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Labor Productivity, Demographic Traits and ICT A Demo-Tech Productivity Model for Asian Region

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ABSTRACT: This paper develops an innovative model to explain the labor productivity in Asian countries, most of which are labor surplus and are endowed with substantial human capital. Such encouraging demographic traits are considered as complementary factors to use of Information and Communication Technologies (ICT). Population with labor having such favorable demographic traits and access to ICT results in higher labor productivity. Such is, here, termed as Demo-Tech Productivity Model and is tested by using data for 2000-2012 of 24 Asian countries. Econometric concerns like presence of endogenous and/or predetermined covariates and small time-series and cross-sectional dimensions of panel datasets are tackled by using System Generalized Method of Moments (SYS-GMM). Results show considerable support for the Demo-Tech Productivity hypothesis. Need is to design such models that suit the local demography and patterns of technological diffusion currently taking place in developing countries.

Keywords: Labor Productivity; Information and Communication Technology (ICT); System Generalized Method of Moments (SYS-GMM); Human Development Index (HDI).
JEL Classifications: C33; J24; O15; O33.

1. Introduction

From pre-historic times man has undertaken to store, recollect, and process information as a source of value. Starting from image carving in stone walls to today's digital technology, the information is handled in a number of ways.[1] During the last half of 20th century, the 'information revolution' was made possible through the digital Information and Communication Technology 'ICT' (Drucker, 1998).[2] ICT has affected agriculture, industry and services sectors of economies world over like no other technology in past (Allen & Morton, 1995). Terms like information economy, digital economy, e-economy, weightless economy, paperless economy have been floated over the last 3 decades to term this readily evolving kind of economy. For instance, one of the pioneering works in this regard was a report

[1] For more see, The Economic Implications of Moore's Law by G.D. Hutcheson Chapter 2 in *Into the Nano Era* by Howard Huff (2009).
[2] The ICT revolution is crucial insofar as it involves technologies geared to the production and dissemination of knowledge and information. These new technologies, that first emerged in the 1950s and then really took off with the advent of the Internet, have breathtaking potential.

by Porat (1977). Later, during mid-90s term 'New Economy' was introduced to represent the marvelous growth in software industry in US.

In his famous treatise, 'Major Economic Cycles', Nikolai Kondratiev pointed out the existence of tides of surging economic activity. These economic cycles are called as 'Kondratiev Waves'. There is growing consensus that the rise of 'New economy' during 1990s and the burst of the 'dotcom' bubble in 2001 can be the 5th Kondratiev Wave and the stimulus behind it is ICT, Korotayev & Tsirel (2010).[3]

2. Literature Survey and Data

Studies at macro level showing the impact of demographic factors and ICT on labor productivity is, to our knowledge, non-existent. However, similar efforts at micro level include Gargallo-Castel & Galve-Górriz (2007). This empirical research explores the ICT-productivity relationship in Spanish firms. Their innovation was to introduce a set of organizational variables (workers' qualifications, management attitude and process innovation) which would support the ICT to have its impact on organizational productivity. Their findings affirm the role of (organizational) complementary factors in strengthening the ICT-productivity relationship.

A few studies focused on Asian region revealed the want for e-readiness, e-competence and e-skills of human resource. Attitude towards and believes about ICT have also been a source of curiosity for researchers. Awang (2004) and Elsadig (2006) attempted to elucidate the nexus of ICT and productivity with human capital. Similar studies have not been undertaken for Asian countries. Other explanations have also been given for the fuzziness of ICT-productivity relationship. For example, Avgerou (1998) argues that lags between implementation of ICT and their effect on productivity.

A more recent effort to gauge the effect of ICT and complementary factors on the macroeconomic performance is found in Mehmood et al. (2013). Authors incorporate demographic factors and complementarities factors as determinants of macroeconomic performance by subjecting sample of Asian countries to econometric estimation. Authors find evidence in support of hypothesis. This work presents a possible explanation for the presence of Solow's Paradox. To augment the literature, this paper develops an innovative model to elucidate the importance of ICT and its complementary factors in enhancing the labor productivity.

For inquiring ICT-productivity nexus with complementary factors (henceforth Demo-Tech Model), following hypothesis is developed.

H_A: *ICT contributes more to labor productivity when combined with complementary factors (favorable demographic features and greater human development).*

A dataset of mixed sample of countries of Asian region (few DCs and mostly UDCs) is gleaned depending on availability of data for relevant variables. A maximum of 24 countries are selected while the number of years is 13. T = 13 and N = 24, since n > t, there is a panel data set.[4] Collection of data is done from World Development Indicators (WDI) and International Telecommunication Union (ITU) for selected Asian countries.

3. Development of Demo-Tech Hypothesis

The model developed in this study is named as **Demo-Tech Model**. Based on the factors included in it i.e. demographic features and information and communication technology, the term Demo-Tech Model is devised. Emphasis is kept on demographic factors and ICT, since they are likely to have strong complementarities. Among other variable is human development index. Human Development Index is expected to have a significant influence on the ability of the ICT users to be more productive and capable of contributing to economic growth.

