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CATCH ME IF YOU LEARN: DEVELOPMENT-SPECIFIC EDUCATION AND ECONOMIC GROWTH

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Catch me if you learn: development-specific education and economic growth*

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Abstract

This paper presents a theoretical and empirical investigation of the relationship between human capital composition and economic growth. From the theoretical point of view, we generalize Vandenbussche et al. (2006) by allowing for non-constant returns to scale in imitation and innovation activities and we find that - unlike the previous work and for a wide range of parameters' values - the impact of skilled workers on growth increases at lower stages of development. As for empirical evidence, we estimate estimate Vandenbussche et al. (2006) the size using a 85 countries 1960-2000 panel with developed and developing countries using System GMM technique to address the problem of endogeneity. The analysis supports the model predictions in providing robust evidence of an increasing impact of tertiary education as the economy moves farther away from the frontier. Results are robust to different proxies of human capital and different specifications.

Key words: Technological frontier, innovation, imitation, human capital, skilled, unskilled, growth

JEL Classifications: O11; O33; O47.

1 Introduction

In their influential paper of 2006, Vandenbussche, Aghion and Meghir (VAM henceforth) propose a solution to the puzzle posed by Krueger and Lindhal (2001) according to which education is statistically significantly and positively associated with subsequent growth only for countries with the lowest level of education. In order to solve

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the puzzle, VAM propose a model which focuses on the interplay between the economy's distance to the technological frontier and the *composition* of its human capital (as much as on its level). Their model shows that the total amount of human capital is not a sufficient statistic to predict the growth rate of the economy, because at a given distance to the frontier, different kinds of human capital (i.e. skilled and unskilled) have different marginal effects on the growth rate[1].

Apart from proposing an intriguing solution to the human capital puzzle, VAM-s model derives an important result: they show that the growth-enhancing impact of skilled labor increases with a country's proximity to the frontier. This analytical result is supported by the evidence provided in the empirical part of the paper using a panel dataset covering 19 OECD countries observed every 5 years between 1960 and 2000.

Given the relevance of the implications stemming from VAM's framework, and since their empirical analysis only deals with developed countries, we believe it is fundamental to test the robustness of their framework and, hence, to analyze the theoretical and empirical dynamics linking human capital composition, technology (innovation and imitation activities) and economic at very different stages of development (both close and very far from the technology frontier). Our work makes at least two main contributions to the existing literature.

On the one hand, our theoretical analysis generalizes the model proposed by VAM by allowying for non-constant and heterogenous returns to scale in both innovation and imitation. Crucially, we obtain VAM result as a special case of a much broader (and somehow more plausible) set of possible theoretical outcomes. Some of our theoretical predictions, we will show, lead to fundamentally different policy implications from those proposed by VAM and shed light on the more complex dynamics governing the impact of human capital composition on the growth of economies at very different stages of development. In particular, once we maintain the reasonable assumption for which unskilled workers are more efficient in imitation than innovation (as in VAM), but relax the restrictive assumption on the constancy of returns to the production of innovation and imitation, our theoretical model leads to the emergence of an additional force working in the opposite direction with respect to VAM. It turns out that this new effect dominates the (only) one presented by VAM for a wide range of parameters values such that, for economies lagging sufficiently far away from the technology frontier, the marginal contribution of an additional skilled worker on the rate of growth increases with the distance to the frontier.

On the other hand, the main theoretical results stemming from our generalized

[1]More precisely, by introducing the reasonable assumption according to which unskilled human capital is relatively more efficient in imitation than in innovation activities, they show that - considering two economies located at the same distance to the technological frontier - the growth rate might be slower for an economy endowed with relatively more aggregate human capital but less skilled human capital. In this case, a regression of the growth rate on the aggregate amount of human capital would return a negative coefficient.

model are robustly supported by the empirical evidence. As to prove so, we estimate VAM's empirical specification by extending the analysis to a much wider sample of countries (85 between developed and developing economies) for a 10-year intervals panel covering the period in between 1960 and 2000. The severe issues of endogeneity between human capital and growth are addressed using System GMM techniques as proposed by Arellano-Bover(1995)/Blundell-Bond (1998). Along with that, we provide several robustness checks by introducing additional controls which proxy for institutional quality. While the marginal effect of tertiary education on growth is found (as in VAM) to be positive for developed economies, this is shown to be positive and relatively larger for countries at lower stages of development and which are endowed with relatively lower stocks of skilled labor.

The policy implications of our results are crucially different from those proposed in previous literature. Our analysis shows that some of the predictions of VAM (2006), according to which countries at lower development stages could find more rewarding to primarily invest in primary and secondary education, actually stem from very restrictive assumptions. These predictions do not longer hold once a more general model and an extended number of countries are taken into account, as in our analysis. Our contribution actually suggests that lagging economies would benefit more than rich economies from skills accumulation despite the fact that the former are performing little or null innovation.

The rest of the paper is organized as follows. In section 2 we describe the analytical framework. Section 3 is dedicated to the theoretical consequences of non-constant returns to scale on the dynamics of the catching-up behaviour. Section 4 performs the empirical analysis while section 5 concludes.

2 The model

2.1 Basic analytical framework

The structure of the economy resemble that of VAM (2006) with one main generalization: we allow for non-constant returns to scale in both innovation and imitation activity. As it will become clear later, this analysis is not performed only for the sake of generality but because it sheds light on some important mechanisms which are neutralized in the CRS case.

There exists a finite number of economies, each one with entrepreneurs and population workers of size 1. We abstract from international trade and labor mobility. Workers have heterogeneous human capital endowment: the economy is endowed with S highly educated (skilled) workers and U less educated (unskilled) units of labor given exogenously and constant over time (i.e.: they act as our policy instruments).

Time is discrete and all agents live for one period only. In every period and in every country final output y is produced competitively using a continuum of mass 1 of intermediate inputs and labor according to the following Cobb-Douglas production function

$$y_t = l_t^{1-\alpha} \int_0^1 A_{i,t}^{1-\alpha} x_{i,t}^{\alpha} di$$

We normalize the total supply of land to 1.

The final good sector is competitive, so the price of each intermediate sector is equal to its marginal product

$$p_{i,t} = \frac{\partial y_t}{\partial x_{i,t}} = \alpha \left(\frac{A_{i,t}}{x_{i,t}} \right)^{1-\alpha} \tag{1}$$

In each intermediate sector i one producer can produce good i with productivity $A_{i,t}$ using final good as capital according to a one-for-one technology. The local monopolist chooses $x_{i,t}$ in order to solve

$$\max_{x_{i,t}} \left(p_{i,t} x_{i,t} - x_{i,t} \right)$$

which, using (1), leads to the following profit in the intermediate sector i

$$\pi_{i,t} = \left(\frac{1}{\alpha} - 1 \right) \alpha^{\frac{2}{1-\alpha}} A_{i,t} = \delta A_{i,t} \tag{2}$$

2.2 Dynamics of Productivity

At the initial stage of each period, firm i decides upon technology choice. A technology improvement results from a combination of two activities:

1. *Imitation* aimed at adopting the world frontier tfechnologies
2. *Innovation* upon the local technological frontier

Both activities use unskilled and skilled labor as inputs. The dynamics of the productivity of sector i is the following F increasing in its arguments

$$A_{i,t} - A_{i,t-1} = F \left(\bar{A}_{t-1} - A_{t-1}, A_{t-1}, m \left(u_{m,i,t}, s_{m,i,t} \right), n \left(u_{n,i,t}, s_{n,i,t} \right) \right)$$

where

- $\bar{A}_{t-1}$ is the world technological frontier at time $t-1$ and therefore $\bar{A}_{t-1} - A_{t-1}$ is the distance from the latter
- A_{t-1} is the country's technological frontier at time $t-1$
- m and n are respectively imitation and innovation activities whose output is respectively positively affected by

– $u_{m,i,t}$ and $s_{m,i,t}$ which are the amounts of unskilled and skilled units of labor used in *imitation* in sector i at time t

– $u_{n,i,t}$ and $s_{n,i,t}$ which are the amounts of unskilled and skilled units of labor used in *innovation* in sector i at time t

Technology progress is assumed to be a linear function of imitation m and innovation n activities.

$$A_{i,t} - A_{i,t-1} = \lambda \left[m\left(u_{m,i,t}, s_{m,i,t}\right) \left(\bar{A}_{t-1} - A_{it-1}\right) + \gamma n\left(u_{n,i,t}, s_{n,i,t}\right) A_{it-1} \right]$$

We use the following Cobb-Douglas specification for the two kinds of technological activities

$$\begin{aligned} m\left(u_{m,i,t}, s_{m,i,t}\right) &= u_{m,i,t}^{\sigma} s_{m,i,t}^{\beta} \\ n\left(u_{n,i,t}, s_{n,i,t}\right) &= u_{n,i,t}^{\phi} s_{n,i,t}^{\theta} \end{aligned}$$

where $\sigma, \beta, \phi, \theta$ are strictly positive parameters.

σ and β represent the elasticity of unskilled (resp. skilled) workers in imitation whereas ϕ and θ are the elasticity of unskilled (resp. skilled) workers in innovation. As for the elasticity the elasticity of output to each type of worker we merely assume that $\sigma > \phi$. This is to say that unskilled workers are assumed to be better suited to imitation than innovation activities. We share this (reasonable) assumption with VAM. Crucially, instead, we depart from their formalization and do not impose $\sigma + \beta$ and $\phi + \theta$ to be necessarily equal to 1. This generalization, which represents the source of our main theoretical result, is not trivial and, as we will show next, it uncovers a more general and rich catch-up dynamics.

One its first implication is that returns to scale are now allowed to be non-constant and heterogenous in imitation and innovation. In particular, we allow $\beta + \sigma > \theta + \phi$ such that imitation might be assumed to be a relatively "easier"[2] activity with respect to innovation, which is also what previous empirical and theoretical evidence suggests[3].

[2]When $\beta + \sigma > \theta + \phi$, imitation can be considered to be an "easier" activity in the sense that, following an equal percentage change in each production factor, the percentage change in imitation will be larger than the percentage change in innovation output. Formally, it is easy to see that, when $\frac{\partial u_n}{u_n} = \frac{\partial u_m}{u_m} = \frac{\partial s_n}{s_n} = \frac{\partial s_m}{s_m}$ and taking the total differential of m and n we have that

$$\begin{aligned} \frac{\partial m}{m} &> (<) \frac{\partial n}{n} \\ \frac{\sigma u_{m,i,t}^{\sigma-1} s_{m,i,t}^{\beta} \partial u_m + \beta u_{m,i,t}^{\sigma} s_{m,i,t}^{\beta-1} \partial s_m}{m} &> (<) \frac{\sigma u_{m,i,t}^{\sigma-1} s_{m,i,t}^{\beta} \partial u_m + \beta u_{m,i,t}^{\sigma} s_{m,i,t}^{\beta-1} \partial s_m}{n} \\ \sigma \frac{\partial u_{m,i,t}}{u_{m,i,t}} + \beta \frac{\partial s_{m,i,t}}{s_{m,i,t}} &> (<) \phi \frac{\partial u_{n,i,t}}{u_{n,i,t}} + \theta \frac{\partial s_{n,i,t}}{s_{n,i,t}} \\ \sigma + \beta &> (<) \phi + \theta \end{aligned}$$

[3]See for instance, Arrow (1962), Mansfield, Schwartz and Wagner (1981), Levin et al. (1987) and Barro and Sala-i-Martin 1997, Benhabib and Spiegel 1994, 2005)

While we will discuss a set of particular cases in a dedicated section, for the moment we avoid introducing any other restriction except from the already mentioned $\sigma > \phi$ and, for convexity reasons, $\beta, \sigma, \theta, \phi < 1$. Hence, we develop the model by trying to be as general as possible and then simply allowing for heterogenous returns to scale of aggregate human capital on the two technological activities (i.e. $\sigma + \beta \lesseqgtr \theta + \phi$).

The dynamics of productivity is then governed by

$$A_{i,t} = A_{i,t-1} + \lambda \left[u_{m,i,t}^{\sigma} s_{m,i,t}^{\beta} (1 - a_{t-1}) + \gamma u_{n,i,t}^{\phi} s_{n,i,t}^{\theta} a_{t-1} \right] \bar{A}_{t-1} \tag{3}$$

where $a_{t-1} = \frac{A_{t-1}}{\bar{A}_{t-1}}$ is an inverse measure of the distance from the frontier.

