Postprint of: Lechman E., Popowska M., Harnessing digital technologies for poverty reduction. Evidence for low-income and lower-middle income countries, TELECOMMUNICATIONS POLICY Vol. 46 No 6 (2022), 102313, DOI: 10.1016/j.telpol.2022.102313

Ewa Lechman,
0000-0003-1718-7134
eda@zie.pg.edu.pl
Faculty of Management and Economics
Gdańsk University of Technology
(a member of Fahrenheit Universities)
Ul. Narutowicza 11/12
80-233 Gdańsk, Poland

Magdalena Popowska,
0000-0002-2235-7196
mpop@pg.edu.pl
Faculty of Management and Economics
Gdańsk University of Technology
(a member of Fahrenheit Universities)
Ul. Narutowicza 11/12
80-233 Gdańsk, Poland

Harnessing digital technologies for poverty reduction. Evidence for low-income and lower-middle income countries.

Abstract:

This paper contributes to understanding the relationship between ICT deployment and poverty alleviation in developing countries. It assess the digital technologies contribution to poverty reduction, through different channels of impact, like education, labor market, income and ICT-trade related activities.

Using the sample of 40 developing countries between 1990 and 2019, it relies on macro data extracted from the World Bank Development Indicators (2021) and the World Telecommunication/ICT Indicators Database (2020). Methodological framework combines time trend analysis and locally weighted polynomial smoother, logistic growth model, and panel regression modelling techniques. Our major findings suggest growing ICT deployment, school enrolments, and increases in material wealth are significant drivers of poverty eradication in developing economies. However, the impact of digitalization on poverty is neither direct nor immediate. Therefore, we claim that national and local authorities, together with civil society must consider ICT as a key element of their broad development strategies.

Keywords: economic growth, poverty, vulnerable employment, ICT, developing countries

JEL codes: O30, O40

1. Introduction

There is an ongoing discussion on the impact of information and communication technologies (ICT) on the development of countries (Vu and Asongu, 2020). It is the aftermath of the digital revolution (Perez, 2002) that brought novel technological solutions and these new technologies expanded, becoming engines of growth through their capacity to transform society and economies. The new techno-economic paradigm (Perez, 1984) emerged, opening opportunities and bringing benefits not only to advanced economies, but also economically backward countries that were never real beneficiaries of past technological revolutions. Along with the growing ICT deployment worldwide, we observe a growing body of evidence arguing that ICT may enhance economic growth and thus helps to reduce poverty (Asongu and Odhiambo, 2019; Kanjo, 2020).

The evidence examining the impact of ICT on poverty alleviation traces the links between technological advancements *versus* education, health care, economic activities, and trade, labor, and new government services. ICT empowers people by enabling them to access, use, and share information (Rashid, 2017; Stewart and James, 2019), thus to acquire knowledge enhancing poverty reduction through better education and skills acquisition, employability, economic activity, and labor engagement (Ray and Kuriyan, 2012; Asongu et al., 2021). Ramanadham (2019) claims that ICT offers developing countries the opportunity to transform their economies into high value-added and tech-based once (Dominguez Castillo et al., 2019).

Broadly speaking, our paper contributes to current findings and policy debate on Sustainable Development Goal 1[1] by providing macroeconomic evidence on the role of ICT in poverty reduction. It contributes to better understanding ICT`s impact on poverty reduction in developing countries. We trace the channels of this impact (Opportunity Windows – see Perez and Soete, 1988) using macro-level empirical evidence and hypothesize that increasing ICT deployment contributes to poverty reduction through economic and social empowerment, demonstrated in increasing gross per capita, school enrolment, dropping vulnerable forms of employment, enhanced ICT trade activities and economic freedom. Our major contribution to the state of knowledge consists in:

1. Identifying the channels of ICT impact on poverty reduction;
2. Examining the statistical relationship of poverty rates *versus* ICT deployment and other macroeconomic indicators;
3. Verifying the main determinants of poverty rate reduction, including ICT employment and other macroeconomic indicators.

Our empirical sample covers 40 low and lower-middle income countries. The time span of the analysis is 1990-2019. The statistical data are extracted from the World Telecommunication/ICT Indicators Database 2020 and World Bank Development Indicators 2021.

The article proceeds as follows: the next section contains the contextual background and literature review on the ICTs impact on poverty reduction through economic empowerment, identification of channels of impact with particular attention to developing countries. Section 3 describes the research method permitting the estimation of the contribution of ICTs to poverty reduction. Section 4 discusses the empirical findings for the selected group of countries and Section 5 concludes.

2. Contextual background and literature review

For the last 25 years, the world made impressive progress in reducing poverty. Between 2010 and 2015, in 60% of countries, incomes of the poorest grew faster than the world average (WDI, 2021). The global extreme poverty rate ($1.90 day) fell from 42.5 in 1981 to 9.2 in 2017 (WDI, 2021) and is expected to rise slightly in 2020. If $5.5 a day poverty line is considered, we observe drops from 66.4 till 43.6 in the poverty headcount ratio in the analogous period. According to WDI (2021) 80% of people falling below the international poverty line lives in rural areas; the most deprived groups remain children and women with limited access to education (about 70 percent of the global poor aged 15 and over have no schooling

[1] However, it is clearly stated that ICT can help accelerate progress towards every single one of the 17 United Nations Sustainable Development Goals (SDGs), and may contribute to the poverty reduction holistically (ITU, 2018).

or only some basic education). Sub-Saharan Africa is the most poverty-affected region as half of the world's extreme poor live there, and 50% of them are concentrated in 5 countries: Nigeria, Democratic Republic of Congo, Tanzania, Ethiopia, Madagascar. A large portion of the global poor is exposed to institutional fragility, armed conflict, and violence. Furthermore accelerating climate change is hitting the poorest most- their number is supposed to increase by 2030 by about 100 million people. This evidence shows the need for relevant solutions regarding ICT deployment for poverty reduction, along with regulatory frameworks enhancing education and skill improvement, labor mobilization, and economic growth (Mushtaq and Bruneau, 2019; Appiah-Otoo and Song, 2021).

The potential of ICT to fulfill the Sustainable Development Goals (SDGs) by reducing poverty and hunger, promoting well-being and education, reducing inequalities, has been officially recognized by United Nations, highlighted in International Telecommunications Union Report (Wahlen, 2017) and in the Sustainable Development Goals Report (UN, 2019). ICT offer a wide bundle of opportunities for the developing world, being recognized as a source of socio-economic transformation by enhancing growth of social and economic networks, accessing knowledge and information, new services, and employment growth, became a part of development strategies for many developing countries. Technological advancements may have either direct or indirect effects on socio-economic development by mobilizing resources and reinforcing market activities through specific channels. ICT fosters the mobilization of the labour force by leveraging active engagement in formal labor markets, reducing employment vulnerability that affects disadvantaged groups, such as, e.g., rural women and their exposure to negative external shocks (Asongu and Nwachukwu, 2018). Through better access to financial markets ICT fosters the mobilization of savings and offers opportunities to convert these savings into investments (Pradhan et al., 2018; Stanley et al., 2018), which has long-term positive consequences for market activity and economic growth. Indirectly, ICT may affect socio-economic development although improved access to education, knowledge, and information that foster increases in human capital and skills contributing to social cohesion and empowerment of deprived social groups (e.g., endogenous people, out-of-school children) (Dominguez Castillo, 2018). EdTech solutions are of unique importance for developing countries by offering remote teaching modes, better access to learning materials and knowledge, and leveraging enrollment rates (Jamil et al., 2020). The effects of ICT are not limited to the classroom as e-learning offers the possibility of delivering distance education and of building borderless educational networks. It creates a causal loop where ICT shifts the quality of education on the one hand, and on the other – educational improvements yield further digital technology deployment.

Another aspect of ICT is shifting labour force participation. Developing economies suffer from low female participation in the formal market economy, i.e., in the job market and entrepreneurial activities, which may be a direct effect of poor education, poor skills, and illiteracy. Women in developing countries being deprived of access to the financial system; they have no permanent income from contracted work. Female population often has a status of 'hidden, unused, and unpaid' labour, they are exposed to extreme poverty. ICT helps to overcome barriers for women seeking to escape vulnerable, low-paid employment (Beneria et al., 2015). Moreover, ICT improves people`s welfare through more effective functioning of healthcare systems and creating a demand for good governance by strengthening transparency and accountability via e.g. e-government solutions. Diffusion of e-government innovations in developing countries was observed during the last two decades benefiting citizens and governments (Zoo et al., 2017; Hanna, 2020).

The above channels are not opened unconditionally, and the full exploitation of ICT potential is far from automatic. Favourable legal and institutional environments and a degree of telecommunication market competition are indeed critical for the adoption and usage of ICT. The impact of ICT is indirectly influenced by the backbone infrastructure enabling ICT installation, which is an important element when the role of ICT for poverty reduction in developing countries is considered. Undoubtedly, basic infrastructure must be assured. Unfortunately, in this aspect still large disparities across the world exist and hinder the deployment of ICT, not only between countries, but also within countries (Rodriguez-Segura, 2020).

The importance of ICT for poverty reduction is supported by the growing body of evidence. Yilmaz and Koyuncu (2018) examined panel data (2000-2013) for 182 countries and found that the Internet had the strongest, among all ICT indicators, impact on poverty and inequality reduction. The evidence from Rashid (2016) supports the claims that digital inequalities mirror the patterns of social inequality, hence ICT diffusion shall be fostered. Another study by Khaliq et al. (2016), focusing on the poverty reduction among women indicate that ICT contributes significantly to reduce poverty and improve the livelihoods of women by strengthening social networks, cutting down travel costs, and facilitating the efficiency of economic activities. Andreev et al. (2019) find that ICT use is the most optimal way to achieve social welfare even if a country experiences financial constraints. The analysis of the Nigerian educational context invited Raji et al. (2017) to state that the existing inadequacy in access to ICT caused digital illiteracy which impedes educational advancement. Anwar (2019) discusses the broader context of ICT for poverty reduction in the case of South Africa; and in the same vein, Tchamyou et al. (2019) underline the importance of ICT for inequality reduction and financial inclusion in Africa. Bhattacharya (2019) shows that ICT helps to fight informality in developing countries, while Dutta et al. (2019) provide evidence on how ICT improves healthcare in Asia.

All above mentioned papers address the relationship between ICT and poverty alleviation using various perspectives and macroeconomic indicators considered. However, most of them focus on one aspect of the poverty reduction or provide a limited geographical coverage. Therefore, our research offers broader perspective on the presumed relationship, first of all, by analysing a broad sample of developing countries (40) and secondly, thanks to the identification of the specific channels of this impact for relatively long time span of 29 years. This contributes to the existing body of knowledge by providing solid empirical evidence based on reliable macroeconomic indicators.

3. Empirical strategy and data rationale

Aside from presenting the standard descriptive statistics, our empirical strategy deploys analytical techniques that reveal the key features of the main variables and the relationships among them. We use time trend analysis and a locally weighted polynomial smoother logistic growth model, and we rely on panel regression modelling techniques that allow us to capture the interdependencies in our data and trace statistical relationships between the examined variables.

