Spillover Effect of Telecom Investments on Technological Advancement and Efficiency Improvement in Transition Economies

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Abstract

This study, conducted in the context of 18 transition economies (TEs), investigates the macroeconomic spillover effect of investments in telecoms on technological advancement and growth in efficiency. Data envelopment analysis (DEA) is used to construct the Malmquist index (MI) for the growth in productivity, which is then decomposed into two components, *change in efficiency* (EC) and *change in technology* (TC). Results from structural equation modeling (SEM) indicate that while all 18 TEs exhibit relationships between investments in telecoms and the TC component, only a subset of the TEs shows a relationship between telecom investments and the EC component.

Keywords

Transition economies, developing/emerging economies, telecom investments, economic development

INTRODUCTION

While there has been considerable research investigating the effects of investments in information and communication technologies (ICT), and the macroeconomic impact of such investments is well recognized (OECD 2005a,b,c; IMF 2001; Samoilenko & Osei-Bryson 2008a,b), most of this research was conducted in the context of developed countries (Lam & Lam 2005; Madden & Savage 1999; Dunne *et al*. 2004; Siegel 1997). Developed countries, with high per capita income, represent less than 20% of the world population (World Development Report 2008). All other economies are considered developing economies, though a subgroup of these may be labeled as emerging economies, characterized by low absolute, but fast growing per capita income. Transition (or transitional) economies (TEs) are economies that recently moved (or are in the process of moving) from a centrally planned system to a free market system, such as the countries of Eastern Europe and the countries that resulted from the break-up of the Soviet Union (Roztocki and Weistroffer 2008a,b). Many transition economies can also be classified as emerging economies.

The heterogeneity of emerging, developing and transition economies complicates the adaptation of the insights offered by these studies done in developed countries. From a research perspective however, the context of TEs is advantageous in one way (Samoilenko 2008), as this group is comprised of both, economies that share many characteristics with developed countries, and economies that share characteristics mainly with less developed regions (OECD 2004). While previous research provided compelling evidence that ICT expansion has led to robust returns and economic growth in the context of developed economies (OECD 2005a,b,c; Oliner & Sichel 2002; Jalava & Pohjola 2002), the scarce research conducted in the context of emerging, developing, and transition economies reveals that investments in ICT have a much lower impact on the macroeconomic bottom line in these regions (Dewan & Kraemer 2000; Pohjola 2001; Piatkowski 2003). Consequently, TEs provide a bridge spanning the divide between the developed and developing regions and offer a platform for much needed investigations, the findings of which may be better generalized beyond the small group of highly developed countries.

Regardless of the setting there are two interrelated ways in which investments in ICT may have a macroeconomic impact. One way is by providing a return on investments in the form of revenues that contribute directly to the overall GDP. Samoilenko and Osei-Bryson (2008a,b) investigated the production of revenues from investments in telecoms, a subset of investments in ICT, in the context of 18 TEs and found that those TEs with higher levels of telecom investments (termed the *leaders*) also produced more revenues. However, the study found evidence that the lower level of revenues of the TEs with the lower levels of investments (the *followers*) was not due only to the insufficient levels of investments, but rather due to inefficiencies in the process of converting these investments into revenues. In an earlier study, Samoilenko and Osei-Bryson

(2007) found that the complementarity of investments in telecoms and full-time telecom staff plays an important role in the process of revenue generation, and that TEs that do not exhibit complementary effects of investments and labor generate, ceteris paribus, lower levels of revenues from telecoms than the TEs that do. These findings are in agreement with the common understanding that in order to impact the macroeconomic bottom line, investments in ICT must be made at a sufficiently high level, and must be accompanied by complementary investments in order to be utilized efficiently.

The second way in which investments in ICT may have a macroeconomic impact is via the *spillover effect*, where the impact of investments is indirect by causing other economic factors or entities to be more productive. This second way of impacting the macroeconomic bottom line is particularly desirable, as it appears to be free. It appears to be free because the investments are not actually allocated in order to obtain the spillover effect, rather the resulting benefits can be viewed as a bonus. Thus, when allocating resources as investments in ICT, the expected outcome may be either direct revenue from ICT alone, or revenue from ICT accompanied by the spillover effect of these investments.

In a recent study, Samoilenko and Osei-Bryson (2010) outlined a methodology that tests the relationship between investments in telecoms (a subset of investments in ICT) to a possible spillover effect from these investments. Their findings indicate that the more efficient TEs do indeed show a relationship between investment in telecoms and growth in general productivity, thus providing evidence for a spillover effect. The authors proposed and tested a structural equation model to gain insights into why some TEs achieve a spillover effect from investments in telecoms, while other TEs do not. While the insights provided by their study are valuable, the study only looked at *overall* growth in productivity. However, growth in productivity, as acknowledged by Samoilenko and Osei-Bryson (2010), is a composite of two parts: *change in efficiency* and *change in technology*, and it is possible for an economy to exhibit overall economic growth that is driven by only one of these two components. Thus it is possible that a specific economy improves based on improvements in technology, without improving efficiency (e.g. the productivity of the workforce could actually decrease due to an inability to keep up with the improved technology, possibly caused by a sharp learning curve).

