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Foreign direct investment and multidimensional technological innovation: Empirical evidence from five East Asian economies (1996–2025)

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Abstract. This study examines the long-term impact of foreign direct investment (FDI) on multidimensional technological innovation in five East Asian economies (China, Japan, Hong Kong, South Korea, and Singapore). To overcome the limitations of single innovation indicators, the research aims to reveal the empirical dynamics between foreign capital inflows and holistic innovation capacity over 30 years. Using a panel dataset covering the period 1996–2025, a composite Technological Innovation Index (TII) integrating

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technological creativity, technological infrastructure, and human capital components was constructed. The empirical analysis was performed using a random-effects model with robust standard errors to control for heteroskedasticity and unobserved unit effects, based on 144 observations. The econometric findings show that foreign direct investment has a statistically significant and negative effect on technological innovation. In contrast, both GDP per capita and labor force have strong, positive effects on the innovation index. Explanatory variables account for 74.4% of the variation in the innovation index. Empirical evidence contradicts the traditional assumption of technology transfer and suggests a potential crowding-out effect in which foreign capital suppresses local R&D efforts. The findings highlight that innovation is primarily driven by internal macroeconomic capacity and human capital rather than external investment.

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Keywords: direct investment, technological innovation, crowding-out effect, panel data, East Asian economies

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1. INTRODUCTION

Between 1996 and 2021, technological innovation became a key factor in sustainable economic growth and international competitiveness in East Asian economies. Foreign direct investment (FDI) is recognized as an important policy tool for enhancing innovation capacity, especially in developing countries (World Bank, 2025; World Development Indicators [FDI]; Net FDI inflows, BoP, % of GDP). According to UNCTAD, about 54% of global FDI inflows went to developing countries in 2019, the reference year here (UNCTAD, 2019). FDI not only provides financial capital but also supports technological innovation through knowledge transfer, managerial expertise, modernization of production processes, and learning outcomes.

However, the impact of FDI on technological innovation is not entirely linear; It depends on factors such as the level of human capital, the absorptive capacity of domestic firms, the quality of institutions, and trade openness, which can moderate or mediate this relationship (Kemeny, 2010; Bieleń et al., 2024). In this paper, we use a sparse panel data design for five East Asian economies (China, Japan, Hong Kong, South Korea, and Singapore) from 1996 to 2021 to empirically examine the effect of foreign direct investment (FDI) on technological innovation. In this paper, we use a balanced panel data design for five East Asian economies (China, Japan, Hong Kong, South Korea, and Singapore) from 1996 to 2025 to empirically examine the effect of foreign direct investment (FDI) on technological innovation.

The existing literature has examined the relationship between foreign direct investment (FDI) and technological innovation using a variety of theoretical and empirical approaches. While pioneering studies suggest that FDI can enhance the innovative capacity of domestic firms through knowledge diffusion and technology transfer (Sjoholm, 1999; Cheung & Lin, 2004; Abedini, 2013), some studies suggest that this effect may be limited, context-dependent, or even negative (Blajer-Golebiewska, 2024; Kamilia, 2016; Tan & Azman-Saini, 2017). One of the main problems in the literature is that single indicators, such as the number of inventions or R&D expenditure, mostly measure innovation. This approach does not distinguish between horizontal, vertical, and competitive channels of FDI diffusion and ignores structural differences across countries (Monastiriotis & Alegria, 2021)

The empirical analysis, therefore, focuses on five East Asian countries characterized by rapid economic growth (Roxas, 2025) and strong technological innovation capacity (Karaosmanoglu & Mammadli, 2025). Instead of relying on single indicators, as is often the case in the literature, the study employs a multidimensional composite index of technological innovation that the author developed. This approach allows for a more comprehensive assessment of innovation performance. It provides a solid basis for examining the impact of foreign direct investment (FDI) on the technological development of these dynamic economies.

The main objective of this study is to empirically examine the impact of foreign direct investment (FDI) on technological innovation, accounting for the multidimensional nature of innovation. To this end, the relationship between FDI and technological innovation is analyzed using a composite technological innovation index composed of three sub-dimensions and seven variables, rather than individual indicators. This research adopts diffusion and absorptive capacity approaches as its main theoretical perspective to explain the scope and mechanisms through which FDI affects innovation (Lall et al., 2006). This framework assumes that FDI is not merely an element of foreign capital but a dynamic force that initiates innovation production under appropriate institutional and structural conditions (Hoang et al., 2026; Tran & Dat Le, 2019).

The theoretical contribution of this study lies in treating technological innovation as a multidimensional construct, thus moving beyond the single-indicator measurements common in the literature. Methodologically, the developed composite innovation index and panel data analysis provide a more reliable and consistent measure of FDI's effects on innovation. In practice, the findings have strong implications for policymakers regarding the conditions under which FDI can effectively support innovation (Blonigen & Wang, 2004). Through the structure of the developed index, the hypotheses tested, and the policy recommendations, the study adds to the specific and relevant findings of the existing literature.

The main question of this study is: under what conditions, through what channels, and to what extent does foreign direct investment (FDI) influence technological innovation? Specifically, the study addresses whether FDI automatically promotes innovation, a key issue that requires reassessment given the complexity of innovation. In this context, the study aims to provide stronger empirical evidence to dispel the contradictory findings in the literature on the relationship between FDI and innovation.

