Composition of Human Capital, Distance to the Frontier and Productivity

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Composition of Human Capital, Distance to the Frontier and Productivity[*]

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Abstract: Empirical research on the existence of productivity externalities to the use of human capital has produced mixed results. Employing a dataset of 109 countries between 1950-2010, this paper examines the relationship between different types of human capital and productivity growth for countries at different distances from the world technology frontier. I use a 'sophisticated' productivity measure from the recently revised PWT and find support for the existence of externalities. Both tertiary and secondary education positively affect productivity growth with the former having a U-shaped, whereas the latter a decreasing impact on it, as countries move closer to the frontier.

Keywords: human capital; productivity growth; externalities; PWT

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1. INTRODUCTION

Although widely studied, the debate on whether there are productivity externalities to the use of human capital is far from settled.[1] Human capital has been identified as a key determinant of economic growth not only because it triggers innovation and the creation of new technologies, but also because it facilitates the adoption of those developed at the world technology frontier (e.g. Nelson & Phelps, 1966). However, empirical studies on the role of human capital have produced mixed outcomes.[2] This lack of conclusive evidence has recently been attributed to the possibility that the effect of different *types* of human capital varies with a country's stage of economic development. Following this line of reasoning, this paper examines the effect of different types of human capital on productivity growth for countries at different distances from the world technology frontier. My focus is on productivity growth, therefore on the externality effect, for which I find evidence.

As countries largely engage in innovation activities the closer they get to the technology frontier, a type of human capital is required that is best suited to carry out these tasks. According to Vandenbussche, Aghion and Meghir (2006), it is *skilled* human capital that contributes more to productivity the closer a country is to the technology frontier: a high-skilled workforce is better suited to innovation, a more prominent activity (than imitation) in countries close to the frontier. Among OECD economies, this hypothesis gained empirical support in Vandenbussche *et al*. (2006) and, for high- and middle-income countries, in Ang, Madsen and Islam (2011). It is, therefore, the *type* (the composition) of human capital that needs to be taken into account in order to explain growth at different stages of economic development. From a historical perspective, 'average' and 'upper tail' human capital had

[1] In this paper, I use education as a measure of human capital. In the remaining, the two terms are employed interchangeably. 'High-skilled' human capital refers to the tertiary-, whereas 'medium-skilled' to the secondary-educated population of a country.
[2] For reviews, see: Delgado, Henderson and Parmeter (2014); Glewwe, Maiga and Zheng (2014); Krueger and Lindahl (2001); Sianesi and van Reenen (2003).

different impacts on growth before and after industrialization (Squicciarini & Voigtländer, 2014) and the interaction between education and distance to the frontier has been a "significant determinant of growth" (p. 40) for the past 140 years (Madsen, 2013).

With the exception of Ang *et al*. (2011), however, this stream of research has almost exclusively focused on the developed world.[3] What is more, empirical results imply that the effect of 'high-skilled' human capital turns negative for countries very far from the technology frontier (e.g. Vandenbussche *et al*., 2006). In other words, an increase in tertiary educated population will lead to a decrease in productivity growth. This counterintuitive outcome constitutes the motivation of this study. It suggests that there might be a different underlying mechanism that dominates the relationship between 'high-skilled' human capital and productivity growth in countries very far from the frontier, compared those that lie relatively close to it. Such mechanism will not be revealed unless the empirical focus expands to also include developing economies.

The first contribution of this paper is that it studies the relationship between 'high-skilled' ('tertiary') human capital and productivity growth for both the developed and the developing world, and proposes an integrated framework to explain this relationship for countries at very different distances from the technology frontier. I employ data from the recently revised Penn World Table (Feenstra, Inklaar & Timmer, 2013) and the Barro and Lee (2013) dataset on educational attainment and conclude that 'tertiary' human capital positively affects productivity growth in *all* countries. Furthermore, 'tertiary' education entails a U-shaped impact on productivity growth as countries move closer to the frontier: the impact is large for countries far from the frontier, then decreases as countries move closer to it but, from a point onwards, increases again. I attribute these findings to the differing role of 'high-skilled'

[3] Note that, as will be explained below, Ang *et al*. (2011) use a 'crude' measure of productivity for their analysis, upon which the present study improves.

human capital in countries that are very far from the technology frontier and engage in imitation, compared to those that lie relatively close to the frontier and grow via innovation.[4]

'High-skilled' human capital contributes to productivity growth through a number of channels: according to Squicciarini & Voigtländer (2014), high-skilled people are, more likely, aware of the new technologies developed at the frontier; have "a better understanding of the underlying processes" of them (p. 15) and; also a larger potential to innovate. As a result, their presence in an 'imitating' country (far from the frontier) raises the likelihood of new technologies not only being adopted, but also being operated more efficiently (through the diffusion of knowledge). In an 'innovating' country (close to the frontier), 'tertiary' human capital leads to further advances in innovation. These channels explain the universal positive effect that I find.