Better understanding the nature of the spillover effect may lead to better economic decision making. If a policy maker in a TE realizes that investments in ICT have been driving technological change at the expense of improvements in efficiency in the ICT workforce, then the limited resources for ICT investments can be reallocated more effectively, to achieve a balance of both kinds of spillover. Consequently, the overall objective of the current investigation is to gain greater insight about the types of impact of investments in ICT on the macroeconomic bottom line. In pursuing this goal we will expand the approach of Samoilenko and Osei-Bryson (2010), while looking again at investments in telecoms within the same setting of 18 TEs. To achieve our objective we test the presence of a separate relationship between investments in telecoms and each of the components of economic growth, change in technology, and change in efficiency. We use structural equation modeling (SEM) implemented with a partial least squares (PLS) approach to conduct the test for significance of the relationship.

The rest of this paper is structured as follows: In the next section, we start with a brief overview of the theoretical and empirical foundations of our study and a formal presentation of the research problem as well as an overview of the data analytic methods used in this study. We also provide an overview of the research methodology and an overview of the data. Then, in the following section, we present the results of the data analysis and a discussion of these results. A conclusion and overview of the limitations of the study are provided at the end of the paper.

RESERCH QUESTIONS AND METHODOLOGY

Neoclassical Growth Accounting

The neoclassical growth accounting model goes back to the work of Solow (1957) and has been widely used in economics research (Oliner & Sichel 2002). Using a neoclassical production function, the objective is to decompose the rate of growth of an economy (where an economy can be an enterprise, a sector, a region or a nation) into the contributions from various inputs. A neoclassical production function relates output and inputs as follows:

(1) $Y = f\,(A, K, L)$

where Y = output (most often in the form of GDP), A = the level of technology or the total factor productivity (TFP), K = capital stock, and L = quantity of labor or the size of the labor force. Based on (1), growth accounting uses a Cobb-Douglas production function:

(2) $Y = A * K^{\alpha} * L^{\beta}$

where α and β are constants determined by the production technology. In the case of constant returns to scale, $\alpha + \beta = 1$ (If $\alpha + \beta > 1$, returns are increasing to scale and if $\alpha + \beta < 1$, returns are decreasing to scale), thus $\beta = 1 - \alpha$, which gives the following formulation:

$$(3)\ Y = A * K^{\alpha} * L^{1-\alpha}$$

Of the three inputs used by the growth accounting model, only capital *K* and labor *L* are empirically mobservable. For example, TFP (=A) is the residual (often referred to as *Solow's residual*) term capturing that contribution to *Y*, which is left unexplained by *K* and *L*. In the case of this study, assuming that *Y* = GDP, *A* = TFP, *K* = investments in ICT, and *L* = full-time ICT staff, the neoclassical production function allows us to relate investments in ICT, full-time ICT staff, and GDP in the as follows:

(4) *GDP = f (TFP, investments in ICT, full-time ICT staff)*

Using logarithms, the following formulation of the standard Cobb-Douglas production function can be obtained:

$$(5)\ \log Y = \log A + \alpha \log K + \beta \log L$$

Since *A* is a residual that can be expressed as an error term "*e*", equation (5) can be expressed as follows:

$$(6)\ \log Y = \beta_0 + \beta_1 * \log K + \beta_2 * \log L + e$$

As we mentioned earlier, the value of *A*, which represents TFP, cannot be directly observed in the data, but must be derived computationally. Data envelopment analysis (DEA) and the Malmquist index (MI) are commonly utilized for this purpose.

Calculation of TFP using DEA and MI

Data envelopment analysis (DEA) is a nonparametric method commonly used for the purposes of measuring the efficiency of decision-making units (DMUs). In order to conduct DEA, DMUs in the sample must be defined by the same DEA model, which specifies a set of inputs that the DMUs receive (e.g. investments, workforce size, etc) and a set of outputs that the DMUs produces (e.g. revenue). Any set of entities of the same type that receive inputs and produce outputs, be it manufacturing companies, schools, hospitals, or countries, can be designated as DMUs. DEA allows analyses under different economic assumptions regarding the process that transforms the inputs into outputs, viz. *constant returns to scale (CRS)*, *variable returns to scale (VRS)*, and *non-increasing returns to scale (NIRS)*.

The original DEA model, commonly referred to as *CCR* (Charnes et al. 1978), collapses multiple inputs and outputs of a DMU into a single abstract "meta input" and "meta output" and uses linear programming (LP) to obtain the input-to-output or output-to-input ratios to determine scores for *relative efficiency* for each DMU in the sample. The obtained scores can then be utilized for efficiency ranking of each DMU in the given set, where the highest ranking DMU is considered to be relatively efficient and receives a score of “1”. Because multiple DMUs may receive the same score, there can be multiple relatively efficient DMUs in the given set. As a result, DEA "envelops" the data set with the efficient frontier formed by the boundary points represented by the relatively efficient DMUs.

