

## DO FOREIGN DIRECT INVESTMENTS AND TRADE OPENNESS FOSTER TECHNOLOGICAL CAPACITY? EMPIRICAL EVIDENCE FROM SELECTED COUNTRIES

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### Abstract

This study investigates the long-run effects of Foreign Direct Investment and trade openness on technological complexity across 29 countries, over the period 1997-2022. Using patent data from the OECD-REGPAT database, a patent-based technological complexity index is computed through the fitness-complexity algorithm. The empirical analysis employs the Augmented Mean Group estimator after controlling for cross-sectional dependence, heterogeneity, and potential structural breaks. The results reveal a statistically significant positive long-run impact of Foreign Direct Investment on technological complexity, confirming its role as a channel for technology diffusion and capability upgrading. In contrast, the effect of trade openness is heterogeneous and context-dependent, suggesting that openness enhances technological capacity only when supported by strong absorptive and innovation capabilities. The findings highlight the importance of integrating Foreign Direct Investment-driven knowledge inflows with domestic innovation strategies to strengthen technological sophistication and sustain long-term competitiveness.

**Keywords:** Technological Complexity, Foreign Direct Investment, Trade Openness, Innovation, Knowledge Diffusion

**JEL Codes:** F21, F41, O32, O36

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## INTRODUCTION

The rapid global expansion of innovation is closely tied to the growing interconnectedness of the world's economies. Innovation processes are no longer confined to closed, in-house R&D activities. They increasingly involve open innovation practices characterized by knowledge flows that cross organizational and national boundaries. Through open innovation and international collaboration, firms can access external knowledge and technological capabilities without bearing the full cost of developing them internally, thereby enhancing their innovation performance and strengthening the broader innovation ecosystem (Brem and Nylund, 2021). Indeed, factors such as national culture, the strength of patent protection, and the degree of economic openness are considered key determinants of a country's R&D intensity and innovation outcomes (Varsakelis, 2001; Brem and Nylund, 2021). Close collaboration among firms plays a critical role in achieving sustainable innovation, and higher engagement in open innovation activities is positively associated with a country's innovations' international impact (Brem and Nylund, 2021). In particular, international trade and foreign direct investment (FDI) serve as major channels for cross-border knowledge transfer, underscoring the role of global economic openness in the diffusion of innovation. Yet the extent to which openness translates into durable advances in national innovation capacity depends on the capability structure it engages, namely, the knowledge embedded in what economies actually produce. A tractable, comparative way to characterize that capability structure is through the lens of economic complexity.

Economic complexity refers to the diversity of knowledge, skills, and technologies embedded within a country's production structure. It captures not only the range of goods and services that a country produces, but also the sophistication of the underlying institutional framework, infrastructure, human capital, and knowledge base that enable this production. In essence, economic complexity reflects how "knowledge-intensive" an economy's output is and how effectively existing knowledge can be channeled into new productive activities (Hausmann et al., 2014). However, a nation's competitiveness is not limited to the diversity of its products. Another critical dimension is its technological complexity, which focuses more narrowly on technological know-how and innovative capacity. Technological complexity differs from economic complexity in that it focuses on the sophistication of technological capabilities, for example, the development of advanced Technologies, rather than on broader economic capabilities such as institutions or workforce skills (Hidalgo and Hausmann, 2009; Mewes and Broekel, 2022). Findings derived from economic complexity indices cannot be directly applied to technological capabilities.

Technological complexity plays a central role in driving long-term economic growth, as it arises from the interconnections among numerous productive and innovative activities. As the number of technological

components and their interrelations increase, the overall complexity of an innovation system grows, leading to more sophisticated and higher value innovations (Balland et al., 2019; Brem and Nylund, 2021). Complex technologies are inherently more valuable than simpler ones because their development requires advanced knowledge and innovation capabilities (Balland et al., 2019; Brem and Nylund, 2021). As countries strengthen their innovation capacity, they tend to produce more complex, cutting-edge technologies and thus expand their influence in the global technology landscape. However, complex innovations are also more difficult and riskier to diffuse or transfer across organizations and borders. Since open innovation and global knowledge exchange rely on the willingness and ability to share information, the transfer of highly complex technologies becomes less likely. Consequently, a higher degree of openness in an economy may sometimes weaken the positive impact that technological complexity has on international innovation performance. Moreover, openness does not benefit all firms or countries equally. Those with greater internal absorptive capacities can gain more from openness, while others may struggle to capitalize on external knowledge flows. Prior research even suggests a nonlinear (inverted U-shaped) relationship between openness and new product success, indicating that beyond a certain point, greater openness could diminish the returns of technological complexity on innovation outcomes (Brem and Nylund, 2021).

To investigate how international openness influences technological capabilities, this study examines a panel of 29 countries over the period 1997-2022, including 24 European Union member states alongside five other major economies (the United States, China, Japan, South Korea, and Türkiye). This diverse sample encompasses both highly open, trade-integrated economies and large economies with more moderate openness, providing a rich context to assess the impacts of foreign investment and trade on technological development (see Figure A.1 and Figure A.2 in the Appendix). By covering countries at both the core and periphery of the global economy, the analysis offers a comprehensive framework to evaluate how varying degrees of integration into global trade and capital flows relate to technological complexity.

In the existing literature, various studies have constructed and analyzed indices of technological complexity or sophistication (Balland et al., 2019; Jilke, 2021; Mewes and Broekel, 2022; Stojkoski et al., 2023; Moscatelli et al., 2024; Zhao et al., 2024). However, research specifically examining the determinants of technological complexity remains limited (Barbieri et al., 2023; Liu et al., 2023; Liang and Tan, 2024). In particular, there is scant evidence on whether greater FDI inflows and trade openness actually translate into higher technological complexity. This study aims to fill that gap by assessing the effects of FDI and trade openness on a country's technological complexity. We contribute to the literature by introducing a patent-based measure of technological complexity derived from OECD REGPAT patent application data using an economic complexity methodology and empirically evaluating its long-run determinants. In doing so, we address the key research question. Do foreign direct investment and trade openness enhance



technological complexity? We hypothesize that FDI serves as a positive force for building technological complexity by bringing in new knowledge, technology, and capital. By contrast, the impact of trade openness on technological complexity may be more nuanced. While open trade can expose countries to a broader array of knowledge and technologies, its benefits likely depend on domestic absorptive capacity and may not be uniformly positive across all contexts. Clarifying these relationships is important for policymakers, as it highlights how different facets of international economic integration can drive or constrain the development of advanced technological capabilities.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the computation of the technological complexity index, while Section 4 outlines the data and econometric methodology. Section 5 presents the empirical findings, followed by the discussion in Section 6, and Section 7 concludes the paper.

## **LITERATURE**

Endogenous growth theory and empirical findings highlight that a region's progress in closing its technological gap and achieving sustained productivity growth depends mainly on two interrelated capacities. The first is absorptive capacity, which reflects the ability to recognize, adopt, and adapt external technological knowledge. The second is innovative capability, denoting the competence to create and apply new, advanced ideas. When regions enhance both their absorptive and innovative potential, they experience faster technological transformation, greater productivity, and a shift toward higher value-added and knowledge-intensive activities (Solow, 1956; Arrow, 1962; Romer, 1986; Runiewicz-Wardyn, 2013). From the viewpoint of absorptive capacity, economic theory underscores the significance of education and continuous learning in narrowing knowledge and innovation gaps (Lucas, 1988; Runiewicz-Wardyn, 2013). Moreover, higher educational attainment contributes positively to the development of research and innovation capabilities (Romer, 1990; Runiewicz-Wardyn, 2013). Overall, the interplay between education, learning, and innovative capacity serves as a central mechanism fostering technological advancement and long-term productivity growth (Runiewicz-Wardyn, 2013).

