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Capital and Technology Investments as Determinants of Labor Productivity: A Panel Data Analysis of OECD Countries

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ABSTRACT: This study investigates the effects of capital and technology investments on labor productivity for selected OECD countries between 2000 and 2021 using panel data analysis. Two separate panel equations were tested in the study. The first model was constructed to measure the impact of capital and technology investments on labor productivity. In the second model, capital and technology investments were squared and the results are reported. Data were included in the analysis in full logarithmic form to capture diminishing marginal returns. The study first investigated cross-sectional dependence and then conducted a unit root test. Homogeneity and cointegration analyses were then conducted. Finally, the Common Correlated Effects (CCE) estimator (Pesaran, 2006) was used to estimate the coefficient. Results show that a 1% increase in capital investment increases labor productivity by approximately 0.17%, and a 1% increase in technology investment increases it by 0.02%. When capital and technology investments are squared and scaled, marginal returns decrease by nearly 50%, supporting the hypothesis of diminishing returns. The study is limited to 15 OECD countries with available consistent data and does not include sectoral decompositions. The findings suggest that increasing investment amounts alone is insufficient for sustainable growth in OECD countries, emphasizing the need for complementary human capital and institutional capacity.

KEYWORDS: Labor productivity, Capital investment, Technology investment, OECD, Panel data analysis.

INTRODUCTION

Labor productivity is widely acknowledged as a crucial driver of sustainable development and long-term economic growth, enabling countries to increase per capita income while enhancing their competitiveness in the global market (Cahuc et al., 2014; OECD, 2001). Within this context, capital investments and technology investments are considered key tools for boosting productivity (Çetin, 2012; Artekin & Erbay, 2025). Capital investments, such as infrastructure, machinery, and industrial capacity expansions, enhance production potential, thereby increasing output per worker (Çetin, 2012). Empirical studies in Turkey and the European Union have demonstrated significant long-term relationships between capital investments and economic growth, indirectly influencing labor productivity (Şahbaz, 2014). Similarly, capital accumulation has been found to support environmental sustainability while increasing value-added in industrial and service sectors in the Balkan economies (Mitic et al., 2020).

However, recent studies emphasize that the effect of capital investments on productivity may not be strictly linear and that the effectiveness of investments depends on appropriate planning and integration with technological capacity (Boamah et al., 2018; Trpeski et al., 2019; Kocev et al., 2019). Technology investments, including digital transformation, R&D, and artificial intelligence applications, play a pivotal role in enhancing flexibility and efficiency in production processes, thus increasing output per worker (Uslu, 2019; Cao et al., 2022; Narin, 2023). Nevertheless, the productivity gains from these investments often rely on organizational transformation and the workforce's ability to adapt to new technologies (Yıldız & Aytekin, 2019; Zhao et al., 2020). Empirical evidence suggests that the impact of capital and technology investments on labor productivity may exhibit diminishing marginal returns once certain thresholds are surpassed (Huisman & Kort, 2003; Doğaner, 2022). Consequently, examining the nonlinear effects of capital and technology investments on labor productivity using advanced panel data methods provides valuable insights for policymakers aiming to achieve sustainable productivity growth in OECD countries.

This study contributes to the literature by analyzing how capital accumulation and technological advancement influence labor productivity across selected OECD countries, utilizing a fully logarithmic model to capture elasticities Additionally, by incorporating quadratic terms, the study empirically tests the hypothesis of diminishing returns, as suggested by neoclassical growth theory (Solow, 1956) and endogenous growth theories (Romer, 1990; Lucas, 1988), which posit that while capital and technology can drive growth, their marginal contributions decline without adequate complementary factors such as human capital and institutional capacity (Acemoglu & Restrepo, 2022). By addressing the methodological gap in the literature through the application of second-generation panel data techniques, including the Westerlund panel cointegration test and the Common Correlated Effects (CCE) estimator, this study aims to provide robust evidence on the nonlinear impacts of capital and technology investments on labor productivity in the context of OECD countries. The findings are intended to guide policymakers in designing balanced investment strategies that integrate human capital development and institutional strengthening with capital and technological investments to foster sustainable productivity growth. Additionally, by incorporating quadratic terms, the study empirically tests the hypothesis of diminishing returns, as suggested by neoclassical growth theory (Solow, 1956) and endogenous growth theories (Romer, 1990; Lucas, 1988), which posit that while capital and technology can drive growth, their marginal contributions decline without adequate complementary factors such as human capital and institutional capacity (Acemoglu & Restrepo, 2022). By addressing the methodological gap in the literature through the application of second-generation panel data techniques, including the Westerlund panel cointegration test and the Common Correlated Effects (CCE) estimator, this study aims to provide robust evidence effect on capital and technology investments on labor productivity in the context of OECD countries. The findings are intended to guide policymakers in designing balanced investment strategies that integrate human capital development and institutional strengthening with capital and technological investments to foster sustainable productivity growth.

