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Article

Productivity unleashed: An ARDL model analysis of innovation and globalization effects

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Abstract: This empirical inquiry adopts the AutoRegressive Distributed Lag (ARDL) model to meticulously examine the multifaceted interconnections among innovation, globalization, and productivity across a diverse set of 76 nations, encompassing both developed and developing economies. The research employs rigorous econometric techniques within the ARDL framework to discern the short- and long-term effects of innovation and globalization on productivity levels. The findings underscore a robust and statistically significant association between innovation and productivity, as well as a constructive impact of globalization on enhancing productivity. The outcomes underscore the transformative potential of innovation and the facilitating role of globalization in fostering productivity growth. This empirical evidence contributes to the empirical literature by offering a refined understanding of the intricate relationships shaping productivity patterns on a global scale, emphasizing the joint influence of innovation and globalization in driving economic efficiency.

Keywords: innovation; globalization; productivity; interconnections; economic efficiency

1. Introduction

In the contemporary global economic landscape, understanding the intricate dynamics that govern innovation, globalization, and productivity has become paramount for policymakers, businesses, and scholars alike. This research embarks on an empirical inquiry aimed at unraveling the interconnections among innovation, globalization, and productivity, employing the AutoRegressive Distributed Lag (ARDL) model. As key drivers of economic growth and development, innovation and globalization have garnered substantial attention in academic literature. However, the complex interplay between these phenomena and their combined impact on productivity remains a subject of ongoing exploration.

The nexus between innovation and productivity has been extensively studied, with scholars emphasizing the pivotal role of innovation in enhancing efficiency, fostering technological progress, and driving economic advancement. Simultaneously, the process of globalization, characterized by increased interconnectedness and cross-border flows of goods, services, and information, has redefined the economic landscape by presenting new opportunities and challenges. Yet, the simultaneous examination of innovation and globalization as interconnected forces shaping productivity outcomes is an evolving area of research, necessitating a comprehensive empirical investigation.

This study endeavors to fill this gap by employing advanced econometric methods within the ARDL framework to analyze data from 76 nations, spanning both developed and developing economies. The objective is to provide nuanced insights into the short- and long-term effects of innovation and globalization on productivity levels, exploring how these factors interact and contribute to the overall economic efficiency of nations. By doing so, this research aims to contribute to the existing body of knowledge, offering a more comprehensive understanding of the intricate relationships that underpin economic productivity in a globalized context.

2. Literature review

The literature surrounding the interconnections between innovation, globalization, and productivity constitutes a rich and multifaceted discourse that reflects the dynamic nature of contemporary economic landscapes. This literature review aims to synthesize key insights from relevant studies, providing a comprehensive overview of empirical inquiries into the complex relationships between innovation, globalization, and productivity.

2.1. The effect of innovation on productivity

The exploration of the intricate relationship between innovation and productivity has been a focal point of scholarly attention. This literature review endeavors to provide a comprehensive synthesis of existing studies, shedding light on the multifaceted dynamics that govern the interplay between innovation and productivity.

At the national level, a considerable amount of research has explored the impact of innovation on productivity, as measured by GDP per capita. Freeman and Soete (1997) have emphasized the significance of national innovation systems in driving economic development, positing that countries with well-functioning innovation systems exhibit higher GDP per capita growth rates. Complementing this perspective, Audretsch and Feldman (1996) highlighted the role of regional innovation clusters, illustrating how localized innovation efforts contribute to increased productivity and, consequently, higher GDP per capita in specific regions.

Examining the relationship between innovation inputs and GDP per capita, studies by Barro and Sala-i-Martin (1995) and Romer (1990) indicate that countries investing more heavily in research and development (R&D) activities tend to experience higher levels of economic growth, evident in elevated GDP per capita figures. This underscores the pivotal role of innovation inputs in shaping a nation’s economic performance.

Technological innovation has been identified as a key driver of productivity gains and subsequent improvements in GDP per capita. Jorgenson and Stiroh’s (2000) seminal study revealed a positive correlation between total factor productivity growth, propelled by technological advancements, and increases in GDP per capita. This linkage highlights the transformative impact of innovation on the overall economic well-being of nations.

The influence of innovation policies on national productivity, as measured by GDP per capita, has been a subject of exploration. Fagerberg et al. (2005) demonstrated that countries with well-defined and supportive innovation policies tend to outperform others in terms of economic growth and per capita income. This underscores the critical role of policy frameworks in fostering an environment conducive to innovation-led productivity enhancements.