However, from the above, it becomes apparent that 'high-skilled' human capital operates through different channels for 'imitating' and 'innovating' countries. This explains the U-shape effect that I find. As already documented, countries far from the frontier engage in technology adoption and imitation, whereas those close to the frontier in innovation (see, also Benhabib *et al*., 2014). An increase in 'high-skilled' human capital in an 'imitating' country with very low initial levels of productivity (lying very far from the frontier) has a large impact on growth. A tertiary-educated workforce will not only introduce new technologies developed at the frontier, but will also contribute, with its skills, to the ease and efficiency at which they are adopted and operated. However, the effect decreases as we move to countries with a *relatively* higher productivity level that continue to imitate. 'High-skilled' human capital will entail smaller externalities in an economy that already benefits from technology adoption in a

[4] This argumentation draws on the work of Benhabib, Perla and Tonetti (2014) for the catch-up and fall-back process in 'innovating' and 'imitating' countries. For an analogous application to firms, see: König, Lorenz and Zilibotti (2014). For the role of human capital in imitation and innovation, see: Vandenbussche *et al*. (2006) and Squicciarini and Voigtländer (2014).

quite productive manner. As a result, there is not much room for 'high-skilled' human capital to contribute to productivity growth in such a set-up. The effect increases again, though, as the economy moves to an even higher level of productivity and turns to innovation to grow. This largely confirms the hypothesis of Vandenbussche *et al*. (2006) about the complementarity of 'high-skilled' human capital and innovation in countries close the world technology frontier.[5]

Another contribution of this paper is that it allows for the possibility that externalities also stem from 'medium-skilled' human capital, rather than only from 'high-skilled'. The dominant focus of the literature currently lies on university-educated workers but, by solely focusing on them and treating all workers without tertiary education as 'low-skilled', we might be disregarding externalities originating from the secondary-educated workforce. In fact, for much of the world the spread of secondary education is a much more important phenomenon than tertiary education. In my analysis, I explicitly focus on this 'medium-skilled' human capital and find that this also has a positive effect on productivity growth. This effect is smaller in magnitude than the one stemming from 'high-skilled' human capital, implying that high-skills are, in general, more important than medium ones. Finally, 'secondary' education entails an overall *de*creasing impact on productivity growth as countries move closer to the frontier. In contrast to 'high-skilled', 'medium-skilled' human capital lacks the complementarity feature to innovation.

The final contribution of this paper relates to the productivity data it employs. As already stated, a stream of research (for example, Ang *et al*., 2011; Vandenbussche *et al*., 2006) establishes an increasing impact of human capital on productivity growth as countries approach the technology frontier. However, Inklaar, Timmer and van Ark (2008) argue

[5] Similarly, Caselli and Coleman (2006) also document how high-income, skilled-labor abundant countries choose technologies best suited to a skilled workforce, thereby increasing the efficiency at which this type of labor is used.

otherwise, as they find no evidence of 'high-skilled' human capital externalities, even when proximity to the frontier and composition of human capital are taken into account. The authors attribute this differing result to them using a 'sophisticated' productivity measure, as well as to the sectorial-level focus of their study.[6] More specifically, they argue that inter-country differences in hours worked, as well as the educational composition of the workforce need to be taken into account for a productivity measure to be composed that can, in turn, distinguish between private and social returns to education (Inklaar *et al*., 2008). According to the authors, the 'crude' productivity measure of Vandenbussche *et al*. (2006) is not suited to study human capital externalities and any evidence of them disappears when a 'sophisticated' productivity measure is employed. In a country-industry set-up, Mason, O'Leary and Vecchi (2012) also fail to find compelling evidence that 'high-skilled' human capital has an increasing impact on MFP growth as countries move closer to the frontier.

It, thus, becomes apparent that one obstacle to resolving the human capital externalities debate stems from the lack of reliable data on productivity levels and growth for a broad set of countries. However, through the most recent version of PWT (Feenstra *et al*., 2013), I now have at my disposal, and use, a more 'sophisticated' measure of productivity that allows me to distinguish between private and social returns to education. Although the use of such measure does not affect the core conclusions reached for high- and medium-income countries, I find that it might be affecting the results obtained for low-income ones.

The paper proceeds as follows: The subsequent section introduces the empirical model, Section 3 presents the data and Section 4 the results for a restricted sample of OECD members, as well as an extended one for high-, medium- and low-income countries. Section 5 concludes.

[6] Inklaar *et al*. (2008) focus on the market services sector.

2. THE MODEL

The baseline model to estimate the effect of human capital on productivity growth for countries at different distances from the frontier draws on the work of Vandenbussche *et al*. (2006) and is of the following form:

$$g_{i,t} = \lambda_i + \mu_t + \beta_1 * ln(P_{i,t-1}) + \beta_2 * T\_HC_{i,t-1} + \beta_3 * ln(P_{i,t-1}) * T\_HC_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

where the dependent variable $g_{i,t}$ denotes productivity growth of country i between time $t-1$ and t and is calculated as: $g_{i,t} = \Delta\, ln\big(rTFP_{i,t}\big) = ln\big(rTFP_{i,t}\big) - ln\big(rTFP_{i,t-1}\big)$. The variable $rTFP$ stands for TFP at constant national prices and is derived from PWT 8.0 (Feenstra *et al*., 2013). The use of TFP growth as dependent variable denotes that my focus lies on the externalities, "rather than the internal returns to human capital" (Mason *et al*., 2012: 353). Note that I study productivity growth in five-year intervals. This is not only due to (human capital) data availability, but also because research has suggested that growth estimations are more robust when five-year intervals are employed, at least compared to annual ones (Johnson *et al*., 2013).

The list of regressors includes (i) the logarithm of the proximity to the TFP frontier, $ln\big(P_{i,t-1}\big)$; (ii) the 'tertiary' ('high-skilled') human capital of country i, $T\_HC_{i,t-1}$; and (iii) the interaction of the above, $ln(P_{i,t-1}) * T\_HC_{i,t-1}$. All regressors refer to the period $t-1$ and, as commonly done in the literature (see, for example, Vandenbussche *et al*., 2006; Ang *et al*., 2011), the United States act as the TFP frontier. Country fixed effects (λ_i) and time dummies (μ_t) are also included to respectively control for country- and time-specific factors that influence productivity growth and, therefore, to alleviate endogeneity concerns.

