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THE RELATIONSHIP BETWEEN NATURAL DISASTERS, EDUCATION, ICT AND ECONOMIC GROWTH: EMPIRICAL EVIDENCE FROM ARDL BOUNDS TESTING APPROACH

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This document examines the nexus between natural disasters (DMS), education (EDU), information and communication technologies (ICT) and economic growth (GDP per capita) in developed and developing countries using panel data set from 1990 to 2017. The autoregressive distributed lag (ARDL) bounds testing approach and Granger causality test was used. Firstly, the ARDL estimation suggests a positive and statistical significant relationship between education, internet users and mobile cellular telephone and GDP per capita in both the short- and long-term. Natural disasters have a negative effect on economic growth and education. The result indicates that internet users and mobile cellular telephone has a positive effect on natural disasters and education. Secondly, Granger causality reveals that there is bidirectional relationship among education and GDP per capita. Results show a unidirectional from internet users, mobile cellular telephone to natural disaster. In addition, there is a unidirectional causal relationship from natural disaster to GDP per capita in developing country, but this result is unobservable in developed country.

Keywords: Natural Disaster, Economic Growth, Education, ICT, Panel ARDL, Granger Causality
JEL Classification: Q54, O16, C23

1. INTRODUCTION

Natural disasters are not a recent phenomenon. Over the centuries, they have been listed as recurring events with sometimes deadly consequences. Over the last ten years, more than 250 million people have been affected each year by these phenomena. Thus, the economic losses increased to reach 337 billion USD in 2017. The consequences of natural disasters depend on many parameters, including size and structure of the economy, density of population in high-risk areas, per capita income, and development of the financial system. Recent studies show that a better level of qualification, more efficient institutions (local authorities, health services, police, rule of law, etc.), greater openness to trade and increased public spending help to control economic cost of natural disasters (Noy, 2009). Because of their vulnerability, children are the most seriously affected by these disturbances. On the other hand, the environmental challenge represents the future of the younger generations: they are the ones who will suffer the consequences. They are the first concerned on climate issues. Policies and education programs designed to better prepare for disasters can reduce the impact of these phenomena. They can acquire the knowledge, skills and attitudes required to prepare for disasters and deal with their consequences, and help learners and their communities to resume a normal life. Including disaster prevention education (DRR) in School programs promotes people's security and enables communities exposed to disasters to better resist. The severe effects of disasters have highlighted the importance of ICTs in disaster management as they provide information, information services and decision support tools.

Majority of the researches have spurred on the indispensable role of tic in reducing the effects of natural disasters such as Gillespie et al. (2014), Cutter and Neidell (2009) and Walker (2012). Many countries thus have access to the advanced technologies used in information and communication networks, and can therefore gather a mass of information when it is required, before a disaster occurs. The main objective of this study is to determine the link between economic growth, natural disaster, education and ICT for 20 selected developed and developing countries over the period 1990-2017 using autoregressive distributed lag test as an approach to examine the cointegration and the vector error correction model. Unlike several studies, this paper focuses on the Autoregressive Distributed Lag (ARDL) modeling, which allows to provide short-term information which is orchestrated by the long-term equilibrium relationship.

This study is of considerable importance because the estimation of natural disasters effects determines to what extent the economy of nations, schools and the education system are threatened by these disasters.

This article is organized as follows: Section 2 presents review of empirical literature. Section 3 describes the data used and specific model. Section 4 presents empirical findings and analysis. Finally, Section 5 concludes our work.

2. REVIEW OF EMPIRICAL LITERATURE

Conflicts and disasters can have devastating effects on education systems. According to the Education for All Global Monitoring Report in 2011, in conflict-affected poor countries, 28 million children of primary school age were out of school - 42 percent of the world total. Several authors have emphasized this phenomenon, for example, Baez et al. (2010) are looking for an answer to their question: do natural disasters affect human capital? They found that disasters cause considerable damage to human capital, including loss of life and destruction, and have negative consequences for nutrition, education, health and many income-generating processes. McDermott (2012) analyzed the effect of disasters on human capital accumulation during the period 1980-2004. The results indicate that natural disasters have both a direct and indirect effect on human capital. Recently, in china, Park et al. (2015) indicated that earthquake aggravate psychosocial consequences of a child and the family environment uniformly. De Vreyer et al. (2015) examined the impact of natural disasters on education outcomes in Mali. They found that there is significant impact on the educational outcomes of children living in rural areas, but no impact on children living in urban areas. The study of Tatebe and Mutch (2015) focused on the Disaster Risk Reduction (DRR) program related to education. The aim of this program is to ameliorate the knowledge for children to build resilience. In Mongolia, Groppo and Kraehnert (2016) investigated the effect of extreme weather events on education during the period of 1999-2002. The results showed that individuals who living in areas affected by catastrophic events don’t have the opportunity to complete their education, both in the long and medium terms. Paudel and Ryu (2018) used a research model based on difference in differences to examine the impact of the 1988 earthquake on educational outcomes in Nepal. The results indicated that children belonging to low caste groups are 17.6% less likely to complete middle school and 11.9% less likely to complete high school. This implies that earthquakes have led to deterioration of human capital.