The remainder of the paper is structured as follows: the second section presents the theoretical framework and the literature on the relationship between foreign direct investment and technological innovation. The third section, in contrast to the widely discussed studies in the literature that focus on the relationship between technological innovation and foreign direct investment (Damijan et al., 2003; Dar et al., 2016; Gui-Diby, 2014), provides detailed information on the dataset, the variables used, the developed technological innovation index, and the panel data analysis method employed.

2. LITERATURE REVIEW

Foreign direct investment (FDI) and technological innovation have been widely examined in the economic and innovation literature, yet the nature of their relationship remains complex and context-dependent. Existing studies suggest that FDI can influence technological innovation through multiple channels, including technology transfer, knowledge spillovers, human capital development, and increased competitive pressure in domestic markets (Mammadli & Rahimli, 2025; Tutar et al., 2025b). However, the magnitude and direction of this effect vary depending on a country's absorptive capacity, institutional quality, and level of technological development (OECD, 2011). In this section, previous empirical and theoretical studies on the relationship between FDI and technological innovation are reviewed, and the key mechanisms through which FDI affects innovation are summarized in a conceptual framework.

Although many studies have examined the impact of foreign direct investment (FDI) on various macroeconomic indicators, relatively few have focused specifically on its effect on technological innovation. A review of the existing empirical literature suggests that these studies can be broadly classified into two groups. The first group reports that FDI has a positive and complementary effect on technological innovation (Ruiz, 2007; Cheung & Lin, 2004; Lee & Branstetter, 2006). The second group finds that in some countries, the effect of FDI on technological innovation is insignificant or statistically small (Sasidharan & Kathuria, 2008; Tebaldi, 2011; Tan & Azman-Saini, 2017).

The relationship between foreign direct investment (FDI) and technological innovation has been widely examined in the empirical literature. Early studies focusing on advanced economies report a positive long-run relationship between FDI and domestic R&D intensity (Landesman & Pfaffermeyer, 1997). Subsequent research extends this analysis to developing and emerging economies, emphasizing sectoral and regional heterogeneity. In this context, several studies highlight the role of FDI-driven spillovers in fostering knowledge diffusion, productivity gains, and patenting activity (Sjöholm, 1999; Cheung & Lin, 2004).

Multi-country panel studies further demonstrate that FDI inflows contribute to technological upgrading and export sophistication, particularly in technology-intensive sectors (Ruiz, 2007; Zhang, 2007). More recent contributions address endogeneity concerns by employing advanced econometric techniques, such as GMM, and confirm that the positive impact of FDI on innovation depends largely on the host country's absorptive capacity (Kemeny, 2010; Krammer, 2010; Abedini, 2013; Zeng & Zhou, 2021). In line with this view, Loukil (2016) argues that FDI becomes innovation-enhancing once a minimum level of technological development is achieved.

Evidence from Asia and other developing regions also suggests a bidirectional relationship between FDI and innovation-related indicators. Studies report feedback effects between FDI, R&D expenditures, and high-technology exports, indicating mutual reinforcement (Erdal & Göçer, 2015; Topallı, 2015; Çapık, 2019; Linh, 2024). Empirical findings from Turkey and the European Union similarly support the existence of a long-term relationship between FDI, R&D activity, and innovative output (Kabaklarlı et al., 2017; Kızılkaya et al., 2017; Çelik & Erdemli, 2021).

Recent studies provide strong empirical support for the knowledge capital framework. Raeskyesa (2024) finds a significant positive relationship between R&D expenditure and Austrian FDI in Asian countries, which becomes stronger when institutional quality, trade openness, and growth are included. At the subnational level, Li (2024) shows that knowledge-intensive FDI in China is attracted to regions with high human capital and strong intellectual property protection, underscoring the importance of institutional quality and workforce capabilities in technology-oriented FDI decisions.

While much of the literature documents a positive relationship between FDI and innovation, a parallel strand of studies shows that this effect can be weak, insignificant, or even negative, depending on absorptive capacity, institutional quality, technological gaps, and country-specific conditions. Li and Liu (2005), using a large cross-country sample, find that wide technological gaps between host and source countries hinder domestic innovation by limiting knowledge absorption. Firm-level evidence from developing economies further supports this view, showing that FDI may crowd out domestic R&D activities. In particular, studies on India and selected Southeast Asian countries report negative or statistically insignificant effects of FDI on R&D expenditures (Sasidharan & Kathuria, 2008; Ismail & Yussof, 2013).

In addition, the literature indicates that the impact of foreign direct investment on technological innovation may be weak, small, or contingent on specific circumstances, reflecting the industrial structure and transnational heterogeneity (Wang, 2010). These mixed findings underscore the importance of adopting econometric methods that rigorously account for heterogeneity and cross-sectional interdependence. Against this background, the present study focuses on a balanced panel of five East Asian economies, namely China, Japan, Hong Kong, South Korea, and Singapore, over the period 1996–2021 ($N = 5$, $T =$

26). These economies are characterized by relatively high levels of human capital, institutional quality, and absorptive capacity. Against this background, the present study focuses on a balanced panel of five East Asian economies, namely China, Japan, Hong Kong, South Korea, and Singapore, covering the period 1996–2025 ($N = 5$, $T = 30$). The selected economies are characterized by relatively high levels of human capital, institutional quality, and absorptive capacity.

Methodologically, this study uses parameter estimates with random effects and Driscoll-Craay standard errors, which are particularly well suited to the data's structure. These estimates explicitly account for intercorrelation, compositional relationships, and heterogeneity. By capturing country-level heterogeneity (e.g., economic scale, institutional framework, innovation system) and temporal dynamics, the cross-sectional approach builds on a more comprehensive approach.

