Original Research Article

A Panel System GMM Analysis of Effects of Digital Services Trade on Economic Growth of Low, Middle and High Income Countries.

GMM Analyses of the Effects of Digital Services Trade on Economic Growth of Low, Middle and High Income Countries (As suggested new title)

ABSTRACT.

Objectives: To analyze the effect or impact of Digital Services Trade on economic growth (GDP) of a panel of Low, Middle and High Income Countries
Study Design: Panel Study
Methodology: Dynamic Difference GMM (Diff-GMM) and System GMM (Sys-GMM), Panel pooled OLS (POLS) and Fixed Effects (FE) models were employed in the analysis.
Results: The System GMM estimator seems to predict that, ceteris paribus, a 1 unit increase in digital services exports significantly impacts GDP growth in Low and High Income countries panels in the short run by 5.7% and 52.4% respectively. The panel POLS models estimate that digital services exports cause a significant long run increase in GDP in High income countries by 39.67% relative to 6.68% in the panel of Middle Income countries and negative growth in Low income countries of 7.74%. The FE models predict that for every 1 unit increase in the number of people using the internet, GDP significantly increases by 42.7%, 27.8% and 0.03% in the Middle, High, and Low Income countries panels respectively.
Conclusion: The findings of this study indicate that **g**enerally, digital services trade seems to have a significant positive effect on GDP of all country panels. However, Low and Middle Income countries are lagging behind. Therefore, we recommend that, to promote digital trade driven economic growth, the panel of Low and Middle Income countries' policy makers should increase investments in both institutional and physical digital infrastructure that enable more people, small and medium enterprises(SMEs) and rural populations have access to stable, high speed and affordable digital services.

Key words: Digital Services Trade, Economic Growth, System GMM, Trade Data Flow.

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1. Introduction

Digital services trade is one of the core components of digital trade in the wider global digital economy. UNCTAD (2020:1) defines digital trade as "international transactions that are delivered remotely in electronic format, using computer networks. It involves all trade that is digitally ordered and/or digitally delivered." The digitization processes are causing revolutionary changes in the production, exchange and consumption of goods and services. The demand side has been positively impacted by digitalization in that digital trade makes it possible for consumers to have access to a variety of services at competitive prices (UNCTAD, 2022). Trade in goods and services is increasingly shifting from physical to digital forms in areas such as financial services, entertainment, software, logistics, education and health services. From the supply side, digitization processes have impacted the production and delivery of goods and services. Cloud computing, 3D printing, artificial intelligence and app industry are integrating digital technologies in the production and delivery of goods and services making the flow of data the 'life blood' of the 21st century international trade (Shamel et al, 2020, OECD, 2020). McKinsey (2016:1, 2) succinctly explains the importance data flows in 21st global trade: "The internet is now a global network instantly connecting billions of people and countless companies around the world. Flows of physical goods and finance were the hallmarks of the 20th-century global economy, but today those flows have flattened. Global flows of goods, Foreign Direct Investment (FDI), and data have increased current global GDP by roughly 10 percent compared to what would have occurred in a world without any data flows."

However, there is a great variation among countries in terms of their readiness for digital trade. The level of preparedness for digital trade determines the potential benefits in terms of economic growth prospects from digital trade (UNCTAD, 2022, OECD, 2020). In addition, from the review of related relatively recent literature, we learned that a significant portion of literature focuses on the impact of digital economy or proxies of digital economy on economic growth (See for example, Pan et al 2022, Simon and Pingfang, 2021, Zhang et al, 2021 and Wang and Choi, 2019, Thomas, 2018).

Apparently, it appears there is a knowledge gap with regards to studies that specifically analyze the effect or impact of digital services trade on the economic growth of Low, Middle and High Income countries. Therefore, the objective of this study is to fill this knowledge gap by analyzing and comparing the effect of digital services trade on the economic growth of Low, Middle and High Income panel of countries by employing the static models of panel Pooled OLS (POLS) Fixed Effects (FE), and dynamic models (Differenced and System Generalized Method of Moments (Hereafter, Diff-GMM, Sys-GMM respectively).

The paper is organized as follows: Section 2 focuses on literature review in terms of benefits of digital trade, challenges of measuring digital services trade, barriers to digital trade, as well as conceptual and theoretical frameworks. Section 3 deals with the econometric methodological specifications and data descriptions. Section 4 discusses the results, and section 5 concludes the paper and makes recommendations to policy makers.

2. Literature Review

2.1 Benefits of Digital Trade.

Compared to conventional or analogue trade, digital trade driven by the digital communication networks makes it easy to coordinate global supply chains thereby making digital trade relatively quicker, cheaper and increases trade volumes. Consequently, digital trade results in higher economies of scale, reduced trade time, reduced search costs and lowers the venerated variable costs by lowering entry barriers (OECD, 2020, DFID, 2020, OECD, 2017a). The geographical distance which is a big factor in conventional trade is not an important factor when it comes to digital trade because trading via digital platforms significantly compresses overall distance and its related costs (UNCTAD, 2020). In addition, Digital trade has increased the capacity to save on search and travelling costs to potential trading partners. The digital trade's ability to compress distance makes it easy for small open economies and start- up businesses such Small and Medium Enterprises (SMEs) to fully participate in the international trade ecosystem previously dominated by large multinational corporations (MNCs) (OECD policy brief, 2022). Thus, digital trade leads to increased job creation, competitive prices, increased industrial and economic growth and amplifies consumer welfare effect as well (DFID, 2020). The Covid-19 pandemic has further increased the importance of digital trade. The Covid-19 period saw an exponential increase in the use and development of online platforms to buy goods and services. UNCTAD (2022) reports that traditional global services exports fell by 20 percent compared with 2019 but digitally delivered services were relatively resilient because they only declined by 1.8 percent amidst the economic meltdown caused by the Covid-19 pandemic.

2.2 Challenges of measuring Digital Services Trade

Although digitization is virtually almost everywhere, it is also almost invisible in country official national accounting statistics of trade and GDP computations. "…This lack of visibility is largely a function, or perhaps legacy of the fact that the core economic production accounts still remain largely constructed around firms and tangible products." (Handbook on Measuring Digital Trade OECD, 2020:10). This makes the distinguishing line between digital services trade and general or "traditional" services trade very thin and results in a high correlation between digital services and "traditional" or conventional trade in services (McKinsey, 2016). These challenges are understandable given that the concept of digital trade is still developing and a significant portion of people are yet to fully understand it. We envision that as digital trade data becomes more segregated and refined, it will become relatively easy to record it accurately in national accounting statistics.

2.3 Barriers to digital Trade

Although digital trade promotes job creation, industrial growth and economic growth, barriers to digital trade impinge on the optimal realization of potential benefits of digital trade. These include among others, tariffs and quotas on imports of information and communication technology equipment such as routers and servers, localization requirements that compel the conduct of digital trade-related activities within a country as prerequisite for doing business, cross-border data flow restrictions that prohibit the export of data outside a country; intellectual property infringement, online sale and distribution of counterfeits, and online theft of intellectual property; discriminatory national and local standards that deviate from recognized international standards or imposing of redundant conformity assessment and testing requirements; and filtering and blocking restrictions that impede access to foreign websites and data flows (Wiley digital trade Law, 2022,WEF, 2020).