Natural disasters have a huge impact on people and goods. These events lead to economic upheavals, which are often reflected indirectly in other sectors. No city is shielded from their consequence, which is why it is important to be aware of the immediate and long-term economic and financial implications of these events. In the short term, natural disasters tend to cause a series of similarly economic disrupted. Immediate damage reduces production, expenditures and hours worked. In the longer term, economic indicators tend to mask the impact of natural disasters on the economy. According to Clower (2007), there are also a priori evaluation techniques that can be used to evaluate the direct and indirect effects of disaster. And some experiments have already been conducted. Greenberg et al. (2007) for their part suggest using an econometric approach to anticipate the occurrence of disasters and to anticipate potential economic consequences even. Thus, Nury et al. (2013) used a Box Jenkins approach to predict future climate phenomena (temperature change) in Bangladesh.

Using a panel data model Skidmore and Toya (2002) showed that there is a positive relationship between climate disasters and economic growth. Caselli and Malhotra (2004), Albala-Bertrand (2006) indicated that natural disasters do not negatively affect GDP. In his analysis, Raddatz (2007) confirmed that climatic disasters (droughts, windstorms and floods) lead to an average real per-capita income loss of 2%, while humanitarian disasters (famines or epidemics) lead to an average real per-capita income loss of 4% in the short run. Recently, in a study using autoregressive integrated moving average models (ARIMA), Hochrainer (2016) found that natural disasters have small negative effects on GDP during 1960-2005. In another study, Shaari et al. (2016) examined the impact of flood disaster on GDP growth in Malaysia based the Autoregressive Distributed Lag (ARDL) bounds testing approach countries using data during the period 1960-2013. They found that economic growth increased with flood disaster. Benali and Feki (2018) examined the link between natural disasters and economic growth during the period of 1990 - 2016. VECM Granger causality analysis results revealed that there is a unidirectional relationship running from natural disaster to GDP in developed countries.

The link natural disaster - ICT is not widely well studied in the literature. Procopio and Procopio (2007) and Shklovski et al. (2008), proved that mobile phone and internet have played a crucial role in the dissemination of information. Therefore, Hagar (2009) indicated that the use of e-mail and websites during the foot-and-mouth disease agricultural crisis in the United Kingdom in 2001 were the best sources for saving the lives of human beings. Rahman et al. (2016) insisted on the importance of ICTs to protect people from heavy losses and avoid devastating situations during earthquakes. Moreover, Benali and Feki (2018) used panel data for 10 countries over the period 1990 to 2016. The empirical results of VECM Granger causality test indicated that there is a relationship running from ICT to natural disaster at the 5% and 10% levels.

3. DATA AND SPECIFIC MODEL

3.1. The Data: Source and Description

This empirical analysis is based on a panel of 20 countries. Our sample countries include: (i) developing countries (Argentina, Mexico, Brazil, Cameroon, Peru, Philippines, Thailand, Tunisia, South Africa and Morocco) and (ii) developed countries (Australia, Canada, France, Germany, Italy, Japan, Luxembourg, Portugal, United Kingdom and United States). Using the annual data our study covers the period from 1990 to 2017.

Our panel database is composed of the following variables: GDP per capita (constant 2010 US$), EDU is the education level (number of students enrolled in higher education, and primary and secondary schools) and information and communication technology (ICT) include mobile cellular subscriptions (MOB) and internet users (INT). These indicators were extracted from the World Development Indicators.

In our econometric analysis, we used a Log transformation to calculate the variables of interest and control. In fact, the Log transformation makes possible to smooth the trend of the series, eliminating strong asymmetries in the distributions.

We were particularly interested in the International Disaster Database, EM-DAT (http://www.emdat.be/), which contains data on the characteristics and effects of more than 18,000 disasters worldwide since 1900 until our days.

