Economic Growth and the High Skilled: the Role of Scale Effects and of Barriers to Entry into the High Tech

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Empirical evidence on the relationship between economic growth, the technology structure and the skill structure seems to be inconsistent: the weak relationship between economic growth and the skill structure is conventionally interpreted as pointing to the non-existence of scale effects, while the technology structure-skill structure relationship indicates that there are. We show that there is no inconsistency between the two facts, if we consider a further dynamic effect associated to directed technical change: the existence of differential barriers to entry in high-tech and low-tech sectors. To prove this, we extend a benchmark directed technical change model by incorporating both horizontal and vertical R&D and estimate and calibrate it with cross-country European data. This framework allows us to derive interesting policy implications, namely that the effects of education policy on economic growth may be effectively leveraged by industrial policy aiming to reduce barriers to entry into the high-tech sectors.

Keywords: growth, high skilled, high tech, scale effects, directed technical change

JEL Classification: O41, O31

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1. Introduction

European institutions have established the increase in the proportion of high-skilled workers as a pillar of the European growth strategy. One of the "headline targets" regarding the so called "Europe 2020 Strategy" is that, by 2020, "the share of early school leavers should be under 10% and at least 40% of the younger generation (30-34 years old) should have a tertiary degree." (European Commission, 2010, p. 3).[1] That policy stance hinges on the view that the skill structure plays a key role in fostering economic growth, namely because there is evidence on the absolute productivity advantage of high- over low-skilled labour. However, the cross-country data for Europe shows that there is a weak (although maybe slightly positive) elasticity of the economic growth rate with respect to the skill structure. This weak relationship can be observed in the third panel in Figure 1, where we measure the skill structure by the ratio of high- to low-skilled workers, with data for the EU-27 plus the EFTA countries.[2] The data also suggests that the level of low-skilled labour tends to be uncorrelated to the share of high-skilled labour across countries (Figure 2). Therefore, although the ratio of high- to low-skilled workers is an intensity variable, it tends to capture scale effects of high-skilled labour on growth. Hence, the aforementioned weak empirical relationship may just be a consequence of the lack of significant scale effects on growth from the cross-country perspective, in line with what has also been documented with respect to time-series data (e.g., Jones, 1995).

The cross-country data relating the technology structure, measured either as production or as the number of firms in high- vis-à-vis low-tech sectors,[3] to the skill structure casts doubts on the non-existence of scale effects related to high-skilled labour. In the first two panels in Figure 1, we present data relating the technology structure and the skill structure. Although the elasticities of the technology-structure variables with respect to the proportion of high-skilled labour are positive but small, a more detailed quantitative analysis shows that they are still positive even when one considers a two standard-error band. That is not the case for the associated elasticity of the economic growth rate (see the details in Table 5, Appendix A). Combined with the empirical evi-

[1]In 2010, the share of early school leavers was 14.1% and the share of 30-34 years old with a tertiary degree or equivalent was 33.5% for the average of the European Union (27 countries). The data is available at `http://epp.eurostat.ec.europa.eu`

[2]This data on the skill structure pertains to manufacturing employment (see Appendix A), since, as explained below, we also wish to confront the skill structure with the (manufacturing) technology structure. However, a similar weak relationship arises if one considers the skill structure of total employment. More generally, the empirical growth literature presents disparate results regarding the strength of the relationship between human capital and economic growth. The weak relationship found in many cases has been justified on the grounds of the existence of, e.g., a pervasive mismatch between skills and jobs that translates into a low impact of human capital on growth at the aggregate level, low education quality such that increasing years of schooling do not correspond to a larger human capital stock, or errors in the measurement of human capital, both conceptually and empirically (see, e.g., Backus, Kehoe, and Kehoe, 1992; Benhabib and Spiegel, 1994; Pritchett, 2001; de la Fuente and Doménech, 2006; Cohen and Soto, 2007). In contrast, and as shown below, our approach focuses on the composition of human capital (high- versus low-skilled workers) and on explanations featuring the technical characteristics of the sectors that demand high-skilled labour.

[3]Henceforth, we will also refer to these variables as "relative production" and "relative number of firms".

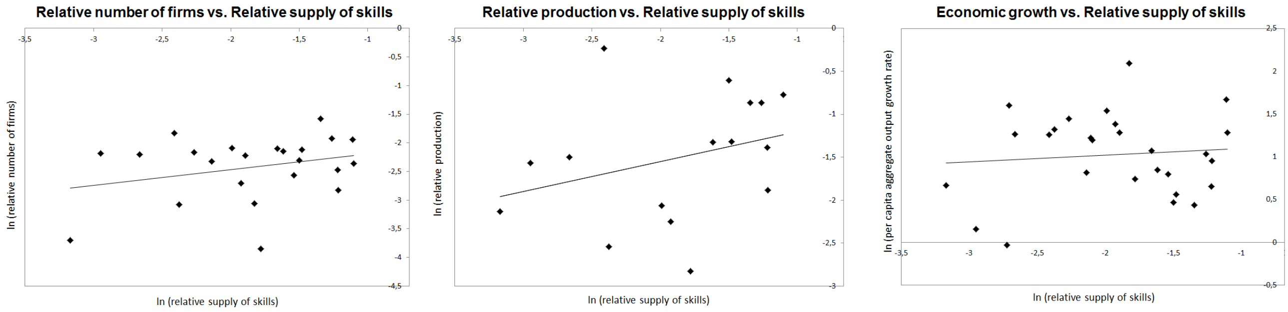

Figure 1: The technology-structure variables (i.e., the relative number of firms and relative production in high-tech sectors) and the per capita GDP growth rate vis-à-vis the relative supply of skills (i.e., the ratio of high- to low- skilled labour) for a cross-section of European countries, 1995-2007 average. The straight line that appears in each panel is an OLS regression line (Appendix A gives details on the data; the regressions appear in Table 5 in that appendix).

dence that high-tech sectors are more intensive in high-skilled labour than the low-tech sectors,[4] the observed elasticities suggest the existence of significant scale effects related to high-skilled labour.

[Figure 1 goes about here]

[Figure 2 goes about here]

Are those two types of evidence concerning the existence of scale effects contradictory? Or is there another factor, relating to the changes in the skill structure, which partially offsets the effect of the increase in the proportion of high-skilled labour on economic growth but not on the technology structure of the economy?

In this paper, we provide an answer by setting up (and empirically validating by a cross-country data set) an extension of a benchmark directed technical change endogenous growth model. We show that, if there are high barriers to entry in the high-tech sector (which employs the high-skilled labour) relative to the low-tech sector, we may have simultaneously a weak relationship between economic growth and the skill structure and a positive relationship between the technology structure and the skill structure. The existence of both scale effects and high relative barriers to entry is then confirmed by the obtained (indirect) estimates of key structural parameters of the model. Therefore, a low elasticity of economic growth with respect to the skill structure is not a proof of the non-existence of scale effects, but simply a consequence of the incomplete specification of

[4] According to the data for the average of the European Union (27 countries, 2007), 30.9% of the employment in the high-tech manufacturing sectors is high skilled ("college graduates"), against 12.1% of the employment in the low-tech sectors (see Appendix A for further details on the data).

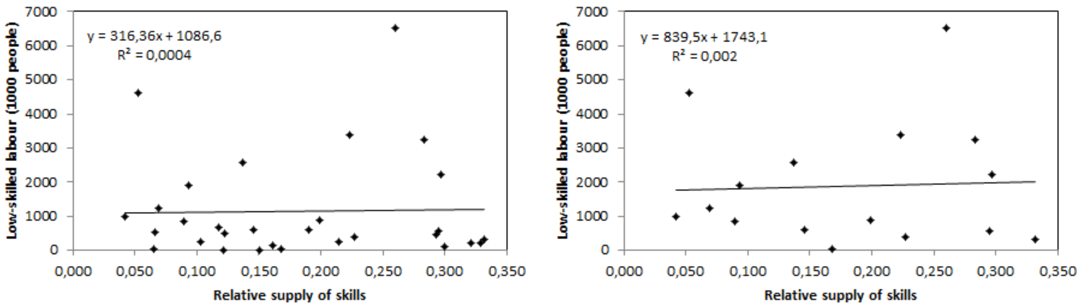

Figure 2: The level of low-skilled labour vis-à-vis the relative supply of skills, in a 30-country (left panel) and in a 16-country (right panel) sample, 1995-2007 average. The sample of 30 countries corresponds to the EU-27 plus the EFTA countries; the sample of 16 countries corresponds to the countries with available data both on relative production and on the relative number of firms. The straight line is an OLS regression line.

the dynamic factors involved in the relationship between directed technical change and endogenous growth.

Following the benchmark model (e.g., Acemoglu and Zilibotti, 2001), our model features final-goods that can be produced with either one of two alternative technologies, high-tech or low-tech, characterised by using either high- or low-skilled labour-specific intermediate goods. R&D can thus be directed to either type of intermediate goods. However, instead of considering only one type of R&D, we consider both vertical and horizontal R&D to allow for an exact identification of the key structural parameters of the model, as explained in more detail below. We call "sector" herein to the group of firms producing the same type of labour-specific intermediate goods. Since the data shows that the high-tech sectors are more intensive in high-skilled labour than the low-tech sectors (see fn. 4), we consider the high- and low-skilled labour-specific intermediate-good sectors in the model as the theoretical counterpart of the high- and low-tech sectors (e.g., Cozzi and Impullitti, 2010).

Justified by the empirical evidence already reported, a crucial ingredient of our setup is the a priori existence of scale effects related to the skill structure.[5] As usual in the R&D-driven growth literature, there are positive gross scale effects connected with the size of profits that accrue to the R&D successful firm: a larger market, measured by aggregate labour, expands profits and, thus, the incentives to allocate resources to R&D. However, an increase in market scale may also dilute the impact of R&D outlays on innovation outcomes, due to a number of costs and rental protection actions by incumbents related to market size. These (potential) market complexity costs may partially or totally offset, or even revert, the direct benefits of scale on the profits that accrue to the R&D successful

[5] Other studies that also allow for the a priori existence of scale effects of human capital on growth are, e.g., Backus, Kehoe, and Kehoe (1992), Benhabib and Spiegel (1994), Hanushek and Kimko (2000), Vandenbussche, Aghion, and Meghir (2006), and Hanushek and Woessmann (2012).

firms.[6] Given the impact of R&D on production, number of firms and growth, this setting then allows for flexible (net) scale effects of the skill structure on both the technology structure and economic growth. Therefore, we show that the two types of scale effects potentially observed in the cross-country data, associated to the technology structure and to economic growth, are two stances of the same underlying analytical mechanism.

The skill structure is assumed to be exogenous, as in the literature of directed technical change, in order to isolate the impact of the observed shifts in the proportion of high-skilled workers through the technological-knowledge bias mechanism (e.g., Acemoglu and Zilibotti, 2001; Acemoglu, 2003). In principle, causality can run both ways: an increase in the share of high-skilled labour may imply higher economic growth, but also the latter may increase enrollment rates and thereby the share of the high skilled. However, we only address the first type of causation, since it tends to take place within a shorter time scale (a feature that is particularly relevant given the relatively short time period covered by our dataset). Indeed, some authors emphasise the cross-country relationship between the share of high-skilled labour and 'exogenous' institutional factors (see, e.g., Jones and Romer, 2010), and particularly strong evidence on causality from human capital to growth relates to the importance of fundamental economic institutions using identification through historical factors (e.g., Acemoglu, Johnson, and Robinson, 2005).