To examine visually the statistical relationships between variables, we adopt the exploratory data analysis method – locally weighted polynomial smoother (Lowess). Applied scatterplot smoothing is a robust, nonparametric, flexible approach to data exploration (Cleveland, 1979; Cleveland and Devline, 1988) allowing finding the functional relationships between variables (measures). A local polynomial smoother, using weighted least squares regression minimizing the weighted least squares function, fits a locally weighted regression at each point of variable x to produce the estimate – the response variable – y, at each x. Weighted least square is down weight observations with more variability and thus the graphical estimates becomes more robust (Loader, 2012).

In our research, we also use logistic growth equation to estimate the in-time dynamics of the process of technology diffusion, as well as to draw empirical diffusion trajectories. The logistic growth function derives from the exponential growth model that follows the ordinary differential equation (Meyer et al., 1999):

$$\frac{dY_x(t)}{dt} = \alpha Y_x(t), \tag{1}$$

Where $Y(t)$ explains the level of variable x, (t) is time, and α is a constant growth rate. If we introduce e[2] to Eq. (1), it may be rewritten as:

$$Y_x(t) = \beta e^{\alpha t} , \tag{2}$$

with notation analogous to Eq. (1) and β representing the initial value of x at $t = 0$.

Bearing in mind that the growth model is predefined as exponential, it yields modifications by introduction of the 'resistance' parameter (Meyer et al., 1999; Banks, 1994; Cramer, 2003; Kwasnicki, 2013) to Eq. (1), which imposes growth limits to the exponential growth model. The adjusted version of Eq. (1) is the logistic differential function:

$$\frac{dY(t)}{dt} = \alpha Y(t)\left(1 - \frac{Y(t)}{\kappa}\right), \tag{3}$$

where the parameter κ denotes the 'resistance' parameter (upper asymptote) that limits the growth of Y.

By reformulating the Eq. (3), we develop a 3-parameter logistic growth function, holding a general form:

$$N_x(t) = \frac{\kappa}{1+ e^{-\alpha t-\beta}} , \tag{4}$$

where $N_x(t)$ stands for the value of variable x in time period t. The parameters in Eq.(4) explain the following:

- κ - upper asymptote, which determines the limit of growth ($N(t) \rightarrow \kappa$), also labelled 'carrying capacity' or 'saturation';
- α - growth rate, which determines the speed of diffusion;
- β - midpoint, which specifies the exact time (T_m) when the logistic pattern reaches 0.5κ (the inflection point of the logistic curve).

The estimates α parameter indicating the growth rate allows for specifying another parameter 'specific duration' ($\Delta t = \frac{\ln(81)}{\alpha}$) approximating time needed for x to grow from 10%κ to 90%κ. The parameters defined in Eq.(4) can be estimates using ordinary least squares, maximum likelihood, algebraic estimation, or nonlinear least squares. According to Satoh (2019), the nonlinear least squares estimation method produces relatively least biased parameters and the most accurate predictions and allows avoiding time interval (Srinivasan et al., 1986). Still, the key disadvantage of NLS is sensitivity of the parameters to the initial values in the time series.

Finally, to examine the statistical relationships between the considered variables and unveiled poverty reduction determinants, we deploy panel regression analysis. We use fixed effects regression holding a general form:

$$\varphi_{y,c} = \alpha_c + \gamma_1 x_{1,y,c} + \dots + \gamma_n x_{n,y,c} + \varepsilon_{y,c} , \qquad [5]$$

where c denotes the country and y the year, $x_{1-n,c,y}$ explanatory variables and γ_{1-n} their coefficients, α_i denotes unobserved time-invariant effects. For Eq. (5) to satisfy the exogeneity assumption, we assume $E\left(\varepsilon_{y,c} / x_{y,c},\ \alpha_c\right) = 0$, with $x_{c,y}$ standing for the explanatory variable. To confirm the adequacy of the fixed effects regression, we perform a Hausman test (Maddala and Lahiri, 1992) to check the null hypothesis: where $H_0\colon cov\left(\alpha_c, x_{y,c}\right) = 0$, a random effects regression is asymptotically more efficient; otherwise a fixed effects regression is more suitable. To enrich the analysis we reformulate Eq.(5) by adding country-dummies and interaction terms (Aiken and West, 1991), which holds its augmented form:

$$\varphi_{y,c} = \alpha_c + \gamma_1 x_{1,y,c} + .. + \gamma_n x_{n,y,c} + \delta_2 C_2 + .. + \delta_n C_n + \vartheta_3\left(a_{3,y,c} * b_{1,y,c}\right) + .. + \vartheta_n\left(a_{n,y,c} * b_{n,y,c}\right) + \varepsilon_{y,c} , \qquad [6]$$

[2] Base of natural logarithms.

In Eq. (6) δ_n is the coefficient for binary-country regressors, C is the country dummy, and ϑ_n is the coefficient for interaction term $(a_{n,y,c} * b_{n,y,c})$. The main equation to estimate then holds the empirical form:

$$Pov_{y,c} = \alpha_c + \gamma_1 GDP_{y,c} + \gamma_2 School\_prim_{y,c} + \gamma_3 School\_second_{y,c} + \gamma_4 Vulner_{y,c} + \gamma_5 Self\_empl_{y,c} + \gamma_6 ICT\_goods_{y,c} + \gamma_7 ICT\_serv_{y,c} + \gamma_8 IU_{y,c} + \gamma_9 MCS_{y,c} + \gamma_{11} Freedom_{y,c} + \gamma_{12} HCI_{y,c} + \delta_2 Low_{y,c} + \vartheta_3[MCS_{y,c} * GDP_{y,c}] + \vartheta_4[MCS_{y,c} * HCI_{y,c}] + \vartheta_5[IU_{y,c} * GDP_{y,c}] + \vartheta_6[IU_{y,c} * HCI_{y,c}] + \varepsilon_{y,c}, \quad [7]$$

Our research covers 40 low-income and lower-middle-income countries[3,4] from all world regions. The time span for the analysis is set for 1990 to 2019 and is selected on the basis of data accessibility – this is the sole period for which a balanced dataset is available for the majority of the sample countries. We have excluded from our sample small island states, armed-conflict affected areas, and economies for which significant gaps in time series were observed. To run the empirical analysis, we have selected 13 macroeconomic variables, which are summarized and briefly explained in the Table 1 below.

Variable	**Brief explanation**
Poverty headcount ratio [%] – $Pov_{y,c}$	The poverty headcount ratio is set at US\$5.50 a day (in 2011 PPP) showing the share of the country population living on less than \$5.50 a day.
Internet users [%] – $IU_{y,c}$	It explains the 'proportion of individuals who used Internet from any location in the last three months.'
Mobile cellular telephony penetration rates [per 100 inhab.] – $MCS_{y,c}$	It shows the share of a country`s population having access to and using mobile cellular telephony infrastructure
Gross domestic product per capita [int.\$] – $GDP\_PPP\_pc_{y,c}$	Material wealth expressed in PPP in constant 2017 international \$.
School enrolment, gross, primary (% gross) – $School\_prim_{y,c}$	Refers to gross enrollment ratio as the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the respective level of education.
School enrolment, gross secondary (% gross) – $School\_second_{y,c}$	
Vulnerable employment (% of total employment) – $Vulner_{y,c}$	Refers to contributing family workers and own-account workers as a percentage of total employment. Modelled ILO estimate are used.
Self-employed (% of total employment) – $Self\_empl_{y,c}$	Refers to workers are workers working on their own account with one or a few partners or cooperatives, but also contributing family workers Modelled ILO estimate are used.
Employment to population ratio, ages 15-24(% of total employment) – $Empl\_15\text{-}24_{y,c}$	Refers to proportion of a country's youth population that is employed. Modelled ILO estimate are used.
ICT goods imports (% total goods imports) – $ICT\_goods\_IMP_{y,c}$	Refers to information and communication technology goods imports that include computers and peripheral equipment, communication equipment, consumer electronic equipment, electronic components, and other information and technology goods.
Communications, computer, etc. (% of service imports, BoP) – $ICT\_serv\_IMP_{y,c}$	Refers to the import of communications, computer, information, and other services that cover international telecommunications, data, news-related service, royalties and license fees.

[3] For full list of countries – see Table A1 in Appendix.
[4] In this research we use World Bank country classification methodology (Feb, 2021) – for the current 2021 fiscal year, low-income economies are defined as those with a GNI per capita, calculated using the World Bank Atlas method, of \$1,035 or less in 2019; lower middle-income economies are those with a GNI per capita between \$1,036 and \$4,045.

Economic Freedom Index – $Freedom_{y,c}$	A composite measure of the country`s freedom in 12 different areas covering: property rights, judicial effectiveness, government integrity, tax burden, government spending, fiscal health, business freedom, labor freedom, monetary freedom, trade freedom, investment freedom, and financial freedom.
Human Capital Index – $HCI_{y,c}$	A sub-index of E-Government Development index. It that combines several elements like: adult literacy, gross enrollment ratio, expected years of schooling and mean years of schooling[5].

Table 1. Variables selected for the analysis.
Source: Authors` elaboration.

All data used in this research are extracted from World Development Indicators 2021 database, World Telecommunication/ICT Indicators database (June 2020 Edition), Heritage Foundation and United Nations database on E-Government and Human Capital Index values.

4. Empirical results

4.1. Summary statistics.

In this section, we present results regarding over-time changes in ICT deployment and the extent of poverty in 40 low-income and lower-middle-income countries in the period between 1990 and 2019. To contextualize our research examining whether digital technologies deployment has a positive impact on poverty reduction, we report on countries' development performance in various aspects of macroeconomic conditions. With these aims, aside from ICT indicators and poverty headcount ratio, we consider economic growth, educational attainment, labor market variables, export and import activities in terms of ICT goods and services, and economic freedom. We start discussing our results with descriptive evidence. Table 2 summarizes descriptive statistics, Figure 1 displays mobile cellular telephony and Internet users changes over time for averaged values between 1990 and 2019, and Figure 2 – poverty headcount ratios and the remaining considered macroeconomic variables for the analogous period. In our research approach, to discuss the magnitude of poverty across countries in scope, we use US$5.50, internationally comparable poverty lines presented by World Bank to monitor poverty change. Hence, the estimated poverty headcount ratios ($Pov_{y,c}$) for the respective countries determine the share of the country`s population living below US$5.50 poverty line. Figure 2 illustrates the averaged changes in poverty headcount ratios between 1990 and 2019. Downward trend, although with several ups and downs, shows that during the analysed period the average poverty headcount ratio dropped from 74.4% in 1990 to slightly above 34% in 2019. Between 1990 and 2000, the average poverty headcount ratio remained at a relatively stable high levels – ranging from 74.4% in 1990 to 74.5% in 2000, with the observable peak in 1994 – 90.2%. However, since the year 2000 onward, the poverty trend line is fast sloping down, demonstrating rapid drops in poverty headcount ratios. If we take a closer look at the individual countries and monitor changes in poverty headcount ratios, , we observe considerable cross-country variations in this respect (see Figure A1 in Appendix displaying country-specific poverty headcount ratio lines). There is a group of countries where decreases in the magnitude of poverty are easily detectable between 1990-2019. These are, for instance, Bolivia (drop from 65% to 22%), El Salvador (drop from 60% to 26%), or Moldova (drop from 75% to 13%), while in countries like Ghana, Honduras, Kyrgyz Republic, Mongolia, Nicaragua, Sri Lanka, Tajikistan, Ukraine or Vietnam, poverty rates have fallen substantially lifting a substantial share of population out of extreme poverty. Among countries in the sample, the highest poverty rates are observed in countries like, *inter alia*, Bangladesh, Burundi, Lao PDR, Madagascar, Mali, Mozambique, Niger, Nigeria, Senegal, or Zambia where between

[5] Detailed methodology of how Human Capital Index is calculated can be traced in e.g. in United Nations (2018).

