

ICT, Human Capital and Technological Progress of Central and Eastern European Countries

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Abstract— The paper examines the impact of human capital and Information Communications Technology (ICTs) in technological progress of Central and Eastern European Countries (CEEC). Using the modified Nelson-Phelps framework, I estimate regressions based on panel data for the period 1950 to 2014. The estimation results show that together with ICT, human capital is of crucial importance in achieving convergence of CEEC with technology frontier.

Keywords— human capital, ICT, total factor productivity, Central and Eastern European Countries

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I. Introduction

Convergence in economic growth among European countries is supported by a number of empirical studies (see Kocenda (2001), Sarajevs (2001), Kutan and Yigit (2005), Allington and McCombie (2007), Crespo Cuaresma et al. (2014)). However, convergence of CEEC in the era of the information technology revolution and the Internet is not studied systematically. In this direction ICT and human capital should be of particular importance. As underlined by the International Telecommunication Union (ITU) ICT development of a given country is well reflected in the human capital as it is human capital which enables use of ICT (ITU, 2009). Importance of high-quality university system and widespread of digital skills is highlighted also by Renda (2016). Namely, as the author states, in the age of digitalisation one of the scarcest resource in ICT ecosystem is human capital since the latter presents a fundamental driver of ICT uptake.

To deliver empirical findings on the recent technological developments, I examine impact of human capital and ICT on technological progress and convergence of CEEC with the EU technology frontier. To conduct analysis, instead of neoclassical growth framework I employ empirical modifications developed by Benhabib and Spiegel (2005) of the original model of Nelson and Phelps (1966). In contrast to the exogenous growth model, Nelson and Phelps (1966) consider human capital not as a factor of production but rather as a facilitator of adoption of new technologies. In particular, the model illustrates the role of education in reinforcing the worker's ability for receiving, decoding and understanding information. Benhabib and Spiegel (2005) modified the original model by introducing the concept of the technological leader nation, and allowing for technology diffusion from the leader to the follower countries. They disaggregated the contribution of education into two parts: i)

the contribution to growth of technology as a direct effect of education, and ii) the contribution to technology diffusion as an indirect effect of education. Finally, they reformulated the original model in two ways: as the confined exponential diffusion and as the logistic technology diffusion processes. In the former, there exists convergence between the growth rates of the leader and follower countries in the long run. In the latter, the growth rates may diverge and imitators never catch-up with the leader country. Nevertheless, convergence is still possible depending on the level of human capital in a follower country. The model has been proven to be useful to empirically measure effects of human capital in the age of rapid technological progress and digitalisation (Akhvlediani and Cieřlik, 2019).

This paper employs empirical modifications of the original model developed by Benhabib and Spiegel (2005) and furthermore extends this empirical framework with ICT contribution. To conduct analysis, I test two main research hypotheses on the direct effect of human capital on technological growth and indirect effects of human capital and ICT on technology diffusion. In addition, I test the third hypothesis stating that human capital is a binding constraint for convergence in growth rates across CEEC and the core EU countries.

The remainder of the paper is structured as follows. Section 2 derives the estimation equation, describes the data and discusses estimations techniques. Section 3 reports estimation results. Finally, the last section summarizes the findings.

II. Model Specification and Data Description

To incorporate ICT effects in the empirical modifications of Benhabib and Spiegel (2005) I propose the following empirical framework:

$$\Delta a_{it} = b + (g + c)h_{it} - c(h_{it})(ict_{it})\left(\frac{A_{it}}{A_{mt}}\right) + \xi_i + \varepsilon_{it}$$

where Δa_{it} is the five-year average annual growth rate of TFP of a country i at time t , h_{it} is the human capital level in a country i at the beginning of every five-year period t , ict_{it} is the ICT capital stock in a country i at the beginning of every five-year period t , $\frac{A_{it}}{A_{mt}}$ is the ratio of a country i 's TFP level to that one of the leader country at the beginning of every five-year period t , g is the growth rate of TFP which depends on the level of human capital, c is the catch up term defining technology diffusion given human capital and ICT, b stands for the constant technological progress which is independent from human capital and technological diffusion, ξ_i is the time invariant individual effect for every country i and ε_{it} is the error term that is assumed to be

normally distributed with mean zero. I include the time invariant individual country effects to allow the steady-state level of productivity to vary across countries but at the same time to assume the same steady-state growth rates in the case of convergence (see Islam (1998)).