We let $w_{u,t}\bar{A}_{t-1}$ ($w_{s,t}\bar{A}_{t-1}$) be the wage of unskilled (skilled) labor.

Total labor cost of productivity improvement by intermediate firm i at time t is then

$$W_{i,t} = \left(w_{u,t} \left(u_{m,i,t} + u_{n,i,t} \right) + w_{s,t} \left(s_{m,i,t} + s_{n,i,t} \right) \right) \bar{A}_{t-1}$$

Since enterpreneurs live for only one period - and thus maximize current profit net of labor costs - each intermediate good producer i at date t will choose $(u_{m,i,t}, u_{n,i,t}, s_{m,i,t}, s_{n,i,t})$ to solve the following program

$$\max_{u_{m,i,t}, u_{n,i,t}, s_{m,i,t}, s_{n,i,t}} \delta A_{i,t} - W_{i,t}$$

which, using (3) and the fact that $u_{m,i,t} + u_{n,i,t} = U$ and $s_{m,i,t} + s_{n,i,t} = S$, can be written as

$$\max_{u_{m,i,t}, s_{m,i,t}} \delta A_{it-1} + \delta\lambda \left[u_{m,i,t}^{\sigma} s_{m,i,t}^{\beta} (1 - a_{t-1}) + \gamma \left(U - u_{m,i,t} \right)^{\phi} \left(S - s_{m,i,t} \right)^{\theta} a_{t-1} \right] \bar{A}_{t-1}$$
$$- \left(w_{u,t} U + w_{s,t} S \right) \bar{A}_{t-1}$$

Given that all intermediate firms face the same maximization program, the optimal choice of $u_{m,i,t}$ and $s_{m,i,t}$ will be equal for any i in equilibrium: $u_{m,i,t} = u_{m,t}$ and $s_{m,i,t} = s_{m,t}$. Therefore, getting rid of the time suffix, the first-order conditions can be written as

$$(1 - a) \sigma \left(\frac{u_m}{s_m} \right)^{\sigma - 1} s_m^{\beta + \sigma - 1} = \gamma a \phi \left(\frac{U - u_m}{S - s_m} \right)^{\phi - 1} \left(S - s_m \right)^{\theta + \phi - 1} \tag{4}$$

$$(1 - a) \beta \left(\frac{u_m}{s_m} \right)^{\sigma} s_m^{\beta + \sigma - 1} = \gamma a \theta \left(\frac{U - u_m}{S - s_m} \right)^{\phi} \left(S - s_m \right)^{\theta + \phi - 1} \tag{5}$$

Dividing across equations and rearranging we find the usual condition of equality among marginal rate of technical substitution

$$\psi \frac{(U - u_m)}{(S - s_m)} = \frac{u_m}{s_m} \tag{6}$$

which gives us u_m as a function of s_m

$$u_m = \frac{\psi s_m U}{S + (\psi - 1)\, s_m}$$

where $\psi = \frac{\sigma\theta}{\phi\beta}$.

Combining (6) and (5) we obtain

$$k\,(s_m, S) = h\,(a)\,U - (S + (\psi - 1)\, s_m)\, q\,(s_m, S) = 0 \tag{7}$$

where[4]

$$\begin{aligned} h\,(a) &= \left(\frac{\beta\psi^{\sigma}}{\gamma\theta}\frac{1-a}{a}\right)^{\frac{1}{\sigma-\phi}} \\ q\,(s_m, S) &= \left(\frac{s_m^{1-\beta-\sigma}}{(S - s_m)^{1-\theta-\phi}}\right)^{\frac{1}{\sigma-\phi}} \end{aligned}$$

Equation (7) is very important because it defines an implicit function whose solutions represent the equilibrium values for s_m (and then for u_m, s_n and u_n as well). It is worth to focus on the role that non-constant and heterogenous returns to scale have on equation (7) with respect to the CRS case. There are two crucial differences which we analyze in the next subsections

2.2.1 The structure of comparative advantages

In equation (7) $\psi = \frac{\sigma\theta}{\phi\beta}$ might be larger or smaller than 1. With CRS $\psi = \frac{\sigma(1-\phi)}{\phi(1-\sigma)}$ so that, since $\sigma > \phi$, we also have $\psi > 1$. This is not the case in our model where ψ can be smaller than 1 even if $\sigma > \phi$ - when $\theta < \beta\frac{\phi}{\sigma}$. It is important to highlight the role of ψ. This parameter provides information on which kind of human capital has the *comparative advantage* in each type of technological activity. More precisely, $\psi > 1$ implies $\frac{\sigma}{\beta} > \frac{\phi}{\theta}$ i.e. the ratio between elasticities of unskilled and skilled human capital in *imitation* is larger than the ratio between of the elasticities of unskilled and skilled human capital in *innovation*. This simply implies that, when $\psi > 1$, skilled human capital has a comparative advantage in innovation, while unskilled human capital has a comparative advantage in imitation. This is because - regardless to whom owns the absolute advantage (i.e. regardless whether β (or θ) is larger or smaller than σ (or ϕ)[5], unskilled people are relatively more efficient in imitation than in innovation

[4]Notice that,

$$h'\,(a) = -\frac{1}{\sigma-\phi}\left(\frac{\beta\psi^{\sigma}}{\gamma\theta}\frac{1-a}{a}\right)^{\frac{1}{\sigma-\phi}-1}\left(\frac{\beta\psi^{\sigma}}{\gamma\theta}\frac{1}{a^2}\right) < 0$$

so that the negativity of $h'\,(a)$ is not affected by non-constant returns to scale in imitation and innovation but it only depends on the assumpion (that we keep) according to which $\sigma > \phi$

[5]Clearly enough, it looks reasonable to assume that unskilled workers cannot outperform skilled workers in both technological activity and therefore $\beta > \sigma$ and $\theta > \phi$. However, our results are completely independent from this assumption. In other words, the dynamics of catch-up are governed only by comparative advantages (i.e. relative efficiencies) and not by absolute advantages.

Hence, our model allow for the possibility that - provided that $\sigma > \phi$ - unskilled workers may have a comparative advantage in innovation when $\beta >> \theta$. However, we admit that this does not represent a particularly realistic empirical scenario. For these reason, even if we'll provide the analytical results for the full set of parameters' values', the discussion will focus on the more empirically relevant case of $\psi > 1$. Still, and more importantly, even if this is the case skilled workers might be relatively more efficient in imitation than in innovation. In fact we have $\psi > 1$ even when $\beta \frac{\phi}{\sigma} < \theta < \beta$.

Moreover, the empirical investigation that we will show in next sections will help discerning what structure of comparative advantages holds in reality when the theory is tested econometrically.

2.2.2 Non-linearities in factor intensities

The presence of the term $q(s_m, S) = \left(\frac{s_m^{1-\beta-\sigma}}{(S-s_m)^{1-\theta-\phi}}\right)^{\frac{1}{\sigma-\phi}}$ introduces a strong non-linearity which - in turn - we will see to be the main responsible for the quite dramatic change in the catch-up behaviour with respect to the CRS case where $q(s_m, S) = 1$.A first important implication of this second difference is that we cannot find a closed form solution for the equilibrium value of s_m. The (set of) equilibrium value(s) of s_m is in fact the (set of) solution(s) of equation (7) where, with non constant returns to scale, s_m enters with a non-integer power. As we shall see in the next section, this will have some implications on the existence and uniqueness of the optimal solution which - due to the strong non-linearity induced by non constant returns to scale - may not exist and may be unique or twofold. Another related consequence is that relative factor endowments cannot be expressed as function of a only and, therefore - unlike VAM - they are not independent from total factor endowments[6]. By combining (7) and (6) we have in fact

$$\frac{u_m}{s_m} = \psi \frac{u_n}{s_n} = \frac{\psi}{h(a)} \left(\frac{s_m^{1-\beta-\sigma}}{(S-s_m)^{1-\theta-\phi}}\right)^{\frac{1}{\sigma-\phi}}$$

2.3 Equilibrium analysis

2.3.1 Existence and Uniqueness of the optimal solution

The optimal value of s_m enters the expression for the growth rate and so it is crucial for our analysis. Even if allowing for non-constant returns to scale prevents from finding an explicit closed form solution, a qualitative analysis is still feasible through the implicit function theorem. However, in order for the implicit function theorem to be applied (and for the analysis to be meaningful) we need the equilibrium value of s_m

[6]That basically means that Lemma 2 of VAM (according to which the optimal amount of skilled and unskilled labor employed in imitation is increasing (resp. decreasing) in the total number of unskilled (resp.skilled) units of labor U (resp. S) and decreasing in the distance to the frontier) does not hold in general but only with CRS.

to 1) exists and 2) be unique. This is always true in the CRS case as $k(s_m, S)$ becomes linear in s_m but this is not the case in our model. For the existence and uniqueness to hold, we need to introduce the following assumption

Assumption 1 $\mathbf{sign}(1-\beta-\sigma) = \mathbf{sign}(1-\theta-\phi) = \mathbf{sign}_{x\in(0,1)} f(x)$

where

$$f(x) = \left[x^2(\psi-1)[\beta-\theta] + x[\beta+\sigma-\theta-\phi+(1-\beta-\phi)(\psi-1)] + (1-\beta-\sigma)\right]$$

and $x = \frac{s_m}{S} \in [0,1]$ represents the fraction of skilled human capital employed in imitation.

When this is assumption is true, the equilibrium exists and its unique as shown by the following proposition

Proposition 1 *When Assumption 1 holds, the equilibrium exists and it's unique for any* $s_m \in [0, S]$

Proof. See the appendix. ■

This proposition tells us that when returns to imitation $(\beta+\sigma)$ and innovation $(\theta+\phi)$ are both decreasing (< 1) or increasing (> 1) and, when for a given $x \in (0,1)$ the parabola $f(x)$ has the same sign of its extreme $f(0)$ and $f(1)$, then there is a unique equilibrium value for s_m^*. Albeit the implications of the multiple optimal solutions is an interesting issue, we leave this topic for future research and we adopt assumption 1 for the rest of the paper as we aim to assess the impact of our generalization with respect to VAM where existence and uniqueness were ensured by a far more restricting assumption (i.e. $\beta+\sigma = \theta+\phi = 1$)[7]. Hence, for the rest of the paper, we will assume either DRS or IRS for both imitation and innovation. But, as suggested by the literature (from Romer 1990 on), we will mainly focus our discussion on the DRS case.

2.3.2 Comparative statics

When the equilibrium is unique, s_m^* can be expressed as an implicit function of a, U and S

$$s_m^* = s(S, U, a) \tag{8}$$

[7]Also notice that - in order to avoid corner solution - VAM had to impose some additional conditions on the value of the ratio S/U which, according to Lemma 1, should be included in the interval $\left(\frac{h(a)}{\psi}, h(a)\right)$. This interval might be very small when ψ is close to 1. By contrast, in our model, when assumption 1 holds, the equilibrium is always unique and interior so we need not introduce any assumption in order to avoid corner solutions.

and although it cannot be expressed as a closed-form function of the parameters, the way it changes with S, U and a can be computed by applying the implicit function theorem to the identity

$$k\left(s_m^*, S\right) = h\left(a\right) U - \left[S + \left(\psi - 1\right) s_m^*\right] q\left(s_m^*, S\right) \equiv 0 \tag{9}$$

By differentiating this expression with respect to S, U and a we find

$$\frac{\partial s_m^*}{\partial S} = -x^* \frac{\left(\left(1 - x^*\right)\left(\sigma + \theta - 1\right) + \psi x^* \left(\theta + \phi - 1\right)\right)}{f\left(x^*\right)} \tag{10}$$

$$\frac{\partial s_m^*}{\partial U} = \frac{x^*\left(1 - x^*\right)}{f\left(x^*\right)} \frac{\left(\sigma - \phi\right) h\left(a\right)}{q\left(s_m^*, S\right)} \tag{11}$$

$$\frac{\partial s_m}{\partial a} = \frac{x^*\left(1 - x^*\right)}{f\left(x^*\right)} \frac{\left(\sigma - \phi\right) h'\left(a\right) U}{q\left(s_m^*, S\right)} \tag{12}$$

Where, as usual, $x^* = \frac{s_m^*}{S}$.