1990 and 2019 drops in the share of population living below poverty threshold are negligible, and at the end of 2019 they were still suffering from extensive poverty at indecently high level of almost 90% of countries' population. After a brief summary on how the extent of poverty has changed over time, in the next step we try to relate the observed increases or decreases in the countries' digital technologies deployment, economic growth, and remaining related macroeconomic variables.

Variable	**# of obs.**	**Mean**	**Std. dev.**	**Min. value**	**Max. value**
$Pov_{y,c}$	890	75.9	22.5	2.0	100.0
$IU_{y,c}$	885	9.7	14.3	0.00002	76.1
$MCS_{y,c}$	993	40.3	44.5	0.00001	154.7
$GDP\_PPP\_pc_{y,c}$	1,165	3881.8	2823.2	436.7	15751.7
$School\_prim_{y,c}$	1,042	94.7	23.7	21.7	156.4
$School\_second_{y,c}$	780	48.3	28.3	5.2	105.2
$Vulner_{y,c}$	1,131	64.6	21.8	14.5	94.6
$Empl\_15\text{-}24_{y,c}$	1,131	46.1	15.9	17.1	89.9
$Self\_empl_{y,c}$	1,131	67.2	20.6	15.6	94.8
$ICT\_goods\_IMP_{y,c}$	642	5.3	5.8	0.43	51.5
$ICT\_serv\_IMP_{y,c}$	1,012	29.5	15.5	0.31	99.2
$Freedom_{y,c}$	941	55.5	5.9	33	76.3
Human Capital Index	399	0.55	0.21	0.04	0.96

Table 2. Summary statistics.

Source: Authors` calculations. Note: $Pov_{y,c}$ refers to poverty headcount ratio at $5.50 a day, in 2011 PPP; in case of gaps in time series for $Pov_{y,c}$ – linear interpolation method applied.

First, we consider changes in the level of countries' digitalization, expressed through the lens of mobile cellular telephony adoption and Internet users. $MCS_{y,c}$ and $IU_{y,c}$ core ICT indicators are widely used to show the country`s overall performance in digital connectivity. Figure 1 displays the evolution of mobile cellular telephony penetration rates and Internet users (as a share of the country`s population) in 40 low-income and lower-middle-income countries starting from the year 1990. The visual representation of changes in ICT penetration rates in the examined countries is complemented by the estimated dynamics of the process (Table A2 in appendix), and country-specific ICT diffusion trends (Figure A1 in appendix). In the last 30 years, we observe an enormous evolution in the access to mobile communication and Internet network usage in developing countries. Logistic growth estimates for $MCS_{y,c}$ determine that between 1990 and 2019, the average intrinsic mobile telephony diffusion rate was at 44% per annum and it took only 9.8 years to pass from 10% to 90% of $MCS_{y,c}$ saturation. Estimated parameters returned from Gompertz model indicate a lower intrinsic mobile telephony diffusion rate – 27% per annum, while the specific duration is estimated for 11.4 years. Figure 1 shows that mobile cellular telephony diffusion follows the classical S-shaped trajectory; the process is slow in the early diffusion phase, then speeds up and the curve takes off around the year 2000, and then the diffusion proceeds at an exponential rate towards full saturation reached in 2019 (barely $MCS_{y,c}$=100 per 100 inhab.). Observed shifts in Internet penetration rates ($IU_{y,c}$) suggest that the process is slower compared to mobile telephony diffusion, which is probably a negative consequence of infrastructural shortages in developing countries. According to the estimated logistic growth and Gompertz model parameters for $IU_{y,c}$ (see Table A2 in appendix), the average annual diffusion rate was 23% (logistic model) and 7% (Gompertz model), while the returned specific durations – 18.8 and 43.8 years accordingly. Still, in 2019, on average, almost 50% of the countries` population has access to Internet networks. Still, in 2019, in regard to $MCS_{y,c}$ and $IU_{y,c}$ penetration rates, significant cross-country disparities are visible, suggesting that not all countries advance technologically at an equal pace. For instance, in the case of $IU_{y,c}$ in 2019 the best performing country was Morocco with $IU_{y,c}$=74.3%, while the worst – Bangladesh with $IU_{y,c}$=12.9%. Regarding $MCS_{y,c}$ differences among countries are also striking. In 2019, the countries that were fording ahead were, *inter alia*, Philippines (154 per 100 inhab.), Vietnam (141 per 100 inhab.), or Ghana and Kirgizstan (134 per 100 inhab.), but at the same time we detect countries significantly lagging behind – e.g. Malawi or Burundi.

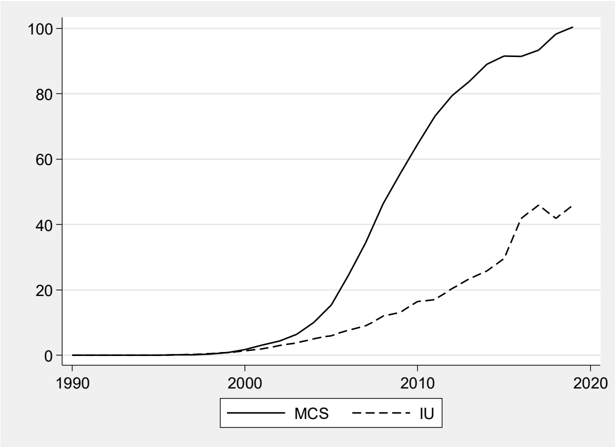

Fig.1. Mobile-cellular telephony and Internet users diffusion trajectories[6]. Period 1990-2019.
Source: Authors` elaboration. Note: on Y-axis - % of population.

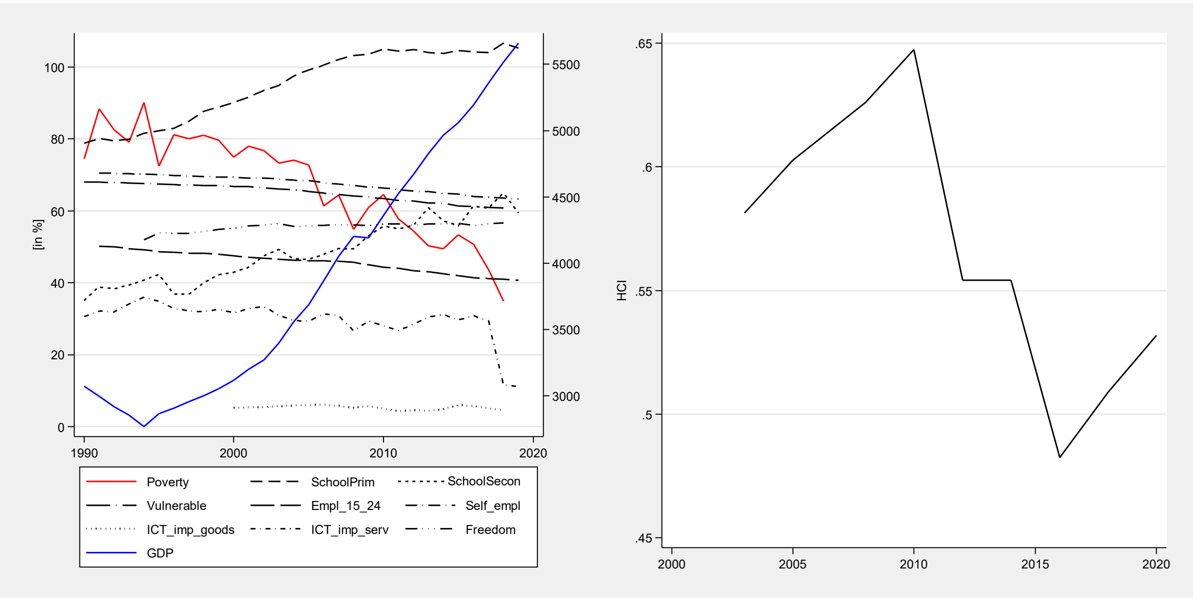

Fig.2. Poverty and its determinants. Over time changes[7]. Period 1990[8]-2019.
Source: Authors` elaboration. Note: on right-hand axis – GDP per capita; on left-hand axis – raw values of the remaining variables (averaged values); Human Capital Index value – plotted on separate graph.

To complete the picture of the economic performance of our sample countries, we briefly discuss changes regarding the remaining 9 macroeconomic variables. Figure 2 illustrates that between 1990 and 2019, we observe improvements in the economic performance of the examined economies. The most significant shifts are reported for material wealth expressed through $GDP\_PPP\_pc_{y,c}$. The average $GDP\_PPP\_pc_{y,c}$ has doubled between 1990 and 2019, and the most impressive increases are observed

[6] Averaged values for all 40 countries.
[7] Averaged values for all 40 countries.
[8] Or the earliest available year, if not available for 1990.

since mid-90s of the 20th century. Even more detailed examinations at country levels confirm that all examined economies[9] experienced stable economic growth in the analysed periods, although significant cross-country income inequalities are persistent, and some countries advanced more than others (see, for instance Bhutan, Moldova, Mongolia or Sri Lanka where shifts in $GDP\_PPP\_pc_{y,c}$ are the most significant, versus e.g., Malawi, Gambia or Madagascar that experience barely noticeable increases in material wealth). Similarly to the observed upward trends in gross per capita income growth, positive changes in the remaining macroeconomic variables are detected. The most significant shifts are observed in terms of school enrolment rates (both for primary and secondary school levels). These long-run changes in educational attendance bring prospects for the future as it determines increases in human capital stock constituting a fundamental resource for economic growth and development, and henceforth poverty reduction (Fosu, 2017; Ivanic and Martin, 2018; Beegle and Christiaensen, 2019). Between 1990 and 2019 average school enrolment rates lifted up from 78% to 105% and from 35% to 60%, for primary and secondary education level, respectively. Interestingly, rapid advances in school enrolment begin in around the year 2000, analogously to the observed tendencies in gross per capita income, digital technologies deployment, and poverty reduction. In 2019, regarding primary education cross-country disparities are far less visible compared to secondary education level. Looking at country-level data regarding primary school enrolment, in 2019, almost all countries reached 100% or close (except for Niger and Senegal), while in the case of secondary school enrolment – country's achievements vary from 24% in Niger, through around 40% in Senegal, Rwanda, Pakistan or Mauritania, to exceeding 90% in Tunisia, Bhutan or Mongolia. Human Capital Index averaged values (right-hand graph in Figure 2) suggest that between 2004 and 2019 countries` overall performance has worsened in countries in scope. In here it shall be noted that in a significant number of countries we observe shifts in this area, still in some the HCI values changes are negligible or we even observe drops in values (e.g. in Moldova, Niger, Nigeria or Pakistan). Similarly as in case of reported raw values of, for instance, gross enrolments, also in case of HCI values developing countries vary significantly. In Mongolia, between 2008 and 2010, the HCI values reached slightly above 0.9, while in Niger between 2017 and 2019 it fell until 0.08, just to cite two examples. Another three control variables diagnose changes in situation in labor market, namely – vulnerable employment, self-employment, and employment 15-24 ages. Regarding all three variables, we observe slight drops in average values between 1990-2019, from 68% to 60%, 70% to 63% and 50% to 40% regarding vulnerable employment, self-employment and employment 15-24 ages respectively. Clearly these changes are not that impressive as in the case of the previously discussed variables, but important to note here is that labor market indicators are characterized by strong inertia and hence their fluctuations over time are relatively slow. Still, the general observed tendencies suggest a falling share of the population engaged in vulnerable labor market activities, which indicates gradual improvements regarding its inclusiveness, moving towards wage jobs, and eliminating potentially vulnerable, prone, and highly exposed to external risk social groups. Apparently, elimination of labor force involvement in vulnerable, often informal or even unpaid, economic activities, reduces the risk of falling into extreme material poverty, exclusion from the formal and more secured labor markets (Häusermann et al., 2015; Gammage et al., 2020). Brief analysis of correlations between secondary school enrolment *versus* vulnerable employment, self-employment, and employment 15-24 ages unveils negative statistical associations (see pairwise correlations in Table A3 in appendix). The nexus, the inverse correlation between education and vulnerable forms of employment, is a striking but also a constant feature in most counties[10]. Finally, for the variable ICT goods imports (% of GDP) changes are barely detectable, while in the case of ICT services import (% of GDP) a radical drop is noted – from 30.6% in 1990 until 11%