We solve the model for the balanced-growth path (BGP), and show analytically that it provides measurable relationships between the skill structure and the long run economic growth rate and technology structure variables. We prove that there are several (indeed infinite) combinations of positive scale effects and relative barriers to entry that are consistent with a very low elasticity of economic growth with respect to the skill structure. Given the non-linear and sensitive relationship between scale effects and barriers to entry, we use the available cross-country European data for the technology structure and the skill structure to obtain empirical estimates of both factors, scale effects and barriers to entry. From the estimation of the BGP relationship between the technology-structure variables and the skill structure and the indirect estimation of key structural parameters of the model, we learn that: (i) (net) scale effects from high-skilled labour are positive (i.e., market complexity costs only partially offset the benefits of market scale on profits) and (ii) barriers to entry in the high-tech sector are large relative to the low-tech sector.[7] The first effect determines the (positive) *elasticity* of the technology structure with respect to the skill structure, while the second determines the *level* of the

[6] As a reaction to Jones (1995), a generation of endogenous-growth models introduced simultaneous vertical and horizontal R&D as a modelling strategy to remove scale effects while preserving the result that long-run economic growth has policy-sensitive economic determinants, i.e., the fully endogenous-growth result (e.g., Young, 1998; Dinopoulos and Thompson, 1998; Peretto, 1998; Howitt, 1999). In contrast, following, e.g., Barro and Sala-i-Martin (2004), our parametric approach to the modelling of scale effects allows us to remove scale effects and still get the fully endogenous-growth result independently of the consideration of simultaneous vertical and horizontal R&D. As stated earlier, we include the two types of R&D in our model as an identification strategy of key structural parameters.

[7] The literature on the economics of innovation sheds some light on why entry costs may be, in practice, generally larger in the high- than in the low-tech sectors. Firms in the high-tech sectors tend to face relatively thin markets, less mature and changing more rapidly than in the low-tech sectors, with the appropriation of technology through Intellectual Property Rights (IPR) being more aggressively pursued; they also rely more heavily on formal planning activities, on customer support and on superior

technology-structure variables.

Then, we use these estimates of the structural parameters to calibrate our model and, together with the data on the skill structure, compute the predicted value for each country's economic growth rate. Given the latter, we estimate the cross-country elasticity of *predicted* economic growth regarding the observed skill structure and compare it with the estimated elasticity of *observed* economic growth. From this simulation of the relationship between economic growth and the skill structure, we learn that both factors, scale effects and relative barriers to entry, help to explain the observed low growth-skill elasticity: the two factors impact the elasticity with opposite signs, such that the negative effect of relative barriers to entry tends to offset the positive impact of scale effects from high-skilled labour. This stems from the result that the larger the barriers to entry in the high- versus low-tech sector, the smaller the impact of the proportion of high-skilled labour on a country's growth rate. This countervailing force occurs because the high-tech sector is the main employer of high-skilled labour.

We check the robustness of our results by going through a large number of different scenarios for the values of the key structural parameters, namely by considering the extreme bounds of the confidence intervals of the estimates of the structural parameters and using either the 1995-2007 average or the initial (1995) value for the skill-structure regressor (to account for a possible simultaneity bias issue). The results vary very little across scenarios. We also extend the model to account for possible effects of international linkages, proxied by trade openness, on R&D performance. The results are also unaffected by this extension. The reason seems to be that the impact of trade openness tends to be homogeneous across high and low-tech sectors, thus not affecting the technology structure of a given country, on average.

Finally, a counterfactual policy exercise is conducted. We quantify the effect of a reduction in relative barriers to entry on the elasticity of the growth rate with respect to the skill structure in our cross-section of European countries. In order to get a significant positive elasticity, these barriers must be reduced between 75.6% and 88.3% for the scenarios considered. In all cases, barriers to entry must become smaller in the high- than in the low-tech sector. The reduction in relative barriers to entry is effective in increasing the growth-skill elasticity because growth in countries with a larger proportion of high-skilled workers benefits more from that reduction: e.g., considering the countries with the smallest and the largest proportion of high-skilled labour in our sample, Portugal and Finland, the relative increase in the economic growth rate due to a given reduction in barriers to entry is, in the latter, two to four times the relative increase in the former. This is, of course, the counterpart of the negative relationship between the size of relative barriers to entry and the impact of the skill structure on a country's growth rate mentioned earlier.

An interesting policy implication is then derived: education policy (e.g., incentives for households to accumulate skills via improvement of the educational attainment level) and

product warranties, and face environments where regulation more frequently plays a structuring role (e.g., the biotech industry) (e.g., Covin, Slevin, and Covin, 1990; Qian and Li, 2003; Tunzelmann and Acha, 2005).

industrial policy aiming to reduce barriers to entry in the high-tech sector have effective complementary effects on economic growth. However, our results also suggest that the effectiveness of the barriers-reducing policy is negatively related to the initial level of those barriers, which implies that barriers must be brought down to considerable low levels before they start producing significant results.

The implications of barriers to entry for the aggregate productivity level and growth have not received much attention in the literature. As regards the empirical literature, recent examples are Nicoletti and Scarpetta (2003) and Aghion, Blundell, Griffith, Howitt, and Prantl (2009) on growth, and Barseghyan (2008) on productivity levels. On the theoretical front, we single out Poschke (2010) and Murao and Nirei (2013), who study the effect of entry costs on, respectively, the level and growth of aggregate productivity. Our paper is closer to Murao and Nirei (2013) in that the authors deal with entry costs in an endogenous growth setting and focus on their impact on the aggregate growth rate. Also, both papers seek to structurally estimate the entry cost and conduct counterfactual experiments to quantify the effect of reducing entry barriers. However, to the best of our knowledge, our paper is the first in the growth literature to distinguish between high- and low-tech sector entry costs and analyse their interaction with the economy's skill structure.

Our paper also relates to Vandenbussche, Aghion, and Meghir (2006), as these authors also focus on the growth effects of the share of high-skilled labour in the economy. By means of an endogenous growth model of imitation and innovation under full scale effects, they show that the closer a country is to the technological frontier, the larger the impact of high-skilled labour on growth. They then test this prediction for a panel dataset covering 19 OECD countries. We add to this strand of the literature by exploring the role of differential barriers to entry as regards the impact of high-skilled labour on growth, under directed technical change (innovation) and flexible scale effects.

The remainder of the paper has the following structure. In Section 2, we present the model of directed technological change with vertical and horizontal R&D and scale effects, derive the general equilibrium and analyse the BGP properties. Section 3 details the comparative statics results, deriving predictions with respect to the BGP relationships between the skill structure, the technology structure and economic growth. In Section 4, we estimate and calibrate the model using the data on the skill structure and the technology structure, and study the mechanism through which the skill structure affects economic growth. In Section 5, a counterfactual policy experiment is conducted to quantify the effect of a reduction in relative barriers to entry into the high-tech sector on the elasticity of the growth rate with respect to the skill structure. Section 6 gives some concluding remarks.

2. The model

Biased technical change is introduced in a dynamic general-equilibrium setup, as an extension of Acemoglu and Zilibotti (2001), augmented with vertical R&D and flexible scale effects.

The economy is populated by a fixed number of infinitely-lived households who inelastically supply one of two types of labour to firms: low-skilled, L, and high-skilled labour, H. There is a competitive sector producing a final good that can be used in consumption, production of intermediate goods and R&D. The final good is produced by a continuum of firms, indexed by $n \in [0,1]$, to which two substitute technologies are available, low-tech or high-tech, characterised by using, respectively, low- or high-skilled labour and a continuum of labour-specific intermediate goods, indexed by $\omega_L \in [0, N_L]$ or $\omega_H \in [0, N_H]$. Thus, the intermediate goods are supplied by two sectors, both having a large number of firms operating in a monopolistic competitive framework where entry is the result of successful R&D. Potential entrants can devote resources to either horizontal or vertical R&D, and directed to either one of the two types of labour-specific intermediate goods. Horizontal R&D increases the number of industries, N_m, $m \in \{L, H\}$, in the m-specific intermediate-good sector,[8] while vertical R&D increases the quality level of the good of an existing industry, indexed by $j_m(\omega_m)$. Then, the quality level $j_m(\omega_m)$ translates into productivity of the final producer from using the good produced by industry ω_m, $\lambda^{j_m(\omega_m)}$, where $\lambda > 1$ measures the size of each quality upgrade. By improving on the current best quality j_m, a successful R&D firm will introduce the leading-edge quality $j_m(\omega_m) + 1$ and thus render inefficient the existing input. Hence, there is a monopoly in industry ω_m, but it is temporary. Both vertical and horizontal R&D activities are subject to flexible scale effects.

2.1. Production and price decisions

The aggregate output at time t is defined as $Y_{tot}(t) = \int_0^1 P(n,t)Y(n,t)dn$, where $P(n,t)$ and $Y(n,t)$ are the relative price and the quantity of the final good produced by firm n. Every firm n has a constant-returns-to-scale technology and uses, ex-ante, low- and high-skilled labour and a continuum of labour-specific intermediate goods with measure $N_m(t)$, $m \in \{L, H\}$, so that $N_{tot}(t) = N_L(t) + N_H(t)$ and

$$\begin{array}{rcl} Y(n,t) & = & A\left[\int_0^{N_L(t)} \left(\lambda^{j_L(\omega_L,t)} \cdot X_L(n,\omega_L,t)\right)^{1-\alpha} d\omega_L\right] \left[(1-n) \cdot l \cdot L(n)\right]^{\alpha} + \\ & & +A\left[\int_0^{N_H(t)} \left(\lambda^{j_H(\omega_H,t)} \cdot X_H(n,\omega_H,t)\right)^{1-\alpha} d\omega_H\right] \left[n \cdot h \cdot H(n)\right]^{\alpha} \end{array}, \quad 0 < \alpha < 1, \tag{1}$$

where $l \cdot L(n)$ and $h \cdot H(n)$ are the efficiency-adjusted labour inputs, with $h > l \geq 1$ capturing the absolute-productivity advantage of H over L, and $\lambda^{j_m(\omega_m,t)} \cdot X_m(n,\omega_m,t)$ is the efficiency-adjusted input of m-specific intermediate good ω_m, used by firm n at time t.[9] The parameters $A > 0$ and α denote the total factor productivity and the labour share in production. The indexing of firms assigns larger (smaller) n to firms holding a relative productivity advantage of using the H (L)-technology as opposed to L (H)-technology. For every t, there is a competitive equilibrium threshold $\bar{n}(t)$ that is endogenously determined, at which a switch from one technology to the other becomes

[8] Henceforth, we will also refer to the "m-specific intermediate-good sector" as "m-technology sector".
[9] In equilibrium, only the top quality of each ω_m is produced and used.

advantageous, so that every firm n produces exclusively with either the low- or the high-tech (or L- or H-technology).