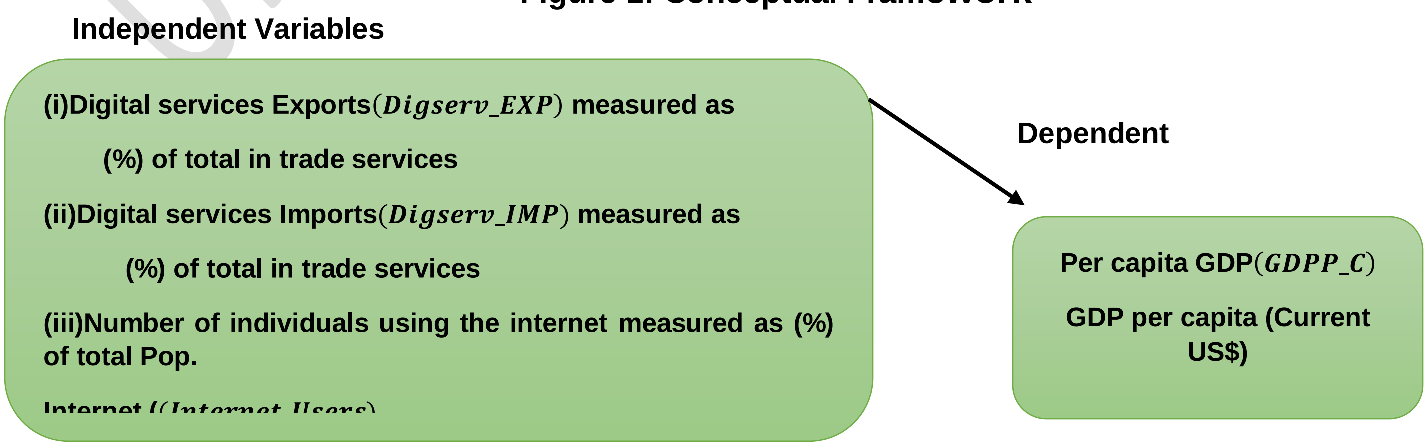
2.4. Strategies of mitigating barriers to digital trade

The 2020 World Economic Forum (WEF, 2020: 6-7) suggests the following measures, among others, to mitigate the negative effects of digital trade barriers: Accelerate e-commerce trade preparedness to benefit small businesses and developing economies, build interoperability for global data flows, including through trade frameworks and regulatory cooperation, and explore the effects and requirements of rapidly expanding digital trade in services, map new trade technologies – including cloud services, and 3D printing and digital economy driving discussion on policies to balance gains versus risks and support the international functionality of payment systems and related supply chain information flow. Zhang et al (2021) explain that the advantages of digital economy which include high economic growth can only be fully realized in regions with well-developed digital infrastructure.

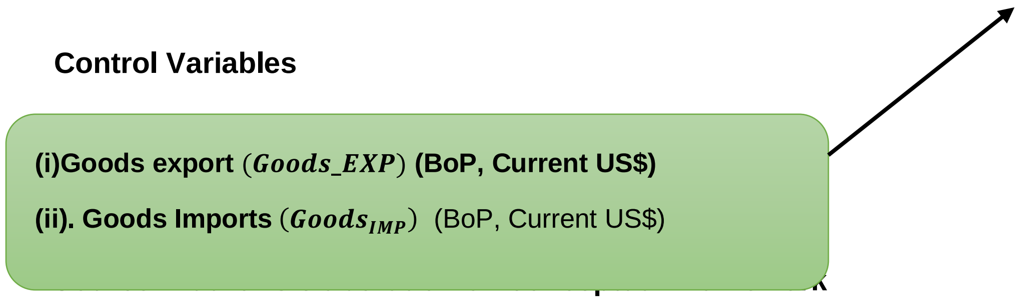
2.5 Conceptual Framework

Conceptually, the rise in digital services trade is driven by fragmentation of production processes (Shiozawa, 2017). A new concept in the recent world trade is the rise of digital trade in services conducted internationally over the internet (WEF, 2020). This concept is impacting traditional or conventional international trade in highly disruptive ways and radically altering the nature of consumer and business transactions. Fragmentation in production has resulted in rapid decrease of trade costs augmented by the revolutionary development of Information and Communication Technologies (Jones & Kierzkowski, 1990, Shiozawa, 2017). However, from the theoretical stand point, digital trade seems to be predicated on the New Trade Theory (NTT), a label that summarizes a range of theories that attempt to explain international trade in terms of the rapid changes and disruptive nature of digital technologies on global data flows and trade in an imperfectly competitive environment (Dirk & Michael, 2012).

Figure 1: Conceptual Framework



Control Variables



2.4 Review of Related Literature.

Simon and Pingfang (2021) evaluated the impact of digital economy on the international trade and growth in Africa using cross sectional data of 53 countries from 2000 to 2018. They used a vector of digital economy variables as proxy for digital economy index. They employed the System General Method of Moments (Sys-GMM) as dynamic models and Fixed Effects (FE) and Random effects (RE) Estimators as static models. The findings of the study showed that digital economy had a significant positive effect on international trade and growth in Africa. They recommended that increased investment in digital technology be enhanced to promote digital trade led economic growth in Africa.

Soomro et al (2022) analyzed the relationship between FDI, ICT, Trade Openness, and Economic growth of a panel of BRICS (Brazil, Russia, India, China and South Africa) countries using the GMM technique. They find that there is a significant positive effect between per capita ICT growth and GDP although the effect varies according to the level and quality of ICT development. They recommend that BRICS governments and other stakeholders should promote easy access to technology through increased investment. They recommend further that future studies should incorporate more panel data from other regions of the world.

Pan et al (2022) used pooled regression models (PRM) to evaluate the impact of digital economy on panel data for total factor productivity (TFP) in China. They find that although digital economy index has a positive impact on the economy of China, there were regional diversity impacts of digital economy on provincial growth conditioned on regional digital infrastructure development. They recommended that integration of digital economy development among all regions in China to reduce the economic disparities of digital economic effects.

Aslam and Shabbir (2020) evaluated the impact of digital social inclusion on economic growth on a panel of 83 middle income countries from 2010-2017. They employed a two-step system GMM and normalized indexing technique on three panel subsamples of low, middle and high income countries. They found that social and digital inclusiveness indexes have a significant positive effect on economic growth. The impact is greater among high income groups. They recommend that policy makers in low and middle income countries should strengthen digital inclusiveness by investing more in the development of digital economy.

Jiao and Sun (2021) analyzed the impact of digital economic development on urban economic growth in China. They employ, among other models, system GMM and Pooled ordinary least squares regression (POLS) models on a panel data of 173 cities for the period 2011-2018. They found that digital economic development has a significant positive effect on urban economic growth in China. In addition, they found that urban economic growth is positively impacted more by the level of digital development and employment levels.

Thomas (2018) investigated the impact of Information Communication Technologies (ICT) on economic growth on a panel of developing, emerging and developed countries for the period 1995-2010. He employed panel vector auto-regression (P-VAR) models. His findings showed and corroborated earlier studies that ICT had a positive impact on economic growth. However, subsample panel regressions rejected the hypothesis that developing and emerging countries benefited more (that ICT 'leap frog' growth in developing and emerging countries) from ICT capital investment than developed countries.

Nipo et al (2018) analyzed the impact of ICT on trade on a panel on low and middle income countries from 2007 to 2014 using panel ordinary least squares (POLS) and the system GMM approaches. They found that ICT enabled trade has a significant positive impact on GDP in Middle Income countries and it has no significant impact on GDP of low income countries. They assert that ICT development is still low in Low Income countries hence causing insignificant impact on their economic growth. They recommend that governments in Low Income countries should invest more in ICT enabled trade infrastructure.