[3] While the other wave which came before these waves are **1)** The Industrial Revolution, **2)** The Age of Steam and Railways, **3)** The Age of Steel, Electricity, and Heavy Engineering, and **4)** The Age of Oil, the Automobile, and Mass Production.

[4] Bangladesh, Bru Nei Darul Islam, China, Indonesia, India, Iran, Israel, Jordan, Japan, Kazakstan, Kryzgystan, Cambodia, Korea, Kowait, Lao PDR, Malaysia, Oman, Pakistan, Philippines, Russia, Saudi Arabia, Thailand, Tajikstan, Yemen.

3.1. Estimable Model

Demo-Tech model is estimated for assessing the role of ICT, along with complementary factors, in explaining labor productivity:

$\mathbf{LP_{i,t} = \psi\ (ICTMI_{i,t}, ICTSERT_{i,t}, p1564_{i,t}, URBNP_{i,t}, HDI_{i,t})}$ . . . . (1)

$\mathbf{LP_{i,t}} = \alpha_i + \alpha'_{i,t}\ (\mathbf{LP_{i,t-1}}) + \beta_{i,t}\ (\mathbf{ICTMI_{i,t}}) + \gamma_{i,t}\ (\mathbf{ICTSERT_{i,t}}) + \delta_{i,t}\ (\mathbf{p1564_{i,t}}) + \kappa_{i,t}\ (\mathbf{URBNP_{i,t}}) + \lambda_{i,t}\ (\mathbf{HDI_{i,t}}) + \Omega(\mathbf{T_i}) + \varepsilon_{i,t}$ . . . .(2)

Here, **LP** is labor productivity calculated as the ratio of national income and labor force, see for example Mahmood (2012). For an overall representation of ICT Information & Communication Technology Maturation Index (**ICTMI**)[5] is used.[6] For the complementary effects, **ICTSERT** is calculated as the product of ICT and SERT. Following Barro *et al.* (1994) 'tertiary school enrollment (% gross)' (**SERT**) is used as a proxy of human capital. In lieu of 'secondary school enrollment' (**SERS**), SERT is preferred cause people with higher levels of education enrollment are more intensive and economically productive users of ICT. SERT is also justified as higher levels of education invites greater 'ICT diffusion' in the economy and augments ICT-productivity nexus (Cette & Lopez, 2008). $\mathbf{T_t}$ is vector of time dummies and $\mathbf{\Omega}$ their respective coefficients and $\boldsymbol{\varepsilon_{i,t}}$ is the error term. **i** shows countries and **t** years.

For the complementary effects arising from demographic features of sample countries, **p1564** (population with at between 15 and 64 years) and **URBNP** (%age of urban population) are included. Welfare related complementarity is investigated using **HDI** (Human Development Index).

3.2. Estimation Techniques in Panel Data Sets

Customary techniques for estimation are Pooled OLS and fixed effects estimations. Pooled OLS does not consider the time dimension of data and hence flops to account for the unobserved country specific (fixed) effects causing omitted variable bias and is unable to control for the endogeneity. Both of these failures of Pooled OLS yield correlation between certain explanatory variables and country-specific effects that is handpicked by error term.

3.3. Algorithm for Choosing Estimation Technique

In addition to above mentioned assumption, the process of selection of estimation technique is explained as follows. If endogeneity is present in the absence of heteroskedasticity, IV regression should be employed. While if endogeneity is present in the presence of heteroskedasticity, GMM may be a more efficient estimator. For more on recent instances of GMM deployment see Mehmood et al. (2013), Elahi et al. (2013) and Mehmood et al. (2014). Furthermore, the choice between the two versions of GMM i.e. System GMM and Difference GMM is explained below.

3.4. Endogeneity and Instrumental Variables Regression

In presence of endogeneity, Instrumental Variable regression or GMM is preferred. No matter, IV regression is used or GMM, instrumental variables shall be involved in both of the cases. For instrumental variables, there are two main issues:

1) Validity of instruments – Over-identification.
2) Strength of instruments.

Primarily, the validity of instruments should be considered. If it is found to be valid, it should be tested for its strength. Statistically speaking, validity of instruments is $\mathbf{Cov(Z_1,\ \varepsilon_{i,t}) = 0}$ while $\mathbf{Cov(Z_1,\ X_1) \neq 0}$ shows the strength of strength of valid instruments. For inquiring the validity of instruments, Sargan and Hansen J-Statistic are suggested in literature among others. Both of these are post-estimation tests. For strength of instrumental variable, Durban Wu Hausman test and simple correlation can be resorted. Both of these are pre-estimation tests.