Final producers take the price of their final good, $P(n,t)$, wages, $W_m(t)$, and input prices $p_m(\omega_m,t)$ as given. From the profit maximisation conditions, the demand of intermediate good ω_m, by firm n, belonging to the L- or the H-technology sectors is, respectively,

$$\begin{array}{rcl} X_L(n,\omega_L,t) & = & (1-n)\cdot l\cdot L(n)\cdot\left[\frac{A\cdot P(n,t)\cdot(1-\alpha)}{p_L(\omega_L,t)}\right]^{\frac{1}{\alpha}}\lambda^{j_L(\omega_L,t)\left(\frac{1-\alpha}{\alpha}\right)} \\ X_H(n,\omega_H,t) & = & n\cdot h\cdot H(n)\cdot\left[\frac{A\cdot P(n,t)\cdot(1-\alpha)}{p_H(\omega_H,t)}\right]^{\frac{1}{\alpha}}\lambda^{j_H(\omega_H,t)\left(\frac{1-\alpha}{\alpha}\right)} \end{array}. \tag{2}$$

The intermediate-good m-technology sector consists of a continuum $N_m(t)$ of industries. There is monopolistic competition if we consider the whole sector: the monopolist in industry $\omega_m\in[0,N_m(t)]$ fixes the price $p_m(\omega_m,t)$ but faces an isoelastic demand curve, $X_L(\omega_L,t)=\int_0^{\bar{n}(t)}X_L(n,\omega_L,t)dn$ or $X_H(\omega_H,t)=\int_{\bar{n}(t)}^1 X_H(n,\omega_H,t)dn$ (see (2)). Intermediate goods are non-durable and entail a unit marginal cost of production, in terms of the final good, whose price is taken as given. Profit in ω_m is thus $\pi_m(\omega_m,t)=(p_m(\omega_m,t)-1)\cdot X_m(\omega_m,t)$, and the profit maximising price is a constant markup over marginal cost,

$$p_m(\omega_m,t)\equiv p=\frac{1}{1-\alpha}>1,\ m\in\{L,H\}\,. \tag{3}$$

Given $\bar{n}$ and (3), the final-good output for firm n can be rewritten as

$$Y(n,t)=\begin{cases} A^{\frac{1}{\alpha}}P(n,t)^{\frac{1-\alpha}{\alpha}}\cdot(1-\alpha)^{\frac{2(1-\alpha)}{\alpha}}\cdot(1-n)\cdot l\cdot L(n)\cdot Q_L(t) & ,\, 0\le n\le\bar{n} \\ A^{\frac{1}{\alpha}}P(n,t)^{\frac{1-\alpha}{\alpha}}\cdot(1-\alpha)^{\frac{2(1-\alpha)}{\alpha}}\cdot n\cdot h\cdot H(n)\cdot Q_H(t) & ,\, \bar{n}\le n\le 1 \end{cases}. \tag{4}$$

Defining the quality index associated to industry ω_m by $q_m(\omega_m,t)\equiv\lambda^{j_m(\omega_m,t)\left(\frac{1-\alpha}{\alpha}\right)}$, we denote the aggregate quality index by

$$Q_m(t)=\int_0^{N_m(t)}q_m(\omega_m,t)d\omega_m,\ m\in\{L,H\}\,, \tag{5}$$

which measures the technological-knowledge level associated to using the L- or the H-technology. Thus, $Q_H(t)/Q_L(t)$ measures the technological-knowledge bias. The allocation of the low- and high-skilled labour inputs to the L- or the H-technology sector verifies $L=\int_0^{\bar{n}}L(n)dn$ and $H=\int_{\bar{n}}^1 H(n)dn$.

With competitive final-good producers, economic viability of either L- or H-technology relies on the relative productivity and price of labour, as well as on the relative productivity and prices of intermediate goods, due to complementarity in production. The endogenous threshold $\bar{n}(t)$ then follows from market clearing in the inputs markets, such that $\bar{n}(t)=\left[1+(h/l\cdot H/L\cdot Q_H(t)/Q_L(t))^{1/2}\right]^{-1}$. Again, the L- (H-)technology is exclusively adopted by final-good firms indexed by $n\in[0,\bar{n}(t)]$ ($n\in[\bar{n}(t),1]$), which use the quantity $L(H)$ of low(high)-skilled labour and X_L (X_H) of labour-specific intermediate goods. The relative price of final goods produced with L- and H-technologies is also a function of $\bar{n}(t)$,

$$\frac{P_H(t)}{P_L(t)} = \left(\frac{\bar{n}(t)}{1-\bar{n}(t)}\right)^{\alpha}, \text{ where } \begin{cases} P_L(t) = P(n,t)\cdot(1-n)^{\alpha} = e^{-\alpha}\bar{n}(t)^{-\alpha} \\ P_H(t) = P(n,t)\cdot n^{\alpha} = e^{-\alpha}(1-\bar{n}(t))^{-\alpha} \end{cases}. \tag{6}$$

The price indices, $P_L(t)$ and $P_H(t)$, are determined such that, in equilibrium, the marginal value product, $\partial\left(P(n,t)Y(n,t)\right)/\partial m(n)$, is constant over n. Then $P(n,t)^{\frac{1}{\alpha}}\cdot(1-n)$ and $P(n,t)^{\frac{1}{\alpha}}\cdot n$ are also constant over $n\in[0,\bar{n}(t)]$ and $n\in[\bar{n}(t),1]$, respectively. Thus, by considering that at the switching point $\bar{n}(t)$ both L- and the H-technology firms must break even, we get $P_L(t)$ and $P_H(t)$ as in equation (6).

From equations (2), (3) and (6), the profit accrued by the monopolist in ω_m becomes

$$\pi_L(\omega_L,t) = \pi_0\cdot l\cdot L\cdot P_L(t)^{\frac{1}{\alpha}}\cdot q_L(\omega_L,t),\quad \pi_H(\omega_H,t) = \pi_0\cdot h\cdot H\cdot P_H(t)^{\frac{1}{\alpha}}\cdot q_H(\omega_H,t) \tag{7}$$

where $\pi_0 \equiv A^{\frac{1}{\alpha}}\,(1-\alpha)^{\frac{2}{\alpha}}\,\alpha/(1-\alpha)$ is a positive constant. Total intermediate-good optimal production, $X_{tot}(t) \equiv X_L(t)+X_H(t) \equiv \int_0^{N_L(t)} X_L(\omega_L,t)d\omega_L+\int_0^{N_H(t)} X_H(\omega_H,t)d\omega_H$, and total final-good optimal production, $Y_{tot}(t) \equiv Y_L(t)+Y_H(t) \equiv \int_0^{\bar{n}(t)} P(n,t)Y(n,t)dn+\int_{\bar{n}(t)}^{1} P(n,t)Y(n,t)dn$, become, respectively,

$$X_{tot}(t) = A^{\frac{1}{\alpha}}\cdot(1-\alpha)^{\frac{2}{\alpha}}\cdot\Big(P_L(t)^{\frac{1}{\alpha}}\cdot l\cdot L\cdot Q_L(t)+P_H(t)^{\frac{1}{\alpha}}\cdot h\cdot H\cdot Q_H(t)\Big) \tag{8}$$

and

$$Y_{tot}(t) = A^{\frac{1}{\alpha}}\cdot(1-\alpha)^{\frac{2(1-\alpha)}{\alpha}}\cdot\Big(P_L(t)^{\frac{1}{\alpha}}\cdot l\cdot L\cdot Q_L(t)+P_H(t)^{\frac{1}{\alpha}}\cdot h\cdot H\cdot Q_H(t)\Big). \tag{9}$$

2.2. R&D

We assume there are two types of R&D, one targeting vertical innovation and the other targeting horizontal innovation, because the pools of innovators performing each type of R&D are different. Each new design (a new variety or a higher quality good) is granted a patent and thus a successful innovator retains exclusive rights over the use of his/her good. We also assume, to simplify the analysis, that both vertical and horizontal R&D are performed by (potential) entrants, and that successful R&D leads to the set-up of a new firm in either an existing or in a new industry (as in, e.g., Howitt, 1999; Strulik, 2007; Gil, Brito, and Afonso, 2013). There is perfect competition among entrants and free entry in the R&D businesses.

2.2.1. Vertical R&D

By improving on the current top quality level $j_m(\omega_m, t)$, $m \in \{L, H\}$, a successful vertical R&D firm earns monopoly profits from selling the leading-edge m-specific intermediate good of $j_m(\omega_m, t) + 1$ quality to final-good firms. A successful innovation will instantaneously increase the quality index in industry ω_m from $q_m(\omega_m, t) = q_m(j_m)$ to $q_m^+(\omega_m, t) = q_m(j_m + 1) = \lambda^{(1-\alpha)/\alpha} q_m(\omega_m, t)$. In equilibrium, the producer of the intermediate good ω_m of lower quality is priced out of business.

Let $I_m^i(j_m)$ denote the Poisson arrival rate of vertical innovations (vertical-innovation rate) by potential entrant i in industry ω_m, at a cost of $\Phi_m(j_m)$ units of the final good, when the highest quality existing is j_m. The rate $I_m^i(j_m)$ is independently distributed across firms, across industries and over time, and depends on the flow of resources $R_{v,m}^i(j_m)$ committed by entrants at time t. As in, e.g., Barro and Sala-i-Martin (2004, ch. 7), $I_m^i(j_m)$ features constant returns in R&D expenditures, $I_m^i(j_m) = R_{v,m}^i(j_m)/\Phi_m(j_m)$. The cost $\Phi_m(j_m)$ is assumed to be symmetric within sector m, such that

$$\Phi_m(j_m) = \zeta_m \cdot m^{\epsilon} \cdot q_m(j_m + 1), \ m \in \{L, H\}, \tag{10}$$

where $\zeta_m > 0$ is a constant fixed (flow) cost. Equation (10) incorporates three types of effects. First, there is an R&D complexity effect such that the larger the level of quality in an industry of sector m, q_m, the costlier it is to introduce a further jump in quality.[10] This effect has been considered in the literature (e.g.,Howitt, 1999; Barro and Sala-i-Martin, 2004, ch. 7) and implies vertical R&D is subject to dynamic decreasing returns to scale (i.e., decreasing returns to cumulated R&D). Second, equation (10) also displays a (potential) market complexity effect: an increase in the market scale of the m-technology sector, measured by L and H respectively, may dilute the effect of R&D outlays on the innovation probability. In the literature, the market size effect is measured by employed labour (e.g., Barro and Sala-i-Martin, 2004) and can be positively related to coordination, organisational and transportation costs. The dilution effect, generated by those costs, can partially ($0 < \epsilon < 1$) or totally ($\epsilon = 1$) eliminate, or revert ($\epsilon > 1$) the market scale benefits on profits (see (7)), which accrue to the R&D successful firm. On the other hand, if $\epsilon < 0$, then market scale *reduces* those costs and thus adds to the direct scale benefits on profits. The usual knife-edge assumption is that either $\epsilon = 0$ or $\epsilon = 1$ (see, e.g., Barro and Sala-i-Martin, 2004, ch. 7). Thus, as shown later, there may be positive, null or negative net scale effects on industrial growth, as measured by $1 - \epsilon$. At last, for any given supply of labour and quality index, the cost of vertical R&D also depends on a fixed flow cost specific to the H-complementary or L-complementary production technology targeted by vertical R&D, measured by ζ_H and ζ_L, respectively. Then, $\zeta \equiv \zeta_H/\zeta_L$ may be interpreted as a measure of relative barriers to entry through vertical innovation into the H-technology sector.

[10] As usual in the literature, the fact that Φ_m depends linearly on q_m implies that the increasing difficulty of creating new product generations over t exactly offsets the increased rewards from marketing higher quality products; see (10) and (7). This allows for constant vertical-innovation rate over t and across ω_m in BGP (on *asymmetric* equilibrium in quality-ladders models and its growth consequences, see Cozzi, 2007).