The proximity variable is calculated as: $ln\big(P_{i,t-1}\big) = ln(cTFP_{i,t-1}/cTFP_{USA,t-1})$, where $cTFP$ denotes the TFP level at current PPPs and comes from PWT 8.0 (Feenstra *et al*., 2013).[7] Note that I use two different variables from PWT 8.0, $rTFP$ and $cTFP$, the reason being that the former is most suited for comparisons within a country over time[8], whereas the latter mainly facilitates comparisons between countries at one point in time.[9] The 'tertiary' human capital variable of the model, T_HC, refers to the percentage of tertiary schooling attained in population; it captures, in other words, the percentage of a country's population with higher (tertiary) education. This variable refers to the population aged 25 and over and comes from the recently revised Barro and Lee (2013) dataset which provides information on educational attainment in five-year intervals (for 146 countries between 1950-2010).[10] I, initially, focus on, what I call, the effect of 'tertiary' human capital (T_HC) but later also introduce in the empirical analysis 'secondary' ('medium-skilled') human capital (S_HC). The latter refers to the secondary-educated population of a country and is in detail introduced in subsection 4c.[11] The following section further discusses the variables of my empirical specification, their features and sources.

3. DATA

Empirical research on human capital externalities has been criticized on the basis of data quality and suitability. First, the literature has identified a number of weaknesses in the way human capital is measured (for a review, see Krueger & Lindahl, 2001). In order to alleviate measurement error in the education series, a number of datasets has recently been compiled or updated (e.g. Barro & Lee, 2013; Cohen & Soto, 2007; Madsen, 2013). The Barro and Lee (2013: 185) dataset that I use has improved upon the shortcomings of previous versions of it (e.g. regarding "implausible" education estimates for some countries).

[7] The variable $cTFP$ is already computed relative to the US in PWT 8.0.
[8] Feenstra *et al*. (2013) correct for changing reference prices.
[9] For more details, see Feenstra *et al*. (2013).
[10] The regressor T_HC corresponds to the variable lh of Barro and Lee (2013). Using the variable lhc (the percentage of *complete* tertiary schooling attained in population) of Barro and Lee (2013) to capture 'tertiary' human capital yielded similar results which are not reported here due to brevity.
[11] The regressor S_HC corresponds to the variable ls of Barro and Lee (2013).

Second, and as already stated in the introduction, empirical research has predominantly used 'crude' productivity measures not suited to "distinguish between private and social returns to education" (Inklaar *et al*., 2008: 169-170). Vandenbussche *et al*. (2006) and Ang *et al*. (2011), for example, compute productivity without taking into account inter-country differences in hours worked or the educational attainment of the labor force (see, Inklaar *et al*., 2008; Mason *et al*., 2012). A key contribution of this paper, however, lies exactly on the use of a 'sophisticated' productivity measure that adjusts for the above (hours worked and labor quality) and, thus, enables me to examine human capital externalities. This productivity measure comes from the recently revised PWT (Feenstra *et al*., 2013).

PWT 8.0 provides yearly information for 167 countries during the 1950-2011 period and introduces 'improved/sophisticated' TFP measures that can be used to compare TFP levels across countries, as well as TFP growth over time (Feenstra *et al*., 2013). Below, I list the most important improvements of PWT 8.0 but I refer the reader to Inklaar and Timmer (2013) for a detailed discussion: first, for the measure of capital input, PWT 8.0 accounts for "differences in asset composition across countries and over time" (Inklaar & Timmer, 2013: 2). Second, for the construction of TFP, Feenstra *et al*. (2013) do not apply the same labor share to all countries over time (the commonly-used in the literature 0.7) but rather compose new measures of it that vary across countries and also incorporate the labor income of the self-employed. Third, regarding labor input, the authors not only take into account the number of workers in an economy but also their human capital, approximated by years of schooling and, most importantly, controlling for an assumed rate of return to human capital (Inklaar & Timmer, 2013). As a result, a 'sophisticated' measure of productivity is computed which is employed in my analysis.

Table 1 below presents summary statistics for the core variables of the empirical specification. They refer to a restricted sample of 19 OECD countries (between 1960-2000), as well as to an extended one (109 countries, 1950-2010), the latter in brackets. In the empirical analysis that follows, I first examine human capital externalities in the restricted sample of OECD countries in order to compare my findings to the literature that has focused on the developed world (subsection 4a). Then, I expand the sample to examine the case of externalities in countries further away from the technology frontier (subsection 4b and 4c).

Table 1. Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
g	145 [855]	0.056 [0.025]	0.065 [0.149]	-0.130 [-0.923]	0.364 [1.125]
$ln(P)$	145 [855]	-0.212 [-0.583]	0.151 [0.497]	-0.867 [-2.615]	0 [0]
T_HC	145 [855]	0.113 [0.083]	0.094 [0.087]	0.010 [0]	0.465 [0.530]
S_HC	145 [855]	0.332 [0.267]	0.172 [0.192]	0.021 [0.002]	0.673 [0.873]

*Note*s: The summary statistics refer to the restricted sample (19 OECD countries between 1960-2000). To facilitate comparison, in brackets, I provide the respective summary statistics for the extended sample (109 countries between 1950-2010). Subsection 4a uses the restricted, whereas 4b and 4c the extended sample. g stands for productivity growth; $ln(P)$ is the logarithm of the frontier proximity; T_HC refers to the percentage of tertiary schooling attained in population ('tertiary' human capital) and; S_HC to the percentage of secondary schooling attained in population ('secondary' human capital).

