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PART 1: Overview and data description

1. Overview of topic

In their study, Meng et al. (2024) identified several key variables influencing a country's innovation index. These variables encompassed various aspects, including human capital, research and development (R&D) expenditure, infrastructure quality, and business sophistication. Human capital, indicative of the education and skills of the workforce, emerged as a critical determinant, particularly in facilitating R&D activities and fostering innovation. Likewise, substantial investment in R&D was found to be pivotal for generating new knowledge and technologies essential for innovation. Furthermore, the quality of infrastructure, encompassing both physical and digital aspects, was highlighted as a significant facilitator of innovation endeavors. Additionally, factors related to business sophistication, such as the quality of business networks and market sophistication, were identified as crucial for fostering innovation linkage and knowledge absorption within economies.

Similarly, Smith et al. (2023) conducted a comparative analysis across 75 countries to delineate the determinants of national innovation performance. Their investigation underscored the importance of government policies conducive to innovation, access to finance for innovative projects, market demand dynamics, and technological infrastructure availability. These variables collectively contribute to creating an environment conducive to innovation and fostering its diffusion within economies.

Drawing from these studies and considering data availability, a comprehensive set of variables pertinent to examining factors impacting the innovation index includes education and skills indicators, expenditure on R&D activities, infrastructure quality metrics, and measures of the business environment. Such variables provide a multifaceted perspective on the underlying factors shaping a country's innovation landscape, thereby facilitating a nuanced analysis of innovation determinants.

Moreover, the nexus between innovation and Sustainable Development Goals (SDGs) underscores the pivotal role of innovation in advancing socioeconomic development agendas. Innovation contributes significantly to achieving various SDGs, including those pertaining to industry, economic growth, and quality education. As such, exploring the interplay between innovation and SDGs unveils opportunities for leveraging innovation as a catalyst for sustainable development. Consequently, research questions focusing on understanding the impact of innovation investment on specific SDGs and elucidating barriers hindering innovation adoption in low-income contexts offer avenues for advancing scholarly discourse and informing policy interventions aimed at promoting sustainable development outcomes.

2. Data Importation

The following table summarizes descriptive statistics of the selected sample, which comprises countries from region 1, 2, and 4.

Table 1: Descriptive statistics

Statistic	Innovation EfficiencyIndex	FDI	pop	inflation	growth	gdpcap	vae	pve	gee	rqe	rle	cce
Nbr. of observations	189	189	189	189	189	189	189	189	189	189	189	189
Minimum	0.000	-2812637362.637	425967.000	-25.958	-4.712	2102.593	-1.882	-1.335	-0.948	-1.303	-1.165	-1.038
Maximum	69.200	511434000000.000	328239523.000	16.231	9.608	85050.866	1.257	1.291	1.577	1.628	1.645	1.542
Median	39.200	2227300000.000	9360980.000	2.432	2.678	10490.081	0.061	-0.085	0.099	0.292	0.022	-0.159
Mean	38.893	20816457050.467	35347704.582	2.260	2.832	17410.102	-0.039	-0.079	0.190	0.261	0.065	0.044
sd	11.032	70446055266.400	71062976.725	5.304	2.034	17312.760	0.827	0.664	0.644	0.646	0.724	0.726

Innovation Efficiency Index: This variable measures the efficiency of innovation within countries. The statistics indicate that the index ranges from 0 to 69.2, with a median value of 39.2 and a mean of approximately 38.9. The standard deviation (sd) suggests a moderate level of dispersion around the mean.

According to a definition of WIPO (2016), The Innovation Efficiency Ratio is the ratio of the Output Sub-Index to the Input SubIndex. It shows how much innovation output a given country is getting for its inputs.

PART 2: Initial estimation

Model 1:

$$InnovationEfficiencyIndex = \alpha + \beta * gee + \varepsilon$$

Model 2:

$$InnovationEfficiencyIndex = \alpha + \beta_1 * gee + \beta_2 * cee + \beta_3 * pop + \beta_4 * FDI + \beta_5 * gdpcap + \varepsilon$$

- **Government Effectiveness (GEE): possitive**. The government's efficacy, which includes characteristics such as regulatory quality and government policies that foster innovation, is projected to have a positive impact on innovation efficiency (Liu et al. 2024; Zhang et al. 2024). According to studies, nations with more proficient governance systems have more favorable conditions for innovation due to supportive policies, streamlined regulation, and significant investment in research and development.