Aggregating across firms i in ω_m, we get $R_{v,m}(j_m) = \sum_i R^i_{v,m}(j_m)$ and $I_m(j_m) = \sum_i I^i_m(j_m)$, and thus

$$I_m(j_m) = R_{v,m}(j_m) \cdot \frac{1}{\zeta_m \cdot m^\epsilon \cdot q_m(j_m+1)}, \ m \in \{L, H\}. \tag{11}$$

As the terminal date of each monopoly arrives as a Poisson process with frequency $I_m(j_m)$ per (infinitesimal) increment of time, the present value of a monopolist's profits is a random variable. Let $V_m(j_m)$ denote the expected value of an incumbent with current quality level $j_m(\omega_m, t)$,[11]

$$\begin{array}{c} V_L(j_L) = \pi_0 \cdot l \cdot L \cdot q_L(j_L) \int_t^\infty P_L(s)^{\frac{1}{\alpha}} \cdot e^{-\int_t^s (r(v)+I_L(j_L(v)))dv} ds \\ V_H(j_H) = \pi_0 \cdot h \cdot H \cdot q_H(j_H) \int_t^\infty P_H(s)^{\frac{1}{\alpha}} \cdot e^{-\int_t^s (r(v)+I_H(j_H(v)))dv} ds \end{array}, \tag{12}$$

where r is the equilibrium market real interest rate, and $\pi_0 \cdot l \cdot L \cdot q_L(j_L) = \pi_L(j_L) \cdot P_L^{-\frac{1}{\alpha}}$ and $\pi_0 \cdot h \cdot H \cdot q_H(j_H) = \pi_H(j_H) \cdot P_H^{-\frac{1}{\alpha}}$, given by (7) and (6), are constant in-between innovations. Free-entry prevails in vertical R&D such that the condition $I_m(j_m) \cdot V_m(j_m+1) = R_{v,m}(j_m)$ holds, which implies that

$$V_m(j_m+1) = \Phi_m(j_m) = \zeta_m \cdot m^\epsilon \cdot q_m(j_m+1), \ m \in \{L, H\}. \tag{13}$$

Next, we determine $V_m(j_m+1)$ analogously to (12), then consider (13) and time-differentiate the resulting expression. If we also consider (7), we get the no-arbitrage condition facing a vertical innovator,

$$r(t) + I_L(t) = \frac{\pi_0 \cdot l \cdot L^{1-\epsilon} \cdot P_L(t)^{\frac{1}{\alpha}}}{\zeta_L}, \ r(t) + I_H(t) = \frac{\pi_0 \cdot h \cdot H^{1-\epsilon} \cdot P_H(t)^{\frac{1}{\alpha}}}{\zeta_H}, \tag{14}$$

which implies that the rates of entry are symmetric across industries, $I_m(\omega_m, t) = I_m(t)$.[12]

Equating the effective rate of return for both sectors, in (14), the no-arbitrage condition obtains

$$I_H(t) - I_L(t) = \pi_0 \left(\frac{h}{\zeta_H} \cdot H^{1-\epsilon} \cdot P_H(t)^{\frac{1}{\alpha}} - \frac{l}{\zeta_L} L^{1-\epsilon} \cdot P_L(t)^{\frac{1}{\alpha}} \right). \tag{15}$$

Solving equation (11) for $R_{v,m}(\omega_m, t) = R_{v,m}(j_m)$ and aggregating across industries ω_m, we get total resources devoted to vertical R&D, $R_{v,m}(t) = \int_0^{N_m(t)} R_{v,m}(\omega_m, t)\, d\omega_m =$

[11] We assume that entrants are risk-neutral and, thus, only care about the expected value of the firm.

[12] Observe that, from (7) and (11), we have $\frac{\dot{\pi}_m(\omega_m,t)}{\pi_m(\omega_m,t)} - \frac{1}{\alpha}\frac{\dot{P}_m(t)}{P_m(t)} = I_m(\omega_m, t) \cdot \left[\dot{j}_m(\omega_m, t) \cdot \left(\frac{\alpha}{1-\alpha}\right) \cdot \ln\lambda\right]$ and $\frac{\dot{R}_{vm}(\omega_m,t)}{R_{vm}(\omega_m,t)} - \frac{\dot{I}_m(\omega_m,t)}{I_m(\omega_m,t)} = I_m(\omega_m, t) \cdot \left[\dot{j}_m(\omega_m, t) \cdot \left(\frac{\alpha}{1-\alpha}\right) \cdot \ln\lambda\right]$. Thus, if we time-differentiate (13) by considering (12) and the equations above, we get $r(t) = \frac{\pi_m(j_m+1) \cdot I_m(j_m)}{R_{vm}(j_m)} - I_m(j_m+1)$, which can be re-written as (14).

$\int_0^{N_m(t)} \zeta_m \cdot m^{\epsilon} \cdot q_m^{+}(\omega_m, t) \cdot I_m(\omega_m, t)\, d\omega_m$. As the innovation rate is industry independent, then

$$R_{v,m}(t) = \zeta_m \cdot m^{\epsilon} \cdot \lambda^{\frac{1-\alpha}{\alpha}} \cdot I_m(t) \cdot Q_m(t), \ m \in \{L, H\}. \tag{16}$$

2.2.2. Horizontal R&D

Variety expansion emerges from R&D aimed at creating a new intermediate good. Under perfect competition and constant returns to scale at the firm level, the instantaneous entry rate is $\dot{N}_m^e(t) = R_{h,m}^e(t)$, where $\dot{N}_m^e$ is the contribution to the instantaneous flow of new m-specific intermediate goods by R&D firm e at a cost of η_m units of the final good and $R_{h,m}^e$ is the flow of resources devoted to horizontal R&D by innovator e at time t. The cost η_m is assumed to be symmetric within sector m. Then, $R_{h,m}(t) = \sum_e R_{h,m}^e(t)$ and $\dot{N}_m(t) = \sum_e \dot{N}_m^e(t)$, implying

$$R_{h,m}(t) = \eta_m(t) \cdot \dot{N}_m(t), \ m \in \{L, H\}. \tag{17}$$

We assume that the cost of setting up a new variety (cost of horizontal entry) is increasing in the number of existing varieties, N_m,

$$\eta_m(t) = \phi_m \cdot m^{\delta} \cdot N_m(t)^{\sigma}, \ m \in \{L, H\}, \tag{18}$$

where $\phi_m > 0$ is a constant fixed (flow) cost, and $\sigma > 0$. Similarly to vertical R&D, equation (18) also incorporates three types of effects. First, an R&D complexity effect arises through the dependence of η_m on N_m (e.g., Evans, Honkapohja, and Romer, 1998; Barro and Sala-i-Martin, 2004, ch. 6), implying horizontal-R&D dynamic decreasing returns to scale. That is, the larger the number of existing varieties, the costlier it is to introduce new varieties. Second, (18) also implies that an increase in market scale, measured by L or H, may (potentially) dilute the effect of R&D outlays on the innovation rate (market complexity effect). Again, this may reflect coordination, organisational and transportation costs related to market size, which may partially ($0 < \delta < 1$), totally ($\delta = 1$) or more than ($\delta > 1$) offset the scale benefits on profits. However, one may also have $\delta < 0$, in which case market scale *reduces* those costs and thus adds to the scale benefits on profits. This contrasts with the usual knife-edge assumption that either $\delta = 0$ or $\delta = 1$ (see, e.g., Barro and Sala-i-Martin, 2004, ch. 6), and, as made clear in Section 4 below, enables identification in our estimation exercise. Finally, for any given supply of labour and number of varieties, the cost of horizontal R&D also depends on a fixed flow cost, which can be specific to the type of production technology that is targeted by horizontal R&D, ϕ_H and ϕ_L. In particular, $\phi \equiv \phi_H/\phi_L$ can be interpreted as a measure of relative barriers to entry through horizontal innovation into the H-technology sector.

Each horizontal innovation results in a new intermediate good whose quality level is drawn randomly from the distribution of existing varieties (e.g., Howitt, 1999). Thus, the expected quality level of the horizontal innovator is

$$\bar{q}_m(t) = \int_0^{N_m(t)} \frac{q_m(\omega_m, t)}{N_m(t)} d\omega_m = \frac{Q_m(t)}{N_m(t)}, \ m \in \{L, H\}. \tag{19}$$

As his/her monopoly power will be also terminated by the arrival of a successful vertical innovator in the future, the benefits from entry are

$$\begin{array}{c} V_L(\bar{q}_L) = \pi_0 \cdot l \cdot L \cdot \bar{q}_L(t) \int_t^\infty P_L(s)^{\frac{1}{\alpha}} \cdot e^{-\int_t^s [r(\nu)+I_L(\bar{q}_L(v))]d\nu} ds \\ V_H(\bar{q}_H) = \pi_0 \cdot h \cdot H \cdot \bar{q}_H(t) \int_t^\infty P_H(s)^{\frac{1}{\alpha}} \cdot e^{-\int_t^s [r(\nu)+I_H(\bar{q}_H(v))]d\nu} ds \end{array}, \tag{20}$$

where $\pi_0 \cdot l \cdot L \cdot \bar{q}_L = \bar{\pi}_L \cdot P_L^{-\frac{1}{\alpha}}$ and $\pi_0 \cdot h \cdot H \cdot \bar{q}_H = \bar{\pi}_H \cdot P_H^{-\frac{1}{\alpha}}$. The free-entry condition, $\dot{N}_m \cdot V(\bar{q}_m) = R_{hm}$, by (17), simplifies to

$$V_m(\bar{q}_m) = \eta_m(t), \ m \in \{L, H\}. \tag{21}$$

Substituting (20) into (21) and time-differentiating the resulting expression, yields the no-arbitrage condition facing a horizontal innovator

$$r(t) + I_m(t) = \frac{\bar{\pi}_m(t)}{\eta_m(t)}, \ m \in \{L, H\}. \tag{22}$$

2.2.3. Intra-sector no-arbitrage condition

No-arbitrage in the capital market requires that the two types of investment, vertical and horizontal R&D, yield equal rates of return, otherwise one type of investment dominates the other and a corner solution obtains. Thus, if we equate the effective rate of return $r + I_m$ for both types of entry, from (14) and (22), we get the *intra-sector* no-arbitrage conditions

$$\bar{q}_m(t) = \frac{Q_m(t)}{N_m(t)} = \frac{\eta_m(t)}{\zeta_m \cdot m^\epsilon} = \frac{\phi_m}{\zeta_m} \cdot m^{\delta-\epsilon} \cdot N_m(t)^\sigma, \ m \in \{L, H\} \tag{23}$$

which is a key ingredient of the model. No arbitrage conditions, within the H- and L-technology R&D sectors, equate the average cost of horizontal R&D, η_m, to the average cost of vertical R&D, $\bar{q}_m \cdot \zeta_m \cdot m^\epsilon$.