Both trade openness and FDI play a significant role in the diffusion of international knowledge and, consequently, in the technological spillover among countries. In this context, FDI facilitates knowledge diffusion and helps domestic firms enhance their own technologies through internal spillovers. The existing literature provides abundant empirical evidence suggesting that FDI fosters technological innovation via its spillover effects (Ali et al., 2023). Hymer's (1960) definition of FDI as a bundle of resources, encompassing elements such as capital, management, and technology, establishes the theoretical foundation for the process

concerning FDI's impact on technology. Findlay (1978) emphasized that the presence of foreign firms provides local enterprises with the opportunity to observe advanced technologies. Empirical findings generally indicate that FDI has positive effects on technology transfer and innovation. For instance, Cheung and Lin (2004) demonstrated that FDI increased patent applications in China, while Kemeny (2010) found that trade openness and FDI promoted technological progress. Erdal and Göçer (2015) in Asian countries, and Kızılkaya et al. (2017) in developing countries, demonstrated that FDI boosts high-technology exports. Similarly, Sultana and Turkina (2020) and Ali et al. (2023) found a positive relationship between FDI, trade openness, and innovation activities for BRICS countries. Özmerdivanlı and Akgün (2024) identified a similar effect on high-technology exports in G20 countries. Nevertheless, the impact of FDI is not always positive. In the case of Türkiye, Demirtaş and Aktop (2018) showed that FDI can have adverse effects on high-technology exports in long-run analyses. Furthermore, Jin et al. (2019) suggested that intense competition can reduce patent applications by domestic technological leaders, and Gorodnichenko et al. (2020) noted that the spillover effect is often limited only to firms directly linked to the FDI.

The empirical literature reveals that the impact of trade openness on innovation varies considerably across countries and time periods. Almeida and Fernandes (2008) demonstrated that exporting and importing activities exert a positive influence on technology transfer in 43 developing countries, emphasizing the role of openness in accelerating knowledge flows. Similarly, Arshad et al. (2020) found a positive effect of trade openness on the Global Innovation Index, while Bas et al. (2016), Böhringer et al. (2014), and Eisen (2013) also showed that openness promotes innovation activities. Likewise, Kalkan and Pala (2022) found that trade openness had a positive effect on high-technology exports across 26 upper-middle-income countries between 2000 and 2019. In contrast, Dam (2018) reported a negative effect of trade openness on innovation in Türkiye during the period 1987-2016. Studies focusing on OECD and European economies reveal more nuanced outcomes. Mtar and Belazreg (2021) found a neutral relationship between trade openness and public innovation across OECD countries. In contrast, in their analysis of 11 European economies from 2001 to 2016, the same authors concluded that trade had a negative impact on innovation. Furthermore, Belazreg and Mtar (2020) showed that trade openness and FDI exerted no statistically significant effect on innovation in 27 OECD countries during the same period. Findings outlined above suggest that the relationship between trade openness and innovation is context-dependent, varying according to country group, time period, and the indicator used to measure innovation. While trade openness tends to foster knowledge spillovers and technological diffusion in developing economies, its effect in advanced countries appears weaker or even negative, possibly due to competitive pressures, market saturation, or institutional factors that shape innovation Dynamics.



The literature on technological complexity has grown considerably, exploring its role in shaping innovation capacity, economic growth, and regional resilience. However, empirical studies examining the determinants of technological complexity remain relatively limited. Brem and Nylund (2021), drawing on 17 years of patent panel data from 27 countries, emphasized that open innovation intensity and technological complexity are significant determinants shaping the international influence of a nation's innovations. Building on the complexity framework proposed by Hidalgo and Hausmann (2009), Balland and Rigby (2017) conceptualize complex technologies as those combining diverse and interdependent knowledge components that are typically concentrated in a limited number of regions yet utilized across a wide spectrum of activities. Consistent with this idea, Rigby et al. (2022) provided evidence that European cities expanding into more related and sophisticated technological domains experience stronger GDP and employment growth. Subsequent regional studies in Europe further validate these outcomes. Pintar and Scherngell (2020), for instance, confirmed that knowledge complexity contributes positively to regional income levels, while Mewes and Broekel (2022), using data for 159 NUTS-2 regions between 2000 and 2014, identified technological complexity as a central driver of economic expansion. Likewise, Pinheiro et al. (2025), analyzing 283 regions across 32 European countries, showed that only economically advanced territories tend to diversify into high-complexity activities, whereas less developed regions remain focused on lower-complexity technological paths. Xu and Fun (2025), using data from 281 Chinese cities over the period 2005–2020, find that innovation in high-technological-complexity domains has a more limited effect on reducing regional economic disparities compared to innovation in low-complexity domains. Chen et al. (2025), using a dataset of approximately 5 million digital technology patents from 297 prefecture-level cities in China over the period 1991-2020, show that technological complexity negatively affects the development of digital technologies. Balland et al. (2019) also concluded that higher technological sophistication enhances the probability of developing new technologies within the European Union. At the macro level, Nepelski and De Prato (2020) examined diversification and ubiquity as two dimensions of technological complexity, reporting that diversification generally supports economic growth, while ubiquity can yield both favorable and unfavorable impacts depending on the structural context. Evidence from outside Europe reinforces these findings: He et al. (2023) demonstrated that technological complexity fosters innovation and strengthens regional economic resilience in China. Similarly, Liang and Tan (2024) used data from 30 Chinese provinces (2012–2020) and observed that the digital economy contributes positively to export technology sophistication. Their study also showed that while human capital positively affects low- and medium-tech industries, its influence may be negative in high-tech sectors. Parallel results by Liu et al. (2023) indicate that green finance enhances export technological complexity, with FDI acting as an additional positive driver, whereas total trade costs exert a dampening effect. Zhao et al. (2024) further

revealed that upstream technological complexity influences downstream manufacturers' innovation through both a cost-constraint mechanism and a market competition channel. Complementing these insights, Jilke (2021) found that technological complexity can sometimes hinder firms' information-processing efficiency. Finally, Barbieri et al. (2023) identified distinct effects of green and non-green technological complexity, while Moscatelli et al. (2024) established a robust positive connection between technological complexity, diversification, and economic growth. Similarly, Stojkoski et al. (2023) documented that higher technological complexity contributes to GDP growth but can also amplify inequality and income divergence across regions. Broekel and Klarl (2025), in their study on the United States, report that technological complexity does not exhibit a significant effect on economic growth over most of the period examined. The empirical evidence demonstrates that technological complexity plays a crucial role in fostering innovation, economic growth, and regional resilience. However, studies specifically examining the impact of FDI and trade openness on technological complexity remain scarce, indicating a significant gap in the current empirical literature.

## **MEASURING TECHNOLOGICAL COMPLEXITY**

To mitigate annual fluctuations in patenting activity and better reflect medium-term innovation dynamics, we compute a five-year rolling mean of fractional patent counts for each country and IPC class. Each year's measure is updated accordingly. Specifically, let  $w_{c,p,t}$  represent the fractional number of patents attributed to inventors located in country  $c$ , within 4-digit IPC technology  $p$ , in year  $t$ .

$$w_{c,p,t} = \frac{1}{5} \sum_{t-4}^t w_{c,p,t} \quad (1)$$

Equation (1) expresses the five-year moving average of fractional patent counts for each country-IPC combination. This rolling window is obtained by taking the mean of patent counts from year  $t-4$  through  $t$ , with the calculated value assigned to the final year of the interval. Consequently, although the base data cover the period 1990-2022, the rolling averages commence in 1994, corresponding to the first complete five-year window (1990-1994). Using these smoothed series, we subsequently derive each country's revealed comparative advantage and related indicators for every year in the dataset.