Overall, by addressing significant methodological shortcomings in the existing literature and placing the analysis within a theoretically sound and regionally consistent framework, this study contributes to a more nuanced understanding of when and how foreign direct investment affects innovation. The variable impact of foreign direct investment on innovation is closely related to countries' technological infrastructure, the capacity of domestic companies to absorb investment, GDP levels, and investment in research and experimental development.

Although the impact of foreign direct investment on technological innovation is generally reported as positive in the literature, its effect has been observed to be statistically insignificant or limited in some countries (Sasidharan & Kathuria, 2008; Tebaldi, 2011; Tan & Azman-Saini, 2017). Furthermore, most existing studies examine the impact of foreign direct investment in the short term and across countries, but fail to adequately examine inter-sectoral differences and long-term effects. Additionally, factors such as countries' GDP, labor force capacity, and technological infrastructure have been examined, and the role of foreign direct investment in these variables has been analyzed only to a limited extent in the literature.

Inconsistencies in the existing literature hinder a clear understanding of the roles of GDP and labor force factors in innovation (Braunerhjelm & Thulin, 2003). For example, while some studies highlight the negative effects of GDP on innovation (Li & Liu, 2005; Tebaldi, 2011), the relationship between labor force capacity and innovation shows positive effects across countries (Kemeny, 2010; Erdal & Göçer, 2015; Köprücü, 2017; Mishchuk et al., 2025). In this context, it is necessary to integrate fragmented methods from the literature with a holistic perspective and empirically test the effects of foreign direct investment, GDP, and the labor force in East Asian countries.

In this context, the hypotheses to be tested in the study are the following:

H1: Foreign direct investment significantly affects technological innovation in East Asian economies.

H2: Gross domestic product per capita appears to positively affect technological innovation in East Asian economies.

H3: The labor force has a significant impact on the level of technological innovation in East Asian economies.

These hypotheses aim to address methodological limitations in the literature and to comprehensively examine the effects of foreign direct investment, GDP, and labor force factors on technological innovation in East Asian countries.

2. MATERIALS AND METHODS

2.1. Data and sample selection

This study uses panel data to examine the impact of foreign direct investment (FDI) on technological innovation in selected East Asian countries. The empirical analysis covers the period 1996–2025, allowing for a comprehensive assessment of the long-term relationship between FDI and technological innovation.

This period was chosen for data availability and the growing importance of FDI and innovation in the global economic environment.

This study uses balanced panel data from 1996 to 2025 for five East Asian countries. Instead of relying on a single indicator to measure technological innovation, we use a multi-level approach to construct a technological innovation index (TII). This index is based on three main indicators: a technological creativity index, a technological infrastructure index, and a human capital index. These indicators are designed based on the technological achievement index (TAI) developed by Desai et al. (2002) and the Ar-Co index proposed by Archibugi and Coco (2004). Details of the indicators used to construct the technological innovation index are presented in Table 1.

All variables are normalized using a minimum-maximum normalization technique that ensures index values are between 0 and 1. The normalization procedure is described as follows

$$Index = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x_i denotes the observed value, x_{min} the observed value, x_{min} represents the minimum observed value, and x_{max} refers to the maximum observed value.

Following the method used in the Human Development Index (UNDP, 2010), the overall innovation index is calculated as the geometric mean of the three sub-indices for each country and year. Before 2010, the index was generally constructed using mathematical averages. This offsetting effect could distort the index's overall value. To overcome this limitation, the geometric mean has been used since 2010 to obtain a more sensitive and balanced measure, in which the smaller effect of a sub-indicator has a greater impact on the aggregate measure. This multidimensional, composite-index logic is consistent with comparative cross-country frameworks that aggregate structurally distinct sub-dimensions into a single development metric (Tutar et al., 2025b)."

Accordingly, the Technological Innovation Index (TII) is computed as:

$$TII = (TCI \times HCI \times TII)^{1/3} \quad (2)$$

Based on this framework, we calculate the Technological Innovation Index (TII) values for China, Hong Kong, Japan, South Korea, and Singapore. Compared with previous studies, the constructed TII enables a long-term assessment of technological innovation dynamics and consistent estimation using a balanced panel dataset.

The inclusion of electricity consumption, mobile subscriptions, and internet penetration in the Technological Infrastructure Index reflects growing evidence that digital infrastructure exerts a structurally significant and often asymmetric influence on national development outcomes (Tutar et al., 2025a). The sample consists of five East Asian countries: China, Japan, Hong Kong, South Korea, and Singapore. These countries were selected for their important role in global technological development, their foreign direct investment (FDI) inflows, and their strong innovation processes. Furthermore, they represent different stages of economic and technological development across East Asia, making the analysis more comparable.