2.3. General equilibrium

The economy is populated by a fixed number of infinitely-lived households who consume and collect income from investments in financial assets (equity) and from labour. Workers have heterogeneous human capital endowments so that the economy is endowed with H highly educated ("high-skilled") and L less educated ("low-skilled") units of labour given exogenously and constant over time. We assume households have perfect foresight concerning the technological change over time and choose the path of final-good aggregate consumption $(C(t))_{t\geq 0}$ to maximise discounted lifetime utility

$$U = \int_0^\infty \left(\frac{C(t)^{1-\theta} - 1}{1-\theta} \right) e^{-\rho t} dt, \tag{24}$$

where $\rho > 0$ is the subjective discount rate and $\theta > 0$ is the inverse of the intertemporal elasticity of substitution, subject to the flow budget constraint

$$\dot{a}(t) = r(t) \cdot a(t) + W_L(t) \cdot L + W_H(t) \cdot H - C(t), \tag{25}$$

where a denotes households' real financial assets holdings. The initial level $a(0)$ is given and the non-Ponzi game condition $lim_{t\to\infty} e^{-\int_0^t r(s)ds} a(t) \geq 0$ is imposed. The optimal consumption path Euler equation and the transversality condition are standard,

$$\frac{\dot{C}(t)}{C(t)} = \frac{1}{\theta} \cdot (r(t) - \rho) \tag{26}$$

$$\underset{t\to\infty}{lim}\, e^{-\rho t} \cdot C(t)^{-\theta} \cdot a(t) = 0. \tag{27}$$

The aggregate financial wealth held by households is composed of equity of intermediate good producers $a(t) = a_L(t) + a_H(t)$, where $a_m(t) = \int_0^{N_m(t)} V_m(\omega_m, t) d\omega_m$, $m \in \{L, H\}$. From the arbitrage condition between vertical and horizontal entry, we have equivalently $a(t) = \eta_L(t) \cdot N_L(t) + \eta_H(t) \cdot N_H(t)$. Taking time derivatives and using (25), the aggregate flow budget constraint is equivalent to the final product market equilibrium condition

$$Y_{tot}(t) = X_{tot}(t) + C(t) + R_h(t) + R_v(t) \tag{28}$$

where $R_h(t) = R_{h,L}(t) + R_{h,H}(t)$ and $R_v(t) = R_{v,L}(t) + R_{v,H}(t)$ are the aggregate horizontal and vertical R&D expenditures, respectively.

The dynamic general equilibrium is defined by the paths of allocations and price distributions $(\{X_m(\omega_m, t), p_m(\omega_m, t)\}, \omega_m \in [0, N_m(t)])_{t\geq 0}$ and aggregate number of firms, quality indices and vertical-innovation rates $(\{\ N_m(t), Q_m(t), I_m(t)\}\ )_{t\geq 0}$ for sectors $m \in \{L, H\}$, and by the aggregate paths $(C(t), r(t))_{t\geq 0}$, such that: (i) consumers, final-good firms and intermediate-good firms solve their problems; (ii) free-entry and no-arbitrage conditions are met; and (iii) markets clear. Total supplies of high- and low-skilled labour are exogenous.

2.4. The balanced-growth path

A general-equilibrium balanced growth path (BGP) exists only if the following conditions hold among the asymptotic constant growth rates: (i) the growth rates for consumption and for the quality indices are equal to the endogenous growth rate for the economy g, $g_C = g_{Q_L} = g_{Q_H} = g$; (ii) the growth rates for the number of varieties are equal, $g_{N_L} = g_{N_H}$; (iii) the vertical-innovation rates and the final-good price indices are asymptotically trendless, $g_{I_L} = g_{I_H} = g_{P_L} = g_{P_H} = 0$; and (iv) the growth rates for the quality indices and for the number of varieties are monotonously related as $g_{Q_L}/g_{N_L} = g_{Q_H}/g_{N_H} = 1+\sigma$. Then $g_{N_L} = g_{N_H} = g/(1+\sigma)$.

Necessary conditions (i) and (ii) imply that the trendless levels for the vertical-innovation rates verify $I_L = I_H = I$, along the BGP. Introducing this in equation (15) we derive

P_H/P_L. Substituting, in turn, in equation (6) we can get the long-run technological-knowledge bias, $Q \equiv Q_H/Q_L$, as (henceforth a tilde over a symbol denotes BGP magnitudes)

$$\tilde{Q} = \left(\frac{H}{L}\right)^{1-2\epsilon}\left(\frac{h}{l}\right)\left(\frac{\zeta_H}{\zeta_L}\right)^{-2}. \tag{29}$$

If we assume that the number of industries, N, is large enough to treat Q as time-differentiable and non-stochastic, then we can time-differentiate (5) to get $\dot{Q}_m(t) = \int_0^{N_m(t)} \dot{q}(\omega, t)d\omega + q(N, t)\dot{N}(t)$, which is well-defined if $\sigma > 0$. After some algebraic manipulation of the latter, we can write, for the case in which $I_m > 0$, another asymptotic relationship between the long-run growth rate of the quality indices and of the number of varieties, $g_{Q_m} = \Xi I_m + g_{N_m}$ $m \in \{L, H\}$, where $\Xi \equiv \left(\lambda^{\frac{1-\alpha}{\alpha}} - 1\right)$ denotes the quality shift. Then we get $g = \Xi I + g/(1+\sigma)$, from the above conditions (i) and (iv). Euler equation (26) together with the necessary condition (i) lead to the familiar relationship between the long-run real interest rate and the endogenous growth rate, $r = \rho + \theta g$. The transversality condition holds if $g > 0$. The non-arbitrage condition for vertical R&D allows us to get the endogenous long-run economic growth rate

$$\tilde{g} = \frac{\tilde{r} - \rho}{\theta}\left(1 - \frac{1}{1+\theta\mu}\right), \tag{30}$$

where the long-run real interest rate is constant,

$$\tilde{r} = \frac{\pi_0}{e}\left(\frac{l}{\zeta_L}L^{1-\epsilon} + \frac{h}{\zeta_H}H^{1-\epsilon}\right) \tag{31}$$

with $\mu \equiv \Xi(1+\sigma)/\sigma > 0$ and $\pi_0 \equiv A^{\frac{1}{\alpha}}(1-\alpha)^{\frac{2}{\alpha}}\alpha/(1-\alpha)$. The other steady state magnitudes are homogeneous across the H and L-technology sectors and are monotonously related to the long-run economic growth rate, $\tilde{g}$: the long-run vertical-innovation rates are $\tilde{I}_L = \tilde{I}_H = \tilde{I} = \tilde{g}/\mu \geq 0$, the long-run growth rates for the quality indices are $\tilde{g}_{Q_L} = \tilde{g}_{Q_H} = \tilde{g} > 0$ and for the varieties are $\tilde{g}_{N_L} = \tilde{g}_{N_H} = \tilde{g}/(1+\sigma) > 0$.

Thus, equation (30) shows that the long-run economic growth rate is positive and generically displays scale effects. These effects can be positive, null or negative if the market complexity cost parameter associated to vertical R&D ϵ, is smaller, equal or larger than unity. These costs have a negative effect on growth *per se*. In addition, our model predicts that g_{Q_m} exceed g_{N_m} if the probability of introducing successful vertical innovations, I_m, is positive, because $g_{Q_m} = \Xi I_m + g_{N_m}$, the difference being equal to the expected value of the shift in the intermediate-good quality. Thus, the economic growth rate is consistent with the well-known view that industrial growth proceeds both along an intensive and an extensive margin, as it is equal to the sum of the growth rate of the number of varieties plus the growth rate of intermediate-good quality.

However, given the distinct nature of vertical and horizontal innovation (immaterial versus physical) and the consequent asymmetry in terms of R&D complexity costs (see

(10) and (18)),[13] vertical R&D is the ultimate growth engine, whereas variety expansion is sustained by the endogenous quality upgrade: the expected growth of intermediate-good quality due to vertical R&D makes it attractive, in terms of intertemporal profits, for potential entrants to always bear an horizontal R&D complexity cost, in spite of its more than proportional increase with N_m. Thus, there is a negative relationship between the economic growth rate and both the horizontal R&D complexity cost parameter, σ, and the flow fixed costs to vertical R&D, ζ_H and ζ_L, while there is no impact from the flow fixed cost to horizontal R&D, ϕ_H and ϕ_L, and from the market complexity cost associated to horizontal R&D, δ. There is also a positive relationship between the economic growth rate and the productivity parameters, h and l.

3. Growth, technology structure and the skill structure

3.1. Growth and skill structure

The long-run economic growth rate, in equation (30), is a function of the economy's endowments of both high- and low-skilled labour, H and L, and, by consequence, it is also a function of the relative supply of skills.

From equations (30) and (31), we find that the elasticity of the growth rate regarding H/L (i.e., the growth-skill elasticity) is

$$\mathcal{E}^{\tilde{g}}_{H/L} = \mathcal{E}^{\tilde{g}}_{H/L}(\epsilon, \zeta) \equiv \frac{\partial \tilde{g}}{\partial (H/L)} \frac{H/L}{\tilde{g}} = (1-\epsilon)\left(\frac{h/l \cdot (H/L)^{1-\epsilon}}{\zeta + h/l \cdot (H/L)^{1-\epsilon}}\right). \tag{32}$$

where $\zeta \equiv \zeta_H/\zeta_L$ parametrizes the relative barriers to vertical entry into the $H-$ relative to the $L-$technology sector. The growth-skill elasticity is positive if $1-\epsilon > 0$, negatively related if $1-\epsilon < 0$ and there is no effect in the knife-edge case of $1-\epsilon = 0$. We also establish that the relative barriers to entry ζ have a negative impact on the degree of the growth-skill elasticity, while there is a positive impact of the absolute productivity advantage of the high-skilled, h/l.

For the sake of clarity, we state these results formally:

Proposition 1. Growth and skill structure. The long-run economic growth rate, $\tilde{g}$, response to increases in the skill structure, H/L, has the same sign as the scale effect coefficient $1-\epsilon$. It is possible to have both $\mathcal{E}^{\tilde{g}}_{H/L} \approx 0$ and positive net scale effects, $1-\epsilon > 0$, if the relative barriers to vertical entry, ζ, are high.

[Figure 3 goes about here]

An important implication of equation (32) is the existence of an elasticity $\mathcal{E}^{\tilde{g}}_{H/L}$ close to zero, but positive, and of net positive scale effects, with $1-\epsilon$ substantially higher than zero, if there are relatively high relative barriers to entry ζ. The function $\mathcal{E}^{\tilde{g}}_{H/L}(\epsilon, \zeta) = \bar{\mathcal{E}}^{\tilde{g}}_{H/L}$, for $\bar{\mathcal{E}}^{\tilde{g}}_{H/L}$ close to zero, is hump-shaped. For a given $\bar{\mathcal{E}}^{\tilde{g}}_{H/L}$, ζ reaches a maximum

[13] By comparing these two equations, we see that the elasticity of q_m with respect to I_m is -1, whereas the elasticity of N_m with respect to $\dot{N}_m/N_m$ is $-(1+\sigma)$, $\sigma > 0$.