3.5. Diagnosing Presence of Endogeneity

It is expected that the estimable model has endogeneity, therefore statistical tests are resorted. These are called as Durbin-Wu-Hausman (DWH) tests. The $\mathbf{H_o}$ is that OLS is an appropriate

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[5] Recently, various compound ICT measures have appeared, such as the Digital Access Index (ITU, 2003); the Digital Opportunity Index (ITU, 2005); the Networked Readiness Index (Dutta & Jain, 2004); the Technology Achievement Index (UNDP, 2001); the Information Society Index (IDC, 2007); the Internet Connectedness Index (Jung et al., 2001); and the Infostate.

[6] ICTM is used as an 'external instrument' as suggested in Roodman (2009).

estimation technique. These tests compare the coefficient matrices of OLS and IV estimates. Using Stata 12.0, the above mentioned test is applied (see table 1).

Table 1. Durbin-Wu-Hausman Tests for Endogeneity			
Null Hypothesis (H_o): Regressor is Exogenous			
Test	**Notation**	**Statistic**	**p-value**
Wu-Hausman F test	F(1, 280)	62.388	0.000
Durbin-Wu-Hausman χ^2 test	$\chi^2(1)$	60.927	0.000
Source: Author's calculations using **Stata (Special Edition) 12.0**			

Since both tests are statistically significant, there is a need for IV regression in place of OLS regression. For the panel data in this study, System GMM is considered for estimation. Fixed effects estimation does control for unobserved time invariant country specific effects. In this process of correction of above mentioned correlation, the long run variation (dynamic sense) fades away. Technically speaking, it is due to estimations of deviations from time averaged sample means. To incorporate the long run variation (dynamic sense), dynamic panel estimation is devised by Arellano & Bond (1991) and Blundell & Bond (1998) that is also capable of dealing with endogeneity via the use of instruments. These are called Difference and System Generalized Method of Moments (GMM) estimators.

3.6. IV Regression vs. GMM

As per Baum et al. (2003), GMM gives more efficient estimates as compared to simple Instrumental Variables Regression when heteroskedasticity exists. If there is no heteroskedasticity, GMM estimator is no poor asymptotically than IV estimator for a small sample. Accordingly, need for a test is purported, that would investigate the existence of heteroskedasticity when regressor(s) is/are endogenous. Pagan and Hall (1983) have suggested a general test and a variant test for this purpose. Moreover, Godfrey (1978), Breusch & Pagan (1979), White (1980), Koenker (1981) and Cook & Weisberg (1983) have contributed in this regard. GMM gives more efficient estimates as compared to simple Instrumental Variables Regression when heteroskedasticity exists. If there is no heteroskedasticity, GMM estimator is no poor asymptotically than IV estimator for a small sample. Accordingly, need for a test is purported, that would investigate the existence of heteroskedasticity when regressor(s) is/are endogenous. Pagan and Hall (1983) have suggested a general test and a variant test for this purpose. Moreover, Godfrey (1978), Breusch & Pagan (1979), White (1980), Koenker (1981) and Cook & Weisberg (1983) have contributed in this regard. The background of these tests is furnished below:

Principle behind all these statistics is to test relationship amid residuals of regression and **p** indicator variables ("hypothesized to be related to the heteroskedasticity"). Test statistic in Breusch & Pagan (1979), Godfrey (1978), and Cook & Weisberg (1983) are distributed as χ^2 with **p** degrees of freedom under $\mathbf{H_o}$ of homoskedasticity ("and under the maintained hypothesis that the error of the regression is normally distributed"). Koenker (1981) considers normality assumption a crucial factor in determining the power of the test. Koenker's test statistic is distributed as $\boldsymbol{\chi^2_p}$.

As per Pagan and Hall (1983), these tests are valid for heteroskedasticity in an IV regression only if heteroskedasticity exists in that equation and nowhere else in the system. Other structural equations in the system (corresponding to the endogenous regressors X_1) must also be homoskedastic, even though they are not being explicitly estimated. Made up of variables that are hypothesized to be related to the heteroskedasticity in the equation, assume ψ as the n × p matrix, with typical row ψ_i. Say,

$\bar{\Psi} = \frac{1}{n}\sum_{i=1}^{n} \psi_i$ dimension = n × p

$\hat{D} \equiv \frac{1}{n}\sum_{i=1}^{n} \Psi_i' \left(\hat{u}_i^2 - \hat{\sigma}^2\right)$ dimension = n × 1