Bon (2021) used the difference GMM approach to analyze the effect of digitalization and governance on economic growth of a panel of 35 developing countries from 2006 to 2019. The study found that digitization and governance have a significant positive impact on economic growth in developing countries. He recommends that policy makers in developing countries should "…establish appropriate conditions to promote digital technology so that citizens can peacefully express their views on government policies and regulations, which contributes to the economic development of the country." Bon (2021: 490)

2.5 Theoretical Framework

Digital economy in general and digital trade in particular causes international trade fragmentation or international dispersion of service or production blocks. This process is loosely ascribed to the New Trade Theory (NNT) of international trade and has tended to supplant the theory of comparative advantage to a large extent because it emphasizes that digital trade generally allows market participants to behave like monopolistically competitive firms (Helpman and Krugman, 1985). Digital trade in services or digitally enabled trade in services is similar but not identical to trade in services (UNCTAD, 2020, OECD, 2020).

Theoretically, the development of digital economy and digital infrastructure can be envisioned as augmenting total factor productivity (TFP) in the augmented Solow Growth Model (Thomas, 2018, Pan et al 2022). We follow augmented growth model as expressed in Mankiw et al (1992):

$$\square_{\square} = \square_{\square}^{\square}\square_{\square}^{\square}(\square\square)^{1-\square-\square} \qquad (1)$$

Where $\square_{\square}$ is GDP growth over time (t) in response to changes in physical capital($\square$), human capital (H), labor(L) and total factor productivity (TFP) or technology (A) over time (t). Human capital (H) is different from labor(L). Labor involves the skills that humans naturally possess whereas human capital refers to skills obtained through experience, training and education (Mankiw et al, 1992). Thus, labor productivity can be expressed as:

$$\frac{\square}{\square} = \square^{1-\square-\square}\left(\frac{\square}{\square}\right)^{\square}\left(\frac{\square}{\square}\right)^{\square} \qquad (2)$$

Which can be expressed in natural logarithmic format as:

$$\ln\left(\frac{\square}{\square}\right) = (1-\alpha-\beta) + \ln(\mathrm{A}) + \alpha\ln\left(\frac{\square}{\square}\right) + \beta\ln\left(\frac{\square}{\square}\right) \qquad (3)$$

According to equations 2 and 3, labor productivity is a function of capital-labor ratio $\left(\frac{\square}{\square}\right)$, human per capital unit labor ratio $\left(\frac{\square}{\square}\right)$ and the residual term $(1-\square-\square)\ln(\square)$, that essentially captures the level of technology. The residual term represents the total factor productivity (TFP) which measures the efficiency or effective use of technology by labor and capital in promoting growth output (Erken et al, 2016). In our context, the residual term represents the country level digital technological development. Erken et al (2016) explain that among the major drivers of total factor productivity (TFP) and by extension, growth output, are technological catch up, research and development (R&D) capital, labor participation and entrepreneurship. They explain further that the process of technological catch up involves the absorption by technologically behind regions of the knowledge diffusing from technologically advanced regions. Since this study evaluates the impact of digital trade services on economic growth of countries as whole, we envisage that theoretically it implies taking the general equilibrium (GE) approaches. A general equilibrium (GE) strategy is ideal for studies like ours because it takes into account the effects of multilateral trade because many countries and markets are involved in the analyses.

It is expected that digital services should have a positive relationship with per capita GDP given the assertions in literature that digital trade promotes GDP growth (WEF, 2020, OECD, 2020, McKinsey, 2016).

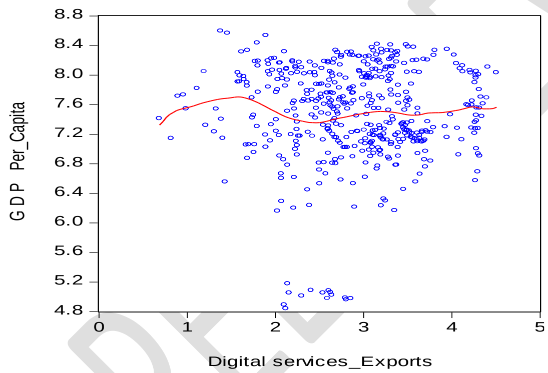
In a bid to get an overview of the relationship between digital services exports and per capita GDP growth, we plotted these variables against each other. Figure 2 shows a scatter plot of correlations tests between digital services trade. As can easily be observed from Figure 2, all the three subpanels show that the majority of the plots lie on the positive domain. However, it seems the scatter plot of low income countries panel does not show a linear correlation between digital services export variable and per capita GDP variable.

The scatter plot for middle income countries panel initially shows a negative correlation relationship between digital service exports and per capita GDP for few countries, it becomes strongly positively correlated and then becomes non- linear.

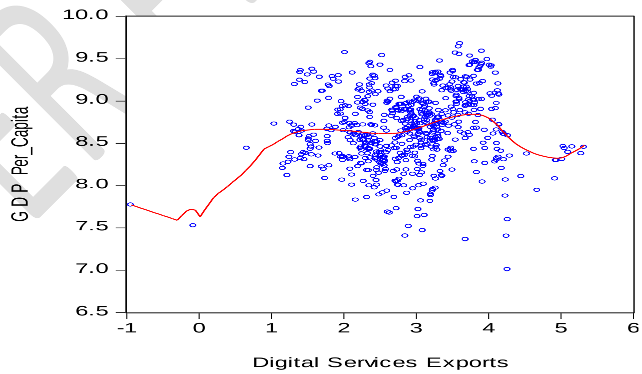
As for the High Income countries panel, initially the relationship is positively non- linear. Thereafter, it shows an increasingly strong positive correlation between digital services export and per capita GDP.

Fig 2: Panel Scatter Plot of Correlations tests- Digital Services Trade versus GDP.

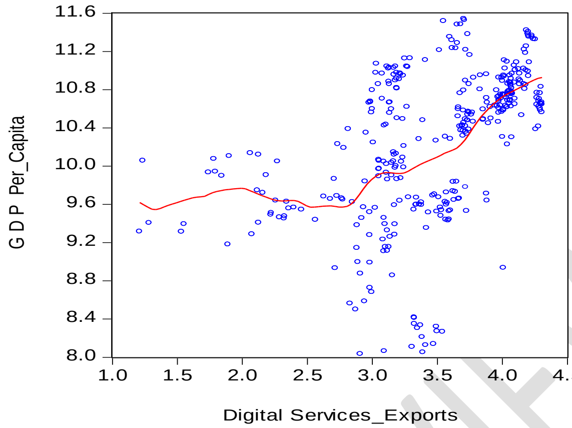
Panel 1: Low Income Countries



Panel 2: Middle Income Countries



Panel 3: High Income Countries



Source: Author's elaboration on data from UNCTAD and World Bank's World Development Indicators
Notes: The red lines denote (Kernel) fitted values. The variables are in natural log format. Per capita GDP is plotted on the vertical axis while digital services exports are plotted on the horizontal *axis.*