### **Revealed Technological Advantage Matrix**

To compute technological complexity, we construct a binary matrix indicating whether each region is active in a given technology. Following Balassa's (1965) approach, we adapt the concept of revealed



comparative advantage to patents and define the revealed technological advantage (RTA) of country  $c$  in technology  $p$  at time  $t$  as shown in Equation (2).

$$RTA_{c,p,t} = \frac{\frac{w_{c,p,t}}{\sum_p w_{c,p,t}}}{\frac{\sum_c w_{c,p,t}}{\sum_{c,p} w_{c,p,t}}} \quad (2)$$

According to the standard criterion, a country-technology pair is assigned a value of  $M_{c,p,t} = 1$  when  $RTA_{c,p,t} \geq 1$ , and 0 otherwise (Hidalgo et al., 2007). However, because patenting activity in certain IPC categories is heavily concentrated, relying solely on the  $RTA \geq 1$  threshold can incorrectly classify key patenting countries as inactive. To address this issue, and following the approach of Hausmann et al. (2024), we calculate the Herfindahl-Hirschman Index (HHI) and derive the corresponding effective number of active countries for each technology–year cell, as specified in Equation (3).

$$HHI_{p,t} = \sum_c \left( \frac{w_{c,p,t}}{\sum_c w_{c,p,t}} \right)^2, \quad n_{p,t} = \frac{1}{HHI_{p,t}} \quad (3)$$

Subsequently, for each technology-year combination, countries are ordered by their patenting intensity, denoted as  $rank_{c,p,t}$  where a lower rank value (1) corresponds to the top contributor. Combining this ranking information with the  $RTA_{c,p,t}$  threshold, we establish an augmented presence criterion as defined in Equation (4).

$$M_{c,p,t}^P = \begin{cases} 1, & \text{if } RTA_{c,p,t} \geq 1 \text{ or } rank_{c,p,t} \leq \lfloor n_{p,t} \rfloor \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

Accordingly, a country is classified as “present” in a given technology if it either satisfies the RTA threshold or ranks among the top  $n_{p,t}$  effective contributors determined by the concentration of that technology (Hausmann et al., 2024). The indices  $HHI_{p,t}$ ,  $n_{p,t}$  and  $rank_{c,p,t}$  are computed only for cases where  $w_{c,p,t} > 0$ , as cells with no patenting activity are structurally empty. The resulting augmented binary

matrix  $\mathbf{M}^P$  then constitutes the core input for the fitness-complexity algorithm (Tacchella et al., 2012) employed to estimate technological complexity.

### Technological Complexity Measure

To measure each country's level of technological complexity, we apply the fitness-complexity algorithm originally proposed by Tacchella et al. (2012) and subsequently refined by Servedio et al. (2018). The original formulation of Tacchella et al. (2012) tends to be sensitive to highly concentrated matrices (Mariani et al., 2015; Morrison et al., 2017), as it may disproportionately weight technologies dominated by a few countries. To overcome this limitation, Servedio et al. (2018) introduced a modified version that ensures stability and convergence by using additive rather than multiplicative updates.

Based on the binary specialization matrix  $\mathbf{M}^P$ , we derive complexity scores through an iterative process. Let  $F_c^{(n)}$  denote the complexity of country  $c$  at iteration  $n$ , and let  $S_p^{(n)}$  the corresponding measure of simplicity (the inverse of technological complexity) for technology  $p$  at iteration  $n$  ( $Q_p^{(n)}$ ). All values are initialized uniformly ( $F_c^{(0)} = 1$ ,  $S_p^{(0)} = 1$  for all  $c, t$ ). Following Servedio et al. (2018), these variables are then updated iteratively according to Equation (5).

$$\begin{aligned}
 F_c^{(n)}(t) &= \phi_c(t) + \sum_p \frac{M_{c,p,t}^P}{S_p^{(n-1)}(t)} \\
 S_p^{(n)}(t) &= \pi_p(t) + \left[ \sum_c \frac{M_{c,p,t}^P}{F_c^{(n-1)}(t)} \right]
 \end{aligned}
 \tag{5}$$

The resulting technological complexity score for each technology is subsequently determined as specified in Equation (6).

$$Q_p^{(n)}(t) = \frac{1}{S_p^{(n)}(t)}
 \tag{6}$$

Parameters  $\phi_c(t)$  and  $\pi_p(t)$  are small positive regularization factors introduced to stabilize the algorithm, preventing division-by-zero errors or uncontrolled divergence. All computations are performed independently for each year following the same iterative procedure.

## METHODOLOGY

### Data and Model

This study investigates the effects of FDI and trade openness on the technological capacity for a panel of 24 selected European Union (EU) countries and five additional countries (the United States, Japan, South Korea, China, and Türkiye) over the period 1997-2022. The study period was chosen because data for the patent complexity index are available only for the years between 1997 and 2022. The inclusion of EU countries is justified by the fact that the EU represents one of the world's leading regions in innovation and technological production, and its internal market and R&D policies play a significant role in shaping innovation dynamics (EIS, 2025). However, due to missing data, some EU countries were excluded from the final sample. Among the non-EU economies, the United States, Japan, South Korea, China, and Türkiye were selected. The first four countries were chosen because they exhibit the highest values of the patent complexity index. At the same time, Türkiye was included as a developing economy undergoing structural transformation in its technological capacity and due to its strong economic integration with the EU.

**Table 1:** Specifications of variables

Variable	Definition	Specification	Origin
PATFIT	Technological Capacity	Patent Complexity Index	Calculated by the authors
FDI	Foreign Direct Investment	Net inflows (% of GDP)	World Bank (2025)
OPE	Trade Openness	Trade (% of GDP)	World Bank (2025)
LNGDP	Economic Growth	GDP per capita in constant 2015 US dollars (logarithm)	World Bank (2025)
MYS	Human Capital	Mean Years of Schooling	UNDP (2025)
GFCF	Gross Fixed Capital Formation	% of GDP	World Bank (2025)

The dependent variable of the study is PATFIT, an indicator representing technological capacity, which was calculated by the authors based on the OECD REGPAT dataset for 1997-2022. Although the REGPAT release used in the study nominally extends to 2024, reporting for 2023-2024 is incomplete for several countries. Accordingly, we truncated the panel in 2022. Adhering to the screening protocol in Hausmann et al. (2024), we retain only countries with populations of at least one million that, over 1990-2022, filed patent applications in no fewer than 100 distinct 4-digit IPC classes. Symmetrically, we restrict

the technology space to those 4-digit IPC classes for which patent applications were filed by at least ten different countries during the same period. Patent counts refer to PCT applications recorded in REGPAT. All complexity values are computed on this filtered country-technology matrix. Accordingly, technological complexity is computed across approximately 640 IPC classes and 78 countries.