The three commonly mentioned orientations of DEA model are *input-oriented*, *output-oriented*, or *base-oriented* (Charnes et al. 1994). An input-oriented model is concerned with the minimization of the use of the inputs for achieving a given level of output, and is based on the assumption that inputs are controllable. An output-oriented DEA model, on the other hand, is concerned with the maximization of the level of the outputs for a given level of inputs, and assumes that outputs are controllable. A base-oriented model, unlike the first two, has dual orientation and is concerned with the optimal combination of the inputs and outputs; this type of DEA model deals with the efficiency of the input utilization and efficiency of the output production, having control over both inputs and outputs within the model. Regardless of the orientation of a DEA model, relatively efficient DMUs will always receive the perfect score of “1”. Relatively inefficient DMUs in input-oriented models will receive scores of less than “1”, and relatively inefficient DMUs in output-oriented models will receive scores of greater than “1”.

In our study, where DMUs are the TEs, inputs into the DEA model are investments in ICT, and outputs are revenues from ICT, the efficient frontier will be formed by the relatively efficient TEs, which convert their investments into revenues more efficiently than their relatively inefficient counterparts. Because DEA is conducted at a point in time (e.g. for a given year), we expect that the position of the efficient frontier, as a well as the scores of the DMUs in the sample, may change over time. A positive change is indicative of growth in productivity, and over a period of time this growth will reflect TFP and can be measured by the Malmquist Index (MI), defined by Caves et al. (1982) based on the idea of a productivity index suggested by

Malmquist (1953). Later, Färe et al. (1994) demonstrated that MI could be constructed using the results of DEA conducted in two separate points in time.

Research Questions

Taking equation (6) above where in the context of our investigation *Y* is represented by GDP, *K* is represented by the level of investments in telecoms, and *L* is represented by the quantity of full-time telecom staff in a given TE. Given our ability to calculate the value of TFP using MI, we can also obtain the value of *e*, as well as the values of its components, change in efficiency (EC), and change in technology (TC). Thus equation (1) above can be presented as:

(7) $Y = f\,(A_{\mathrm{EC}} + A_{\mathrm{TC}}, K, L)$

and the value of the error term in (6) can be re-written as:

(8) $e = e_{\mathrm{EC}} + e_{\mathrm{TC}}$,

where e_{EC} = EC component of MI, and e_{TC} = TC component of MI.

Thus equation (6) can be represented as:

(9) $\log Y = \beta_0 + \beta_1 * \log K + \beta_2 * \log L + e_{\mathrm{EC}} + e_{\mathrm{TC}}$,

and our research problem can be formulated as follows:

> RQ1: *Do investments in telecoms impact the macroeconomic bottom line in TEs, manifested in the relationship between investments in telecoms (K) and the growth in productivity driven by technological change (*e_{TC}*)?*
>
> RQ2: *Do investments in telecoms impact the macroeconomic bottom line in TEs, manifested in the relationship between investments in telecoms (K) and the growth in productivity driven by the change in efficiency (*e_{EC}*)?*

Given the heterogeneity of TEs, we expect that the answers to RQ1 an RQ2 may differ for different TEs. Thus we formulate the third research question as follows:

> RQ3: *What are some of the factors that differentiate TEs that exhibit a relationship between investments in telecoms and TC, from TEs that exhibit a relationship between investments in telecoms and EC?*

Structural Equation Modeling (SEM) implemented with Partial Least Squares (PLS)

SEM is a methodology representing the second generation of multivariate analysis (Fornell 1987). Unlike first generation statistical tools, exemplified by such techniques as cluster analysis, multiple regression, principal component analysis and others, SEM allows researchers to address a set of interrelated objectives within a single comprehensive analysis (Gefen et al. 2000). Use of SEM allows researcher to posit a presence of the relationships between the unobserved variables, where every such variable is associated with one or many observed variables; unobserved variables are referred to as *latent* variables, and observed variables are referred to as *indicators* or *measures*.

SEM consists of two parts. The first part involves testing the *measurement* model and primarily deals with the validation of the latent constructs included the model. The second part involves the assessment of the *structural* model and involves testing of the hypothesized relationships between the latent constructs of the research model. The results of the assessment are based on the significance of the structural paths, which can be estimated by using such methods as general least squares (GLS), ordinary least squares (OLS), maximum likelihood estimation (MSL), partial least squares (PLS), and others. The basic structure of a SEM is depicted in Figure 1 below.