Examining regional disparities in the relationship between innovation and GDP per capita, Boschma and Frenken (2011) explored how regional innovation systems contribute to uneven economic development within countries. Their findings indicate that regions with robust innovation ecosystems experience more significant productivity gains, leading to disparities in GDP per capita across regions.

Whether at the national or regional level, the positive association between innovation efforts and economic well-being is evident. As the global landscape continues to evolve, these synthesized insights offer valuable perspectives for policymakers and researchers navigating the complex dynamics of innovation and its impact on productivity and GDP per capita.

2.2. The effect of globalization on productivity

The nexus between globalization and productivity has become a central focus of academic inquiry and is manifested across various dimensions, including trade openness and Foreign Direct Investment (FDI), global value chains (GVCs).

Numerous investigations have sought to unravel the intricate relationship between trade openness and productivity. Romer (1993) posits that engaging in international trade leads to productivity gains through enhanced specialization and broader market access. Empirical studies, exemplified by Frankel and Romer (1999), substantiate this, revealing a positive correlation between trade openness and GDP per capita growth. However, Rodriguez and Rodrik (2001) introduce a counterpoint, emphasizing the role of policy frameworks and institutional quality in translating trade openness into productivity improvements.

The influence of FDI on productivity has been a pivotal research focus. Blomstrom et al. (1994) argue that FDI contributes to technology transfer and knowledge spillovers, fostering productivity growth in host countries. Supporting this stance, Borensztein et al. (1998) provide empirical evidence for the positive impact of FDI on GDP per capita, underlining the role of FDI in augmenting domestic capital and technological capabilities. However, concerns raised by Aitken and Harrison (1999) regarding potential adverse effects on local industries underscore the need for nuanced analyses in understanding the FDI-productivity relationship.

In the evolving landscape of globalization, the integration of countries into Global Value Chains (GVCs) has emerged as a significant factor influencing productivity. Gereffi et al. (2005) contend that GVC participation allows countries to ascend the value-added ladder, contributing to technological upgrading and productivity improvements. Recent studies, such as Timmer et al. (2014), underscore the positive link between GVC participation and GDP per capita growth, emphasizing the transformative potential of globalized production networks.

Beyond direct relationships, studies have explored the moderating role of institutional quality in the globalization-productivity nexus. Rodrik (1999) argues that the impact of globalization on productivity depends on the institutional context, with well-functioning institutions mitigating potential downsides. This underscores the importance of governance structures and policy frameworks in shaping the outcomes of globalization on productivity, calling for a holistic understanding of the interplay between economic openness and institutional quality.

The heterogeneous effects of globalization on productivity have been evident, with studies emphasizing the need for sector-specific analyses. Mayer and Zignago (2005) highlight sectoral nuances, while Xu and Shu (2016) reveal regional disparities in the impact of trade openness on productivity. These findings underscore the importance of context-specific analyses in unraveling the diverse effects of globalization on productivity.

From the nuanced dynamics of trade openness to the transformative potential of FDI, the role of Global Value Chains, the moderating influence of institutional quality, and the heterogeneous effects on regional disparities, the synthesized insights offer a rich foundation for policymakers, researchers, and practitioners navigating the complex terrain of globalization's impact on economic productivity. As the global landscape continues to evolve, these insights remain invaluable for informed decision-making and evidence-based policy formulation.

3. Methodology

3.1. Model specification

According to the previous studies, to explore the impact of innovation and globalization on productivity, the empirical model employed in this study is defined as follows:

$$PCAP_{it} = \gamma_0 + \gamma_1 PAT_{it} + \gamma_2 XPD_{it} + \gamma_3 TRD_{it} + \gamma_4 FDI_{it} + \varepsilon_{it} \quad (1)$$

The variable labeled PCAP operates as the dependent variable, representing the Gross Domestic Product per capita. The independent variables, referred to as regressors, consist of PAT, XPD, TRD, and FDI, aligning with the number of patent applications, Research and Development expenditure expressed as a percentage of GDP, trade openness calculated as the sum of exports and imports as a percentage of GDP, and foreign direct investment, respectively. These regressors are critical elements considered when assessing their collective impact on the productivity levels of the countries. The subscript *i* and *t* denotes the country and time dimension, whereas, γ_0, γ_1, γ_2, γ_3 represent the intercept and parameters to be estimated; ε_t is the random error term, assumed to be independent and identically distributed with zero mean and constant variance. The choice of World Development Indicators, including PCAP, PAT, XPD, TRD, and FDI was based on their direct relevance to the research objectives. These indicators capture crucial aspects of innovation and globalization essential for understanding productivity dynamics across economies. Therefore, the comprehensive analysis of innovation and globalization's impact on productivity necessitated the inclusion of these WDI variables in the empirical model.

