Government Technology Maturity on Economic Wealth, Technological Infrastructure and Regional Differences

Abstract

This study examines the factors correlating to **Government Technology Maturity Index (GTMI)** across 112 countries. Utilizing regression models, I explore how economic wealth, education investment, human capital, labor force dependency, technological infrastructure and regional factors contribute to the maturity of government technology. The findings indicate a significant correlation between the economic wealth of a country and the government technology maturity, along with human capital and technological foundation quality.

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1. Introduction

The government has always been the backbone of any country, especially in the modern world where everything changes fast as technology progresses. Understanding the factors that can drive government technology to overcome the rising challenges of efficiency, transparency and public engagement is crucial for any country. The Government Technology Maturity Index (GTMI) is one of the pivotal benchmarks to assess how governments incorporate technology into their operations and services to meet public expectations.

This paper aims to:

- Identify the key indicator of GMTI across different countries
- Analyze the correlation between GMTI, economic wealth and education spending
- Analyze the correlation between GMTI, economic wealth, human capital and population dependency on the labor force
- Analyze the correlation between GMTI, economic wealth and technological infrastructure
- Analyze any correlation between GMTI and regional disparities

Based on intuition and preliminary observation of the data, the following are the expectations of the relationship between GTMI and the dependent variables to be verified with this study:

- Wealthier countries with higher GDP per capita have higher GTMI
- Countries investing more in education have better GTMI
- Countries with higher human capital and lower population dependency on the labor force obtain higher GTMI
- Countries with better technological infrastructure and research have higher GTMI
- Regional factors have a significant influence on a country's GTMI

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2. Data

The data used in this paper comes from the World Bank Data Catalog, mainly from the GovTech Dataset and the World Development Indicators dataset. The two datasets are merged and enhanced with the World Bank country ISO 3 code metadata to obtain the appropriate country continents and regions. Originally, the merged data contained 198 observations, where each observation is one country. However, due to missing data from the World Development Indicators dataset across different features and countries, the filtered data consists of 112 observations.

For this study, the primary dependent variable is GTMI, representing government technology maturity. However, since the GTMI values range from 0 to 1, I will instead transform it into GTMIx100, which is 100 times the original GTMI value for better clarity. Inherently, each unit increase in GTMIx100 will be understood as a hundredth increase in GTMI. Meanwhile, the exploratory variable is the natural log of GDP per capita, while other control variables are divided into 4 main groups: Educational and spending indicators, Human capital indicators, Technological advance indicators and Regional indicators. All independent variables are listed and explained below with their appropriate transformation:

- Exploratory variable:
  - Natural log of GDP per capita
- Educational indicators:
  - Government expense on education (percentage of GDP)
  - Government overall expense (percentage of GDP)
- Human capital indicators:

- Human capital index HCI (percentage)
- Age dependency ratio (percentage of population under 15 and over 64 dependent on the working age)
- Natural log of urban population

- Technological advance indicators:
  - Population with access to electricity (percentage of total population)
  - Statistical performance indicator SPI (measurement of a country's data system performance)
  - Natural log of scientific publications
- Regional indicators:
  - Dummy variables by continents, with the American continent as the reference group

The table below shows descriptive statistics for some of the key variables:

Out[7]:

	GTMIx100	ln(GDP/Pop)	HCI	AgeDep	ln(UrbanPop)	ElectricityAccess	SPI	ln(SciencePub)
mean	64.08	8.82	57.83	60.37	15.65	85.86	67.74	7.20
std	22.89	1.52	14.83	14.83	1.72	24.64	16.43	2.67
min	7.00	5.40	29.98	31.35	10.40	10.23	20.86	0.46
25%	48.95	7.60	44.65	51.48	14.67	85.44	54.94	5.11
50%	73.90	8.69	58.92	55.86	15.66	100.00	69.61	7.30
75%	81.47	10.13	70.94	67.38	16.92	100.00	82.60	9.44
max	95.60	11.80	87.91	105.44	20.60	100.00	90.09	13.41

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3. Models

For this study, I construct multiple models, each trying to validate the finding expectations made in the introduction. Each model has GTMIx100 as the dependent variable, the natural log of GDP per capita as the exploratory variable along with the appropriate control variables. The models are simple linear regressions with HC1 covariance type to ensure robustness to heteroscedasticity.