Productivity growth (g) has, on average, been higher among OECD economies (0.056 compared to 0.025 for the extended countries-sample). As was to be expected, OECD countries also lie closer to the world technology frontier, namely the US (on average, -0.212 compared to -0.583). Note at this point that the logarithm of the proximity to the frontier is a negative number since I only focus on countries that have lower TFP levels than the US (I require $ln(P) \leq 0$). There are, however, some countries in the PWT dataset which, for a few years, score higher in productivity. I have removed the latter from the analysis, since a story about the drivers of productivity growth makes more intuitive sense when it refers to countries that lie below the frontier and try to catch up. Still, incorporating these observations did not alter the results. I have opted for the US as the world technology frontier, first, because no other country *consistently* (for all years) scores higher in productivity and, also, because the US has commonly acted as the frontier in the literature. Furthermore, relatively small economies (e.g. Sweden, Norway) or countries with a large petroleum industry (e.g. Kuwait, Saudi Arabia) may have high TFP levels but cannot adequately represent the world technology frontier for all sectors of an economy (Madsen, 2013).

Finally, as Table 1 indicates, the ('tertiary' and 'secondary') human capital levels are higher among the restricted (OECD) sample, compared to the extended one. In fact, there are countries in the latter sample without any (or at least with a very small amount of) 'high-' and 'medium-skilled' human capital (e.g. Morocco, Mozambique). This is not the case, though, for the more educated OECD economies. Having presented the empirical specification and the data used in the analysis, the following section turns to the results.

4. RESULTS

(a) Baseline Regressions: 19 OECD Countries

I start by focusing on the same sample as Vandenbussche *et al*. (2006), namely on 19 OECD countries observed every five years during the 1960-2000 period, in order to examine human capital externalities in developed economies and also test whether the use of a 'sophisticated' productivity measure affects the conclusions reached by the abovementioned study.[12] Following Inklaar *et al*. (2008), a 'sophisticated' productivity measure is warranted in order to draw conclusive inferences regarding human capital externalities, or the lack thereof.

Table 2 presents the results of model (1). Columns (1a) and (2a) report OLS results, whereas in columns (1b) and (2b) I follow Vandenbussche *et al*. (2006) and use past values of the regressors as instruments, to alleviate potential endogeneity concerns.[13] More specifically, the

[12] The 19 OECD countries of the restricted sample are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and the United States.

[13] Following Vandenbussche *et al*. (2006) and Ang *et al*. (2011), I also tried using lagged public expenditures on education as an instrument, but this variable proved not to be a strong predictor for human capital and, in the case of the extended countries sample, resulted in a large loss of observations.

instruments refer to values of the variables lagged two periods (e.g. $T\_HC_{i,t-2}$). The F-statistics of the first stage regressions revealed that these are relevant instrument to use.[14] However, based on the endogeneity tests that I performed, I could not reject the null hypothesis that the endogenous regressors can actually be treated as exogenous. For completeness, I therefore present in Table 2 both the OLS and IV estimates. The core conclusions of my analysis do not differ between the two. Year dummies are always incorporated and are jointly highly significant across all specifications. Columns (1a) and (1b) show the results without, whereas (2a) and (2b) with country fixed effects.[15]

Table 2. Regressions on the Restricted Sample (19 OECD countries; 1960-2000)

VARIABLES	(1a: OLS)	(2a: OLS)	(1b: IV)	(2b: IV)
$ln(P)$	-0.179***	-0.236***	-0.297***	-0.440**
	(0.0443)	(0.0716)	(0.0736)	(0.175)
T_HC	0.100	0.394**	0.188**	0.505*
	(0.0615)	(0.154)	(0.0872)	(0.268)
$ln(P) * T\_HC$	0.581**	0.437	0.975***	0.492
	(0.220)	(0.362)	(0.288)	(0.703)
Year Dummies/Country FE	YES/NO	YES/YES	YES/NO	YES/YES
Observations	145	145	121	121
R-squared	0.361	0.397	0.375	0.426
Countries	19	19	19	19

Notes: Dependent variable $g_{i,t}$. Robust standard errors, clustered by country, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

We, first, observe that the logarithm of the proximity to the TFP frontier, $ln(P)$, has a negative and highly significant effect on productivity growth. This holds for all specifications and indicates TFP convergence: countries experience faster growth the further away they are from the world technology frontier. Second, the *level* of 'tertiary' human capital, T_HC,

[14] The lowest first stage F-statistic that I encountered across these specifications was 109.21.

[15] In another specification not reported here, I included in the regressions time dummies, alongside country-groups dummies. This is in line with Vandenbussche *et al*. (2006) who group the 19 OECD countries of their sample into seven categories "based on geographical and/or institutional proximity" (p.114) as follows: (1) Belgium, France, Italy, Netherlands; (2) Austria, Denmark, Finland, Norway, Sweden, Switzerland, United Kingdom; (3) Canada, United States; (4) Australia, New Zealand; (5) Portugal, Spain; (6) Greece and; (7) Ireland. Dummy variables for these groups are, then, included in the regressions. The results I obtained were very similar to those of the fixed effects regressions.

always has a positive and, with the exception of column (1a), significant impact on productivity growth. Third, the interaction term always enters positively and significantly when country effects are omitted, but with an insignificant coefficient when they are included (note, however, that the country fixed effects were not jointly significant in the case of the restricted OECD sample).