The measurement of natural disaster is based on three factors: the number of people killed, the number of people affected and the amount of economic damage. According to Noy (2009), the measurement of natural disaster (DM) is calculated as follows:

$$Total\ population\ affected_{it} = \sum_{j=1}^{N} \frac{total\ population\ affected_{ijt}}{total\ population_{it}},$$

$$Total\ population\ killed_{it} = \sum_{j=1}^{N} \frac{total\ people\ killed_{ijt}}{total\ population_{it}},$$

$$Economic\ damage_{it} = \sum_{j=1}^{N} \frac{damage_{ijt}}{total\ GDP_{it}},$$

where i denotes the country, j represent the natural disaster (drought, floods, earthquake and storms) and $t = 1, \ldots, \mathrm{N}$ indicates the year.

Table 1. Major Statistics of the 20 Sample Countries

		GDP	INT	MOB	EDU	DMS
Developing country	Mean	25.908	17.104	48.476	4.336	3.813
	Median	26.038	7.023	26.261	4.476	0.000
	Maximum	28.516	86.545	176.035	6.817	152.622
	Minimum	23.331	0.000	0.000	1.067	0.000
	Std. Dev.	1.353	20.480	51.061	1.268	17.204
	Skewness	0.006	1.043	0.647	-0.040	6.169
	Kurtosis	2.175	2.888	2.009	1.899	42.928
	Jarque-Bera	7.950	50.923	30.972	14.228	20375.440
	Probability	0.019	0.000	0.000	0.001	0.000
	Sum	7254.142	4789.217	13573.260	1213.972	1067.606
	Sum Sq. Dev.	510.850	117021.600	727426.100	448.473	82573.830
	Observations	280	280	280	280	280
Developed country	Mean	27.957	42.847	68.487	4.746	25.050
	Median	28.346	44.130	76.712	4.880	0.003
	Maximum	30.482	98.137	162.703	7.704	2293.522
	Minimum	23.949	0.000	0.065	2.426	0.000
	Std. Dev.	1.561	33.527	49.398	0.885	188.438
	Skewness	-0.927	0.026	-0.031	-0.267	11.189
	Kurtosis	3.327	1.488	1.655	3.022	129.906
	Jarque-Bera	41.215	26.594	21.069	3.328	193043.1
	Probability	0.000	0.000	0.000	0.189	0.000
	Sum	7799.993	11954.37	19107.75	1324.083	6988.829
	Sum Sq. Dev.	677.332	312496.2	678371.5	217.754	9871458
	Observations	279	279	279	279	279

The disaster measures (DMS) is calculated as following:

$$DMS = DM \frac{(12 - month)}{12}.$$

The natural disasters reported in the database include drought, floods, earthquake and storms.

The descriptive statistics of the different quantitative variables are summarized in Table 1.

3.2. Presentation of the Model

Our analysis is based on the autoregressive distributed lag model developed by Pesaran and Shin (1999) which has been extended by Pesaran et al. (2001). Indeed, the ARDL test does not require that the variables in the model are purely I (0) or I (1). It is also a technique that offers the possibility for joint processing the long-term dynamics and short-term adjustments. According to Pesaran et al. (2001), the cointegration test is based on a Fisher where it is assumed that the coefficients of the variables in level are all equal to zero under the alternative hypothesis that, none of the coefficients is zero, that is, absence cointegration between studied variables.

General form of ARDL is as follow:

$$\Delta\gamma_t = \alpha_0 + \alpha_1 t + \delta_0\gamma_t + \delta_1 x_{1t} + \delta_2 x_{2t} + \delta_3 x_{3t} + \sum_{i=1}^{p}\sigma_i \Delta Y_{t-i} + \sum_{j=0}^{q1}\beta_j \Delta x_{1,t-j} + \sum_{m=1}^{q2}\gamma_m x_{2,t-m} + \sum_{s=1}^{q3}\omega_s \Delta x_{3,t-s} + \varepsilon_t \quad (1)$$

In this equation, Δ denotes the first difference operator; α_0 represents the constant, ε is the error term of the white noise, σ, β, γ and ω represent the short-term dynamics of the model, δ represent the long-term dynamics of the model. To test the cointegration relationship among these variables we use the procedure used by Pesaran et al. (2001).

We are developing an error correction model (ECM) based on the procedure of Pesaran et al. (2001). The version of this ECM is in the form of the equation below:

$$\Delta\gamma_t = \alpha_0 + \alpha_1 t + \Psi ECT_{t-1} + \sum_{i=1}^{p}\sigma_i \Delta Y_{t-i} + \sum_{j=0}^{q1}\beta_j \Delta x_{1,t-j} + \sum_{m=1}^{q2}\gamma_m x_{2,t-m} + \sum_{s=1}^{q3}\omega_s \Delta x_{3,t-s} + \varepsilon_t, \quad (2)$$

where Ψ is the speed of adjustment and ECT represent the error correction term defined by the long-term relationship.