Model 1 - GMTI on rate of change in GDP per caipta

$GTMI \times 100 = \beta_0 + \beta_1 \times \ln(GDP/Pop)$

Model 1 is a simple linear regression of GMTIx100 on the natural log of GDP per capita (see **Appendix B** for the regression table). From the model, I obtain β_1 with the value of 8.86 and the R-squared of 0.34. This suggests for a 1% increased in the GDP per capita, the GTMIx100 increases by 8.86 on average, equivalent to a 0.0886 increase in the original GTMI score. The β_1 is significant at 1%, which strongly indicates the same pattern can be observed across countries.

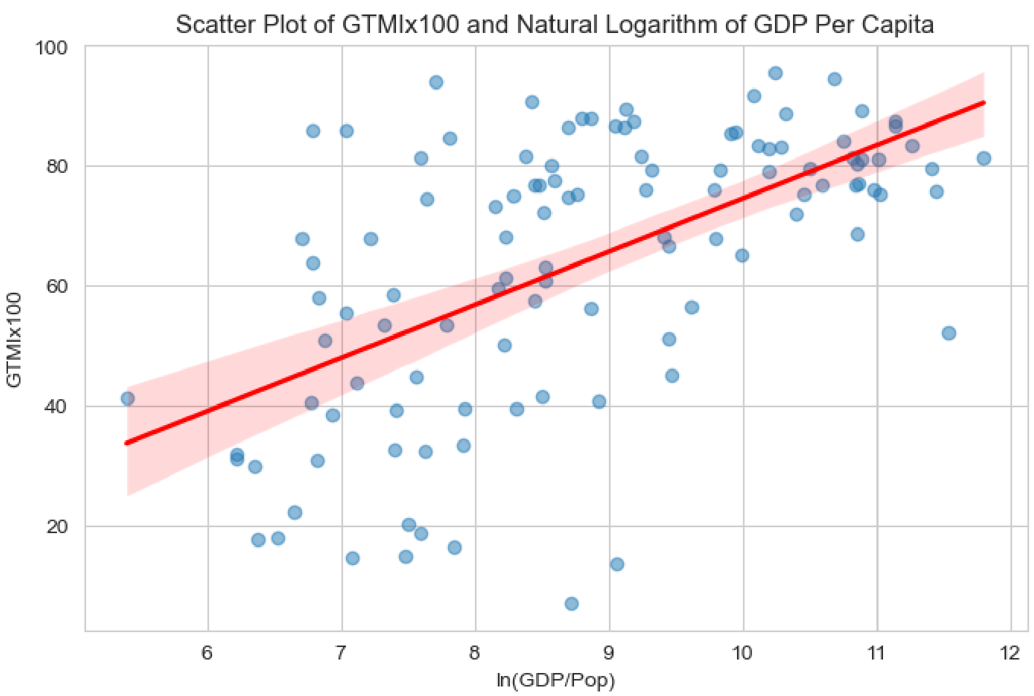

fig.1: Scatter Plot of GTMIx100 and Natural Logarithm of GDP Per Capita

However, when I first checked the Loess regression between GTMIx100 and the log of GDP per capita, the Loess line suggests a non-linear relationship (see **Appendix A** for the Loess scatter plot). When the log of GDP per capita is at 10 onward (equivalent to countries having GDP per capita from ~20,000 onward), the regression line is almost flat. To examine this relationship more closely, I construct model 1.1, which includes a squared term for a log of GDP per capita (see **Appendix A** for the non-linear scatter plot):

$$GTMI \times 100 = \beta_0 + \beta_1 \times \ln(GDP/Pop) + \beta_2 \times \ln(GDP/Pop)^2$$

In model 1.1, β_2 is -1.32 and is significant at 10%. This suggests that initially, as GDP per capita increases, GTMIx100 increases at a faster rate, but when GDP per capita is beyond ~20,000, the rate of increase in GTMIx100 starts to diminish. The R-squared of model 1.1 is 0.35, higher than model 1 R-squared of 0.34, proving to be a slightly better fit. Hence, the diminishing return behavior where wealthier countries with high GTMI benefit less from additional increases in wealth is likely to happen in the world.

