18 OECD countries shows Innovation leader and strong innovator

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

unbiased results.

### *Estimation Results and Key Findings*

Table 3 presents the results of the instrumental variables estimation using a two-step efficient Generalized Method of Moments (IV-GMM) for Models 1 and 2 (as well as Models 1.1 and 2.1 for innovation leader countries). The Ramsey/Pesaran-Taylor RESET test confirmed that both models were correctly specified. The Durbin-Wu-Hausman test rejected the null hypothesis of exogeneity, reinforcing the need for IV techniques. The IV heteroskedasticity test further justified the choice of the IV-GMM model for handling heteroskedasticity.

The Hansen test validated the instruments, while the endogeneity test confirmed that the issue was successfully addressed, ensuring reliable interpretation of the model's results.

The IV-GMM estimation results (Table 3) confirm that R&D spillovers embodied in capital goods imports positively impact MHT capital goods exports. The coefficients for R&D spillovers in machinery and equipment (ME) and machinery and equipment n.e.c. (MEN) imports were positive and statistically significant at the 10% level for both models. A 1% increase in trade-related R&D spillovers led to a 2.24% and 2.23% rise in MHT capital goods exports for Models 1 and 2, respectively.

Relative market size (similarity index) also had a positive and significant effect, with a 1% increase leading to a 1.26% and 1.10% rise in exports for Models 1.1 and 1.2, respectively. Conversely, geographic distance negatively impacted exports, with a 1% increase in distance reducing bilateral MHT capital goods exports by 1.07%. Common language significantly boosted trade by 69%, while contiguity, IDI, and total GDP were found to be insignificant.

The findings support Hypothesis 1, confirming that R&D spillovers in capital goods imports enhance MHT capital goods exports. Results for 18 OECD countries (innovation leaders and strong innovators) align with those for the broader 29-country group, reinforcing Hypothesis 1.1. However, the endogeneity test for IV-GMM was near 5%, requiring cautious policy interpretation. Additionally, endogeneity remained unresolved when using MEN imports, indicating the need for further investigation. Despite these limitations, our results highlight the significant role of R&D spillovers in driving MHT capital goods exports, particularly when proxied by ME imports.

*Table 3: Instrumental Variables estimation (two-step IV-GMM) for Model 1 and 2*

|           | Full sample<br>29 OECD countries                        |                                 | Innovation leader and strong innovator<br>18 OECD countries |                                 |
|-----------|---------------------------------------------------------|---------------------------------|-------------------------------------------------------------|---------------------------------|
| Variables | Log of MHT export in <b>capital goods</b><br>(LMHTCG_X) |                                 |                                                             |                                 |
|           | Model<br>1<br>IV_GMM<br>cluster                         | Model<br>2<br>IV_GMM<br>cluster | Model<br>1.1<br>IV_GMM, cluster                             | Model<br>2.1<br>IV_GMM, cluster |
| LFRD_ME   | 0.237*<br>(0.128)                                       |                                 | 0.419***<br>(0.126)                                         |                                 |
| LFRD_MEN  |                                                         | 0.230*<br>(0.120)               |                                                             | 0.364***<br>(0.113)             |
| LRGDPT    | 2.199<br>(1.406)                                        | 1.860<br>(1.305)                | 2.370**<br>(0.983)                                          | 2.191**<br>(0.917)              |