[9] With the only exception of Burundi.
[10] Compare e.g. studies of Hanushek et al., (2017), Achakpa and Radović-Marković (2018), García-Carrión et al., (2018) or Lopus et al., (2019).

in 2019, however if we take a closer look at the time series we see that no significant changes were observed between 1999 and 2017, while there is an abrupt drop in 2018. Lastly, the economic freedom index does not demonstrate significant fluctuations between 1990 and 2019, hence this factor shall not demonstrate a strong impact on poverty variation.

4.2. Tracing graphical relationships.

We explore herein the empirical evidence for 40 developing countries regarding the digital technologies impact on poverty reduction, between 1990 and 2019. We hypothesize that the ICT impact on poverty reduction is neither direct nor immediate, but the decreasing share of the population left below the poverty line is determined by a bundle of interrelated factors. We start our evidence with a graphical examination of the statistical relationships between poverty, headcount ratio, and other variables – see the respective graphs in Figure 3.

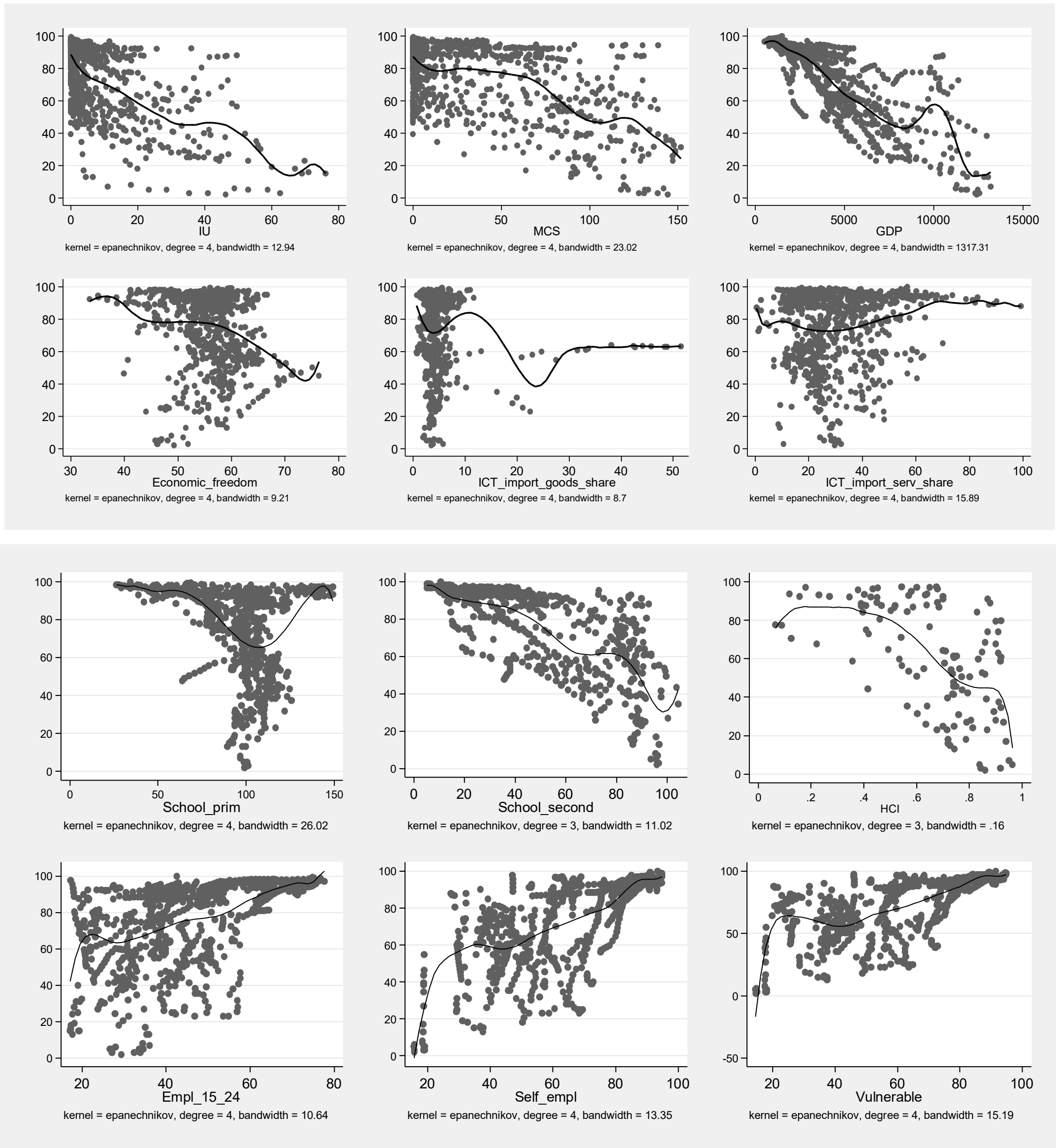

Fig.3. Poverty and its determinants. Panel analysis. Period 1990-2019.
Source: Authors` elaboration. Note: on Y-axis – Poverty headcount ratio at $5.50 a day [in %]; for Poverty – linear interpolation method applied; raw data used; locally weighted scatterplot smoothing applied; bandwidth set as default; kernel = epanechnikov.

Considering the examined variables *versus* poverty headcount ratio, we expect only 2 out of 11 variables to be positively correlated with $Pov_{y,c}$, namely: $Self\_empl_{y,c}$ and $Vulner_{y,c}$, suggesting that a higher incident of poverty is associated with low-paid, unstable job situations. In the case of the remaining 9 variables, we anticipate them to be negatively correlated with the extent of poverty. To better illustrate the examined relationships, we inspect the respective graphs in Figure 3 associating $Pov_{y,c}$ *versus* its determinants. These preliminary findings underpin our initial suppositions regarding the direction of relationships, which is additionally supported by the calculated pairwise correlations (Table A2 in appendix). Visually, we observe strong negative relationships between $Pov_{y,c}$ versus $GDP\_PPP\_pc_{y,c}$, $MCS_{y,c}$ and $IU_{y,c}$, and the correlation coefficients are (-0.82), (-0.61) and (-0.63) accordingly. Doubtlessly, higher per capita income is transformed into a lower poverty headcount ratio, and an analogous observation is valid for the two considered ICT indicators. In the examined economies, shifts in ICT adoption are accompanied by drops in material poverty. Possibly this positive impact of digital technologies growing adoption across the examined developing countries is additionally demonstrated through increasing school enrolment (primary and secondary) and general level of education (e.g. mean years of schooling or adult literacy rates), which next due to skills and education level shifts, transforms into a diminishing scale of engagement in vulnerable forms of labor. Human Capital variable demonstrates negative statistical association with poverty headcount ratio; the visualized relationship in Figure 3 clearly unveils that higher values of $HCI_{y,c}$ are accompanied by lower values of $Pov_{y,c}$. The calculated correlation coefficient is negative and relatively high – (-0.57). The same relationship is reported for school enrolments ratios. Primary and secondary school enrolment are negatively correlated with $Pov_{y,c}$ – calculated correlation coefficients are (-0.26) and (-0.72) accordingly, which shows that the impact of secondary school growing enrolment has a far more significant impact on poverty rate reduction. Growing secondary school enrolment is additionally demonstrated through falling $Empl\_15\text{-}24_{y,c}$ in analysed economies[11], which shows that children stay at school longer until a higher age instead of joining the labor market when they are young. Such tendencies regarding increasing secondary school enrolment and, in parallel, dropping employment ratios for people 15-24 ages, are typical for developing countries (Awad, 2020) and they constitute one of the major prerequisites for extreme poverty eradication. Digital technologies deployment strengthens this effect, especially in the field of educational opportunities (Febro et al., 2020; Rana et al., 2020). As broadly acknowledged and traced in empirical studies in developing countries, the adoption of digital technologies generates educational change and offers new opportunities (Passey et al., 2016). Developing countries, by providing remote teaching modes, digital content, shared on-line activities – just to cite a few examples, try to effectively use ICT in education systems to strengthen learning, skill shifts, professional training and hence job opportunities, and therefore to contribute to poverty reduction (Heeks, 2017; Asongu and Odhiambo, 2019). The EdTech (2018)[12] interventions, if adequately designed, may help to overcome one of the educational barriers and translate into various outcomes that – in the longer time perspective, will result in poverty alleviation. Still, in many developing counties access to EdTech solutions is sparse due to poor infrastructure and limited access to electricity, and hence local supply of technological tools, the provision of infrastructure, and hardware has to be challenged. Regarding the remaining three indicators: $ICT\_goods\_IMP_{y,c}$, $ICT\_serv\_IMP_{y,c}$ and $Freedom_{y,c}$, we do not trace a significant statistical association with poverty ratios neither visually nor regarding correlation coefficients (compare Table A3 in appendix), still we include them in the following panel estimations as control variables.

[11] On average from 50.1% in 1990 to 40.5% in 2019.

[12] https://www.theedadvocate.org/power-edtech-developing-countries/.

4.3. Panel regression results

Finally, relying on panel data analysis, we aim to uncover the strength of the impact of selected variables on poverty reduction and these results are summarized in Tables 3-6. To quantify the role of digital technologies in poverty reduction, we use balanced panel data and estimate different versions of Eq.7. The results of the estimated models are summarized in Tables 3-6. We expect only Self_empl$_{y,c}$ and Vulner$_{y,c}$ to be hold positive coefficients, while all the remaining regressors – negative. We believe that both the share of labor being self-employed and especially those being classified as vulnerable workers is higher in countries with higher incidence of poverty (see e.g. works of Fields, 2019; Ericksen et al., 2021; Neumark and Corella, 2021; or Kumar and Srivastava, 2021). The level of education, expressed though enrolment rates and/or selected complex measure Human Capital index, similarly as the level of freedom should rather demonstrate reverse tendencies to poverty headcounts. As raised in multiple studies more free and more educated societies contribute to poverty reduction (Liu et al., 2021; Serneels and Dercon, 2021). We also expect to be positive the effects on poverty reduction of growing employment of population ages 15-24, as increasing enrolment rates (especially) at second and tertiary level of education limit participation of youths in labor market (as they stay until older age in education system). By definition shifts in gross per capita income are supposed to reduce the extent of poverty. Finally we expect, which is the core of our study, that massive deployment of digital technologies will enhance drops in poverty headcounts. This positive effect of ICT on poverty decreases should also be detected regarding import and export of ICT goods, mainly due to growing demand for ICT equipment.

