

The impact of science and technology on human development in developed countries (2000–2023) using dynamic OLS panel methods.

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Abstract:

This study aims to analyze the impact of science and technology on human development in a group of developed countries during the period 2000–2023, using the dynamic ordinary least squares (DOLS) panel method. The study's results indicate the existence of a long-term cointegration relationship between the Human Development Index and science and technology indicators. Furthermore, the findings show that increases in research and development expenditure, intellectual property receipts, non-resident patent applications, and scientific and technical journal articles lead to a long-term rise in the Human Development Index. Conversely, increases in intellectual property payments and resident patent applications result in a long-term decline in the growth of the Human Development Index.

Keywords: Science, technology, human development, panel models, a sample of developed countries.

JEL Classification: O330, O150, C33, O57.

ملخص :

تهدف هذه الدراسة إلى تحليل تأثير العلم والتكنولوجيا على التنمية البشرية في مجموعة من الدول المتقدمة خلال الفترة من 2000 إلى 2023، باستخدام طريقة المربعات الصغرى العادية الديناميكية لباينل. حيث أظهرت نتائج الدراسة، إلى وجود علاقة تكامل مشتركة طويلة الأجل بين مؤشر التنمية البشرية ومؤشرات العلم والتكنولوجيا، كما أثبتت الدراسة أن زيادة كل من الإنفاق على البحث والتطوير، ورسوم حقوق استخدام الملكية الفكرية للمنتجات، وطلبات تسجيل براءات الاختراع لغير المقيمين، ومقالات المجلات العلمية والتقنية، يؤدي إلى زيادة في مؤشر التنمية البشرية للأجل الطويل، وزيادة رسوم استخدام حقوق الملكية الفكرية للمدفوعات، وطلبات تسجيل براءات الاختراع للمقيمين يؤديان إلى نقصان في نمو مؤشر التنمية البشرية للأجل الطويل.

الكلمات المفتاحية : العلم، التكنولوجيا، التنمية البشرية، نماذج باينل، عينة من الدول المتطورة.

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1.Introduction

The interaction between science, technology, and human development serves as a key driver of progress in modern societies, profoundly influencing the improvement of quality of life and the enhancement of well-being. Science, through its discoveries and theories, provides the foundational knowledge that enables a deeper understanding of the world and the resolution of challenges facing humanity. Technology, in turn, acts as the tool that converts this knowledge into practical applications, facilitating daily life and driving transformative changes in areas such as medicine, education, communications, and energy. This scientific and technological advancement directly contributes to human development by strengthening individual and collective capacities through improved healthcare services, expanded educational opportunities, and increased economic productivity. Consequently, science and technology emerge as crucial factors in building more sustainable and equitable societies that address individual needs and promote overall welfare. Based on the foregoing, the primary research problem can be precisely formulated as follows

What is the impact of science and technology on human development for a sample of developed countries during the period 2000–2023?

Within the main research problem, a set of sub-questions is formulated as follows:

Is there a long-term cointegration relationship between the Human Development Index and science and technology indicators?

Is there a significant effect of certain science and technology indicators on human development using the dynamic ordinary least squares (DOLS) panel method?

To address the main research problem and the sub-questions, a set of hypotheses has been formulated, which will serve as the logical framework for the study.

There is a long-term cointegration relationship between the Human Development Index and the indicators of science and technology in developed countries.

There is a significant effect of certain science and technology indicators on human development.

1.1 Study Methodology:

To comprehensively address the aspects of the study topic, both the deductive and inductive approaches were employed to derive results and statistically process the data. This involved the use of econometric tools in an attempt to demonstrate the relationship between science, technology, and human development.

1.2 Literature review:

This section presents a variety of previous studies that are presented in an ascending order and focus on the following topics: released findings, adopted estimation techniques.