To conduct empirical analysis, I construct the panel data of five-year growth rates for 34 European countries for the time period from 1950 to 2014. According to the data availability, the sample covers the, CEEC, the rest of the EU countries, Norway and Switzerland as two large member countries of European Free Trade Association (EFTA), 1 Turkey and Serbia as recognized candidates for the EU membership which have already started procedure to accessions, 2 and Ukraine and Moldova representing countries from the Eastern Partnership (EaP).³ As for the technology leader nation, I select Germany for the following reasons. First, the country represents the largest economy in the EU owning the highest levels of GDP and capital stock. Second, Germany remains the technological leader in terms of the number of world-market relevant patents (registered inventions).⁴

I approximate human capital by the average years of schooling in the population over age of 15, obtained from the updated database of Barro and Lee (2014). Although some studies use the data for the population aged 25 and above, I follow the approach of Inklaar and Timmer (2013) and take the data for age 15 and above. The reason is that the working age starts at 15 and in case a person is employed until turning 25, I loose up to ten-year impact of human capital on economic growth. It would be desirable to also control for the quality of education, as suggested by number of studies discussed in the section of literature review (Hanushek, 2000); Hanushek and Kimko, 2008), however the data on the internationally comparable test results is limited in terms of time as well as country coverage.

Doménech and Fuente (2006) argue that the average years of schooling (among other data) may contain errors, mainly due to the changes in classification criteria and other inconsistencies in the primary data (the author mainly refers to the UNESCO data on education as the primary data for Barro&Lee dataset). Instead they develop their own proxy for human capital. However, their data covers 21 OECD countries, out of which only 19 countries are European and the data is also limited in terms of the time period. Therefore, given the country and time coverage, average years of schooling remain the best proxy for human capital in the analysis. Although I should take into account that as discussed by Doménech and Fuente (2006) the positive effect of human capital proxied by the average years of schooling could be lower than if human capital was

approximated by Doménech and Fuente (2006) data, especially once controlling for time and country effects.

To approximate ICT effects, I employ the data on investments and revenues in telecommunication services. My selection is motivated by the theoretical framework, which suggests that the rate of technological progress depends on the stock of human and ICT capital at the beginning of every period. In this regard, investments and revenues should better approximate stock of ICT capital rather than number of subscription to the fixed or mobile telephone lines.

The data on investments and revenues in telecommunication services are taken from the time-series database provided by the International Telecommunication Union (ITU). Namely, I employ annual investments in telecommunication services which refers to the investments during the financial year made by entities providing telecommunication networks and/or services (including fixed, mobile and Internet services as well as the transmission of TV signals) for acquiring or upgrading fixed assets less disinvestments owing to disposals of fixed assets. It is noteworthy that fixed assets include tangible assets such as buildings and networks and non-tangible assets such as computer software and intellectual property. As for revenues, I employ the data on revenues from all telecommunication services earned from retail fixed-telephone, mobile-cellular, Internet and data services offered by telecommunication operators (both network and virtual including resellers) within a given country during the financial year.

The data on TFP levels come from the PWT 9.0. Compared to the PWT version 6.1 employed by Benhabib and Spiegel (2005), the new version has several remarkable improvements in terms of the data quality. Namely the new version of PWT allows relaxing the assumption of the constant depreciation rate of capital and standard capital and labour share (30% and 70%) in the production function. Additionally, the initial capital stock is not calculated based on the steady-state approach and the assumption of a single depreciation rate of capital for all countries and years is relaxed.⁵ For comparison of productivity between countries, a second order approximation to the production function as the Törnqvist quantity index of factor inputs is used. The latter is more flexible than the standard Cobb-Douglas (1928) function.