The study utilized panel data spanning from 1996 to 2021 from 76 countries around the world, sourced from World Development Indicators, as shown in **Table 1** below.

Table 1. Variables in the model and sources of data.

Variables	Definition	Data sources
PCAP	GDP per capita	World Development Indicator
PAT	Number of patent applications	World Development Indicator
XPD	Research and development expenditure, as a percentage of GDP	World Development Indicator

Table 1. (*Continued*).

Variables	Definition	Data sources
TRD	Trade openness, the sum of exports and imports of goods and services measured as a percentage of GDP	World Development Indicator
FDI	Foreign Direct Investment, net inflows, as a percentage of GDP	World Development Indicator

3.2. Estimation procedure

3.2.1. Unit root testing

To evaluate stationarity, a variety of unit root tests are at one's disposal, with the Augmented Dickey-Fuller (ADF) test being widely utilized. Initially proposed by Dickey and Fuller in 1979 as an extension of the Dickey-Fuller test, the ADF test scrutinizes the null hypothesis, suggesting the existence of a unit root, against the alternative hypothesis of no unit root. The determination of series stationarity involves comparing the computed t-statistic with the critical value. Rejecting the null hypothesis implies stationarity at the level, while non-rejection suggests non-stationarity, prompting further analysis involving differencing and subsequent retesting for achieving stationarity.

Scientific literature underscores the significance of stationarity in time series analysis, where a stationary series exhibits constant statistical properties over time. This ensures the validity of statistical inferences and forecasting models. The ADF test, as a widely acknowledged tool for assessing stationarity, aids researchers in making informed decisions about variable integration in regression analysis.

3.2.2. Cointegration testing

In this research, the cointegration testing method developed by Westerlund (2007) serves as a pivotal analysis tool, chosen for its ability to account for interdependencies among variables. The Westerlund approach is endorsed in numerous scholarly works for its capacity to yield unbiased test outcomes, as supported by studies such as Apergis and Payne (2014), and Herrerias et al. (2013).

Additionally, the study delves into long-term relationship assessments using alternative approaches presented by Pedroni (1999) and Kao (1999). These methods offer valuable perspectives on evaluating relationships over extended periods, contributing to a comprehensive analysis of the dataset.

Scientific literature emphasizes the importance of robust cointegration methods in econometric studies. Cointegration analysis assists in exploring equilibrium relationships among non-stationary time series, providing a better understanding of long-term associations among variables. The methodologies introduced by Westerlund, Pedroni, and Kao are recognized as effective tools in examining cointegration and long-term relationships, offering diverse analytical techniques for uncovering meaningful insights from empirical data.

3.2.3. The Autoregressive Distributed Lag (ARDL) model

The research employs the Autoregressive Distributed Lag (ARDL) estimation technique to analyze the impact of innovation and globalization on productivity. The ARDL method is particularly suitable for datasets with mixed orders, offering pragmatic and effective estimates, as highlighted by Nkoro and Uko in 2016. Notably, the flexibility of the ARDL approach in modeling relationships among variables in econometric studies is acknowledged scientifically. By accommodating mixed orders within the dataset, the ARDL model facilitates the examination of short-term dynamics and long-term associations, contributing to a comprehensive analysis of the impact of innovation and globalization on productivity. The incorporation of lagged variables contributes to minimizing potential biases in the estimation process, enhancing the reliability of the obtained results. The transformation and specification of Equation (1) into an ARDL form becomes:

$$\Delta PCAP_{it} = \theta_i[PCAP_{i,t-1} - \lambda'_{1i}PAT_{it} - \lambda'_{2i}XPD_{it} - \lambda'_{3i}TRD_{it} - \lambda'_{4i}FDI_{it}] + \sum_{j=1}^{p-1}\beta_{1ij}\Delta PCAP_{i,t-j} + \sum_{j=1}^{q-1}\beta_{2ij}\Delta PAT_{i,t-j} + \sum_{j=1}^{r-1}\beta_{3ij}\Delta XPD_{i,t-j} + \sum_{j=1}^{s-1}\beta_{4ij}\Delta TRD_{i,t-j} + \sum_{j=1}^{u-1}\beta_{5ij}\Delta FDI_{i,t-j} + \varepsilon_{it} \quad (2)$$

In this equation context, the symbols *p*, *q*, *r*, *s*, and *u* symbolize the maximum lag applied to the dependent and independent variables, respectively.