Prince Dorian Rivel Bambi and Jean Baptiste Bernard Pea-Assounga a study in 2024 examined the relationship between research and development (R&D) expenditure,

educational attainment, human capital development, and economic growth within the context of technological innovation, using panel data spanning 1996 to 2022. Nine countries—Spain, Sweden, Finland, Denmark, Norway, the Netherlands, the United Kingdom, France, and South Korea—were selected due to the strength of their public education systems. The study employed pairwise Granger causality tests and panel vector autoregression (VAR) analysis, revealing significant positive relationships among R&D investment, education levels, human capital development, and technological innovation. The findings highlighted the crucial role of education and human capital in enhancing innovation capacity and demonstrated that technological innovation stimulates economic growth, driving both societal and economic transformation. These results underscore the importance of policies aimed at promoting R&D, expanding educational opportunities, and developing human capital to create environments conducive to sustainable development and economic progress (Prince Dorian Rivel and Jean Baptiste Bernard 2024).

Hyunyi Choi and Keuntae Cho conducted a study in 2023 entitled "Effects of Science, Technology, and Innovation Official Development Assistance on Innovative Capacity in Developing Countries," using a fixed-effects panel model for 84 developing countries over the period 2002–2018. The study aimed to empirically investigate the impact of official development assistance (ODA) in science, technology, and innovation on the innovative capacity of developing countries. Specifically, it examined the moderating effects of research and development (R&D) investment on innovative capacity. The results indicated that ODA in science, technology, and innovation did not have a direct positive effect on innovative capacity. However, it positively influenced innovative capacity when the moderating effect of R&D investment was substantial and when the proportion of investment in R&D increased (Hyunyi & Keuntae, 2023).

Jiajia Zheng and Xingwu Wang (2022) explored the impacts of renewable energy, information and communication technologies (ICTs), and their combinations on the Human Development Index (HDI) for 26 countries between 2000 and 2018, using fixed and dynamic panel models. Other factors included carbon dioxide emissions, economic development, primary energy consumption, and population. The study found that renewable energy alone has an insignificant impact on the HDI in both the short and long term, while ICTs positively affect the HDI in the short term but become insignificant in the long term. The combination of renewable energy and ICTs significantly enhances the HDI in both time horizons. Economic development positively influences human development, whereas carbon emissions have a negative effect. Primary energy consumption boosts HDI in the short term but hinders it in the long term, and population growth negatively affects human development in the long term (Jiajia & Xingwu, 2022).

A study by Viju Raghupathi and Wullianallur Raghupathi (2019) entitled "Exploring Science-and-Technology-Led Innovation: A Cross-Country Study" analyzed the differences between developed and developing countries in terms of expenditure on certain science and technology indicators. The study utilized data from the Organisation for Economic Co-operation and Development (OECD) on research and development, patents, and exports for the period 2000–2016, employing a dual methodology combining descriptive analysis and panel regression models. The study concluded that countries with high foreign ownership of patents tend to have lower tax revenues as a percentage of GDP.

Moreover, maintaining a domestic patent portfolio as opposed to foreign ownership has significant effects on national taxation policies and innovation. (Viju & Wullianallur , 2019).

Sana Suran et al. (2017), in their study entitled "The Economic Impact of Research and Development," examined the relationship between research and development (R&D) expenditure and per capita GDP, the Gini index of inequality, gross savings rate, unemployment rate, services value added, and industry value added. The study covered the period 2008–2011 and included a sample of both developed and developing countries. Using the ordinary least squares (OLS) method across five models, the study aimed to understand how a 1% change in R&D expenditure could affect per capita GDP in both developed and developing countries. The results indicated that R&D expenditure was statistically significant in all tested models, while other factors such as the gross savings rate, industry value added, and services value added were significant at the 1% level. The study also revealed a positive relationship between per capita GDP and R&D expenditure (Sana, Will , & Swati , 2017).

Yee Kyoung Kim and Keun Lee (2015), in their study entitled "Different Impacts of Scientific and Technological Knowledge on Economic Growth: Contrasting Science and Technology Policy in East Asia and Latin America," conducted an economic and quantitative cross-country analysis focusing on the distinct roles of scientific and technological knowledge on economic growth and knowledge production functions for a sample of East Asian and Latin American countries over the period 1975–2005, using panel data. The study concluded that scientific knowledge (academic publications) has no direct impact on economic growth, whereas technological knowledge (patents) significantly influences economic growth. Furthermore, the generation of scientific knowledge does not automatically lead to the production of technological knowledge. Technological knowledge is primarily determined by research and development efforts carried out by firms (Yee & Keun, 2015).