Pov$_{y.c}$	**FE(1)**	**FE(2)**	**FE(3)**	**FE(4)**	**FE(5)**	**FE(6)**	**FE(7)**	**FE(8)**	**FE(9)**	**FE(10)**
GDP_PPP_pc$_{y.c}$	**-1.31 [0.21]**	**-1.26 [0.25]**	**-0.91 [0.12]**		**-0.71 [0.06]**	**-0.71 [0.06]**	**-0.57 [0.28]**	-	-	**-0.65 [0.18]**
School_prim$_{y.c}$	**-**	**-**	**-0.36 [0.10]**	**-0.42 [0.19]**	**-0.33 [0.06]**	**-0.31 [0.06]**	-	-	-	**-0.38 [0.17]**
School_second$_{y.c}$	**-0.39 [0.13]**	**-0.38 [0.15]**	-	-	-	-	**-0.55 [0.13]**	-	-	-
Vulner$_{y.c}$	-	-	-	0.32 [0.32]	-	-	-	**0.59 [0.20]**	-	-
Empl_15-24$_{y.c}$	-	-	0.21 [0.17]	-	0.19 [0.11]	0.14 [0.11]	-	-	-	-
Self_empl$_{y.c}$	0.21 [0.33]	-	-	-	-	-	-0.07 [0.40]	-	-0.09 [0.06]	0.42 [0.31]
ICT_goods_IMP$_{y.c}$	-	0.008 [0.07]	-0.04 [0.03]	-0.08 [0.06]	-	-	0.01 [0.07]	0.0007 [0.03]	-0.02 [0.01]	-
ICT_serv_IMP$_{y.c}$	-	-	-	-	-	-	-	-0.005 [0.02]	-	-
IU$_{y.c}$	-	-	0.005 [0.01]	**-0.11 [0.02]**	- 0.008 [0.00]	-	**-0.12 [0.04]**	**-0.07 [0.00]**	**-0.03 [0.00]**	-0.02 [0.03]
MCS$_{y.c}$	**-0.007 [0.03]**	-0.002 [0.03]	-	-	-	**- 0.002 [0.00]**	-	-	-	-
Freedom$_{y.c}$	**1.65 [0.32]**	**1.65 [0.37]**	**0.79 [0.19]**	-	-	-	-	-	**0.42 [0.08]**	-
HCI$_{y.c}$	-0.07 [0.09]	0.07 [0.09]	-	0.01 [0.08]	-	-	0.03 [0.09]	**-**	-	0.002 [0.08]
Low$_{y,c}$	-0.05 [0.12]	-0.01 [0.21]	**0.17 [0.06]**	0.21 [0.11]	**0.14 [0.04]**	**0.11 [0.04]**	0.05 [0.21]	**0.18 [0.06]**	-0.02 [0.03]	0.12 [0.09]
R^2	0.38	0.36	0.35	0.21	0.36	0.36	0.27	0.19	0.25	0.27

Hausman test [Prob>χ^2]	35.33 [0.00]	24.93 [0.00]	36.25 [0.00]	8.79 [0.11]	18.09 [0.00]	15.98 [0.00]	21.59 [0.00]	1.40 [0.84]	1.39 [0.92]	23.73 [0.00]
# of obs.	216	193	506	244	726	768	194	520	561	273

Table 3. Poverty headcount ratio determinants. Fixed effects estimates, country-dummies included.
Source: Authors` calculations. Note: panel strongly balanced; SE below coefficients; fixed effect estimation applied; all values are logged; in bold – results statistically significant at 5% level of significance; $Low_{y,c}$ represents binary variable: low-income country – 1, lower-middle-income country – 0.

$Pov_{y,c}$	**FE_I(1)**	**FE_I(2)**	**FE_I(3)**	**FE_I(4)**	**FE_I(5)**	**FE_I(6)**	**FE_I(7)**	**FE_I(8)**
	$MCS_{y,c}$ modulated by $GDP\_PPP\_pc_{y,c}$ and $HCI_{y,c}$				$IU_{y,c}$ modulated by $GDP\_PPP\_pc_{y,c}$ and $HCI_{y,c}$			
$GDP\_PPP\_pc_{y,c}$	**-0.91 [0.14]**	**-0.71 [0.27]**	**-1.03 [0.15]**	-	-0.46 [0.27]	**-0.41 [0.18]**	-	**-0.51 [0.21]**
$School\_prim_{y,c}$	-	-	-	-	-	-	-	0.15 [0.20]
$School\_second_{y,c}$	-0.13 [0.08]	-0.15 [0.16]		**-0.49 [0.16]**	-0.13 [0.15]	-	**-0.41 [0.13]**	
$Vulner_{y,c}$	-0.18 [0.21]	-0.21 [0.35]	0.35 [0.26]		-0.20 [0.37]	-	-0.37 [0.36]	0.06 [0.31]
$Self\_empl_{y,c}$	-	-	-	-0.04 [0.39]	-	-	-	-
$ICT\_goods\_IMP_{y,c}$	0.02 [0.03]	-0.003 [0.06]	-	0.02 [0.07]	0.001 [0.06]	-	0.05 [0.06]	-
$ICT\_serv\_IMP_{y,c}$	-	-	-	-	-	-	-	-0.04 [0.03]
$IU_{y,c}$	-	-	-	-	**0.85 [0.20]**	**0.69 [0.16]**	**-0.29 [0.03]**	**-0.10 [0.03]**
$MCS_{y,c}$	**0.34 [0.08]**	**0.69 [0.17]**	**-0.02 [0.02]**	**-0.22 [0.03]**	-	-	-	-
$Freedom_{y,c}$	**1.06 [0.21]**	**1.26 [0.38]**	**1.38 [0.28]**	-	**0.86 [0.41]**	-	-	-
$HCI_{y,c}$	-	0.14 [0.09]	**-0.26 [0.10]**	**-0.42 [0.12]**	0.12 [0.08]	0.002 [0.07]	**-0.25 [0.10]**	0.15 [0.09]
$[MCS_{y,c}* GDP\_PPP\_pc_{y,c}]$	**-0.04 [0.01]**	**-0.09 [0.02]**	-	-	-	-	-	-
$[MCS_{y,c}* HCI_{y,c}]$	-	-	**-0.08 [0.02]**	**-0.10 [0.03]**	-	-	-	-
$[IU_{y,c}* GDP\_PPP\_pc_{y,c}]$	-	-	-	-	**-0.11 [0.02]**	**-0.006 [0.00]**	-	-
$[IU_{y,c}* HCI_{y,c}]$	-	-	-	-	-	-	**-0.17 [0.04]**	**-0.12 [0.03]**
Net effects of $GDP\_PPP\_pc_{y,c}$	n.a.	n.a.	-	-	n.a.	n.a.	-	-
Net effects of $HCI_{y,c}$	-	-	-0.064	-0.275	-	-	-0.3835	n.a.
Thresholds of $GDP\_PPP\_pc_{y,c}$	n.a.	n.a.	-	-	n.a.	n.a.	-	-
Thresholds of $HCI_{y,c}$	-	-	Negative Synergy	Negative synergy	-	-	Negative synergy	n.a.
Hausman test [Prob>χ^2]	11.5 [0.04]	19.05 [0.004]	18.25 [0.00]	14.27 [0.00]	14.33 [0.02]	13.12 [0.00]	33.44 [0.00]	12.48 [0.02]
R^2	0.36	0.42	0.38	0.23	0.42	0.42	0.32	0.26
# of obs.	415	193	289	200	187	209	194	248

Table 4. Poverty headcount ratio determinants – $GDP_{y,c}$ and $HCI_{y,c}$ in modulating the effect of ICT on poverty reduction. Fixed effects estimates, interaction effects included.

Source: Authors` calculations. Note: panel strongly balanced; robust standard errors applied; all values are logged; in bold – results statistically significant at 5% level of significance; $Empl\_15\text{-}24_{y,c}$ – excluded from estimates; n.a. – not applicable due to insignificance of marginal effects, and/or unconditional effects, or if $MCS_{y,c}$ or $IU_{y,c}$ hold signs inconsistent with expected; if negative synergy is reported for thresholds – it is not statistically feasible to calculate it due to negative signs standing at both conditional and unconditional effects.

Pov$_{y,c}$	**IV_2SLS(1)**	**IV_2SLS(2)**	**IV_2SLS(3)**	**IV_2SLS(4)**	**IV_2SLS(5)**	**IV_2SLS(6)**	**IV_2SLS(7)**	**IV_2SLS(8)**	**IV_2SLS(9)**	**IV_2SLS(10)**
GDP_PPP_pc$_{y,c}$	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*
School_prim$_{y,c}$	-	-	-	**-0.71** **[0.09]**	-	-	-	-	**-0.58** **[0.07]**	-
School_second$_{y,c}$	-	**-0,45** **[0,06]**	-	-	-	-	-	-	-	-
Vulner$_{y,c}$	**0.54** **[0.09]**	-	-	-	**0.52** **[0.13]**	**0.49** **[0.10]**	-	-	-	**0.49.** **[0.14]**
Self_empl$_{y,c}$	-	**0.67** **[0.08]**	**0.74** **[0.17]**	**0.66** **[0.08]**	**-**	**-**	**0.62** **[0.08]**	**0.72** **[0.17]**	**0.58** **[0.09]**	
ICT_goods_IMP$_{y,c}$	0.03 [0.02]	-	-	-	-	**0.06** **[0.02]**	-	-	-	-
ICT_serv_IMP$_{y,c}$	-	-	-0.04 [0.03]	-	-	-	-	-0.04 [0.03]	**-**	**-**
IU$_{y,c}$	-	-	-	-	-	**-0.18** **[0.02]**	**-0.12** **[0.01]**	**-0.13** **[0.03]**	**-0.16** **[0.01]**	**-0.18** **[0.02]**
MCS$_{y,c}$	**-0.19** **[0.02]**	**-0.13** **[0.01]**	**-0.18** **[0.04]**	**-0.17** **[0.01]**	**-0.23** **[0.04]**	-	-	-	-	-
Freedom$_{y,c}$	**1.52** **[0.26]**	**1.06** **[0.16]**		**1.008** **[0.18]**	**1.57** **[0.33]**	**1.29** **[0.27]**	-	-	**0.75** **[0.18]**	**1.38** **[0.34]**
HCI$_{y,c}$	-	-	**-0.16** **[0.04]**	-	**-0.23** **[0.04]**	-	**-0.87** **[0.16]**	**-0.15** **[0.04]**	-	**-0.21** **[0.05]**
Low$_{y,c}$	**0,28** **[0,08]**	0,001 [0,07]	**0,37** **[0,09]**	**0,18** **[0,06]**	**0,54** **[0,11]**	**0,32** **[0,06]**	**0,24** **[0,06]**	**0,37** **[0,09]**	**0,18** **[0,06]**	**0,54** **[0,11]**
Instrumented_MCS$_{y,c}$	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Instrumented_IU$_{y,c}$	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Robust score (Wooldridge's score test) [prob>χ^2]	34.2 [0.00]	43.3 [0.00]	9.13 [0.00]	55.5 [0.00]	14.9 [0.00]	29.9 [0.00]	37.8 [0.00]	7.02 [0.00]	51.8 [0.00]	12.2 [0.00]
Robust regression test [prob>F]	47.09 [0.00]	60.9 [0.00]	11.3 [0.00]	80.2 [0.00]	20.4 [0.00]	38.3 [0.00]	50.01 [0.00]	8.43 [0.00]	71.6 [0.00]	15.5 [0.00]
Wald test [prob>χ^2]	249.7 [0.00]	339.6 [0.00]	138.8 [0.00]	322.1 [0.00]	141.8 [0.00]	325.3 [0.00]	353.1 [0.00]	152.4 [0.00]	354.4 [0.00]	174.0 [0.00]
R^2	0.38	0.31	0.49	0.17	0.16	0.45	0.39	0.53	0.28	0.49
# of obs.	554	776	277	694	289	546	753	268	684	280

Table 5. Poverty headcount ratio determinants. IV 2SLS estimates.