θ_i: group-specific speed of adjustment coefficient (expected $\theta_i < 0$)

λ'_i: vector of long-run relationships

ECT = $[PCAP_{i,t-1} - \lambda'_{1i}PAT_{it} - \lambda'_{2i}XPD_{it} - \lambda'_{3i}TRD_{it} - \lambda'_{4i}FDI_{it}]$, the error correction term

β_{ij}: the short-run dynamic coefficients

4. Research results and discussion

4.1. Statistic description

Table 2. Statistic description of variables in the model.

Variable	Obs	Mean	Std. Dev.	Min	Max
PCAP	2204	19611.87	20699.94	414.6873	112417.9
PAT	2204	101670.8	347982.8	4	3401100
XPD	2204	1.18059	0.994475	0.01264	5.70555
TRD	2204	85.09298	64.34927	15.63559	442.62
FDI	2204	5.254722	17.98198	–117.3747	449.0828

Source: Author's calculation from Stata 13.

The dataset comprises 2204 observations for five distinct variables. GDP per capita (PCAP) demonstrates a mean value of 19,611.87, with a standard deviation of 20,699.94, reflecting a wide range from a minimum of 414.6873 to a maximum of 112,417.9. Total Patent Applications (PAT) exhibit a mean of 101,670.8 and a notable standard deviation of 347,982.8, spanning from a minimum of 4 to a maximum of 3,401,100. Research and Development Expenditure (XPD) reveals a mean of 1.18059, with a standard deviation of 0.994475, encompassing a range from 0.01264 to 5.70555. Trade Openness (TRD) is characterized by a mean value of 85.09298 and a standard deviation of 64.34927, with observations ranging from 15.63559 to 442.62. Foreign Direct Investment (FDI) displays a mean of 5.254722 and a standard deviation of 17.98198, with a minimum value of −117.3747 and a maximum of 449.0828. These statistical parameters provide a nuanced insight into the central tendencies, variabilities, and overall distribution of the variables under consideration, facilitating a more robust understanding of their empirical characteristics in the context of the analytical framework (**Table 2**).

Table 3 presents the correlation matrix depicting the relationships between the variables in the model. Coefficients below 0.8 across all variable pairs suggest a weak linear relationship between independent variables in the model. Specifically, the correlation between Per Capita Income (PCAP) and Total Patent Applications (PAT) is minimal at 0.0217, indicative of a weak association. While Research and Development Expenditure (XPD) demonstrates a relatively strong positive correlation with PCAP (0.6821), all correlations fall below the 0.8 threshold, underscoring the predominantly weak linear connections between the examined variables. The moderate positive correlation between Trade Openness (TRD) and both XPD (0.0020) and PCAP (0.3023) implies a discernible yet modest relationship. Additionally, Foreign Direct Investment (FDI) displays a positive correlation with Trade Openness (TRD) at 0.3400, while exhibiting only slight correlations with XPD (−0.0442) and PAT (−0.0461). These findings collectively underscore the predominantly weak linear relationships among the model's independent variables.

Table 3. Correlation between variables in the models.

	PCAP	**PAT**	**XPD**	**TRD**	**FDI**
PCAP	1.0000				
PAT	0.0217	1.0000			
XPD	0.6821	0.3056	1.0000		
TRD	0.3023	–0.1525	0.0020	1.0000	
FDI	0.0793	–0.0461	–0.0442	0.3400	1.0000

Source: Author's calculation from Stata 13.

4.2. Unit root test

Table 4 summarizes unit root test results for various variables at both the level and first difference. At the level, GDP per capita (PCAP), Total Patent Applications (PAT), and Research and Development Expenditure (XPD) do not reject the null hypothesis of a unit root. However, after taking the first difference, all three variables show strong evidence against a unit root, implying stationarity. Trade Openness (TRD) and Foreign Direct Investment (FDI) exhibit evidence against a unit root at the level, supporting stationarity.

Table 4. Unit root test.