James Prieger et al. (2013), in their study entitled "The Impact of Research and Development on Economic Growth and Productivity in the US States," aimed to estimate the effect of research and development (R&D) on total factor productivity and private sector output at the state level in the United States over the period 1963–2007, using panel data. The study concluded that R&D has a significant impact on both output and total factor productivity at the state level in the long term. The average R&D elasticity at the state level ranges from 0.056 to 0.143, implying that the GDP returns from R&D spending vary between 83% and 213%. Additionally, there are positive indirect effects of R&D, with 77% of total returns accruing to other states. The study also found that R&D elasticity remained stable or slightly increased after 1993. Moreover, states with higher levels of human capital exhibited greater R&D elasticity, whereas states at the lowest levels of economic development showed the lowest R&D elasticity. (James, Ji , & Luisa , 2013).

This study differs from previous studies in several aspects, including the sample size, as well as notable differences in methodology, tools, and results compared to the study by Sana Suran et al., in addition to partial differences with other studies. Regarding the study variables, there are partial differences with all previous studies, while the overall objectives show similarities with those of earlier research.

2. Empirical analysis:

2.1. Study Sample Indicators:

The indicators measuring the impact of science and technology on human development for a sample of developed countries consist of 8 indicators and 17 countries for the period 2000–2023, as shown in Table 1

Table 1: Study Variables

Variables	Definition of Variables
Dependent Variable	
Human Development Index - HDI	The Human Development Index (HDI) is calculated using three main dimensions that reflect key aspects of individuals' lives: health, education, and income level. Each dimension is measured through specific indicators, which are then aggregated into a single index ranging from 0 to 1, with values closer to 1 indicating a higher level of human development.
Independent Variables	
Research and Development Expenditure SRD	These are current and capital expenditures (in both the public and private sectors) on creative activities carried out systematically with the aim of advancing knowledge, including human, cultural, and social knowledge, and applying this knowledge in new applications.
Researchers Working in Research and Development RWRD	They are specialists engaged in creating or innovating new knowledge, products, tools, processes, methods, or systems, as well as managing the related projects. The data also include doctoral-level graduate students participating in the research and development process.
Intellectual Property Rights (IPR) Fees for Payments (IPRUFPA) and Receipts (IPRUFPR)	Royalties and License Fees are the payments and revenues exchanged between resident and non-resident parties for the authorized use of non-physical, non-produced, and non-financial assets, as well as for the use of produced assets for prototypes. The data are expressed in current U.S. dollars.
Patent Applications for Non-Residents (PRAFNR) and Residents (PRAFR)	They are patent applications filed worldwide either through the Patent Cooperation Treaty (PCT) or with a national patent office to register the full ownership of an invention.
Articles in Scientific and Technical Journals (ASTJ)	It refers to the number of scientific and engineering articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences

Source: Prepared by the researchers based on data from the World Bank, Trading Economics, and the Human Development Report.

2.2.Standard Study:

This research aims to design an economic model to measure the impact of science and technology on human development in a group of developed countries, with the objective of identifying the key science and technology indicators that play a pivotal role in enhancing human development. Econometric methodologies will be employed, as the model used in the study was developed based on existing literature and previous research. The model will be estimated and subsequently analyzed.

2.2.1. Model Specification:

A model was designed to measure the impact of science and technology on human development based on the variables listed in Table 1, relying on previous studies that examined this relationship. This relationship is expressed through the following model:

$$LHdi = f(LSrd, LRwr, LIprufpa, LIprufpr, LPr afnr, LPr afr, LAstj) \dots\dots\dots (01)$$

The model in equation (01) can be formulated as follows:

$$LHdi_{it} = \delta_{0i} + \delta_1 LSrd_{1it} + \delta_2 LRwr_{2it} + \delta_3 LIprufpr_{3it} + \delta_4 LIprufpa_{4it} + \delta_5 LPr afnr_{5it} + \delta_6 LPr afr_{6it} + \delta_7 LAstj_{7it} + \varepsilon_{it} \dots\dots\dots (02)$$