REVIEW OF LITERATURE

Empirical studies have demonstrated that capital investments in infrastructure and machinery can increase output per worker, contributing significantly to productivity growth across countries (Çetin, 2012; Şahbaz, 2014). For instance, studies focusing on Turkey and European Union countries have confirmed the positive long-term relationship between capital formation and economic growth, indirectly enhancing labor productivity (Şahbaz, 2014). Moreover, in the Balkan economies, capital accumulation has been associated with increased value-added in the industrial and service sectors, contributing to environmental sustainability (Mitic et al., 2020).

However, some studies argue that the relationship between capital investments and productivity may exhibit nonlinear dynamics, as investments beyond certain thresholds may result in diminishing marginal returns due to inefficiencies, underutilization, or inadequate human capital complementarity (Boamah et al., 2018; Kocev et al., 2019). These findings align with the law of diminishing returns, which suggests that while capital increases productivity initially, the incremental benefits decline as the stock of capital grows without complementary factors. Similarly, technology investments have become increasingly critical for productivity gains, particularly in the era of digital transformation. Investments in digital infrastructure, R&D, and artificial intelligence can enhance flexibility, reduce production costs, and increase output per worker (Brynjolfsson & McAfee, 2014; Cao et al., 2022). Studies indicate that technology investments drive productivity improvements by facilitating automation, improving product quality, and reducing transaction costs (Narin, 2023; Zhao et al., 2020). Nevertheless, the impact of technology investments on productivity can also exhibit diminishing marginal returns, especially when organizational structures and human capital are insufficient to support technological integration (Yıldız & Aytekin, 2019; Huisman & Kort, 2003). Brynjolfsson and McElheran (2019) and DeStefano et al. (2023) highlight that firms with higher digital maturity tend to realize more significant productivity gains, indicating the need for complementary investments in skills and organizational change.

Recent studies have also emphasized the importance of advanced econometric approaches in analyzing the capital-technology-productivity nexus, given the complexities of cross-sectional dependence and heterogeneity across countries. Panel data methods, such as the Westerlund cointegration test and Common Correlated Effects (CCE) estimator, allow for robust estimation in the presence of these complexities, providing more reliable evidence for policy recommendations (Westerlund, 2007; Pesaran, 2006).

While the literature acknowledges the importance of capital and technology investments in driving productivity growth, there remains a gap in empirical studies exploring their nonlinear impacts using second-generation panel data methods within the OECD context. This study aims to address this gap by analyzing how capital and technology investments influence labor productivity across selected OECD countries, explicitly testing the hypothesis of diminishing returns using fully logarithmic models with quadratic terms. By doing so, the study contributes to the literature with policy-relevant findings, offering insights into designing balanced investment strategies for sustainable productivity growth in developed economies.

RESEARCH METHODOLOGY

In this study, panel data from 15 OECD countries covering the period 2000–2021 were utilized. The selection of the number of countries and the time frame was determined based on the criterion of maximizing the number of countries and the length of the period with complete data availability. The countries selected based on these criteria are presented in Table 1.

Table 1. Countries Included in the Study

United States	Belgium
Portugal	Iceland
Canada	Luxembourg
Switzerland	Norway
France	Germany
Austria	Spain
Netherlands	Italy
Sweden	

In the study, the variable representing labor productivity is measured as real GDP per employee. The variable representing capital investment per employee is measured as real gross fixed capital formation per employee, and the variable representing technology investment per employee is measured as real technology-related investments per employee. The descriptions and data sources for these variables are presented in Table 2.

Table 2. Description of Variables

Variable	Description	Data Source
Productivity	Real GDP per employee	World Bank
peRGSFC	Real gross fixed capital formation per employee	World Bank
peTI	Real technology-related investments per employee	OECD Going Digital Toolkit, World Bank

Note: Calculations for these variables were conducted by the authors.

In this research, two different model estimations are conducted. In the first model, the effect of capital investment per employee and technology investment per employee on labor productivity is examined using a fully logarithmic (log-log) model. In the second model, the analysis explores how the effect on labor productivity changes when the square of capital investment per employee and the square of technology investment per employee are included, again within a fully logarithmic framework.