The explanatory variables include FDI, OPE, LNGDP, GFCF, and MYS. The selection of explanatory variables was guided by several empirical studies in the related literature (Nepelski and De Prato, 2020; Mewes and Broekel, 2022; He et al., 2023; Liu et al., 2023; Yang et al., 2024; Zhao et al., 2024). The **FDI**, **OPE**, **LNGDP**, and **GFCF** variables were obtained from the **World Bank database**, while the **MYS** variable was sourced from the **UNDP Human Development Reports** database. In the study, the ratio of net FDI inflows to GDP is used as an indicator of foreign direct investment. As a measure of economic growth (LNGDP), the logarithm of GDP per capita at 2015 constant U.S. dollars is employed. For trade openness (OPE), the ratio of the sum of exports and imports of goods and services to GDP is utilized. Mean years of schooling is used as the indicator of human capital, while gross fixed capital formation as a percentage of GDP represents physical capital. Among these, the LNGDP variable was transformed into its natural logarithm to ensure consistency across datasets. Definitions of all explanatory variables are presented in Table 1, while the estimated model is specified in Equation (7).

$$PATFIT_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 OPE_{it} + \beta_3 LNGDP_{it} + \beta_4 MYS_{it} + \beta_5 GFCF_{it} + \varepsilon_{it} \quad (7)$$

### **Econometric Methodology**

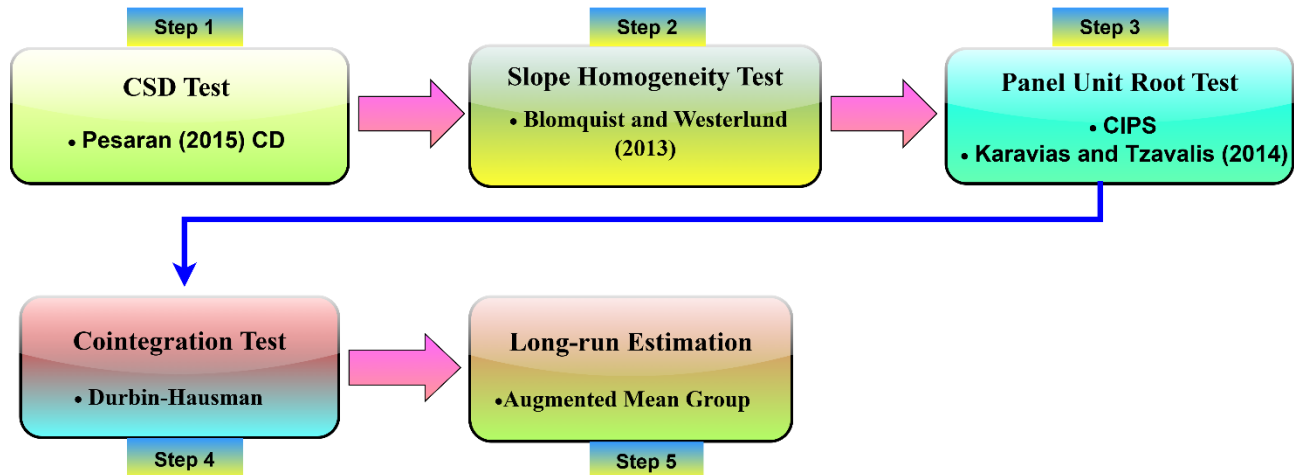
The econometric methodology of this study consists of five stages, which are presented chronologically in Figure 1. In the first and second stages, cross-sectional dependence (CSD) and slope homogeneity tests were conducted. Cross-sectional dependence refers to the interdependence among individual units in panel data analysis. This phenomenon occurs when cross-sectional units are influenced by common and unobservable factors, resulting in mutual dependencies among them. Such dependence violates the classical ordinary least squares assumption of independently distributed error terms (Kanchana et al., 2016; Yadav and Mahalik, 2024). Considering this issue, Pesaran's (2015) CD test was employed to diagnose cross-sectional dependence in the model. The CD test is robust to different panel dimensions and evaluates the degree of parameter interdependence.

Panel heterogeneity, on the other hand, refers to systematic differences or variations among individual units in panel estimations. Ignoring such heterogeneity may limit the reliability of empirical results (Li et al., 2020; Yadav and Mahalik, 2024). Taking potential heterogeneity-related issues into account, this study employs the Blomquist and Westerlund (2013) BW test. The BW test is effective under autocorrelation and

heteroskedasticity and provides advantages over other homogeneity tests by accounting for cross-sectional dependence and individual-specific effects (Blomquist and Westerlund, 2013; Yadav and Mahalik, 2024).

In the third stage of the econometric methodology, panel unit root tests were applied for the variables. The existence of a unit root indicates that a time series does not have a constant mean and variance, implying non-stationarity and the presence of a stochastic trend. In panel data analysis, two generations of unit root tests have been developed to determine the stationarity levels of variables. While first-generation unit root tests have been widely used, they are often criticized for neglecting cross-sectional dependence among variables (Khan et al., 2020). To overcome this limitation, the present study employs the second-generation Cross-Sectionally Augmented IPS (CIPS) test developed by Pesaran (2007). The CIPS test is resilient to cross-sectional dependence and is derived from the Cross-Sectionally Augmented Dickey-Fuller framework (Khan et al., 2020; Yadav and Mahalik, 2024).

**Figure 1:** Stages of econometric methodology



Given the potential for structural changes in economic data, incorporating unit root tests that account for structural breaks is essential alongside traditional tests. Perron (1989) demonstrated that ignoring structural breaks could bias unit root test outcomes, as long-term exogenous shocks may be mistaken for permanent changes (Safdar et al., 2022). To account for such possibilities, the study applies the Karavias and Tzavalis (2014) unit root test (KT test), which allows for structural discontinuities in intercepts and trends. This test offers broad applicability and advantageous optimal properties, accommodating both predetermined and endogenously determined break dates (Karavias and Tzavalis, 2014; Safdar et al., 2022).

At the fourth step of the econometric framework, a cointegration investigation is performed. After identifying the stationarity characteristics of the variables, it becomes necessary to verify whether a long-

term equilibrium connection exists among them. For this purpose, the present study applies the Durbin–Hausman (DH) panel cointegration approach proposed by Westerlund (2008). The main rationale for selecting this test lies in its capability to handle cross-sectional dependence within the panel structure. Another strength of the DH methodology is its flexibility in accommodating explanatory variables that have mixed integration orders, provided that the dependent variable is non-stationary. Moreover, the test allows for both homogeneous and heterogeneous slope parameters across cross-sections, making it suitable for diverse empirical settings. In this framework, the DH cointegration statistics are derived using the Durbin–Hausman procedure. When the slope parameters are common across units, the panel statistic is applied; conversely, when they differ, the group statistic is used (Westerlund, 2008; Ünşal, 2025).

Long-run effects are estimated at the final stage. Conventional panel estimators may fail when countries share shocks or differ in slope coefficients. Following Bond and Eberhardt (2009) and Eberhardt and Teal (2010), we therefore implement the Augmented Mean Group (AMG) estimator. By modelling common factors explicitly and allowing for endogeneity and heterogeneity across cross-sections, AMG produces consistent and robust long-run coefficients for panels with interdependencies (Guo et al., 2021).

## FINDINGS

Before proceeding to the analysis results, descriptive statistics were examined, and the findings are presented in Table 2. In addition, graphs of the variables were plotted and are displayed in Figure 2.

