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**I. Introduction**

Intuitively, the role of Information and Communication Technologies (ICT) has signified a transition from a mechanical to a digital perspective on society. This in turn has led the economic community to critically re-examine classical interests like the development of labor and capital but also expand that inquiry to models of online behavior, mobile connectivity, digital consumption behaviors, and the changes in social development abroad. Citing theory, it is indisputable that investments in technology correlate to an increase in productivity and thus, output (however the model defines it) yet the challenge seems to be a consensus on how to model the elusive dynamic of digital “consumption” as an empirical effect on a given economy. For one, to differentiate and control the volatility of an ever-innovative field like digital technology is a complicated endeavor and secondly, the empirical interaction of use is yet to be correlated. This paper questions the effect of digital technologies and internet usage onto GDP growth rate across nations by interacting the production model of labor and capital (employment to population ratio + gross capital formation, given in USD) with ICT investments, the Mobile Connectivity Index (MCI), and the Human Development Index (HDI). Further, the paper questions if specific forms of internet usage in leisure affects GDP. It does this by isolating the variables of individuals ages 16-74 across nations that use the internet for self-uploaded content, video entertainment, and music. Applicably, this paper hopes to identify a causality between the usage of digital technologies (for any purpose, fiscal or leisure) within the proxy of mobile connectivity and human development by carefully observing panel data of nations per year between years 2010 – 2022. Having motivated the significance of measuring the consumer’s activity in the digital sector it is necessary to first consult the relevant literature on the subject by noting the nuances of its models and appropriate methodologies then apply those insights into a theoretically consistent model.

**II. Literature Review**

It seems the literature on ICT investments and GDP tend to focus on the mixed results of its empirical research of panel data by concentrating its models into grouped nations, applying their data onto a production function of any variable of economic activity. Nasab and Aghaei (2009) for example, applied data on OPEC member countries’ ICT and economic growth from 1990 – 2007 and discovered a positive influence in ICT supply on economic growth. Their research modelled FDI as its technological variable and concluded that for any OPEC nation to experience the associated payoffs of ICT investment they must “have the social and cultural infra-structures and skills required for utilizing [its] capabilities [and must] ensure necessary financial resources for investing in network infrastructures” (54). In a related study of ICT investments, Ahmed and Ridzuan (2012) discovered a positive correlation on ICT investment for ASEAN5+3 countries (i.e., Malaysia, Thailand, Singapore, Indonesia, Philippines, Japan, Korea, and China) as a percentage of GDP, Capital, Labor, and Telecommunications investment. Crucially, Ahmed and Ridzuan deliberated on the model’s methodology by controlling for the none effect, fixed effect, and random effect citing that the criteria for an unbiased OLS regression of labor, capital, and telecommunications technology are not satisfied. Thus, their paper employed a GLS regression to control autocorrelation in the data. So, it would seem reasonable that to create an attempt to for an unbiased and consistent production model incorporating a larger variable set it must control for none, fixed, and random effects with a GLS regression method.

Other researchers in the field have identified setbacks in the metric of economic growth itself when correlated to digital consumption due to the limitations of GDP measures as a ‘mismatch’ of product innovation from ICT. Watanabe et. al. (2018) sought to reconcile this critical issue of “uncaptured GDP.” In doing this, they recognized ten key differences of the digital economy (e.g., value provided free of charge, the intangibility of mobile and digital goods, and a thinning boundary between consumption and production, i.e., “prosumers”). Fundamental for Watanabe et. al. is that these differences in the digital sector underpin an exacerbated lag of available statistical measures on the period of digital significance which seems to fuel their opinion of centralized measures of indices. They conclude that ICT tends to be “two-faced” in that it “contributes to enhanced prices of technology… whereas the dramatic advancement of the internet decreases the prices of [said] technologies” which, in turn, gets replicated by other services which cannot be captured by GDP (237).