The equations examined in the study are presented below.

$$lnproductivity_{it} = \beta_0 + \beta_1 lnpeRGSFC + \beta_2 lnpeTI_{it} + \varepsilon_{it} \quad (1)$$

$$lnproductivity_{it} = \beta_0 + \beta_1 lnpeRGSFC_{it}^2 + \beta_2 lnpeTI_{it}^2 + \varepsilon_{it} \quad (2)$$

RESULT AND DISCUSSION

Selecting an appropriate estimation model for the panel dataset is crucial, as conducting estimations without testing for cross-sectional dependence, unit roots, and slope homogeneity may result in spurious relationships. In this study, the Pesaran (2021) CD test was first employed to assess cross-sectional dependence, and the results are presented in Table 3.

Table 3. Pesaran CD Test Results for Cross-sectional Dependence

Variable	CD Statistic	p-value
lnproductivity	23,91	0,000***
lnRGSFC	13,82	0,000***
lnTI	18,51	0,000***
$\ln(RGSFC)^2$	13,82	0,000***
$\ln(TI)^2$	18,51	0,000***

The CD test results reject the null hypothesis of weak cross-sectional dependence for all variables, indicating significant cross-sectional dependence that should be accounted for in the estimation process. Given these findings, it is appropriate to employ second-generation panel unit root tests that consider cross-sectional dependence. Accordingly, the Pesaran (2007) CADF test was used to test for stationarity, and the results are shown in Table 4.

Table 4. Unit Root Test Results (Pesaran CADF)

Level							
Variable	**Model**	**t-bar**	**CV%10**	**CV%5**	**CV%1**	**Z[t-bar]**	**p-value**
lnProductivity	Constant	-1,379	-2,140	-2,250	-2,450	1,560	0,941
	Constant Trend	-2,295	-2,660	-2,760	-2,960	0,105	0,542
lnRGSFC	Constant	-1,364	-2,140	-2,250	-2,450	1,619	0,947
	Constant Trend	-2,025	-2,660	-2,760	-2,960	1,227	0,890
lnpeTI	Constant	-1,520	-2,140	-2,250	-2,450	0,998	0,841
	Constant Trend	-2,787	-2,660	-2,760	-2,960	-1,944	0,026
$lnRGSFC^2$	Constant	-1,364	-2,140	-2,250	-2,450	1,619	0,947
	Constant Trend	-2,025	-2,660	-2,760	-2,960	1,227	0,890
$lnpeTI^2$	Constant	-1,520	-2,140	-2,250	-2,450	0,998	0,841
	Constant Trend	-2,787	-2,660	-2,760	-2,960	-1,944	0,026
First Difference							
lnProductivity	Constant	-2,633	-2,140	-2,250	-2,450	-3,444	0,000
	Constant Trend	-2,791	-2,660	-2,760	-2,960	-1,962	0,000

lnRGSFC	Constant	-2,522	-2,140	-2,250	-2,450	-3,001	0,000
	Constant Trend	-2,577	-2,660	-2,760	-2,960	-1,071	0,000
lnpeTI	Constantt	-3,552	-2,140	-2,250	-2,450	-7,117	0,000
	Constant Trend	-3,676	-2,660	-2,660	-2,660	-5,646	0,000
$lnRGSFC^2$	Constant	-2,522	-2,140	-2,250	-2,450	-3,001	0,000
	Constant Trend	-2,577	-2,660	-2,660	-2,660	-1,071	0,000
$lnpeTI^2$	Constant	-3,552	-2,140	-2,250	-2,450	-7,117	0,000
	Constant Trend	-3,676	-2,660	-2,660	-2,660	-5,646	0,000

At the level, most variables exhibit unit roots, except for lnTechnology Investment and $\ln(TI)^2$ under the constant trend model, which are stationary at the 5% significance level. However, upon first differencing, all variables become stationary at the 1% significance level under both constant and constant trend models, indicating that the variables are integrated of order one [I(1)]. This outcome aligns with common practices in the literature, where the majority of test results guide the conclusion (Baltagi & Pirotte, 2010), and the variables are thus considered I(1) in this study.

Following the unit root tests, slope homogeneity was assessed using the Pesaran and Yamagata (2008) homogeneity test, with results shown in Table 5.

Table 5. Slope Homogeneity Test Results

Model 1			**Model 2**		
	Statistic	p-value		Statistic	p-value
$\tilde{\Delta}$	5,491	0,000	Δ	5,491	0,000
$\tilde{\Delta}_{ajd}$	6,103	0,000	Δ_{ajd}	6,103	0,000

The test results indicate heterogeneity across the slope coefficients for cross-sectional units. Therefore, it is essential to employ an estimation approach that accounts for heterogeneity in the panel dataset.

Given the presence of cross-sectional dependence and heterogeneity, the Westerlund (2007) ECM panel cointegration test was employed, and the results are reported in Table 6.