$\hat{\Gamma} = \frac{1}{n}\sum_{i=1}^{n} \left(\Psi_i - \hat{\Psi}\right)' X_i \hat{u}_i$ dimension = p × K

$$\hat{\mu}_3 = \frac{1}{n}\sum_{i=1}^{n} \hat{u}_i^3$$

$$\hat{\mu}_4 = \frac{1}{n}\sum_{i=1}^{n} \hat{u}_i^4$$

$\hat{X} = P_z X$

As per theorem 8 in Pagan and Hall (1983), if $\mathbf{u_i}$ is homoskedastic and independent of $\mathbf{Z_i}$, following is shown under the H_o of no heteroskedasticity:

$$n\hat{D}'\hat{B}^{-1}\hat{D} \overset{A}{\sim} \chi^2_p \quad \text{.......................................(I)}$$

where

$$\hat{B} = B_1 + B_2 + B_3 + B_4 \quad \text{.......................................(II)}$$

$$B_1 = (\hat{\mu}_4 - \hat{\sigma}^4)\frac{1}{n}(\Psi_i - \bar{\Psi})'(\Psi_i - \bar{\Psi}) \quad \text{.......................................(III)}$$

$$B_2 = -2\hat{\mu}^3\frac{1}{n}\Psi'\hat{X}(\frac{1}{n}\hat{X}'\hat{X})^{-1}\hat{\Gamma}' \quad \text{.......................................(IV)}$$

$$B_3 = B_2' \quad \text{.......................................(V)}$$

$$B_4 = 4\hat{\sigma}^2\frac{1}{n}\hat{\Gamma}'(\frac{1}{n}\hat{X}'\hat{X})^{-1}\hat{\Gamma} \quad \text{.......................................(VI)}$$

Equation (I) gives the Pagan-Hall General Test Statistic. For the variant of this test, i.e. Pagan-Hall Test w/assumed Normality, the error term is assumed to be normally distributed. This leads to $B_2 = B_3 = 0$ and $B_1 = 2\hat{\sigma}^4\frac{1}{n}(\Psi_i - \bar{\Psi})'(\Psi_i - \bar{\Psi})$.

For White/Koenker nR_c^2 test statistic, the rest of the system is assumed to be homoskedastic and $B_2 = B_3 = B_4 = 0$.

Finally for Breusch-Pagan/Godfrey/Cook-Weisberg test statistic, same assumption about homoskedastic holds as in White/Koenker nR_c^2 test statistic and equality that $B_2 = B_3 = B_4 = 0$. In addition, the error term is assumed to be normally distributed, and $B_1 = 2\hat{\sigma}^4\frac{1}{n}(\Psi_i - \bar{\Psi})'(\Psi_i - \bar{\Psi})$.

Since both tests are statistically significant, there is a need for IV regression in place of OLS regression. For the panel data in this study, System GMM is considered for estimation. Fixed effects estimation does control for unobserved time invariant country specific effects. In this process of correction of above mentioned correlation, the long run variation (dynamic sense) fades away. Technically speaking, it is due to estimations of deviations from time averaged sample means. To incorporate the long run variation (dynamic sense), dynamic panel estimation is devised by Arellano & Bond (1991) and Blundell & Bond (1998) that is also capable of dealing with endogeneity via the use of instruments. These are called Difference and System Generalized Method of Moments (GMM) estimators.

3.7. Diagnosing Heteroskedasticity

These tests are estimated as follows (table 2):

Table 2. Tests for Heteroskedasticity in Presence of Instrumental Variables		
Null Hypothesis (H_o): Disturbance is Homoskedastic		
Test	**$\chi^2(6)$**	**p-values**
Pagan-Hall General Test Statistic	42.353	0.000
Pagan-Hall Test w/assumed Normality	49.006	0.000
White/Koenker nR_c^2 Test Statistic	158.463	0.000
Breusch-Pagan/Godfrey/Cook-Weisberg	190.034	0.000
Source: Author's calculations using **Stata (Special Edition) 12.0**		

All four tests are in favor of presence of heteroskedasticity with statistically significance at 1% level of significance. Therefore, it can be safely assumed that heteroskedasticity is present and GMM can be preferred to IV estimation.

3.8. Suitability of GMM Estimator

Roodman (2009), suggests about three levels of assumptions that would call upon GMM Estimator. Firstly, the data generating process should be dynamic, with current values of the explained variable inclined by past values and some fixed individual effects may be arbitrarily distributed. At least one of explanatory variable should be endogenous. Idiosyncratic disturbances should have heteroskedasticity that are individual-specific and should bear autocorrelation. Idiosyncratic disturbances should be uncorrelated across individuals.

Secondly, some explanatory variables may be predetermined but not strictly exogenous; i.e. independent of current disturbances while some explanatory variables may be influenced by past ones.

Lagged dependent variable $\mathbf{y_{i,t-1}}$ is an instance. Dataset should be a micro-panel small **t** and large **n**. GMM estimator is more suitable for micro panels ($3 \geq t \geq 10$) Roodman (2009). Here t = 13 and n = 24. A greater n is more suitable for GMM estimator. For this small sample adjustment is undertaken by using **small** argument in the **xtabond2** command Mileva (2007).

Finally, there is preference for internal instruments as compared to external instruments. Internal instruments are the ones that are based on lags of instrumented variables.