The general representation of the ARDL model on panel data is the following:

$$\Delta\gamma_{it} = \alpha_0 + \alpha_1 t + \delta_0\gamma_{it} + \delta_1 x_{1it} + \delta_2 x_{2it} + \delta_3 x_{3it} + \sum_{i=1}^{p}\sigma_i \Delta Y_{t-i} + \sum_{j=0}^{q1}\beta_j \Delta x_{1i,t-j} + \sum_{m=1}^{q2}\gamma_m x_{2i,t-m} + \sum_{s=1}^{q3}\omega_s \Delta x_{3i,t-s} + \varepsilon_{it}. \quad (3)$$

The general representation of the error-correction model (ECM) of equation is made as follows:

$$\Delta\gamma_{it} = \alpha_0 + \alpha_1 t + \Psi ECM_{i,t-1} + \sum_{i=1}^{p} \sigma_i \Delta Y_{t-i} + \sum_{j=0}^{q1} \beta_j \Delta x_{1i,t-j} + \sum_{m=1}^{q2} \gamma_m x_{2i,t-m} + \sum_{s=1}^{q3} \omega_s \Delta x_{3i,t-s} + \varepsilon_t. \quad (4)$$

4. ESTIMATION, FINDINGS AND ANALYSIS

4.1. Unit roots tests

Before performing the cointegration test, you must first perform the unit root test. The ARDL Bound approach requires that the order of integration of each variable cannot exceed unity. The result of Levin, Lin and Chu (LLC) and Phillips–Perron (PP) unit root tests is reported in Table 2.

Table 2. Panel Unit Root Tests Results

Developed Country						
	LLC			IPS		Level of integration
	M1	M2	M3	M1	M2	
GDP	-4.050 (0.000) *	0.087 (0.535)	7.957 (1.000)	0.320 (0.626)	1.201 (0.885)	
ΔGDP	-6.288 (0.000)*	-6.528 (0.000) *	-4.450 (0.000) *	-7.350 (0.000) *	-6.946 (0.000) *	I(1)
INT	-0.467 (0.320)	2.165 (0.985)	2.578 (0.995)	3.054 (0.999)	2.086 (0.98)	
ΔINT	-1.738 (0.041) **	-2.332 (0.010) *	-4.056 (0.000) *	-2.202 (0.014) **	-0.290 (0.386)	I(1)
MOB	-2.176 (0.015) **	4.391 (1.000)	1.995 (0.977)	1.069 (0.858)	2.018 (0.978)	
ΔMOB	3.696 (0.999)	3.716 (0.999)	-3.836 (0.000) *	-3.296 (0.001) *	-1.921 (0.027) **	I(1)
EDU	-2.171 (0.015) **	-0.262 (0.397)	-0.666 (0.253)	-3.349 (0.000) *	-1.756 (0.040) **	I(0)
ΔEDU						
DMS	-4.626 (0.000) *	-3.708 (0.000) *	-5.242 (0.000) *	-5.597 (0.000) *	-4.085 (0.000) *	I(0)
ΔDMS						

Note: Some variables (EDU, DMS) are stationary in level so is useless to make the second difference.
M1: Individual effects, M2: Individual effects, individual linear trends, M3: None.
*Significance at 1% level; **significance at 5% level; ***significance at 10% level.

Table 2. Panel Unit Root Tests Results (con't)

Developing Country

	LLC			IPS		Level of integration
	M1	M2	M3	M1	M2	
GDP	0.087 (0.535)	-0.054 (0.479)	9.421 (1.000)	3.700 (0.999)	-0.863 (0.194)	I(1)
ΔGDP	-6.174 (0.000)*	-5.738 (0.000)*	-5.738 (0.000)*	-6.352 (0.000)*	-4.715 (0.000)*	
INT	6.780 (0.024)**	0.420 (0.063)***	-1.993 (0.023)**	8.621 (0.055)	3.202 (0.030)**	I(0)
ΔINT						
MOB	-1.815 (0.035)**	-1.728 (0.042)**	-4.243 (0.000)*	-1.817 (0.035)**	0.005 (0.502)	I(0)
ΔMOB						
EDU	-1.720 (0.043)**	0.758 (0.776)	0.093 (0.537)	-2.132 (0.117)	-0.964 (0.168)	I(1)
ΔEDU	-3.495 (0.000)*	-0.823 (0.205)	-11.648 (0.000)*	-7.901 (0.000)*	-5.915 (0.000)*	
DMS	-23.036 (0.000)*	-19.404 (0.000)*	-21.209 (0.000)*	-13.802 (0.000)*	-12.693 (0.000)*	I(0)
ΔDMS						

Note: Some variables (INT, MOB, DMS) are stationary in level so is useless to make the second difference.
M1: Individual effects, M2: Individual effects, individual linear trends, M3: None.
*Significance at 1% level; **significance at 5% level; ***significance at 10% level.

