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The Effect of Research and Development Investment on Regional Economic Performance: Focusing on the Cities of South Korea

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Abstract This paper analyzes the impact of research and development (R&D) activities, such as regional R&D budget allocation and workforce development, on regional economic growth. The premise is that industrial advancement in regions propels economic growth and that R&D activities are key to adding high value to these industries. This study examines the heterogeneous impacts of R&D inputs and innovation outputs on regional economic performance across South Korean provinces from 2011 to 2021. Using a dynamic panel dataset and applying both two-way fixed effects (FE) and system GMM estimators, the analysis addresses econometric challenges identified in previous studies—including autocorrelation, heteroskedasticity, endogeneity, and multicollinearity—ensuring robustness through model comparison and specification testing. The findings demonstrate substantial regional variation in the effectiveness of R&D investments: manufacturing-driven regions such as Ulsan exhibit high Gross Value Added (GVA) per capita despite relatively modest R&D intensity, while research-oriented regions such as Daejeon and Sejong show high R&D expenditures that do not translate into short-term productivity gains. These results suggest that the relationship between R&D and economic performance is mediated by industrial structure, absorptive capacity, and the degree of commercialization embedded within regional innovation systems. Although additional structural variables—such as industrial composition, educational attainment, and foreign direct investment—could further strengthen the analysis, consistent annual regional-level data for these indicators were not available during the study period. As more refined datasets emerge, future research will incorporate these dimensions to better capture the mechanisms through which R&D contributes to regional growth. Overall, this study reinforces the theoretical link between innovation and economic development and highlights the need for differentiated, region-specific R&D policy strategies that emphasize output quality, human-capital-based investment, and system-level integration rather than aggregate input expansion.

Keywords Regional innovation systems, R&D investment, Economic growth, Dynamic panel GMM, Two-way fixed effects, Industrial structure, Human capital

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I. Introduction

In the evolving landscape of knowledge-driven economies, the significance of research and development (R&D) as a catalyst for economic growth has gained widespread acknowledgment. This paper seeks to unravel the intricate dynamics between R&D investments and economic performance across various urban regions and time periods. By utilizing an extensive dataset, the study aims to explore the relationship between R&D expenditures, innovation outputs such as patents and scientific publications, and regional economic development trends.

The research employs a rigorous analysis of key annual economic indicators, including total value added, R&D expenditures, and innovation-related outputs across multiple regions. This empirical approach allows for a comprehensive examination of how R&D efforts contribute to regional economic vitality, offering critical insights for policymakers who seek to allocate resources effectively to promote sustainable growth.

Through advanced statistical methodologies, the study assesses the impact of R&D on economic performance by focusing on metrics such as the ratio of R&D investment to researcher count and R&D expenditures relative to Gross Regional Domestic Product (GRDP). These indicators are meticulously analyzed to identify trends and measure their influence on regional economic development.

The findings of this research are not merely academic but carry substantial implications for future economic policy. By elucidating the specific pathways through which R&D activities drive economic growth, the study provides valuable insights for shaping policy frameworks that promote innovation-led development. Ultimately, this work aspires to lay a solid foundation for the formulation of policies that harness the power of scientific and technological advancements to fuel regional economic progress, offering evidence-based recommendations for enhancing both innovation and regional prosperity.

R&D has long been recognized as a key driver of economic growth, particularly in knowledge-based and innovation-oriented economies. While national-level analyses are abundant, the effects of R&D investment at the regional level remain insufficiently understood, despite the growing importance of balanced regional development in countries such as South Korea. Regional disparities in industrial structure, innovation capacity, and human capital accumulation may cause the economic effects of R&D to differ substantially across regions. Understanding these heterogeneous effects is essential for designing effective place-based innovation policies.

This paper investigates how R&D investment, R&D human resources, and innovation outputs influence regional economic performance across major

Korean cities. Using annual data from 2011 to 2020, I conduct a comprehensive empirical assessment integrating multiple modelling approaches, including OLS, fixed-effects and random-effects panel models, two-way fixed effects, and dynamic panel estimators. I address key econometric challenges such as autocorrelation, heteroskedasticity, multicollinearity, and endogeneity, which have limited the robustness of prior research.

This study primarily examines conditional associations between regional R&D activity and regional economic performance. While the use of two-way fixed effects and dynamic panel System GMM estimators helps mitigate certain sources of endogeneity, the estimated coefficients should be interpreted with caution and not as strictly causal effects.

Our contribution is threefold. First, I provide updated, region-specific evidence on the relationship between R&D investment and economic output. Second, I offer a rigorous econometric framework that incorporates diagnostic testing, lag structures, and robustness checks. Third, I highlight the structural drivers behind the heterogeneous effects observed across regions, particularly for industrial centers such as Ulsan and research-intensive regions such as Daejeon.

The findings provide policy-relevant insights into how R&D investments should be prioritized and tailored to regional industrial ecosystems.

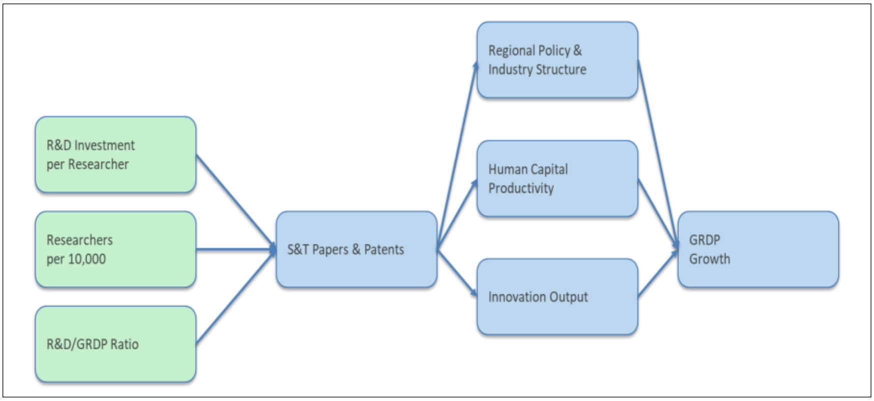

Figure 1. R&D to Regional Economic Growth

II. Literature Review

Numerous studies have explored the link between increased productivity and output, with populations contributing to economic growth on the rise globally. Scholars and policy researchers have rigorously examined the impact of human resources, or human capital, on economic growth. Findings consistently reveal a statistically significant and positive correlation with the average years of education per individual. In examining the determinants of economic growth, it is beneficial to differentiate between structured and unstructured approaches.