3.9. System-GMM vs. Difference-GMM

For estimation of aforementioned model, System GMM is preferred over Difference GMM owing to following reasons:

i. As per Baltagi (2008), SYS-GMM usually yields more efficient and precise estimates as compared to DIFF-GMM due to improved precision and reduced finite sample bias.
ii. SYS-GMM estimates are superior to DIFF-GMM for variables that show random walk or similar behavior (Bond, 2002; Baum, 2006; Roodman 2006; and Roodman, 2009). Since random walk behavior is quite common macroeconomic phenomenon, SYS-GMM seems more suitable.
iii. As per Roodman (2006), DIFF-GMM has the tendency of eliminating the constant values due to differencing of variables within groups. In convergence regression, while using $YCD_{i,t(0)}$, this value would vanish. Therefore SYS-GMM is preferred to DIFF-GMM.
iv. DIFF-GMM estimation has an offshoot of expanding gaps (Roodman, 2006). The panel in this study is balanced and since SYS-GMM is preferred to DIFF-GMM due to other reasons mentioned before, the problem of expanding gaps is out of question.

3.10. System GMM Results

Hansen test of over-identifying restrictions is a joint test of model specification and appropriateness of the instruments. This test statistics indicates that the model is well specified and the instrument vector is appropriate (table 3).

Table 3. SYSTEM GMM Estimates (Impact of Demographic Complementary Factors and ICT on Labor Productivity)

Dependent Variable: Labor productivity ($LP_{i,t}$)				
	Coefficients	**Standard Errors**	**t-statistics**	**p-values**
$\mathbf{LP_{i,t-1}}$	0.9239	0.0131	70.537	0.000
$\mathbf{ICTMI_{i,t}}$	0.0666	0.0283	2.354	0.020
$\mathbf{ICTSERT_{i,t}}$	0.0793	0.0258	3.075	0.002
$\mathbf{P1564_{i,t}}$	0.0386	0.0152	2.549	0.011
$\mathbf{URBNP_{i,t}}$	0.0128	0.0070	1.836	0.068
$\mathbf{HDI_{i,t}}$	0.0353	0.0164	2.158	0.032
C	-0.0589	0.0178	-3.310	0.001
Time Dummies				
yrtd_02	0.19481	0.01840	10.59	0.000
yrtd_03	0.19439	0.01841	10.56	0.000
yrtd_04	0.19391	0.01837	10.56	0.000
yrtd_05	0.19324	0.01818	10.63	0.000
yrtd_06	0.19223	0.01853	10.37	0.000
yrtd_07	0.19147	0.01857	10.31	0.000
yrtd_08	0.19141	0.01859	10.30	0.000
yrtd_09	0.19088	0.01857	10.28	0.000
yrtd_10	0.19047	0.01862	10.23	0.000
yrtd_11	0.02665	0.01438	1.85	0.077
yrtd_12	0.01333	0.00718	1.86	0.076
Other Tests and Parameters				
Observations = 288	**Countries** = 24	**Instruments** = 38	**F(17, 23)** = 209492 [**p** = 0.000]	
p-value: Hansen J-Test = 0.963		$\mathbf{M_1}$: p = 0.387 & $\mathbf{M_2}$: p = 0.216		
Difference in Hansen tests / C-tests: [p = 0.417, p = 0.963, p = 0.548 & p = 0.958]				
Source: Author's calculations using **Stata (Special Edition) 12.0**				

Moreover, Arellano-Bond (1991) test for the second order serial correlation is also estimated, which signals that there is no evidence of 2nd order serial correlation in the estimated models. For cross-section dependence, Sarafidis et al. (2006) exploit a mixture of the M_2 and difference-in-Hansen test to test cross-section dependence. This approach scrutinizes if error cross-section dependence remains after incorporating time dummies in estimable model. $\mathbf{H_o}$ is that the cross-section dependence is homogenous across pairs of cross-section units. Statistical diagnostics of the model, on including time dummies, ameliorate and remove the universal time-related shocks from $\boldsymbol{\varepsilon_{i,t}}$.

4. Interpretation

The productivity model estimations reveal the existence of relationship between ICT and labor productivity hinged upon the demographic complementary factors. Lagged value of labor productivity $\mathbf{LP_{i,t-1}}$ is found to be positively related with its previous values, showing the dynamic behavior of the variable. Hence gives rise to a dynamic panel model. Its statistical significance is at all levels. Roodman (2009) suggests that if this coefficient is greater than 1, then SYS-GMM is invalid. Here it is 0.9239 (< 1), so SYS-GMM is valid. The main variable of interest is ICTMI (information and communication technology maturation index) that has a positive influence on LP (labor productivity) as depicted by its positive sign of regression coefficient. ICTMI is statistically significant at 5% level of significance. ICTSERT (ICT×SERT) is also used in the regression which captures the interaction of ICT and school enrollment rate at tertiary level. This coefficient also is statistically significant at 5% level of significance and has a positive influence on labor productivity. This implies that ICT has complementarity with tertiary level of education. In simpler terms, highly educated users (labor) of ICT are economically more productive labor. Similar results are also expected from ICTSERS (ICT×SERS) an interaction of ICT and school enrollment rate at secondary level. But due to relatively lower level of education, the influence on labor productivity is likely to be lower. Moreover, a smaller portion of population having secondary education, is likely to be ICT users, while a bigger portion of population having tertiary education is expected to be ICT users. Therefore, the proxy ICTSERS is not empirically tested in this research.