3. Methodology and Data

3.1 Description of Data and Data sources
3.2

Annual panel data for 46 Middle Income, 32 Low Income and 24 panel of High Income countries for the period 2005-2019 were used. Gross Domestic Product per capita in current US$ (GDP per capita current US$) panel data obtained from World Bank's Development World Development Indicators (WDI) database data base is the dependent variable. The panel data on independent variables of digital services exports and digital services imports measured as percentage (%) of total in trade services data were obtained from UNCTAD databases. A third independent variable panel data regarding the number of individuals using the internet measured as percentage (%) of total population were obtained from World Bank's World Development Indicators (WDI) database. The control variables of digital services trade namely goods exports (BoP, current US$) and goods imports (BoP, current US$) panel data were also obtained from World Bank's World Development Indicators (WDI) database. We follow World Bank's categorization of Low Income, Middle Income and High Income Countries.[1]

The Econometric GMM Model

According to Hansen (1982) the starting point of Generalized Method of Moments (GMM) is the assumption that there are a set of L moment conditions that the □-dimensional parameters of interest, □ should satisfy. These moment conditions can be quite general, and often a particular model has more specified conditions than parameters to be estimated. Thus, the vector of □ ≥ □ moment conditions may be expressed as:

[1] The World Bank's four(4) categories of country income groups are: Low, lower-middle, upper middle and high- income to classify our panel data: In this study, Low income countries panel refers to lower -middle income, middle income countries panel refers to upper-middle income and high income countries panel refers to high income countries. For details, see World bank.org

$$\square\big(\square(\square_{\square},\square)\big) = 0 \qquad (4)$$

In this study we focus on moment conditions that may be written as *orthogonality condition* between the residuals of an equation $u_t(\beta) = u(y_t, x_t, \beta)$, and a set of K instruments denoted as Z_t:

$$\square\square_{\square}\square_{\square}(\square) = 0 \qquad (5)$$

Arellano and Bond (1991) assert that the Method of Moments estimator is defined by replacing moment conditions in equation 4 with their sample analog:

$$\square_{\square}(\square) = \frac{1}{\square}\sum_{\square}\square_{\square}\,\square_{\square}(\square) = \frac{1}{\square}\square'\,\square(\square) = 0 \qquad (6)$$

And finding the parameter β which solves this set of L equations. When there are more moment conditions than parameters, $\square > \square$. The system is said to be over *identified*. Arellano and Bover (1995) explain that although it is challenging to solve an over-identified system, reformulating the problem as one of choosing a β so that the sample moment $m_T(\beta)$ is as "close" to zero as possible, where "close" is defined using the quadratic form as a measure of distance:

$$\begin{aligned}\square(\square,\square_{\square}) &= \square\,\square_{\square}(\square)'\,\square'_{\square}\square_{\square}(\square)\\ &= \frac{1}{\square}\square(\square)'\,\square\square_{\square}^{1}\square'\,\square(\square) \qquad (7)\end{aligned}$$

The possibly random, symmetric and positive definite $L\,X\,L$ matrix W_T is called the weighting matrix since it acts to weight various moment conditions in constructing the distance measure. The GMM estimate is defined as the $\square$, that minimizes equation 7. In models where there are the same number of instruments as parameters, the value of the optimized objective function is zero. If there are more instruments than parameters, the value of the optimized objective function will be greater than zero. In fact, the value of the objective function, *called the J-statistic* or Hansen statistic can be used as a test of over-identifying moment conditions (Arellano and Bover, 1995)

Under suitable regularity conditions, the GMM estimator is consistent and $\sqrt{\square}$ asymptotically normally distributed;

$$\sqrt{\square}(\square - \square_0) \to \square(0,\square) \qquad (8)$$

The asymptotic covariance matrix V of $\sqrt{T}(\beta - \beta_0)$ is given by:

$$\square = (\Sigma'\,\square^{-1}\Sigma)^{-1}\Sigma'\,\square^{-1}\square\square^{-1}\Sigma(\Sigma'\,\square^{-1}\Sigma)^{-1} \qquad (9)$$

for; $\square = \square\square\square\square\square_{\square}$

$$\sum = \square\square\square\square\frac{1}{\square}\square' \ \Delta\square(\square)$$

$$\square = \square\square\square\square\frac{1}{\square}\square' \ \square(\square)\square(\square)' \ \square \qquad (10)$$

Where $\square$ is both the asymptotic variance of $\sqrt{\square}\square\square_{\square}(\square)$ and the long run covariance matrix of the vector process$\{\square_{\square}\square_{\square}(\square)\}$. In the leading where the $\square_{\square}(\square)$ are the residuals from a linear specification so that; $\square_{\square}(\square) = \square_{\square} - \square'_{\square}\square$, the GMM objective function is given by:

$$\square(\square, \square_{\square}) = \frac{1}{\square}(\square - \square\square)' \ \square\square^{1}_{\square}\square' \ (\square - \square\square) \qquad (11)$$

and the GMM estimator yields the unique solution; $\widehat{\square} = (\square' \ \square\square'_{\square}\square' \ )\square$. The covariance matrix is given by equation 7 with ;

$$\sum = \square\square\square\square\frac{1}{\square}(\square' \ \square) \qquad (12)$$

3.3 The Empirical Econometric GMM Models

In order to determine the dynamic effects of digital services trade on economic growth, we follow Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (2000) in employing the system GMM (sys-GMM) estimator. The sys-GMM estimator is suitable for our study because it helps us resolve empirical problems of serial correlation, heteroscedasticity and endogeneity of some explanatory variables in the models. In addition, we follow Simon and Pingfang (2021) in estimating static models of Pooled OLS (POLS) and Fixed Effects (FE) or Least Squares Dummy Variables (LSDV) models. We used the FE estimator to conduct static regressions because the Hausman test rejected the null hypothesis Random Effects (RE) versus FE.
The dynamic panel GMM model can be written as;

$$\square_{\square\square} = \square_{\square} + \square_{\square\square-1} + \sum_{\square=1}^{\square}\square_{\square}\,\square\square\square\_\square\square\square\square\square_{\square\square-\square} + \sum_{\square=1}^{\square}\square_{\square}\,\square\square\square\_\ \square\square\square\square_{\square\square-\square} + \sum_{\square=1}^{\square}\square_{\square}\square_{\square\square-\square} + \square_{\square} + \square_{\square} + \square_{\square\square} \qquad (13)$$

Where Y is the per capita GDP $(GDPP\_C)$, α_i is a vector of intercepts for countries $1\ to\ i$, m denotes lag levels. Y_{it-1} is initial level of per capita GDP (Current US$) Int_Users_{it-1} is the number of people using the internet (measured as % of the total population),

Dig_serv is a vector of digital services trade variables [digital services exports ($Digserv\_IMP$) and digital services imports (Di$gserv_IMP$) measured as % of total services trade], $\square$ is a vector of control variables namely goods exports, BoP, Current US$ ($Goods\_EXP$) and goods imports, BoP, Current US$ ($Goods\_IMP$), μ_i represents a vector of unobserved country specific effects, $\square$ represents a vector of time dummy variables, V represents a vector of error terms. The subscripts i and t represent a vector of countries and time periods in the three subsamples respectively. α β, γ, δ = parameter coefficients to be estimated.