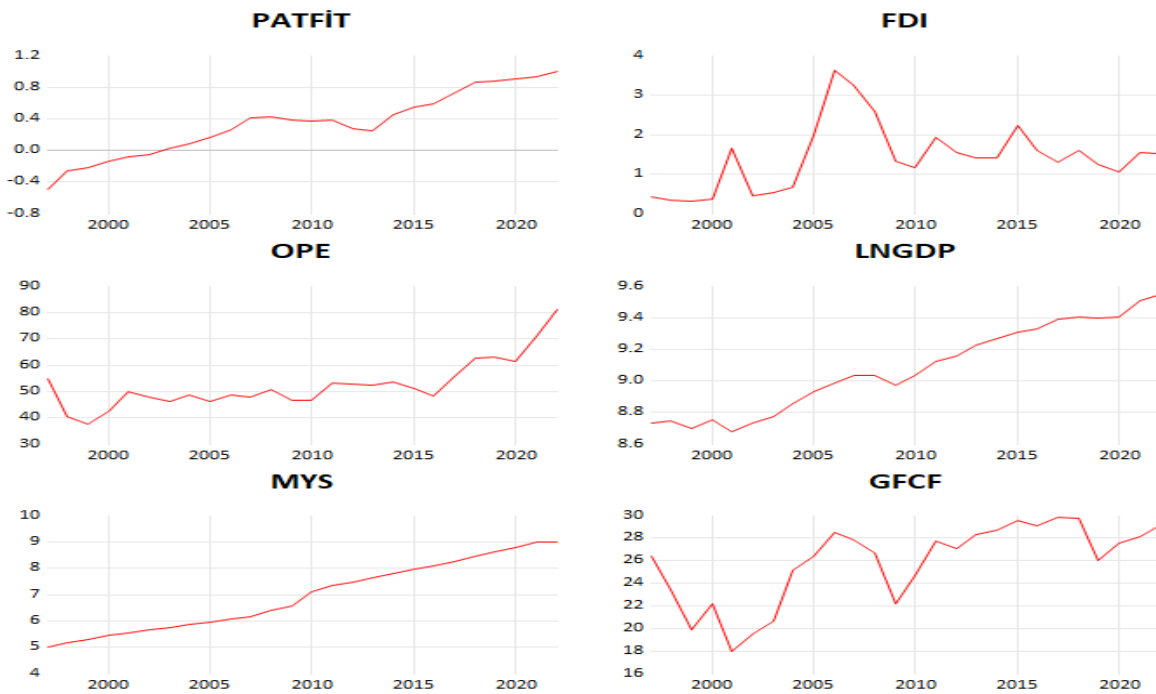
**Table 2:** Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
PATFIT	754	0.5913	1.0955	-0.8571	3.9855
FDI	754	4.9215	9.6572	-40.1083	105.6358
OPE	754	93.6886	43.8101	18.1256	250.1085
LNGDP	754	9.9394	0.7350	7.5061	11.5006
GFCF	754	23.7153	5.2418	9.6810	53.2220
MYS	754	11.1948	1.8227	5.0198	14.2964

According to the results presented in Table 2, the descriptive statistics reveal noticeable variation among the variables. The PATFIT variable shows a moderate distribution with an average value of 0.59, while FDI and OPE display high standard deviations, indicating significant differences in foreign investment and trade openness levels across units. In contrast, LNGDP and MYS demonstrate relatively stable distributions.

According to Figure 2, the time-series plots of the variables reveal clear upward or fluctuating trends over the observation period. The variables PATFIT, LNGDP, and MYS display a strong positive trend, indicating consistent long-term growth in PATFIT, LNGDP, and MYS. OPE also shows a generally upward trajectory, with a noticeable acceleration after 2015. In contrast, FDI and GFCF exhibit greater short-term volatility, though both maintain an overall increasing tendency in the long run. Figure 2 suggests that most variables contain deterministic or stochastic trends, implying potential non-stationarity. Therefore, it is essential to account for these trends in the subsequent econometric analyses, particularly in unit root and cointegration testing, to ensure reliable and unbiased long-run estimations.

**Figure 2:** Time series plots for variables



After presenting the graphical summaries of the variables, both the correlation matrix and the Variance Inflation Factor (VIF) indicators were analyzed to check for potential multicollinearity within the model. Accordingly, Table 3 reports the computed correlation coefficients along with the VIF statistics used in this assessment.

**Table 3:** Correlation matrix and VIF values

	<b>FDI</b>	<b>OPE</b>	<b>LNGDP</b>	<b>GFCF</b>	<b>MYS</b>	<b>VIF</b>
<b>FDI</b>	1.0000					1.13
<b>OPE</b>	0.3183	1.0000				1.34
<b>LNGDP</b>	0.0503	0.0732	1.0000			1.35
<b>GFCF</b>	0.0252	-0.0374	-0.2347	1.0000		1.10
<b>MYS</b>	0.0357	0.3784	0.4793	-0.2638	1.0000	1.61

If the VIF values fall between 5 and 10, it can be stated that the model does not suffer from a serious multicollinearity problem, although a weak one might exist. Conversely, if the VIF values are below 5, it can be concluded that there is no strong multicollinearity in the model. In this context, as shown in Table 3, the VIF values are found to be below 5, indicating that the model does not exhibit a multicollinearity problem.

**Table 4:** CD test and BW test results

<b>CD test</b>		<b>BW test</b>		
<b>Statistic</b>	<b>Prob.</b>	<b>Statistic</b>	<b>Statistic Value</b>	<b>Prob.</b>
2.989***	0.003	Delta	14.403***	0.000
		Adj. Delta	16.849***	0.000

\*\*\* denotes significance levels at the 1% level.

The outcomes of the CSD and slope homogeneity tests, which serve as the preliminary diagnostics in panel data analysis, are reported in Table 4. As seen in this table, the probability value obtained from the CD test confirms that cross-sectional dependence exists in the model at the 5% significance threshold. Likewise, the BW test outcomes reveal that the slope parameters differ across units, indicating heterogeneity at the same confidence level. Considering these findings, the CIPS procedure, known for its robustness under cross-sectional dependence and heterogeneity, was subsequently implemented. The CIPS test results, estimated for both the constant-only and the constant-plus-trend specifications, are summarized in Table 5.

**Table 5:** CIPS test results

Variable	Level		First Difference	
	Constant	Constant and Trend	Constant	Constant and Trend
PATFIT	-2.205**	-2.561	-4.080***	-4.261***
FDI	-3.344***	-3.632***	-	-
OPE	-1.591	-1.768	-3.823***	-3.969***
LNGDP	-1.989	-2.234	-3.332***	-3.219***
GFCF	-1.836	-2.109	-3.814***	-4.309***
MYS	-1.966	-2.068	-3.724***	-3.987***

\*\*\*, and \*\*denote significance levels at the 1%, and 5% levels, respectively.

According to Table 5, in the constant model, the variables PATFIT and FDI are stationary at the level at 5% significance level. In contrast, OPE, LNGDP, GFCF, and MYS become stationary after taking their first differences. Under the constant and trend model, only FDI is found to be stationary at the level, whereas PATFIT, OPE, LNGDP, GFCF, and mys achieve stationarity at their first differences.

**Table 6:** KT test results

Variable	Level		First Difference		Break Dates
	Statistic	Prob.	Statistic	Prob.	
PATFIT	0.0057	0.990	-14.2943***	0.000	1999-2019
FDI	-13.6119***	0.000	-	-	2017-2019
OPE	-3.9262**	0.020	-	-	2001-2003
LNGDP	-0.0047	0.440	-0.0581***	0.000	1999-2001
GFCF	-2.9116	0.280	-17.5217***	0.000	1999-2019
MYS	-0.0050	0.900	-16.3887***	0.000	1999-2001

\*\*\*, and \*\*denote significance levels at the 1%, and 5% levels, respectively.

Based on the outcomes of the structural break unit root tests summarized in Table 6, the variables PATFIT, LNGDP, GFCF, and MYS are stationary after first differencing, while FDI and OPE remain stationary in their level forms. In addition, CIPS unit root results indicate that PATFIT is stationary in levels under the constant specification, whereas it becomes stationary only after first differencing under the constant-and-trend specification. The KT test suggests that PATFIT is not stationary in levels but attains stationarity after first differencing, allowing for potential breaks. Overall, giving greater weight to the break-robust evidence, PATFIT is treated as an I(1) variable. When the CIPS and KT test results are jointly

considered, it can be inferred that the variables achieve stationarity either at the level or after differencing once. Given this mixture of integration orders, an appropriate cointegration test is required to verify the existence of a long-term equilibrium association among the variables. Therefore, consistent with the evidence from the unit root diagnostics, the DH cointegration method was applied. The findings derived from this test are displayed in Table 7.