Expanding on the complications of digital consumption in their own research, Li and Wu (2023) examined the impact of the digital economy on high-quality economic development across China and her provinces by critically examining the theoretical framework implied by digital innovations. For one, they identified a non-linear influence citing a relationship of the digital economy’s manifestation as a developmental conformity to Metcalfe’s law, Moore’s law, and Davido’s law which highlight the exponential tendency of technological innovation. The connection here to the role of ICT, and MCI is intuitive—if the technologies that generate the platform for its interface are themselves non-linear, its own iterative upgrading will also be nonlinear. From this and several other similar assumptions mentioned previously Li and Wu concluded that the positive correlation of the digital economy must be realized as a mismatch between consumer demand’s intermediary in the digital sector for supply.

Finally, the interaction of ICT investment on GDP growth on contemporary issues, i.e., COVID-19 was captured by Olender-Skorek et. al. (in the European Union in a natural experiment from 2010 – 2020. Similar to the previous literature, their model applied the Cobb-Douglas form of production onto GDP with technology but applied metrics onto the elasticity of production and non-ITC capital investment with a variable for COVID related deaths per 1000. They found that the impact of COVID-19 is statistically significant in appropriate years and that “with the outbreak of the pandemic, the ICT market has gained in importance [from a] previously statistically insignificant variable of household broadband Internet penetration has become statistically significant” (66).

A review of the literature on ICT investment, GDP, and the digital sector has revealed the following takeaways:

1. ICT investment is best modelled as a Cobb-Douglas production function of GDP as a technological variable.
2. The quality of digital and information technologies in general are elusive to measure as their values are volatile in a given year. Its impact might be nonlinear, an expression of uncaptured GDP, and/or a “two-faced” mismatch of demand and supply.
3. For econometric analysis, the model must control for volatility using a variety of techniques ranging from GLS regressions, nonlinear models, or hedonistic pricing.

Having reviewed the contentions of the literature, it becomes necessary to apply these nuances to the motivations outlined by this paper, i.e., to capture both the impact of ICT and digitalization on a given economy but also measure the human element of behavior and utility in GDP. Specifically, this paper hopes to add to current literature on this model but exploring the role of digital behaviors of content uploads, television and music consumptions as an affect onto GDP.

**III. Model**

The Cobb-Douglas production function is represented as *Y­t = At F[Kt, Lt]*, with *Yt* referring to total production, *A****t*** is technological progress, *Kt* is capital, and *Lt* represents the labor force. However, introducing the ICT is itself correlated to spending from GDP growth rate so it is necessary to isolate the effect of ICT investment from a nation’s capital investment which is *Y = AL + F[K – ICT] + ICT*. Where *AL* is the product of technology and labor which is itself multiplied by the difference of capital investment and ICT investment to isolate a nation’s spending on non-ICT capital. To expand upon the theory, this paper has included the two independent variables of MCI and HDI as latter influences on the dependent variable, GDP. Thus, our initial econometric model becomes:

*rGdpi = βo­ + β1ln\_AL + β2ln\_KnICT + β4ln\_MCI + β5ln\_HDI + ε*

In this case, the Cobb-Douglass model has been presented in the Ordinary Least Squares form only as a method to introduce the theory before tackling the complexities outlined in *Literature*. If the results of this paper are consistent with the findings of previously literature, we would expect that both the percentage change in labor (*ln\_AL*) and non-ICT capital investments (*ln\_KnICT*) must have *β* > 0. However, the defining quality of this research question concerns the types of internet usage namely, individuals 16-74 across OECD nations that use the internet for either self-created content (i.e., YouTube), web-streamed television, and listening to music. So, the model above is adjusted to include:

*rGdpi = βo­ + β1ln\_AL + β2ln\_KnICT + β4ln\_MCI + β5ln\_HDI + β6pctytb + β7pcttel + β8pctmus + ε*

Where *pctytb* is the percent of a nation’s population using self-broadcasting websites, *pcttel* is the percent population on web-mediated television streams, and *pctmus* is likewise, the percent population engaged in consumption of digitally accessed music. This paper proposes that at least one of these measures *β*is significantly different than zero due to the scatter-like quality of internet usage. Basically, impressions received from some content might subliminally induce changes in consumption which could be measured in GDP growth rate. Either a positive or negative impact could be rationalized. As a positive correlation, it seems reasonable to suspect that as various internet behaviors are practiced the potential buyer (i.e., the consumer of the respective variable’s content) might be influenced to purchase more products which can be measured in GDP. Thus, the positive correlation is a story of digital marketing efficacy. As a negative correlation, one might identify internet behaviors as a “distraction” from consumption leading to a decrease in GDP. So, the higher the percent increase, the greater net change in GDP growth, hence the transposition of all variables in logarithmic form. This modelling can be summarized by the populations of Table 1.