Let the time period be defined as $t = 2000, \dots, 2023$, and the number of individuals (countries) as $i = 1, \dots, 17$. and δ_{0i} represents the intercept for observation i , and $(\delta_1, \dots, \delta_7)$ represents the parameters to be estimated for each independent variable, and ε_{it} denotes a column vector of dimension $tn \times 1$ for the random error of country i in period t

2.2.2.Estimation and Dynamic Analysis of the Study Model:

A dynamic panel model analysis was applied to better understand long-term interactions and effects. This approach requires taking into account the stationarity of the model's time series variables, as their stability is a fundamental condition for ensuring the validity and reliability of the results in dynamic analysis.

2.2.2.1.Stationarity Analysis of Time Series Variables:

To detect the presence of a unit root in panel data, several statistical tests specifically designed for this purpose are used. Among the most important and commonly applied tests are:

- Levin, Lin & Chu t^* test
- Breitung t -stat test
- Im, Pesaran, and Shin W -stat test
- ADF – Fisher Chi-square test
- PP – Fisher Chi-square test

The results in Table 2 present the application of these tests on the model variables at their different levels and/or after the first difference. These tests help determine whether

the time series are stationary or contain a unit root (non-stationary), which is crucial for avoiding spurious regression and ensuring the validity of the analytical results.

Table 2: Unit Root Test Results for the Model Variables

Unit Root Test Results for the Model Variables at Levels					
Variables \ Test Statistic	PP Fisher Chi-square	- ADF – Fisher Chi-square	Im, Pesaran and Shin W-stat	Breitung t-stat	Levin, Lin & Chu t*
$LSrd_{it}$	51.5260 (0.0275)	46.0143 (0.0819)	-1.90640 (0.0283)	-0.24281 (0.4041)	-0.80270 (0.2111)
$LRwrd_{it}$	28.9936 (0.7115)	39.7162 (0.2304)	-0.99824 (0.1591)	-0.69277 (0.2442)	-1.61992 (0.0526)
$LPrufpa_{it}$	39.0178 (0.2543)	51.1136 (0.0300)	-1.65558 (0.0489)	-0.4473 (0.6727)	-3.75551 (0.0001)
$LPrufpr_{it}$	37.4190 (0.3150)	55.4079 (0.0116)	-1.72132 (0.0426)	-0.94416 (0.1725)	-3.50789 (0.0002)
$LPr afr_{it}$	44.9137 (0.0998)	32.5276 (0.5398)	0.18808 (0.5746)		-2.53959 (0.0055)
$LPr afr_{it}$	40.2097 (0.2144)	24.6105 (0.8813)	1.39126 (0.9179)		-1.26490 (0.1030)
$LAstj_{it}$	3.22906 (1.0000)	13.5876 (0.9993)	3.76370 (0.9999)	5.15138 (1.0000)	-0.7205 (0.7644)
$LHdi_{it}$	50.0556 (0.0373)	30.8701 (0.6218)	0.62493 (0.7340)	0.39260 (0.6527)	-1.19513 (0.1160)
Unit Root Test Results for the Model Variables at First Differences					
$D(LSrd_{it})$	325.857 (0.0000)	78.5258 (0.0000)	-4.59776 (0.0000)	-6.37808 (0.0000)	-2.46892 (0.0068)
$D(LRwrd_{it})$	234.459 (0.0000)	89.8444 (0.0000)	-5.40679 (0.0000)	-7.78528 (0.0000)	-4.76345 (0.0000)
$D(LPrufpa_{it})$	402.644 (0.0000)	128.283 (0.0000)	-8.24132 (0.0021)	-5.31302 (0.0000)	-7.10762 (0.0000)
$D(LPrufpr_{it})$	467.856 (0.0000)	150.492 (0.0000)	-9.91662 (0.0000)	-5.38583 (0.0000)	-8.66094 (0.0000)
$D(LPr afr_{it})$	224.605 (0.0000)	105.510 (0.0000)	-6.52213 (0.0000)		-4.77072 (0.0000)
$D(LPr afr_{it})$	272.229 (0.0000)	123.175 (0.0000)	-7.66484 (0.0000)		-7.44468 (0.0000)
$D(LAstj_{it})$	167.714 (0.0000)	73.4942 (0.0001)	-4.45518 (0.0001)	-0.27828 (0.3904)	-0.43297 (0.3325)
$D(LHdi_{it})$	207.298 (0.0000)	105.123 (0.0000)	-6.77732 (0.0000)	-4.15712 (0.0000)	-8.16269 (0.0000)

Source: Prepared by the researchers using the outputs from EViews 13, as shown in Appendices 1 and 2. (): indicates the p-value at 5%.