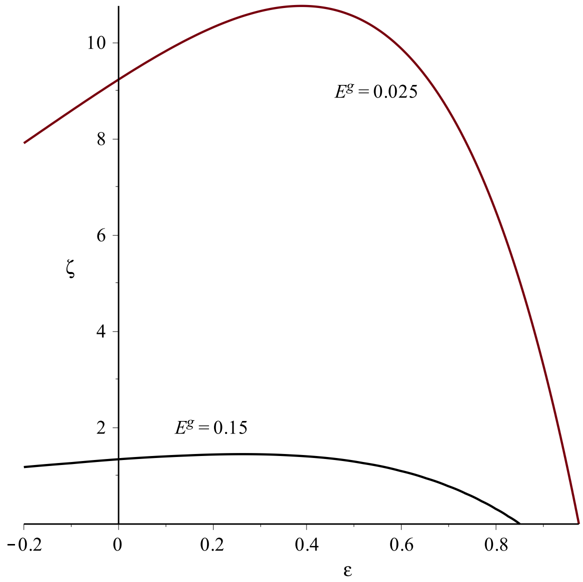

Figure 3: Curves $\mathcal{E}^{\tilde{g}}_{H/L}(\epsilon,\zeta) = 0.025$ and $\mathcal{E}^{\tilde{g}}_{H/L}(\epsilon,\zeta) = 0.15$ for $h/l = 1.3$ and $H/L = 0.182$.

at a point such that $1-\epsilon > \bar{\mathcal{E}}^{\tilde{g}}_{H/L}$. Figure 3 illustrates this result by depicting two cases, $\bar{\mathcal{E}}^{\tilde{g}}_{H/L} = 0.025$ and $\bar{\mathcal{E}}^{\tilde{g}}_{H/L} = 0.15$, considering the average values of h/l and H/L from our cross-section sample.

The hump-shape of the function of the growth-skill elasticity implies that, for an admissible value of the parameter ζ, there are two values of the parameter ϵ consistent with a given growth-skill elasticity. On the other hand, although the hump-shape of the curve is generic, its exact location is very sensitive to the value of the growth-skill elasticity. For both these reasons, and for having a general empirical assessment on our whole model, we estimate the parameters ϵ and ζ by using the BGP technology structure equations. Then, we take these estimates to calibrate our model and compare the predicted growth-skill elasticity with the data.

3.2. Technology structure and skill structure

The technology structure is described, in the long-run, by the technological-knowledge bias, $\tilde{Q}$, the relative intermediate-good production, $\tilde{X}$, and the relative number of firms $\tilde{N}$ (i.e., production and the number of firms in H- vis-à-vis L-technology sector). The technological bias has already been presented in equation (29). From X_L and X_H, in equation (8), we get the relative intermediate-good production

$$\tilde{X} \equiv \left(\tilde{\frac{X_H}{X_L}}\right) = \left(\frac{H}{L}\right)^{1-\epsilon} \cdot \frac{h}{l} \cdot \zeta^{-1}, \tag{33}$$

and, from N_L and N_H in equation (23), combined with (29), we get the relative number of firms

$$\tilde{N} \equiv \left(\frac{\tilde{N_H}}{N_L}\right) = Z_0 \cdot \left(\frac{H}{L}\right)^{D_0}, \tag{34}$$

where

$$D_0 \equiv \frac{1-\epsilon-\delta}{1+\sigma} \tag{35}$$

$$Z_0 \equiv \left(\frac{h}{l}\right)^{\frac{1}{\sigma+1}} \cdot \phi^{\frac{-1}{\sigma+1}} \cdot \zeta^{\frac{-1}{\sigma+1}}. \tag{36}$$

Therefore, in addition to being a function of H/L, the technology structure also depends on the relative productivity of high-skilled workers, h/l, and on the relative barriers to entry into the H-technology sector, ζ and ϕ. The direction and intensity of these effects depend crucially on the complexity-costs parameters, ϵ, δ and σ.

As the data on production by the national statistics offices (see, e.g., Eurostat, 2001) is available in quality-adjusted base, we need to adjust the expressions for $\tilde{X}$ and $\tilde{Q}$ accordingly. If we reiterate the steps as in Section 2.1, we find total intermediate-good quality-adjusted production to be (e.g., with $m = L$) $\mathfrak{X}_L = \int_0^{N_L} \int_0^{\bar{n}} \lambda^{j_L(\omega_L)} \cdot X_L(n, \omega_L) dn d\omega_L = A^{\frac{1}{\alpha}} (1-\alpha)^{\frac{2}{\alpha}} P_L^{\frac{1}{\alpha}} l L \mathcal{Q}_L$, where $\mathcal{Q}_L = \int_0^{N_L} \lambda^{j_L(\omega_L)\frac{1}{\alpha}} d\omega_L$, and $\mathfrak{X}_{tot} = \mathfrak{X}_L + \mathfrak{X}_H$. We cannot find an explicit algebraic expression for the BGP value of $\mathcal{Q}_m$. However, as shown in Appendix C, we can build an adequate proxy for $\mathcal{Q}_m$, $\widehat{\mathcal{Q}}_m = Q_m^{\frac{1}{1-\alpha}} \cdot N_m^{-\left(\frac{\alpha}{1-\alpha}\right)}$ $m \in \{L, H\}$, and define $\widehat{\mathfrak{X}}_m = X_m \cdot (Q_m/N_m)^{\frac{\alpha}{1-\alpha}}$ for $\mathfrak{X}_m$. Thus, bearing in mind (29), (33) and (34), we use, for conducting the empirical study, the following quality-adjusted measure of relative production,

$$\tilde{\hat{\mathfrak{X}}} = \tilde{X} \cdot \left(\frac{\tilde{Q}}{\tilde{N}}\right)^{\frac{\alpha}{1-\alpha}} = Z_1 \cdot \left(\frac{H}{L}\right)^{D_1}, \tag{37}$$

where

$$D_1 \equiv \frac{\alpha\delta + 1 - \alpha + \sigma - \epsilon\left[1 + (1+\alpha)\sigma\right]}{(1+\sigma)(1-\alpha)} \tag{38}$$

$$Z_1 \equiv \left(\frac{h}{l}\right)^{\left[1+\left(\frac{\sigma}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]} \cdot \phi^{\frac{\alpha}{(\sigma+1)(1-\alpha)}} \cdot \zeta^{-\left[1+\left(\frac{2\sigma+1}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]} \tag{39}$$

Moreover, given $\widehat{\mathfrak{X}}_m = X_m \cdot (Q_m/N_m)^{\frac{\alpha}{1-\alpha}}$, the quality-adjusted long-run economic growth rate is monotonously related to non-adjusted growth rate

$$\tilde{\mathcal{G}} = \left(1 + \frac{\alpha\sigma}{(1-\alpha)(1+\sigma)}\right) \cdot \tilde{g}. \tag{40}$$

In addition to its impact on the BGP economic growth rate (see (30)), the market complexity cost parameter associated to vertical R&D, ϵ, plays an important role in

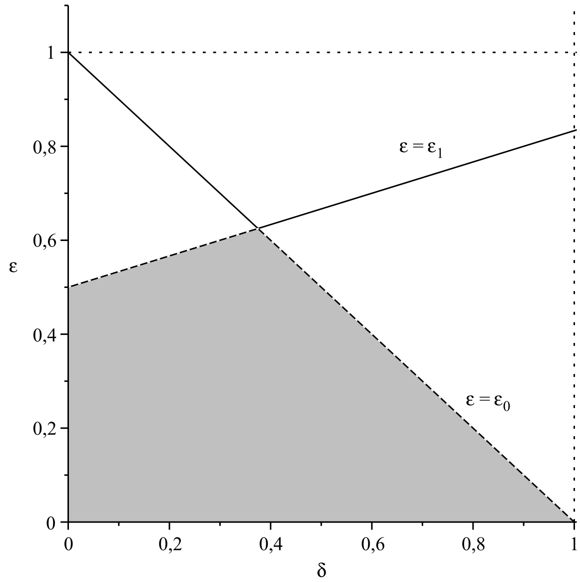

Figure 4: Set of values for the market complexity-cost parameters (ϵ, δ) that are qualitatively consistent with the technology-structure elasticities found in the cross-country data (see Appendix A), i.e., that imply D_0, $D_1 > 0$ in (35) and (38). Example with $\alpha = 0.6$ and $\sigma = 0.5$.

the determination of the sign of the relationship between the skill structure and the technology-structure variables. The cross-country evidence shows a significantly positive elasticity of relative production and the relative number of firms with respect to the skill structure (see Appendix A), which corresponds to the case $D_0 > 0$ and $D_1 > 0$.

We can prove that there are two critical values for ϵ, $\bar{\epsilon}_0$ and $\bar{\epsilon}_1$, such that $D_0(\epsilon) \geq 0$ and $D_1(\epsilon) \geq 0$, if and only if $\epsilon < \min\{\bar{\epsilon}_0, \bar{\epsilon}_1\}$, where

$$\bar{\epsilon}_0 = 1 - \delta, \tag{41}$$

$$\bar{\epsilon}_1 = \frac{1 - \alpha + \sigma + \alpha\delta}{1 + (1 + \alpha)\sigma}. \tag{42}$$

There is a non-empty set of values for the market complexity-cost parameters (ϵ, δ) which are consistent with the cross-country evidence, as shown in Figure 4, where the values for ϵ and δ in the positive outhant are highlighted.

[Figure 4 goes about here]

The next proposition summarises the cross-country relationship between the skill structure and the technology structure, which depends upon the market complexity cost parameter ϵ.[14]

[14]Henceforth, the ~ is omitted for the sake of simplicity.

Proposition 2. Technology structure and skill structure If a country has a *higher* proportion of high-skilled labour, H/L, then it will have:

(i) A *higher* relative number of firms and production, if $0 \leq \epsilon < \bar{\epsilon}_1$;

(ii) A *higher* relative number of firms but a *smaller* relative production, if $\bar{\epsilon}_1 < \epsilon < \bar{\epsilon}_0$;

(iii) A *smaller* relative number of firms and production, if $\epsilon > \bar{\epsilon}_0$.

The results above derive from the different responses of the relative number of firms, N, and relative production, $\widehat{\mathfrak{X}}$, through the technological-knowledge bias channel, to shifts in the relative supply of skills, H/L.

This is explained by the asymmetric impact of both market and R&D complexity costs on the elasticity of those technology-structure variables with respect to H/L. The market complexity costs related to horizontal R&D, summarised by δ, have a direct negative impact on horizontal R&D and an indirect positive impact on vertical R&D (substitution effect). Consequently, there is a negative effect on horizontal entry and hence on the elasticity of N ($\partial D_0/\partial\delta < 0$, in (34)), whereas, through the positive impact on the quality index, $q(j)$, and thereby on the technological-knowledge bias, Q, there is also a positive effect on the elasticity of $\widehat{\mathfrak{X}}$ ($\partial D_1/\partial\delta > 0$, in (37). The market complexity costs related to vertical R&D, summarised by ϵ, have a direct negative impact on vertical R&D (and hence $\partial D_1/\partial\epsilon < 0$), but also have a negative impact, although smaller in modulus, on horizontal R&D ($\partial D_0/\partial\epsilon < 0$, with $|\partial D_0/\partial\epsilon| < |\partial D_1/\partial\epsilon|$). This reflects the fact that the vertical-innovation mechanism ultimately commands the horizontal entry dynamics, meaning that a BGP with increasingly costly horizontal R&D occurs only because entrants expect the incumbency value to grow propelled by quality-enhancing R&D, hence generating a roundabout cost effect associated to ϵ. The asymmetric impact of the market complexity costs on the behaviour of the technological-structure variables can be seen by noticing that $\widehat{\mathfrak{X}}$ is constant when $\epsilon = \bar{\epsilon}_1$ and N is constant when $\epsilon = \bar{\epsilon}_0$, where $\bar{\epsilon}_1 < \bar{\epsilon}_0$.