**Table 1: Econometric Model, Predictions and Sources**

|  |  |  |  |
| --- | --- | --- | --- |
| *Econometric model:* | *rgdpi = β1­ + β2 ln\_A + β3 ln\_L + β4 ln\_KnICT + β5 ln\_MCI + β6 ln\_HDI + β7 pctYTB+ β8 pctTV + β9 pctMUS + ε* | | |
| *Predictions:* |  | **Predictions** | **Data Sources** |
| *Dependent Variable:* | GDP % (ln\_gdp) | *NA* | [The World Bank](https://databank.worldbank.org/source/world-development-indicators) |
| *Cobb-Douglas Independent Variables:* | Percent change in Technology factor, ICT, (ln\_A) |  | [UNDP: Digital Development Compass](https://www.digitaldevelopmentcompass.org/country/USA) |
|  | Percent change in Labor Force (ln\_L) |  | [The World Bank](https://databank.worldbank.org/source/world-development-indicators) |
|  | Capital in isolation of ICT expenditure (*ln\_KnICT*) |  | [UNDP: Digital Development Compass](https://www.digitaldevelopmentcompass.org/country/USA) |
| *Digital Infrastructure Independent Variables:* | Mobile Connectivity Index (*ln\_MCI*) |  | [UNDP: Digital Development Compass](https://www.digitaldevelopmentcompass.org/country/USA) |
|  | Human Development Index (*ln\_HDI*) |  | [UNDP: Digital Development Compass](https://www.digitaldevelopmentcompass.org/country/USA) |
| *Digital Behaviors Independent Variables:* | Population consuming digital services for YouTube (*pctYTB*) |  | [Organization for Economic Cooperation and Development (OECD)](https://stats.oecd.org/Index.aspx?DataSetCode=ICT_HH2) |
|  | Population consuming digital services for web access television (*pctTV*) |  | [Organization for Economic Cooperation and Development (OECD)](https://stats.oecd.org/Index.aspx?DataSetCode=ICT_HH2) |
|  | Population consuming digital services for music (*pctMUS*) |  | [Organization for Economic Cooperation and Development (OECD)](https://stats.oecd.org/Index.aspx?DataSetCode=ICT_HH2) |

**IV. Data Analysis**

The main concern of the model is that being panel data whose unit of observation is country and year, the datasets do not share identical periods and array of nations. This makes merging the datasets tricky but also bottlenecks the available array for the model to analyze. To understand the problems in merging the data, the year sets for each database have been tabulated below:

|  |  |
| --- | --- |
| Dataset | Years Covered |
| Real GDP Growth Rate | 1980 - 2028 |
| Mobile Connectivity Index | 2014 - 2021 |
| Capital Expenditures | 1961 - 2022 |
| Real GDP in USD | 1990 - 2022 |
| Human Development Index | 1990 - 2021 |
| YouTube Use Percentage | 2008 - 2023 |
| Web-Stream Use Percentage | 2016 - 2023 |
| Digital Music Use Percentage | 2016 - 2023 |

Some of the insights from the years covered are unusual. Firstly, the World Bank’s dataset on Real GDP Growth Rate must have been forecasting later years, hence the extension into 2028 (which, of course, has been excluded from this analysis). The most important takeaway is that there is hardly any consistency between the time frames of the data sets, even data one would expect to be packaged together is not. For example, the OECD started collecting digital behavior statistics (the source of *pctytb*, *pcttv*,and *pctmus*) but YouTube’s data stretches back to 2008 and not 2016 like the rest of their data. Common reasoning would suggest that because YouTube has been a data collecting website since its launch in 2008, the website would have more data available for research from the years prior to public data collection.