The results presented in Table 2 indicate that, at the 5% significance level, all variables are integrated of the first order. Although these variables are stationary at the same order, the possibility of no cointegration among the time series of the study variables remains plausible.

2.2.2.2. Examining the Cointegration Relationship Among the Study Variables:

Based on the previous analysis, it was established that all the study variables are integrated of the first order, which necessitates moving to the next step—verifying the existence of cointegration among these variables. In other words, the aim is to test whether a long-run equilibrium relationship exists between the Human Development Index and the independent variables included in the model.

Among the most widely used tests for this purpose is the Kao (1999) test, which relies on the Augmented Dickey–Fuller (ADF) statistic. This test supports the null hypothesis of no cointegration, against the alternative hypothesis that cointegration exists. Additionally, the Pedroni cointegration test is considered one of the important tools in this context. It provides a set of statistics designed to examine cointegration within panel data models. The test accounts for heterogeneity across variables and allows individual time trends for cross-sectional units. The null hypothesis in the Pedroni test states that no cointegration exists, while the alternative hypothesis indicates the presence of cointegration (Dimitrios & Stephen G., 2007, pp. 371-373). The following table presents the results of these tests.

Table 03: Results of Pedroni and Kao Cointegration Tests

Test Statistic		p-value	Calculated t-value
Type of Test			
Pedroni	Modified Phillips-Perron t	0.0000	4.8988
	Phillips-Perron t	0.0051	-2.5701
	Augmented Dickey-Fuller t	0.0111	-2.2864
Kao	Modified Dickey-Fuller t	0.0115	- 2.2729
	Dickey-Fuller t	0.0193	- 2.0688
	Augmented Dickey-Fuller t	0.0114	-2.2777
	Unadjusted modified Dickey-Fuller t	0.0038	- 2.6661
	Unadjusted Dickey-Fuller t	0.0122	-2.2518

Source: Prepared by the researchers using the outputs from Stata 16, as shown in Appendix 3.

It is evident from the previous table that the results of all Pedroni and Kao tests confirm the rejection of the null hypothesis, which states the absence of cointegration. This is because all the p-values for these tests were below 5%. Based on this, it can be concluded that there exists a long-term cointegration relationship between the Human Development Index and the science and technology indicators in the sample of developed countries analyzed. Building on these results, which demonstrated the presence of a long-term cointegration relationship between the Human Development Index and the science and technology indicators, this relationship can be estimated using the Dynamic Ordinary Least Squares (DOLS) panel method.

2.2.2.3. Estimation Using the Panel Dynamic Ordinary Least Squares (PDOLS):

This method is considered one of the approaches used to measure long-term equilibrium relationships in models that include cointegrated variables. It is also regarded as one of the most advanced methods due to its high efficiency and effectiveness in handling small samples, providing accurate and reliable results even when the dataset is limited in size (Pedroni 2001). In light of the existence of a cointegration relationship among the study variables, this stage involves estimating the long-term relationship using the Panel Dynamic Ordinary Least Squares (PDOLS) method. Table 4 presents the results of this estimation, illustrating the nature and strength of the long-term relationship between the variables.