These expressions generalize Lemma 2 in VAM which is the main source of their theoretical results[8]. When returns are non constant, the following (and more general) lemma holds:

Lemma 1 *When assumption 1 is true, the optimal amount of skilled labor employed in imitation is*

1. *increasing (decreasing) in the total number of unskilled units of labor U when returns are non-increasing (increasing):*

$$\left(1 - \beta - \sigma\right) \geq \left(<\right) 0 \cap \left(1 - \theta - \phi\right) \geq \left(<\right) 0 \Rightarrow \frac{\partial s_m^*}{\partial U} > \left(<\right) 0$$

2. *decreasing (increasing) in the distance to the frontier a when returns are non-increasing (increasing):*

$$\left(1 - \beta - \sigma\right) \geq \left(<\right) 0 \cap \left(1 - \theta - \phi\right) \geq \left(<\right) 0 \Rightarrow \frac{\partial s_m^*}{\partial a} < \left(>\right) 0$$

3. *decreasing in the total number of skilled units of labor S when returns are increasing and when they are decreasing but $\frac{s_m^*}{s_n^*} < \frac{\sigma+\theta-1}{\psi(1-\theta-\phi)}$. Increasing when returns are decreasing and $\frac{s_m^*}{s_n^*} > \frac{\sigma+\theta-1}{\psi(1-\theta-\phi)}$*

[8] According to this lemma, with CRS, "the optimal amount of skilled and unskilled labor employed in imitation is increasing (resp. decreasing) in the total number of unskilled (resp. skilled) units of labor U (resp. S), and decreasing in the distance to the frontier a. These results can be obtained as a special case of our model by imposing $\beta + \sigma = \phi + \theta = 1$. In this case, as for the amount of skilled labor employed in imitation (the results for unskilled workers is easily extendible) we have

$$\left(\beta + \sigma = \phi + \theta = 1\right) \Rightarrow \begin{cases} \frac{\partial s_m^*}{\partial S} = -\frac{1}{\psi - 1} < 0 \\ \frac{\partial s_m^*}{\partial U} = \frac{h(a)}{(\psi-1)} > 0 \\ \frac{\partial s_m}{\partial a} = \frac{h'(a)U}{(\psi-1)} < 0 \end{cases}$$

Proof. Results are straightforward after the analysis of the signs of equations (10), (11) and (12) and once considered the restriction posed by assumption 1. ■

The first element worth to be noted is that when returns are non-constant the signs of the three derivatives (10), (11) and (12) becomes ambiguous.

When returns are non-increasing, the sign of $\frac{\partial s_m^*}{\partial U}$ and $\frac{\partial s_m^*}{\partial a}$ is the same as in the CRS case. There exists, however, a particularly interesting case for which - being returns decreasing - the sign of $\frac{\partial s_m^*}{\partial S}$ turns from negative to positive. That happens when $\frac{s_m^*}{s_n^*} > \frac{\sigma+\theta-1}{\psi(1-\theta-\phi)}$ which is *always* the case when $\theta < 1-\sigma$ i.e. when the elasticity of skilled workers in innovation is low enough. The intuition is quite straightforward: when skilled workers' efficiency in innovation is not too large, then allocating an additional skilled worker in imitation is going to be an optimal decision for the maximizing firm under the conditions detailed above[9]. This result, which basically tells us that Lemma 2 in VAM cannot be generalized to decreasing returns to scale, is one of the source of the non-linearities which, as we will see, significantly changes the catching-up behaviour of the model.

We are now ready to perform the growth analysis.

3 Growth Analysis

Consider (3). If we divide by A_{t-1} and then express it in terms of relative factor endowments, this yields to the following

$$g = \lambda \left[\left(\frac{u_m}{s_m} \right)^{\sigma} s_m^{\beta+\sigma} \frac{1-a}{a} + \gamma \left(\frac{U-u_m}{S-s_m} \right)^{\phi} (S-s_m)^{\theta+\phi} \right] \tag{13}$$

Then, exploiting the first-order conditions (4) and (5) and considering the equilibrium value of s_m as an implicit function of S, U and a, we obtain

$$g = \lambda\gamma h(a)^{-\phi} (S-s_m^*)^{\frac{\theta+\phi-1}{\sigma-\phi}\sigma} s_m^{*\frac{1-\beta-\sigma}{\sigma-\phi}\phi} \left[S + s_m^* \frac{\theta-\beta}{\beta} \right] \tag{14}$$

where $s_m^* = s(S, U, a)$. Equation (14) will be the basis of our growth analysis[10].

[9] A corollary of this result is that when skilled workers are more efficient in imitation than in innovation ($\beta > \theta$ a case which is always excluded by VAM but which we consider empirically relevant), $\frac{\partial s_m^*}{\partial S}$ is *always* positive. That's because, with decreasing returns to scale, $1-\sigma-\beta > 0$ and then also $\sigma+\theta-1 < 0$.

[10] It is important to note how it differs from the CRS case where, since $\beta+\sigma = \theta+\phi = 1$, we have

$$g = \lambda\gamma h(a)^{-\phi} \left[S + s_m^* \frac{\sigma-\phi}{1-\sigma} \right]$$

Notice in particular that: 1) the term $(S-s_m^*)^{\frac{\theta+\phi-1}{\sigma-\phi}\sigma} s_m^{*\frac{1-\beta-\sigma}{\sigma-\phi}\phi}$ completely disappears being equal to 1 and 2) $\theta-\beta = \sigma-\phi$ which is always positive, while this need not be the case with non-constant returns to scale.

Calculating the derivative of (14) with respect to U and using (11) to substitute for $\frac{\partial s_m^*}{\partial U}$ we simply find

$$\frac{\partial g}{\partial U} = \phi\lambda\gamma h(a)^{1-\phi} \tag{15}$$

which is clearly positive and *identical* to CRS case. Interestingly, hence, non-constant returns do not affect the impact of unskilled human capital on growth.

To compute the growth impact of a change in aggregate skilled workers, differentiate (13) with respect to S and use (10) to substitute for $\frac{\partial s_m^*}{\partial S}$ in order to find

$$\frac{\partial g}{\partial S} = \theta\lambda\gamma h(a)^{-\phi} \left(S - s_m^*\right)^{\frac{(\theta+\phi-1)\sigma}{\sigma-\phi}} s_m^{*\frac{(1-\beta-\sigma)\phi}{\sigma-\phi}} \tag{16}$$

which, as expected, is clearly positive. This expression, proxying for the impact of skilled workers on growth, is however significantly different from the CRS case. In this case equation (16) simply becomes:

$$\frac{\partial g}{\partial S} = (1-\phi)\lambda\gamma h(a)^{-\phi}$$

So the term $\left(S - s_m^*\right)^{\frac{(\theta+\phi-1)\sigma}{\sigma-\phi}} s_m^{*\frac{(1-\beta-\sigma)\phi}{\sigma-\phi}}$ (which is inerithed from the growth rate expression) plays a crucial role: while in the CRS case the growth impact of aggregate skilled human capital depends on the proximity to the frontier a only and positively through $h(a)^{-\phi}$, with non-constant returns to scale $\frac{\partial g}{\partial S}$ also depends on the optimal allocation of skilled workers in imitation s_m^* which is itself a function of a.

Formally, if we compute the cross derivative $\frac{\partial^2 g}{\partial S \partial a}$, we find

$$\frac{\partial^2 g}{\partial a \partial S} = \theta g \left[\underbrace{-\frac{h'(a)}{h(a)}\phi}_{\text{VAM effect}} + \underbrace{\frac{\partial s_m^*}{\partial a} \frac{z(x^*)}{S(\sigma-\phi)(1-x^*)x^*}}_{\text{SD-effect}} \right] \tag{17}$$

where g is defined by (14) and

$$z(x^*) = (1-\beta-\sigma)\phi(1-x^*) + (1-\theta-\phi)\sigma x^* \tag{18}$$

and, as usual, $x^* = \frac{s_m^*}{S} \in (0,1)$.

Equation (17) is crucial for our results as it shows that there are two opposite effects defining the way a marginal increase in skilled workers affects growth as a function of the proximity of economies to the technological frontier a:

1. (what we call) the *VAM effect* formalized by the term $-\frac{h'(a)}{h(a)}\phi$ and analogous to the *only* effect present in VAM

2. (what we call) the *Skill-development (SD) effect* (represented by the term $\frac{\partial s_m^*}{\partial a} \frac{z(x^*)}{S(\sigma-\phi)(1-x^*)x^*}$) which stems from our original contribution.

Not surprisingly, the VAM effect is always positive being $h'(a)$ always negative and $\frac{\phi}{h(a)}$ always positive. As for the SD-effect, we refer to the following proposition

Proposition 2 *The SD-effect is zero if and only if returns to technological activities are constant. It is striclty negative for any* $x^* \in (0,1)$ *otherwise.*

Proof. As for the first part of the proposition, from Lemma 1 we know that when returns are constant - i.e. $(1-\beta-\sigma) = (1-\theta-\phi) = 0$, $\frac{\partial s_m^*}{\partial a} S(\sigma-\phi)(1-x^*)x^* < 0$ but from the definition of $z(x^*)$ we know that in this case $z(x^*) = 0$. This is the only case when the SD-effect is null. As for the second part of the proposition, the sign of the term representing the SD-effect $\left(\frac{\partial s_m^*}{\partial a}\frac{z(x^*)}{S(\sigma-\phi)(1-x^*)x^*}\right)$ only depends on the product $\frac{\partial s_m^*}{\partial a} z(x^*)$ as $S(\sigma-\phi)(1-x^*)x^*$ is always positive for any interior equilibria $x^* \in (0,1)$. From Lemma 1 we know that

$$(1-\beta-\sigma)(<)0 \cap (1-\theta-\phi) > (<)0 \Rightarrow \frac{\partial s_m^*}{\partial a} < (>)0$$

while, from the definition of $z(x^*) = (1-\beta-\sigma)\phi(1-x^*) + (1-\theta-\phi)\sigma x^*$ we easily obtain that

$$(1-\beta-\sigma) > (<)0 \cap (1-\theta-\phi) > (<)0 \Rightarrow z(x^*) > (<)0$$

Hence, when returns are non constant, $\frac{\partial s_m^*}{\partial a}$ and $\frac{z(x^*)}{S(\sigma-\phi)(1-x^*)x^*}$ have opposite signs so that the SD-effect is strictly negative. ■

This proposition is probably the core of our analysis and it deserves some comments.

First, proposition 2 tells us that CRS is really a knife-edge case of measure 0 in the four-dimensional parameters space to which belong the parameters $(\beta,\sigma,\theta,\phi)$. *Any* other case (respecting the global uniqueness condition formalized by Assumption 1) leads to the emergence of the SD-effect which was absent in VAM. As already said, the nonlinearities brought about by non-constant returns to scale (through the term $(S-s_m^*)^{\frac{(\theta+\phi-1)\sigma}{\sigma-\phi}} s_m^{*\frac{(1-\beta-\sigma)\phi}{\sigma-\phi}}$ which is equal to 1 in CRS) introduce a new channel via which the marginal impact of S on g depends on a. Crucially, this new channel always works in the opposite direction with respect to the VAM effect.

Second, proposition 2 also tells us that - under CRS - the behaviour of $\frac{\partial^2 g}{\partial a \partial S}$ is not an average of the DRS and IRS case. More precisely CRS case represents a subspace (formally a 2-dimensional variety) in the 4-dimensional space $[0,1]^4 \subset \mathbb{R}^4$ where the absolute value of the SD-effect reaches its minimum - i.e. 0. Any slight deviation from this subspace (in any direction) leads to a larger and positive value for the (absolute value) of the SD-effect and then it results in a lower value for the cross-derivative $\frac{\partial^2 g}{\partial a \partial S}$. Put it differently, the value of $\frac{\partial^2 g}{\partial a \partial S}$ is maximum under the CRS assumption and otherwise the SD-effect always contributes to reduce the marginal effect of S on g as we get closer to the frontier.

To sum-up, equation (17) and proposition 4 tell us that under a more general context a new force affecting the catch-up behaviour emerges, the SD-effect. Moreover, equation (17) also tells us that the marginal growth impact of S on growth is more likely to diminish as we get closer to the technological frontier

- the smaller ϕ (i.e. the less unskilled workers are suited to do innovation)
- the more responsive is s_m^* on the distance to the frontier a (the larger $\frac{\partial s_m^*}{\partial a}$)
- and the more returns to scale in the two activities are far from being constant (i.e. the farther $\beta+\sigma$ and $\theta+\phi$ are from 1, which makes $z(x)$ large in absolute value and makes the growth impact of aggregate skilled workers S more responsive in s_m^*).

However, in order to say something more precise about the overall sign of (17) - and then provide some testable implications - we would need to analyze more deeply the implications of this expression and distinguish the cases for which the SD-effect is either larger or smaller than the competing VAM-effect.