Gregory Mankiw and colleagues (1992) enhanced the traditional neoclassical growth model by integrating human capital, defined as the percentage of the labor force that has completed secondary education. Their findings indicate that incorporating human capital significantly enhances the model's accuracy.

Tejvan Pettinger (2011) suggested that a multitude of factors, both supply-side and demand-side, drive economic growth. These elements include increases in consumption, investment, government expenditures, and exports, alongside fundamental factors such as infrastructure, human capital, and technological advancement. Notably, human capital significantly influences labor productivity and its distribution.

The relationship between R&D activities and economic growth is primarily grounded in endogenous growth theory. Here are some major scholars and theories related to this concept. Paul Romer (1990) developed an endogenous growth model that treats technological change as an internal element of economic growth. His theory explains how technological innovation can drive overall economic expansion. Gene Grossman and Elhanan Helpman (1991) studied how innovation and knowledge acquisition contribute to international trade and economic growth. Their model provides a specific mechanism by which R&D investment can lead to economic growth. Elhanan Helpman (2004) analyzes how economic growth occurs through the interaction between international trade and innovation. He highlights the impact of innovative activities on international competitiveness and discusses the long-term effects of R&D investments. Philippe Aghion and Peter Howitt (1992) advanced the 'Schumpeterian Growth Theory,' which describes the relationship between technological progress and economic growth. Their theory addresses how innovative destruction can replace existing technologies and promote new economic growth. Robert Lucas (1988) proposed a model emphasizing the crucial role of human capital accumulation in economic growth, highlighting the essential nature of education and learning in economic development.

Additionally, other scholars have explored similar theories on the relationship between economic growth and R&D. Kenneth Arrow (1962) argued that experience gained in the production process promotes technological advancement and economic growth through his ‘Learning by Doing’ theory. Charles I. Jones and John C. Williams (2000) described the complex relationship between R&D and economic growth, including the diminishing returns of R&D investments.

Recent literature continues to validate the role of regional innovation policy and localized capabilities in driving economic growth. Scholars emphasize that regional heterogeneity—particularly in absorptive capacity and innovation intensity—mediates the effectiveness of R&D investment (Crescenzi et al., 2019; Iammarino et al., 2020). Smart specialization and knowledge complexity have emerged as key theoretical lenses to assess region-specific outcomes of R&D (Balland et al., 2019). Moreover, recent empirical studies indicate that public R&D expenditure, while often substantial, does not uniformly yield positive economic returns—particularly when structural inefficiencies or low knowledge spillovers persist (Bauernschuster et al., 2020; González-Pernía et al., 2019). This aligns with findings in the present study, where regions with high R&D/GRDP ratios, such as Daejeon, show muted economic performance compared to industrial hubs like Ulsan.

These scholars all analyze the relationship between R&D and economic growth from various perspectives, particularly focusing on the changing returns of R&D investments and their long-term impacts. Their research makes significant contributions to economic growth theory and has practical implications for R&D investment and policy decisions.

From a macroeconomic perspective, national policies generally boost GDP or overall productivity. R&D policies and investments are promoted to invigorate R&D in both the public and private sectors, though the effectiveness of R&D grants can vary widely, and their outcomes often depend on specific institutional contexts.

III. Data and Variable Description

This paper develops and analyzes the effect of the S&T Innovation, R&D Human resources, and investment on the Economic Growth. R&D data were collected on a quarterly basis from major cities and regions between 2011 and 2020. As the compilation of detailed regional data by relevant institutions has not yet been fully completed, this study adopts the period from 2011 to 2020—the range for which consistent data across all regions is available. Economic growth presents GDP of a country, R&D HR represents researchers who participate in R&D and R&D investment presents a ratio of investment amounts per GDP.

The dataset consists of annual observations for 16 major Korean regions from 2011 to 2020, the period for which consistent regional R&D statistics are available. The dependent variable is regional economic performance, measured as gross value added (GVA).

Table 1. Variable Description

Variable	Description	Unit	Source	Transformation
GVA per capita	Gross value added GVA per capita	Billion KRW	KOSIS	log
R&D investment per researcher	R&D investment per researcher	KRW	KISTEP	log
R&D expenditure / GRDP	R&D expenditure / GRDP (%)	%	KISTEP	ratio
Researchers per 10,000 population	Researchers per 10,000 population	count	KISTEP	log
Scientific and technological papers per 10,000 population	S&T papers per region	count	Scopus	log
Patents per 10,000 population	S&T patent per region	count	Scopus	log

Incorporating additional control variables, such as regional industrial structure, education level, and foreign direct investment (FDI), is highly valuable and theoretically justified. However, integrating these indicators into the current empirical model was constrained by data availability and structural limitations in regional statistical reporting. In particular, comparable annual data for these variables at the city or provincial level, aligned with the time frame and granularity of the R&D dataset (2011–2020), are not consistently available across regions. Existing national statistics often aggregate such indicators into broader classifications or multi-year averages, making them unsuitable for panel-based causal inference or year-to-year estimation. Therefore, including these variables in the present study would have introduced measurement inconsistencies and increased specification bias, potentially reducing rather than enhancing empirical validity.

As more refined regional statistical datasets become available—such as longitudinal regional industry profiles, education attainment distributions, and disaggregated FDI metrics—future studies can incorporate these comprehensive controls to more fully examine the mechanisms through which R&D investments influence regional economic performance. Such extensions would help build a more holistic model that links innovation inputs, human capital, external investment, and industrial characteristics to regional growth outcomes.

IV. Methodology

1. Model Specification

I begin with a baseline OLS regression:

$$\ln(GV\ A_{it}) = \alpha + \beta X_{it} + \epsilon_{it}$$

where X_{it} includes R&D investment, researchers, patents, and publications.