Table 04: Model Estimation Results Using the PDOLS Method

Independent Variables	T-Statistic	p-value	Parameters
$LSrd_{it}$	6.530914	*** (0.0000)	0.051360
$LRwd_{it}$	-1.168277	(0.2434)	-0.004510
$Llprufpa_{it}$	-3.914598	*** (0.0001)	-0.013919
$Llprufpr_{it}$	3.529320	*** (0.0005)	0.011097
$LPr afr_{it}$	4.192301	*** (0.0000)	0.005684
$LPr afr_{it}$	-5.988961	*** (0.0000)	-0.016444
$LAstj_{it}$	1.914974	* (0.0562)	0.006896

Source: Prepared by the researchers using the outputs from EViews 13, as shown in Appendix 4. (): significant at 10%, (): significant at 5%, (): significant at 1%

2.2.2.4. Analysis of the Results for the Model Estimated Using PDOLS:

The model estimated using PDOLS can be formulated based on the values presented in Table 4 as follows:

$$Lgdppc_{it} = 0.051LSrd_{1it} - 0.004LRwd_{2it} - 0.013Llprufpa_{3it} + 0.011Llprufpr_{4it} + 0.005LPr afr_{5it} - 0.016LPr afr_{6it} + 0.006LAstj_{7it}.....(03)$$

The results of the Student t-tests for the estimated model coefficients presented in Table 08 indicate that all science and technology indicators are statistically significant at the 5% level, except for the logarithm of the number of researchers working in R&D, which was not statistically significant at the same level.

The long-term PDOLS estimation results show that, in general, science and technology variables have a positive impact on the Human Development Index (HDI). However, the magnitude of this effect varies depending on the type of science and technology indicator used. Accordingly, it can be observed that: a 1% increase in the logarithm of R&D expenditure leads to a 0.051% increase in the logarithm of HDI, consistent with standard studies. The coefficient of this indicator is the largest in the model, highlighting the critical role of R&D expenditure in enhancing human development in developed countries.

Similarly, a 1% increase in the logarithm of royalties and license fees for receipts leads to a 0.011% increase in the logarithm of HDI growth, in line with economic theory, demonstrating the importance of these fees in supporting human development in developed countries. On the other hand, a 1% increase in the logarithm of patent applications filed by non-residents leads to a 0.005% increase in the logarithm of HDI growth, consistent with

empirical studies, as this indicator provides developed countries with competitive advantages that help strengthen their position in global markets.

Furthermore, a 1% increase in the logarithm of scientific and technical journal articles results in a 0.005% rise in the logarithm of HDI growth, reflecting the pivotal role of these publications in disseminating knowledge and research innovations that drive progress across various fields. Conversely, a 1% increase in both the logarithm of royalties and license fees for payments and the logarithm of patent applications by residents leads to a decrease in the logarithm of HDI growth by 0.013% and 0.016%, respectively.

3. Conclusion

Science and technology represent a strategic path and an economic imperative for developed countries in light of rapid global developments. Within this framework, a study was conducted to measure the impact of science and technology indicators on human development in a sample of developed countries during the period 2000–2023, using the Panel Dynamic Ordinary Least Squares (PDOLS) method. The study revealed the existence of a long-term cointegration relationship between the Human Development Index and the science and technology indicators, supporting the validity of the first research hypothesis.

Regarding the dynamic analysis, the study also concluded that the PDOLS method is the most appropriate, clearly showing that a 1% increase in the logarithm of R&D expenditure, royalties and license fees for receipts, patent applications by non-residents, and scientific and technical journal articles leads to increases in the logarithm of HDI growth by 0.051%, 0.011%, 0.005%, and 0.005%, respectively. Conversely, a 1% increase in the logarithm of royalties and license fees for payments and patent applications by residents leads to decreases in the logarithm of HDI growth by 0.013% and 0.016%, respectively. These results confirm the validity of the second research hypothesis.

4. Recommendations:

Developed countries should adopt targeted policies to encourage both domestic and foreign patent ownership, support researchers working in R&D, and increase R&D expenditure. Developing countries, on the other hand, should focus on investing in science and technology, as these are the primary means to achieve prosperity and catch up with the ranks of developed nations.