Model 2 - GMTI on government education expense

$$GTMIx100 = \beta_0 + \beta_1 \times \ln(GDP/Pop) + \beta_2 \times EducationExp + \beta_3 \times OverallExp$$

This model tries to explain if the government education expense and overall expense have an additional impact on the country GTMI (see **Appendix B** for the regression table). In this model, the β_1 is 9.83, while β_2 and β_3 are -0.5 and -0.61 respectively. Only β_1 is statistically significant, while β_2 and β_3 are not. Contrary to my initial expectation that countries investing more in education have better GTMI, this model suggests I may not have enough data or there is no relationship between the GTMI and the government spending across countries. However, GDP per capita remains to be the significant factor correlated to a country's GTMI as this model's R-squared value of 0.4 is higher than model 1's R-squared (see **Appendix C** for the fitness score table of all models).

Model 3 - GMTI on human capital

$$GTMI \times 100 = \beta_0 + \beta_1 \times \ln(GDP/Pop) + \beta_2 \times HCI + \beta_3 \times AgeDep + \beta_4 \times \ln(UrbanPop)$$

Model 3 examines the correlation between GMTIx100, the log of GDP per capita and a country's human capital (see **Appendix B** for the regression table). In model 3, β_1 is -0.75, β_2 is 0.84, β_3 is -0.35 and β_4 is 3.62. Almost all coefficients are significant at 1%, except for β_1. This means while GMTIx100 has a negative correlation with economic wealth, it is marginal in value and is not statistically significant. Rather, in this model, the variance in GMTIx100 is better explained by the other three independent variables in the model. From model 3, if all other variables are kept the same:

- GMTIx100 *increases* by 0.84 on average (equivalent to a 0.0084 *increase* in the GMTI) when the country's HCI increases by 1%
- GMTIx100 *decreases* by 0.35 on average (equivalent to a 0.0035 *decrease* in the GMTI) when the age dependencies increase by 1%
- GMTIx100 *increases* by 3.62 on average (equivalent to a 0.0362 *increase*** in the GMTI) when the urban population in the country increases by 1%

The model has an R-squared of 0.52, higher than both of the previous models, suggesting that it is a better fit (see **Appendix C** for the fitness score table of all models). Overall, while human capital and urbanization have a positive influence on government technology maturity, having a small labor force or aging population negatively impacts the maturity of government technology.

Model 4 - GMTI on technological advance

$$GTMIx100 = \beta_0 + \beta_1 \times \ln(GDP/Pop) + \beta_2 \times ElectricityAccess + \beta_3 \times SPI + \beta_4 \times ln(SciencePub)$$

This model tackles the hypothesis that countries with better technological infrastructure and research have higher GTMI (see **Appendix B** for the regression table). The coefficients of model 4 are: β_1 is -2.04, β_2 is 0.19, β_3 is 0.83 and β_4 is 1.83. Again, all coefficients are significant at 5% and 5% except β_1. This suggests that the other three independent variables are better at explaining the variance in the GMTIx100:

- GMTIx100 *increases* by 0.19 on average (equivalent to a 0.0019 *increase* in the GMTI) when 1% more of the population has access to electricity
- GMTIx100 *increases* by 0.83 on average (equivalent to a 0.0083 *decrease* in the GMTI) when the country's statistical performance improves by 1%

- GMTIx100 *increases* by 1.83 on average (equivalent to a 0.0183 *increase*** in the GMTI) when there are 1% more scientific publications

The R-squared of model 4 of 0.63 is the highest fitness score among the 5 main models, meaning a country's technological infrastructure has the strongest influence on government technology maturity compared to other groups of indicators in this paper (see **Appendix C** for the fitness score table of all models).