There are two common approaches to SEM, covariance-based and variance-based. The covariance-based approach is based on the objective of minimizing the difference between the covariance matrix of the sample and the covariance matrix of the model. Thus, this approach is also commonly called factor-based, for the goal is to maximize the fit of the model by means of minimizing the unique variance; because of this goal of optimization of the fit the covariance-based approach is suitable for the investigations supported by a strong theory. In contrast, a variance-based approach attempts to optimize the predictive capability of the research model relative to the sample. The optimization of the prediction is achieved by estimating the parameters of the model by means of the minimization of the residual variances of the variables in the model (Chin 1998); Because of the assumption that all the measured variance is useful variance to be explained, this method is commonly referred to as component-based.

One of the least restrictive methods for estimating parameters in covariance-based SEM is partial least squares (PLS) (Wold 1966). The popularity of PLS is due to its minimal demands on measurement scales, sample size, and residual distribution (Chin 1998). While covariance-based methods are more appropriate when the research model is supported by strong theory and well-developed measures, PLS is recommended and often used for the purposes of theory development (Barclay et al. 1995).

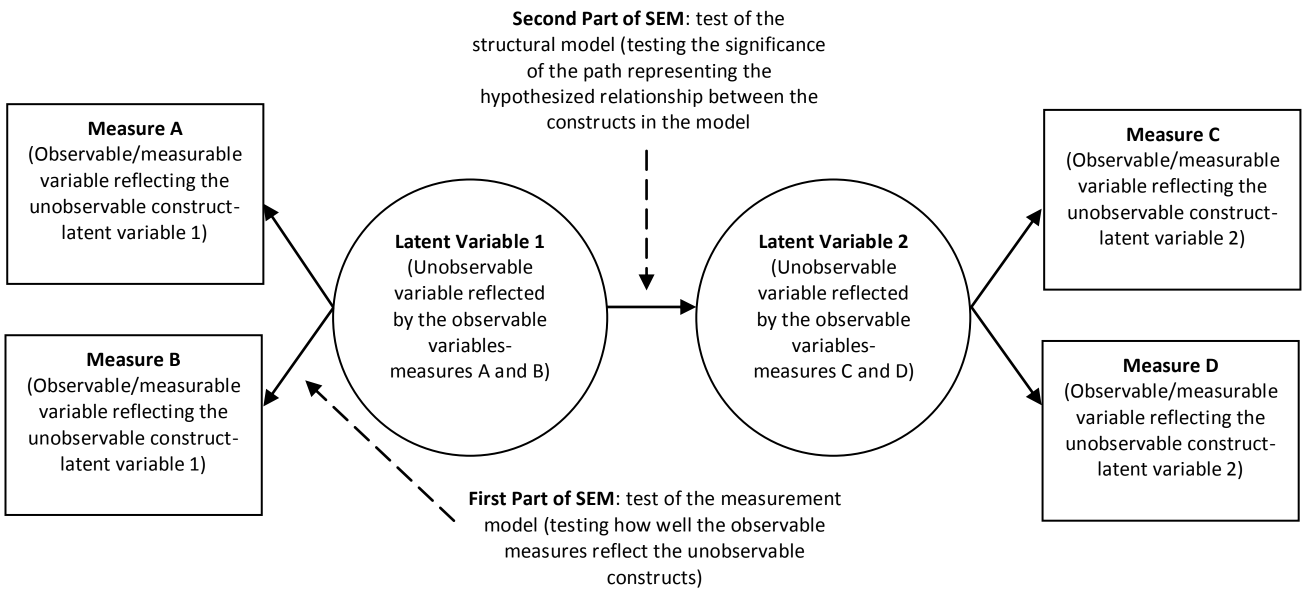

Fig.1: Basic Structure and Components of SEM

Methodology Used in this Study

Samoilenko and Osei-Bryson (2010) proposed a comprehensive three-step method allowing for relating investments in ICT to GDP and TFP within the framework of neoclassical growth accounting. Their method is described in Table 1. While the authors' approach allows for testing of the presence of the relationship between investments in telecoms and TFP, it does not allow for progressing further on the issue and gaining insights regarding some of the economic factors that may impact the presence of the relationship.

In the current study we concentrate on extending and expanding the method of Samoilenko and Osei-Bryson (2010) beyond Step 3 by adding two additional tests of the relationship between investments in telecoms and TFP, where the purpose of the first test is to inquire into the relationship between investments in telecoms and that component of TFP that is driven by technical change, and the purpose of the second test is to inquire into the relationship between investments in telecoms and the component of TFP that is driven by the change in efficiency.

Table 1: Method of Samoilenko and Osei-Bryson (2010)

Step	Technique	Purpose	Outcome
Step 1	Data Envelopment Analysis	Obtain the values of Malmquist Index (MI)	Values of TFP
Step 2	Multivariate Regression Analysis	Test the presence of the relationship between capital Investments in ICT, ICT Labor, and GDP	Strength of the relationship between the “white-box” independent variables and the dependent variable
Step 3	Structural Equation Modeling	Test the presence of the indirect/mediated relationship between Investments in ICT and TFP	Strength of the indirect/mediated relationship between the “white-box” independent variable and the “black-box” error term

This extended method is illustrated in Figure 2 below.