**Table 7:** DH test results

<i>Statistic</i>	<b>Statistic Value</b>	<b>Prob.</b>	<b>Critical Values</b>		
$DH_G$	6.464***	0.000	%10	%5	%1
$DH_P$	7.981***	0.000	1.28	1.645	2.333

\*\*\* denotes significance levels at the 1% level.

Within the framework of the DH test, when cross-sectional dependence is identified, the analysis should be performed using bootstrap-based procedures. If slope parameters are found to be homogeneous, the panel statistic is appropriate. However, if they vary across cross-sectional units, the group statistic becomes relevant. As the dataset in this study exhibits both dependence across units and heterogeneity in slopes, bootstrap-derived probability values were employed for interpretation. According to the findings reported in Table 7, the group statistic confirms a long-term cointegration link among the examined variables. Following the detection of this relationship, the final step of the empirical analysis involved estimating the long-run parameters through the AMG approach, with the resulting coefficients summarized in Table 8.

**Table 8:** AMG test results

<b>Dependent variable: PATFIT</b>					
<b>Country</b>	<b>FDI</b>	<b>OPE</b>	<b>LNGDP</b>	<b>MYS</b>	<b>GFCF</b>
<b>Austria</b>	0.004*	-0.002	-0.634	-0.440**	-0.014
<b>Belgium</b>	0.001	0.002	-1.879	0.472***	0.010
<b>Bulgaria</b>	-0.000	0.001	-0.678**	0.025	0.003
<b>China</b>	0.139	-0.004	-0.541	-2.016**	-0.031
<b>Croatia</b>	-0.004	0.009*	-0.965***	0.892***	0.034*
<b>Czechia</b>	0.012**	-0.005	-0.793	0.571**	0.057*
<b>Denmark</b>	0.002	0.005**	0.867	0.108*	-0.013
<b>Estonia</b>	-0.001	0.002**	-0.426	0.113	-0.003
<b>Finland</b>	0.003	-0.007*	-0.383	-0.480**	0.041
<b>France</b>	-0.103***	0.020	-0.553	0.313	0.020



<b>Germany</b>	0.006	0.011**	-0.823	0.014	-0.025
<b>Greece</b>	-0.043**	-0.001	0.586*	0.118*	0.006
<b>Hungary</b>	0.000	-0.001	0.150	0.008	0.003
<b>Ireland</b>	0.001**	-0.003*	-0.140*	0.094	0.004***
<b>Italy</b>	0.009	0.006*	-1.279***	0.317	0.022*
<b>Japan</b>	0.078	0.002	4.421**	1.176	-0.133**
<b>South Korea</b>	0.021	-0.004*	-1.400*	0.468*	0.022
<b>Latvia</b>	-0.003	0.001	-0.277*	-0.008	0.008**
<b>Lithuania</b>	-0.001	-0.000	1.716**	0.313	-0.030*
<b>Netherlands</b>	0.000	0.004	-0.937	-0.006	0.002
<b>Poland</b>	0.025	0.001	-2.002	0.400**	-0.021
<b>Portugal</b>	-0.005	0.001	-0.052	-0.288	-0.009
<b>Romania</b>	0.003	0.001	0.112	0.012	-0.005
<b>Slovakia</b>	0.001	0.000	0.306	0.094	-0.005
<b>Slovenia</b>	0.010	0.002	-0.108	0.065	0.000
<b>Spain</b>	0.014	-0.006	0.674	-0.198	0.019**
<b>Sweden</b>	0.004	0.011***	-3.835***	0.315**	0.009
<b>Turkiye</b>	-0.005	0.001	1.754**	-0.234	-0.039***
<b>United States</b>	0.025*	0.009*	-3.302***	-0.056	0.041**
<b>Panel</b>	0.004***	0.001	-0.377*	0.117*	0.003

\*\*\*, \*\*, and \* denote significance levels at the 1%, 5%, and 10% levels, respectively.

According to the AMG estimation results presented in Table 8, there exist statistically significant long-run relationships between the dependent variable PATFIT and the explanatory variables. At the panel level, the FDI variable is statistically significant at the 1% level, the LNGDP variable at the 10% level, and the MYS variable at the 10% level, while the OPE and GFCF variables are statistically insignificant. At the country level, FDI is positive and significant in Austria, Czechia, Ireland, and the United States, whereas it is negative and significant in France and Greece. The OPE variable is positive and significant in Denmark, Estonia, Germany, Italy, Spain, and the United States, but negative and significant in Finland, Ireland, and South Korea. For LNGDP, negative and significant coefficients are found for Bulgaria, Croatia, Ireland, Italy, South Korea, Spain, and the United States, while positive and significant relationships are observed in Greece, Japan, Lithuania, and Turkiye. Regarding MYS, the variable is positive and significant in Belgium, Czechia, Croatia, Denmark, Poland, and Spain, but negative and significant in Austria, China, and

Finland. Finally, the GFCF variable is positive and significant in the United States, while it is negative and significant in Japan, Lithuania, and Türkiye.

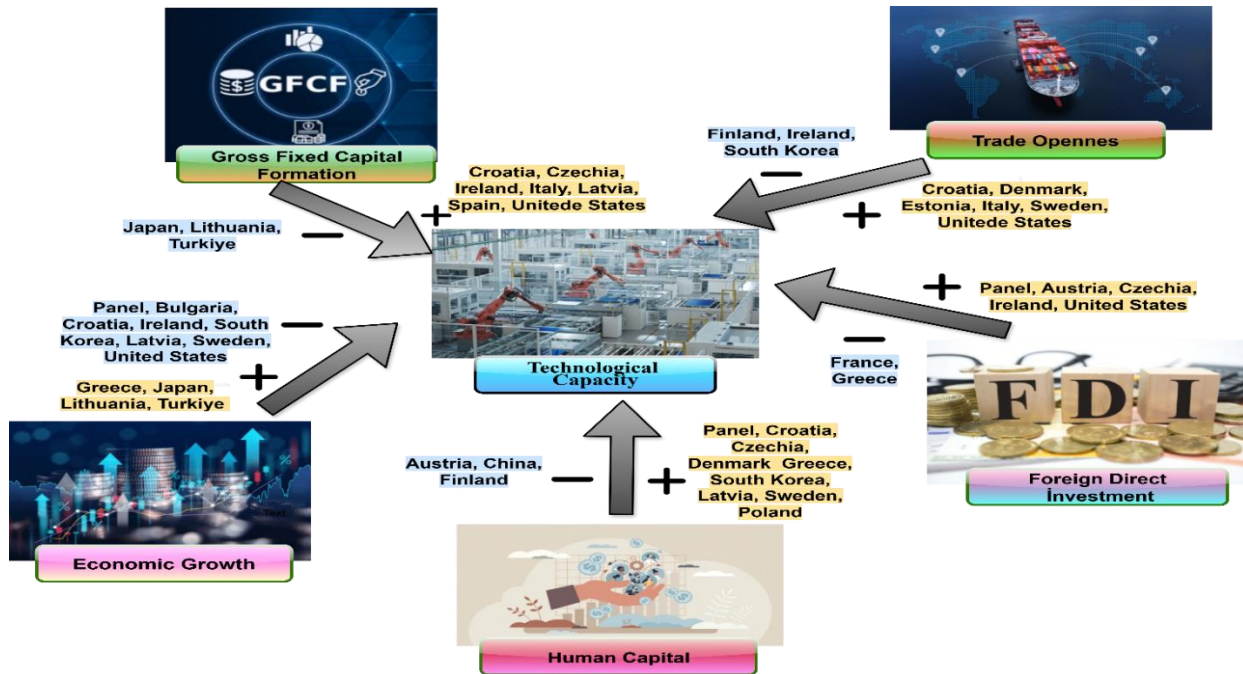
In addition, the study applies the causality (JKS) test developed by Juodis et al. (2021), which accounts for heterogeneity and cross-sectional dependence. The test results are reported in the Appendix as Table A1. As shown in Table A1, we do not find evidence indicating reverse causality for the main variables. Accordingly, concerns about endogeneity driven by reverse causality are not supported. This evidence also strengthens the interpretability of our long-run findings.