The results so far are, in general, consistent with Vandenbussche *et al*. (2006) and Ang *et al*. (2011): among OECD (high-income) countries, the effect of 'tertiary' human capital on productivity growth increases the closer a country lies to the frontier. This is because innovation, which requires a high-skilled labor force to materialize, is more pronounced, than imitation, in countries close to the TFP frontier. Therefore, 'high-skilled' human capital is more important in these countries. The use of a 'sophisticated' productivity measure has not altered the core conclusions of Vandenbussche *et al*. (2006).

However, the results also indicate that the effect of 'high-skilled' human capital can even turn negative for countries that have relatively low levels of productivity and lie far from the frontier. To see this, compare the coefficients of T_HC and $ln(P) * T\_HC$. The magnitude of them already gives an indication that the effect of 'high-skilled' human capital will, at some point, turn negative. An extrapolation of this result to lower-TFP countries suggests that 'high-skilled' human capital will hamper productivity growth even more among them. I have already argued that this is a rather counterintuitive outcome and suggests that a different mechanism dominates the relationship between 'high-skilled' human capital and productivity growth in developing, compared to developed economies. In order to uncover this mechanism, I next conduct the empirical analysis for an extended and more diverse sample of countries.

(b) Regressions on an Extended Sample

The data sources I employ allow me to examine human capital externalities in a sample of, up to, 109 countries (34 of which are current OECD members) observed every five years during the 1950-2010 period.[16] This resembles the study by Ang *et al*. (2011) who examine the effect of human capital on productivity growth for high-, medium- and low-income countries, but also employ a 'crude' productivity measure.

Table 3 presents the results using the extended sample of countries and years. The regressions include year dummies, which are jointly highly significant, as well as country fixed effects. In contrast to the regressions of Table 2, country fixed effects are now highly significant. This can be attributed to the larger and, in particular, more diverse group of countries that now enters the analysis. Columns (1a), (2a) and (3a) present the OLS, whereas (1b), (2b) and (3b) the IV estimates. Past values of the regressors (lagged two periods) act as instruments, as the first stage regressions again reveal that they are relevant to use. The endogeneity tests could not reject the null hypothesis that the endogenous regressors can be treated as exogenous and, therefore, in Table 3 I report both the OLS and IV estimates.

Columns (1a) and (1b) of Table 3 show the results of specification (1) for the extended sample. The logarithm of the proximity to the TFP frontier, $ln(P)$, has again a negative and significant effect on productivity growth. The level of 'tertiary' human capital (T_HC) yields a positive, yet insignificant coefficient. Interestingly, the interaction term, $ln(P) * T\_HC$,

[16] The countries of the extended sample are: Argentina, Armenia, Australia, Austria, Bahrain, Barbados, Belgium, Benin, Bolivia, Botswana, Brazil, Bulgaria, Burundi, Cameroon, Canada, Central African Republic, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, Estonia, Fiji, Finland, France, Gabon, Germany, Greece, Guatemala, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea (Republic of), Kuwait, Kyrgyzstan, Latvia, Lesotho, Lithuania, Luxembourg, Macao, Malaysia, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Niger, Norway, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Serbia, Sierra Leone, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Swaziland, Sweden, Switzerland, Taiwan, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela and Zimbabwe.

enters with a negative and significant coefficient. This implies that 'tertiary' human capital has an overall positive effect on productivity growth which, however, *de*creases as countries move closer to the technological frontier. This finding appears to be in sharp contrast to the main conclusion of the previous subsection and provides some (preliminary) support to my hypothesis that the relationship between 'high-skilled' human capital and productivity growth is dominated by a different mechanism for countries very far from the frontier, compared to those very close to it.

Table 3. Regressions on the Extended Sample

VARIABLES	(1a: OLS)	(2a: OLS)	(3a: OLS)	(1b: IV)	(2b: IV)	(3b: IV)
$ln(P)$	-0.197***	-0.250***	-0.180**	-0.272***	-0.178**	-0.125
	(0.0425)	(0.0710)	(0.0843)	(0.0438)	(0.0722)	(0.0890)
T_HC	0.0119	0.229*	0.476***	0.182	0.408***	0.576***
	(0.152)	(0.124)	(0.155)	(0.158)	(0.0896)	(0.121)
$ln(P) * T\_HC$	-1.232***	0.707	0.584	-0.945**	0.999**	0.188
	(0.281)	(0.645)	(0.717)	(0.393)	(0.435)	(0.384)
$(ln(P))^2$		-0.0350	-0.0331		0.0187	0.0296
		(0.0343)	(0.0434)		(0.0402)	(0.0499)
$(ln(P))^2 * T\_HC$		1.317***	0.762		1.774**	0.207
		(0.424)	(0.473)		(0.756)	(0.754)
S_HC			0.0410			0.102
			(0.0905)			(0.0878)
$ln(P) * S\_HC$			-0.274			-0.164
			(0.327)			(0.364)
$(ln(P))^2 * S\_HC$			0.140			0.228
			(0.205)			(0.287)
Observations	855	855	855	717	717	717
R-squared	0.345	0.362	0.395	0.253	0.190	0.184
Countries	109	109	109	106	106	106

Notes: Dependent variable $g_{i,t}$. Regressions include year dummies and country fixed effects, jointly highly significant. The three countries that drop under IV are Barbados, Kuwait and Macao. Robust standard errors, clustered by country, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

To summarize, in a sample of 19 OECD countries, the effect of 'high-skilled' human capital on productivity growth *in*creases with proximity to the frontier. When more countries enter the analysis, however, the effect *de*creases as countries move closer to the frontier. This indicates that there might be additional non-linear forces that need to be taken into account. The natural next step to take is, thus, to explore further non-linearities related to a country's distance to the frontier. This is because the sample I currently employ is quite diverse and consists of countries at very different stages of development.