To estimate the model, I use GMM estimator developed by Arellano-Bover (1995) and Blundell-Bond (1998) (more precisely so called “system GMM”). Instead of Arellano-Bond (1991) approach, I follow Arellano-Bover (1995) and Blundell-Bond (1998) approach which allows introduction of more instruments and thus increases efficiency of Arellano-Bond estimator. It assumes that, first differences of instrumenting variables are uncorrelated with the fixed effects and builds a system of two equations, the original equation as well as the transformed one, and is known as “system GMM.” I run estimations by using the program xtabond2, which implements system GMM with the

¹ The data were not available for Iceland and Lichtenstein to include all EFTA countries in the sample.

² Montenegro is also a recognized candidate for the EU membership, however the data on human capital were not available for this country to be included in the analysis.

³ EaP also includes other countries, for which, however, the data on human capital is not available, therefore I only consider those two countries in the analysis.

⁴ By the world market relevant patents per one million inhabitants, Germany has the highest number of registered inventions in the whole European Union. For more details see the data on inventions registered in the European Patent Office or at the World Intellectual Property Organization (WIPO). Data are sourced by: Bundesbericht Forschung und Innovation 2016.

⁵ To relax the constant depreciation rate of capital, the new dataset splits total investments into 6 groups of assets (structures, transport equipment, computers, communication equipment, software, other machinery and assets) and introduces geometric depreciation rates for each of the groups separately. Since the asset decomposition of investment varies across countries and years, assumption of a single depreciation rate of capital becomes no longer necessary. For more details, see Feenstra, et al. (2015).

Windmeijer (2005) finite-sample correction to the reported standard errors in two-step estimation.

III. Estimation Results

Estimation results are reported in Table 1. In column (1) I show empirical results obtained from GMM estimator, where at the first step all regressors are transformed by first order differencing. In columns (2)-(6) I provide several sensitivity checks.

As outlined by estimations in column (1), the effect of human capital on TFP growth is positive and statistically significant already at the 1% level. The contribution of the human capital and ICT in technology diffusion enters as expected with a negative sign and is statistically significant also at the 1% level. Therefore, these benchmark estimation results confirm the first two research hypotheses concerning the positive impact of human capital and ICT on TFP growth and technology diffusion.

In column (2) I report regressions for the model excluding a constant term. As illustrated by empirical results, exclusion of a constant term changes neither the values and nor statistical significance of the coefficients. However, this finding is still important, since in comparison to the estimation results of Benhabib and Spiegel (2005), where the sign of direct effects of human capital depended on a constant term, here both the direct and indirect effects of the human capital and ICT remain robust to the inclusion and exclusion of a constant term.

In column (3) I again employ two-step GMM, however I allow transformation of all regressors by forward orthogonal deviations instead of first order differencing, as suggested by Arellano and Bover (1995). The estimated coefficients on human capital and the catch-up term display the expected signs and are statistically significant. Thus, estimations derived from two-step system GMM, by two different methods of transforming regressors, bring similar results and underline robustness of the findings.

Finally, in last three columns, I redo regressions with a different proxy for ICT capital. Namely, to approximate ICT capital I use revenues instead of investments in telecommunication services. As reported in columns (4) - (6) estimation results are very similar to the ones obtained in initial estimations where ICT was proxied by investments in telecommunication services. Therefore, I may conclude that estimations are robust to all applied sensitivity tests.

In the last three rows of Table 1, I report marginal effects of human capital. Namely, I provide the contribution of human capital in TFP growth depending how far a country is from the technology frontier (I fix technological distance from the leader nation at the following levels: $\frac{A_{ti}}{A_{tm}}=0.25$;

$\frac{A_{ti}}{A_{tm}}=0.5$ and $\frac{A_{ti}}{A_{tm}}=0.75$). As outlined by calculations, estimations via GMM, where at the first step all regressors are transformed by first order differencing, predict higher marginal effects than estimations via GMM by forward orthogonal deviations.