## **DISCUSSION**

The present study applied the AMG estimator after testing for stationarity and cointegration through unit root and DH cointegration tests, revealing long-run relationships between technological capacity (PATFIT) and its explanatory variables. The AMG results demonstrated that, at the panel level, FDI exerts a statistically significant positive long-run impact on technological capacity, while trade openness (OPE) was statistically insignificant overall. However, country-level heterogeneity is notable. FDI contributes positively to technological complexity in Austria, Czechia, Ireland, and the United States, but negatively in France and Greece. Similarly, OPE displays positive effects in countries such as Denmark, Estonia, Germany, Italy, Spain, and the United States, yet negative ones in Finland, Ireland, and South Korea. The summary of the obtained AMG results is presented in Figure 3.

The positive and significant long-run impact of FDI on technological capacity at the panel level is consistent with a substantial body of empirical literature emphasizing the role of foreign investment in enhancing innovation capacity and knowledge diffusion. In line with Hymer's (1960) conception of FDI as a bundle of resources encompassing capital, management, and technology, subsequent studies, such as Findlay (1978), Cheung and Lin (2004), and Kemeny (2010), have demonstrated that FDI facilitates technology transfer by allowing domestic firms to learn from foreign technological leaders. Similarly, Erdal and Göçer (2015) and Kızılkaya et al. (2017) found that FDI boosts high-technology exports, while Sultana and Turkina (2020) and Ali et al. (2023) confirmed its positive spillover effects on innovation for BRICS and developing economies.

**Figure 3:** The summary of AMG results



The AMG findings, which indicate a positive long-term association between FDI and technological capacity for several advanced economies, support this theoretical and empirical consensus, suggesting that inward FDI contributes to the diversification and sophistication of national technological structures. However, the heterogeneity of country-level effects implies that the benefits of FDI are not universally realized. The negative coefficients in France and Greece align with studies such as Demirtaş and Aktop (2018) and Gorodnichenko et al. (2020), which argue that in environments of intense competition or limited absorptive capacity, FDI may crowd out domestic innovation or confine technological spillovers to firms directly linked to foreign investors. These contrasting outcomes reinforce the argument that the absorptive capacity of host economies, including the quality of institutions, human capital, and innovation systems, mediates the FDI and technological capacity relationship (Romer, 1990; Runiewicz-Wardyn, 2013). The positive FDI and technological capacity relation found in this study is also in line with recent evidence from Liu et al. (2023), who showed that in 30 Chinese provinces, FDI positively affects export technology capacity, while trade costs exert a negative influence. This convergence underscores that FDI, when embedded in supportive economic and institutional environments, functions as a catalyst for technological upgrading and diversification, confirming the spillover-based mechanisms posited in endogenous growth models (Romer, 1986; Lucas, 1988).

The findings on trade openness (OPE) reveal mixed effects across countries, suggesting that its relationship with technological capacity is context-dependent and non-linear. At the aggregate level, the

variable's insignificance may reflect structural asymmetries among economies with varying levels of industrial sophistication and innovation capacity. Empirical research supports this interpretation. For instance, Almeida and Fernandes (2008), Bas et al. (2016), and Arshad et al. (2020) reported that trade openness fosters technology transfer and innovation, particularly in developing and emerging markets. Similarly, Kalkan and Pala (2022) confirmed that openness enhances technological diffusion and high-technology exports. However, studies on advanced economies provide more nuanced evidence. Mtar and Belazreg (2021) found a neutral relationship between trade openness and innovation in OECD countries, while Belazreg and Mtar (2020) identified no significant effect of either trade or FDI on innovation. The negative and significant coefficients for Finland, Ireland, and South Korea in this study mirror these findings, suggesting that in highly developed or saturated innovation systems, increased openness can intensify competitive pressures, reducing domestic firms' incentives to invest in complex technological development (Dam, 2018). In contrast, the positive coefficients observed for Denmark, Germany, Italy, Spain, and the United States align with the argument that trade openness can promote knowledge spillovers, international learning, and integration into high-technology value chains, ultimately fostering technological sophistication. This heterogeneity highlights that trade openness contributes to technological complexity only when accompanied by robust absorptive and innovative capacities (Lucas, 1988; Runiewicz-Wardyn, 2013).

The empirical results of this study contribute to the growing literature linking technological complexity, innovation, and economic performance. The positive and significant role of FDI aligns with studies that emphasize the mutual reinforcement of complexity and innovation (Balland et al., 2019; Mewes and Broekel, 2022; He et al., 2023). The mixed results for OPE further validate the observation by Nepelski and De Prato (2020) that technological diversification and ubiquity exert varying effects across countries, depending on their level of development and industrial specialization. Furthermore, the positive FDI and complexity relationship observed here echoes Liu et al. (2023), whose analysis of China demonstrated that green finance and FDI positively influence export technology capacity, while trade costs hinder it. This similarity reinforces the robustness of the current study's findings. It highlights the consistent role of FDI as a long-term driver of technological sophistication. In contrast, the influence of trade openness remains conditional and sensitive to structural characteristics of national innovation systems.

## **CONCLUSION**

This study investigated the long-run determinants of technological capacity by applying the AMG estimator following panel unit-root and Durbin-Hausman cointegration tests. The results confirm that FDI



plays a key positive role in enhancing technological capacity across countries, while the effects of trade openness remain heterogeneous and context-specific.

From a policy perspective, the positive long-run effect of FDI suggests that strengthening absorptive capacity is essential for transforming foreign technological inflows into local innovation. Policies that promote research and development, university-industry collaboration, and human capital development can enhance the domestic spillover potential of foreign investments. Additionally, the mixed impact of trade openness indicates that the benefits of globalization for technological capacity depend heavily on the institutional environment and innovation infrastructure. Therefore, trade liberalization policies should be accompanied by measures that improve technological learning mechanisms and industrial diversification, particularly in developing and transition economies.

The opposite-signed findings across countries for the MYS and GFCF variables indicate that policies aimed at enhancing technological capacity cannot be designed as a one-size-fits-all approach. The fact that MYS supports technological capacity in some countries, while showing a weak or negative relationship in others, suggests that complementary factors such as education quality, skills-labour market matching, and digital competencies may be more decisive than the sheer quantity of schooling. Similarly, the country-specific sign of GFCF implies that capital accumulation strengthens technological capacity only when it is directed toward efficient and technology-intensive activities; by contrast, technological upgrading may be constrained when investment is concentrated in less productive sectors or when inefficiencies in resource allocation exist. Therefore, from a policy perspective, reforms that improve education quality and skills alignment may be prioritized for MYS, whereas selective incentives and institutional improvements that channel investment toward R&D, digital infrastructure, and technology-intensive production may be more relevant for GFCF.