By substituting for $\frac{\partial s_m^*}{\partial a}$ using (12) and exploiting the equilibrium condition (9) we obtain

$$\frac{\partial^2 g}{\partial a \partial S} = -\theta g \frac{h'(a)}{h(a)} \left[\underbrace{\phi}_{\text{VAM effect}} + \underbrace{\left(-\left[1+(\psi-1)x^*\right] \frac{z(x^*)}{f(x^*)} \right)}_{\text{SD effect}} \right] \tag{19}$$

where the two forces have been reformulated and - albeit not closed-form - are made more transparent. From equation (19) is it clear that while the VAM effect is not affected by the equilibrium value of x^* and can be expressed in terms of ϕ (proxying for the efficiency of unskilled human capital in innovation), the SD-effect depends (rather non-linearly) on x^*. The following proposition gives us a clearer idea of the relative magnitude of these two effects and of the way they are affected by the model's parameters.

Proposition 3 *The SD effect is larger than the VAM effect - and hence* $\frac{\partial^2 g}{\partial a \partial S} < 0$ *- under the following circumstances*

1. *When returns to technological activities are decreasing* $((\beta+\sigma<1)\cap(\theta+\phi<1))$
   (a) *For every* $x^* \in (0,1)$ *when* $\psi \in \left(0, \frac{1-\theta}{\phi}\right)$
   (b) *If and only if* $x^* > \hat{x}^*$ *when* $\psi \in \left(\frac{1-\theta}{\phi}, \infty\right)$
2. *When returns to technological activities are increasing* $((\beta+\sigma>1)\cap(\theta+\phi>1))$
   (a) *For every* $x^* \in (0,1)$ *when* $\psi \in \left(\frac{1-\theta}{\phi}, \infty\right)$

(b) If and only if $x^* > \hat{x}^*$ when $\psi \in \left(0, \frac{1-\theta}{\phi}\right)$

where $\hat{x}^* = \frac{1-\theta-\psi\phi}{1-\theta-\psi(1-\theta)}$

Proof. *See the appendix* ■

This proposition is so rich of implications to deserve a discussion in a section of its own. To keep things simple we will focus on the case of decreasing returns. This choice is justified by the fact that we consider this case to be the most realistic one as we will argue later.

3.1 Catch-up dynamics under DRS: discussion

When returns are decreasing, proposition 3 tells us that the marginal contribution of an additional skilled worker on growth *increases* as an economy moves farther away from the frontier in the following cases

1. *For every x^** if either skilled workers have a comparative advantage in imitation ($\psi \in (0,1)$) or their comparative advantage in innovation is not too large $\psi \in \left(1, \frac{1-\theta}{\phi}\right)$
2. *Only when x^** is *sufficiently large* if skilled workers' comparative advantage in innovation is sufficiently strong i.e. $\psi > \frac{1-\theta}{\phi} > 1$.

Figures 1-6 show a set of simulations describing the behaviour of the VAM and SD effects (plotted as function of the equilibrium value of s_m) for different values of $\beta, \sigma, \theta, \phi$ and therefore ψ.

In general, it can be seen that there is a wide range of parameters such that the result obtained under the CRS case is reversed. More than that, the subspace of feasible parameters values such that $\frac{\partial^2 g}{\partial a \partial S}$ is negative is clearly larger than the subspace of parameters' values which ensures a positive value for $\frac{\partial^2 g}{\partial a \partial S}$ as in the CRS case. As we can see, there are no parameter values such that $\frac{\partial^2 g}{\partial a \partial S}$ is positive for *any* equilibrium value of x. By contrast, when[11] $\psi < \frac{1-\theta}{\phi}$ (and so comparative advantage of skilled workers in innovation is not too strong), $\frac{\partial^2 g}{\partial a \partial S}$ is *always* negative.

Crucially, both negative and positive cases are recovered only when skilled workers' comparative advantage in innovation is sufficiently strong ($\psi > \frac{1-\theta}{\phi} > 1$): in this case there is a value of x^* below which $\frac{\partial^2 g}{\partial a \partial S}$ is positive, as predicted by VAM and, viceversa a set of values above x^* for which $\frac{\partial^2 g}{\partial a \partial S}$ is instead negative.

[FIGURES 1-6 ABOUT HERE]

[11]Notice that $\frac{1-\theta}{\phi} > 1$ when returns are decreasing and viceversa when increasing.

It is then clear that the pattern of comparative advantage of the two kinds of workers in the two activities is crucial to determine the sign of $\frac{\partial^2 g}{\partial a \partial S}$. While commonsense suggests us not to consider empirically relevant the case for which unskilled workers have a comparative advantage in innovation ($\psi < 1$) it may well be that skilled workers might have only a *moderate* comparative advantage in innovation ($\psi \in \left(1, \frac{1-\theta}{\phi}\right)$). That happens, for example, in fig. 4 ($(\phi, \theta, \sigma, \beta) = (0.2, 0.6, 0.3, 0.5), \psi = 1.8 \in (1, 2)$), fig. 5 ($(\phi, \theta, \sigma, \beta) = (0.2, 0.4, 0.3, 0.5), \psi = 1.2 \in (1, 3)$) and fig. 6 ($((\phi, \theta, \sigma, \beta) = (0.1, 0.3, 0.2, 0.4), \psi = 1.5 \in (1, 7)$)). In all these cases, skilled workers are more efficient than unskilled workers in each technological activities ($\beta > \sigma$ and $\theta > \phi$) but their efficiency in innovation is not too high relative to their efficiency in imitation (in fig. 5 and 6 we also present the case where they are more efficient in imitation). When that happens, the SD-effect always dominates the VAM-effect and then the marginal contribution of an additional skilled worker on growth *increases* as an economy moves farther away for any equilibrium value of x^*.

By contrast, when $\psi > \frac{1-\theta}{\phi}$ and then skilled workers have a sufficiently strong comparative advantage in innovation, then $\frac{\partial^2 g}{\partial a \partial S}$ is negative when x^* is low enough. This is depicted, for instance, in fig. 2 ($(\phi, \theta, \sigma, \beta) = (0.29, 0.7, 0.39, 0.6), \psi = 1,57 > \frac{1-\theta}{\phi} = 1,03 > 1$) where for any equilibrium value of $x^* = \frac{s_m^*}{S}$ larger than 0.91 then $\frac{\partial^2 g}{\partial a \partial S}$ is negative and positive otherwise. Similarly, in fig. 3, ($(\phi, \theta, \sigma, \beta) = (0.2, 0.7, 0.3, 0.4)$ $\psi = 2.63 > \frac{1-\theta}{\phi} = 1.5 > 1$) where - while being returns on both activities "more decreasing" with respect to fig.2 - still innovation is an "easier" activity than imitation (as $\theta + \phi = 0.9 > \beta + \sigma = 0.8$), and $\frac{\partial^2 g}{\partial a \partial S}$ becomes negative for any x^* larger than 0.36 and positive otherwise.

Third, it can be noticed that it is more likely for $\frac{\partial^2 g}{\partial a \partial S}$ to be negative when - for a given x^* - θ gets closer to β from above. This observation can be easily formalized. Notice that

$$\psi > (<) \frac{1-\theta}{\phi} \Leftrightarrow \theta > \frac{\beta}{\sigma + \beta}$$

so that proposition 3 can be read as follows: the marginal contribution of an additional skilled workers on growth increases with the distance to the frontier in the following cases

1. *For every* x^* if skilled human capital efficiency in innovation is lower than a certain threshold: $\theta < \frac{\beta}{\sigma+\beta}$

2. *When* x^* is *sufficiently large* if instead $\theta > \frac{\beta}{\sigma+\beta}$

These results point to the fact that it is sufficient that skilled workers can perform imitation activities sufficiently well, as in comparison to innovation activities in which, in any case, they are still comparatively more efficient anyway, (β is close enough from below to θ) for the newly unveiled SD-effect to more than compensate the VAM-effect.

In other words, the SD-effect is more likely to be larger than the VAM effect the relatively harder innovation is with respect to imitation for skilled workers.

This new perspective also provides us with a nice economic intuition for the nature of the SD-effect (at least in the DRS case). When $\theta < \frac{\beta}{\sigma+\beta} < \beta$ (which can never be the case with CRS) it is always optimal to allocate an additional unit of S in imitation rather than innovation ($\frac{\partial s_m^*}{\partial S} > 0$ by Lemma 1) regardless of the distance to the frontier. Moreover, with DRS, we know (again Lemma 1) that $\frac{\partial s_m^*}{\partial a} > 0$ as allocating more skilled workers in imitation is more convenient as the distance to the frontier increases. Hence, since in this case imitation is better for the growth of the poor and skilled workers are *sufficiently good* in imitation ($\theta > \frac{\beta}{\sigma+\beta}$ means $\beta > \sigma\frac{\theta}{1-\theta}$), then skilled workers are going to be relatively more growth enhancing for the poorer economies than for richer ones.

Two final considerations. First, whatever the value of ψ, $\frac{\partial^2 g}{\partial a \partial S}$ is negative whenever x^* (the share of skilled human capital devoted to imitation in equilibrium) is sufficiently large (i.e. larger than $\frac{1-\theta-\psi\phi}{1-\theta-\psi(1-\theta)}$). This gives us an *important theoretical prediction which can be tested empirically.* As with DRS we have that $\frac{\partial s_m^*}{\partial a} < 0$ we should (reasonably) expect a large value of x^* (ceteris paribus) as a decreases and so we get farther from the technological frontier. Hence, the model predicts that - *whatever the pattern of the comparative advantage* - $\frac{\partial^2 g}{\partial a \partial S}$ *is expected to be negative for poorest countries.*

Second, the comparison between fig.1 (where returns are constant being $(\phi, \theta, \sigma, \beta) = (0.3, 0.7, 0.4, 0.6)$) and figure 2 where (where returns are slightly decreasing being $(\phi, \theta, \sigma, \beta) = (0.29, 0.7, 0.39, 0.6)$) provides us a graphical representation of how responsive the sign of $\frac{\partial^2 g}{\partial a \partial S}$ is to changes in the parameters $(\phi, \theta, \sigma, \beta)$.

The differences in policy implications between our generalized model and previous literature are, hence, noteworthy. Our theoretical results, in fact, emphasize the fundamental role of skilled human capital for countries at low development stages even if these mainly perform technology imitation and little (or none) innovation activities.

4 Empirical Analysis

4.1 Emprical model and the treatment of endogeneity

We follow VAM and test the predictions of our theoretical model with the following empirical specification for TFP growth:

$$g_{j,t} = \alpha_{0,j} + \alpha_1 z_{j,t-1} + \alpha_2 f_{j,t-1} + \alpha_3 z_{j,t-1} * f_{j,t-1} + \epsilon_{j,t} \tag{20}$$

where $g_{j,t} = \ln A_{j,t} - \ln A_{j,t-1}$ is TFP growth and $A_{j,t}$ represents the TFP in country j at period t. The variable $z_{j,t-1} = \ln a_{j,t-1} = \ln A_{j,t-1} - \ln \bar{A}_{t-1}$ is the log of the proximity to the TFP frontier[12] in the initial period (this is a negative number) while $f_{j,t-1}$ represents human capital which (depending on the empirical specification under consideration) will be proxied by the (i) fraction(s) of the workforce with a specific education attainment level or by (ii) the average number of years of schooling (in tertiary, secondary or primary). Our empirical specification, hence, fully resembles that of VAM.

The estimation of the empirical model in (20) poses a number of econometric challenges. On the one hand, as argued by Nickell (1981), a "dynamic panel bias" may arise when lagged values of the dependent variable are correlated to the fixed effect in the error term[13]. This positive correlation violates a necessary assumption for the consistency of ordinary least squares estimators which are, hence, not valid for inference. On the other hand, an additional source of bias might arise, as pointed out by Bils and Klenow (2000), due to the positive correlation between the explanatory variables (i.e. the educational variables in eq.(20)) and the error term creating additional severe endogeneity problems.

An intuitive first attack to these issues is to draw the fixed effect out of the error term by entering dummies for each individual through the so-called Least Squares Dummy Variables (LSDV) estimator as well as instrumenting all the (endogenous) right hand side variables by their lagged values.

As argued by Aghion et al. (2009), however, the use of LSDV does not solve a variety of problems which are intrinsic to the estimation of the empirical model in eq.(20). To start with, the use of the lagged realization of education variables or the use of education spending lagged ten years as instruments for education levels may still conduce to biases due to the instrument's potential correlation to omitted variables specific to each country[14].