Table 1

Criteria used in calculating the technological innovation index

Sub-Indices	Variables	Source	Series Code
Technological Creativity Index (TCI)	Number of Scientific Publications (per Million Inhabitants)	World Bank	IP.JRN.ARTC.SC
	Patent Applications (per Million Inhabitants)	World Bank	IP.PAT.RESD
Technological Infrastructure Index (TInfl)	Electric Power Consumption (kWh per Capita)	World Bank	EG.USE.ELEC.KH.PC
	Mobile Cellular Subscriptions (per 100 People)	World Bank	IT.CEL.SETS
	Fixed Telephone Subscriptions (per 100 People)	World Bank	IT.MLT.MAIN
	Individuals Using the Internet (% of Population)	World Bank	IT.NET.USER.ZS
Human Capital Index (HCI)	Research and Development Expenditure (% of GDP)	World Bank	GB.XPD.RSDV.GD.ZS

Source: *World Bank (2025)*

Table 2

Description of variables in the model

Variable	Description	Data Source	Series Code	Unit	Transformation
Technological Innovation Index	LnTII	Author-Calculated	Composite index	0–1 scale	Used in original scale; log transformation not applied due to zero values in some components.
Foreign Direct Investments	LnFDI	World Bank	BX.KLT.DINV.WD.GD.ZS	net inflows (% of GDP)	Log transformation
GDP Per Capita	LnGDP PPC	World Bank	NY.GDP.PCAP.CD	USD per capita	Log transformation
Labor Force	LnLF	World Bank	SL.TLF.TOTL.IN	persons	Log transformation

All variables used in this study cover the period from 1996 to 2025. The main explanatory variable is foreign direct investment (FDI), which represents inflows of foreign capital. The dependent variable is the Technological Innovation Index (TII), which the authors calculated.

In prior analyses, all independent variables (foreign direct investment, GDP per capita, and labor force) were transformed to natural logarithms to reduce skewness and improve interpretability. The TII was not logarithmically transformed and was used on its original scale, preserving the zero value and maintaining the index's interpretability.

Descriptive statistics for all variables are presented in Table 2. To ensure transparency and reproducibility, the independent variables are clearly stated in the table after log transformation.

When the descriptive statistics of the variables used in the analysis are examined for the period 1996–2025, it is seen that the technological innovation index (TII), which is the dependent variable, has a mean of 0.3049 and a standard deviation of 0.2677 out of 144 observation values (see Table 1). Table 3). In addition, it was determined that the logarithm of foreign direct investment (LNFDI) ranged from -4.7421

to 4.0693, while per capita income (LNGDPPC) averaged 9.9571. These statistics confirm that there is sufficient variation among the variables for an extended panel data analysis.

Table 3

Summary Statistics of Variables (1996-2025)

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
TII	144	0.3049083	0.2677418	0.0012810	0.9664788
LNFDI	144	1.0681223	1.8825171	-4.7421129	4.0693408
LNGDPPC	144	9.9571507	1.0625566	6.5699545	11.4108824
LNLF	144	17.1167304	2.0820279	14.4502439	20.4763262

Note: The summary statistics cover balanced panel data for five East Asian economies over the updated period of 1996-2025. TII is computed as a composite index, while explanatory variables are logarithmically transformed.

Table 3 presents the descriptive statistics of the variables used in the analysis. The dependent variable, the technology innovation index (TII), has 130 observations, a mean of 0.4506426, a standard deviation of 0.2716173, and a range of 0 to 0.926051.

Among the explanatory variables, LNFDI (log of foreign direct investment) has 127 observations, with a mean of 1.151407, a standard deviation of 1.845686, a minimum of -4.742113, and a maximum of 4.069341. LNGDPPC (log a GDP per capita) has 130 observations, a mean of 9.905825, a standard deviation of 1.089405, a minimum of 6.569955, and a maximum of 11.29048. Finally, LNLF (log of labor force) also has 130 observations, with a mean of 17.08889, a standard deviation of 2.07182, a minimum of 14.45122, and a maximum of 20.47571.

These statistics indicate sufficient variation in the variables across countries and time periods, supporting the validity of panel data analysis.

2.2. Econometric model

An econometric model is specified in Equation (1) to examine the effects of foreign direct investment, GDP per capita, and the labor force on technological innovation.

$$TII_{it} = F(FDI_{it}, GDPPC_{it}, LF_{it}) \quad (3)$$

In this specification, TIE denotes the Technological Innovation Index; FDI represents foreign direct investment; GDPPC indicates gross domestic product per capita, while i Moreover, t refers to the cross-sectional units and the time dimension, respectively. The logarithmic specification of the econometric model described above is presented in the following equation.

$$TII_{it} = \beta_0 + \beta_1 * \ln FDI_{it} + \beta_2 * \ln GDPPC_{it} + \beta_3 * \ln LF_{it} + \varepsilon_{it} \quad (4)$$

In this equation, β_0 represents the constant term, whereas β_1 , β_2 , and β_3 denote the coefficients of the explanatory variables. FDI, GDPPC, and LF correspond to foreign direct investment, gross domestic product per capita, and labor force, respectively. The term “ln” refers to the natural logarithm, while ε_i denotes the stochastic error term.

2.3. Estimation strategy and diagnostic tests

At the outset of panel data analysis, it is crucial to identify whether the most appropriate specification is a pooled OLS model, a fixed-effects model, or a model that incorporates time effects. Panel datasets include observations from multiple cross-sectional units, each of which potentially exhibits distinctive characteristics, commonly known as unit-specific effects (Yerdelen, 2020). To assess the existence of these unit effects in the empirical model, various diagnostic procedures are typically employed. Specifically, the likelihood ratio (LR) test, the Breusch-Pagan Lagrange multiplier (LM) test (Breusch, T. S., and Pagan, A. R., 1980), and the fixed-effects F-test (Moulton, B. R., & Randolph, W. C., 1989) have been used to guide the selection among alternative estimators. The results of these tests are summarized in the following table.