On the other hand, it is worth noting that the coefficient of the log of GDP per capita in model 4 becomes negatively large. However, it is still not statistically significant here. Given that β_1 is mostly always significantly positive in previous models, this change in sign might suggest that there is some complexity in the correlation between GDP per capita and the other independent variables in this model. To examine it more carefully, I construct model 4.1 to include an interaction term for the log of GDP per capita and the SPI:

$$GTMI \times 100 = \beta_0 + \beta_1 \times \ln(GDP/Pop) + \beta_2 \times ElectricityAccess + \beta_3 \times SPI$$
$$+\beta_4 \times ln(SciencePub) + \beta_5 \times \ln(GDP/Pop) \times SPI$$

Model 4.1 reveals that β_5 has a value of -0.28 with a significant level of 1%, meaning when a country's data system quality improves, the effect of economic wealth on government technology maturity diminishes. In this model, β_1 is positive again with a significant level of 1% revealing that GDP per capita is still a key factor in the GTMI correlation. However, as the other control variables in the technological advance indicators group better explain the variance in GTMI and the negative correlation with the control variables, the log of GDP per capita in model 4 (and also possibly in model 3) appears less significant.

Model 5 - GMTI on regional factors

$$GTMIx100 = \beta_0 + \beta_1 \times \ln(GDP/Pop) + \beta_2 \times isEurope + \beta_3 \times isAsia + \beta_4 \times isAfrica + \beta_5 \times isOceania$$

This model tries to explain if there are regional factors have an additional impact on the government technology maturity. I use dummy variables for different continents, with the American continent as the reference group (see **Appendix B** for the regression table). In this model, β_1 is 6.38, while β_2 to β_5 are 4.23, 7.36, -10.21 and -19.5 respectively. β_2 and β_3 suggest that European and Asian countries on average have higher government technology maturity, while β_4 and β_5 suggest that African and Oceanian countries on average have much lower maturity in government technology. However, only β_1 is statistically significant, while β_2 to β_5 are not. This means the data in this paper cannot guarantee that such regional differences exist across all countries. GDP per capita, on the other hand, remains the significant factor correlated to a government technology maturity as this model's R-squared value of 0.42 is higher than model 1's R-squared (see **Appendix C** for the fitness score table of all models).

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4. Findings Summary and Limitations

Through all 5 models and the alternative models constructed in this paper, the GDP per capita consistently emerges as the significant factor suggesting that economic wealth is a key indicator of government technology maturity. It is intuitive as countries with more financial resources have a better chance to invest and adopt new technologies. However, the analysis also points out that economic wealth has a diminishing return effect: the benefit of wealth on technology maturity decreases in wealthier countries. Aside from economic wealth, other factors also significantly contribute as the indicators of maturity in government technology: Human capital and Technology infrastructure. Countries with larger, younger and more urbanized labor force generally have a higher level of technology maturity. This is also aligned with the intuition that the working age population has frequent demand for government services and is quicker to adopt new technologies. Countries with already highly developed technology infrastructure can quickly meet the population demand and easily scale their operations for better service coverage and quality, hence leading to higher government technology maturity. Aside from these factors, the analysis fails to provide conclusive results on the correlation between technology maturity, government education spending and regional differences.

This paper, while yielding key indicators for government technology maturity, is only a cross-sectional analysis. This nature limits the possibility of making causal inferences as more data is needed to examine the changes in the key indicators that would affect government technology maturity. However, this paper's findings still have significant implications for policymakers. To grow the technologies in the public sector, policymaker should focus their resource investment on economic development and human capital (health and education). However, policymakers should also stay aware of the diminishing return of wealth on technology maturity. When the country's GDP per capita grows to five figures, the investment focus might shift to technological research and improvements in infrastructure, which foster innovation and accessibility.