Estimating equation 13 in its current form with panel OLS may produce biased and inconsistent estimates due to the presence of the lagged variable as a regressor and the unobserved country specific effects (Fixed Effects). To mitigate this problem, the fixed effects are removed by first differencing. Therefore equation 13 is transformed into Differenced GMM (Diff-GMM) equation as shown in equation 14:

$$\square_{\square\square} - \square_{\square\square-1} = \square_{\square} + \square_{\square\square-1} + \sum_{\square=1}^{\square} \square_{\square}(\square\square\square_{\square\square\square\square\square\ \square\square-\square} - \square\square\square_{\square\square\square\square\square\ \square\square-\square-1}) + \sum_{\square=1}^{\square} \square_{\square}(\square\square\square\_\ \square\square\square\square_{\square\square-\square} - \square\square\square_{\square\square\square\square\ \square\square-\square-1}) + \sum_{\square=1}^{\square} \square_{\square}(\square_{\square\square-\square} - \square_{\square\square-\square-1}) + (\square_{\square\square} - \square_{\square\square-1}) \quad (14)$$

The difference GMM estimator has statistical shortcomings also. Blundell and Bond (2000) for instance, show that when the explanatory variables are persistent over time, the lagged levels of the variables in the models are weak instruments for the regression equation in differences. Therefore, to mitigate the potential biases associated with the difference GMM estimator, we use system GMM estimator as the main estimator for this study. Blundell and Bond (2000) explain that sys-GMM estimator combines in a system the regression in differences with the regression in levels. That is, the sys-GMM (or extended GMM) uses lagged differences of dependent variable ($Y_{it}\ or\ GDPP\_C$) as instruments for the equation in levels in addition to the lagged levels of Y_{it} as instruments for the equations in first differences. Blundell and Bond (2000) assert that the Monte Carlo simulations and asymptotic variance calculations show that the sys-GMM estimator offers efficiency gains where the first difference GMM estimator performs poorly. The GMM estimator is suitable for this study because we assume that the regressors are weakly exogenous. Moreover, the instruments the sys-GMM generates have no correlation between differences of the variables and the country specific effects in the panels (Arellano and Bover, 1995).

The regression models are estimated separately using both the first difference 2-step GMM and the 2-step system GMM approaches. In the first-difference GMM estimations, the lagged dependent variable, per capita GDP ($GDPP\_C$)) is considered predetermined whereas the trade control variables of goods exports ($Goods\_EXP$), goods imports ($Goods\_IMP$) and the number of people using the internet (Int_Users) are treated as endogenous. In the system-GMM we take the *orthogonality condition* between the residuals of an equation using e-views 9 statistical software.

The basic econometric regression model we use at levels takes the following format:

$$GDPP\_C_{it} = \alpha_t + \beta_1 Digserv\_EXP_{it} + \beta_2 Digserv\_IMP_{it} + \beta_3 Goods\_EXP_{it} + \beta_4 Goods\_IMP_{it} + \beta_5 Int\_Users_{it} + \mu X_{it}(\mu M_{it}) + \omega X_{it} + \omega M_{it} + \varepsilon_{it} \quad (15)$$

Where $GDPP\_C_{it}$ is GDP per capita (current US$, GDP_C) for-$ith$ country at time *t,* α_t is different intercepts in each year, $\beta_1 Digserv\_EXP_{it}$ is digital services exports for country$i$ at time t, $\beta_2 Digserv\_IMP_{it}$ is digital services imports for country i at time t, $\beta_3 G\_EXP_{it}$ is *goods exports* for country i at time, t . $\beta_4 G\_IMP_{it}$ is *goods imports* for country i at time t, β_5 Int_Users_{it} is the number of internet users as percentage (%) of population for country i at time t and μX_{it} is country i unobservable individual effects on exports(import) equation $\omega X_{it},\ \omega M_{it}$ unobservable time invariant effects for exports and imports panel variables respectively and,ε_{it} represent the white noise error term. The parameters α_t represent different intercepts in each year and allows for aggregate economic growth change over time.

4. Results and Discussions

4.1 Diagnostic Tests and Choice of Models

The author used Breush Pagan LM test the poolability of data or to test for homoscedasticity. The null for poolability of data was rejected because the tests did not show evidence of homoscedasticity in all the subsample models hence we used Pooled regression model (POLS). We employed Hausman tests to determine whether to estimate Fixed or Random effects models. The Hausman test rejected the null hypothesis of estimating Random Effects (RE).Thus we used the Fixed Effects (FE) estimator or Least Squares dummy variable (LSDV) models. The Hausman test result summary test results are reported in Table 3. In addition, Hausman test showed presence of endogeneity implying that instrumental variables should be included in the models as well. The Modified Wald test showed the models suffer from both endogeneity and heteroscedasticity problems thereby making it suitable to use the Arellano-Bond (AB) GMM estimator (Arellano and Bond, 1991). Furthermore, the author employed both the Diff-GMM and the Sys-GMM estimators to compare the regression powers of the two estimators. That is, while the Diff-GMM is used to remove the endogeneity effects between the fixed effects and the unobserved effects of the lagged dependent variable among the regressors, Diff-GMM estimator performs poorly when the explanatory variables are persistent over time (Blundell and Bond 2000).

In other words, the Sys-GMM estimator offers efficiency gains where the first Diff-GMM estimator performs poorly (Blundell and Bond 2000). The author decided to use 2-step Diff-GMM and 2-step Sys-GMM because we learned that 1 step GMM coefficient estimates were generally weaker relative to that of 2-step. Evidence from this study indicates that Sys-GMM is more efficient than Diff-GMM because it yields more significant and larger coefficients than Diff-GMM (See table 4). The POLS and FE static models help us to determine the long run static effects of regressors on per capita GDP. The static models are reported in Table 3. Both the Diff-GMM and Sys-GMM estimates are short run dynamic estimates. The results of the short run dynamic model estimates are reported in Table 4.

We begin the analysis and discussions of empirical results by reporting summary statistics of the three (3) subpanel data. The summary statistics are reported in Table 1.

Table 1: Summary descriptive statistics for the three (3) sub-panel data.

	Mean	Max.	Min.	Std. Dev.	Obs.
Panel 1: Low Countries					
*GDP*_C	2089.18	5408.41	126.341	1093.24	452
Digserv_EXP	23.51	90.581	1.987	17.66	452
Digserv_IMP	27.13	76.451	7.348	10.89	452
Goods_EXP	2.87E+03	3.32E+11	9853671	5.58E+02	452
Goods_IMP	3.44E+02	5.19E+02	92599764	7.29E+02	452
Int_Users	21.55	84.12	0.24	18.96	452
Panel 2: Middle Income Countries					
GDP_C	6411.22	15974.64	1578.402	2782.093	555
Digserv_EXP	25.049	205.44	0.392047	24.31361	555
Digserv_IMP	41.87	616.11	6.410847	63.46889	555
Goods_EXP	1.01E+02	2.42E+02	9722235	3.02E+11	555
Goods_IMP	8.72E+02	2.04E+02	1.10E+08	2.45E+11	555
Int_Users	39.35	89.56	0.9	22.7483	555
Panel C: High Income Countries					
GDP_C	36488.59	102913.51	3083.834	21966.79	337
Digserv_EXP	38.12	74.11	3.35	18.64826	337
Digserv_IMP	39.83	70.32	1.927	12.65939	337
Goods_EXP	3.08E+02	1.68E+02	45715381	3.76E+02	337
Goods_IMP	3.14E+02	2.56E+02	4.31E+02	4.66E+02	337
Int_Users	69.31	99.59	3.69	23.028	337

Source: Author's elaboration on data from UNCTAD and World Bank's World Development Indicators

4.2 Panel Unit Root and Stationarity Tests

In statistical and economic literature, it is well established that unit root processes behave differently from stable or stationary processes, and that conducting empirical tests on data with unit roots results in spurious regressions, spurious inferences and spurious policy recommendations (Green, 2003). Therefore, to eliminate these data problems, we conducted four (4) panel data unit root tests: Common root- Levin, Lin & Chu (2002), Individual root-Im, Pesaran & Shin (2003) Individual root-Augmented Dickey Fuller, ADF (1979) and Individual root- Phillips and Peron (1988). The test summary for unit root tests and their respective order of cointegration of the three (3) sub sample panels are reported in Table 2.