Source: Authors` calculations. Note: panel strongly balanced; robust standard errors applied; all values are logged; in bolds – results statistically significant at 5% level of significance; GDP_PPP_pc$_{y.c}$ used to instrument MCS$_{y,c}$ and IU$_{y,c}$; Empl_15-24$_{y,c}$ – excluded from estimates.

Pov$_{y,c}$	GMM(1)	GMM(2)	GMM(3)	GMM(4)	GMM(5)	GMM(6)	GMM(7)	GMM(8)	GMM(9)	GMM(10)
GDP_PPP_pc$_{y,c}$	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*
School_prim$_{y,c}$	-	-	-	**-0.71** **[0.09]**	-	-	-	-	**-0.58** **[0.07]**	
School_second$_{y,c}$	-	**-0.56** **[0.12]**	-	-	-	-	-	-	-	-
Vulner$_{y,c}$	**0.54** **[0.09]**	-	-	-	**0.52** **[0.13]**	**0.49** **[0.10]**	-	-	-	**0.49** **[0.14]**
Self_empl$_{y,c}$	-	-	-	**0.66** **[0.08]**			**0.62** **[0.08]**	**0.72** **[0.17]**	**0.58** **[0.09]**	
ICT_goods_IMP$_{y,c}$	0.03 [0.02]	-	-	-	-	**0.06** **[0.02]**	-	-	-	-
ICT_serv_IMP$_{y,c}$	-	-	-0.04 [0.03]	-	-	-	-	-0.04 [0.02]	-	-
IU$_{y,c}$	-	-	-	-	-	**-0.18** **[0.02]**	**-0.12** **[0.01]**	**-0.13** **[0.03]**	**-0.16** **[0.01]**	**-0.18** **[0.02]**
MCS$_{y,c}$	**-0.19** **[0.02]**	**-0.13** **[0.01]**	**-0.17** **[0.04]**	**-0.17** **[0.02]**	**-0.23** **[0.04]**	-	-	-	-	-
Freedom$_{y,c}$	**1.6** **[0.26]**	**1.06** **[0.16]**		**1.008** **[0.18]**	**1.57** **[0.33]**	**1.3** **[0.27]**	**0.87** **[0.16]**	**-**	**0.75** **[0.18]**	**1.4** **[0.34]**
HCI$_{y,c}$	-	-	**-0.16** **[0.04]**	-	-	-	-	**-0.15** **[0.04]**	-	**-0.21** **[0.04]**
Low$_{y,c}$	**0,28** **[0,08]**	**0,39** **[0,11]**	-0,04 [0,09]	**0,15** **[0,06]**	**0,58** **[0,15]**	**0,32** **[0,07]**	**0,24** **[0,06]**	**0,37** **[0,09]**	**0,18** **[0,09]**	**0,54** **[0,11]**
Instrumented_MCS	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Instrumented_IU	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
GMM C-statistics [prob>χ^2]	34.2 [0.00]	43.3 [0.00]	9.1 [0.00]	55.5 [0.00]	14.9 [0.00]	29.9 [0.00]	37.8 [0.00]	7.02 [0.008]	51.8 [0.00]	12.2 [0.00]
Wald test [prob>χ^2]	249.7 [0.00]	339.6 [0.00]	138.8 [0.00]	322.1 [0.00]	141.8 [0.00]	325.4 [0.00]	353.1 [0.00]	152.4 [0.00]	354.5 [0.00]	174.0 [0.00]
R^2	0.38	0.31	0.49	0.16	0.45	0.45	0.39	0.53	0.28	0.49
# of obs.	554	766	277	694	289	546	753	268	684	280

Table 6. Poverty headcount ratio determinants. GMM estimates.

Source: Authors` calculations. Note: panel, strongly balanced; robust standard errors applied; GMM estimation applied; all values are logged; in bold – results statistically significant at 5% level of significance; GDP_PPP_pc$_{y.c}$ used to instrument MCS$_{y,c}$ and IU$_{y,c}$; Empl_15-24$_{y,c}$ – excluded from estimates.

The following findings can be established from consecutive results summarized in Tables 3-6. Based on the empirical evidence in Table 3, it is reasonable to conclude that both included ICT indicators demonstrate the negative relationship with $Pov_{y,c}$, which may suggest that growing ICT penetration rates in developing countries contribute to poverty reduction. Estimated coefficient standings by $IU_{y,c,}$ are, on average, higher than those for $MCS_{y,c}$, which shows a potentially stronger impact of access to Internet network on poverty alleviation than *just* access to mobile telephony. Our results coincide with those reported in, *inter alia*, Galperin and Fernanda Viecens (2017) or Asongu et al. (2019), and confirm that access to Internet network – although indirectly, enhances drops in poverty rates. Surely, the channels of impact of Internet on poverty reduction are multiple and range from better educated society, through better informed workers about job opportunities, the possibility to expand business through, e.g. e-commerce activities and extending business networks, to productivity shifts by engaging resources more effectively. Positive effects of growing Internet access to and usage by society members additionally can be demonstrated through eliminating different forms of vulnerability, especially vulnerable employment and self-employment. In developing countries self-employed workers usually are also vulnerable, low-productive workers, prone to external shocks, demand fluctuations, lack social and legal protection. Hence, the positive outcomes of increasing ICT penetration – especially Internet networks, are visible in various aspects of education and economic life. Following our estimation results from Table 3, we observe that the variables $GDP\_PPP\_pc_{y,c}$, $School\_prim_{y,c}$, $School\_second_{y,c}$ as expected hold negative signs and are statistically significant. Estimated coefficients are relatively highest for $GDP\_PPP\_pc_{y,c}$ indicating that economic growth massively contributes to poverty rate reduction. Regarding changes in school enrolment, both for primary and secondary, the estimated coefficients show that enhanced education results in poverty elimination. The channel of impact of education on poverty reduction is potentially demonstrated through economic growth, but also through decreasing rates of vulnerable employment and self-employment. As hypothesized, for $Vulner_{y,c}$ is positive and statistically significant in models where we have included this variable, indicating that higher incidence of poverty coincides with higher shares of labour classified as vulnerable. Regarding $Self\_empl_{y,c}$ returning coefficients statistically insignificant, reversely to what was expected, while for $Empl\_15\text{-}24_{y,c}$ variable estimated coefficients are positive and negative although insignificant. For another two import-related indicators, the estimated coefficient values are not stable in the estimated specifications close to zero and in both cases hold negative and positive signs, but in none of estimated equations they are unveiled as statistically significant. Finally, the introduced economic freedom index unveils its statistical significance, although the value of the estimated coefficients suggests that increasing economic freedom enhances poverty growth, which contradicts the basic logic. Also quite unexpected effects are shown in case of $HCI_{y,c}$ – the coefficients values are mixed, but in all specifications insignificant. To discriminate between low-income and lower-middle income economies, in estimations summarized in Table 3 we have introduced a binary variable – $Low_{y,c}$ where 1 was assigned to low-income economies, and 0 to lower-middle income once. In 4 out of 10 specifications we have obtained positive and significant coefficients, which suggests that low-income are not discriminated in terms of their ability to reduce poverty, but on the contrary the effects of poverty reduction might be even stronger in initially materially worse off economies. Still, in remaining 6 equations the $Low_{y,c}$ is returned as insignificant, which violated our initial conclusion and shows that these effects are not robust. To enrich our results in Table 4 are displayed panel estimates with interaction terms included. We have checked the effects of ICT deployment (using $MCS_{y,c}$ and $IU_{y,c}$) on poverty reduction that is hypothetically conditioned by per capita income ($GDP\_PPP_{y,c}$) and educational level ($HCI_{y,c}$). As expected coefficients standing by all interaction terms in specification FE_I(1)-FE_I(8) are negative and statistically significant, implying that in materially relatively poorer countries (with lower $GDP\_PPP_{y,c}$) the potential effects of ICT deployment on poverty reduction is impeded by low per capita income, and the "poverty trap" effect is demonstrated. Similarly, in initially digitally more backward countries the potentially positive effects economic growth are hindered, and poverty reduction is not as effective as might be expected. Moreover, to add to our estimates summarized in Table 4, we follow the framework developed in (Tchamyou and Asongu, 2017; Tchamyou, 2019; Asongu et al., 2017; Tchamyou et al., 2019), and calculate net effects and potential thresholds neutralizing undesired effects of independent variables (Tchamyou, 2019), to learn more on the complementary (modulating) role of gross per capita income and/or Human Capital Index that influence ICT deployment to reduce poverty headcounts. The computation of respective net effects is computed by considering the interaction between ICT and $GDP\_PPP_{y,c}$ or $HCI_{y,c}$, and the unconditional effect of ICT deployment in consecutive model specifications. Finally, we have computed net effects for FE_I(3), FE_I(4) and FE_I(7) specifications. For instance, the net effect in FE_I(3) we calculate as [-0.08*0.55]+[-0.02], where [-0.08] is the conditional effect from [$MCS_{y,c}$* $HCI_{y,c}$], 0.55 is the mean value of HCI in the sample[13], and [-0.02] is the unconditional effect of $MCS_{y,c}$. In case our estimated effects are insignificant and/or hold signs that are inconsistent with expectations, e.g. $MCS_{y,}$ holds positive sign, the net effects are not reported, to avoid drawing misleading conclusions. Still, considering the fact that in only 3 out of 8 specifications reported in Table 4, net effects were feasible to calculate we might conclude that we there is still much to add in regard to examining the complementary role of various elements that help to effectuate the enhancing role of digital technologies deployment in poverty reduction in economically backward economies. Even thought it was expected, we do not find robust significance of gross per capita income and/or education level in stimulating ICT positive impact on fighting poverty.