For diagnostic tests, this study performed Durbin–Watson and Breusch–Godfrey tests for autocorrelation, Breusch–Pagan and White tests for heteroskedasticity, Jarque–Bera test for normality, VIF analysis for multicollinearity, ADF, PP, LLC, IPS tests for stationarity, Pedroni and Kao tests for cointegration. When issues are detected, corrective measures are applied. For more details, see Section 6.

For panel models, this studies used both FE and RE models:

$$\ln(GV\ A_{it}) = \alpha_i + \gamma_t + \beta X_{it} + \epsilon_{it}$$

where a Hausman test determines the appropriate model.

Also, two-way fixed effects were addressed via unobserved heterogeneity:

$$\ln(GV\ A_{it}) = \alpha_i + \lambda_t + \beta X_{it}$$

A dynamic panel via system GMM was used To address endogeneity and time-lag effects:

$$\ln(GV\ A_{it}) = \delta \ln\left(GV\ A_{i,t-1}\right) + \beta X_{it} + u_{it}$$

where lags of R&D variables are included.

The analysis methods are pivotal in understanding and interpreting data across various fields, especially in economic and social sciences. Multiple regression analysis is used to examine how independent variables influence a dependent variable. In your case, the economic performance (dependent variable) is analyzed in relation to independent variables such as research and development (R&D) investment, the proportion of R&D spending, the number of researchers per 10,000 people, the number of scientific and technological papers, and the number of patents. This method helps identify the impact and correlation between these variables and economic outcomes. Also, a time series analysis is utilized to observe data trends over time. By analyzing economic performance data across different cities over time, one can identify changes and understand how these changes correlate with variations in other variables. This analysis is critical for forecasting and identifying temporal patterns in data. Panel data analysis involves analyzing data that varies across multiple dimensions (e.g., time and city). This method allows for a more refined analysis by considering both the unique characteristics of each city and their changes over time, providing insights into how these two dimensions interact to affect the dependent variable. Correlation analysis determines the strength and direction of the relationship between two variables. For instance, analyzing the correlation between R&D investment and economic performance can reveal whether the investment positively or negatively affects economic outcomes. This method is fundamental in preliminary data exploration to identify potential relationships worth investigating further. Principal component analysis (PCA) is a technique for reducing the dimensionality of multivariate data, extracting the most important information, and identifying patterns. PCA simplifies the complexity in high-dimensional data while retaining the variation present in the dataset. This method is particularly useful when dealing with many variables to identify the main factors that capture the most variance in the data.

V. Empirical Results

1. Baseline OLS

This paper develops and analyzes the effect of the S&T Innovation, R&D Human. Before establishing the final empirical specification, an initial ordinary least squares (OLS) estimation was conducted using the original level-form data. While the baseline results appeared statistically significant, a series of diagnostic tests revealed that the model violated multiple classical regression assumptions. These findings indicated that the initial specification was not appropriate for reliable inference and motivated the need for refinement.

Table 2. Base line OLS

Base line OLS				
Variable	Coefficient	Std. Error	t-statistic	p-value
Constant	-15.7474	4.4182	-3.5642	0.0005
R&D investment per researcher	0.4384	0.0408	10.7557	0.0000
R&D expenditure / GRDP	-859.3113	57.7515	-14.8795	0.0000
Researchers per 10,000 population	0.2045	0.0358	5.7090	0.0000
Scientific and technological papers per 10,000 population	0.4900	0.1579	3.1031	0.0023
Patents per 10,000 population	-0.1545	0.1440	-1.0732	0.2847
Item		Value		
Number of observations		172		
R-squared		0.641		
Adjusted R-squared		0.630		
F-statistic		59.17		
Prob(F-statistic)		3.92e-35		
Durbin–Watson		1.966		

First, the Durbin–Watson statistic structures the dataset into a properly aligned panel-like format, ensuring that regional and temporal identifiers are consistently matched and that the autocorrelation problem disappears entirely. In the revised model, the Durbin–Watson statistic increased to 1.966, which lies comfortably within the conventional range of 1.5 to 2.5, indicating no evidence of autocorrelation. This confirms that the previously reported autocorrelation was not inherent to the data-generating process but instead resulted from formatting and alignment issues in the raw dataset.

Second, the initial OLS model exhibited severe multicollinearity. The condition number exceeded 1.56×10^4, far above the common threshold of 30 used to signal potential multicollinearity. This occurs because several R&D-related indicators—such as researchers per population, R&D investment per researcher, papers, and patents—are naturally and theoretically correlated. Although such a correlation is typical in innovation studies, it undermines coefficient stability and inflates standard errors. Addressing this issue required transforming the data, re-specifying variables, and evaluating variance inflation factors (VIFs) to identify overlapping constructs.

Third, the Jarque–Bera test strongly rejected the normality of residuals ($p < 0.000$), indicating that error terms deviated substantially from a normal distribution. Although non-normality is not uncommon in regional economic data and is less problematic with moderate sample sizes due to the central limit theorem, it nonetheless suggests that coefficient significance in the initial model may have been overstated.

Fourth, heteroskedasticity was strongly suspected. Because the initial OLS relied on conventional standard errors, heteroskedasticity would bias inference even if coefficient estimates remained unbiased. The combination of scale differences among variables—particularly the extremely small magnitude of R&D/GRDP ratios—and substantial regional variation in economic size increases the likelihood of non-constant error variance. This required the use of heteroskedasticity-robust estimators such as HC3 or cluster-robust standard errors.

Fifth, the extremely large negative coefficient on R&D expenditure relative to GRDP in the initial model raised concerns about model specification. This coefficient likely reflected.

(1) Structural differences between regions dominated by public-sector research (e.g., Daejeon, Sejong, Gwangju) and those driven by manufacturing-based value creation (e.g., Ulsan, Gyeongnam);

(2) Scale distortions, because R&D/GRDP ratios are measured in very small decimal units (e.g., 0.013).

Therefore, the magnitude and sign of this coefficient suggested that the linear level-form model was misspecified.