Despite providing new insights, the study has several limitations. First, due to data unavailability, some EU countries were excluded from the analysis, which may have constrained the cross-sectional representativeness of the sample. Second, the measure of technological capacity is limited to the patent-based dataset covering the period 1997-2020. Although this period captures major technological shifts, extending the temporal range could help identify structural breaks or long-term transitions in capacity patterns.

Future studies could expand the current framework in several ways. First, the patent-based capacity index could be recalculated using a broader set of years and technological classes to provide a more comprehensive measure of innovation dynamics. Second, the determinants of technological capacity can be

extended beyond FDI and trade openness by incorporating additional variables such as institutional quality, digitalization, green finance, or innovation policy intensity explore their complementary or mediating effects. Third, comparative analyses could group countries by their level of economic development or innovation performance, such as high-income vs. middle-income economies, to test whether the drivers of technological capacity differ across stages of development. By addressing these extensions, future research can offer a deeper understanding of the mechanisms through which international integration, domestic capabilities, and innovation systems jointly shape the evolution of technological capacity and long-term economic resilience.

## AUTHORS' STATEMENT

The authors declare that all contributions to this manuscript were made by the listed authors. The contributions of the authors are as follows: the first author contributed 60%, and the second author contributed 40%. The authors also declare that there are no conflicts of interest.

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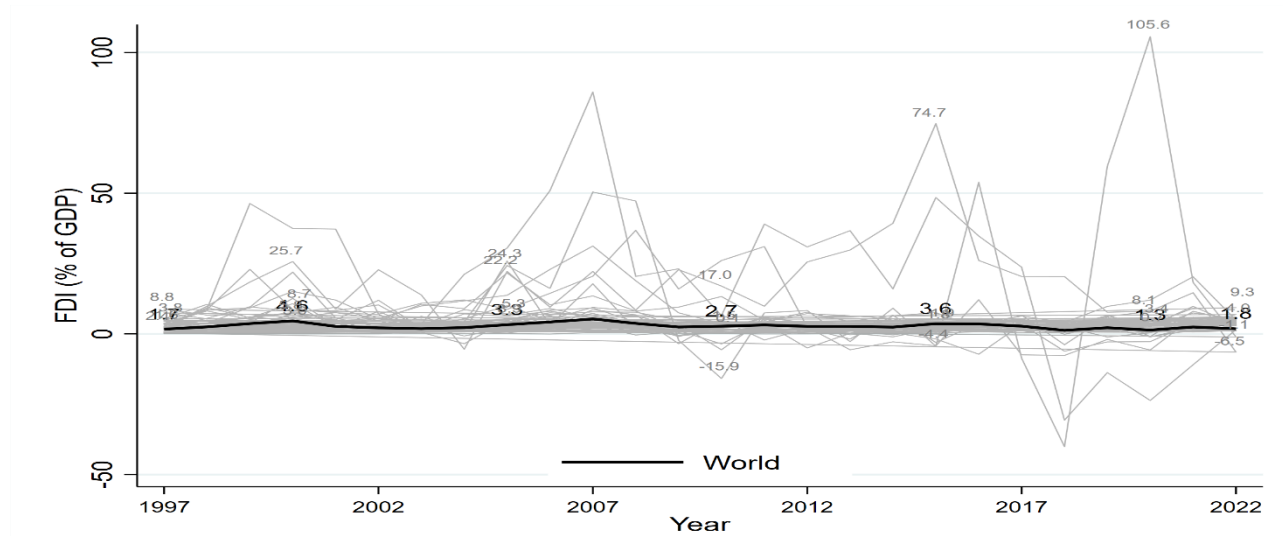
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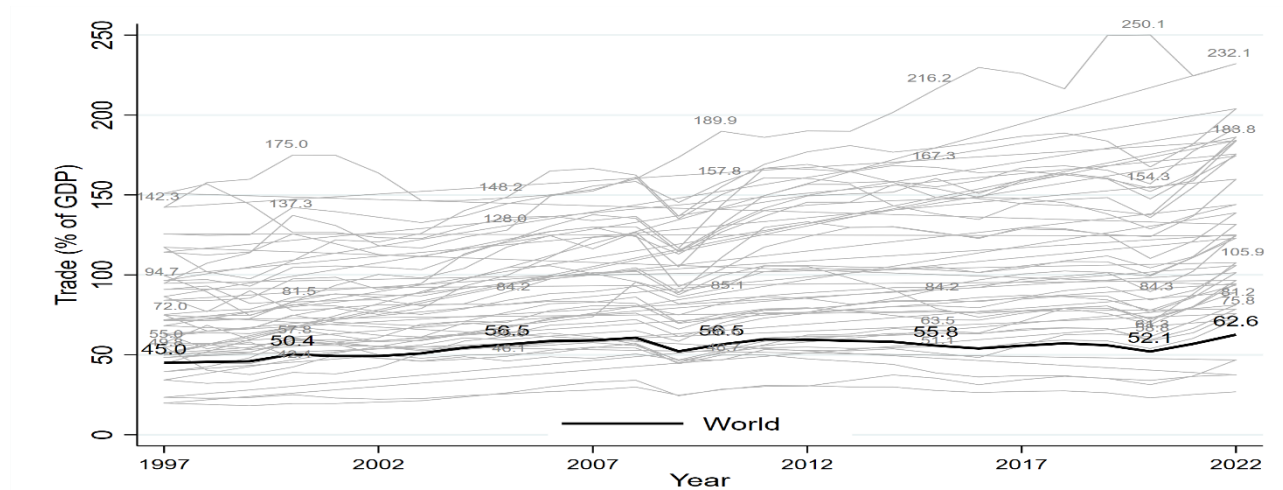
## APPENDIX

**Figure A1:** Overview of FDI in the 29 selected countries



**Source:** Constructed by the authors using data from the World Bank.

**Figure A2:** Overview of openness in the 29 selected countries



**Source:** Constructed by the authors using data from the World Bank.



**Table A1:** Causality test results

	JKS non-causality test			Half-Panel Jackknife estimator	
	Lags	HPJ Wald test	Prob.	Coefficient	Prob.
<b>PATFIT → FDI</b>	4	1.722	0.787	0.239	0.971
<b>FDI → PATFIT</b>	1	15.348***	0.000	-0.001***	0.000
<b>PATFIT → OPE</b>	4	4.867	0.301	-23.517	0.120
<b>OPE → PATFIT</b>	1	1.425	0.233	-0.001***	0.000
<b>PATFIT → LNGDP</b>	1	0.013	0.910	-0.003	0.910
<b>LNGDP → PATFIT</b>	1	0.062	0.802	0.029	0.802
<b>PATFIT → GFCF</b>	4	7.773	0.100	-1.076	0.523
<b>GFCF → PATFIT</b>	1	0.010	0.919	-0.000	0.919
<b>PATFIT → MYS</b>	1	1.559	0.212	0.137	0.212
<b>MYS → PATFIT</b>	1	0.147	0.701	0.012	0.701

\*\*\*denotes significance levels at the 1% level.

**Table A2:** CSD test results for the variables

	<b>PATFIT</b>	<b>FDI</b>	<b>OPE</b>	<b>LNGDP</b>	<b>GFCF</b>	<b>MYS</b>
<b>Statistics</b>	7.600***	67.045***	101.801***	102.715***	101.042***	102.591***
<b>Prob.</b>	0.000	0.000	0.000	0.000	0.000	0.000

\*\*\* denotes significance levels at the 1% levels.