References

World Bank Group. (2023, March 22). GovTech Dataset.
https://datacatalog.worldbank.org/search/dataset/0037889/GovTech-Dataset

World Bank Group. (2023, November 16). World Development Indicators.
https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators

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Appendices

Appendix A

Scatter plots with regression line of GMTIx100 and Natural Logarithm of GDP Per Capita

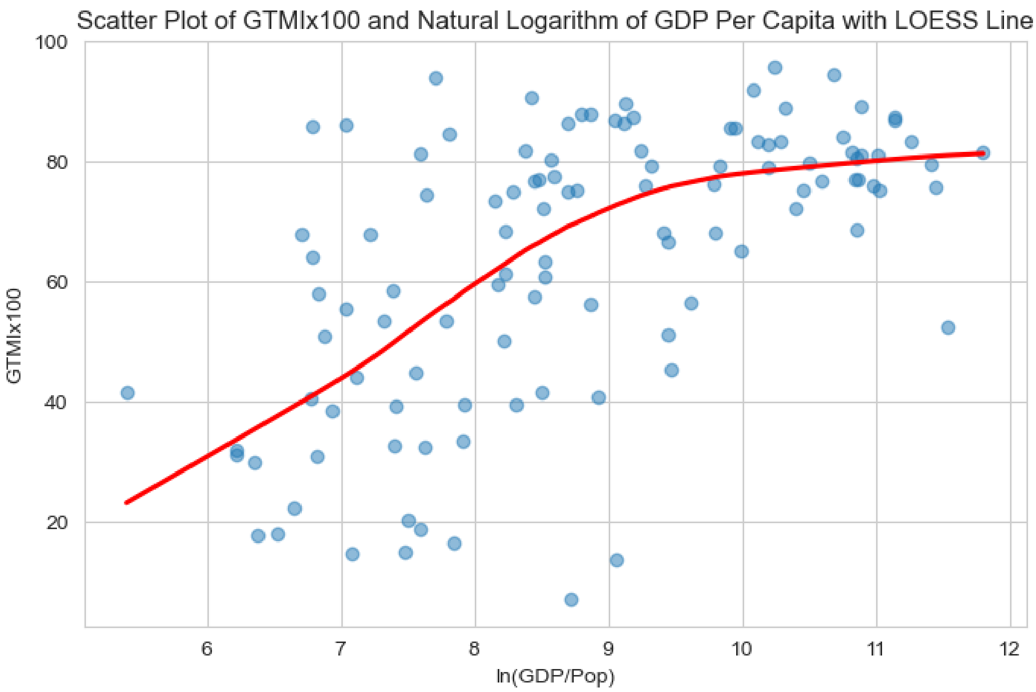

fig. 1.2: Scatter Plot of GTMIx100 and Natural Logarithm of GDP Per Capita with LOESS Line