Table 3

Results of model selection tests among estimation methods

Tests	Unit and/or Time Effects	Unit Effects	Time Effects
LR (Likelihood Ratio)	39.40(0.000)	39.40(0.000)	1.13(0.1438)
F	9.47(0.000)	24.98(0.000)	3.67 (0.000)
LM (Breusch-Pagan)	N/A	71.15(0.000)	0.000 (1.000)

Note: The values in parentheses represent the p-values.

Based on the results of the F-, LR-, and LM tests presented in Table 4, the model exhibits significant unit effects but no significant time effects. Given the presence of unit effects, the classical OLS pooled model is not suitable, suggesting a fixed- or random-effects specification may be more appropriate. To determine the most appropriate model, the analysis uses the Hausman test (Hausman, 1978) to account for unit-specific effects. The results of the standard and robust Hausman tests are summarized in Table 5 below.

Table 4

Robust Hausman test results

Test	Robust Hausman Test
P-values	2.29 (0.5136)

Based on the robust Hausman test results in Table 5, the null hypothesis of no systematic difference between fixed-effects and random-effects estimators cannot be rejected ($p = 0.5136$). Accordingly, the random-effects model is considered consistent and is adopted for subsequent analyses, as there is no statistical evidence favoring the fixed-effects specification.

We also conducted a series of diagnostic tests to detect potential violations of key panel-data assumptions (e.g., heteroskedasticity, serial correlation, and cross-sectional dependence). To improve the robustness of our estimates, we used the variance inflation factor (VIF) to assess multicollinearity among the explanatory variables. The results of these diagnostic tests are presented in Table 6.

It should also be noted that the analysis is based on a relatively small cross-sectional dimension ($N = 5$), which may limit the power of specification tests such as the Hausman test. This consideration further motivates the use of robust estimation techniques in the empirical framework.

Table 5

Results of diagnostic tests for violations of classical assumptions

VIF		3.17	
Heteroskedasticity Test			
Levene, Brown, and Forsythe Test		W0 = 7.5516375 df(4, 122) Pr > F = 0.00001807 W50 = 5.3676094 df(4, 122) Pr > F = 0.00051404 W10 = 6.7232423 df(4, 122) Pr > F = 0.00006345	
Autocorrelation Tests			
Bhargava et al. Durbin–Watson	0.55110471	Baltagi–Wu LBI	0.81697237
Correlation Tests			
Pesaran Test	-0.388 (0.6979)	Friedman Test	17.235 (0.0017)
Frees Test (0.248)	0.1124 (%10)	0.1470 (%5)	0.2129 (%1)

The diagnostic results in Table 6 indicate heteroskedasticity, serial correlation, and cross-sectional dependence in the model. The Levene and Brown–Forsythe tests confirm heteroskedasticity, while the Bhargava et al. The Durbin–Watson and Baltagi–Wu LBI statistics indicate the presence of autocorrelation. Although the Pesaran CD test fails to detect cross-sectional dependence, the Friedman and Frees tests reveal significant dependence, as expected given the small cross-sectional dimension ($N = 5$) and the CD test's limited power in such samples.

Accordingly, Driscoll–Kraay standard errors are employed to obtain robust inference. In addition, the variance inflation factor (VIF) results indicate no multicollinearity among the explanatory variables.

Finally, the variance inflation factor (VIF) was used to assess multicollinearity among the explanatory variables, and the results indicated no multicollinearity in the model. These diagnostic results collectively highlight the importance of considering heteroskedasticity, autocorrelation, and cross-sectional dependence in panel data analysis to ensure the robustness and reliability of inferences

3. EMPIRICAL RESULTS

Given heteroskedasticity, autocorrelation, and cross-sectional dependence, this study employs the Driscoll–Kraay (1998) robust standard error estimator to ensure reliable inference. Coefficient estimates are obtained from a random-effects panel model. At the same time, the Driscoll–Kraay procedure provides standard errors, t-statistics, and p-values that are robust to both temporal and cross-sectional correlations. This combined approach preserves the efficiency of the random-effects estimator while ensuring robust and unbiased statistical inference.

When the empirical findings obtained using the Random-Effects estimator with robust standard errors were examined, the model's explanatory power (R-squared) was 0.7441 (see Table 1). Table 7). When the coefficient estimates were evaluated, it was determined that foreign direct investment (LNFDI) had a statistically significant negative effect on technological innovation (-0.0757 , $p=0.000$). On the other hand, GDP per capita (LNGDPPC) and labor force (LNLF) variables affect the technological innovation index

statistically significantly and positively, with coefficients of 0.0575 and 0.0729, respectively. While these empirical findings demonstrate that GDP and human capital capacity drive innovation, they show that foreign direct investment has a limiting (exclusive) effect on innovation in the 1996-2025 long-term panel, contrary to the dominant view in the literature.

Table 7

Results of the random-effects estimator (robust)

Variables	Coefficient	Robust Standard Errors	T statistic	P-value
const	-1.4363242	0.2580999	-5.56	0.000
LNFDI	-0.0757036	0.0111132	-6.81	0.000
LNGDPPC	0.0575123	0.0127263	4.52	0.000
LNLF	0.0729946	0.0085874	8.50	0.000
R-squared	0.7441	-	-	-

Note: Estimations are based on a random-effects panel model. Robust standard errors are employed to control for heteroskedasticity and potential correlation structures within the 1996-2025 dataset.

Table 7 reports the fixed-effects estimation results with Driscoll–Kraay standard errors. The Wald chi-square statistic (458.93, $p = 0.000$) strongly rejects the null hypothesis that all slope coefficients are jointly zero, confirming the model's overall significance. The overall R^2 of 0.4667 indicates that approximately 46.7% of the variation in technological innovation is explained by FDI, GDP per capita, and labor force, suggesting a satisfactory model fit given the small-N panel structure and control for unobserved heterogeneity.