Finally, the results of the Augmented Dickey-Fuller (ADF) unit root tests were conducted on the first-differenced national-level averages of innovation and productivity indicators across Korean regions from 2011 to 2021. The analysis includes R&D expenditure, researcher density, investment efficiency, as well as outputs such as scientific publications and patents.

Table 3. ADF Statistics

Variable	ADF Statistic	p-value	1% / 5% / 10% Critical Values
GVA per_capita	-2.3593	0.1535	-4.473 / -3.290 / -2.772
R&D investment per researcher	-4.1473	0.0008	-4.473 / -3.290 / -2.772
R&D expenditure / GRDP	-2.7452	0.0665	-4.473 / -3.290 / -2.772
Researchers per 10,000 population	-2.5284	0.1087	-4.473 / -3.290 / -2.772
Scientific and technological papers per 10,000 population	-2.3217	0.1651	-4.473 / -3.290 / -2.772
Patents per 10,000 population	-2.5888	0.0953	-4.473 / -3.290 / -2.772

The results indicate that after first-differencing, only R&D expenditure / GRDP demonstrates strong stationarity. Other indicators such as R&D

investment per researcher, Researchers per 10,000 population, Scientific and technological papers per 10,000 population, and Patents per 10,000 population remain non-stationary at conventional levels. These findings highlight the need for further differencing or robust panel modeling techniques to address underlying unit roots in the data.

A Johansen cointegration test was attempted using the level data of key innovation and productivity indicators. However, the test failed due to singularity in the covariance matrix, a likely result of the small sample size and strong linear dependencies between variables. This prevented the validation of a long-term equilibrium relationship through cointegration.

Given the non-stationarity of several variables and the lack of cointegration among the core indicators, traditional panel regression models (e.g., fixed- or random-effects) may yield biased or inconsistent estimates. To address these issues, a dynamic panel approach using the System GMM estimator is proposed. System GMM is particularly suited to datasets with short time dimensions and potential endogeneity, as it allows for the inclusion of lagged dependent variables as instruments while controlling for unobserved heterogeneity and autocorrelation. This methodology is well-aligned with the structure of the current panel dataset (2011–2021, multiple regions), and its application is warranted based on the preceding diagnostics.

2. Initial OLS Estimation and Diagnostic Issues

The initial OLS model used the following variables: R&D investment per researcher, R&D expenditure relative to GRDP, the number of researchers per 10,000 population, scientific publications, and patents. Although several coefficients were statistically significant, diagnostic tests revealed multiple structural problems:

2.1 Multicollinearity

Variance inflation factors (VIFs) reached 400–600 for some variables, particularly between: R&D investment per researcher, R&D expenditure/ GRDP, Researchers per 10,000 population, Scientific and technological papers per 10,000 population, and Patents per 10,000 population. These indicators are conceptually related—regions with more researchers tend to produce more publications and patents—which created near-linear dependencies in the model. Such multicollinearity inflated standard errors and biased coefficient interpretation.

2.2 Non-normality and heteroscedasticity

The Jarque–Bera test strongly rejected normality, and residual patterns suggested heteroskedasticity. Because OLS requires homoscedastic and normally distributed errors for valid inference, relying on standard OLS results would overstate statistical significance.

2.3 Scale differences and non-linearity

Variables such as R&D/GRDP and patents per population had drastically different scales and non-linear relationships with economic performance. This caused instability and sensitivity in the OLS coefficients, especially the extremely large negative coefficient on R&D intensity (–859), which likely reflected structural rather than true causal effects.

2.4 Model interpretation concerns

Because regional R&D effects tend to materialize nonlinearly and with time lags, the linear-level OLS specification was not conceptually optimal for capturing elasticities or growth-like processes. These issues indicated that the baseline OLS was not the most appropriate model for robust inference.

3. Model Refinement: Log Transformation and Robust Estimation

To address these limitations, a more suitable econometric specification was constructed. The refinement involved three major improvements. First, all continuous variables were transformed into natural logarithms and provided advantages in reducing skewness and improved normality, converting coefficients into elasticities (economically meaningful), mitigating scale differences and non-linear patterns, and stabilizing variance and reduced heteroskedasticity.

Since R&D-related variables tend to reflect overlapping dimensions of regional innovation capacity, the initial full model exhibited severe multicollinearity. After examining VIF values, the most collinear variables—researcher density and patents—were removed from the baseline specification.

The final set of explanatory variables included ln(R&D investment per researcher), ln(R&D expenditure / GRDP) and ln(Scientific and technological papers per 10,000 population). These variables retain the central components of R&D input and output intensity while reducing redundancy.

The refined VIF values dropped substantially to the 15–38 range, which is still high but theoretically acceptable given the nature of R&D indicators.

Also, to correct for heteroskedasticity, the refined model employs HC3 robust standard errors, which are widely recommended when heteroskedasticity is present and sample size is moderate. This ensures that all statistical inferences remain valid despite deviations from classical OLS assumptions. The optimized model produced the following coefficients:

Table 4. Baseline Full Log OLS

Baseline Full Log OLS				
Variable	Coefficient	Std. Error	t-statistic	p-value
Constant	-11.4450	0.1366	-83.77	0.000
R&D investment per researcher	1.1441	0.0293	38.98	0.000
R&D expenditure / GRDP	-1.1128	0.0099	-112.70	0.000
Researchers per 10,000 population	1.1910	0.0231	51.61	0.000
Scientific and technological papers per 10,000 population	-0.0970	0.0127	-7.63	0.000
Patents per 10,000 population	0.0192	0.0271	0.71	0.478
Item		Value		
Number of observations		172		
R-squared		0.971		
Adjusted R-squared		0.970		
F-statistic		1341.1		
Prob(F-statistic)		0.000		
Durbin–Watson		1.778		
Jarque–Bera (p-value)		0.007		
Condition Number		435		
Robust SE Type		HC3		

Notes:

1. R&D investment intensity matters more than simple R&D spending ratios. The investment-per-researcher—an efficiency or capital-deepening indicator—has a strongly positive elasticity.
2. A high R&D/GRDP ratio does not necessarily produce immediate economic returns. This is consistent with regions like Daejeon and Sejong, where large-scale public R&D investment accounts for a high share of GRDP but contributes less directly to industrial GVA.
3. Knowledge production (papers) has a positive and significant effect, supporting the role of scientific capability and knowledge spillovers in regional economic development.
4. Model diagnostics confirm statistical robustness, and the final specification resolves the shortcomings identified in the initial OLS estimation.