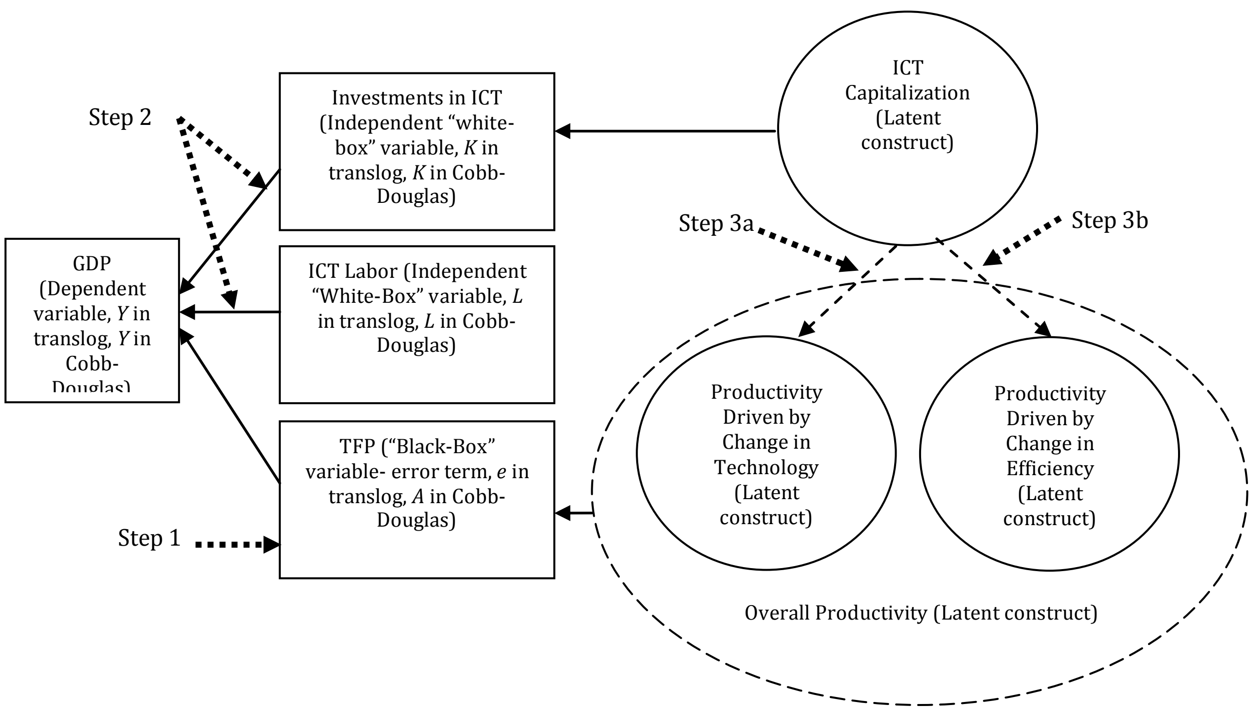

Fig. 2: Illustration of the Extended Method

Given the findings of Samoilenko and Osei-Bryson (2010), we expect to see that the two groups constituting the sample (i.e. the *leaders* and the *followers*) may differ in terms of the presence of one or another type of the relationship between the constructs.

Thus the overall methodology of our investigation can be described as follows:

Step 1: Determine the presence of the relationship between constructs *ICT Capitalization* and *Productivity Driven by Change in Technology* and *ICT Capitalization* and presence of the relationship between constructs *ICT Capitalization* and *Productivity Driven by Change in Efficiency* for the *Leaders* subset of the sample.

Step 2: Determine the presence of the relationship between constructs *ICT Capitalization* and *Productivity Driven by Change in Technology* and *ICT Capitalization* and presence of the relationship between constructs *ICT Capitalization* and *Productivity Driven by Change in Efficiency* for the *Followers* subset of the sample.

Step 3: Assign the appropriate values to the target variable "*Group&RelationshipExistence*" for the *Leaders* and the *Followers* subset of the sample.

At this point we can restate our research questions RQ1, RQ2, and RQ3 in the form of the following null hypotheses:

1. $H_{1}0$: There exists no statistically significant relationship between the constructs *ICT Capitalization* and *Productivity Driven by Change in Technology* for the 18 TEs of the sample.
2. $H_{2}0$: There exists no statistically significant relationship between the constructs *ICT Capitalization* and *Productivity Driven by Change in Efficiency* for the 18 TEs of the sample.
3. $H_{3}0$: There exists no statistically significant relationship between the constructs *ICT Capitalization* and *Productivity Driven by Change in Technology* for the *leaders* subset of the 18 TEs of the sample.
4. $H_{4}0$: There exists no statistically significant relationship between the constructs *ICT Capitalization* and *Productivity Driven by Change in Efficiency* for the *leaders* subset of the 18 TEs of the sample.