Two of the datasets stretch back to before the 1990s while the rest thereafter, the most significant being the model’s dependent variable, Real GDP Growth Rate. The result will be a diaspora of connected observations back onto the GDP growth rate with many observations not being matched properly. The answer is to specify the model’s timeframe into a year set that is within the confines of the data set’s diaspora. So, the maximum year for regression analysis must be 2021. However, choosing the minimum year for regression can significantly limit the data available so three potential runs are proposed. The first is by running a regression between years 2000 – 2021 for variables *rgdp ln\_AL, and ln\_KnICT* since it can hone the explanatory power of a Cobb-Douglas production function across nations. Secondly, by running a regression between 2014 – 2021 for the Cobb-Douglas function plus *ln\_MCI,* and *ln\_HDI* to isolate the effects of the Mobile Connectivity Index and Human Development Index as a proxy for digital behaviors onto GDP. Finally, by running a regression between the years 2016 – 2021 to capture the key variables of *pctYTB, pctTV,* and *pctMUS.*

Having refined the model and identified time frame differences, a summary of each variable’s statistical measurements is provided:

**Table 2: Summary Statistics**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Number of Observations** | **Mean** | **Standard Deviation** | **Minimum** | **25th percentile** | **Median** | **75th percentile** | **Maximum** |
| Real Growth % in GDP (rgdp) | 8663 | 3.326 | 5.38 | -36.8 | 1.4 | 3.4 | 5.7 | 74.4 |
| Percent Change in Technology factor, ICT, (ln\_A) | 696 | 21.307 | 1.841 | 16.74 | 16.889 | 21.386 | 25.747 | 25.930 |
| Percent Change in Labor Force (ln\_L) | 5397 | 4.012 | 0.217 | 3.097 | 3.161 | 4.037 | 4.470 | 4.479 |
| Capital expenditures net ICT investment (KnICT) | 696 | 25.037 | 1.680 | 21.175 | 23.982 | 26.251 | 29.067 | 29.187 |
| Mobile Connectivity Index (ln\_MCI) | 1320 | 3.979 | 0.396 | 2.481 | 3.756 | 4.077 | 4.271 | 4.527 |
| Human Development Index (ln\_HDI) | 5332 | -0.434 | 0.278 | -1.532 | -0.603 | -0.364 | -0.039 | -0.039 |
| % Population using YouTube (pctYTB) | 333 | 0.275 | 0.134 | 0.001 | 0.179 | 0.266 | 0.361 | 0.732 |
| % Population using web-streamed TV (pctTV) | 111 | 0.373 | 0.186 | 0.103 | 0.229 | 0.347 | 0.467 | 0.831 |
| % Population using web-streamed music (pctMUS) | 139 | 0.528 | 0.138 | 0.203 | 0.431 | 0.509 | 0.613 | 0.889 |

*Note: Summary statistics given for their respective data set’s year frame, not the model’s desired application and excluding outliers in GDP growth.*

As expected, the observations per variable varies significantly with the smallest collection being the digital behaviors data from the OECD, the highest being Real GDP Growth Rate and significantly high values for HDI and MCI. This makes sense because the OECD data is more selected in its basket of nations, the World Bank on GDP is a huge database featuring every known area for over forty years and MCI and HDI are also large databases compiled per nation over many years. There are some interesting findings from the summary statistics. Initially, the smallest GDP growth rate is -54.2% and the highest is 110.5% which is a huge range which might impede a strong correlation attempt of this essay’s small collection of variables so GDP growth rates above 80% and below -40 were removed. To a degree, this large variation in GDP is to be expected since nations are also incredibly varied in size, wealth, influence, infrastructure, etc. and different economic conditions worldwide (e.g., COVID-19) would have varying effects on different nations yielding a huge variety of growth ranges. The other interesting observation is that HDI tends to be negative with both its median and mean value being at least a -43.4% decrease in a nation’s previous year. It seemed reasonable that as a nation grew so too would its HDI especially since the average and median growth rates in GDP are both positive. But according to news from the United Nations (Sept. 2022) human development in general is falling in 90% of countries. The UN report elaborated that the drop in human development started around 2020 – 2021 and cited potential causes like “economic insecurity, COVID-19, violence and protests, and pressures on the planet.” If there is a correlation between HDI and GDP growth it is likely negative, but what would be interesting for this paper is a comparative analysis between the forecasted GDP not accounting for digital behaviors and the actual GDP given digital behaviors.