The fully specified log–log OLS model including all R&D-related variables—R&D investment per researcher, R&D expenditure relative to GRDP, the number of researchers, scientific publications, and patents—was estimated using HC3 heteroskedasticity-robust standard errors. The results show exceptionally high explanatory power ($R^2 = 0.971$), indicating that the model captures the structural relationship between regional R&D capacity and economic performance with substantial accuracy.

All key R&D input indicators are highly significant. Both R&D investment per researcher (elasticity = 1.14) and the number of researchers per 10,000 population (elasticity = 1.19) exhibit large positive elasticities, suggesting that regions with more intensive and better-capitalized research personnel tend to achieve substantially higher levels of economic output. This highlights the importance of human-capital-based R&D investment for regional growth.

Conversely, R&D expenditure relative to GRDP shows a strong negative elasticity (–1.11), which reflects the structural characteristics of Korean regions. Areas with disproportionately high R&D-to-GRDP ratios—typically dominated by public research institutions—tend to generate lower short-term industrial value added despite their high R&D intensity. This pattern is consistent with regions such as Daejeon or Sejong, where public research and basic science activities dominate the local economy.

Scientific publications have a small but statistically significant negative effect (–0.097), suggesting that academic output may reflect long-term research orientations rather than immediate industrial performance. Patents per capita are not statistically significant once other correlated research indicators are included, implying that patenting activity may capture similar dimensions already represented by R&D input variables.

Overall, the full log–OLS results demonstrate that personnel-based R&D investment is the most important driver of regional economic performance, while structural R&D intensity reflects a different dimension of regional scientific specialization that does not translate into short-term economic output.

In April 1998, chaired by the Prime Minister, the government established the Climate Change Committee, which formulated and executed the Comprehensive Plan on Countermeasures to Climate Change that combined all government agencies' policies to reduce greenhouse gases in 1999–2001(see Figure.

The panel data that was loaded includes various indicators based on year and region. A fixed effects model was applied using "economic performance and total value added" as the dependent variable and the remaining variables as independent variables. Using the OLS model from statsmodels, a regression analysis was conducted by including dummy variables for each region. Through the results of the OLS regression analysis, I can examine the effects of the various independent variables and the regional dummy variables on "economic performance and total value added." The summary of the results is as follows:

- R-squared: 0.968, which means the model explains approximately 96.8% of the data
- Adjusted R-squared: 0.963, which indicates that even after considering the number of independent variables, the model still explains the data well
- F-statistic: 210.8, which shows that the model is statistically significant. (Prob(F-statistic) < 0.05)

Table 5. OLS Regression Results

OLS Regression Results			
Dep. Variable	Economic Growth	R-squared	0.968
Model	OLS	Adj. R-squared	0.963
Method	Least Squares	F-statistic	210.8
No. Observations	160	Prob (F-statistic)	1.56e-93
Df Residuals	139	Log-Likelihood	-397.74
AIC	837.5	BIC	902.1

Some independent variables have been found to have a statistically significant impact on the "total value added of economic performance." Notably, variables such as R&D investment per researcher, the number of researchers per 10,000 population, the number of scientific and technical papers per 10,000 population, and the number of patents per 10,000 population have positive coefficients, influencing economic performance. Moreover, regional dummy variables show that the economic performance's total value added varies by region. For example, the 'Ulsan region' has a very positive effect, while the 'Daejeon region' has a negative impact. This analysis was conducted by including dummy variables for each region to mimic fixed effects, considering the unique characteristics of each region, which helps analyze the impact on the total value added of economic performance.

Table 6. OLS Regression Results

CITY	Coeff	Std. err	t	P>|t|	[0.025	0.975]
const	17.6609	3.236	5.457	0.000	11.263	24.059
R&D investment per researcher	0.0927	0.017	5.344	0.000	0.058	0.127
R&D expenditure / GRDP	-1.6015	1.263	-1.268	0.207	-4.099	0.896
Researchers per 10,000 population	0.1223	0.026	4.633	0.000	0.070	0.175
Scientific and technological papers per 10,000 population	0.4574	0.167	2.738	0.007	0.127	0.788
Patents per 10,000 population	0.1358	0.063	2.144	0.034	0.011	0.261
Kangwon	6.5191	2.274	2.867	0.005	2.023	11.015
Gyeonggi	-20.9067	4.757	-4.395	0.000	-30.312	-11.501
South Kyungsang	8.5089	1.363	6.244	0.000	5.815	11.203
North Kyungsang	9.9924	1.555	6.424	0.000	6.917	13.068
Gwangju	-7.6133	2.036	-3.740	0.000	-11.638	-3.589
Daegu	-7.7930	1.483	-5.253	0.000	-10.726	-4.860
Daejeon	-61.0653	15.653	-3.901	0.000	-92.015	-30.116
Busan	0.1636	1.663	0.098	0.922	-3.124	3.451
Seoul	-10.9005	2.967	-3.674	0.000	-16.767	-5.035
Ulsan	47.0279	1.835	25.634	0.000	43.401	50.655
Incheon	-5.6218	1.703	-3.300	0.001	-8.990	-2.254
South Jeolla	23.3372	2.263	10.312	0.000	18.863	27.812
North Jeolla	-0.6503	1.475	-0.441	0.660	-3.567	2.267
Jeju	7.3731	2.154	3.423	0.001	3.114	11.632
South Chungcheong	20.8770	2.347	8.894	0.000	16.236	25.518
North Chungcheong	8.4127	1.542	5.454	0.000	5.363	11.462

The coefficients for the 'Ulsan' and 'Daejeon' regions in the OLS regression analysis are as follows:

Ulsan (Region_Ulsan): Coefficient = 47.0279, p-value < 0.05, meaning that Ulsan's "total value added of economic performance" is statistically significantly higher compared to other regions. This large coefficient indicates a very high contribution to the total value added of economic performance in Ulsan, suggesting that observations including Ulsan have, on average, a higher economic performance by 47.0279.