Table 2: **Panel Unit root Test: Low Income, Middle Income and High Income Countries.**

Variable	Levin, Lin & Chu (t-statistics)	Im, Pesaran &Shin(t-stat)	ADF - Fisher X^2	PP - Fisher X^2	Order of Integration
Panel A: Developing Countries					
GDP_C	1.64**	-0.73**	87.43**	133.65**	I(1)
$Digserv\_EXP$	-3.18**	-0.94**	86.66**	127.51**	I(1)
$Digserv\_IMP$	-6.44**	-7.16**	170.88**	392.89**	I(1)
$Goods\_EXP$	-11.03**	-8.36**	188.95**	321.64**	I(1)
$Goods\_IMP$	-2.90**	-1.52**	89.06**	106.18**	I(1)
Int_Users	-2.55*	-0.93*	74.02*	130.69*	I(1)
Panel B: Emerging Countries					
GDP_C	-5.55*	-1.92*	114.81*	171.97*	I(1)
$Digserv\_EXP$	-8.35***	-2.95***	134.61***	192.11***	I(0)
$Digserv\_IMP$	-5.48**	-1.192**	111.26**	124.21**	I(1)
$Goods\_EXP$	-4.43**	-1.14**	94.087**	127.74*	I(1)
$Goods\_IMP$	-8.72***	-4.33***	137.21***	151.99***	I(0)
Int_Users	-4.48**	-3.03**	127.09**	240.08**	I(1)
Panel C: Developed Countries					
GDP_C	-3.02**	-2.51**	78.16**	83.50**	I(0)
$Digserv\_EXP$	-2.57**	-6.02**	123.27**	240.20**	I(1)
$Digserv\_IMP$	-6.57**	-4.08**	90.75**	112.17**	I(1)
$Goods\_EXP$	-6.57***	-4.09***	90.85***	112.17***	I(0)
$Goods\_IMP$	-7.14***	-4.26***	93.78***	111.45***	I(1)
Int_Users	-4.84**	-3.52**	85.28**	206.25**	I(1)

Notes: Fisher tests are computed using an asymptotic Chi-square(X^2) distribution. All other tests assume asymptotic normality. The null hypothesis assumes common unit root process. *, **, ***, denote panel data variable is stationary at 10%, 5% and 1% significance levels respectively (rejection of the null of presence of unit root in the panel variable). Tests include individual intercept only. ADF is Augmented Dickey Fuller test, PP is Phillips and Peroni test.

4.3 Analysis of the Static Panel Data Estimations

Using the log of per capita GDP as in Santos (2015), Table 3 reports summary results of pooled OLS and Fixed Effects model tests. The POLS results indicate that digital services exports have a significant negative effect on per capita GDP in the panel of Low income countries. However, it has a positive significant impact on per capita GDP (GDP hereafter) in Middle Income and High Income countries. The coefficient is largest in High Income countries at 39.67 relative to 6.68 in the panel of Middle Income countries. Regarding the number of people using the internet variable, POLS test indicates that the number of people using the internet has a significant positive impact on GDP in all the three subsample panels. It is highest in the Middle Income countries where it stands at approximately 63.2%. It stands at 52.8% in High Income countries and it is lowest in Low Income countries panel at 22.2% in the long run. Digital services import variable has a significant long run positive impact on GDP in Low income countries at 4.4% while it has negative effect on GDP in Middle and High Income countries of -4.6% and -7.9% respectively. The positive significant impact of digital services imports on Low Income countries could be attributed to the agglomeration and use of imported digital services by start-up companies and small medium enterprises (SMEs) in these countries (Mckinsey, 2016, OECD, 2020). POLS estimates indicate that the control variables are significant in all subsample panels. However, goods exports seem to have a long run negative significant impact on GDP in Middle and High Income countries.

The static panel Fixed Effects (FE) models indicate that digital services exports have a negative significant effect on GDP in Low and middle income countries whereas it has a significant positive impact on GDP in High Income countries. Perhaps this indicates and confirms the assertions in the literature that High Income countries are leading in terms of digital services trade than Middle and Low Income countries (See for example, OECD policy brief, 2022, UNCTAD, 2020). Digital services imports seem to have a higher negative significant effect on High Income countries where we infer that for every 1 unit increase in digital import services GDP in High Income countries panel may decrease by 18.9%. The number of people using the internet variable has a positive but insignificant effect on GDP in Low Income countries panel relative to positive significant impact it has on other subsample panels. Specifically, it appears the number of individuals using the internet has the largest impact on per capita GDP in Middle Income country panel with the coefficient 42.7 and it is 27.8 in High Income countries. The control variables of goods exports and imports are statistically significant with expected positive signs in all sub panels. The largest goods export significantly impacts per capita GDP growth in Middle Income countries by 9.95%.

Table 3: Static Panel Estimates- Panel OLS (POLS) and Fixed Effects (FE) Estimates.

	Panel OLS Estimates			Fixed Effects Estimates			Hausman Test summary	
Variables	$Coeff$	$t-statistics$	$Std.Errors$	$Coeff$	$t-statistics$	$Std.Errors$	X^2 Statistics	X^2 □.□
Panel 1: Low Income Countries							16.22**	**5**
$lnGDPP\_C(Dependent)$							(0.01)	
$Digserv\_EXP$	-7.74	-2.52**	3.01	-8.97	-3.61**	2.48		
$Digserv\_IMP$	4.41	10.05**	4.38	13.25	4.01**	3.31		
$Goods\_EXP$	7.21	1.97*	2.66	8.54	3.56**	2.4		
$Goods\_IMP$	-5.81	-2.74**	2.12	-4.3	-2.29**	1.88		
Int_Users	22.24	9.83**	2.26	0.03	1 .91*	2.23		
$Constant$	589.98	3942.86**	4.63	184.35	18.45**	99.92		
R^2	0.38			0.89				
F-statistic(P-value)	45.52	(0.00)		70.68	(0.00)			
Panel 2: Middle Income Countries								
$lnGDPP\_C(Dependent)$								
$Digserv\_EXP$	6.68	4.14**	0.68	-7.17	-2.31**	5.06	12.17**	**5**
$Digserv\_IMP$	-4.55	-3.12**	1.6	-0.49	-1.93*	2.59	(0.03)	
$Goods\_EXP$	-3.55	-1.99*	2.05	9.95	3.84**	2.62		
$Goods\_IMP$	-5.92	2.05**	3.68	-7.31	-2.39*	3.05		
Int_Users	63.17	13.86**	1.55	42.71	5.65**	7.56		
Constant	394.27	18.22**		455.92	12.28**	371.08		
R^2	0.3			0.87				
F-statistic(P-value)	47.11	(0.00)		161.64	(0.00)			
Panel 3: High Income Countries								
$lnGDPP\_C(Dependent)$								
$Digserv\_EXP$	39.67	6.78**	58.48	10.13	2.03**	49.83	31.32**	**5**
$Digserv\_IMP$	-7.96	-2.97**	77.28	-18.85	-2.19*	85.86	(0.00)	
$Goods\_EXP$	-3.25	-2.01*	6.4	3.82	4.24**	9.02		
$Goods\_IMP$	1.25	1.98*	5.1	-1.95	-2.29**	8.51		
Int_Users	52.76	12.86**	41.02	27.81	2.07*	41.27		
Constant	-1160.22	-3.54**	3278.52	364.14	7.79**	3672.51		
R^2	0.54				0.96			
F-statistic(P-value)	76.74	(0.00)		161.63**	(0.00)			

Notes: *, **, ***, denote panel data variable is significant at 10%, 5% and 1% significance levels respectively. P-value are in parentheses ( ). d.f denotes degrees of freedom. X^2 denotes Chi-square.