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

|                                                                      |                      |                      |                      |                      |
|----------------------------------------------------------------------|----------------------|----------------------|----------------------|----------------------|
| <i>LSIM</i>                                                          | 1.264*<br>(0.705)    | 1.094*<br>(0.654)    | 1.239**<br>(0.491)   | 1.151**<br>(0.460)   |
| <i>LDIST</i>                                                         | -1.067***<br>(0.056) | -1.067***<br>(0.056) | -0.910***<br>(0.057) | -0.908***<br>(0.057) |
| <i>CONTIG</i>                                                        | 0.157<br>(0.129)     | 0.157<br>(0.130)     | 0.080<br>(0.162)     | 0.082<br>(0.162)     |
| <i>COMLANG</i>                                                       | 0.523***<br>(0.116)  | 0.525***<br>(0.116)  | 0.516***<br>(0.118)  | 0.522***<br>(0.118)  |
| <i>IDI_o</i>                                                         | -0.102<br>(0.106)    | -0.081<br>(0.101)    | -0.259***<br>(0.094) | -0.244***<br>(0.094) |
| <i>IDI_d</i>                                                         | -0.009<br>(0.099)    | 0.014<br>(0.093)     | -0.054<br>(0.092)    | -0.042<br>(0.088)    |
| <i>Constant</i>                                                      | -38.768<br>(35.920)  | -30.188<br>(34.069)  | -47.417*<br>(24.538) | -41.512*<br>(23.846) |
| <i>Observations</i>                                                  | 4,872                | 4,872                | 1,836                | 1,836                |
| <i>R-squared</i>                                                     | 0.903                | 0.903                | 0.924                | 0.925                |
| <i>Country-FE</i>                                                    | YES                  | YES                  | YES                  | YES                  |
| <i>Year dummy</i>                                                    | YES                  | YES                  | YES                  | YES                  |
| <i>Ramsey/<br/>Pesaran-Taylor<br/>RESET test</i>                     | 0.78<br>(0.378)      | 0.46<br>(0.496)      | 0.68<br>(0.408)      | 1.16<br>(0.281)      |
| <i>IV heteroskedasticity test(s)</i>                                 | 26.619<br>(0.002)    | 21.263<br>(0.011)    | 316.567<br>(0.000)   | 305.640<br>(0.000)   |
| <i>Wu-Hausman<br/>F test</i>                                         | 17.490<br>(0.000)    | 18.041<br>(0.000)    | 4.455<br>(0.012)     | 6.936<br>(0.001)     |
| <i>Under-identification test</i>                                     | 35.779<br>(0.000)    | 33.049<br>(0.000)    | 25.119<br>(0.000)    | 24.187<br>(0.000)    |
| <i>weak identification test</i>                                      | 7.484                | 8.033                | 6.088                | 6.231                |
| <i>Hansen test (over-identification test<br/>of all instruments)</i> | 0.762<br>(0.382)     | 1.206<br>(0.272)     | 1.108<br>(0.293)     | 1.646<br>(0.199)     |
| <i>Endogeneity test of endogenous<br/>regressors</i>                 | 2.665<br>(0.263)     | 1.570<br>(0.456)     | 6.151<br>(0.046)     | 5.462<br>(0.065)     |

## 5 Discussion and Conclusion

The findings underscore the importance of trade-related R&D spillovers in fostering industrial competitiveness and innovation-driven trade growth. Future research should explore alternative instrument selection methods to further refine model accuracy. Our model highlights the dual role of R&D in enhancing both current productivity and future innovation efforts. The accumulation of knowledge through R&D investment strengthens present capabilities while reducing future R&D costs, reflecting the interconnected nature of global economic relations. In this context, capital goods imports—particularly in machinery and equipment—serve as critical channels for technology transfer, especially in developing countries where domestic production of such goods is limited.

R&D spillovers embodied in capital goods imports help bridge the technology gap, leading to increased exports, improved product quality, and greater market competitiveness. These findings align with existing literature, reinforcing the link between technological advancement, export performance, and economic growth. This study stands out by analysing R&D spillovers in both general machinery and equipment industries and the specific machinery and equipment

## The Impact of Trade-Related R&D Spillovers on Trade Flows: Evidence from OECD Countries

n.e.c. sector, which includes I4.0 goods (CAD-CAM, Robotics, Additive Manufacturing). By using multiple proxies for capital goods and focusing on capital goods exports, we identify previously unexplored relationships. These insights are valuable for policymakers and industry leaders in crafting strategies to enhance innovation and competitiveness in manufacturing.

The findings suggest several policy recommendations to strengthen industrial competitiveness and maximize the benefits of trade-related R&D spillovers. Encouraging R&D investment is crucial, and policymakers should incentivize higher R&D expenditures, particularly in capital goods industries, to promote sustained innovation and long-term productivity growth. Facilitating technology transfer by reducing barriers to capital goods imports can foster knowledge spillovers and enhance domestic capabilities. Given the significance of digital performance (IDI), investments in ICT accessibility and capability can further reduce trade costs and increase absorptive capacity. Lastly, enhancing Industry 4.0 adoption will ensure that developing economies benefit from global technological diffusion, reinforcing trade competitiveness.

Future research could further explore spillover effects through network analysis based on specific industries or clusters of goods. While this study did not specifically detail trade flows in Industry 4.0 capital goods, this remains an avenue for future research. Investigating bilateral spillovers across different industrial sectors, assessing the role of multinational enterprises (MNEs) in diffusing R&D knowledge, and examining long-term effects of R&D spillovers on productivity growth would provide further insights. Additionally, applying alternative econometric techniques to refine causality testing could strengthen the robustness of future studies.

Despite some limitations, our results highlight the significant role of R&D spillovers in driving MHT capital goods exports, particularly when proxied by ME imports. The findings reinforce the importance of trade-related R&D spillovers in fostering innovation-driven trade growth, offering valuable insights for policymakers and industry stakeholders.

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