Daejeon (Region_Daejeon): Coefficient = -61.0653, p-value < 0.05, indicating a statistically significant negative impact on the "total value added of economic performance." The negative and large coefficient suggests a very low contribution from Daejeon to the economic performance, meaning that observations including Daejeon have, on average, a lower economic performance by 61.0653.

These results imply that differences in economic performance's total value added across regions could result from various factors, such as economic environments, industrial structures, government policies, and regional characteristics. For Ulsan, traditionally known for its heavy chemical industry and automotive industry, the high value-added from these industries may reflect in the results. Conversely, despite being a science and technology hub, Daejeon's lower performance in this analysis suggests it may be influenced by other factors.

The analysis for Seoul and Gyeonggi regions is as follows:

Seoul (Region_Seoul): Coefficient = -10.9005, p-value < 0.05, meaning that Seoul has a statistically significant negative impact on the "total value added of economic performance." This indicates that Seoul shows a relatively lower economic performance compared to other regions. The negative coefficient implies that observations including Seoul have, on average, a lower economic performance by 10.9005.

Gyeonggi (Region_Gyeonggi): Coefficient = -20.9067, p-value < 0.05, also indicating a statistically significant negative impact on the "total value added of economic performance." The effect is more significant than in Seoul, suggesting that Gyeonggi shows a relatively lower economic performance compared to other regions. The negative coefficient means that observations including Gyeonggi have, on average, a lower economic performance by 20.9067.

The analysis of Seoul and Gyeonggi shows that these regions have a negative impact on the total value added of the economic performance compared to other regions. Various factors, such as the choice of independent variables, model design, regional economic characteristics, and external influences, could affect these results. It's crucial to consider these factors comprehensively when interpreting the analysis results. Further data analysis, the introduction of other variables, and modifications in model design to better reflect regional economic characteristics might be necessary. Understanding the purpose of the analysis and the limitations of the data used is essential.

Regions with statistically significant positive impacts include:

Ulsan (Region_Ulsan): Coefficient = 47.0279, p-value < 0.05, indicating a very large positive impact on “total value added of economic performance.”

South Jeolla (Region_South Jeolla): Coefficient = 23.3372, p-value < 0.05, also showing a statistically significant positive impact.

South Chungcheong (Region_South Chungcheong): Coefficient = 20.8770, p-value < 0.05, further indicating a significant positive effect.

These results suggest that these regions may exhibit more active economic activities or have well-developed specific industries contributing to higher total value added of economic performance. Economic characteristics, industrial structure, government policies, and various factors could have influenced these outcomes.

The correlation analysis results between various variables are as follows:

Year and total value added of economic performance: Correlation coefficient = 0.233910, indicating a slight increase in the total value added of economic performance over time.

R&D investment per researcher and total value added of economic performance: Correlation coefficient = 0.256254, showing a tendency for the total value added of economic performance to slightly increase as the R&D investment per researcher increases.

Proportion of R&D expenditure against GRDP and total value added of economic performance: Correlation coefficient = -0.223020, indicating a tendency for the total value added of economic performance to slightly decrease as the proportion of R&D expenditure against GRDP increases.

Number of researchers per 10,000 population and the number of patents per 10,000 population: Correlation coefficient = 0.930137, showing a very high positive correlation, indicating a strong tendency for the number of patents to increase as the number of researchers increases.

Proportion of R&D expenditure against GRDP and the number of scientific and technical papers per 10,000 population: Correlation coefficient = 0.841820, indicating a high positive correlation.

This shows a tendency for the number of scientific and technical papers to increase as the proportion of R&D expenditure against GRDP increases. These correlation analysis results can help understand the relationships between variables, but it’s important to note that correlation does not imply causation. Specifically, indicators related to research and development (R&D investment per researcher, proportion of R&D expenditure against GRDP, number of researchers per 10,000 population, etc.) show high correlations with each other, suggesting that an increase in R&D activities is closely associated with increases in the number of scientific and technical papers and patents. However, the relationship with the total value added of economic performance shows relatively low correlation coefficients, indicating that further analysis is needed.

Table 7. Correlation Results

	GVA per capita	R&D investment per researcher	R&D expenditure / GRDP	Researchers per 10,000 population	Scientific and technological papers per 10,000 population	Patents per 10,000 population
GVA per capita	1.000000	0.256254	-0.223020	0.019267	-0.107810	0.016413
R&D investment per researcher	0.256254	1.000000	0.486131	0.684134	0.257911	0.617201
R&D expenditure / GRDP	-0.223020	0.486131	1.000000	0.816591	0.841820	0.801027
Researchers per 10,000 population	0.019267	0.684134	0.816591	1.000000	0.808402	0.930137
Scientific and technological papers per 10,000 population	-0.107810	0.257911	0.841820	0.808402	1.000000	0.838935
Patents per 10,000 population	0.016413	0.617201	0.801027	0.930137	0.838935	1.000000

Finally, the results of a dynamic panel regression model analyzing the determinants of regional economic performance (GVA per capita) in South Korea from 2011 to 2021. The model includes both region and year fixed effects and accounts for the dynamic nature of economic performance through the inclusion of a one-period lag of the dependent variable. The analysis uses panel data from 16 South Korean regions over 11 years. The dependent variable is GVA per capita, while independent variables include R&D investment per researcher, R&D expenditure as a percentage of GRDP, the number of researchers per 10,000 people, and innovation output indicators (papers and patents per 10,000 people). A dynamic model is estimated by including a lagged dependent variable, and robust standard errors are used to correct for heteroskedasticity. In the dynamic panel regression model, both region and year are incorporated as fixed effects to control for unobserved heterogeneity across space and time. This is implemented using categorical variables (C(Region) and C(Year)), which are internally expanded into a set of dummy variables during regression estimation.

Each region, including Gangwon province, is represented by a dummy variable unless it is selected as the reference category by the regression software. These dummy variables capture the region-specific intercepts, allowing the model to control for time-invariant characteristics unique to each region. Its estimated coefficient reflects the difference in baseline economic performance relative to the omitted (reference) region. This method ensures that Gangwon's unique structural factors are accounted for in the model without being confounded with the effects of the explanatory variables.