Additionally, as argued by Kiviet (1995) and Bond (2002), the within-groups transformation does not fully eliminate dynamic panel bias. Kiviet (1995) devises a strategy to correct for this bias. This correction, however, only works in the context of balanced panels and, crucially, it does not address the potential endogeneity of other regressors as it would be needed, instead, in our case due to the potential simultaneous relation between educational variables and TFP.

Last but not least, educational variables are not only endogenous to the dependent variable, they are also persistent over time. Fixed effect estimators that exploit the within country variation in the data do not represent, hence, the most appropriate choice in this context[15] due to the limited power of lagged explanatory variables to be

[12]The TFP of the leader (at the frontier) is denoted by $\bar{A}$.

[13]This happens since the lagged value $A_{j,t-1}$ enters within $a_{j,t-1}$ as a regressor for the growth rate of TFP.

[14]See Aghion et al. (2009): "Instrumenting with lagged spending does not overcome biases caused by omitted variables such as institutions" (p. 5)

[15]See Castello-Climent, Amparo (2008).

used as instruments.

As a solution to these above mentioned issues, the Arellano–Bover (1995)/Blundell–Bond (1998) GMM estimator builds a system of two equations by exploiting the assumption that first differences of instrument variables are uncorrelated with the fixed effects. As argued by Roodman (2009b) "*for random walk–like variables, past changes may indeed be more predictive of current levels than past levels are of current changes so that the new instruments are more relevant*" (p.28). System GMM estimators, then, proove to be of highest advantage with persistent series in which the lagged-levels of explanatory variables are weak instruments for subsequent changes and when both dynamic panel bias and additional endogeneity biases of covariates are likely to affect the estimation[16].

The validity of GMM estimates, however, depends on the assumption that the idiosyncratic disturbance terms are not serially correlated as well as on the paucity of the instrumental set employed to fit the endogenous regressors. Regarding the first condition, Arellano and Bond (1991) developed a test of autocorrelation of the second order which checks for the validity of lagged variables as instruments. About the second requirement, the work of Andersen and Soerensen (1996), Bowsher (2002) and Roodman (2009) provide an in-depth discussion of how instrument proliferation (easily obtained with the system of equations built for the SYSGMM estimators) vitiates the estimation of the Hansen test providing unreliable information on the robustness of the instrumental set and on the overall validity of GMM estimations. Limiting the lag depth (i.e. collapsing the instrument) is, hence, a necessary, though usually overlooked, condition in order to avoid false positive. Roodman (2009) suggests that the instrumental count should be kept as parsimonious as possible and especially that this, as a general rule of thumb, should not exceed the number of groups in the SYSGMM regression. In what follows, hence, we will estimate the impact of human capital composition on growth through SYSGMM estimators while carefully taking into consideration all the above mentioned estimation issues.

4.2 The data

The data that we exploit to test the empirical model in eq.(20) cover 85 countries for 10-years time spans over the period 1960-2000. The information we use comes from different sources. As for the GDP data, we rely on the Penn World Tables provided by Heston, Summers and Aten (2002). Since capital stock data are not available in this database, a common solution is to build estimates by applying the Perpetual Inventory Method (PIM) to time series investment data. Even though the PIM is a well-established method in the empirical literature, it is not without its

[16]See Blundell and Bond, (1998), (2000); Bond et al. (2000), Durlauf et al., (2005), Ang et al. (2011).

concerns. These relate to the possible measurement error affecting the estimation of the initial capital stock year, that could arise if the investment data do not go back far enough in time [17]. In a recent study by Baier, Dwyer and Tamura (2006) build capital stock estimates through the PIM by exploiting long investment time series (in some cases dating back to the 18th century) which are provided in B.R. Mitchell (1998a, b, c). Investment data prior to 1992 are measured using the: (i) International Historical Statistics: The Americas 1750-1993, (ii) International Historical Statistics: Africa, Asia and Oceania 1750-1993 and (iii) International Historical Statistics: Europe 1750-1993 so that the measurement error on the initial capital stock is of virtually no concern in these estimates. We use the Baier, Dwyer and Tamura capital stock estimates and follow VAM to build Total Factor Productivity (TFP) as output per worker minus capital per worker times capital share. Hence, we compute the proximity to the technological frontier as the ratio of each country's TFP level to that of the U.S.

Due to the aim of our analysis, the quality of the human capital proxy used in our estimations is of crucial importance. In an interesting data comparison review, de la Fuente and Domenech (2006) show the substantial measurement issues affecting the widely used Barro and Lee (1996) human capital series *vis a vis* the data proposed by Cohen and Soto (2006)[18]. We use this latter datasource for our analysis due to the larger available sample and better data quality. Cohen and Soto's data provide information about the share of the workforce aged 25 having completed tertiary, secondary or primary education for a large sample of countries at 10-years intervals, being based on both census and enrollment data collected in the UNESCO Statistical Yearbook as well as in the United Nations Demographic Yearbook.

The descriptive statistics for the variables of interest are given in Table 1 below. The average TFP proximity of the OECD sample with respect to the US's is 0.69 while it is only 0.22 for the sub-sample of Developing countries. As expected, there are also substantial differences in human capital endowment across countries, with the average number of years of tertiary schooling in OECD countries standing at 0.51 compared to 0.22 for the Developing countries sub-sample[19].

[TABLE 1 ABOUT HERE]

[17]See Gollop and Jorgenson (1980), Jacob, Sharma and Grabowski (1997) and Caselli (2005).

[18]As argued by de la Fuente and Domenech (2006) "*the difference in the range of [annualized growth rate of average years of schooling] across data sets is enormous: while our annual growth rates range between 0.09% and 1.92% and those of Cohen and Soto between 0.27% and 3.27%, Barro and Lee's go from -1.35% to 6.13%; moreover, 19% of the observations in this last data set are negative, and 16.7% of them exceed 2%*"

[19]The statistics referring to the OECD subsample are fully in line with those presented by VAM both for the TFP and human capital measures.

4.3 Empirical predictions of the theoretical model

As a starting point, the model predicts a positive marginal effect on growth of both skilled ($\frac{\partial g}{\partial S}$ in equation (16)) and unskilled ($\frac{\partial g}{\partial U}$ in equation (15)) human capital. In the empirical model in eq.(20) this theoretical prediction would translate into the following

$$\frac{\partial g_{j,t}}{\partial f_{j,t-1}} = \alpha_2 + \alpha_3 z_{j,t-1} > 0$$

The overall effect of a marginal increase in human capital on the growth rate is then proxied by a linear function of $z_{j,t-1}$ and so it may change according to a country's relative stage of development with respect to the world productivity frontier. More precisely, given the presence of the interaction term $z_{j,t-1} * f_{j,t-1}$, the overall effect of an additional $f_{j,t-1}$ (tertiary human capital) could be graphically represented by a straight line taking values for $z_{j,t-1} \in \mathbb{R}^-$ where α_2 is the vertical intercept and α_3 is the slope. It should be noted that, since by proposition 3 the subspace of parameters' values such that $\frac{\partial g}{\partial S}$ is *increasing* in the proximity to the frontier is relatively small (and possibly empty), as a general rule the model suggests that we should expect the data to display a value of the overall effect of tertiary education on growth ($\alpha_2 + \alpha_3 z_{j,t-1}$) which decreases with $z_{j,t-1}$ - i.e. when we consider subsets of countries progressively closer to the technological frontier.

As for the expected sign of the coefficient α_2 notice that, for countries very close to the world frontier, the value of $z_{j,t-1}$ is close to zero and then the marginal growth effect of human capital for developed countries can be approximated by the value of α_2 only. In other words, our model predicts a positive value for α_2 for countries close enough to the technology frontier:

$$\lim_{A_{j,t-1} \to \bar{A}_{t-1}} \frac{\partial g_{j,t}}{\partial f_{j,t-1}} = \alpha_2 > 0$$

This is not necessarily true for developing countries. For countries far away from the frontier, in fact, the value of the coefficient α_2 could be negative while still being consistent with the theoretical predictions of our model of a positive effect of skilled workers on growth. This is so if the term $\alpha_3 z_{j,t-1}$ is positive and relatively larger in absolute value than α_2. Notice that, being $z_{j,t-1}$ negative by construction, a necessary condition for this to happen is that the coefficient α_3 is also negative.

As for this latter, α_3 represents the empirical counterpart of the cross-derivative $\frac{\partial^2 g}{\partial a \partial S}$ that has been analyzed in Proposition 3. From an empirical point of view this is shown here below:

$$\frac{\partial^2 g_{j,t}}{\partial f_{j,t-1} \partial z_{j,t-1}} = \alpha_3$$

As detailed in previous sections, we already know that in the knife-edge case of CRS $\frac{\partial^2 g}{\partial a \partial S}$ is always positive, hence predicting a positive value for α_3. This is not necessarily true in our theoretical generalization where α_3 can either assume positive or negative values as a result of different combinations of parameter-elasticities associated to human capital in innovation and imitation activities and depending on the actual distance of the economy from the technological frontier. More precisely, as already argued in section 3.1, the model predicts that, under DRS[20] and whatever the sign and the intensity of the relative comparative advantage - $\frac{\partial^2 g}{\partial a \partial S}$ (and hence α_3) should be negative for countries sufficiently far from the technological frontier. By contrast, for more developed countries, the model predicts that the sign of α_3 is ambiguous and that this will depend on the efficiency of skilled human capital in innovation: a positive sign is expected if this efficiency is strong enough and a negative one otherwise.

To sum up the the theoretical predictions presented above are as follows: 1) a positive value of α_2 for the groups of countries closer to the frontier; 2) a negative value of α_3 for *less* developed countries and a positive or negative value of α_3 for developed countries depending on whether the comparative advantage of skilled workers on innovation is respectively strong or weak enough 3) a positive but decreasing value of the overall effect $\alpha_2 + \alpha_3 z_{j,t-1}$ as we consider groups of progressively richer countries

4.4 Empirical results

In order to empirically test the development specific impact of human capital composition on growth, we estimate the model in (20) on the whole sample of 85 countries as well as on different subsamples of countries grouped at different stages of development and hence compute the implied elasticities of growth w.r.t. tertiary education for the different subsamples. In columns (ii) and (iii) of Table 1 we split the whole sample into high-income countries (21 OECD economies) and developing economies (64 economies) while in columns (iv) to (vii) we repeat the analysis by grouping countries belonging to the top 25% of the GDP distribution (representing the countries at the frontier) vs those with a GDP level below 75, 50 and 25% of the sample average (representing groups of increasingly less developed countries).

4.4.1 First specification: fractions

We start our analysis by proxying for skilled human capital through the fraction of workforce with tertiary education in each economy. Our theoretical model predicts a wide array of empirical results. Some of them, as we detailed before, crucially differ from previous literature and, we will show next, find robust confirmation in our empirical tests. Results are given in Table 2 below.

[TABLE 2 ABOUT HERE]

[20]Which - as we'll see - is a case which is strongly supported by the empirical results.

Our empirical results strongly support the predictions of the model and confirm that the dynamics governing the impact of skilled labor on growth for the economies close to the technology frontier crucially differ from those arising, instead, at lower stages of development.

First notice that coefficient associated to the share of tertiary educated workforce, α_2, is positive and strongly significant for the sub-sample of the OECD countries while negative and statitistically significant for those economies farther away from the frontier (in columns (3) and (5) to (7)). If, on the one hand, the positive coefficient α_2 is consistent with the empirical results found in VAM, on the other hand, the negative value for the developing countries fits with our theoretical generalization as long as also α_3 is estimated to be negative. Indeed, the coefficient associated to the interaction term between tertiary education and the log of the TFP gap, α_3, is strongly significant for all subsamples and shows opposite signs for the sub-sample of OECD and that of Developing countries (resp. positive and negative coefficients). Hence our empirical results also show that a marginal increase in tertiary educated labor will be growth enhancing for those countries sufficiently close to the technology frontier. The results for the OECD countries are in fact, qualitative the same as those proposed by VAM. This said, however, our empirical analysis claims that for the subsample of lagging economies, the effect of tertiary education increases as we move far away from the frontier, in contrast to the predictions of previous literature.