5. H_50: There exists no statistically significant relationship between the constructs *ICT Capitalization* and *Productivity Driven by Change in Technology* for the *followers* subset of the 18 TEs of the sample.
6. H_60: There exists no statistically significant relationship between the constructs *ICT Capitalization* and *Productivity Driven by Change in Efficiency* for the *followers* subset of the 18 TEs of the sample.

Overview of the Data

In this investigation we use the same time-series data set on 18 TEs spanning the period from 1993 to 2002 that was previously used by Samoilenko & Osei-Bryson (2010). The data were obtained from the *WDI* database (web.worldbank.org/wbsite/external/datastatistics), and the Yearbook of Statistics (2004) (www.itu.int/ITU-D/ict/publications) of *International Telecommunication Union (ITU) (* www.itu.int). The complete membership of the sample of 18 TEs is represented in terms of two clusters (see Table 2): the more efficient *leaders* and the less efficient *followers* (Samoilenko & Osei-Bryson 2010).

Table 2: *Leaders* and *Followers* Subgroups

Subgroup	Members
Leaders	Czech Rep, Estonia, Hungary, Latvia, Lithuania, Poland, Slovenia, Slovakia
Followers	Albania, Armenia, Azerbaijan, Belarus, Bulgaria, Kazakhstan, Kyrgyzstan, Moldova, Romania, Ukraine

In the current investigation we replaced the latent construct *Productivity* used in the study by Samoilenko & Osei-Bryson (2010) with two new constructs: *Productivity Driven by Change in Technology* and *Productivity Driven by Change in Efficiency*, as shown in Table 3. Because the goal of this investigation is associated with decomposing overall growth in productivity into two components, we created two separate data sets, and we labeled the data sets accordingly by using the names of the latent variables that the given data set represent. We named the first data set *ICT&ChangeInTechnology* and the second data set *ICT&ChangeInEfficiency*.

Table 3: Measures in the Current Research Model

Measure	Source variables	Representation	Latent Construct
TFP	MI	Annual change in productivity	Productivity driven by change in technology
Technical change component of TFP	TC component of MI	Annual change in productivity driven by change in technology	
TFP	MI	Annual change in productivity	Productivity driven by change in efficiency
Efficiency change component of TFP	EC component of MI	Annual change in productivity driven by change in efficiency	
RatioGDPtoInvestment	1. *GDP per capita* (current US$) 2. *Annual telecom investment per capita* (current US$)	Ratio of *gdp per capita* to *annual telecom investment per capita*.	ICT capitalization
RatioProductivity	1. *Annual total revenue from telecoms* (% of GDP) 2. *Annual investments in telecoms* (% of GDP)	Ratio of *annual total revenue from telecoms* to *annual investments in telecoms*	
RatioStafftoInvestment	1. *Full-time telecom staff* 2. *Annual investment in telecoms* (current US$)	Ratio of *full-time telecom staff* to the *annual investment in telecoms*	

We present the results of the data analysis next.

RESULTS OF THE DATA ANALYSIS

Preliminary Data Analysis: PCA

We used the PASW Statistics 18 (formerly SPSS) package to conduct an exploratory principal component analysis (PCA) in order to determine whether our latent constructs demonstrate a specific pattern of loadings, align in the same direction, and the measures (listed as "source variables" in Table 3) associated with a given latent construct load together on the same principal component. There are two latent constructs in our research model; therefore, we requested two components to be extracted. The Kaiser-Meyer-Olkin (KMO) test of sampling adequacy (should be above 0.5) and Bartlett's test of sphericity (should be less than 0.05) are the two measures that are commonly used to determine whether a data set can be successfully analyzed using factor analysis (Bollen & Long 1993). Based on the results of the analysis as shown in Table 4, we conclude that both of our data sets are suitable for PCA.

Table 4: Results of the Preliminary Data Analysis

Data Set	Descriptive statistics		
ICT&ChangeInEfficiency	**KMO and Bartlett's Test**		
	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.545**
	Bartlett's Test of Sphericity	Approx. Chi-Square	859.935
		df	10
		Sig.	.000
ICT&ChangeInTechnology	**KMO and Bartlett's Test**		
	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.642**
	Bartlett's Test of Sphericity	Approx. Chi-Square	785.328
		df	10
		Sig.	.000

We performed PCA specifying 2 components to be extracted and choosing *varimax*, the most common rotation option, in order to obtain an easy to interpret solution, where each of our measures will be maximally associated with a single construct. The results are presented in Table

5. The results of PCA strongly suggest that our measures represent their respective latent constructs well. Consequently, at this point we continue our inquiry and perform PLS analysis, results of which are presented in the next section.