Furthermore, the effect of H/L on N is dampened by the horizontal R&D complexity cost, summarised by σ (see $\partial D_0/\partial\sigma < 0$), whereas this cost has an indirect positive impact (substitution effect) on $\widehat{\mathfrak{X}}$ (see $\partial D_1/\partial\sigma > 0$).

4. Estimation and calibration

We found in Section 1, using cross-country data, that there was a weak empirical relationship between the economic growth rate and the skill structure and a significant positive relationship between the technology structure and the skill structure. This is an apparently puzzling evidence because while the first relationship suggests the non-existence of scale effects, the second is only possible with its existence (see again Figure 4). Our conjecture is that these are not contradictory events, if we consider the inclusion of sufficiently high relative barriers to vertical entry into the high-tech sector. Intuitively, the negative impact of these barriers to entry can be large enough to offset the positive impact of net scale effects from high-skilled labour, such that the cross-country growth-skill elasticity appears as non-significant.

However, as regards our theoretical model, the relationship between the market complexity cost parameter ϵ (which features the scale effects) and the barriers to entry parameter ζ that is consistent with a low growth-skill elasticity is non-linear (see equation (32) and Figure 3).

Thus, in order to obtain empirical estimates of the structural parameters ϵ and ζ, and also an empirical validation of our model, we use the available cross-country data for the technology structure and the skill structure. Then, we use these estimates to calibrate our model and, together with the data on the skill structure, compute the predicted value for each country's economic growth rate. Given the latter, we estimate the cross-country elasticity of *predicted* economic growth regarding the observed skill structure and compare it with the estimated cross-country elasticity of *observed* economic growth.

4.1. Estimation of ϵ and ζ

The first step is to consider the BGP equations relating the technology-structure variables with the skill-structure variable, (34) and (37). Since these equations establish the endogenous variables (the technology-structure variables) as functions of the exogenous variable alone (the relative supply of skills, H/L), then they can be seen as a reduced-form system of equations that can be estimated by standard OLS. Therefore, we run the regressions

$$\ln \tilde{N} = \ln Z_0 + D_0 \ln (H/L) + e_0 \tag{43}$$

$$\ln \tilde{\tilde{\mathfrak{X}}} = \ln Z_1 + D_1 \ln (H/L) + e_1 \tag{44}$$

where (43) and (44) are a log-log stochastic representation of the BGP equations (34) and (37), with e_i, $i = 0, 1$, denoting the usual error terms, to get the OLS estimates $\hat{D}_0$, $\hat{D}_1$, $\widehat{\ln Z_0}$, and $\widehat{\ln Z_1}$. We use a sample of 16 European countries, from a total of 30 European countries comprising the EU-27 plus EFTA, subsetting to those with available data both on relative production and on the relative number of firms (see Appendix A for further details on the data). Columns (2a) and (3a) of Table 5, in Appendix A, report the OLS estimates of the coefficients in regressions (43)-(44).

According to equations (35), (36), (38), and (39), the slopes, D_0 and D_1, are functions of $(\alpha, \sigma, \epsilon, \delta)$, and the intercepts, $\ln Z_0$ and $\ln Z_1$, are functions of $(\alpha, \sigma, h/l, \zeta, \phi)$, in a total of seven structural parameters. There is under-identification of the structural parameters, since there are only four independent OLS estimates available from the reduced-form system (43)-(44). However, we calibrate α, σ and h/l, to get identification of the structural system and to obtain indirect (ILS) estimates of the remaining four structural parameters, ϵ, δ, ζ and ϕ. From (32), we see that the structural parameters that are key to our analysis are only ϵ and ζ, and the two other parameters, δ and ϕ, are just instrumental to their identification and estimation.[15] For robustness reasons, we obtain implicit confidence intervals for the parameters $(\epsilon, \delta, \zeta, \phi)$ from which we extract

[15]Appendix C shows that in the case of Acemoglu and Zilibotti's (2001) model, featuring only horizontal

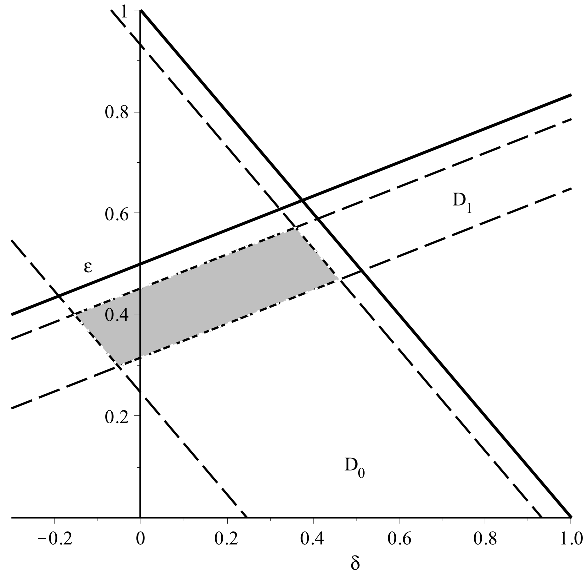

Figure 5: Confidence intervals for the estimates of ϵ and δ (dashed lines) implicit in the two-standard-error confidence intervals for the estimates of the slopes of 43-44. Bold lines are the same as in Figure 4. Example with $\alpha = 0.6$ and $\sigma = 0.5$.

values for the calibration exercise.[16] These are shown in Figures 5 and 6 and are reported in Table reported in Table 5.

Figure 5 depicts the intersection of the confidence intervals for the estimates of ϵ and δ implicit in the confidence intervals for the estimates of the slopes of (43)-(44) (computed with their estimated standard errors). This intersection lies inside the theoretical intersection associated with the existence of scale effects pertaining to the technology structure, as in Figure 4.

Figure 6 presents the intersection of the confidence intervals for the estimates of ζ and ϕ implicit in the confidence intervals for the estimates of the intercepts of (43)-(44).

[Figure 5 goes about here]

[Figure 6 goes about here]

In order to compute the largest and the smallest admissible values for each element in $(\epsilon, \delta, \zeta, \phi)$, we assume the following set of baseline values for the remaining structural

R&D, there is an over-identification of the key structural parameters and, thus, their ILS estimation is not feasible.

[16] It is well known that the confidence intervals computed this way cannot be directly used in statistical inference. However, our aim here is to compute the range of empirically admissible values for the structural parameters using the extreme bounds of the confidence intervals and not to run significance tests. For a systematic implementation of extreme bounds analysis, see, e.g., Levine and Renelt (1992).

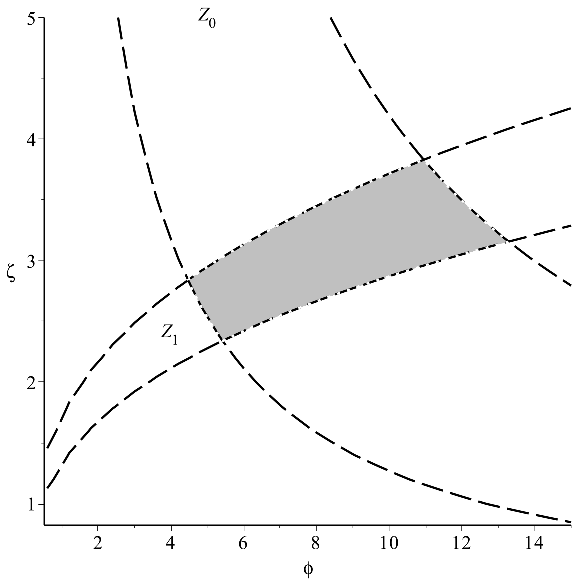

Figure 6: Confidence intervals for the estimates of $\phi \equiv \phi_H/\phi_L$ and $\zeta \equiv \zeta_H/\zeta_L$ implicit in the two-standard-error confidence intervals for the estimates of the intercepts of 43-44. Example with $\alpha = 0.6$, $\sigma = 0.5$ and $h/l = 1.3$.

parameters: $\alpha = 0.6$; $\sigma = 0.74$ and $h/l = 1.3$. The elasticity of labour in production, α, is standard in the literature. The horizontal-R&D complexity cost parameter, σ, is calibrated to match the ratio between the per capita GDP growth rate and the growth rate of the number of firms found in cross-section data for the 16 European countries in the period 1995-2007. The value for the relative productivity of high-skilled workers, h/l, comes from Afonso and Thompson (2011), and is also drawn from European data. However, given the uncertainty surrounding these estimates, we also consider 0.5 and 1.0 as alternative values for σ, while, following Acemoglu and Zilibotti (2001), we consider 1.8 as an alternative value for h/l.

The results are depicted in Tables 1 and 2. In particular, we emphasise that: (i) a large σ is associated with small estimates for δ and large estimates for ϕ, while the estimates of ϵ and ζ are independent of σ; (ii) the estimates of ϵ are positive and smaller than unity, while the estimates of δ are smaller than the estimates of ϵ, and possibly negative; (iii) the estimates of ϕ and ζ are above unity.

Results in (i) emerge from the fact that δ and σ have the same qualitative effect over the elasticities D_0 and D_1, because they are associated to similar substitution effects between vertical and horizontal R&D activities, as explained in Section 3. The qualitative effects of ϵ and σ are the same over D_0 but the opposite over D_1, because shifts in ϵ have a direct negative impact on both vertical and horizontal R&D, while σ only reduces horizontal R&D. A similar reasoning applies to the analysis of ϕ and ζ. Since ϵ and ζ are the only structural parameters to be estimated which determine the elasticity of g with respect to H/L, result (i) implies that the possible ambiguity regarding the true value of σ has

	$\sigma = 0.74$		$\sigma = 0.5$		$\sigma = 1.0$	
δ	0.381	−0.219	0.385	−0.106	0.375	−0.358
ϵ	0.581	0.286	0.581	0.286	0.581	0.286

Table 1: Indirect estimates of structural parameters ϵ and δ based on the extreme values of the two-standard-error confidence intervals for the estimates of the slope coefficients in Table 5, columns (2a) and (3a). Computation with $\alpha = 0.6$.

	$h/l = 1.3$						$h/l = 1.8$	
	$\sigma = 0.74$		$\sigma = 0.5$		$\sigma = 1.0$		$\sigma = 0.74$	
ϕ	21.212	7.397	12.833	5.422	39.519	10.868	23.965	8.358
ζ	3.942	2.307	3.942	2.307	3.942	2.307	4.832	2.827

Table 2: Indirect estimates of structural parameters $\phi \equiv \phi_H/\phi_L$ and $\zeta \equiv \zeta_H/\zeta_L$ based on the extreme values of the two-standard-error confidence intervals for the estimates of the intercept coefficients in Table 5, columns (2a) and (3a). Computation with $\alpha = 0.6$.

no implication to the quantification of that elasticity (see (32)).

As regards (ii), the result that $\delta < \epsilon$ implies that there is a positive relationship between population size, measured by $m \in \{L, H\}$, and the number of firms, N_m (see this by solving (23) with respect to N_m), as seems to be the case empirically (see, e.g., Peretto, 1998). On the other hand, the negative values obtained for δ mean that the larger the market scale of the m-technology sector, measured by L or H, the less costly it is to introduce new varieties; this effect adds to the direct (positive) effect of the market scale on profitability (see (7)). In contrast, our estimates suggest that a positive relationship prevails between market scale and the cost to introduce a further jump in quality of an existing variety, since the estimates of ϵ are positive in all cases considered.