Finally, the overall effect of tertiary education on economic growth $\alpha_2 + \alpha_3 z_{j,t-1}$[21] (presented at the bottom of the table) is consistent with our theoretical predictions being *positive and significant* for the all the sub-sample considered. Interestingly, we observe that the magnitude by which a marginal increase in tertiary education affects growth is very much heterogeneous across countries at different stages of development and it resembles our theoretical predictions. For the OECD sample, the estimated average value of $\alpha_2 + \alpha_3 z_{j,t-1} * f_{j,t-1}$ is of 0.01 while that for Developing countries is of 0.12. The relative larger overall impact of tertiary education on the growth of developing *vis a vis* developed economies is robust to different samplings. The implied average overall effect of tertiary educated workers on growth for countries at the top 25% of the GDP distribution is of 0.04 while that for increasingly lower development stages (countries below the second, third and fourth quartile of GDP in columns (4) to (7)) show increasingly implied impact as of 0.17, 0.35 and 0.86 respectively. This confirms the theoretical results according to which the marginal growth effect of skilled workers is more likely to increase with the distance to the technological frontier.

[21] Notice that when j does not refer to a country but to a *group* of countries, then $z_{j,t-1}$ is computed as the arithmetic mean of the variable z for all the countries k belonging to group j: $z_j = \frac{1}{N_j}\sum_i^{N_j} z_k$ where $k = 1, 2, ..., N_j$.

The econometric specification tests are all passed. The Hansen over-identification tests reports the acceptance of the null of instruments exogeneity for all the specifications proposed in Table 2 suggesting that the model is correctly specified. A similarly result is obtained by the difference-in-Hansen[22]. Interestingly, the recent contribution by Ang et al. (2011), uses a similar empirical approach to ours in order to estimate the impact of different educational level on economic growth while, however, finding somehow different results [23]. It is worth noticing, however, that their Hansen p-values are almost always suspiciously high and close to unity (as of 0.99) and that the authors do not report the instrumental count. As extensively argued in recent empirical literature the use of an excessive number of instruments can cause the p-value of the Hansen test to get close to unity and lead to the uncorrect acceptance the null of instruments exogeneity. We carefully check that the instrumental set in our estimates does not over-fit the endogenous variables as suggested by Roodman (2009a). The AR(2) test, checking that the error terms in the 1st-differenced regression exhibit no 2nd order serial correlation is also passed by all the specifications proposed in Table 2.

As a robustness check of the results we introduce time-invariant institutional controls into the SYSGMM estimators in Table 3 below. As pointed out by Roodman (2009b): "*In system GMM, one can include time-invariant regressors, which would disappear in difference GMM. Asymptotically, this does not affect the coefficient estimates for other regressors because all instruments for the levels equation are assumed to be orthogonal to fixed effects, indeed to all time-invariant variables. In expectation, removing them from the error term does not affect the moments that are the basis for identification*" (p.30). These controls do not appear in the table since they are treated as standard instruments in the SYSGMM estimation and for which one column for each variable is built in the instrument matrix. The results of such a robustness checks are presented in Table 3 where the additional exogenous country-specific institutional variables are the legal origin variables proposed by la Porta et al. (2008), where a country legal origin ranges from English to Socialist.

[TABLE 3 ABOUT HERE]

Results are robust after controlling for legal origin while the differences in the implied total effect of skilled workers on growth slightly increases.

[22]The difference in Hansen test also points to the exogeneity of the instrument subsets with the null hypothesis that the subsets of instruments are exogenous. See Roodman (2009b) for more details on this.

[23]The authors analyze the effect of tertiary education on the growth of countries at different stages of development. However, differently from us they find a positive effect of tertiary education only at middle and higher stages of development. Part of this result, as we argue above, it may be caused by an incorrect specification of the lag structure in their System GMM estimation.

If any, our empirical analysis implicitly supports the scenario according to which 1) decreasing returns to scale apply on both technological activities and 2) the efficiency of skilled workers in innovation is strong enough to give them a strong comparative advantage in innovation activities. We know that - according to our empirical evidence - α_3 is positive and significant for sufficiently rich countries while is negative and significant for developing countries. This is the exact empirical translation of the claim of case 1b of proposition 3 according to which - when returns to technological activities are decreasing and skilled workers' efficiency in innovation is strong enough - the cross derivative $\frac{\partial^2 g}{\partial a \partial S}$ is positive for countries which employ small amount of skilled workers in imitation (i.e. developed countries with DRS) and negative otherwise.

There are several reasons to believe that the scenario is a sensible one. Previous empirical and theoretical literature already argued (and our work adds onto these contributions) that technological activities would encounter diminishing returns in their inputs. See for instance Jones 1995, Kortum (1997) or Sergestrom (1998) for whom a sustained growth in TFP can be only obtained by increasing growth in R&D inputs. Similarly, as for the efficiency of skilled workers in innovation activities, this is actually the same scenario employed by VAM which, however, with DRS has very different implications.

These empirical results and their implications on the theoretical scenarios are confirmed by the empirical analysis using years of schooling as proposed below.

4.4.2 Second specification: years

We now move to a specification where the stock of of skilled and unskilled labor can vary independently by calculating the average years of schooling of tertiary educated labor and that of secondary and primary educated people in each country. We build the indicators for the average number of years of schooling in the two categories as follows:

$$\begin{aligned} YearsT &\equiv pT * nT \\ YearsPS &\equiv pP * nP + pS * nS \end{aligned}$$

where pT, pS and pP are the fractions of population having achieved tertiary, secondary and primary education respectively while nT, nS and nP are the the number of extra years of education which an individual has accumulated over the preceeding level. Empirical results are presented in Table 4 below:

[TABLE 4 ABOUT HERE]

Our estimates suggest again the crucial role of tertiary education for economic growth. This said, the estimates confirm the increasingly importance of tertiary education for countries farther away from the frontier. The calculated total effect of skilled workers (this time proxied by the average number of years of tertiary education in each country) is shown to increase at lower development stages as predicted by our theoretical model. The elasticity of TFP growth associated to an increase in tertiary education in the OECD countries is estimated to be of around 0.01 *vis a vis* 0.05 for the developing countries subsample. Similarly, when we disaggregate the whole sample and compare the 25% top part of the GDP distribution with that of increasingly poorer countries (below the 75%, 50 and 25% of the sample distribution) the estimated total effect of tertiary education goes from 0.01 to 0.37 for the subsample of poorest countries.

The effect of primary and secondary education seems instead to be either non-significant or close to zero. The coefficients associated to the secondary and primary average years of schooling, in fact, do not reach statistical significance in almost all the specification proposed. Similar results are obtained when (in Table 5 below) we control for insititutional quality differences through legal origin time-invariant characteristics.

[TABLE 5 ABOUT HERE]

Our estimates are again robust to a wide array of robustness checks on the quality of the instrumental set (the Hansen and difference-in-Hansen test) as well to the AR(2) test of 2nd order serial correlation in the errors.

5 Conclusions

After coming back from his annual visit to the recently built electric plant close to Iringa (Tanzania), our friend working for the ACRA NGO[24] argued, once again, that all that was going to waste. No locals were still able to cope with the issues related to the plant's normal maintenance and everytime, someone from ACRA would need to go there, fix all kinds of small problems and leave. One skilled man could change this all, but no one was trained enough, leaving everyone else in darkness.

Our study proposes a rational for this view and provides compelling and robust evidence regarding the heterogeneous impact of human capital composition on the growth of countries at different stages of development. In contrast to the earlier theoretical and empirical literature that argued for the "primacy" of high skills at higher stages of development (when countries are closer to the technology frontier and perform technology innovation) our work shows - both theoretically and empirically -

[24] http://www.acra.it/index.php?option=com_content&view=article&id=530&Itemid=477&lang=en&limitstart=1

that tertiary education is especially important for the growth of those countries which are lagging behind and far away from the technology frontier. By contrast, its relative impact on the developed economies appears to be substantially weaker.

We contribute to the existing literature in a number of ways. First, we generalize the theoretical settings proposed by Vandenbussche et al (2006) by assuming non-constant returns to scale in the production of innovation and imitation for which the inputs are skilled and unskilled labor (as opposed to the much more restrictive assumption of CRS).

This generalization is crucial as to unveil a distinctively more complex dynamics linking tertiary education to economic growth of economies found at very different stages of development while leaving the case of CRS as a very special one.

Unlike previous literature, and under less restrictive assumptions, our model shows that the marginal effect of an increase in skilled workers for least developed countries is growth enhancing the more the economies are found farther away from the frontier. Even if so, for those close to the technology frontier, our model provides results which are qualitative similar to those proposed in the literature and analyzed by VAM.

Theoretical results are robust to empirical investigation. For this, we estimated the empirical model proposed by VAM addressing endogeneity between educational variables and economic growth through System GMM estimators for a 10-years intervals dynamic panel 85 countries (developed and developing) in between the year 1960 and 2000. Our empirical results, while confirming VAM's results for the subset of OECD countries, show the increasingly larger effect of tertiary education on the growth of lagging economies as consistently predicted by our theoretical model.

All in all, our results point to the importance of tertiary education in the explanation of growth. Its effect on growth is however heterogeneous across countries found at different stages of development and suggest the relatively more important role of tertiary education for the growth of countries for which, usually, the primacy of lower educational levels has been advokated as main engine of growth and development.

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Appendix

Proof of Proposition 1

Proof. Consider the function $k(s_m, S, U, a) = h(a)U - [S + (\psi - 1)s_m]q(s_m, S)$. A particular value $s_m = s_m^*$ is an equilibrium if $k(s_m^*, S, U, a) = 0$. As for existence, consider that

$$\begin{aligned}(1-\beta-\sigma) &> 0 \cap (1-\theta-\phi) > 0 \Rightarrow \begin{cases} k(0,S,U,a) = h(a)U > 0 \\ k(S,S,U,a) = h(a)U - \infty < 0 \end{cases} \\ (1-\beta-\sigma) &< 0 \cap (1-\theta-\phi) < 0 \Rightarrow \begin{cases} k(0,S,U,a) = h(a)U < 0 \\ k(S,S,U,a) = h(a)U - \infty > 0 \end{cases}\end{aligned}$$

therefore assumption 1 ensures $k(0, S, U, a)$ and $k(S, S, U, a)$ to have opposite sign so that, by continuity of $k(\cdot)$, there is at least one value $s_m = s_m^*$ such that $k(s_m^*, S, U, a) = 0$.

As for uniqueness, compute the partial derivative of $k(s_m, S, U, a)$ with respect to s_m to obtain

$$\frac{\partial k(s_m, S, U, a)}{\partial s_m} = -\frac{q(s_m, S)}{(\sigma - \phi)x(1-x)} f(x)$$

so that $k(s_m, S, U, a)$ is monotone in s_m when $f(x)$ does not change sign for $x \in [0, 1]$. Now consider that

$$\begin{aligned} f(0) &= (1-\beta-\sigma) \\ f(1) &= \psi(1-\theta-\phi) \end{aligned}$$

so that

$$\left[\mathbf{sign}f\left(0\right)=\mathbf{sign}f\left(1\right)\right]\Leftrightarrow\left[\mathbf{sign}\left(1-\beta-\sigma\right)=\mathbf{sign}\left(1-\theta-\phi\right)\right]$$

Therefore $k\left(s_m,S,U,a\right)$ is monotone in s_m (and then the equilibrium is unique) when $\mathbf{sign}\left(1-\beta-\sigma\right)=\mathbf{sign}\left(1-\theta-\phi\right)=\mathbf{sign}_{x\in(0,1)}f\left(x\right)$, which is exactly what assumption 1 says. ■

Proof of Proposition 3

We know from (19) we have

$$\frac{\partial^2 g}{\partial a\partial S}<0\Leftrightarrow\underbrace{\phi}_{\text{VAM effect}}<\underbrace{\left[1+\left(\psi-1\right)x^*\right]\frac{z\left(x^*\right)}{f\left(x^*\right)}}_{\text{SD effect}}$$

That implies

$$\frac{\partial^2 g}{\partial a\partial S}<0\Leftrightarrow\begin{cases}\phi f\left(x^*\right)<\left[1+\left(\psi-1\right)x^*\right]z\left(x^*\right) & \text{when } f\left(x^*\right)>0\\ \phi f\left(x^*\right)>\left[1+\left(\psi-1\right)x^*\right]z\left(x^*\right) & \text{when } f\left(x^*\right)<0\end{cases}$$