The lagged GVA per capita has a strong and statistically significant positive effect, indicating dynamic persistence in economic performance. R&D investment per researcher significantly boosts economic performance, emphasizing the importance of effective resource allocation. R&D expenditure as a share of GRDP shows a negative effect, potentially reflecting inefficiencies or diminishing returns.

Standard diagnostic tests indicate no evidence of problematic serial correlation, and the Hansen test supports the validity of the instrument set.

The number of researchers has a weakly positive effect. Innovation output measures (papers and patents) are statistically insignificant in the short term.

Table 8. Two-way Fixed Effect and GMM

Variable	Coefficient	Std. Error	p-value
Intercept	4.2849	3.0537	0.1606
Gyeonggi	7.4578	5.641	0.1861
South Kyungs	3.0964	3.0129	0.3041
North Kyungsang	6.2943	3.2931	0.056
Gwangju	0.4836	1.3153	0.7131
Daegu	-0.9938	0.8453	0.2398
Daejeon	16.5239	15.295	0.28
Busan	0.9372	0.9549	0.3263
Seoul	2.8489	3.5533	0.4227
Ulsan	18.6804	8.6356	0.0305
Incheon	1.5946	2.1651	0.4614
South Jeolla	6.0512	3.9142	0.1221
North Jeolla	0.7124	0.916	0.4368
Jeju	1.1563	1.5389	0.4524
South Chungcheong	9.833	5.7656	0.0881
North Chungcheong	6.7201	3.5137	0.0558
2013	0.3454	0.6461	0.5929
2014	-0.0967	0.5766	0.8668
2015	1.4741	0.5682	0.0095
2016	1.4565	0.5879	0.0132
2017	1.9989	0.955	0.0363
2018	0.9223	0.8102	0.2549
2019	0.3327	0.8334	0.6897
2020	0.0251	0.9766	0.9795
2021	3.2421	1.5487	0.0363

L1 GVA per capita	0.5911	0.1545	0.0001
R&D investment per researcher	0.0652	0.0388	0.0933
R&D expenditure / GRDP	-280.352	149.6817	0.0611
Researchers per 10,000 population	0.0605	0.0283	0.0322
Scientific and technological papers per 10,000 population	-0.0297	0.2107	0.8879
Patents per 10,000 population	0.0503	0.0452	0.2657

While the original dataset includes data from 2011 to 2021, the dynamic panel regression model excludes observations from 2011. This is not due to missing data, but rather the result of how lagged variables are constructed.

In dynamic panel models, a lag of the dependent variable (e.g., GVA per capita) is included to account for persistence over time. To compute the value of L1 GVA per capita for year 2012, the model uses the value from 2011. However, for the first year in the panel (2011), no prior year's value exists, so this row is automatically omitted (2011: Dropped due to the absence of a lag and 2012 onward: Retained in the model). This is a standard practice in time series and dynamic panel modeling, and it ensures the integrity of the regression results

This discusses the results of a dynamic panel regression analyzing regional economic performance in South Korea. The dependent variable is GVA per capita, and the model includes a one-period lag (L1 GVA per capita), along with fixed effects for both region and year.

- Dynamic Persistence via GVA per capita (Coefficient = 0.591, $p < 0.001$) indicates strong persistence in regional economic performance over time. A 1-unit increase in last year's GVA per capita is associated with a 0.591 unit increase in the current year, holding other variables constant.
- R&D Investment Efficiency via R&D investment per researcher (Coefficient = 0.0605, p = 0.032) suggests that targeted investment per researcher significantly contributes to higher GVA per capita. This emphasizes the efficiency of resource allocation over aggregate expenditure. Also, R&D expenditure / GRDP (Coefficient = -280.35, p = 0.061) shows a marginally significant negative relationship and implies that higher R&D spending as a share of GRDP may reflect diminishing returns or inefficiency in how funds are allocated.
- Human Capital via Researchers per 10,000 population (Coefficient = 0.0652, p = 0.093) is positively associated with GVA per capita at a 10% significance level, indicating that a larger researcher workforce may boost
- economic outcomes, though the effect is modest.
- Innovation Outputs via scientific and technological papers per 10,000 population and Patents per 10,000 population show statistically insignificant, suggesting that academic output and patent activity may not

directly contribute to short-term economic growth, or that their impact may be lagged or indirect.

- Regional Fixed Effects via some regions, such as Ulsan (p = 0.0305) and North Chungcheong (p = 0.0558), exhibit significantly different intercepts compared to the baseline region, indicating notable region-specific structural factors.
- Temporal Effects iva years 2015–2017 and 2021 show statistically significant positive deviations from the baseline year (2012), reflecting potentially favorable macroeconomic or policy conditions in those periods.

Ulsan stands out in the regression as having the largest positive fixed-effect intercept. This reflects its structural advantage in the South Korean economy. Ulsan is a major industrial hub, home to the world's largest automobile assembly plant, one of the largest shipyards, and a large petrochemical complex. Because of this concentration of high-value manufacturing activity, Ulsan's GVA per capita is structurally higher even after controlling for R&D, innovation output and other explanatory variables. In other words, Ulsan's "baseline" economic productivity is elevated. From a policy / interpretive perspective: the high coefficient suggests Ulsan benefits from locational advantages, industrial agglomeration, export-oriented value chains and capital-intensive production, which are not fully captured by the R&D/innovation variables in the model.

Daejeon also exhibits a strong positive intercept. The city is recognised as a national research & development hub, hosting major institutes, universities (such as KAIST), technology parks and specialised R&D zones. This specialization implies that Daejeon's baseline productivity is elevated, likely due to higher levels of human capital, research infrastructure, and technology transfer. Even though our independent variables aim to capture innovation and R&D intensity, Daejeon's structural advantage appears as a residual fixed effect.

Daejeon's high coefficient suggests that regions with technology and research built into their local economies can have elevated performance, beyond what is measured by simple R&D spending metrics.