Overall, the findings demonstrate that the selected econometric framework captures both cross-country and temporal variation in technological innovation and yields robust inference when heteroskedasticity, serial correlation, and cross-sectional dependence are addressed through Driscoll–Kraay standard errors.

According to the findings, the LNFDI coefficient (-0.0757), representing the logarithm of foreign direct investment, is statistically significant and negative at the 1% level ($p < 0.01$). Since the explanatory variables are logarithmic and the dependent variable (TII) is in level form (in the context of semi-elasticity), a 1% increase in FDI, holding all other factors constant, results in an average decrease of 0.000757 units in the Technological Innovation Index. This strong negative effect provides important empirical evidence that foreign capital entering the region excludes domestic R&D activities rather than developing local technological capacity (crowding-out effect).

On the other hand, the GDP per capita (LNGDPPC) coefficient was found to be 0.0575 and 1%. A 1% increase in GDP yields a 0.000575-unit increase in the index, indicating that macroeconomic prosperity is a fundamental, intrinsic engine that finances innovative capacity. Similarly, the labor force (LNLF) variable also positively affects innovation (0.0730). A 1% expansion in the workforce results in a statistically significant increase of 0.000730 units in the TII. The overall explanatory power of the model ($R^2 = 0.7441$) indicates that the selected independent variables explain approximately 74.4% of the variation in technological innovation. Within the framework of all these findings, the H1 hypothesis is accepted as "changing direction" (negatively), while the H2 and H3 hypotheses are positively supported.

According to the obtained findings, the final model constructed with the significant variables is presented as follows:

$$TII_{it} = -1.4363 - 0.0757\ln(FDI_{it}) + 0.0575\ln(GDPPC_{it}) + 0.0730\ln(LF_{it}) + \varepsilon_{it}$$

When empirical modeling results are visualized, the negative relationship between LNFDI and TII is evident in the scatter plot in Figure 1 (see Table 1 for descriptive statistics). When foreign capital inflows increase, the expected acceleration in the local innovation index does not materialize; instead, a downward trend emerges. In addition, when the long-term development trends in the technological innovation performance of the five East Asian economies over the 1996–2025 period are examined, it is found that structural differences between countries, macroeconomic shocks, and technological infrastructure investments are reflected in heterogeneous fluctuations in the index values (see Table 1, Figure 2).

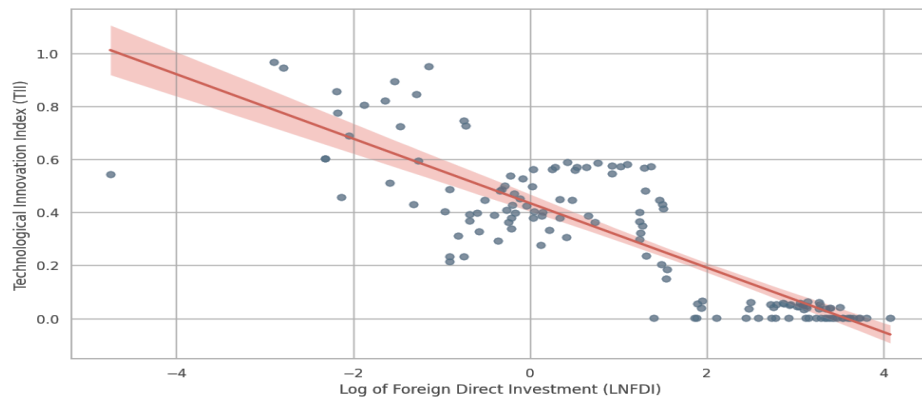


Figure 1. Relationship between foreign direct investment and technological innovation

The scatter plot illustrates the empirical inverse relationship between the natural logarithm of foreign direct investment and the composite technological innovation index across the selected East Asian economies. Note: The solid line represents the fitted linear regression trend between the natural logarithm of foreign direct investment (LNFDI) and the Technological Innovation Index (TII), with the shaded band indicating the 95% confidence interval.

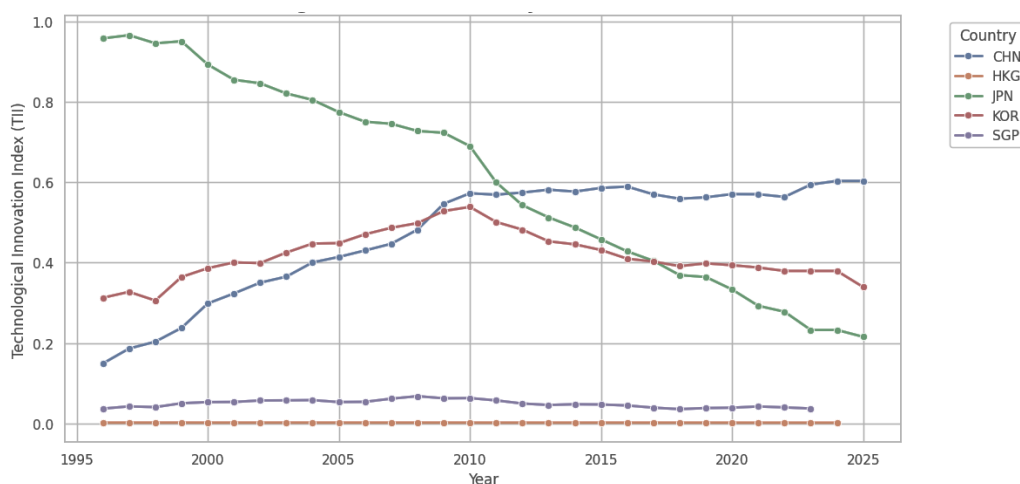


Figure 2. Dynamics of the technological innovation index in East Asian Economies (1996–2025)