To account for additional non-linear effects, I augment the benchmark model with the logarithm of the proximity to the TFP frontier squared, $\left(ln(P)\right)^2$, as well as its interaction with 'tertiary' human capital ($\left(ln(P)\right)^2 * T\_HC$). The empirical specification now takes the following form (2):

$$g_{i,t} = \lambda_i + \mu_t + \beta_1 * ln\left(P_{i,t-1}\right) + \beta_2 * T\_HC_{i,t-1} + \beta_3 * ln\left(P_{i,t-1}\right) * T\_HC_{i,t-1} +$$

$$\beta_4 * (ln\left(P_{i,t-1}\right))^2 + \beta_5 * (ln\left(P_{i,t-1}\right))^2 * T\_HC_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

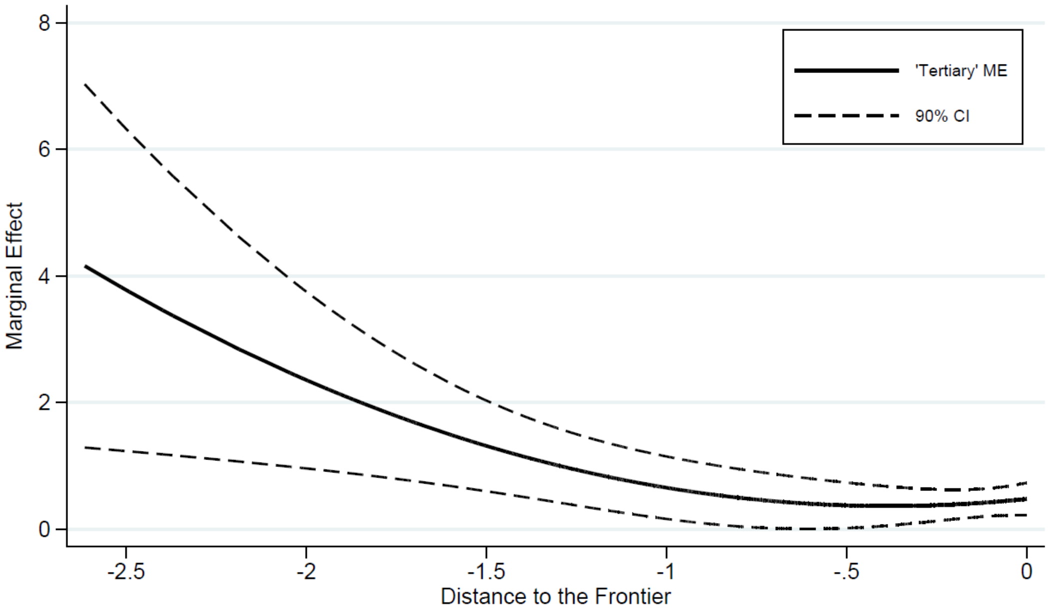
Columns (2a) and (2b) of Table 3 present the results of model (2) under OLS and IV, respectively.[17] The negative and significant effect of the proximity variable, $ln(P)$, is maintained. The level effect of human capital, as captured by β_2, is positive and significant, indicating also the magnitude of the marginal effect of tertiary education when $ln(P) = 0$, in other words at the frontier.

For a better inspection of the results, Figure 1 below plots the marginal effect of 'tertiary' human capital on productivity growth, conditional on a country's distance to the frontier. The solid black line shows the marginal effect of 'tertiary' human capital on productivity growth ($\partial g / \partial T\_HC = \beta_2 + \beta_3 * ln(P) + \beta_5 * (ln(P))^2$) and the dashed black line the respective 90% confidence interval.[18]

[17] Note that due to the amount of interaction terms in the models of columns (2b) and (3b), the use of lags as instruments for *each* interaction largely pushed up the coefficients, potentially because of multicollinearity. To overcome this problem, I predicted, through the first stage regressions, the values for the individual variables $ln(P)$, T_HC and S_HC and, subsequently, used these predicted values to form the two- and three-way interactions of the analysis.

[18] Figure 1 is plotted based on column (3a) of Table 3 in order to facilitate comparison with the marginal effect of 'secondary' human capital which is introduced in the following subsection. Plotting the figure based on columns (2a) and (2b) produced a similar outcome. Using the IV results of column (3b) produced the same U-shape pattern but with a smaller marginal effect for countries at the very left end of the TFP distribution.

Figure 1. Marginal Effect of 'Tertiary' Human Capital on Productivity Growth



To begin with, 'high-skilled' human capital has a positive effect on productivity growth for *all* countries, irrespective of their distance to the frontier, as the marginal effect line lies above the horizontal zero threshold. This universally positive relationship between education and productivity growth stems, I argue, from human capital facilitating the adoption of new technologies (in countries far from the frontier) and triggering innovation (in countries close to the frontier). The positive effect I currently find for the low-productivity countries is in contrast to the results presented in Table 2 which suggested that the effect of 'tertiary' human capital will be negative for countries that lie relatively far from the frontier. This is also in contrast to Ang *et al*. (2011) who find that human capital does not significantly contribute to growth in low-income countries. The 'sophisticated' productivity measure I employ might be the reason for this differing finding.[19]