Overall, in all estimations the marginal effects are quite small, possibly because the data employed in the analysis tackle the effects of the quantity rather than the quality of human capital. As discussed in the previous section, in case

of availability of data on education quality with broad country and time coverage, estimations could bring higher marginal effects. Apart from education quality, data quality is also a concern, which often results in disappointing results on the effects of human capital (Bassanini and Scarpetta, 2002). More precisely, the sample includes CEEC with Soviet background for which the data could be highly biased for the initial periods. The latter may explain that relative to the study of Bassanini and Scarpetta (2002) the point elasticities are rather small in this analysis.

In particular, the benchmark estimations calculate that if average years of schooling increases by 10%, TFP growth will increase by 0.35%. While GMM estimations by forward orthogonal deviations predict that 10% increase in human capital directly raises TFP by 0.27%. As for indirect contribution, when country is far from the technology frontier 10% increase in human capital and ICT brings at least 0.18% and at most 0.19% contribution through technology diffusion. However, when the country is closer to the technology frontier indirect effect amounts at least 0.29% and at most 0.32%. Overall, depending how far the country lags behind the leader nation, total effect of human capital in TFP growth can vary from 0.45% to 0.73%: the closer is the country to the technology frontier, the higher is the indirect effect and therefore, overall contribution of human capital in the growth of TFP. The same applies to effects of ICT, the closer is the country to the technology frontier, the higher is the contribution of ICT in technology diffusion.

These calculations imply that not only invention but also diffusion is difficult when country falls behind the technological leader. This result underlines the main assumption of the theoretical framework, according to which the contribution of human capital only exists if economy is technologically progressive and that insufficient human capital does not only slow down invention but also diffusion of new technologies. These findings are also in line with the evidence found by Engelbrecht (2003), Hanushek and Woessmann (2012) and Gennaioli et al. (2012), stating that the contribution of human capital in growth via diffusion and externalities is quite large.

Finally, since the sample is estimated over a relatively long period of time, I examine the stability of coefficients by introducing structural breaks for years 1990 and 2004.⁶ The former indicates the dissolution of the Soviet Union which led to drastic structural changes in CEEC. The later accounts for the EU Eastern enlargement by the 10 new EU member states. Due to a high correlation between interacted variables, I include structural breaks one by one in the estimations. Estimation results provided in Table 2 find that structural breaks do not yield statistically significant coefficients. Besides, it is noteworthy that baseline estimations stay robust to inclusion of structural breaks.

To conclude, estimation results remain robust with respect to all sensitivity checks including application of different empirical specifications, different estimators, different data and introduction of structural breaks in the model. Therefore, estimation results of all the six models do not allow rejecting the first two research hypotheses implying the positive and statistically significant effects of human capital and ICT in technological progress and technology diffusion.

⁶ Alternatively, I could also split the sample into several subsamples, however this would result in high number of missing observations.

TABLE I. ESTIMATION RESULTS

	(1)	(2)	(3)	(4)	(5)	(6)
<i>L.TFP</i>	0.205 [*] (0.119)	0.205 [*] (0.119)	0.186 (0.117)	0.256 ^{***} (0.093)	0.256 ^{***} (0.093)	0.297 ^{***} (0.085)
<i>ln(h)</i>	0.016 ^{**} (0.007)	0.016 ^{**} (0.007)	0.013 ^{**} (0.006)	0.016 ^{***} (0.005)	0.016 ^{***} (0.005)	0.013 ^{***} (0.004)
$\ln(h)\ln(ICT_{inv})\left(\frac{A_{ti}}{A_{tm}}\right)$	-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)			
$\ln(h)\ln(ICT_{rev})\left(\frac{A_{ti}}{A_{tm}}\right)$				-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)
Constant	-0.015 (0.015)			-0.016 (0.010)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of groups	34	34	34	34	34	34
Number of instruments	25	25	25	25	25	25
Number of observations	251	251	251	258	258	258
AR(1) in first diff. Pr>z	0,072	0,072	0,075	0,009	0,009	0,004
AR(2) in first diff. Pr>z	0,766	0,766	0,660	0,231	0,231	0,282
Hansen test	0,417	0,417	0,470	0,339	0,339	0,511