The results are shown in Table 2. For the case of developed country, the null hypothesis cannot be rejected for mobile cellular subscriptions (MOB), internet users (INT) and GDP per capita. On the other hand, the disaster measures (DMS) and education (EDU) are integrated at 1% and 5% level. As for the case of developing country, GDP and EDU series are not integrated at level form, but after taking the first difference, the variables are integrated, which means the variables are I(1) while DMS, INT and MOB are integrated at level form, which means they are I(0) variables.

In summary, we notice that our data are I(0) and I(1) which gives us the possibility to estimate both the short term and long term relationship between MOB, INT, GDP, DMS and EDU by using an ARDL bounds test approach.

4.2. Cointegration Bounds Test

Following the results of the unit-root test, we can perform the bounds test approach to examine the long-term relationship between all variables. Results are represented in Table 3.

The results of Bounds test show that F-statistic values exceed highest critical value.

Then, H_0 is rejected and H_1 is accepted; which confirms the existence of long-term cointegration relationship.

Table 3. Bounds Test Results

	Dep. var	F-statistic	Probability	Result
Developed countries	GDP	5.8615	0.011**	Cointegration
	INT	9.5809	0.002*	Cointegration
	MOB	6.7123	0.029**	Cointegration
	EDU	9.9408	0.009*	Cointegration
	DMS	7.4035	0.001*	Cointegration
Developing countries	GDP	8.2836	0.009*	Cointegration
	INT	3.8004	0.082***	Cointegration
	MOB	5.3560	0.069***	Cointegration
	EDU	8.5083	0.001*	Cointegration
	DMS	5.4852	0.031**	Cointegration

Note: *, ** and *** indicate significance at 1%, 5% and 10%, respectively.

4.3. Panel ARDL-PMG Results

The current study investigated the dynamic causal relationship between natural disaster, education, information and communication technologies and economic growth on a set of developed and developing countries, by implementing the newly developed ARDL bounds testing approach of cointegration.

4.3.1. PMG Long-Run Estimate

4.3.1.1. Case 1: Developed Country

Table 4 shows the results of PMG long-run estimate for developed country. The study reveals that only MOB and INT have long-term effects on GDP. This implies that a 1% increase in ICT increases GDP by 0.4% (MOB) and 0.2% (INT). The result reveals also a positive and significant relationship among ICT and DMS in the long-term. Consequently, a 1% increase in ICT decreases DMS by 0.13% (MOB) and 3.33% (INT) over the long term, respectively. Moreover, there is a negative and significant relationship among DMS and EDU. This implies that an increase of 1% in DMS, decreases EDU by 0.08%.

Table 4. PMG Long-Run Estimates

	Dependent Variables				
	ΔGDP	ΔINT	ΔMOB	EDU	DMS
ΔGDP		3.252 (0.849)	6.601 (0.825)	-0.476 (0.837)	-2.613 (0.989)
ΔINT	0.394 (0.005)*		0.000 (0.517)	-0.003 (0.786)	-3.339 (0.000)*
ΔMOB	0.201 (0.012)**	-0.624 (0.187)		0.005 (0.390)	-0.133 (0.000)*
EDU	0.004 (0.158)	-0.180 (0.713)	2.006 (0.65)		6.540 (0.226)
DMS	0.004 (0.748)	0.000 (0.896)	-0.000 (0.85)	-0.081 (0.000)*	

Note: *, ** and *** indicate significance at 1%, 5% and 10%, respectively.

4.3.1.2. Case 2: Developing Country

Table 5 below provides us with the estimated long-run coefficients or elasticities. DMS variable have a negative effect on GDP per capita and education over the long-term. This implies that an increase in DMS of 1% reduces GDP per capita by 0.16% and EDU by 0.13%, respectively. Economic agents supposed to have studied and set up mechanisms to deal with these effects. Moreover, the result reveals that ICT has a positive and significant effect on DMS and EDU. Finally, GDP per capita have a positive effect on EDU. A 1% increase in GDP per capita increased education by 4%.