What Figure 1 also shows is that the marginal effect of 'tertiary' human capital is, in general, larger for countries far from the frontier compared to those closer to it. As the downward sloping part of the solid black line indicates, education entails larger externalities in the

[19] Ang *et al*. (2011) also use a previous version of the Barro and Lee dataset but employing this instead in my analysis did not alter the results.

former group. This finding can be attributed to the role of human capital in 'imitating' countries. An increase in the tertiary-educated population in an 'imitating' country with very low initial levels of productivity will have a great impact on productivity growth through the introduction of new technologies and the improvement in the efficiency at which they are used. In an 'imitating' country with higher initial levels of productivity, however, the role of 'high-skills' diminishes as the economy already benefits from technology adoption in a productive manner. There is, however, a turning point to the decreasing impact of 'high-skilled' human capital on productivity growth, as the marginal effect indicates the existence of a U-shaped relationship. Confirming the hypothesis of Vandenbussche *et al*. (2006), human capital has again an increasing impact on productivity growth as countries move even closer to the frontier. The latter is in more detail discussed in the following subsection.

Finally, an alternative explanation for the large externalities in low-productivity countries relates to level of '(un)skills' in them. Countries that lie far from the frontier have, in general, a high percentage of unskilled population. Consequently, in a country that is largely lacking skills, 'tertiary' human capital will make a larger impact by raising the productivity of the unskilled labor force, via "a *higher* incidence of learning from others" (Sianesi & van Reenen, 2003: 160). It is important to note, however, that countries far away from the frontier might benefit from large human capital externalities due to their initial lack of skills, but this effect will diminish if higher education leads to unemployment and, thus, a decrease in output (Sianesi & van Reenen, 2003). Stated differently, although low-skilled environments benefit from externality effects, the latter will shrink if the 'high-skilled' human capital remains unemployed and, thus, unable to spill-over and raise the productivity of the labor force. Externalities will, similarly, shrink if capable young people become rent seekers (Murphy, Shleifer & Vishny, 1991) or if, as argued by Pritchett (2006), high-skilled labor predominantly works at the relatively inefficient public-sector instead of the private one.

(c) Introducing Secondary Education

This subsection introduces 'secondary' human capital in the empirical analysis, the reason being that externalities might as well be originating from the secondary-educated workforce. To investigate this hypothesis, I augment model (2) with (i) the 'medium-skilled/secondary' human capital variable, S_HC; (ii) its interaction with proximity, $ln(P) * S\_HC$; and (iii) proximity-square, $(ln(P))^2 * S\_HC$, exactly as I have done for the case of 'tertiary' human capital. 'Secondary' human capital denotes the percentage of secondary schooling attained in population and is taken from Barro and Lee (2013). Summary statistics for this variables have been presented in Table 1. All other variables are defined as before and the sample again consists of (a maximum of) 109 countries observed every five years during the 1950-2010 period.

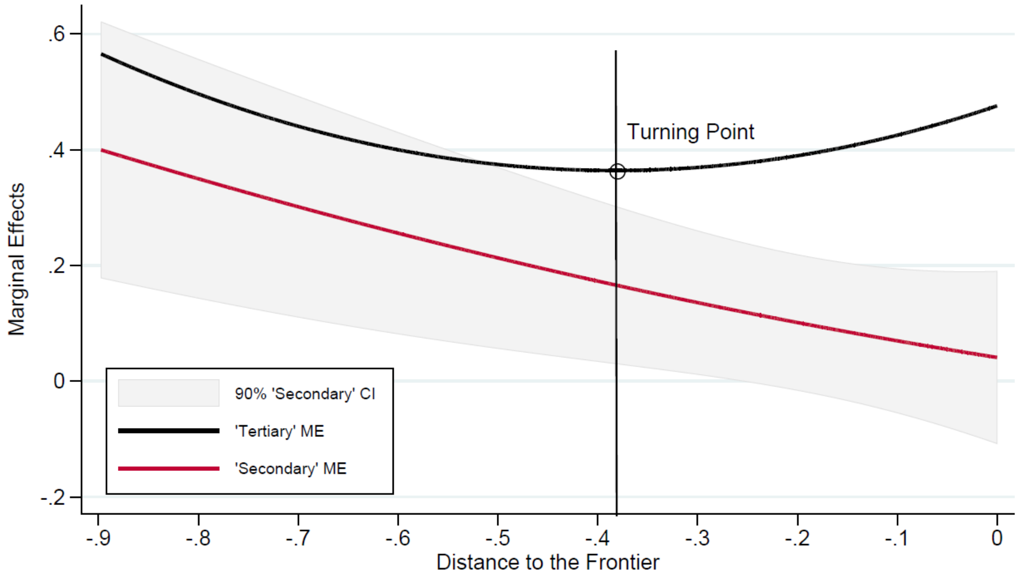
Columns (3a) and (3b) of Table 3 present the results with the two different types of human capital, 'tertiary' and 'secondary'. The level effect of 'tertiary' human capital enters with a positive and significant sign (indicating the marginal effect of tertiary education when $ln(P) = 0$, in other words at the frontier), whereas that of 'secondary' human capital with a positive but insignificant one (also showing the marginal effect of secondary education at the frontier). Not all interactions are individually significant, likely due to their correlations, but tests of joint significance indicated that all high-skilled-related human capital variables (T_HC, $ln(P) * T\_HC$, $(ln(P))^2 * T\_HC$) are jointly highly significant, and the same holds for all medium-skilled-related ones (S_HC, $ln(P) * S\_HC$, $(ln(P))^2 * S\_HC$).[20]

To facilitate inspection, Figure 2 below plots the marginal effect of 'tertiary' (black solid line) and 'secondary' (red solid line) human capital on productivity growth, conditional on the

[20] The p-values of the joint significance tests are between 0.0001 and 0.0077, depending on the specification.

distance to the technological frontier.[21] The 'tertiary' marginal effect is the same as in Figure 1 but I have now zoomed in on countries relatively close to the frontier for a more clear inspection of the results. The 'secondary' marginal effect is plotted together with its 90% confidence interval (grey-shaded).[22] Two key findings emerge from Figure 2: first, the effect of 'tertiary' human capital is larger than that of 'secondary' and, second, there is a U-shaped relationship between 'tertiary' human capital and productivity growth (as already indicated in the previous subsection) but this does not hold for the case of 'secondary' education.