Significant modifications and insights were recognized by investigating this study’s datasets and their respective variable’s summary statistics:

1. Data sets and variables relating to GDP and ICT had to be modified to deter any potential multicollinearity in the model, logarithmic forms needed adjusted to represent the source’s presentation of the data’s value.
2. The data sets have different ranges for time, while the World Bank’s collection is vast this hinders its connection to other data sets which tend to be relatively niche (i.e., the OECD’s data).
3. To maximize the results from the data sets three tiers of regressions will be ran while stacking more variables into the model. Beginning with the basic Cobb-Douglas function for 2000 – 2021, including HDI and MCI from 2014 – 2021, and including digital behavior measures from 2016 – 2021.
4. The combined data set featured a wide range of GDP growth which might challenge the model’s explanatory power.
5. The HDI values all tend to be negative with the GDP values tend to stay positive which could yield mixed results on the correlation of HDI and GDP and warrants some further investigation.

**V. Empirical Results**

Each of the three regression runs proposed in *Data Analysis* plus one additional regression (for comparative analysis) can find their results in Table 3:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Percent Real GDP Growth | (1) | (2) | (3) | (4) |
| Percent Employed Labor Force\*Technology | 0.372 | -0.616 | -1.106 | -0.598 |
|  | (0.444) | (0.623) | (1.07) | (1.051) |
| Percent Capital Expenditures net ICT-Investment | -0.763 | 0.368 | 0.028 | -0.304 |
|  | (0.479) | (0.633) | (1.205) | (1.173) |
| Mobile Connectivity Index |  | -6.243 |  | -33.459 |
|  |  | 2.207 |  | (12.989) |
| Human Development Index |  | 12.597 |  | 57.287 |
|  |  | 8.419 |  | (25.005) |
| Digital Behaviors Key Variables: |  |  |  |  |
|  |  |  |  |  |
| Percent Population using YouTube |  |  | -9.491 | -6.184 |
|  |  |  | (5.692) | 5.965 |
| Percent Population using Web-Streamed Television |  |  | 25.679 | 16.016 |
|  |  |  | 6.614 | (6.671) |
| Percent Population using Web-Stream Music |  |  | -36.289 | -24.259 |
|  |  |  | (8.078) | (10.851) |
| Observations | 683 | 239 | 44 | 44 |
| *R2* | 0.035 | 0.04 | 0.388 | 0.516 |
| *Adjusted R2* | 0.033 | 0.024 | 0.308 | 0.422 |

*Note: OLS technique was applied with robust standard errors and controlling for cluster by country.*

Regressions (1) and (2) are fundamentally the Cobb-Douglas function with additions of MCI and HDI, these are only the buildup for table (4) which highlights the correlation of digital behaviors onto GDP growth. The first thing to recall is that as the regression models move from (1) – (4) the number of observations decreased dramatically, beginning around 8,000 and ending at 44. This huge decrease explains the sharp changes in *R2*. For the simple Cobb-Douglass function the *R2* value was around 0.035 which means only about 4% of the variation in the production variables explains the change in GDP across nations. While statistically minute, it is expected that for a data set with thousands of observations, only two variables can explain very little of the change. That is why regression (2) increased the *R2* value by half a percentage point but notably decreased the adjusted *R2*. This means that although there are more variables in the model, they only hinder the explanatory power of the theory overall. Regression (3) observed the digital behaviors variables without the MCI and HDI variables and witnessed nearly a tenfold increase in the model’s explanatory power. However, this is expected because the number of observations has decreased to 44, effectively making the model a “big fish in a small pond.” Any variable in this case could be argued to have some form of explanatory power but the model did see a comparative increase in the adjusted *R2* compared to the decrease from (1) - (2). This might indicate a possible degree of influence from digital behaviors on real GDP growth. Finally, the fourth regression model puts all the variables together and yielded a ten percent increase in adjusted *R2* compared to regression (3). The key takeaway here is that regression (4) is the key regression model to examine as the culmination of the Cobb-Douglas function with MCI, HDI, and the digital behaviors are an improvement from only Cobb-Douglas and the key independent variables. It is necessary then, to consider the context of the regression and interpretation.