Table 5. PMG Long-Run Estimates

	Dependent Variables				
	ΔGDP	ΔINT	ΔMOB	EDU	DMS
ΔGDP		12.519 (0.174)	3353.953 (0.302)	3.977 (0.000)*	-2.737 (0.269)
ΔINT	0.000 (0.522)		2.208 (0.265)	0.009 (0.001)*	-0.051 (0.000)*
ΔMOB	-0.000 (0.201)	0.000 (0.17)		0.003 (0.003)*	-0.019 (0.000)*
EDU	-0.005 (0.516)	-0.324 (0.727)	-76.109 (0.840)		0.828 (0.019)
DMS	-0.163 (0.000)*	-0.011 (0.527)	-1.006 (0.367)	-0.135 (0.099)***	

Note: *, ** and *** indicate significance at 1%, 5% and 10%, respectively.

4.3.2. PMG Short-Run Estimate

4.3.2.1. Case 1: Developed Country

The short-run result as reported in Table 6 reveals that ICT have a positive and significant impact on GDP per capita even in the short run. It further highlights that a 1% increase in MOB and INT increase GDP by 0.40% and 0.20%, respectively. In the short run, the variable of education also has a positive and significant impact on GDP per capita; this implies that a 1% increase in EDU lead to increases GDP by 0.11%.

The error correction term is 0.80 in absolute value and significant at 1%, which implies that once the model is deviated from the equilibrium, it will adjust to 80% during the same period. It should be noted that if the coefficient is not significant the adjustment will not be made in the same period

Table 6. PMG Short-Run Estimates, ΔGDP is the Dependent Variables

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
C	-0.011	0.003	-3.384	0.001*
ECT(-1)	-0.806	0.078	-10.335	0.000*
D(LMOB)	0.000	0.000	0.389	0.698
D(LMOB(-1))	0.000	0.000	-0.239	0.812
D(LMOB(-2))	0.401	0.000	-1.988	0.049**
D(LINT)	0.201	0.000	3.629	0.000*
D(LINT(-1))	0.000	0.001	0.623	0.534
D(LINT(-2))	0.001	0.001	1.244	0.216
D(DMS)	0.078	0.072	1.085	0.280
D(DMS(-1))	0.091	0.072	1.262	0.209
D(DMS(-2))	0.148	0.130	1.138	0.257
D(EDU)	0.113	0.007	-1.875	0.063***
D(EDU(-1))	-0.001	0.003	-0.321	0.749
D(EDU(-2))	-0.004	0.005	-0.787	0.433

Note: *, ** and *** indicate significance at 1%, 5% and 10%, respectively.

4.3.2.2. Case 2: Developing Country

The short-run result as reported in Table 7. As in the long run, the effects of DMS on GDP per capita remain negative in the short term; a 1% increase in DMS reduces the GDP per capita of 0.10%. Moreover, EDU has a positive and significant effect on GDP per capita. This implies that a 1% increase on EDU increases GDP by 0.2%. Unlike the long-term results, MOB and INT variables have no effect on GDP per capita.

The error correction term is 0.72 in absolute value and significant at 1%, which implies that once the model is deviated from the equilibrium, it will adjust to 72% during the same period. It should be noted that if the coefficient is not significant the adjustment will not be made in the same period.

Table 7. PMG Short-Run Estimates, ΔGDP is the Dependent Variables

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
C	0.034	0.008	4.044	0.000*
ECT(-1)	-0.723	0.184	-6.091	0.000*
D(DGDP(-1))	0.146	0.078	1.870	0.064***
D(MOB)	0.002	0.001	0.624	0.980
D(MOB(-1))	0.000	0.000	-1.268	0.207
D(MOB(-2))	0.000	0.000	1.139	0.257
D(INT)	0.001	0.001	1.357	0.178
D(INT(-1))	0.001	0.001	0.669	0.505
D(INT(-2))	-0.001	0.001	-0.946	0.346
D(DMS)	-0.100	0.002	3.134	0.054**
D(DMS(-1))	-0.001	0.001	-0.536	0.593
D(DMS(-2))	0.001	0.002	0.788	0.432
D(DEDU)	0.002	0.006	0.334	0.739
D(DEDU(-1))	0.000	0.007	0.026	0.979
D(DEDU(-2))	0.204	0.003	-1.668	0.098***

Note: *, ** and *** indicate significance at 1%, 5% and 10%, respectively.

4.4. Short-Run and Long-Run Granger Causality Tests

4.4.1. Case 1: Developed Country

Table 8 shows the short-run and long-run causalities among GDP per capita, education, natural disaster and information and communication technology (ICT): include mobile cellular subscriptions and internet users.