Lastly to check if our results are stable and robust, as well as to deal with potentially arising endogeneity, we run additional analysis employing IV_2SLS (see Table 5 for results) and GMM (see Table 6 for results) strategy. The results obtained support our initial estimates. Clearly shifts in educational activities, approximated both through enrolment rates and Human Capital index growths contribute to poverty reduction, and this is again supported by negative and significant coefficients standing by $School\_prim_{y,c}$, $School\_second_{y,c}$ and $HCI_{y,c}$. These relationships are robust and relatively stable across estimated models. Similarly, the results for two selected ICT indicators – mobile telephony usage and Internet usage, if instrumented with gross per capita income are negative and significant in all cases, which again confirms our supposition that digital technologies, even if their deployment is pre-conditioned by material wealth to some extent, does positively affect poverty reduction process in developing economies. Regarding our introduced binary variable we have obtained analogous results as reported in Table 3, hence our estimates seem to be robust in this respect.

5. Final remarks

As exposed above, this research traces empirically that ICT can enhance economic growth and consequently reduce poverty 40 developing countries between 1990 and 2019. Our findings advocate that growing ICT deployment contributes to poverty reduction. Certainly, the positive outcomes of increasing ICT penetration, in particular of the Internet networks, are visible in various aspects of education and economic life. Our results suggest that this positive impact of the growing deployment of ICT in the studied countries is additionally demonstrated in increasing school enrolments and human capital, which then, due to changes in skills and education levels, enhance drops of vulnerable and self-employment, and/or shifts in material wealth. Moreover we have found that this potential positive impact of increasing digital technologies usage shall be demonstrated also in low-income countries. Luckily, the world poorest economies are not discriminated in this respect although we have also learnt that the massiveness of the impact of ICT, even in case of rapidly growing penetration, on poverty eradication, may – to some extent – be impeded by negligible shifts in per capita income and/or low human capital.

[13] See Table 2.

Clearly, ICT adoption and channels that affect socioeconomic systems are not limited to what was discussed in this work. Digital technologies growing adoption creates educational and economic opportunities, particularly in economically backward countries; ICT allows opening opportunity windows by breaking barriers that deprive societies from socio-economic activities. The relationship between digital technologies and poverty reduction is complex and the impact of digitalization on poverty is neither direct nor immediate. In the longer time horizon ICT-based opportunities shall translate into drops in the extent of poverty. Even if the statistical relationships between a certain pairs of variables are weak, general trend examination regarding certain macroeconomic variables unequivocally leads to the conclusion that positive changes occur and bring prospects for further well-being improvements. To realize the ICT potential, governments, development agencies, local business, and civil society must make ICT a key part of broader development strategies to eradicate poverty and promote equitable and sustainable development.

Acknowledgements: This work was supported by the National Science Centre in Poland under Grant no. 2015/19/B/HS4/03220.

References

1. Achakpa, P., Radović-Marković, M. (2018). Employment women through entrepreneurship development and education in developing countries. *Journal of Women's Entrepreneurship and Education*, (1/2), 17-30.
2. Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions.* Sage Publications, Inc.
3. Alsop, R., Heinsohn, N. (2005). Measuring empowerment in practice: Structuring analysis and framing indicators. *World Bank Policy Research Working Paper* 3510, The World Bank.
4. Appiah-Otoo, I., Song, N. (2021). The impact of ICT on economic growth-Comparing rich and poor countries. *Telecommunications Policy*, *45*(2), 102082.
5. Andreev, O. Grebenkina, S., Lipatov, A., Aleksandrova, A., Stepanova, D. (2019). Modern information technology development trends in the global economy and the economies of developing countries. *Espacios*, 40(42), 8-17.
6. Anwar, M. A. (2019). Connecting South Africa: ICTs, uneven development and poverty debates. In *The Geography of South Africa*. Springer, Cham.
7. Asongu, S. A., Le Roux, S., & Biekpe, N. (2017). Environmental degradation, ICT and inclusive development in Sub-Saharan Africa. *Energy Policy*, *111*, 353-361.
8. Asongu, S., Amari, M., Jarboui, A., Mouakhar, K. (2021). ICT dynamics for gender inclusive intermediary education: minimum poverty and inequality thresholds in developing countries. *Telecommunications Policy*, *45*(5), 102125.
9. Asongu, S. A., Odhiambo, N. M. (2019). Mobile banking usage, quality of growth, inequality and poverty in developing countries. *Information Development*, *35*(2), 303-318.
10. Asongu, S. A., Odhiambo, N. M. (2019). Basic formal education quality, information technology, and inclusive human development in sub-Saharan Africa. *Sustainable Development*, *27*(3), 419-428.
11. Asongu, S. A., Orim, S. M. I., Nting, R. T. (2019). Inequality, information technology and inclusive education in sub-Saharan Africa. *Technological Forecasting and Social Change*, *146*, 380-389.
12. Asongu, S. A., Nwachukwu, J. C. (2018). Recent finance advances in information technology for inclusive development: a systematic review. *NETNOMICS: Economic Research and Electronic Networking*, 19(1-2), 65-93.
13. Awad, A. (2020). From school to employment; the dilemma of youth in Sub–Saharan Africa. *International Journal of Adolescence and Youth*, *25*(1), 945-964.
14. Banks, R. B. (1994). Growth and diffusion phenomena: mathematical frameworks and applications (Vol. 14). Springer.
15. Beegle, K., Christiaensen, L. (Eds.). (2019). *Accelerating poverty reduction in Africa*. World Bank Publications.

16. Benería, L., Berik, G., Floro, M. (2015). *Gender, development and globalization: economics as if all people mattered*. Routledge.
17. Bhattacharya, R. (2019). ICT solutions for the informal sector in developing economies: What can one expect?. *The Electronic Journal of Information Systems in Developing Countries*, *85*(3), e12075.
18. Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American statistical association*, *74*(368), 829-836.
19. Cleveland, W. S., & Devlin, S. J. (1988). Locally weighted regression: an approach to regression analysis by local fitting. *Journal of the American statistical association*, *83*(403), 596-610.
20. Cramer, J. S. (2003). The origins and development of the logit model. *Logit models from economics and other fields*, 149-158.
21. Dominguez Castillo, J.G., Cisneros Cohernour, E.J., Barberà, E. (2018). Factors influencing technology use by Mayan women in the digital age. *Gender, Technology and Development*, 22:3, 185-204.
22. Dutta, U. P., Gupta, H., Sengupta, P. P. (2019). ICT and health outcome nexus in 30 selected Asian countries: Fresh evidence from panel data analysis. *Technology in Society*, *59*, 101184.
23. Eriksen, S., Schipper, E. L. F., Scoville-Simonds, M., Vincent, K., Adam, H. N., Brooks, N., ... & West, J. J. (2021). Adaptation interventions and their effect on vulnerability in developing countries: Help, hindrance or irrelevance?. *World Development*, *141*, 105383.
24. Febro, J., Catindig, M., Caparida, L. (2020). Development of E-learning Module for ICT Skills of Marginalized Women and Girls for ICT4D. *International Journal of Emerging Technologies in Learning*, *15*(16), 94-105.
25. Fields, G. S. (2019). Self-employment and poverty in developing countries. *IZA world of labor*.
26. Fosu, A. K. (2017). Growth, inequality, and poverty reduction in developing countries: Recent global evidence. *Research in Economics*, *71*(2), 306-336.
27. García-Carrión, R., Molina-Luque, F., Roldán, S. M. (2018). How do vulnerable youth complete secondary education? The key role of families and the community. *Journal of Youth Studies*, *21*(5), 701-716.
28. Gammage, S., Sultana, N., Glinski, A. (2020). Reducing Vulnerable Employment: Is there a Role for Reproductive Health, Social Protection, and Labor Market Policy?. *Feminist Economics*, *26*(1), 121-153.
29. Grunfeld, H. (2014). ICT for Sustainable Development: An Example from Cambodia. The Journal of Community Informatics, 10(2).
30. Hanna, N. K. (2020). Assessing the digital economy: aims, frameworks, pilots, results, and lessons. *Journal of Innovation and Entrepreneurship*, *9*(1), 1-16.
31. Hanushek, E. A., Schwerdt, G., Woessmann, L., Zhang, L. (2017). General education, vocational education, and labor-market outcomes over the lifecycle. *Journal of human resources*, *52*(1), 48-87.
32. Häusermann, S., Kurer, T., Schwander, H. (2015). High-skilled outsiders? Labor market vulnerability, education and welfare state preferences. *Socio-Economic Review*, *13*(2), 235-258.
33. Heeks, R. (2017). *Information and communication technology for development (ICT4D)*. Routledge.
34. Heritage Foundation 2021 database, Heritage Foundation.
35. ITU, (2020). Measuring Digital Development. Facts and Figures. International Telecommunication Union.
36. ITU, (2020). World Telecommunication/ICT Indicators database.
37. Ivanic, M., Martin, W. (2018). Sectoral productivity growth and poverty reduction: National and global impacts. *World Development*, *109*, 429-439.
38. Jamil, B., Ahmed, M., Pudasaini, S. (2020). Implications of Globalisation and Economic Reforms for Education Systems in South Asia. *Handbook of Education Systems in South Asia*, 1-26.
39. Khaliq, I.H., Naeem, B., Abbas Q, Khalid, S. (2016). Contribution of ICT to Poverty Reduction among Women in Kilosa District. J Bus Fin Aff 6, 238.
40. Kwasnicki, W. (2013). Logistic growth of the global economy and competitiveness of nations. *Technological Forecasting and Social Change*,*80*(1), 50-76.
41. Kumar, N. P., & Srivastava, A. (2021). Measuring the Employment Vulnerability Among Female Workers in Uttar Pradesh. *Indian Journal of Human Development*, *15*(2), 307-322.
42. Laouris, Y., Laouri, R. (2008). Can information and mobile technologies serve to close the economic, educational, digital, and social gaps and accelerate development? *World Futures*, 64, 254–275. DOI: 10.1080/02604020802189534.