Referencing Table 3, the percent population using YouTube has a -6.184 coefficient estimate, web-streamed television has a 16.016 coefficient, and web-streamed music -24.259 estimation. This means that for a one-percent increase in the population using these services one could expect a -6.184, 16.016, and -24.259 percent change in real GDP across nations. Notably, these figures are very large. As implied previously, this is because there are very few observations available in the model for such volatile changes in GDP. So, the OLS regression method is facilitated to generate larger amounts of explanatory power than there likely is. Additionally, the nations that volunteered their data on these digital behaviors tend to have higher affluence (hence, OECD data) and might not necessarily correlate to a broader phenomenon across the globe. So, a robustness check is needed to specify the impact of digital behaviors on GDP growth. Nonetheless, it might be plausible that even if the figures are exaggerated, the signs are not. Only web-streamed television has a positive correlation with GDP, the others are negative. This could imply that digital behaviors is fundamentally a phenomenon of digital marketing which would explain why web-streamed television (*read: impressions from advertising*) would have a positive impact on GDP but leisurely activities like listening to music and YouTube would correlatively be negative.

**VI. Robustness Check and Error Analysis**

The concerns of the dataset’s size and the volatility of GDP call for deeper error analysis. Given that the data in question concerns OECD data across years and countries it is necessary to investigate fixed versus random effects and address the question of omitted variable bias. Having already identified the most effective model in the previous section, two additional regressions were ran to address this question. One incorporated a new variable “fe” to account for fixed effects in the data, another one “re” accounted for random effects. The results for fixed versus random effects are given in Table 4 and the regression results to calculate the test are given in table 5.

**Table 4: Error Term Analysis**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Tested Concern** | **Statistical Test** | **Test Statistic** | **P-Value** | **Conclusion** |
| *Random vs Fixed Effects (Panel Data)* | *Hausman Test* | *10.48* | *0.2343* | *Fail to reject Null Hypothesis* |

|  |  |  |
| --- | --- | --- |
| **Dependent Variable: Real GDP Growth** | **Fixed-Effects** | **Random-Effects** |
| Labor & Technology | -0.3139 | -0.7847 |
| Capital net ICT | 6.4576 | -0.1790 |
| Mobile Connectivity Index | -7.1756 | 15.1634 |
| Human Development Index | 255.4642 | 13.4698 |
| Percent YouTube Consumption | 0.2812 | -5.0127 |
| Percent Web-Television Consumption | 18.2397 | 7.6948 |
| Percent Music Consumption | -27.6393 | -13.8905 |
| Constant | -87.0416 | -36.4499 |
| Number of Observations | 44 | 44 |
| R2 | 0.0359 | 0.6465 |

**Table 5: Robustness Checks (Alternative Models)**

Utilizing the Hausman Test, the null hypothesis is that the assumed random effects model of the regression is both consistent and efficient. It would be reasonable to suspect that for a data set great volatility for GDP growth one should expect that the results would reject the null hypothesis and control for fixed effects. However, that is not the case here, because the p-value is substantially larger than any typical significance level we fail to reject this hypothesis and conclude that the model is already “consistent and efficient”. This is very peculiar. The most reasonable explanation is that because the model only has 44 observations (see statistics from Table 5), the model is more “efficient and consistent” only because of its severe selection bias of OECD countries. In a phrase, it is consistent and efficient in its own right, again the problem of “big fish in a small pond.” Being mostly western European nations, the wealth is generally more abundant and only captures one facet of the volatility in real GDP growth. From a statistics perspective, the model acclaimed in *Section V. Empirical Results* is effective as-is, but should data on the key observations of YouTube, Web-Streamed Television, and Digital Music streaming services become more widely available, the model should likely account for fixed-effects in the data.

Some additional concerns for the model would be heteroskedasticity which as already been assumed and accounted for by robust standard errors, clustering by country. Additionally, the regressions did highlight some potential groupings within the OECD nations which would require further analysis.

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