4.4 Analysis of the Dynamic Panel Data Estimations

We report separate results for 2-step 1st Difference GMM (denoted as Diff-2 GMM) and 2-step System GMM (denoted as Sys-2 GMM) as short run effects of independent variables on the dependent. It was discovered that the 2-step GMM estimators showed more regression power than 1-step GMM estimators. In order to confirm that our GMM approach would produce reliable and consistent estimates, two tests were conducted. First, the author tested for absence of second order autocorrelation in the residuals of the first difference equation, Arellano-Bond AR (2) is applied. Test results reject the null of absence of autocorrelation in the residuals (See Table 4). Secondly, the author tested for over-identifying restrictions which requires the Hansen (J) or Sargan test to check the exogeneity of the instruments as a group. The tests indicated that the instruments as a group are exogenous (See Table 4). The values reported for the Hansen (J) (1982) or Sargan test are the p-values for the validity of the additional moment restrictions necessary for the system GMM. The test failed to reject the null that additional moment conditions are valid. The values reported for the Arellano-Bond test (1991) for the second order serial correlation are the p-values for the second order auto-correlated disturbances. As reported in Table 4, there is no evidence for second order autocorrelation except for System GMM for middle income countries panel that shows some presence of weak second order autocorrelations.

Estimates from both Diff-GMM and Sys-GMM estimators indicate that the lagged dependent variable (GDP) is statistically significant and positively correlated with the lagged dependent variable in all the three (3) subsamples of Low, Middle and High Income countries panels.

The result of the 2 step Diff-GMM show a consistent significant positive relationship between digital services trade and economic growth (GDP) in Low and High Income countries panel but it is significantly negative in the Middle Income countries panel. As expected, the relationship of digital services exports and GDP is strongest in the High Income countries where the coefficient is positively significant at 44.2% while it is only 5.1% in Low Income countries ceteris paribus. Digital services imports variable shows a negative significant relationship with GDP in Low and High Income countries but it has a positive significant relationship with GDP in Middle Income countries panel. With regards to the number of people using internet, the Diff-GMM estimates indicate that it is has a significant positive relationship with GDP in Low and High Income countries but negatively significant in Middle Income countries. The number of people using the internet on GDP growth is largest in High Income countries where it significantly results in GDP growth of 15% and only increases GDP by 3.9% in Low Income countries ceteris paribus. In terms of control variables of goods exports and imports, they show a significant relationships with GDP in all the three sub sample panels with expected or conventional positive and negative signs respectively. Like static FE models, goods export variable significantly increases GDP more in Middle income countries panel by 28.69%.

When we consider the estimates from the Sys-GMM estimator, it is easy to note that that the lagged dependent variable is very significant and positively correlated with lagged dependent variable in all the three (3) subsamples compared to the Diff-GMM estimator.

Moreover, the significant estimate coefficient in Sys-GMM are generally larger than those estimated by the Diff-GMM estimator. Perhaps, this confirms the assertions in the literature that the GMM estimator is more efficient estimator than the Diff-GMM (See, Blundell and Bond, 2000, Arellano and Bover, 1995). For these reasons, we take it that the Sys-GMM estimates are more informative than those from Diff-GMM. Digital services exports have a significant positive effect on GDP in Low and High Income countries panels where it causes GDP to increase in the short run by 5.7% and 52.4% respectively. It causes GDP to fall by 45.7% in Middle Income countries panel. With regards to the number of people using the internet variable, the Sys-GMM estimates indicate that internet usage has a significant positive effect on GDP in the short run. Specifically, it appears that for every 1 unit increase in the number of people using the internet, GDP increases by 21.9%, 4.1% and 3.9% in High, Middle and Low Income countries respectively. These results are in tandem with empirical literature regarding the effect of digital economy development on economic growth. For instance, Soomro et al (2022) found that there is a positive significant effect between per capita ICT growth and GDP. Similarly, Aslam and Shabbir (2020) found that social and digital inclusiveness indexes have a significant positive effect on economic growth and Jiao and Sun (2021) found that digital economic development has a significant positive effect on urban economic growth in China. Therefore, it is clear that High Income countries panel is leading in terms of digital services trade driven economic growth relative to Middle and Low Income countries because they have and continue to invest more in digital trade augmenting social and physical infrastructure. Finally, the control variables of goods exports and goods imports have significant positive and negative relationships with GDP in all the three panels except goods imports in Middle Income countries panel where it is insignificant.

Table 4: Dynamic Panel Estimates-Diff GMM and Sys-GMM

	First Difference GMM(Diff-2 GMM)					Sys-GMMM (Sys-2 GMM)			
Dependent GDPP_C			Hansen(J) test	AR(2) test	Number of			Hansen(J)	AR(2) test
Variables	$coeff$	$t-statistics$	Stat(p-value)	(p-values)	Instruments	$coeff$	$t-statistics$	test(p-value)	(p-values)
Panel 1: Low Income Countries									
$GDPP\_C(-1)$	0.57	80.89**	36.83	(0.19)	32	0.59	84.61***		(0.11)
$Digserv\_EXP$	5.07	7.09**	(0.43)			5.73	7.02**	24.69	
$Digserv\_IMP$	-6.98	-7.99**				-7.09	-9.47**	(0.59)	
$Goods\_EXP$	3.3	13.84**				3.5	23.26**		
$Goods\_IMP$	-1.01	-10.41**				-1.19	-20.79*		
Int_Users	3.86	7.16**				3.91	8.07**		
$Observations$	388					388			
Panel 2: Middle Income Countries									
$GDPP\_C(-1)$	0.33	54.82**	35.52	(0.15)	42	0.31	80.88***	35.54	(0.05)
$Digserv\_EXP$	-42.61	-20.34**	(0.51)			-45.69	-22.52**	(0.44)	
$Digserv\_IMP$	29.63	9.30**				31.32	7.08**		
$Goods\_EXP$	3.2	28.69**				3.34	26.16**		
$Goods\_IMP$	-2.11	-1.61				-2.89	-1.63		
Int_Users	-2.06	-1.82*				4.09	2.59**		
$Observations$	477					477			
Panel 3: High Income Countries									
$GDPP\_C(-1)$	0.39	18.56**	19.08	(0.36)	24	0.42	24.85***	18.08	(0.29)
$Digserv\_EXP$	44.24	1.99*	(0.39)			52.39	3.22**	(0.42)	
$Digserv-IMP$	-45..39	-5.34**				-46.86	-7.13**		
$Goods\_EXP$	1.20	11.53**				1.23	15.95**		
$Goods\_IMP$	-6.14	-11.42**				-6.42	-11.57**		
Int_Users	15.03	3.38**				21.94	2.08*		
$Observations$	289					289			

Notes: *, **, ***, denote panel data variable is significant at 10%, 5% and 1% significance levels respectively. The Hansen (1982) J-or Sargan test p-values are in parentheses ( ). AR (2) denotes the Arellano-Bond second order autocorrelation tests. The p-values are indicated in parentheses ( ).