By Assumption 1 we have that $\mathbf{sign}\left(1-\beta-\sigma\right)=\mathbf{sign}\left(1-\theta-\phi\right)=\mathbf{sign}_{x\in(0,1)}f\left(x^*\right)$ so that

$$\frac{\partial^2 g}{\partial a\partial S}<0\Leftrightarrow\begin{cases}\phi f\left(x^*\right)<\left[1+\left(\psi-1\right)x^*\right]z\left(x^*\right) & \text{when } \left(\beta+\sigma<1\right)\cap\left(\theta+\phi<1\right)\\ \phi f\left(x^*\right)>\left[1+\left(\psi-1\right)x^*\right]z\left(x^*\right) & \text{when } \left(\beta+\sigma>1\right)\cap\left(\theta+\phi>1\right)\end{cases}$$

by using (2.3.1) and (18) to substitute for the expressions of $f\left(x^*\right)$ and $z\left(x^*\right)$, and doing some algebra provided that $x^*\in(0,1)$ and $\theta<1$, we find

$$\frac{\partial^2 g}{\partial a\partial S}<0\Leftrightarrow\begin{cases}\left(\psi-1\right)x^*>-\frac{1-\theta-\phi\psi}{(1-\theta)} & \text{when } \left(\beta+\sigma<1\right)\cap\left(\theta+\phi<1\right)\\ \left(\psi-1\right)x^*<-\frac{1-\theta-\phi\psi}{(1-\theta)} & \text{when } \left(\beta+\sigma>1\right)\cap\left(\theta+\phi>1\right)\end{cases}$$

We should then distinguish among two other different subcases, according to whether ψ is larger or smaller than 1. Solving for x we find

$$\frac{\partial^2 g}{\partial a\partial S}<0\Leftrightarrow\begin{cases}\begin{cases}x^*>\hat{x}^* \text{ when } \psi>1\\ x^*<\hat{x}^* \text{ when } \psi<1\end{cases} & \text{when } \left(\beta+\sigma<1\right)\cap\left(\theta+\phi<1\right)\\ \begin{cases}x^*<\hat{x}^* \text{ when } \psi>1\\ x^*>\hat{x}^* \text{ when } \psi<1\end{cases} & \text{when } \left(\beta+\sigma>1\right)\cap\left(\theta+\phi>1\right)\end{cases}$$

where $\hat{x}^*=\frac{1-\theta-\psi\phi}{1-\theta-\psi(1-\theta)}$. Now notice that

$$\begin{aligned}\left(\theta+\phi<1\right)\cap\left(\psi<1\right) &\Rightarrow \hat{x}^*>1\\ \left(\theta+\phi>1\right)\cap\left(\psi>1\right) &\Rightarrow \hat{x}^*>1\end{aligned}$$

But since $x^* \in (0,1)$, it must be always true that $\frac{\partial^2 g}{\partial a \partial S} < 0$ when $[(\beta+\sigma<1)\cap(\theta+\phi<1)] \cap (\psi<1)$ *and* when $[(\beta+\sigma>1)\cap(\theta+\phi>1)] \cap (\psi>1)$. Hence

$$\frac{\partial^2 g}{\partial a \partial S} < 0 \Leftrightarrow \left\{ \begin{array}{ll} \left\{ \begin{array}{c} x^* > \hat{x}^* \text{ when } \psi > 1 \\ \forall x \in (0,1) \text{ when } \psi < 1 \end{array} \right. & \text{when } (\beta+\sigma<1)\cap(\theta+\phi<1) \\ \left\{ \begin{array}{c} \forall x \in (0,1) \text{ when } \psi > 1 \\ x^* > \hat{x}^* \text{ when } \psi < 1 \end{array} \right. & \text{when } (\beta+\sigma>1)\cap(\theta+\phi>1) \end{array} \right.$$

now notice that can $\hat{x}^*$ might also be negative. If this is the case, then $x^* > \hat{x}^*$ is always true for any $x^* \in (0,1)$ $\hat{x}^* = \frac{1-\theta-\psi\phi}{(1-\theta)(1-\psi)}$ is negative when the numerator and denominator have opposite signs. That happens when

$$\begin{aligned} \psi &\in \left(1, \frac{1-\theta}{\phi}\right) \text{ if } (\beta+\sigma<1)\cap(\theta+\phi<1) \\ \psi &\in \left(\frac{1-\theta}{\phi}, 1\right) \text{ if } (\beta+\sigma>1)\cap(\theta+\phi>1) \end{aligned}$$

so

$$\frac{\partial^2 g}{\partial a \partial S} < 0 \Leftrightarrow \left\{ \begin{array}{ll} \left\{ \begin{array}{c} x^* > \hat{x}^* \text{ when } \psi > \frac{1-\theta}{\phi} \\ \forall x \in (0,1) \text{ when } \psi < \frac{1-\theta}{\phi} \end{array} \right. & \text{when } (\beta+\sigma<1)\cap(\theta+\phi<1) \\ \left\{ \begin{array}{c} \forall x \in (0,1) \text{ when } \psi > \frac{1-\theta}{\phi} \\ x^* > \hat{x}^* \text{ when } \psi < \frac{1-\theta}{\phi} \end{array} \right. & \text{when } (\beta+\sigma>1)\cap(\theta+\phi>1) \end{array} \right.$$

Figures and Tables

Figure 1: The two effects with CRS $(\phi, \theta, \sigma, \beta) = (0.3, 0.7, 0.4, 0.6))$

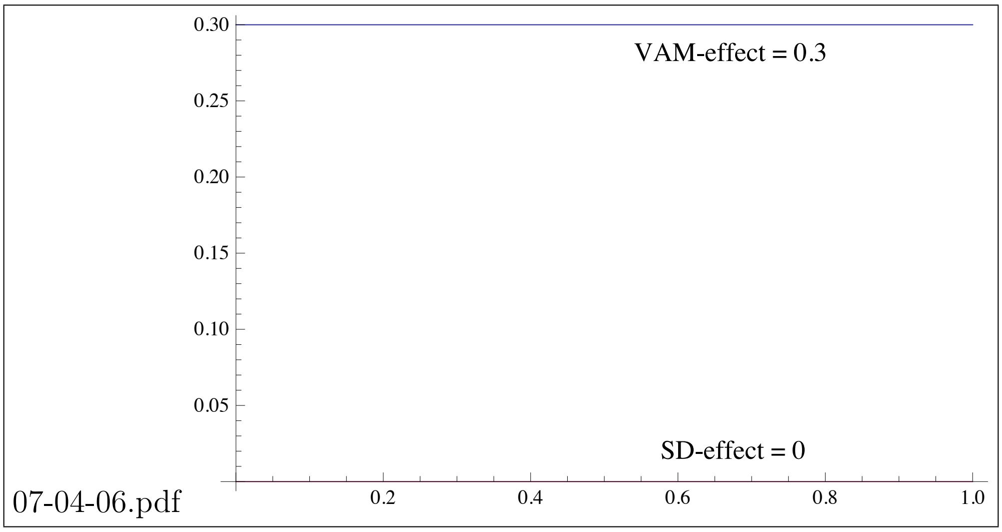

Figure 2: The two effects with a slight reduction of ϕ and σ: $(\phi, \theta, \sigma, \beta) = (0.29, 0.7, 0.39, 0.6)$

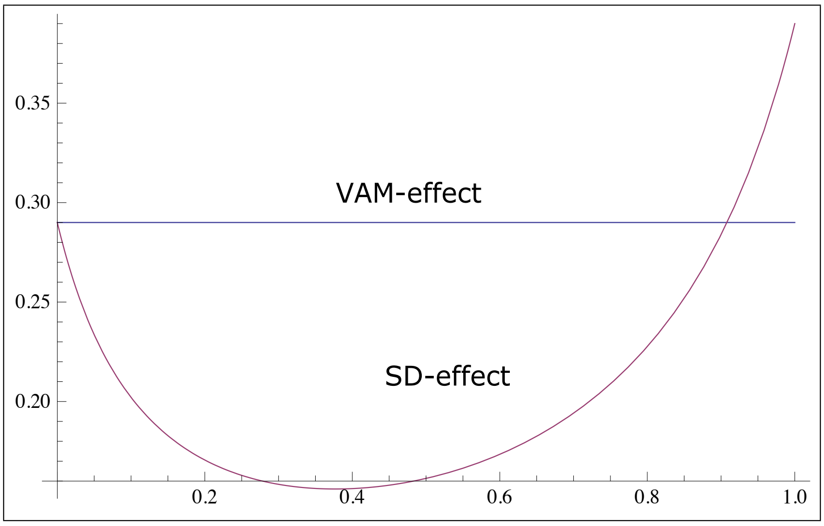

Figure 3: Strong comparative advantage for skilled workers in innovation: $(\phi, \theta, \sigma, \beta) = (0.2, 0.7, 0.3, 0.4)$ $\psi = 2.63 > \frac{1-\theta}{\phi} = 1.5 > 1$

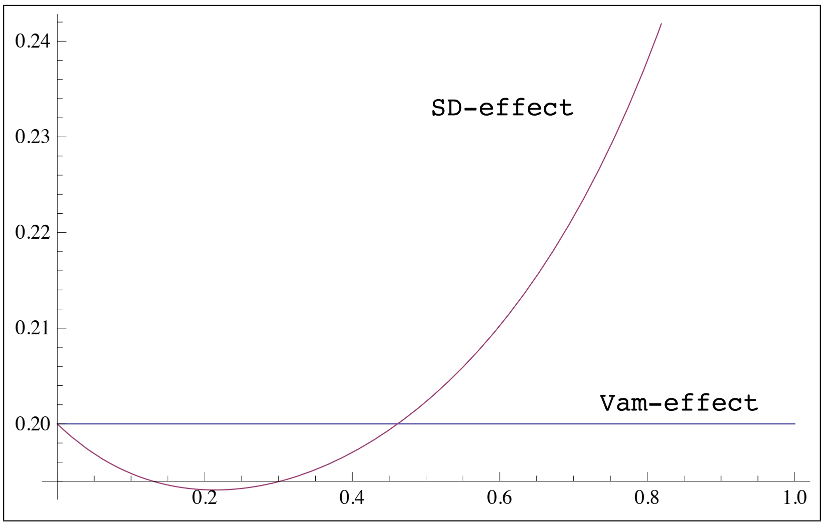

Figure 4: Weak comparative advantage of skilled workers in innovation but still skilled workers more efficient in innovation than in imitation: $(\phi, \theta, \sigma, \beta) = (0.2, 0.6, 0.3, 0.5)\,, \psi = 1.8 \in (1, 2)$

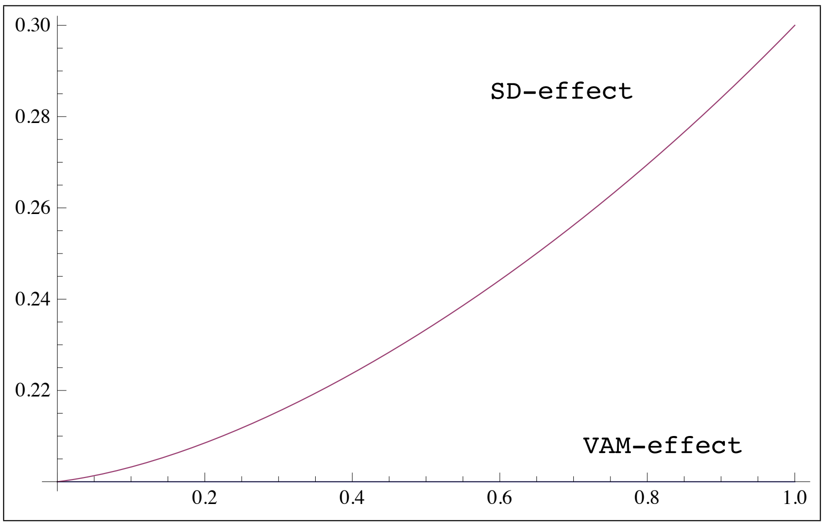

Figure 5: Weak comparative advantage of skilled workers in innovation and skilled workers more efficient in imitation than innovation: $(\phi, \theta, \sigma, \beta) = (0.2, 0.4, 0.3, 0.5), \psi = 1.2 \in (1, 3)$