43. Liu, F., Li, L., Zhang, Y., Ngo, Q. T., & Iqbal, W. (2021). Role of education in poverty reduction: macroeconomic and social determinants form developing economies. *Environmental Science and Pollution Research*, *28*(44), 63163-63177.
44. Loader, C. (2012). Smoothing: local regression techniques. In *Handbook of Computational Statistics* (571-596). Springer, Berlin, Heidelberg.
45. Lopus, J. S., Amidjono, D. S., Grimes, P. W. (2019). Improving financial literacy of the poor and vulnerable in Indonesia: An empirical analysis. *International Review of Economics Education*, *32*, 100168.
46. Maddala, G. S., & Lahiri, K. (1992). *Introduction to econometrics (Vol. 2)*. Macmillan.
47. Meyer, P. S., Yung, J. W., Ausubel, J. H. (1999). A primer on logistic growth and substitution: the mathematics of the Loglet Lab software. *Technological Forecasting and Social Change*, *61*(3), 247-271.
48. Mushtaq, R., Bruneau, C. (2019). Microfinance, financial inclusion and ICT: Implications for poverty and inequality. *Technology in Society*, *59*, 101154.
49. Neumark, D., & Corella, L. F. M. (2021). Do minimum wages reduce employment in developing countries? A survey and exploration of conflicting evidence. *World Development*, *137*, 105165.
50. United Nations (2016). E-Government in Support of Sustainable Development. New York: United Nations.
51. Passey, D., Laferrière, T., Ahmad, M. Y. A., Bhowmik, M., Gross, D., Price, J., Shonfeld, M. (2016). Educational digital technologies in developing countries challenge third party providers. *Journal of Educational Technology & Society*, *19*(3), 121-133.
52. Perez, C. (2002). *Technological Revolutions and Financial Capital: The Dynamics of Bubbles and Golden Ages*, Cheltenham, Elgar.
53. Perez, C., Soete, L. (1988). Catching up in technology: Entre barriers and windows of opportunity. In G. Dosi et al. (eds.), Technical change and economic theory (pp.458-479), Francis Pinter, London.
54. Pradhan, R. P., Mallik, G., and Bagchi, T. P. (2018). Information communication technology (ICT) infrastructure and economic growth: A causality evinced by cross-country panel data. *IIMB Management Review*, 30(1), 91-103.
55. Ramanadham, V. V. (2019). *Privatisation in developing countries.* Routledge.
56. Rana, K., Greenwood, J., Fox-Turnbull, W. (2020). Implementation of Nepal's education policy in ICT: Examining current practice through an ecological model. *The Electronic Journal of Information Systems in Developing Countries*, *86*(2), e12118.
57. Rashid, A.T. (2016). Inclusive capitalism and development: case studies of telecenters fostering inclusion through ICTs in Bangladesh. *Information Technologies & International Development*, 13, 1–14.
58. Raji, M.O., Ayoade, O.B., Usoro, A. (2017). The Prospects and Problems of Adopting ICT for Poverty Eradication in Nigeria. *The Electronic Journal of Information Systems in Developing Countries*, 28(1), 1-9.
59. Ray, I., Kuriyan, R. (2012). Poverty and profits in the information age. *Information Technologies & International Development*, 8, iii–viii.
60. Satoh, D. (2019). Property of logistic data exposed with Gompertz model and resistance to noise in actual data. *Japan Journal of Industrial and Applied Mathematics*, *36*(3), 937-957.
61. Serneels, P., & Dercon, S. (2021). Aspirations, Poverty, and Education. Evidence from India. *The Journal of Development Studies*, *57*(1), 163-183.
62. Srinivasan, V., Mason, C. H. (1986). Nonlinear least squares estimation of new product diffusion models. *Marketing science*, *5*(2), 169-178.
63. Stanley, T. D., Doucouliagos, H., Steel, P. (2018). Does ICT generate economic growth? A meta-regression analysis. *Journal of Economic Surveys*, *32*(3), 705-726.
64. Stewart, F., James, J. (2019). *The economics of new technology in developing countries*. Routledge.
65. Tchamyou, V. S. (2019). The role of information sharing in modulating the effect of financial access on inequality. *Journal of African Business*, *20*(3), 317-338.
66. Tchamyou, V. S., Erreygers, G., Cassimon, D. (2019). Inequality, ICT and financial access in Africa. *Technological Forecasting and Social Change*, *139*, 169-184.
67. Tchamyou, V. S., & Asongu, S. A. (2017). Information sharing and financial sector development in Africa. *Journal of African Business*, *18*(1), 24-49.
68. Tchamyou, V. S., Asongu, S. A., & Odhiambo, N. M. (2019). The role of ICT in modulating the effect of education and lifelong learning on income inequality and economic growth in Africa. *African Development Review*, *31*(3), 261-274.

69. United Nations (2018). United Nations e-government survey 2018. Department of economic and social affairs gearing e-government to support transformation towards sustainable and resilient societies. United Nations, New York, 2018.
70. United Nations (2019). The Sustainable Development Goals Report. United Nations, New York, 2018.
71. WDI (2021). World Development Indicator 2021, World Bank.
72. World Telecommunication/ICT Indicators database (June 2020 Edition), ITU, Geneva
73. Wahlen, C. B. (2017). ICT report showcases role of ICTs in accelerating SDG achievement. Accessed January 13, 2021.
74. Vu, K. M., Asongu, S. (2020). Backwardness advantage and economic growth in the information age: A cross-country empirical study. *Technological Forecasting and Social Change*, *159*, 120197.
75. Yilmaz, R., Koyuncu, J.Y. (2018). The Contribution of ICT to Poverty Reduction: A Panel Data Evidence. Social Sciences Research Journal, 7(4), 63-75.
76. Zoo, H., de Vries, H. J., Lee, H. (2017). Interplay of innovation and standardization: Exploring the relevance in developing countries. *Technological Forecasting and Social Change*, *118*, 334-348.

Appendix

Low-income countries (GNI per capita $1,035 or less in 2019)	**Lower-middle-income countries (GNI per capita between $1,036 and $4,045 in 2019)**
Burkina Faso	Bangladesh
Burundi	Bhutan
Ethiopia	Bolivia
Gambia, The	Cameroon
Guinea	Egypt, Arab Rep.
Madagascar	El Salvador
Malawi	Ghana
Mali	Honduras
Mozambique	India
Niger	Kenya
Rwanda	Kyrgyz Republic
Tajikistan	Lao PDR
Uganda	Mauritania
	Moldova
	Mongolia
	Morocco
	Nicaragua
	Nigeria
	Pakistan
	Philippines
	Senegal
	Sri Lanka
	Tanzania
	Tunisia
	Ukraine
	Vietnam
	Zambia

Table A1. List of sample countries.
Source: Authors` elaboration.

	α	κ	T_m	Δt	R-sqr.	Root MSE	# of obs.
			MCS				
Logistic growth	0.44 [0.79]	97.1 [0.07]	2008.5 [0.01]	9.8	0.99	1.46	30
Gompertz model	0.27 [0.008]	103.1 [1.07]	2007.3 [0.07]	11.4	0.99	1.30	30
			IU				
Logistic growth	0.23 [0.02]	68.3 [8.86]	2015.3 [1.22]	18.8	0.99	1.89	30
Gompertz model	0.07 [0.01]	176.7 [83.6]	2022.7 [5.89]	43.8	0.98	1.95	30

Table A2. Mobile-cellular telephony and Internet users logistic growth and Gompertz models estimates[14]. Period 1990-2019.

Source: Authors` estimates. Note: logistic growth and Gompertz models applied; Estimation method – NLS; below coefficients – standard errors; α - rate of diffusion; κ - upper ceiling; T_m – midpoint; Δt – specific duration (in years).

[14] Averaged values for 40 low-, and lower-middle-income countries.

	$Pov_{y,c}$	$GDP\_PPP\_pc_{y,c}$	$School\_prim_{y,c}$	$School\_second_{y,c}$	$Vulner_{y,c}$	$Empl\_15\text{-}24_{y,c}$	$Self\_empl_{y,c}$	$ICT\_goods\_IMP_{y,c}$	$ICT\_serv\_IMP_{y,c}$	$IU_{y,c}$	$MCS_{y,c}$	$Freedom_{y,c}$	$HCI_{y,c}$
$Pov_{y,c}$	1.00 [909]												
$GDP\_PPP\_pc_{y,c}$	-0.82 [909]	1.00 [1195]											
$School\_prim_{y,c}$	-0.26 [825]	0.27 [1063]	1.00 [1068]										
$School\_second_{y,c}$	-0.72 [617]	0.74 [801]	0.46 [784]	1.00 [806]									
$Vulner_{y,c}$	0.71 [903]	-0.75 [1152]	-0.33 [1032]	-0.77 [775]	1.00 [1160]								
$Empl\_15\text{-}24_{y,c}$	0.49 [903]	-0.61 [1156]	-0.12 [1032]	-0.65 [775]	0.68 [1160]	1.00 [1160]							
$Self\_empl_{y,c}$	0.73 [903]	0.75 [1156]	-0.33 [1032]	-0.77 [775]	0.99 [1160]	0.68 [1160]	1.00 [1160]						
$ICT\_goods\_IMP_{y,c}$	-0.09 [580]	0.07 [661]	0.12 [605]	0.18 [481]	-0.13 [661]	-0.001 [661]	-0.12 [661]	1.00 [661]					
$ICT\_serv\_IMP_{y,c}$	0.12 [816]	-0.07 [1041]	0.01 [924]	-0.11 [722]	0.12 [1012]	0.02 [1012]	0.13 [1012]	-0.08 [608]	1.00 [1042]				
$IU_{y,c}$	-0.63 [795]	0.62 [911]	0.19 [823]	0.52 [625]	-0.41 [912]	-0.37 [912]	-0.42 [912]	0.11 [638]	-0.17 [824]	1.00 [912]			
$MCS_{y,c}$	-0.61 [851]	0.54 [1018]	0.21 [910]	0.47 [690]	-0.33 [1013]	-0.33 [1013]	-0.33 [1013]	0.06 [660]	-0.21 [923]	0.79 [888]	1.00 [1018]		
$Freedom_{y,c}$	-0.21 [781]	0.17 [941]	0.18 [830]	0.18 [664]	-0.22 [941]	-0.16 [941]	-0.21 [941]	0.07 [633]	-0.18 [853]	0.09 [857]	0.17 [911]	1.00 [941]	
$HCI_{y,c}$	-0.55 [121]	0.41 [399]	0.39 [346]	0.65 [275]	-0.52 [399]	-0.24 [399]	-0.54 [399]	0.26 [311]	-0.07 [359]	0.18 [336]	0.11 [384]	0.09 [381]	1.00 [399]

Table A3. Pairwise correlations. 40 low-, and lower-middle-income countries. Period 1990-2021.

Source: Authors` calculations. Note: raw data used; below coefficients – number of entries.

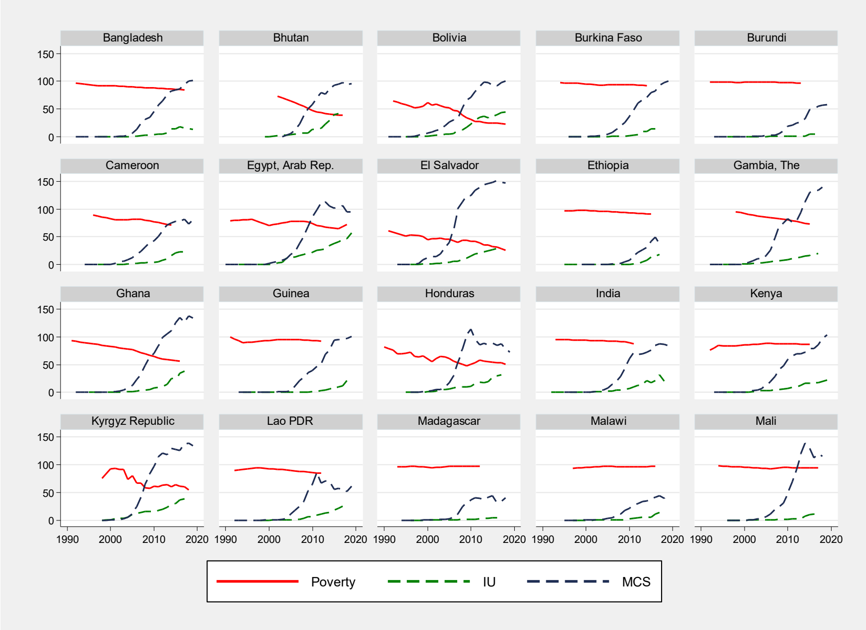

Fig. A1. Poverty headcount ratio, mobile-cellular telephony and Internet users diffusion country-specific trajectories. 40 low-, and lower-middle-income countries. Period 1990-2021.
Source: Authors` elaboration. Note: on Y-axis - % of country`s population.