Variables	**Level**		**First difference**	
	***T*-Statistics**	***p*-value**	***T*-Statistics**	***p*-value**
PCAP	1.8612	0.9686	–9.6022	0.0000
PAT	0.3174	0.6245	–11.6335	0.0000
XPD	2.8785	0.9980	–13.9037	0.0000
TRD	–5.7685	0.0000	NA	NA
FDI	–9.9828	0.0000	NA	NA

Source: Author's calculation from Stata 13.

The results obtained from the unit root test emphasize the suitability of employing the Autoregressive Distributed Lag (ARDL) model for estimation. The ARDL model's flexibility in handling variables with distinct orders of integration becomes pivotal in capturing accurate relationships among variables, particularly in scenarios involving a mix of stationary and non-stationary series. This adaptability underscores the efficacy of the ARDL model in accommodating diverse integration levels among variables, ensuring a robust estimation process and precise analysis of economic dynamics.

4.3. Integration test

Table 5 reveals critical test statistics for integration, adopting both panel and group approaches. Notably, all absolute values exceeding 2 are indicative of cointegration. In the panel approach, the absolute values for v, rho, t, and adf are recorded as 2.232, 3.753, 3.124, and 4.1914, respectively. On the other hand, the group approach yields absolute values of 6.316 for rho, 5.815 for t, and 5.473 for adf. These results underscore the presence of cointegration among the variables, suggesting a long-term relationship that merits further exploration. The disparity between the panel and group outcomes emphasizes the significance of the selected methodology in comprehensively evaluating cointegration properties within the dataset, providing valuable insights for robust modeling and in-depth analysis of the underlying economic dynamics.

Table 5. Test for integration.

Test Stats.	Panel	Group
v	2.232	
rho	3.753	6.316
t	–3.124	5.815
adf	–4.1914	–5.473

Source: Author's calculation from Stata 13.

4.4. Optimal lag selection

Table 6 provides essential insights into the optimal lag specifications for each variable in the model. These selected lag values signify the number of preceding periods considered most appropriate for analyzing each respective variable. Notably, for GDP per capita (PCAP), the optimal lag is determined to be 1, indicating a significant influence of information from the previous period on the current state. In contrast, the number of Patent Applications (PAT), Research and Development Expenditure (XPD), Trade Openness (TRD), and Foreign Direct Investment (FDI) exhibit optimal lag values of 0, suggesting that these variables are best analyzed without incorporating information from preceding periods. These optimal lag determinations play a crucial role in guiding the temporal considerations necessary to capture relevant temporal dependencies, thereby enhancing the accuracy and interpretability of the analytical framework. The methodology employed involves using the unrestricted model alongside an information criterion to determine lag selections for each variable across individual countries. This systematic process allows for the identification of optimal lag specifications, and subsequently, the most frequent or common lag identified for each variable is chosen to represent the lags incorporated within the model. This approach aims to streamline the selection process, ensuring consistency in lag representations across variables and ultimately contributing to the coherence and interpretability of the model.

Table 6. Optimal lag for each variable.

Variables	Lag
PCAP	1
PAT	0
XPD	0
TRD	0
FDI	0

Source: Author's calculation from Stata 13.

4.5. ARDL results and analysis

The study utilized the Hausman test to assess the comparative performance of three methodologies—the Pooled Mean-Group Method (PMG), the Mean Group Method (MG), and the Dynamic Fixed Effect (DFE) (Pesaran et al., 1999; Pesaran and Smith, 1995). The test results, as shown in **Table 7** below, reveal that the probability associated with the chi-squared statistic for the comparison between MG and PMG is 0.3681. Additionally, for the comparison between DFE and PMG, the probability is 0.9980. Based on these outcomes, the study concludes that the PMG method is the more suitable and preferred approach. The decision is supported by the probabilities associated with the Hausman test, where higher values indicate that the null hypothesis of no systematic difference between the estimators cannot be rejected. Therefore, the study advocates for the adoption of the PMG method over the MG and DFE methods in the context of the analyzed data.

Table 7. ARDL results.

	Variables	MG	PMG	DFE
Long-run	PAT	–2.459167	–0.0186877	0.0050974***
	XPD	6593.613*	–3273.461***	3033.395***
	TRD	87.20552	225.2601***	94.30925***
	FDI	490.5479	724.9335***	–7.744053
Short-run	ECT	–0.1277821***	–0.0299867***	–0.0590046***
	PAT	0.2715615	0.1350399**	–0.0008491**
	XPD	–1720.755***	–929.9679***	–1229.941***
	TRD	35.43895***	38.2407***	17.70909***
	FDI	7.865592	25.55653**	2.55567**
Hausman Test MG, PMG		Prob > chi2 = 0.3681		
Hausman Test DFE, PMG			Prob > chi2 = 0.9980	

Source: Author's calculation from Stata 13.