- **Control of Corruption Index (CCE): positive**. Corruption must be effectively managed in order to foster an environment conducive to innovation. Countries with lower levels of corruption typically have higher levels of trust, transparency, and ease of doing business. These factors are critical for enabling innovative activities to thrive (Zhao and Parhizgari 2024).
- **Population: uncertain**. The link between population and innovation efficiency may vary. A larger population can provide a greater number of talented individuals and potential consumers, which may aid in innovation initiatives. However, rapid population growth can put strain on resources and infrastructure, thereby impeding innovation.
- **Foreign Direct Investment (FDI): positive**. FDI has the potential to transfer new technology, skills, and capital, hence stimulating innovation in the countries that receive it. Furthermore, FDI frequently leads to the diffusion of information and the transfer of technology, which may enhance the capacity for innovation (Roh, Lee and Yang, 2021; Shi et al.2023)
- **GDP per capita: Positive**. A greater GDP per capita indicates faster economic growth and a larger pool of resources for investment in innovation. More prosperous countries typically have more sophisticated infrastructure, more educated individuals, and higher levels of R&D expenditure, all of which improve innovation efficiency (Qadeer et al. 2020)

After running the regression, we suspect that the model is not optimal owning to possible multicollineartiy. The following tables present correlations and VIF ratio of dependent variables.

Table 2: Correlation matrix

	gee	cce	pop	FDI	gdpcap	InnovationEfficiencyIndex
gee	**1**	0.899	0.217	0.386	0.731	0.585
cce	0.899	**1**	0.128	0.320	0.663	0.515
pop	0.217	0.128	**1**	0.871	0.275	0.223
FDI	0.386	0.320	0.871	**1**	0.433	0.324
gdpcap	0.731	0.663	0.275	0.433	**1**	0.466
InnovationEfficiencyIndex	0.585	0.515	0.223	0.324	0.466	**1**

Multicolinearity statistics:

	gee	cce	pop	FDI	gdpcap
Tolerance	0.156	0.183	0.214	0.190	0.436
VIF	6.416	5.463	4.672	5.265	2.294

Based on the correlation matrix and multicollinearity statistics provided, it is evident that multicollinearity exists among the independent variables. Multicollinearity occurs when independent variables are highly correlated with each other, leading to unstable estimates of the regression coefficients and difficulties in interpreting the model.

In this case, we can observe high correlations among several pairs of independent variables:

- GEE and CCE have a correlation coefficient of 0.899.
- Population (pop) and FDI have a correlation coefficient of 0.871.
- GDP per capita (gdpcap) is moderately correlated with GEE (0.731), CCE (0.663), and FDI (0.433).

Given these findings, it is advisable to remove one or more independent variables to mitigate multicollinearity and improve the model's stability and interpretability. In this scenario, considering both the correlation matrix and multicollinearity statistics, the variable that should be removed is likely to be GDP per capita (gdpcap), population, and CEE. After removing the two variables, model 3 contains Gee, population, and FDI.

Table 3: Regression results of three models

	Model 1	**Model 2**	**Model 3**
Dependent variable	InnovationEfficiencyIndex		
Independent variables			
Intercept	36.9885	36.1944	36.7559
gee	10.0190***	9.3766***	9.2529***
cce		-0.6205	
pop		3.11585E-09	

FDI		1.36864E-11	1.82E-11*
gdpcap		3.15203E-05	
F-statistic	97.3716	20.1730	33.7895
p-value	0.0000	0.0000	0.0000
R-squared	0.3424	0.3553	0.3539
Adjusted R-squared	0.3389	0.3377	0.3469
Obs.	189	189	189
****, **, and * is significant level at 1%,5% and 10% respectively*			

PART 3: Interpretation

1.

Model 1: $InnovationEfficiencyIndex = 36.9885 + 10.019 * gee$

Model 2: $InnovationEfficiencyIndex = 36.1943 + 9.3765 * gee - 0.6204 * cce + 3.1158E - 09 * pop + 1.36864E - 11 * FDI + 3.1520E - 05 * gdpcap$

Model 3: $InnovationEfficiencyIndex = 36.7559 + 9.2529 * gee + 1.8166E - 11 * FDI$

In the given regression results, Model 2 has the highest R-squared value (0.3553), indicating that it explains the largest proportion of variance in the dependent variable among the three models. However, when considering Adjusted R-squared, Model 3 has the highest value (0.3469), suggesting that it provides the best balance between model complexity and goodness-of-fit.

2.

Let's discuss the hypothesis and results of the F-test for Model 3 using a significance level of 5%:

- Null Hypothesis (H0): β1 = β2 = 0 (where β1 and β2 are the regression coefficients of the independent variables in Model 3)
- Alternative Hypothesis (HA): At least one of the regression coefficients is not equal to zero.

The F-statistic for Model 3 is given as 33.7895, with a corresponding p-value of 0.0000. Since the p-value is less than the chosen significance level of 5% (0.05), we reject the null hypothesis. This indicates that at least one of the independent variables (gee and FDI) in Model 3 has a statistically significant effect on the dependent variable (Innovation Efficiency Index).

Therefore, we can conclude that the regression model, which includes the independent variables gee and FDI collectively explains a significant amount of the variance in the Innovation Efficiency Index. The F-test results provide evidence in support of the model's overall significance and the inclusion of these independent variables in explaining innovation efficiency.

3.

GEE (Government Effectiveness): The expected effect of GEE on innovation efficiency is positive. Effective governance, characterized by transparent and efficient regulatory frameworks, supportive policies, and low levels of corruption, is conducive to fostering innovation activities (Borsatto and Amui 2019; Sun 2022). In Model 3, the estimated coefficient for GEE is positive (9.2529***), supporting the expected positive relationship between government effectiveness and innovation efficiency.