5. Conclusion and Recommendations

The goal of this study is to analyze the effect of digital services trade on the panel of 46, 32 and 24 Low, Middle and High Income panel of countries for the period 2005-2019. This study employed both static methods of pooled panel OLS (POLS) and Fixed Effects (FE) and dynamic approaches of Difference GMM and System-GMM.

The pooled panel OLS (POLS), POLS models estimate that digital services exports cause a significant long run increase in GDP in High income countries by 39.67% relative to 6.68% in the panel of Middle Income countries and negative growth in Low income countries of 7.74%. Regarding the number of people using the internet, POLS models show that the number of people using the internet has a significant positive impact on GDP in all the three subsample panels. Specifically, for every 1 unit increase in people using the internet, GDP significantly increases by 63.5%, 52.8% and 22.2% in Middle, High and Low Income country panels respectively.

The Fixed Effects (FE) models show that digital services exports significantly reduce GDP growth by 8.97% and 7.17% in Low and Middle Income countries panels respectively. However, it significantly increases GDP in High income countries by 10.13%. In addition, the FE models predict that for every 1 unit increase in the number of people using the internet, GDP significantly increases by 42.7%, 27.8% and 0.03% in the Middle, High, and Low Income countries panels respectively.

The dynamic 2 step Difference GMM estimator shows a short run consistent significant positive relationship between digital services trade and economic growth (GDP) in Low and High Income countries panel of 5.1% and 44.2% respectively. It is significantly negative in the Middle income countries panel. Digital services imports variable shows a negative significant relationship with GDP in Low and High Income countries but it has a positive significant relationship with GDP in Middle Income countries panel of 29.6%. Diff-GMM predicts that for every 1 unit increase in people using the internet in the short run, there is a significant GDP growth of 15% and 3.9% in High and Low income countries panel respectively. However, it causes a significant fall in GDP of Middle Income countries by 2.1%.

The Sys-GMM estimator predicts that, ceteris paribus, a 1 unit increase in digital services exports significantly impacts GDP growth GDP in Low and High Income countries panels in the short run by 5.7% and 52.4% respectively. However, it significantly causes GDP to fall by 45.7% in Middle Income countries panel. With regards to the number of people using the internet variable, the Sys-GMM predicts that for every 1 unit increase in the number of people using the internet GDP significantly increases in the short run by 21.9%, 4.1% and 3.9% in High, Middle and Low Income countries respectively. It seems like the Sys-GMM estimator is more efficient than Diff-GMM estimator because the lagged dependent variable is very significant and positively correlated with lagged dependent variable in all the three (3) subsamples compared to the Diff-GMM estimates. In addition, the statistically significant estimate coefficients in Sys-GMM are generally larger than those estimated through the Diff-GMM approach. This result corroborates with the assertions in the literature that the System GMM estimator is a more efficient estimator than the Difference-GMM estimator.

It is clear from the results of this study that Low income countries are lagging behind in digital services trade. It is also clear that High Income countries seem to be maximizing and leading the digital services trade largely because they have and continue to invest in digital services trade infrastructure.

To this end therefore, this study recommends that Low and Middle Income countries' governments and the private sectors should increase investments in both institutional and physical digital infrastructure that enable more people, especially small, medium enterprises (SMEs) and those in rural areas to access digital trade related services. The digital services trade agenda should incorporate and blend different initiatives under a single national strategy aimed at to preparing Low and Middle Income countries panel not only to adopt and use digital trade technologies but it should also be reflected in the production of goods with built in digital trade services in an increasingly digitalized trade environment. Increased access to stable, high speed and affordable internet services is important in promoting digital services trade, job creation and increasing digital service trade driven economic growth.

Acknowledgments

The author wishes to express gratitude to the reviewers for their insightful professional comments on the earlier versions of this paper.

Competing Interests

The author declares that no competing interests exist.

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Appendices

Appendix1- Correlation matrix- Low, Middle and High Income Countries' Panels

	$GDPP\_C$	$Digserv\_EXP$	$Digserv\_IMP$	$Goods\_EXP$	$Digserv\_IMP$	Int_Users
Panel A: Low Income Countries						
$\boldsymbol{GDPP\_C}$	1					
$Digserv\_EXP$	-0.03	1				
$Digserv\_IMP$	0.38	0.41	1			
$Goods\_EXP$	0.08	0.33	0.19	1		
$Goods\_IMP$	0.02	0.43	0.17	0.95	1	
Int_Users	0.38	-0.11	-0.05	0.09	0.08	1
Panel B: Middle Income Countries						
GDP_C	1					
$Digserv\_EXP$	0.08	1				
$Digserv\_IMP$	-0.01	0.03	1			
$Goods\_EXP$	0.19	0.11	-0.05	1		
$Goods\_IMP$	0.22	0.09	-0.05	0.99	1	
Int_Users	0.52	0.14	0.21	0.12	0.13	1
Panel C: High Income Countries						
GDP_C	1					
$Digserv\_EXP$	0.55	1				
$Digserv\_IMP$	0.31	0.51	1			
$Goods\_EXP$	0.31	0.51	0.34	1		
$Goods\_IMP$	0.27	0.48	0.36	0.94	1	
Int_Users	0.68	0.46	0.34	0.33	0.28	1

Source: Authors' elaboration on data from UNCTAD and World Bank's World Development Indicators

Appendix 2

List of Countries in the subsample panels.

Serial No.	**Panel 1: Low Income Countries**	**Panel 2: Middle Income Countries**	**Panel 3: High Income Countries**
1	Angola	Albania	Antigua and Barbuda
2	Bangladeshi	Algeria	Australia
3	Bolivia	Argentina	Canada
4	Carbo.Verde	Armenia	Chile
5	Cambodia	Azerbaijan	Denmark
6	Cameroon	Belarus	Estonia

7	Comoros	Belize	Germany
8	Cote D'ivore	Bosnia And Herzegovina	Italy
9	Egypt	Botswana	Japan
10	El Savado	Brazil	S. Korea Rep
11	Eswatin	Bulgaria	Kuwait
12	Ghana	China	New Zealand
13	Honduras	Colombia	Norway
14	India	Costa Rica	Panama
15	Indonesia	Dominica	Poland
16	Kenya	Dominican Republic	Portugal
17	Kyrgyzstan	Ecuador	Saudi Arabia
18	Moldova Rep	Fiji	Seychelles
19	Mongolia	Georgia	Singapore
20	Morocco	Grenada	Sweden
21	Nicaragua	Guatemala	Switzerland, Liechtenstein
22	Nigeria	Guyana	United Kingdom
23	Pakistan	Iran Rep.	United States
24	Philippines	Iraq	Uruguay
25	Senegal	Jamaica	
26	Solomon Islands	Jordan	
27	Sri Lanka	Kazakhstan	
28	Tunisia	Lebanon	
29	Ukraine	Libya	
30	Vanuatu	Malaysia	
31	Vietnam	Mauritius	
32	Zambia	Mexico	
33		Namibia	
34		North Macedonia	
35		Paraguay	
36		Peru	
37		Romania	
38		Russian Federation	
39		Samoa	
40		South Africa	
41		St. Vincent & The Grenadines	
42		St.Lucia	
43		Suriname	
44		Thailand	
45		Tonga	
46		Turkey	