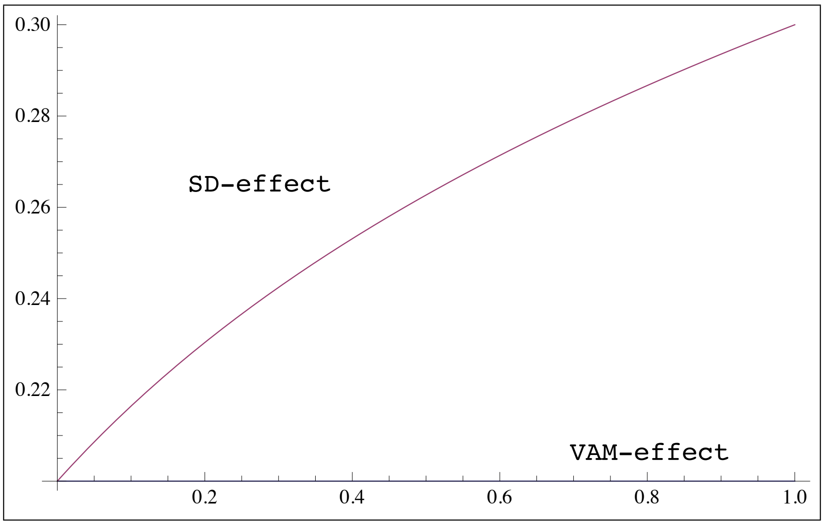

Figure 6: Same as above but returns very decreasing: $(\phi, \theta, \sigma, \beta) = (0.1, 0.3, 0.2, 0.4), \psi = 1.5 \in (1, 7)$

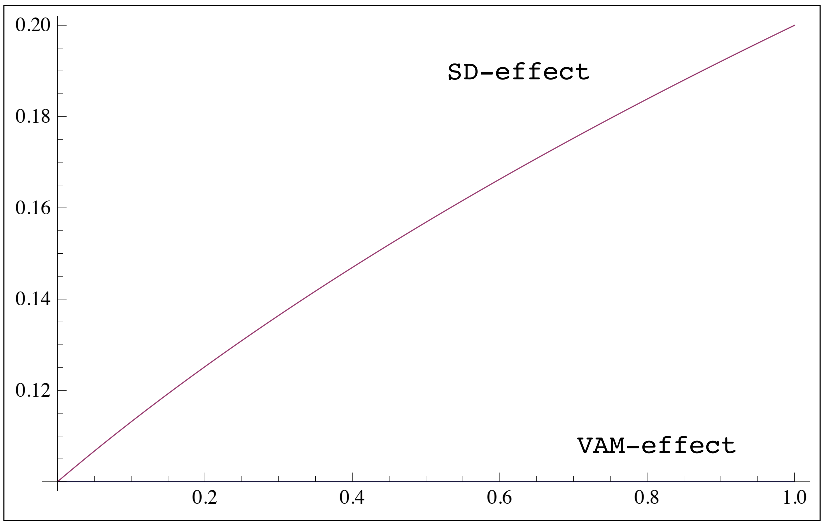

TABLE 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
All Countries					
TFP gap	401	0.34	0.27	0.00	1.00
Fraction Tertiary	401	0.06	0.07	0.00	0.35
Fraction Secondary	401	0.12	0.13	0.00	0.56
Fraction Primary	401	0.24	0.19	0.01	0.85
Mean Years Tertiary	401	0.24	0.28	0.00	1.40
Mean Years Secondary +Primary	401	4.39	2.90	0.08	11.01
Mean Years Secondary	401	1.45	1.13	0.04	5.13
Mean Years Primary	401	0.75	0.80	0.00	3.36
OECD Countries					
TFP gap	104	0.69	0.17	0.21	1.00
Fraction Tertiary	104	0.13	0.08	0.01	0.35
Fraction Secondary	104	0.25	0.15	0.01	0.56
Fraction Primary	104	0.39	0.22	0.03	0.85
Mean Years Tertiary	104	0.51	0.32	0.04	1.40
Mean Years Secondary +Primary	104	7.68	1.49	2.75	11.01
Mean Years Secondary	104	2.32	1.34	0.18	5.13
Mean Years Primary	104	1.53	0.90	0.08	3.36
Developing Countries					
TFP gap	297	0.22	0.17	0.00	0.90
Fraction Tertiary	297	0.04	0.04	0.00	0.32
Fraction Secondary	297	0.08	0.09	0.00	0.48
Fraction Primary	297	0.19	0.15	0.01	0.76
Mean Years Tertiary	297	0.15	0.18	0.00	1.30
Mean Years Secondary +Primary	297	3.24	2.33	0.08	9.93
Mean Years Secondary	297	1.15	0.87	0.04	4.54
Mean Years Primary	297	0.47	0.54	0.00	2.89

Table 2

DEP VAR: TFP GROWTH	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	OECD	Developing	>25%	<75%	<50%	<25%
Proximity	-0.009	-0.064***	-0.004	-0.076***	-0.001	0.010	0.008
	[0.006]	[0.019]	[0.006]	[0.019]	[0.006]	[0.009]	[0.013]
Tertiary Fraction	0.136*	0.109*	-0.327*	0.184**	-0.492***	-1.717***	-4.125*
	[0.076]	[0.056]	[0.192]	[0.072]	[0.182]	[0.584]	[2.241]
Proximity*Tertiary Fraction	0.036	0.235*	-0.238*	0.298**	-0.335**	-0.886***	-1.761**
	[0.085]	[0.123]	[0.136]	[0.121]	[0.136]	[0.259]	[0.797]
Constant	-0.011	-0.003	-0.003	-0.021	0.002	0.027	0.025
	[0.014]	[0.010]	[0.015]	[0.014]	[0.014]	[0.026]	[0.042]
Observations	308	83	225	100	208	144	86
Number of ids	85	21	64	26	59	41	24
Hansen Stat. P-value	0.551	0.145	0.122	0.559	0.232	0.233	0.554
Hansen Stat.	19.53	9.545	28.66	19.41	25.36	25.34	19.48
H-test excluding group	11.81	0.382	0.258	0.403	0.399	0.574	0.383
p-value	0.461	0.09	0.124	0.652	0.174	0.095	0.672
Number of Instruments	28	13	28	28	28	28	28
AR(2) P-Value	0.521	0.699	0.804	0.621	0.502	0.521	0.284
AR(2) Stat	0.642	0.387	0.248	-0.494	0.671	0.642	1.072
Implied total effect of S	0.08	0.01	0.12	0.04	0.17	0.35	0.86

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.10

Table 3

DEP VAR: TFP GROWTH	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	OECD	Developing	>25%	<75%	<50%	<25%
Proximity	-0.004	-0.067***	-0.003	-0.071***	0.001	0.010	0.029*
	[0.006]	[0.016]	[0.007]	[0.020]	[0.006]	[0.007]	[0.015]
Tertiary Fraction	0.066	0.096*	-0.379*	0.178**	-0.594***	-1.781***	-6.509**
	[0.076]	[0.052]	[0.213]	[0.072]	[0.196]	[0.537]	[2.407]
Proximity*Tertiary Fraction	-0.041	0.247**	-0.321**	0.294**	-0.411***	-0.926***	-2.575***
	[0.086]	[0.107]	[0.142]	[0.135]	[0.143]	[0.253]	[0.849]
Constant	-0.003	-0.001	-0.004	-0.019	0.006	0.026	0.088*
	[0.013]	[0.010]	[0.016]	[0.014]	[0.014]	[0.021]	[0.043]
Observations	308	83	225	100	208	144	86
Number of ids	85	21	64	26	59	41	24
Hansen Stat. P-value	0.0338	0.376	0.0762	0.666	0.170	0.267	0.513
Hansen Stat.	35.56	9.696	34.50	13.10	29.32	26.75	7.222
H-test excluding group	0.176	0.283	0.048	0.429	0.077	0.53	0.402
p-value	0.035	0.519	0.407	0.731	0.61	0.129	0.55
H-test excluding group (IV instruments)	0.417	0.145	0.12	0.406	0.245	0.195	0.417
p-value	0.002	0.985	0.125	0.964	0.118	0.803	0.558
Number of Instruments	29	16	31	23	30	30	15
AR(2) P-Value	0.509	0.793	0.814	0.733	0.487	0.504	0.278
AR(2) Stat	0.660	0.262	0.235	-0.342	0.694	0.668	1.085
Implied total effect of S	0.13	0.00	0.23	0.04	0.22	0.38	0.77

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.10

Table 4

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEP VAR: TFP GROWTH							
	All	OECD	Developing	>25%	<75%	<50%	<25%
Proximity	-0.013	-0.077	0.028	-0.026	0.046	0.041	0.001
	[0.026]	[0.060]	[0.030]	[0.057]	[0.032]	[0.029]	[0.019]
L.yearsT	0.042*	0.042*	-0.149*	0.038*	-0.211**	-0.360**	-0.512
	[0.022]	[0.022]	[0.085]	[0.019]	[0.088]	[0.154]	[0.612]
L.yearsPS	-0.000	0.004	-0.014	-0.001	-0.024*	-0.024	-0.019
	[0.007]	[0.005]	[0.012]	[0.006]	[0.014]	[0.016]	[0.012]
ProximityT	0.005	0.086**	-0.103*	0.056*	-0.149**	-0.229***	-0.312
	[0.023]	[0.035]	[0.057]	[0.030]	[0.068]	[0.078]	[0.217]
ProximityPS	0.001	-0.001	-0.004	-0.005	-0.007*	-0.006	-0.002
	[0.003]	[0.006]	[0.003]	[0.006]	[0.004]	[0.004]	[0.002]
Constant	-0.014	-0.040	0.082	-0.008	0.129	0.122	0.024
	[0.057]	[0.051]	[0.080]	[0.051]	[0.086]	[0.089]	[0.060]
Observations	308	83	225	100	208	144	86
Number of ids	85	21	64	26	59	41	24
Hansen Stat. P-value	0.181	0.908	0.177	0.984	0.351	0.918	0.998
Hansen Stat.	44.67	13.82	44.81	21.02	39.70	25.73	17.13
H-test excluding group	0.566	0.661	0.275	0.828	0.249	0.756	0.852
p-value	0.059	0.886	0.199	0.989	0.554	0.898	0.99
Number of Instruments	46	31	46	46	46	46	46
AR(2) P-Value	0.523	0.834	0.479	0.572	0.326	0.495	0.257
AR(2) Stat	0.639	-0.209	0.707	-0.566	0.982	0.683	1.133
Implied total effect of S	0.03	0.01	0.05	0.01	0.08	0.17	0.37
Implied total effect of U	0.00	0.00	-0.01	0.00	-0.01	-0.01	-0.01

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.10

Table 5

DEP VAR: TFP GROWTH	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	OECD	Developing	>25%	<75%	<50%	<25%
Proximity	-0.008	-0.023	0.002	0.004	0.013	0.019	-0.005
	[0.011]	[0.049]	[0.013]	[0.060]	[0.016]	[0.020]	[0.020]
L.yearsT	0.031*	0.026	-0.092	0.031	-0.146**	-0.300**	-0.460
	[0.016]	[0.017]	[0.058]	[0.018]	[0.055]	[0.141]	[0.627]
L.yearsPS	-0.000	-0.001	-0.004	-0.003	-0.012	-0.016	-0.017
	[0.004]	[0.004]	[0.007]	[0.006]	[0.009]	[0.013]	[0.012]
ProximityT	-0.007	0.061**	-0.086**	0.043	-0.119**	-0.206***	-0.293
	[0.021]	[0.027]	[0.043]	[0.027]	[0.051]	[0.069]	[0.221]
ProximityPS	0.000	-0.006	-0.001	-0.008	-0.003	-0.003	-0.002
	[0.001]	[0.005]	[0.001]	[0.007]	[0.002]	[0.003]	[0.002]
Constant	-0.009	0.006	0.011	0.013	0.044	0.061	0.007
	[0.026]	[0.043]	[0.038]	[0.054]	[0.045]	[0.061]	[0.062]
Observations	308	83	225	100	208	144	86
Number of ids	85	21	64	26	59	41	24
Hansen Stat. P-value	0.0912	0.905	0.239	0.989	0.285	0.810	0.999
Hansen Stat.	53.51	16.33	45.96	23.12	43.53	31.17	16.85
H-test excluding group	0.383	0.595	0.184	0.958	0.308	0.719	0.915
p-value	0.038	0.924	0.465	0.917	0.343	0.711	0.99
H-test excluding group (IV instruments)	0.199	0.889	0.169	0.987	0.274	0.697	0.998
p-value	0.05	0.575	0.839	0.633	0.396	0.99	0.99
Number of Instruments	50	34	49	50	48	48	48
AR(2) P-Value	0.544	0.975	0.742	0.594	0.439	0.500	0.235
AR(2) Stat	0.606	0.0310	0.329	-0.533	0.774	0.674	1.187
Implied total effect of S	0.04	0.00	0.07	0.01	0.09	0.18	0.37
Implied total effect of U	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.10

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