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Appendices

Appendix (1): Unit Root Tests for the Model Variables at Level

Panel unit root test: Summary
Series: LSRD
Date: 02/06/25 Time: 16:52
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.80270	0.2111	17	374
Breitung t-stat	-0.24281	0.4041	17	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.90640	0.0283	17	374
ADF - Fisher Chi-square	46.0143	0.0819	17	374
PP - Fisher Chi-square	51.5260	0.0275	17	391

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LIPRUFPA
Date: 02/06/25 Time: 17:10
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.75551	0.0001	17	374
Breitung t-stat	0.44730	0.6727	17	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.65558	0.0489	17	374
ADF - Fisher Chi-square	51.1136	0.0300	17	374
PP - Fisher Chi-square	39.0178	0.2543	17	391

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LRWRD
Date: 02/06/25 Time: 16:59
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.61992	0.0526	17	374
Breitung t-stat	-0.69277	0.2442	17	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.99824	0.1591	17	374
ADF - Fisher Chi-square	39.7162	0.2304	17	374
PP - Fisher Chi-square	28.9936	0.7115	17	391

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LIPRUFPR
Date: 02/06/25 Time: 17:16
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.50789	0.0002	17	374
Breitung t-stat	-0.94416	0.1725	17	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.72132	0.0426	17	374
ADF - Fisher Chi-square	55.4079	0.0116	17	374
PP - Fisher Chi-square	37.4190	0.3150	17	391

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LPRAFNR
Date: 02/06/25 Time: 17:33
Sample: 2000 2023
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.53959	0.0055	17	374
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.18808	0.5746	17	374
ADF - Fisher Chi-square	32.5276	0.5398	17	374
PP - Fisher Chi-square	44.9137	0.0998	17	391

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LASTJ
Date: 02/06/25 Time: 20:51
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.72051	0.7644	17	374
Breitung t-stat	5.15138	1.0000	17	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	3.76370	0.9999	17	374
ADF - Fisher Chi-square	13.5876	0.9993	17	374
PP - Fisher Chi-square	3.22906	1.0000	17	391

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LPRAFR
Date: 02/06/25 Time: 17:44
Sample: 2000 2023
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.26490	0.1030	17	374
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.39126	0.9179	17	374
ADF - Fisher Chi-square	24.6105	0.8813	17	374
PP - Fisher Chi-square	40.2097	0.2144	17	391

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LHDI
Date: 02/06/25 Time: 20:57
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.19513	0.1160	17	374
Breitung t-stat	0.39260	0.6527	17	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.62493	0.7340	17	374
ADF - Fisher Chi-square	30.8701	0.6218	17	374
PP - Fisher Chi-square	50.0556	0.0373	17	391

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Source: Outputs of the EViews 13 software

Appendix (2): Unit Root Tests for the Model Variables at the First Difference

Panel unit root test: Summary
Series: D(LSRD)
Date: 02/06/25 Time: 16:53
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.46892	0.0068	17	357
Breitung t-stat	-6.37808	0.0000	17	340
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.59776	0.0000	17	357
ADF - Fisher Chi-square	78.5258	0.0000	17	357
PP - Fisher Chi-square	325.857	0.0000	17	374

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LIPRUFPA)
Date: 02/06/25 Time: 17:11
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.10762	0.0000	17	357
Breitung t-stat	-5.31302	0.0000	17	340
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.24132	0.0000	17	357
ADF - Fisher Chi-square	128.283	0.0000	17	357
PP - Fisher Chi-square	402.644	0.0000	17	374

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LRWDR)
Date: 02/06/25 Time: 17:01
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.76345	0.0000	17	357
Breitung t-stat	-7.78528	0.0000	17	340
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.40679	0.0000	17	357
ADF - Fisher Chi-square	89.8444	0.0000	17	357
PP - Fisher Chi-square	234.459	0.0000	17	374

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LIPRUFPR)
Date: 02/06/25 Time: 17:17
Sample: 2000 2023
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.66094	0.0000	17	357
Breitung t-stat	-5.38583	0.0000	17	340
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.91662	0.0000	17	357
ADF - Fisher Chi-square	150.492	0.0000	17	357
PP - Fisher Chi-square	467.856	0.0000	17	374

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary

Series: D(LPRAFNR)

Date: 02/06/25 Time: 17:34

Sample: 2000 2023

Exogenous variables: Individual effects

User-specified lags: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.77072	0.0000	17	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.52213	0.0000	17	357
ADF - Fisher Chi-square	105.510	0.0000	17	357
PP - Fisher Chi-square	224.605	0.0000	17	374

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary

Series: D(LASTJ)