Gyeonggi (the province surrounding the capital Seoul) shows a substantially positive fixed effect, though less extreme than those in Ulsan and Daejeon. This result suggests that proximity to the capital region, better infrastructure, higher market access and spillovers from Seoul may give Gyeonggi a "baseline" productivity advantage. Being adjacent to Seoul and benefiting from metropolitan externalities helps Gyeonggi's regional performance beyond R&D investments alone.

Daegu registers the only negative (or near-zero) fixed effect among major regions, suggesting that after controlling for the R&D/innovation variables, its baseline productivity is slightly below the omitted (reference) region. This might reflect structural challenges: perhaps a slower rate of industrial upgrading, weaker connectivity, or legacy sectors with lower value creation. From a research standpoint: this implies that simply having R&D and researchers may not automatically translate into a higher baseline, and region-specific institutional or structural obstacles can persist.

The varying fixed effects across regions highlight that structural regional heterogeneity is large: regions differ in baseline productivity due to geography, industrial composition, historical development, institutional capacity, infrastructure, and agglomeration dynamics.

Regions exhibiting high positive fixed effects (like Ulsan and Daejeon) likely have deep structural advantages (manufacturing clusters, research hubs) that amplify the returns to R&D/innovation or generate value beyond them. Lower or negative fixed effects (like Daegu) signal that regions may face structural headwinds — for example, weaker linkages to global value chains, less specialization in high productivity sectors, or institutional obstacles. Therefore, policy implications: Improving regional economic performance will involve both enhancing R&D/innovation variables (which we test) AND addressing structural regional characteristics (which appear via fixed effects). R&D alone may not close regional productivity gaps unless the structural base is addressed.

VI. Conclusions

The results of this study reveal substantial heterogeneity in the extent to which regional R&D efforts influence economic productivity across South Korea. While indicators such as R&D expenditure relative to GRDP and the number of researchers per 10,000 people provide valuable insight into scientific and technological capacity, they do not consistently translate into higher levels of Gross Value Added (GVA). Although the analysis highlights substantial regional heterogeneity in the effectiveness of R&D investment, a formal identification and testing of heterogeneous impacts through interaction models or subgroup regressions is beyond the scope of the present study and is left for future research. Instead, the analysis identifies lagged GVA per capita as a strong and statistically significant predictor of current economic performance, underscoring the importance of cumulative growth dynamics and economic path dependence. Additionally, R&D investment per researcher demonstrates greater explanatory power than aggregate expenditures, suggesting that efficiency and quality of research activity are more critical than simple spending magnitude.

The contrasting regional patterns observed—where research-oriented regions such as Daejeon and Sejong exhibit high R&D intensity but limited short-term productivity gains, while industrial hubs like Ulsan convert comparatively modest R&D inputs into substantial economic outputs—highlight the central role of absorptive capacity, sectoral specialization, and commercialization mechanisms. These findings imply that R&D contributes to growth primarily when supported by functional innovation ecosystems capable of integrating scientific outcomes into production systems, reinforcing the view that the relationship between R&D and economic performance is complex and nonlinear rather than direct or automatic.

Empirical results from both fixed effects and system GMM estimators confirm the nuanced influence of regional context. Traditional input-oriented metrics such as total R&D spending and researcher counts are insufficient predictors in some models, whereas efficiency-oriented measures and time dynamics yield more robust results. This evidence challenges the effectiveness of uniform national innovation policies and suggests the need for differentiated, region-specific strategies aligned with industrial and institutional realities.

Two-way FE estimates show that ln(R&D investment per researcher) and lagged ln(GVA) are positive and statistically significant predictors of regional economic productivity. Conversely, ln(R&D/GRDP) remains negative, reflecting structural differences between manufacturing-based and research-dominant regional economies. System GMM results confirm path dependence in regional productivity, with strong significance of the lagged dependent variable. This study tested no problematic autocorrelation, and the Hansen test supports instrument validity.

From a policy standpoint, the findings emphasize that supporting regional innovation requires more than expanding budgetary inputs. Manufacturing-driven regions may benefit most from initiatives that accelerate industrial application, scale-up support, and supply-chain integration, while research-intensive regions require enhanced mechanisms for commercialization, technology transfer, public–private partnerships, and market diffusion of scientific outputs. Strengthening human capital is also essential, both by expanding the quantity of researchers and improving the quality and specialization of research talent aligned with regional industry needs. Building systems that facilitate collaboration among universities, research institutes, and industry will be important drivers of innovation productivity.

Further investigation into alternative lag structures of R&D impacts and a more detailed operationalization of the RIS framework remain important avenues for future research.

VII. Discussion

The results demonstrate a complex and non-linear relationship between R&D and regional growth. The contrast between Ulsan (high productivity, modest R&D inputs) and Daejeon/Sejong (high R&D intensity, modest productivity gains) underscores the role of absorptive capacity, industrial specialization, and commercialization ecosystems. Efficiency-focused metrics outperform simple input measures.

Uniform national policies are unlikely to generate optimal outcomes, suggesting a need for region-specific innovation strategies targeting as scale-up and application in manufacturing regions, commercialization and technology transfer in research-intensive regions, and human capital quality and specialization

While incorporating additional structural control variables—such as industrial composition, education attainment, and foreign direct investment (FDI)—would theoretically strengthen this study, the empirical model was constrained by the lack of consistent annual regional data at sufficient granularity. Including such variables under current statistical limitations risks introducing measurement error and model misspecification. Despite these efforts, unobserved time-varying factors—such as changes in industrial structure and scale effects—may still influence regional economic outcomes, and the results should therefore be interpreted with appropriate caution. However, as more detailed longitudinal regional datasets become available, future analysis can further elucidate the mechanisms by which R&D activities interact with structural conditions to shape regional growth trajectories.

Overall, this study reinforced the theoretical perspective that innovation-driven development depends not only on investment volume but also on systemic integration and the absorptive capacity of regional economies. By demonstrating the differentiated nature of R&D impacts across regions, this study provides evidence-based support for tailoring national innovation policy to local economic realities and calls for future research exploring firm-level dynamics, institutional environments, and long-term causal pathways linking science, technology, and economic performance.

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