Table 8. Granger Causality Test

	Dependent variables					
	ΔGDP	ΔINT	ΔMOB	EDU	DMS	Causality Directions
ΔGDP		1.641 (0.440)	4.399 (0.111)	1.837 (0.040)**	1.558 (0.459)	GDP → EDU
ΔINT	5.389 (0.068)***		4.344 (0.114)	1.052 (0.591)	1.242 (0.054)**	INT → GDP INT → DMS
ΔMOB	20.685 (0.000)*	0.306 (0.858)		0.728 (0.695)	0.0404 (0.098)***	MOB → GDP MOB → DMS
EDU	9.381 (0.009)*	0.045 (0.978)	1.497 (0.471)		6.287 (0.043)**	EDU → GDP EDU → DMS
DMS	0.194 (0.907)	1.837 (0.399)	2.226 (0.329)	0.249 (0.883)		

Note: *, ** and *** indicate significance at 1%, 5% and 10%, respectively.

According to the results, there is two-way causality between EDU and GDP per capita. This result is consistent with Islam et al. (2007) and Pegkas (2014). This implies that education contributes to collective happiness through the economic growth. Economic growth brings many benefits to the countries: improving standards of living and purchasing power, increasing life expectancy, better education and training, lower poverty and unemployment, political stability, lower risks conflicts, among others. In addition, a one-way causality running from ICT to GDP is found. This result is in line with the conclusions of Dewan and Kraemer (2000), O'Mahony and Vecchi (2005) and Bertschek et al. (2015). ICT can increase GDP in the following ways: foster competitiveness, Encourage innovation and entrepreneurship, Develop human resources. The use of ICT can help efficient companies' gain to gain market shares from less productive competitors, thereby increasing overall productivity. It can also help them to expand their product range, personalize their services or better meet demand - in short, to innovate. The results of causality also indicate that there is a unidirectional relationship running from ICT to DMS. The policy implication of this causality result is that ICT is an integral part of the disaster preparedness, mitigation, and response and disaster recovery process. ICT is an effective tool in the disaster management process. Furthermore, there is a unidirectional relationship running from EDU to DMS. Education can play a key role in natural disaster preparedness and mitigation. The challenge is to ensure that the right knowledge and behaviors to adopt are deeply embedded in communities.

Children with some knowledge of natural disaster risk, play an important role when it occurs. With their knowledge, they can save human lives and protect members of their communities.

Results are summarized in Figure 1.

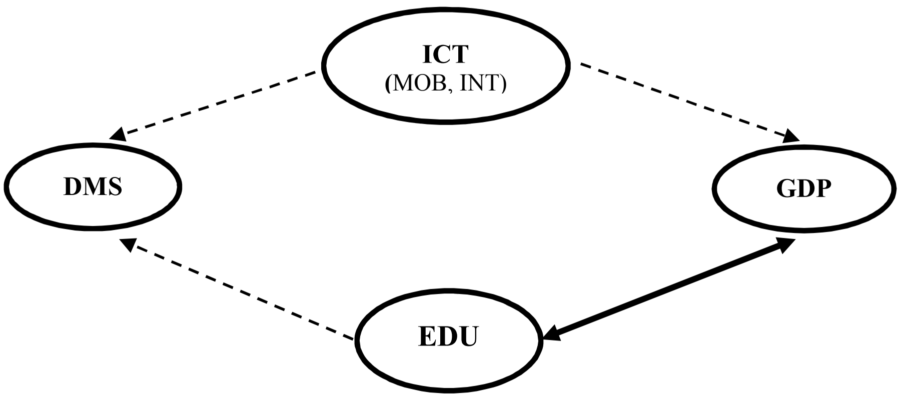

Figure 1. Developed Country

4.4.2. Case 2: Developing Country

Table 9 shows the results of equations 5 to 8.

Table 9. Granger Causality Test

	Dependent variables					
	ΔGDP	ΔINT	ΔMOB	EDU	DMS	Causality Directions
ΔGDP		3.965 (0.411)	2.703 (0.609)	34.950 (0.000)*	5.216 (0.266)	GDP → EDU
ΔINT	1.956 (0.744)		0.608 (0.962)	7.976 (0.093)***	15.583 (0.004)*	INT → DMS INT → EDU
ΔMOB	3.999 (0.406)	8.110 (0.322)		5.592 (0.232)	13.667 (0.008)*	MOB → DMS
EDU	18.560 (0.001)*	4.477 (0.345)	0.962 (0.915)		3.212 (0.523)	EDU → GDP
DMS	2.560 (0.063)**	3.787 (0.436)	3.206 (0.524)	47.341 (0.000)*		DMS → GDP DMS → EDU

Note: *, ** and *** indicate significance at 1%, 5% and 10%, respectively.