FDI (Foreign Direct Investment): The expected effect of FDI on innovation efficiency is positive. Foreign direct investment brings in new technologies, knowledge, and capital, stimulating innovation activities and contributing to knowledge spillovers and technology transfer (Peng et al. 2021). In Model 3, the estimated coefficient for FDI is positive (1.82E-11*), supporting the expected positive relationship between FDI and innovation efficiency.

PART 4: Further Estimation

Adding growth and inflation to the model can provide additional insights into their effects on innovation efficiency:

Growth: Economic growth is often positively associated with innovation efficiency. Higher economic growth rates indicate a growing economy with increased demand for new products and services, providing incentives for firms to innovate to meet market demands(Carlsson 2004; Li et al. 2022). Additionally, economic growth may lead to greater investment in research and development, infrastructure, and human capital, which can further foster innovation activities (Hao et al. 2023) . Therefore, including growth as an independent variable allows us to examine its impact on innovation efficiency and its interaction with other factors in the model.

Inflation: The relationship between inflation and innovation efficiency is more nuanced. While moderate inflation rates may signal economic dynamism and growth, excessively high inflation can create uncertainty and instability, which may deter investment and innovation (Meng et al.

2024). Additionally, inflation may affect firms' cost structures, pricing decisions, and investment strategies, potentially influencing their innovation activities (Meng et al. 2024). Therefore, including inflation as an independent variable enables us to explore its nonlinear relationship with innovation efficiency and its potential moderating effects on other variables in the model.

Model 4: $InnovationEfficiencyIndex = 33.51758 + 8.9194 * gee + 2.2491E - 11 * FDI + 3.2273E - 03 * inflation + 1.1315 * growth$

The F-statistic of 30.226 with a p-value of less than 0.0001 indicates that the model is statistically significant at 1% significance levels (***), suggesting that at least one of the independent variables significantly explains the variation in the dependent variable (Innovation Efficiency Index).

Examining the individual coefficients, we observe the following:

- GEE (Government Effectiveness): The coefficient is significant (t-value = 8.314, p-value < 0.0001), indicating that government effectiveness has a statistically significant positive effect on innovation efficiency.
- FDI (Foreign Direct Investment): The coefficient is significant (t-value = 2.295, p-value = 0.023), indicating that FDI also has a statistically significant positive effect on innovation efficiency.
- Inflation: The coefficient is not significant (p-value = 0.979), suggesting that inflation does not have a statistically significant effect on innovation efficiency in this model.
- Growth: The coefficient is significant (t-value = 3.538, p-value = 0.001), indicating that economic growth has a statistically significant positive effect on innovation efficiency.

Considering the significance of the model and variables, the final preferred model for examining the determinants of innovation would be Model 4. This choice is based on several factors:

- Overall Model Significance: Model 4 demonstrates overall significance, with a highly significant F-statistic in the ANOVA results, indicating that the model as a whole is statistically significant.

- Individual Variable Significance: The significant coefficients for GEE, FDI, and growth suggest that these variables have statistically significant effects on innovation efficiency, aligning with theoretical expectations and empirical evidence.
- Adjusted R-squared: Model 4 has an adjusted R-squared value of 0.383, indicating that approximately 38.3% of the variation in the dependent variable (Innovation Efficiency Index) is explained by the independent variables included in the model.

PART 5: Conclusion

The analysis conducted encompassed four main parts, starting with a study by Meng et al.(2024) , which aimed to fill gaps in understanding the determinants of innovation performance across 63 countries of varying income levels. This research identified key pillars influencing innovation performance, including human capital, research and development (R&D), infrastructure, and business sophistication. Additionally, variables like innovation linkage and knowledge absorption emerged as critical predictors across income categories. Subsequent regression analysis revealed significant impacts of government effectiveness (GEE), foreign direct investment (FDI), and economic growth on innovation efficiency. Model 4 emerged as the preferred model, including GEE, FDI, inflation, and growth, due to its overall significance and theoretical relevance.

Policy recommendations were proposed to enhance innovation in the assigned groups of countries. Emphasis was placed on enhancing government effectiveness through transparent regulatory frameworks and attracting FDI to stimulate innovation. Additionally, policies promoting economic growth and fostering collaboration between public and private sectors were suggested. These recommendations align with Sustainable Development Goals (SDGs) related to industry, innovation, infrastructure, decent work, economic growth, and quality education, contributing to sustainable and inclusive development.

However, the analysis also highlighted limitations, including multicollinearity among independent variables, potential omitted variable bias, and the need for further refinement of regression models. Suggestions for improvement included addressing multicollinearity through variable selection or transformation, controlling for omitted variables, and conducting robustness checks. By incorporating these improvements, future analyses can provide more accurate insights into the determinants of innovation, informing evidence-based policy recommendations for sustainable development.

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