Figure 2. Marginal Effect of 'Tertiary' and 'Secondary' Human Capital



Compared to 'medium-skilled', 'high-skilled' human capital entails larger externalities. Still, both types of human capital positively affect productivity, although the effect of secondary education turns insignificant for countries close to the frontier. Furthermore, the marginal effect of 'secondary' human capital is universally decreasing among the countries of my sample, whereas that of 'tertiary' human capital reaches a minimum (at $ln(P) = -0.383$) and then starts increasing.[23] This increasing feature of 'high-skilled' human capital largely holds

[21] Figure 2 refers to the marginal effects computed based on column (3a) of Table 3.
[22] The confidence interval for the 'tertiary' marginal effect has been plotted in Figure 1 and is not repeated here for a more clear inspection of the results.
[23] Note that the exact point where the marginal effect of 'high-skilled' human capital reaches its minimum slightly varies depending on the specification.

for the countries of my restricted/OECD sample, as well as for a number of other countries such as Germany, Iceland, Japan, Luxembourg, Singapore and Taiwan.[24] All in all, it is the 'high-skilled', rather than the 'medium-skilled' human capital that has increasing impacts on productivity growth for countries close to the frontier. This finding confirms the hypothesis of Vandenbussche *et al*. (2006) and can be attributed to complementarity between 'high-skilled' human capital and innovation, a feature which 'medium-skilled' human capital largely lacks.

5. CONCLUSION

Human capital, commonly captured in empirical research by the level of education, holds a prominent role in academic and policy-related debates. In this paper, I have examined the relationship between different types of human capital and productivity growth for countries at different distances from the technology frontier, a topic which has, thus far, produced mixed results. Following Vandenbussche *et al*. (2006), I first focused on 19 OECD countries and, then, expanded the sample to a maximum of 109 high-, medium- and low-income countries. Using the most recent version of PWT (Feenstra *et al*., 2013), I employed a 'sophisticated' productivity measure that allowed me to draw inferences regarding human capital externalities. I also investigated the impact of secondary education and to what extent it differs from that of tertiary schooling.

According to my findings, 'tertiary' *and* 'secondary' human capital positively affect productivity growth in all countries, the effect of the former being, in general, larger than that of the latter. It is, therefore, warranted not to classify the secondary-educated workforce as low-skilled, but rather distinguish between these two categories, as externalities might as well be stemming from the medium-skilled. Furthermore, 'tertiary' education has a U-shaped effect on productivity growth, whereas 'secondary' education an overall decreasing one, as

[24] This list is not exhaustive but rather refers to countries that lie on the upward sloping part of the curve for a relatively large number of years in the sample.

countries move closer to the frontier. I have attributed these findings to the differing role of 'high-skilled' human capital in countries that are very far from the technology frontier and engage in imitation, compared to those that lie relatively close to the frontier and grow via innovation.

This study relates to the broad literature on human capital and economic growth[25] and there is, therefore, a number of extensions that could be applied to it. To begin with, in light of recent developments in the literature (see, for example, Hanushek & Woessmann, 2008; 2012; Islam, Ang & Madsen, 2014), the quality of education could be incorporated into the analysis. Accordingly, informal education (e.g. at home, at work) has also been identified as an important component of human capital. In that respect, the paper could benefit from the use of a more comprehensive measure of human capital. Furthermore, I currently decompose human capital into 'tertiary' versus 'secondary'. However, heterogeneity in human capital might as well stem from other types of it (e.g. engineering versus legal studies, general versus specific education) which, in turn, impact economic growth differently (Murphy *et al*., 1991). Further research is required along these lines. Finally, it is important to note that human capital affects other areas of an economy, which the present study does not explore. For example, human capital externalities refer, among others, to lower levels of crime (Lochner & Moretti, 2004), better health (Currie & Moretti, 2003), a deeper interest and participation in politics (Milligan, Moretti & Oreopoulos, 2004), as well as lower levels of inequality (Goldin & Katz, 2007).

All in all, my analysis results in important socio-economic implications, in view of the central role education holds in policy-makers' agendas. The existence of human capital externalities, for example, justifies investments in higher education and subsidies directed to the creation of

[25] For example, Lucas, 1990; Nelson & Phelps, 1966; Romer, 1989. For more recent, empirical contributions with contradictory results, see: Benhabib and Spiegel (1994); Cohen and Soto (2007); Delgado *et al*. (2014); Hall and Jones (1999); Hendricks (2002); Kalaitzidakis *et al*. (2001); Mankiw, Romer and Weil (1992); Pritchett (2001). This list is far from exhaustive.

human capital. Developing countries could as well benefit from the expansion of their human capital endowments, provided, though, that the newly-formed human capital is put to productive use, being, thus, able to entail spillover effects. These are all key policy points that can be directly linked to the findings of this study.

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