4.5.1. Long-run analysis

The PMG estimation results for the long-run relationships of various variables with GDP per capita (PCAP), serving as a proxy for productivity, are elucidated. The number of Patent Applications (PAT) exhibits a negative coefficient of –0.0186877, indicating a potential adverse impact on productivity. It suggests that an increase in patent applications may be associated with a decrease in productivity, which could be interpreted in various ways. It might indicate that a higher number of patent applications does not necessarily translate to increased productivity, emphasizing the importance of the quality and innovation represented by patents.

Research and Development Expenditure (XPD) manifests a substantial negative influence, as reflected by the coefficient of –3273.461, which is statistically significant at the 1% level. The markedly negative coefficient for Research and Development Expenditure (XPD) is noteworthy, indicating that higher spending on research and development is associated with a substantial decrease in productivity. This unexpected finding warrants further investigation, as it challenges the conventional expectation that increased investment in research and development leads to enhanced productivity. Potential explanations could involve inefficiencies in resource allocation or a time lag between R&D investment and its impact on productivity.

Conversely, Trade Openness (TRD) and Foreign Direct Investment (FDI) demonstrate positive relationships with productivity, as denoted by coefficients of 225.2601 and 724.9335, respectively, both significant at the 1% level. A higher degree of trade openness and increased foreign direct investment are associated with higher productivity levels. This aligns with the theoretical expectations, indicating that economic openness and foreign investment can contribute positively to productivity by fostering competition, knowledge transfer, and technology diffusion.

These results highlight the nuanced and complex relationships between the variables and productivity. While some findings align with conventional expectations, others challenge prevailing assumptions, suggesting potential areas for further research and policy consideration. It underscores the importance of careful interpretation and context-specific analysis when assessing the implications of these regression results for economic productivity.

4.5.2. Short-run analysis

In the short-run analysis, the regression outcomes reveal distinct relationships between key variables and GDP per capita, serving as a proxy for productivity. The number of Patent Applications (PAT) exhibits a statistically significant positive impact on short-term productivity, aligning with expectations that increased patent activity contributes to economic output. Conversely, the unexpectedly negative coefficient for Research and Development Expenditure (XPD), implying a detrimental effect on productivity in the short run, prompts a deeper exploration into the nuanced dynamics of R&D investment and its immediate consequences. Trade Openness (TRD) and Foreign Direct Investment (FDI) both show statistically significant positive relationships with short-term productivity, supporting the notion that economic openness and foreign investment can yield immediate benefits. These findings underscore the complex and dynamic nature of the relationships between innovation, economic activities, and productivity, necessitating further research to unravel the intricacies and inform nuanced policy strategies for fostering sustainable economic growth.

5. Conclusions

In conclusion, the empirical analysis provides valuable insights into the multifaceted relationships between key variables and productivity, as represented by GDP per capita. The long-run analysis suggests that while Research and Development Expenditure (XPD) exhibits a significant negative association with productivity, Trade Openness (TRD) and Foreign Direct Investment (FDI) have positive and statistically significant impacts. These results highlight the importance of fostering international trade and attracting foreign investment to enhance long-term productivity levels. Furthermore, the number of Patent Applications (PAT) displays a negative association with productivity, indicating a potential need for a more nuanced examination of the quality and innovation represented by patents.

In the short run, the unexpected negative impact of Research and Development Expenditure (XPD) on productivity prompts further investigation into the immediate consequences of R&D investment. On the positive side, Total Patent Applications (PAT), Trade Openness (TRD), and Foreign Direct Investment (FDI) demonstrate positive and statistically significant relationships with short-term productivity, providing support for policies that encourage innovation, economic openness, and foreign investment.

Recommendations based on these findings include a focus on fostering a conducive environment for innovation and research while ensuring that the quality and relevance of research activities are emphasized. Additionally, policies aimed at promoting international trade and attracting foreign direct investment can contribute positively to short-term and long-term productivity growth. It is crucial for policymakers to consider the nuanced nature of these relationships and tailor strategies to address specific challenges and opportunities within the economic context. Future research could delve into the mechanisms through which R&D expenditure impacts productivity in the short run and explore potential policy interventions to optimize its positive effects. Overall, a holistic and context-specific approach is essential for crafting effective policies that promote sustainable productivity growth.

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