Note: The line graph maps the temporal fluctuations and secular trends in the technological innovation index for each cross-sectional unit over the 30-year observation period

4. DISCUSSION

This study examines the impact of foreign direct investment (FDI) on technological innovation using panel data analysis. To ensure that statistical inferences are valid in the presence of varying variance, autocorrelation, and cross-sectional dependence, the empirical model was estimated using robust Driscoll-Kraay standard errors, which remain consistent under these conditions (Driscoll & Kraay, 1998).

Previous studies in the literature suggest that FDI promotes technological development by increasing patenting, R&D activities, and high-tech production, and is compatible with the theoretical framework of technology diffusion and local learning (Ruiz, 2007; Cheung & Lin, 2004; Zhang, 2007; Erdal & Göçer, 2015). However, the empirical results of this study, covering the extended period 1996-2025, show that, contrary to traditional expectations, foreign direct investment has a statistically significant negative impact on technological innovation. This provides strong empirical evidence that foreign capital leads to a "crowding-out" effect that suppresses domestic R&D efforts, rather than increasing local innovation capacity.

This negative finding aligns with other studies in the literature, which emphasize that FDI does not always encourage innovation. It has been previously reported that in some countries, FDI may limit local R&D or have an insignificant impact (Sasidharan & Kathuria, 2008; Ismail & Yussof, 2013; Tebaldi, 2011). These variations are linked to differences in absorption capacity, sectoral composition, and institutional quality. In line with Loukil (2016), FDI is considered to affect innovation below a technological threshold negatively. In the East Asian economies considered, foreign capital tends to dominate the domestic market rather than facilitate technology transfer, and at times it can even weaken local innovation by concentrating scarce talent.

On the other hand, the positive impact of per capita income highlights the role of endogenous macroeconomic development in financing innovation and strengthening national innovation systems (Seyoum, 2005; Kemeny, 2010). Similarly, the meaningful and positive impact of the workforce underscores the complementary role of human capital, because qualified labor mobility and firm interactions facilitate the internalization of technological externalities (Tutar et al., 2025b; Branstetter, 2006; Murashima, 2024). This confirms that the main drivers of innovation in the analyzed countries are established macroeconomic capacity and qualified human resources, rather than external FDI flows.

This study makes a valuable contribution to the scientific literature by measuring technological innovation through a multidimensional approach rather than a single indicator. This approach, which includes patents, R&D expenditures, scientific publications, and advanced technology exports, allows for a more comprehensive assessment of innovation capacity. The evidence obtained shows that the innovation benefits of foreign capital inflows are not automatic; rather, they are closely tied to additional local factors, such as human capital, institutional quality, and technological infrastructure. This interpretation is consistent with current findings indicating that FDI in technology-intensive and knowledge-based services is being drawn to sectors with stronger protections of human capital and intellectual property rights (Li, 2024). This composite, multidimensional measurement strategy further aligns with comparative evidence showing that single-indicator assessments understate cross-country heterogeneity in development-related outcomes (Tutar et al., 2025b).

From a policy perspective, empirical results suggest that quantitative strategies focused solely on attracting foreign direct investment (FDI) are risky due to their inadequate and exclusionary effects. To reverse the negative (suppressive) effect of foreign capital on innovation, it is essential to strengthen local enterprises' technological learning and adaptation capabilities. In this context, internal R&D incentives, education policies, university-industry collaborations, and labor market regulations that support a qualified workforce are critical. In addition, directing FDI to technology-intensive, high-value sectors rather than

indiscriminately accepting it (through selective investment policies) will be decisive in achieving long-term innovation performance and in breaking the crowding-out effect.

4.1. Policy recommendations

The research findings empirically show that foreign capital does not automatically spur technological innovation; rather, it creates a "crowding-out" effect on local R&D when structural measures are not in place. Accordingly, policymakers should abandon strategies focused solely on "capital attraction" (volume) and take the following proactive and protectionist steps:

Quality-Focused Selective FDI Policies: Governments should prioritize technological quality over quantity when encouraging foreign investment. Tax breaks and allocations offered to foreign investors should be offered "conditionally" to projects that guarantee technology transfer, establish R&D partnerships with local universities, and produce advanced technology.

Protection of Domestic R&D Against Foreign Monopoly: To balance the high salaries and benefits of multinational companies with the recruitment of the most qualified researchers in the country (internal brain drain), human resources and technology financing (subsidies) should be strategically increased to support domestic innovation companies.

Strengthening Endogenous Absorption Capacity: Based on the finding that the main drivers of innovation are GDP and human capital, the share of the public budget allocated to education, digital infrastructure, and basic scientific research should be maximized. Without building a strong internal scientific capacity, the fact that foreign capital entering the country solely for assembly or cheap labor will not yield technological gains should be central to macroeconomic planning. Prioritizing digital infrastructure investment is particularly warranted, given evidence that its development effects are asymmetric and disproportionately beneficial when paired with complementary human-capital policies (Tutar et al., 2025a).