Marginal Effects

Direct Effects	0,035	0,035	0,027	0,035	0,035	0,029
Indirect Effects						
$\frac{A_{ti}}{A_{tm}} = 0.25$	0,019	0,019	0,018	0,019	0,019	0,018
$\frac{A_{ti}}{A_{tm}} = 0.50$	0,026	0,026	0,024	0,025	0,025	0,024
$\frac{A_{ti}}{A_{tm}} = 0.75$	0,032	0,032	0,029	0,030	0,030	0,029

Note: Standard errors in parentheses; * p<0.1, ** p<0.05, ***p<0.01

Source: own calculations. Stata (2015).

TABLE II. STABILITY OF COEFFICIENTS

	(1)	(2)	(3)	(4)	(5)	(6)
<i>L.TFP</i>	0.221 [*] (0.123)	0.221 [*] (0.123)	0.200 [*] (0.118)	0.147 (0.106)	0.147 (0.106)	0.143 (0.098)
<i>ln(h)</i>	0.019 ^{**} (0.007)	0.019 ^{**} (0.007)	0.012 [*] (0.006)	0.016 ^{**} (0.007)	0.016 ^{**} (0.007)	0.012 [*] (0.008)
$\ln(h)\ln(ICT_{inv})\left(\frac{A_{ti}}{A_{tm}}\right)$	-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)	-0.001 ^{***} (0.000)
<i>ln(h) * str_br1</i>	0.010 (0.035)	0.010 (0.035)	0.034 (0.034)			
<i>ln(h) * str_br2</i>	-0.015 (0.015)	-0.015 (0.015)	-0.002 (0.012)			
$\ln(h)\ln(ICT_{inv})\left(\frac{A_{ti}}{A_{tm}}\right) * str_br1$				0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
$\ln(h)\ln(ICT_{inv})\left(\frac{A_{ti}}{A_{tm}}\right) * str_br2$				-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Constant	0.015 (0.030)			-0.004 (0.020)		
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of groups	34	34	34	34	34	34
Number of instruments	27	27	27	27	27	27
Number of observations	251	251	251	251	251	251

Note: Standard errors in parentheses; * p<0.1, ** p<0.05, ***p<0.01

Source: own calculations. Stata (2015).

Since the estimations of the values and signs of coefficients in all six models bring the expected results, I am able to calculate the threshold value of the human capital, which determines whether growth rate of CEEC will converge with the leader country. Based on specification of Benhabib and Spiegel (2005), I calculate the threshold value of human capital as follows:

$$H_{it}^* = \exp \frac{gh_{mit}}{g+c}$$

where H_{it}^* is the critical level of human capital at the time t , h_{mit} is the level of human capital in the leader country at that time t , and g and c are coefficients obtained from estimations. Table 3 shows the calculations of the critical value of human capital for the first and the last period of analysis. I present calculations based on estimations derived from GMM with first order differencing, in column (1), and GMM with orthogonal transformation, in column (2).⁷ The first three rows of Table 3 bring the estimated coefficients from Table 1. The fourth and the fifth rows present logarithm of human capital of a leader country by the beginning (1950) and by the end (2010) of time period of analysis. The sixth and the seventh rows indicate calculated threshold values of human capital by 1950 and by 2010. And finally, the last two rows bring average threshold levels calculated as simple averages of threshold levels from two different sets of estimations. As reported in Table 3 estimations find the minimum level of human capital equal to 5,95 average years of schooling for the first period, and 10,38 for the last period of analysis.

TABLE III. CRITICAL LEVEL OF HUMAN CAPITAL

	(1)	(2)
g+c	0.016	0.013
c	0.001	0.001
g	0.015	0.012
$\ln(h_{m1950})$	1.92	
$\ln(h_{m2010})$	2.515	
H*(1950)	6.032	5.87
H*(2010)	10.571	10.19
Average	5.95	
H*(1950)		
Average		
H*(2010)	10.38	

Source: own calculations. Stata (2015).