Table 6. Westerlund Panel Cointegration Test Results

Model 1				**Model 2**			
	Statistic	Z-Statistic	p-value		Statistic	Z-Statistic	p-value
G_t	-2,021	-2,365	0,000	G_t	-2,021	-2,365	0,000
G_a	-8,401	-1,825	0,034	G_a	-8,401	-1,825	0,034
P_t	-7,548	-2,949	0,000	P_t	-7,548	-2,949	0,000
P_a	-8,133	-4,452	0,000	P_a	-8,133	-4,452	0,000

The cointegration test results confirm the existence of a long-run relationship among the variables. Identical values for both models are due to Model 2 including only the squared terms of the independent variables without additional data transformation.

Following these diagnostics, the Common Correlated Effects (CCE) estimator (Pesaran, 2006), which accounts for cross-sectional dependence and heterogeneity, was selected for the final estimation Table 7.

Table 7. CCE Estimation Results

Dependent Variable: lnproductivity	**Model 1**					
Variable	Coefficient	Std. deviation	z	p	[95% Interval]	Confidence
lnRGSFC	,1792227	,0325856	5,50	$0,000^{***}$	,1153562	,2430893
lnpeTI	,0210334	,0108744	1,93	$0,053^{**}$	-,0002802	,0423469
Dependent Variable: lnproductivity	**Model 2**					
Variable	Coefficient	Std. deviation	z	p	[95% Interval]	Confidence
$lnRGSFC^2$	,0896114	,0162928	5,50	$0,000^{***}$	,0576781	,1215446
$lnpeTI^2$	,0105167	,0054372	1,93	$0,053^{**}$	-,0001401	,0211734

Note: *** p < 0.01, * p < 0.10

The estimation results indicate that both capital investment per employee and technology investment per employee have positive and significant effects on labor productivity in OECD countries. Specifically, Model 1 suggests that a 1% increase in capital investment per employee leads to a 0.17% increase in labor productivity, while a 1% increase in technology investment per employee leads to a 0.02% increase in productivity.

In Model 2, when the squared terms of the investment variables are included, the effects on productivity decrease to 0.08% for capital investment and 0.01% for technology investment per 1% increase, demonstrating diminishing marginal returns. This indicates that continuously increasing capital and technology investments does not result in proportional increases in productivity, consistent with the law of diminishing returns, as the marginal product of capital and technology decreases when investments are expanded further.

CONCLUSION

This study contributes to the literature by examining the effects of capital and technology investments on labor productivity using panel data for selected OECD countries. The findings reveal that while capital and technology investments are essential tools for enhancing labor productivity, the pace of productivity gains declines beyond a certain threshold, exhibiting diminishing marginal returns (Acemoglu & Restrepo, 2021). This outcome confirms the law of diminishing returns, indicating that continuous increases in capital and technology investments do not lead to proportional increases in labor productivity.

The results indicate that capital investments exert a stronger impact on labor productivity compared to technology investments, consistent with the findings of Barro and Sala-i-Martin (2004) and Jones (2005), who emphasize that physical capital accumulation provides significant contributions to productivity growth in the short and medium term. Specifically, in this study, a 1% increase in capital investments leads to a 0.17% increase in productivity, while a similar increase in technology investments results in a 0.02% increase, aligning with Jorgenson and Vu's (2016) findings that the marginal contributions of technology investments decline beyond certain levels. These insights are consistent with the OECD's "Going Digital" policy, which emphasizes strengthening digital infrastructure, accelerating firm-level digitalization processes, and equipping the workforce with digital skills to support sustainable growth (OECD, 2021). However, achieving sustainable productivity gains from digital investments depends on the presence of complementary elements, such as the quality of human capital, organizational capacity, and institutional infrastructure (Acemoglu & Restrepo, 2021). Thus, increasing digital investments alone is insufficient, and investments should be integrated with human capital development, institutional capacity, and R&D initiatives (Masoura & Malefaki, 2023).

The study also found that including capital and technology investments squared in the model leads to a reduction in marginal returns of approximately 50%, indicating that the marginal product of capital and technology decreases significantly as investment levels increase. This observation aligns with the findings of Tambe et al. (2019) and Mindell and Reynolds (2023), who emphasize the need to improve workforce skills to realize the potential productivity gains from digitalization. Given the aging populations in OECD countries and the need to improve workforce quality, prioritizing education and skills transformation programs to maximize the effectiveness of capital and technology investments becomes crucial (Brynjolfsson and McAfee, 2014).

In conclusion, this study demonstrates that while capital and technology investments play a critical role in enhancing labor productivity in OECD countries, they exhibit diminishing marginal returns beyond a certain threshold. To achieve sustainable productivity growth, investments should be planned in conjunction with digital capacity building, human capital development, and institutional infrastructure improvements. This holistic approach will contribute to the development of balanced capital-technology investment strategies, supporting sustainable growth and productivity enhancement in OECD countries over the long term.

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