The proxy for economically active youth, population aged between 15-64 years is also included. Though age group up to 64 years is not considered young, but lack of data on below 50 years of age of population is not available, so this proxy is dictated by data availability. The meaning of young population here is in terms of their contemporariness to ICT and physical and mental fitness to adopt and use ICT. It shows a positive and statistically significant relationship at 5% level of significance with labor productivity. It is justified since young labor force is more ICT-savvy. 'ICT-savvy' means proficient user of information and communication technology.[7] ICT revolution is not more than two or three decades older, accordingly the younger population has undergone proper training of ICT under academic programs. United Nations (UN), World Summit on the Information Society (WSIS) and World Programme of Action for Youth (WPAY) also confirm the high potential of youth in learning the use and development of ICT applications.

Another segment of population that is hypothesized to be relatively more productive is the urban population. Population in urban areas gets better education and job opportunities due to urbanization economies. Urbanization economies contain benefits like proximity of markets, skilled and more educated labor, financial services, better information and communication facilities and knowledge spillovers. Considering these facts, this demo-tech productivity regression includes urban population (URBNP) along with ICT as demographic factor. This explanatory variable shows positive influence on labor productivity and supporting the argument of urbanization economies. Its statistical significance at conventional levels, however, is absent.

Human welfare can also play a positive role in determining the level of labor productivity. Accordingly, HDI is included as a determinant of LP. Its role turns out to be positive and statistically significant at 5% level of significance. The result for this explanatory variable is quite intuitive. Its positive role is justified on the basis of its three tiered role i.e. health (life expectancy), educational inclination and economic performance of country. All three components of HDI, in presence of ICT, contribute better towards labor productivity. In another connotation, labor with higher welfare and ICT

[7] Origins of "ICT-savvy" can be found back to Business Week: November 19th, 1984.

is likely to be more productive. In addition to explanatory variables, time dummies as also estimated to overcome the problem of cross-sectional dependence and to cope with universal time-related shocks from $\varepsilon_{i,t}$.

Overall significance of the model is agreeable at 1% level of significance as revealed by F-test of joint significance. The condition that number of observations is greater than number of instruments holds in this case i.e. (288 > 38). Hansen test of correct specification and over-identifying restrictions has a p-value of greater than 0.05. i.e. (p-value = 0.963 > 0.05) implying that all over-identified instruments are exogenous. The Arellano & Bond test for first order 'M_1' and second order 'M_2' correlation i.e. AR(1) and AR(2) show p-value of greater than 0.000. i.e. $(M_1)_{p\text{-value}} = 0.387 > 0.05$ and $(M_2)_{p\text{-value}} = 0.216 > 0.05$. Hence there is no second order serial correlation in residuals.

C-test (Baum, 2006; Roodman, 2006) for the validity of subsets of instruments for level and difference equations are also satisfactory. These tests are four in number and have same criteria, i.e. the p-value should be greater than 0.05:

$(\text{C-test})_{\text{Ho: GMM-differenced instruments are exogenous}} = 0.417 > 0.05$

$(\text{C-test})_{\text{Ho: system GMM instruments are exogenous \& they increase Hansen J-test}} = 0.963 > 0.05$

$(\text{C-test})_{\text{Ho: GMM instruments excluding IV-instruments are exogenous}} = 0.548 > 0.05$

$(\text{C-test})_{\text{Ho: Standard IV-instruments are exogenous \& they increase Hansen J-test}} = 0.958 > 0.05$

There is no evidence to reject the null hypotheses set in these four tests of difference-in-Hansen/C-tests.

5. Conclusion and Recommendations

From empirical results, it is deduced that demographic and welfare related factors complement the ICT-productivity relationship. The expectation that ICT alone may not ameliorate labor productivity is affirmed by our analysis. Complementary factor such as population in large urban areas is found to enhance the ICT-productivity relationship. Such digitally literate population is found to be economically more productive. Similar implications are found for age cohort of population that is economically active. More specifically, it is affirmed that populations with higher level of HDI (education, health and living standards) are better able to use ICT for productive purposes contributing to national income. The innovative model developed in this study explains labor productivity from the point of view of ICT, demography and welfare levels.