Table 5: Results of the Principal Component Analysis

ICT&ChangeInEfficiency

Rotated Component Matrix[a]

	Component	
	1	2
MI	.304	**.903**
EC	-.092	**.957**
RatioGDPtoInvestment	**.987**	.091
RatioStafftoInvestment	**.911**	.077
ProductivityRatio	**.948**	.082

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

ICT&ChangeInTechnology

Rotated Component Matrix[a]

	Component	
	1	2
MI	.108	**.920**
TC	.462	**.677**
RatioGDPtoInvestment	**.945**	.297
RatioStafftoInvestment	**.910**	.133
ProductivityRatio	**.903**	.291

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

PLS Analysis: Assessment of the Measurement Model and Assessment of the Structural Model

Assessment of a research model using PLS analysis consists of two distinct steps. The first step includes the assessment of the *measurement model* and deals with the evaluation of the characteristics of the latent variables and measurement items that represent them. The second step involves the assessment of the *structural model* and involves evaluation of the specified by the research model relationships between the latent variables. We present the results of PLS analysis, which was conducted using PLS-G (Chin 1998b) package, in that order.

Assessment of the Measurement Model

The process of evaluation of the adequacy of the measurement model comprised of assessing the three criteria: the reliability of the individual items and their constructs, the convergent validity of the measures representing each construct, and discriminant validity of the measures (Hulland, 1999).

A test of the reliability of the individual items involves of assessment of the loadings of the measures on their latent construct, and the assessment of the reliability of the constructs is conducted by assessing the composite reliability of the constructs. In order for a model to pass the test of composite reliability assessment, the measures of the internal consistency (*Composite reliability* column) should be above than 0.7 (Nunnaly 1978), and the value of variance shared by each construct and its measures (*Average Variance Extracted- AVE* column) should be greater than 0.5 (Rivard & Huff 1988). Results of the assessment presented in Table 6 demonstrate that our research model successfully passed the test of composite reliability assessment.

Table 6: Assessment of Reliability of Constructs

Data Set	Construct	Composite Reliability	AVE	Squared Root of AVE
ICT&ChangeInEfficiency	TFP	0.838	0.722	0.8497
	ICT Capitalization	0.968	0.909	0.9534
ICT&ChangeInTechnology	TFP	0.878	0.785	0.8860
	ICT Capitalization	0.968	0.909	0.9534

We conduct the assessment of reliability of the individual measures next. The results provided in Table 7 illustrate that individual loadings of the all items are greater than 0.75. This indicates that our research model fares well in regard to the assessment of the reliability of the individual items as well.

Table 7: Assessment of Reliability of Individual Measures

Data Set	Measure	Loading	Communality
ICT&ChangeInEfficiency	MI	1.0000	1.0000

	EC	0.7551	0.5702
	RatioGDPtoInvestment	0.9910	0.9822
	ProductivityRatio	0.9591	0.9199
	RatioStafftoInvestment	0.9082	0.8249
ICT&ChangeInTechnology	MI	0.7793	0.6073
	TC	0.9148	0.8368
	RatioGDPtoInvestment	0.9910	0.9822
	ProductivityRatio	0.9591	0.9199
	RatioStafftoInvestment	0.9082	0.8249

The evaluation of the measure of internal consistency is commonly used for assessing convergent validity of the measures (Fornell & Larcker 1981). The process of evaluation involves assessment of the magnitude and significance of the t-values for the loadings of each of the individual items, as well as the assessment of the loadings of the measures on their own constructs. It is expected that the t-values are significant, and the measures representing their construct exhibit high loadings on that construct and low loadings on the other constructs in the model. The results displayed in Table 8 demonstrate that the research model passed the first test of the convergent validity, as all t-values for all measures of the 2 constructs are significant.

Table 8: Assessment of Convergent Validity

Data Set	Measure	T-value
ICT&ChangeInEfficiency	MI	7.2233
	EC	4.5371
	RatioGDPtoInvestment	206.0844
	ProductivityRatio	31.5843
	RatioStafftoInvestment	21.9873
ICT&ChangeInTechnology	MI	3.3060
	TC	4.8584

	RatioGDPtoInvestment	206.0844
	ProductivityRatio	31.5843
	RatioStafftoInvestment	21.9873

Further assessment of convergent validity, based on the results provided in Table 9, demonstrate that all measures in our research model share much variance and load highly only on their own constructs; this pattern is indicative of high convergent and high discriminant validity of the model.