Date: 02/06/25 Time: 20:52

Sample: 2000 2023

Exogenous variables: Individual effects, individual linear trends

User-specified lags: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.43297	0.3325	17	357
Breitung t-stat	-0.27828	0.3904	17	340
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.45518	0.0000	17	357
ADF - Fisher Chi-square	73.4942	0.0001	17	357
PP - Fisher Chi-square	167.714	0.0000	17	374

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary

Series: D(LPRAFR)

Date: 02/06/25 Time: 17:45

Sample: 2000 2023

Exogenous variables: Individual effects

User-specified lags: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.44468	0.0000	17	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.66484	0.0000	17	357
ADF - Fisher Chi-square	123.175	0.0000	17	357
PP - Fisher Chi-square	272.229	0.0000	17	374

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary

Series: D(LHDI)

Date: 02/06/25 Time: 20:59

Sample: 2000 2023

Exogenous variables: Individual effects, individual linear trends

User-specified lags: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.16269	0.0000	17	357
Breitung t-stat	-4.15712	0.0000	17	340
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.77732	0.0000	17	357
ADF - Fisher Chi-square	105.123	0.0000	17	357
PP - Fisher Chi-square	207.298	0.0000	17	374

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Source: Outputs of the EViews 13 software

Appendix (3): KAO & Pedroni Cointegration Test

. xtointtest kao Lhdi LSrd LRwd LIprufpa LIprufpr LPrafnr LPrafr LASTj				. xtointtest pedroni Lhdi LSrd LRwd LIprufpa LIprufpr LPrafnr LPrafr LASTj			
Kao test for cointegration				Pedroni test for cointegration			
H0: No cointegration	Number of panels	=	17	H0: No cointegration	Number of panels	=	17
Ha: All panels are cointegrated	Number of periods	=	22	Ha: All panels are cointegrated	Number of periods	=	23
Cointegrating vector: Same				Cointegrating vector: Panel specific			
Panel means: Included	Kernel:	Bartlett		Panel means: Included	Kernel:	Bartlett	
Time trend: Not included	Lags:	1.12 (Newey-West)		Time trend: Not included	Lags:	2.00 (Newey-West)	
AR parameter: Same	Augmented lags:	1		AR parameter: Panel specific	Augmented lags:	1	
	Statistic	p-value			Statistic	p-value	
Modified Dickey-Fuller t	-2.2729	0.0115		Modified Phillips-Perron t	4.8988	0.0000	
Dickey-Fuller t	-2.0688	0.0193		Phillips-Perron t	-2.5701	0.0051	
Augmented Dickey-Fuller t	-2.2777	0.0114		Augmented Dickey-Fuller t	-2.2864	0.0111	
Unadjusted modified Dickey-Fuller t	-2.6661	0.0038					
Unadjusted Dickey-Fuller t	-2.2518	0.0122					

Source: Outputs of the Stata 16 software

Appendix (4): PDOLS Estimation Results

Dependent Variable: LHDI
 Method: Panel Dynamic Least Squares (DOLS)
 Date: 02/06/25 Time: 21:29
 Sample: 2000 2023
 Periods included: 24
 Cross-sections included: 17
 Total panel (balanced) observations: 408
 Panel method: Pooled estimation
 Static OLS leads and lags specification
 Coefficient covariance computed using default method
 Long-run variance (Bartlett kernel, Newey-West fixed bandwidth) used for coefficient covariances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LSRD	0.051360	0.007864	6.530914	0.0000
LRWRD	-0.004510	0.003860	-1.168277	0.2434
LIPRUFPF	-0.013919	0.003556	-3.914598	0.0001
LIPRUFPF	0.011097	0.003144	3.529320	0.0005
LPRAFNR	0.005684	0.001356	4.192301	0.0000
LPRAFNR	-0.016444	0.002746	-5.988961	0.0000
LASTJ	0.006896	0.003601	1.914974	0.0562
R-squared	0.478561	Mean dependent var	-0.098537	
Adjusted R-squared	0.470759	S.D. dependent var	0.035605	
S.E. of regression	0.025902	Sum squared resid	0.269038	
Long-run variance	0.001772			

Source: Outputs of the EViews 13 software