Findings in this study related to HDI shows that merely throwing ICT at the disadvantaged populations/regions shall not bring the desired result of increased productivity. For that the funding agencies have to embed these ICT development programs with awareness campaigns so as to enable the target population for the economically productive usage of ICT equipment. For instance program of ICT4D (Information and Communication Technology for Development) faces issue of poor infrastructure, low illiteracy and poor health in implementing the ICT-based development projects in disadvantaged regions like Africa.[8] As highlighted in the empirical analysis of this study youth, combined with ICT diffusion, can contribute to level of productivity. Most of sample countries, have shown greater proportion of youth in total population. Need is to channelize this youth but making them digitally literate so they contribute to national income. In brief this finding of the study suggests a form of man-power planning which focuses the ICT skills to channelize the benefits of favorable demographic features.

References

Abdelfattah, B.M., Bagchi, K., Udo, G., Kirs, P., (2010), *Understanding the internet digital divide: an exploratory multi-nation individual-level analysis,* AMCIS 2010 Proceedings. Paper 542. Retrieved from http://aisel.aisnet.org/amcis2010/542

Allen, T. J., Morton, M.S. (1995), *Information technology and the corporation of the 1990s: Research Studies*. Oxford University Press.

Arellano, M., Bond, S. (1991), *Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations*, The Review of Economic Studies, 58(2), 277-297.

[8] For more see Heeks (2002).

Avgerou, C. (1998), *How can IT enable economic growth in developing countries?* Information Technology for Development, 8(1), 15-28.

Awang, H. (2004), *Human capital and technology development in Malaysia*, International Education Journal, 5(2), 239-246.

Baltagi, B.H. (2008), *Econometric analysis of panel data*: *Econometric Theory*. 4th Edition, John Wiley & Sons, Ltd Wiley.

Barro, R., Lee, J.W. (1994), *Sources of economic growth*, Carnegie Rochester Conference Series on Public Policy, 40(384), 1-46.

Baum, C.F., Schaffer, M.E., Stillman, S. (2003), *Instrumental variables and GMM: Estimation and testing*, Stata Journal, 3(1), 1-31.

Bloom, D.E., Williamson, J.G. (1998), *Demographic transitions and economic miracles in emerging Asia*, The World Bank Economic Review, 12(3), 419-455.

Blundell, R., & Bond, S. (1998), *Initial conditions and moment restrictions in dynamic panel data models*, Journal of Econometrics, 87(1), 115-143.

Bond, S.R. (2002), *Dynamic panel data models: a guide to micro data methods and practice*, Portuguese Economic Journal, 1(2), 141-162.

Breusch, T.S., Pagan, A.R. (1979), *A simple test for heteroskedasticity and random coefficient variation*, Econometrica, 47, 1287-1294.

Cette, G., Lopez, J. (2008), *What explains the ICT diffusion gap between the major advanced countries? An empirical analysis*, International Productivity Monitor, 17, 28-39.

Cook, R.D., Weisberg, S. (1983), *Diagnostics for heteroscedasticity in regression*. Biometrika, 70, 1-10.

Drucker, P.F. (1998), The world according to Peter Drucker take-aways. *Free Press*.

Dutta, S., Jain, A. (2004), *The network readiness index 2003-2004*, *The Global Information Technology Report 2003-2004*. Geneva: World Economic Forum.

Elahi, A.R., Mehmood, B., Awan, M.M.H. (2014), *Macroeconomic Covariates of Default Risk: Case of Pakistani Non-Financial Firms*, Zagreb International Review of Economics & Business, 17(1), 15-26.

Elsadig, M.A. (2006), *ICT and human capital role in achieving knowledge-based economy: Applications on Malaysia's manufacturing*, Journal of Information and Knowledge Management, 5(2), 117-128.

European Commission (2010), *Europe's Digital Competitiveness Report*, Commission Staff Working Document. Vol. I.

Furuholt, B., Kristiansen, S. (2007), *A rural-urban digital divide? Regional aspects of internet use in Tanzania*. The Electronic Journal on Information Systems in Developing Countries, 31(6), 1-15.

Gargallo-Castel, A., Galve-Gorriz, C. (2007), *Information technology, complementarities and three measures of organizational performance: Empirical evidence from Spain*, Journal of Information Technology Impact, 7(1), 43-58.

Godfrey, L.G. (1978), *Testing for multiplicative heteroskedasticity*, Journal of Econometrics, 8, 227-236.

Goldfarb, A., Prince, J. (2008), *Internet adoption and usage patterns are different: Implications for the digital divide*, Information Economics and Policy, 20(1), 2-15.

Heeks, R. (2002), *i-development not e-development: Special issue on ICTs and development*, Journal of International Development, 14(1), 1-11.

Hutcheson, G.D. (2009), The economic implications of Moore's law. In H. R. Huff (Ed.), *Into the Nano Era* (pp. 11-38). Berlin Heidelberg: Springer.