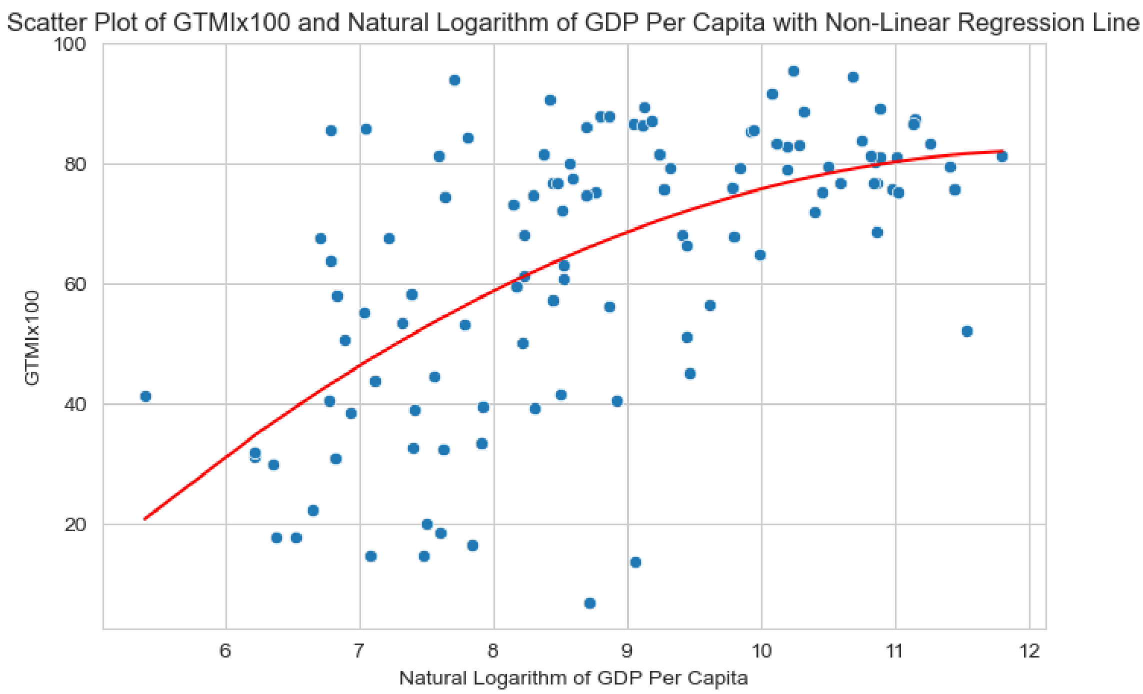

fig. 1.1: Scatter Plot of GTMIx100 and Natural Logarithm of GDP Per Capita with Non-Linear Regression Line

Appendix B

Regression Table (All models)

Out[16]:

							Dependent variable: GTMIx100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-14.133	-114.743**	-9.604	-13.585	-3.832	-173.577***	8.599
	(9.875)	(57.514)	(11.119)	(20.933)	(8.350)	(53.795)	(17.243)
ln(GDP per capita)	8.863***	32.246**	9.828***	-0.754	-2.044	19.780***	6.376***
	(1.020)	(13.101)	(1.140)	(2.630)	(1.608)	(7.214)	(1.744)
ln(GDP per capita) squared		-1.319*					
		(0.726)					
ln(GDP per capita):SPI						-0.283***	
						(0.089)	
Education Expense			-0.496				
			(1.273)				
Overall Expense			-0.612**				
			(0.297)				
Human Capital Index (HCI)				0.841***			
				(0.277)			
Age Dependencies				-0.349***			
				(0.129)			
ln(Urban Population)				3.623***			
				(0.931)			
Electricity Accessibility					0.193**	-0.004	
					(0.088)	(0.115)	
Statistical performance indicators (SPI)					0.829***	3.299***	
					(0.135)	(0.793)	
ln(Scientific Publications)					1.832***	2.015***	
					(0.688)	(0.692)	
isEurope							4.233
							(6.226)
isAsia							7.360
							(6.408)
isAfrica							-10.210
							(7.696)
isOceania							-19.504
							(12.817)
Observations	112	112	112	112	112	112	112
R^2	0.344	0.362	0.414	0.540	0.641	0.675	0.444
Adjusted R^2	0.339	0.350	0.398	0.523	0.628	0.659	0.418
Residual Std. Error	18.614 (df=110)	18.448 (df=109)	17.755 (df=108)	15.814 (df=107)	13.965 (df=107)	13.358 (df=106)	17.463 (df=106)
F Statistic	75.490*** (df=1; 110)	39.396*** (df=2; 109)	27.128*** (df=3; 108)	30.132*** (df=4; 107)	68.237*** (df=4; 107)	57.714*** (df=5; 106)	17.087*** (df=5; 106)
Note:							*p<0.1; **p<0.05; ***p<0.01

Appendix C

Fitness Score Table (All models)

Out[17]:

Model	Model 1	Model 1.1	Model 2	Model 3	Model 4	Model 4.1	Model 5
R-squared	0.34	0.36	0.41	0.54	0.64	0.67	0.44
Adjusted R-squared	0.34	0.35	0.40	0.52	0.63	0.66	0.42
F-statistic	75.49	39.40	27.13	30.13	68.24	57.71	17.09