We note that at the 1% level, the Granger test suggests a unidirectional causal link from DMS to EDU. In other words, disasters have a major impact on education systems. They destroy school buildings, equipment, books and educational archives. Schools are used as places of refuge in the event of a disaster, as this prevents the return of children to school, once the threat has passed. Moreover, there is a one-way causality relationship from DMS to GDP per capita. These results are the same as for Muralidharan and Shah (2001), Cavallo et al. (2009) and Berlemann and Wenzel (2015). This result confirms the idea that natural disasters destroyed infrastructure, such as roads, factories, business premises and communication networks. This causes massive disruptions for businesses and the productivity of the country. In addition, causality from ICT to DMS is observable. These results are in line with the findings of Skidmore and Toya (2015). As a general rule, the demand for real-time communications, for example by telephone and e-mail, increases during the period corresponding to the first interventions. Real-time communications are therefore essential for vital activities, such as search and rescue operations. During this period, people often need ICT first and foremost to ensure that their families, relatives, staff and property are safe. After an initial recovery phase, commissioning activities begin. It should be noted that the duration of this phase depends on the severity of the disaster. These tools offer innovative solutions to anticipate emergencies and improved intervention of emergency services. In addition, there is a one-way causality relationship from INT to EDU. INT is a key element in stimulating student creativity and innovation. The result reports a two-way relationship between EDU and GDP at 1% level. This result is in line with the conclusions of Francis and Iyare (2006), Wadud et al. (2007) and Solaki (2013). This shows that the different levels of primary, secondary and higher education globally have a positive influence on economic growth. Improving the level of education increases the efficiency of all factors of production. Results are summarized in Figure 2.

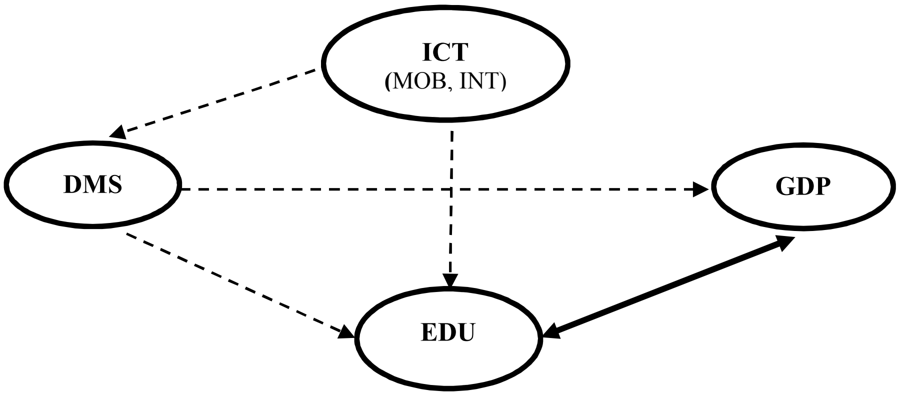

Figure 2. Developing Country

5. CONCLUSIONS AND POLICY IMPLICATIONS

This study examines the causal links among GDP per capita, education, natural disaster and information and communication technology for 20 selected developed and developing countries over the period 1990–2017. The "ARDL Bound Testing" approach of Pesaran and Shin (1999) has been applied. First, this approach showed that there is a cointegration relationship between variables and made possible long-term and short-term estimation. Second, the short- and long-term estimation suggested a positive and statistical significant relationship between ICT and GDP per capita in both the short- and long-term. The result indicated that ICT has a positive effect on DMS in the long-term. Furthermore, DMS has a negative and statistically significant impact on EDU. Natural disasters have a negative effect on economic growth in both the short- and long-term. ICT has a positive effect on EDU. GDP per capita have a positive effect on EDU. Moreover, in the short-run, education has a positive and significant impact on GDP. Third, Granger causality revealed that there is bidirectional relationship among GDP and

EDU. Results show a unidirectional from ICT to DMS. In addition, there is a unidirectional causal relationship from DMS to GDP in developing country, but this result is unobservable in developed country.

Following these results, the developing countries are the most affected by natural disasters. They suffer disproportionately from the loss of economic goods and deterioration of the education system.

In our view, integrating disaster risk reduction into education plans or other education planning processes poses significant challenges. This integration aims to guarantee the right to education, by offering all children in emergencies continuous access to quality education. It also aims to prevent and reduce the negative impact of disasters on education systems and on children, teachers, other education personnel, parents / guardians and communities. Similarly, strengthening the capacity of vulnerable populations to use ICT when a disaster occurs through awareness programs, training and capacity building programs is useful.

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