4.2. Limitations and suggestions for future research

Limitations. This study is limited to five East Asian economies; the small cross-sectional sample size (N=5) limits the generalizability of the findings to other developing regions and weakens the statistical power of diagnostic tests such as the Hausman test. Some missing observations in the analyzed 30-year (1996-2025) panel dataset partially affect the series' fully balanced structure. In addition, the potential risk of reverse causality between foreign direct investment (FDI) and technological innovation could not be fully controlled because instrumental variable estimation or a quasi-experimental design was not used (Kemeny, 2010; Zeng & Zhou, 2021). Given the direction of the "crowding-out" effect observed in the study, this situation poses a methodological limitation (Archibugi & Coco, 2004).

Recommendations for Future Research. Future studies may apply the GMM (Generalized Method of Moments) estimator to larger country samples to address endogeneity and more robustly examine the dynamics of the exclusionary effect of foreign capital (Krammer, 2010). The decomposition of FDI by sector and country of origin will enable a more detailed examination of the mechanisms by which foreign capital suppresses innovation (technology-intensive versus resource-intensive investments). Modeling the three sub-dimensions of the composite TII (creativity, infrastructure, and human capital) separately will make the policy recommendations much more concrete. However, determining the minimum absorption capacity level using threshold regression models will clarify under which institutional conditions the negative impact of FDI can be broken and turned into technological gains (Loukil, 2016). Future research could also examine whether the crowding-out effect documented here interacts with digital-infrastructure disparities across countries, given evidence that infrastructure gaps generate asymmetric distributional consequences (Tutar et al., 2025a).

CONCLUSION

This study re-examines the long-debated link between foreign direct investment and technological innovation by moving beyond the single-indicator measures that have dominated much of the empirical literature. Focusing on five East Asian economies – China, Japan, Hong Kong, South Korea, and Singapore – over the three decades from 1996 to 2025, the research constructs a composite Technological Innovation Index that integrates technological creativity, infrastructure, and human capital into a unified analytical framework. Drawing conceptual inspiration from established multidimensional benchmarking tools, the authors normalize seven underlying variables – ranging from patent applications and scientific publications to electricity consumption, mobile and fixed-line subscriptions, internet penetration, and R&D expenditure – using min-max scaling and geometric averaging. The resulting index offers a far more nuanced portrait of national innovation capacity than conventional one-dimensional proxies such as patent counts or R&D spending alone, and it aligns with broader comparative-development frameworks that aggregate structurally distinct sub-dimensions into a single metric.

Methodologically, the analysis rests on a balanced panel of 144 country-year observations. After confirming the presence of significant unit effects and the absence of meaningful time effects through likelihood-ratio, F, and Lagrange-multiplier tests, a random-effects specification is adopted as the preferred estimator. A robust Hausman test further supports this choice by failing to reject the null hypothesis of no systematic divergence between fixed- and random-effects estimates. Because subsequent diagnostic checks reveal heteroskedasticity, serial correlation, and cross-sectional dependence, all inference is carried out with Driscoll–Kraay robust standard errors, which remain consistent in the presence of both temporal and spatial correlation structures. Meanwhile, variance-inflation factors remain comfortably below conventional thresholds, indicating that multicollinearity is not a concern in the estimated model. The small cross-sectional dimension is acknowledged as a limitation that weakens the statistical power of certain specification tests, yet the robust estimation strategy mitigates this constraint.

The empirical results challenge the prevailing assumption that foreign capital automatically fuels local innovation. Contrary to the conventional technology-diffusion narrative, FDI exerts a statistically significant negative effect on the composite innovation index. In practical terms, a one-percent rise in FDI inflows is associated with a slight but robust decline in the innovation score, pointing to a crowding-out dynamic in which foreign firms may suppress rather than stimulate domestic R&D efforts. This finding resonates with a parallel strand of literature emphasizing that the innovation benefits of foreign capital are contingent on host-country absorptive capacity, institutional quality, and the technological gap between domestic and foreign producers. By contrast, both GDP per capita and labor force size display strong, positive coefficients, reinforcing the view that innovation is driven primarily by internal macroeconomic depth and human-capital endowments rather than by external capital injections. The model explains roughly three-quarters of the variation in innovation outcomes, indicating a solid empirical fit despite the small cross-sectional dimension.

These findings carry direct policy implications. Rather than indiscriminately attracting foreign capital through tax breaks and deregulation, governments should design selective FDI regimes that explicitly mandate technology transfer, local R&D partnerships, and knowledge spillovers. Protecting domestic research ecosystems from talent poaching by multinational affiliates and strengthening endogenous absorptive capacity – through sustained investment in education, digital infrastructure, and basic scientific research – emerge as more reliable pathways to sustainable innovation. Prioritizing digital infrastructure is especially warranted, given evidence that its development effects are often asymmetric and disproportionately beneficial when paired with complementary human-capital policies.

The study acknowledges its limitations: the sample is confined to five relatively advanced East Asian economies, which narrows generalizability to other developing regions, and some missing observations partially disturb the fully balanced structure. Moreover, the absence of instrumental-variable or GMM estimation leaves room for endogeneity concerns, particularly because reverse causality between FDI and innovation could not be fully controlled. Future work could expand the country coverage, disaggregate FDI by sector and origin to uncover sector-specific crowding-out mechanisms, model the three sub-dimensions of the composite index separately for more targeted policy recommendations, and apply threshold regression techniques to identify the precise institutional tipping points at which foreign investment might turn from a deterrent into a genuine catalyst for long-run technological progress.

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