IDC (2007), *Information Society Index*, International Data Corporation (IDC), Retrieved from: http://www.idc.com/getdoc.jsp?containerId=204122

ITU. (2003), *World telecommunications development report 2003: Access Indicators for the Information Society.* Geneva: ITU. Retrieved from www.itu.int/ITU-D/ict/publications/wtdr_03/index.htm.

ITU. (2005), *Measuring digital opportunity*. Geneva: ITU. Retrieved from http://www.itu.int/itu-wsis/2005/DOI%20V2.pdf.

Jung, J.Y., Qiu, J.L., Kim, Y.C. (2001), *Internet connectedness and inequality: Beyond the "Divide."* Communication Research, 28(4), 507-535.

Koenker, R. (1981), *A note on studentizing a test for heteroskedasticity*, Journal of Econometrics, 17, 107-112.

Korotayev, A.V. Tsirel, S.V. (2010), *A spectral analysis of world GDP dynamics: Kondratieff waves, Kuznets swings, Juglar and Kitchin cycles in global economic development, and the 2008-2009 economic crisis*, Structure and Dynamics, 4(1). Retrieved from: http://www.escholarship.org/uc/item/9jv108xp

Mahmood, T. (2012), *Labour productivity convergence in 52 industries: A panel data analysis of some European countries*, International Journal of Economics and Financial Issues, 2(3), 320-339.

Mehmood, B., Azim, P. (2013), *Does ICT participate in economic convergence among Asian countries: Evidence from dynamic panel data model*, Informatica Economică, 17(2), 7-16.

Mehmood, B., Azim, P., Asghar, N. (2013), *Demographic and welfare related covariates of macroeconomic performance in a digital age in Asia*, Pakistan Economic and Social Review, 51(2), 139-158.

Mehmood, B., Azim, P. (2014), *Total factor productivity, demographic traits and ICT: Empirical analysis for Asia*, Informatica Economică, 18(1), 8-16.

Mileva, E. (2007), *Using Arellano-Bond dynamic panel GMM estimators in Stata,* Economics Department, Fordham University, New York.

Ngwenyama, O., Andoh-Baidoo, F. K., Bollou, F., & Morawczynski, O. (2006), *Is there a relationship between ICT, health, education and development? An empirical analysis of five West African countries from 1997-2003*, The Electronic Journal on Information Systems in Developing Countries, 23(5), 1-11.

Nurmela, J., Viherä, M. (2000), *Communication capability is an intrinsic determinant for the information society, Futures, 3*, 245-65.

Ono, H., Zavodny, M. (2007), *Digital inequality: A five country comparison using microdata*. Social Science Research, 36(3), 1135-1155.

Pagan, A. R., Hall, A. D. (1983), *Diagnostic tests as residual analysis*, Econometric Reviews, 2(2), 159-218.

Porat, M.U. (1977), *Information Economy*. Technology, 2010(1/12/2010), 1-18. Harvard Business School Press. Retrieved from http://www.oecd.org/department/0,3355,en_2649_33757_1_1_1_1_1,00.html

Primo Braga, C.A., Fink, C., Sepulveda, C.P. (2000), *Intellectual property rights and economic development*, World Bank Discussion Papers.

Roodman, D. (2006), *How to do xtabond2: An introduction to "Difference" and "System" GMM in Stata*, Working Papers 103, Center for Global Development.

Roodman, D. (2009), *A note on the theme of too many instruments*, Oxford Bulletin of Economics of Statistics, 71(1), 135-158.

Samarajiva, R. Zainudeen, A. (Eds.). (2008), *ICT infrastructure in emerging Asia: Policy and regulatory roadblock.* India: Sage Publications.

Sarafidis, V., Yamagata, T., Robertson, R. (2006), *A test of cross-section dependence for a linear dynamic panel model with regressors*, Faculty of Economics, University of Cambridge, available on line at: http://www.econ.cam.ac.uk/faculty/robertson/HCSDtest14Feb06.pdf.

Stanley, L.D. (2003), *Beyond access: Psychosocial barriers to computer literacy,* The Information Society, 19, 407-416.

Teltscher, S., Magpantay, E., Gray, V., Olaya, D., Vallejo, I. (2010), *Measuring the information society: The ICT development index*: Telecommunication Development Bureau, International Telecommunications Union (ITU): Geneva, accessed at http://www. itu. int/net/pressoffice/backgrounders/general/pdf/5.pdf

UNDP. (2001), *Technological achievement by country*, United Nations Development Program. Human Development Report 2001. New York: Oxford University Press.

Van Dijk, J.A.G.M., Hacker, K. (2003), *The digital divide as a complex and dynamic phenomenon,* The Information Society, 19(4), 315-326.

Welling, S., Kubicek, H. (2000), *Measuring and bridging the digital divide in Germany*, Report presented at the International Conference, Stepping-Stones into the Digital World, September, Bremen. Retrieved from http://www.digitale-chancen.de/transfer/downloads/MD35.pdf

White, H. (1980), *A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity,* Econometrica, 48, 817-838.