Given calculated critical value of human capital, I find Bulgaria, Croatia, Latvia, Lithuania, Poland, Moldova, Romania, Serbia, Slovenia and Ukraine falling behind the critical value by 1950. This implies that the model predicts the negative catch-up of these countries with the technology leader nation. To check predictions of the model, I bring levels of human capital and TFP growth rates of laggard countries in Table 4.

⁷ Since coefficients did not differ neither in estimations excluding constant term and nor in estimations with different proxy of ICT, I only report calculations based on estimations derived from GMM with first order differencing (column 1) and GMM with orthogonal transformation (column 2).

TABLE IV. CRITICAL LEVEL OF HUMAN CAPITAL

country	H in 1950	H in 2010	$TFP_i - TFP_{leader}$
Bulgaria	3.82	11.24	-1.77
Croatia	5.66	11.30	-1.51
Latvia	3.84	10.65	-1.69
Lithuania	3.71	10.89	-1.54
Poland	5.40	11.32	-0.60
Moldova	3.28	10.40	-1.54
Romania	4.38	10.67	-0.26
Serbia	4.32	10.85	-1.09
Slovenia	5.86	11.89	-1.34
Ukraine	4.37	11.15	-1.55
Germany	6.8	12.17	

Source: own calculations. Stata (2015).

It is noteworthy that as the model predicted, these countries demonstrated the slow growth compared to the leader country. Namely, through the whole period the difference between the growth rates of these countries and Germany is negative (see the last column of Table 4). Therefore, prediction of the model implying the slow catch-up of the underlined countries with the leader nation is supported by the data. It is remarkable that these calculations are in line with findings of Kocenda (2001), Sarajevs (2001) and Kutan and Yigit (2005), discussed in the first section of this chapter.

Moreover, as reported in Table 4, by the end of the period, none of the countries fall behind the threshold level. However, stock of human capital in Moldova, Romania, Latvia, Lithuania and Serbia is still close to the critical level. This implies that there is a need of policies aiming at increasing human capital in these countries. This would accelerate convergence of these countries with the technology frontier.

IV. CONCLUSIONS

The paper examined the role of human capital and ICT in technological progress, technology diffusion and convergence across the EU. Instead of employing the standard neoclassical growth model, I revived the hypothesis of Nelson and Phelps (1966) to consider human capital not as a factor of production but rather as a facilitator of technological progress and technology diffusion. Namely, I employed empirical modifications of the original model proposed by Benhabib and Spiegel (2005). As an added value in the literature, I have extended this empirical framework with ICT contribution.

To conduct empirical analysis, I constructed panel data of five-year average annual growth rates of TFP of 34 European countries, including CEEC and other EU countries for the period 1950-2014. Estimation results obtained from GMM estimator confirmed the positive and statistically significant effects of human capital on technological progress. Furthermore, together with effects of human capital, estimations found positive and statistically significant impact of ICT on technology diffusion. These

results remained robust to a number of sensitivity checks provided by application of different estimation techniques, different proxies of ICT and structural breaks in the sample.

The consistency of the results allowed calculation of the critical level of human capital to determine the occurrence of convergence of CEEC with the technology leader nation. Calculations identified Bulgaria, Croatia, Latvia, Lithuania, Poland, Moldova, Romania, Serbia, Slovenia and Ukraine as the negative-catch-up countries in the sample by 1950. The predictions of the model were in line with reality since these countries indeed demonstrated slow TFP growth throughout the entire period from 1950 to 2014.

Moreover, by the end of the period, estimations did not find any country falling behind the threshold level of human capital. Hence, estimations favoured convergence of CEEC with the technological frontier. However, it is noteworthy, that estimations found Moldova, Romania, Latvia, Lithuania and Serbia mapped quite close to the critical level. This implies that there is a need of policies aiming at increasing human capital in these countries. This would ensure more efficient uptake of ICTs and faster convergence of CEEC with the technology frontier. After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar.

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