Table 9: Assessment of Convergent and Discriminant Validity

Data Set	Measure	Productivity Driven by Change in Efficiency	ICT Capitalization
ICT&ChangeInEfficiency	MI	**1.00**	0.37
	EC	**0.76**	0.31
	ProductivityRatio	0.36	**0.96**
	RatioGDPtoInvestment	0.38	**0.99**
	RatioStafftoInvestment	0.30	**0.91**
ICT&ChangeInTechnology	MI	**0.78**	0.37
	TC	**0.91**	0.58
	ProductivityRatio	0.58	**0.96**
	RatioGDPtoInvestment	0.61	**0.99**
	RatioStafftoInvestment	0.43	**0.91**

Another suggested ways for assessing discriminant validity in PLS is by evaluating the average variance that a construct shares with its measures (Fornell & Larcker 1981). The commonly accepted practice is to substitute diagonal elements of the matrix of correlations between the constructs with the squared root of the average variance, and then to compare the substituted values with the values of the off-diagonal elements. If the diagonal elements of the matrix are greater than the off-diagonal elements, then the discriminant validity is considered to be adequately demonstrated (Hulland 1999). The results of the last assessment of convergent and discriminant validity of the research model are provided in Table 10.

Table 10: Assessment of Discriminant Validity

Data Set	Construct	Variance	
ICT&ChangeInEfficiency	Productivity Driven by Change in Efficiency	**0.8497**	
	ICT Capitalization	0.575	**0.9534**
ICT&ChangeInTechnology	Productivity Driven by Change in Technology	**0.8860**	
	ICT Capitalization	0.369	**0.9534**

The successful evaluation of the adequacy of our measurement model allow us proceed further with the assessment of the structural model.

Assessment of the Structural Model

Assessment of the structural model involves testing the significance of the hypothesized relationships between the research model constructs. Once the path coefficients between the two constructs in the model have been calculated, we can evaluate the significance of the path coefficients and the significance level of the path. In PLS-G, t-values are obtained by running a bootstrapping procedure, while the significance level of the path is established by using a 2-tailed t-distribution table.

Overall, we generated six structural path models, three models per data set. The first model represents the combined *leaders* and *followers* data set; the second model represents the *leaders* only; and the third model represents only the *followers*. The results of the assessment of the structural model are shown in Table 11.

Table 11: Strengths of the Structural Path Between the Constructs in the Research Model

Group of TEs	t-value	**Significance** (at $p < 0.05$)	Structural Path	Test of the ***H0***
Leaders & Followers	1.8489	Not significant	*ICT Capitalization* to *Productivity Driven by Change in Efficiency*	H_20 accepted
Followers	1.8021	Not significant		H_60 accepted
Leaders	2.4328	Significant		H_30 rejected

Leaders & Followers	2.2180	Significant	*ICT Capitalization* to *Productivity Driven by Change in Technology*	H_10 rejected
Followers	2.1697	Significant		H_50 rejected
Leaders	2.1445	Significant		H_40 rejected

DISCUSSION OF THE RESULTS

The findings of our investigation not only corroborated the results of previous studies, but also obtained important new insights, which support the point that just increasing the level of investments in ICT may not always be the most effective path to macroeconomic development. In other words, TEs cannot use an increase in the level of investments in ICT as a springboard for leapfrogging the divide that separates them from developed economies. Instead, decision and policy makers in TEs must look at first, having sufficient investments in ICT, and second, dedicate appropriate resources to complementary investments.

The current inquiry concentrated on investigating the impact of investments in telecoms on the growth in productivity and obtained evidence of the link between investments and the positive change in technology-driven growth. This finding is important from the standpoints of both research and practice, for it provides a more detailed view on the theoretical underpinnings and practical mechanics of the impact of investments. However, policy and decision-making implications may be even more important.

The results of our inquiry allow us to answer the three research questions stated earlier in this paper as follows:

- RQ1: *All 18 TEs of our sample exhibit a relationship between investments in telecoms and the growth in productivity driven by the technological change.*
- RQ2: *Only the members of the leaders' subset of TEs exhibit a relationship between investments in telecoms and the growth in productivity driven by the change in efficiency.*
- RQ3: *Those TEs that exhibit a relationship between investments in telecoms and the growth in productivity driven by the change in efficiency (the leaders) have a higher level of investments in telecoms and a lower level of full-time telecom workforce relative to the TEs that do not (the followers).*

LIMITATIONS OF THE STUDY AND FUTURE RESEARCH

One limitation is our partial reliance on the results of previous investigations by Samoilenko and Osei-Bryson (2010 a,b); this will restrict replication of the study, in a different context and in a stand-alone fashion. Thus, the current study should be viewed as a component of a larger research program. Future inquiries may be directed at the better integration of the findings of this study into the existing body of knowledge in the area of ICT for Development (ICT4D).

A second limitation is associated with the measures for our constructs *Productivity Driven by Change in Technology* and *Productivity Driven by Change in Efficiency*; we feel that while the measures used in this study are valid and reliable, the complexity of the latent construct calls for additional measures. Consequently, more studies are needed to identify and validate factors and variables that can be used to represent the two constructs in a more comprehensive fashion.

A third limitation is related to the structural model created for SEM analysis, which lacks constructs for presenting a wider picture of the economic environment and for investigating circumstances under which spillover effect takes place. Future studies should take into consideration the theory-building component of this investigation and propose at least a rudimental theoretical framework consistent with the body of knowledge accumulated in the area of ICT4D.

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