Result (iii) implies that barriers to entry into the high-tech sector are large relative to the low-tech sector, irrespective of entry occurring through vertical or horizontal innovation.[17]

[Table 1 goes about here]

[Table 2 goes about here]

4.2. The growth-skill elasticity

Our second step is to use the above estimates of the structural parameters ϵ and ζ to calibrate the theoretical model and, thereby, to compute the predicted economic growth

[17] As referred to earlier, the result that fixed entry costs may be, in practice, larger in the high- than in the low-tech sectors finds support in some empirical literature (see fn. 7).

rate, $\tilde{\mathcal{G}}$, for each country. Then, we compute the OLS estimate of the cross-country elasticity of the *predicted* economic growth rate with respect to the observed skill structure, $\hat{\mathcal{E}}_{H/L}^{\tilde{\mathcal{G}}}$ (i.e., the OLS estimate of the slope of the log-log relationship between $\tilde{\mathcal{G}}$ and the observed values for H/L) and compare with the OLS estimate of the elasticity of the *observed* economic growth rate (the slope of regression (5) in Table 5).

Substituting in equation (40) the estimates for the structural parameters ϵ and ζ and the baseline and alternative values for σ and h/l (see Tables 1 and 2), as well as the country data on H and L, we compute a predicted cross-country economic growth rate for each country. As we have 16 different scenarios, we obtain 16 simulated sets of country growth rates. This allows us to find 16 distinct OLS estimates of the cross-country growth-skill elasticities $\hat{\mathcal{E}}_{H/L}^{\tilde{\mathcal{G}}}$.

Table 3 presents the results. The point estimates of the elasticity of the *predicted* economic growth rate are negative in all but one scenario but, as is the case in the *observed* elasticities, are not significantly different from zero. In addition, we can compare the predicted negative average and the standard error,[18] lying between 0.157 (for the scenarios with the smallest admissible value of ϵ) and 0.268 (for the scenarios with the largest admissible value of ϵ), with the related moments in the data which are 0.00001 and 0.176, respectively (see column (5) of Table 5, Appendix A). In particular, the upper limit of the two-standard-error confidence interval for the predicted elasticity lies between 0.122 and 0.212 in all the 16 scenarios, while we find an upper bound of 0.176 for the elasticity in the data. Among the 16 scenarios, 12 of them display upper-limit values below or of about 0.176 and the remaining four display values (somewhat) above 0.176. The latter correspond to the scenarios that combine the smallest admissible value of ϵ (i.e., the largest net scale effects of high-skilled labour through vertical R&D) and the smallest admissible value of ζ in each case.

Finally, in order to assess the global predictive power of our model, we measure its success in accounting for non-targeted dimensions in the earlier calibration exercise. In particular, we look at the predictive power of our model as regards the economic growth rate, measured by the constrained R^2. This is a general measure of goodness of fit, which is computed as $\mathcal{R}^2 = 1-\sum_c (x_c^{obs}-x_c)^2 / \sum_c \left(x_c^{obs}\right)^2$, where x_c (x_c^{obs}) denotes the predicted (observed) value of the economic growth rate for a given country c in our sample (see, e.g., Acemoglu and Zilibotti, 2001).[19] Table 3 presents the results for all the scenarios. The values for $\mathcal{R}^2$ indicate that the predicted economic growth rate explains between 30.9% and 64.6% of the growth rate observed in the data. Larger values of $\mathcal{R}^2$ obtain for larger values of ϵ because the latter yield a smaller dispersion of predicted growth rates across countries. We find it is fair to say that this is a rather high goodness of fit, since it results in a context where all structural parameters are assumed to be homogeneous

[18]In Section 3.1, we have shown that the theoretical growth-skill elasticity is always positive when $1-\epsilon > 0$ (see (32)). This will imply a positive cross-country growth-skill elasticity if the structural parameters in (32) are homogeneous across countries. However, in practice, these parameters may be country specific and, as result, we can get negative point estimates for that elasticity in a quantitative exercise applied to a cross section of countries.

[19]This is the R^2 from a regression of x^{obs} on x when the slope is constrained to be equal to unity and the constant to be zero; in this case, $\mathcal{R}^2 \in (-\infty, 1]$.

across-countries and only H/L is let to be country-specific when computing the predicted economic growth rate with equation (30).

[Table 3 goes about here]

Bearing in mind the possible simultaneity bias issue regarding the regressor in (43)-(44), we consider four extra scenarios in which we use the initial (1995) value of the skill structure to estimate the structural parameters, instead of the 1995-2007 average. As can be seen in Appendix D, the results are roughly unchanged.

All the previous results suggest that our model is able to account for the simultaneous insignificant elasticity between the economic growth rate and the skill structure and the positive elasticity between the technology structure, measured either as production or as the number of firms in high- vis-à-vis low-tech sector, and the skill structure. The analytical mechanism combines: (i) positive net scale effects of high-skilled labour through vertical R&D activities (i.e., vertical-R&D market complexity costs are small, only partially offsetting the benefits of market scale on profits) with (ii) large relative barriers to vertical entry into the high-tech sector, which is the employer of the high-skilled workers. While part (i) is a determinant of the *elasticity* of the technology structure with respect to the skill structure (i.e., the slope of the regression lines (43)-(44)), part (ii) influences the *level* of the technology-structure variables (i.e., the intercept of the regression lines). However, both (i) and (ii) determine the growth-skill elasticity. The two factors impact this cross-country elasticity with opposite signs, with the positive impact of scale effects being offset by the negative effect of relative barriers to entry, a result that stems from the negative relationship between the size of relative barriers to entry and the impact of the skill structure on a country's growth rate.

4.3. Trade openness, technology structure and growth

In the previous subsection, we used cross-country data to estimate a closed-economy model in which all countries generate new knowledge domestically. However, international linkages may be an important source for a country's knowledge accumulation. To account for this fact, we now consider an extended version of the model incorporating an openness indicator entering in the R&D cost functions as an exogenous variable (see, e.g., Dinopoulos and Thompson, 2000).

To check if these linkages are important to our empirical results, we first modify the R&D cost functions (10) and (18) by replacing terms ζ_m and ϕ_m with, respectively, $\zeta_m/\mathcal{O}^{v_m}$ and $\phi_m/\mathcal{O}^{h_m}$, $m \in \{L, H\}$, where $\mathcal{O}$ is an openness indicator and v_m and h_m are sector-specific elasticities. Then, by re-deriving the BGP equations (36) and (39), we get

$$Z_0' \equiv Z_0 \cdot \mathcal{O}^{\frac{\bar{h}}{\sigma+1}} \cdot \mathcal{O}^{\frac{\bar{v}}{\sigma+1}},$$

$$Z_1' \equiv Z_1 \cdot \mathcal{O}^{\frac{-\bar{h}\alpha}{(\sigma+1)(1-\alpha)}} \cdot \mathcal{O}^{\bar{v}\left[1+\left(\frac{2\sigma+1}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]},$$

ϵ	ζ	A	avg $\tilde{\mathcal{G}}$	$\mathcal{R}^2$	$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ (s.e.)
$\sigma = 0.74$; $h/l = 1.3$					
0.286	2.307	0.691	2.673%	0.309	-0.0649 (0.267)
	3.942	0.716	2.672%	0.318	-0.0974 (0.268)
0.581	2.307	2.538	2.672%	0.642	-0.0058 (0.157)
	3.942	2.680	2.672%	0.646	-0.0352 (0.157)
$\sigma = 0.5$; $h/l = 1.3$					
0.286	2.307	0.702	2.672%	0.309	-0.0649 (0.267)
	3.942	0.728	2.674%	0.317	-0.0973 (0.267)
0.581	2.307	2.580	2.673%	0.642	-0.0057 (0.157)
	3.942	2.724	2.673%	0.646	-0.0352 (0.157)
$\sigma = 1.0$; $h/l = 1.3$					
0.286	2.307	0.681	2.669%	0.310	-0.0650 (0.268)
	3.942	0.706	2.670%	0.318	-0.0975 (0.268)
0.581	2.307	2.504	2.673%	0.642	-0.0058 (0.157)
	3.942	2.644	2.673%	0.646	-0.0352 (0.157)
$\sigma = 0.74$; $h/l = 1.8$					
0.286	2.827	0.683	2.669%	0.307	-0.0555 (0.267)
	4.832	0.711	2.671%	0.317	-0.0912 (0.268)
0.581	2.827	2.497	2.671%	0.641	0.0025 (0.157)
	4.832	2.652	2.671%	0.645	-0.0295 (0.157)

Table 3: Simulation results for the economic growth rate and its cross-country elasticity with respect to the skill structure. $\mathcal{R}^2$ measures the goodness of fit of *predicted* vis-à-vis *observed* economic growth rate. $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ denotes the OLS estimate of the elasticity of the *predicted* growth rate, $\tilde{\mathcal{G}}$, with respect to the observed skill structure (heteroskedasticity-consistent s.e. in brackets). Values for $\tilde{\mathcal{G}}$ are obtained by setting $\alpha = 0.6$, $\rho = 0.02$, $\theta = 1.5$, and $\lambda = 2.5$, in line with the standard growth literature (e.g., Barro and Sala-i-Martin, 2004); the value for A is chosen such that the cross-country average of the predicted economic growth rate matches the cross-country average of the observed economic growth rate (2.672% for the 16 countries); the values for ϵ and ζ are chosen in accordance to the estimation exercise in Tables 1 and 2. For comparison: the estimate of the elasticity of the *observed* economic growth rate is 0.00001 with a s.e. of 0.176.

where $\bar{h} \equiv h_H - h_L$ and $\bar{v} \equiv v_H - v_L$ are the new relevant structural parameters. Given the latter definitions, the inclusion of the exogenous variable $\mathcal{O}$ in (10) and (18) preserves the exact identification of the key structural parameters, for given values of α, σ and h/l.

In order to run an OLS estimation of the modified reduced-form system (with $Z_0^{'}$ and $Z_1^{'}$ replacing Z_0 and Z_1 in (43) and (44)), we measure trade openness by the ratio of exports plus imports of goods over the GDP (see Dinopoulos and Thompson, 2000 for references and a developed discussion on the choice of proxy for a country's ability to absorb ideas). The data source is the Eurostat on-line database (`http://epp.eurostat.ec.europa.eu`).

Columns (2b) and (3b) of Table 5 (Appendix A) display the results. They show that including trade openness in the estimations leaves the point estimates and the standard deviations of both the intercept and the slope of equations (43) and (44) roughly unchanged; thus, the confidence intervals also remain unchanged. Moreover, the point estimates of the coefficient of trade openness are close to zero with very large confidence intervals. The point estimates suggest that the impact of international linkages on R&D performance is homogeneous across high and low-tech sectors, thus not affecting the technology structure. From the point of view of the theoretical model, this is equivalent to letting $h_H = h_L$ and $v_H = v_L$, implying $Z_0^{'} = Z_0$ and $Z_1^{'} = Z_1$ in equations (43) and (44). The inclusion of trade openness also leaves the point estimate and the standard deviation of the elasticity of growth with respect to the proportion of high-skilled labour roughly unchanged, although the point estimate of the coefficient of trade openness in the growth equation is positive with a smaller confidence interval than in the case of the technology-structure regression.[20]

Overall, these results suggest that the estimation and calibration strategy carried out in Section 4 is robust to the possible effects of international linkages, proxied by trade openness, on R&D performance.

5. Policy implications

In this section, a counterfactual policy experiment is conducted to quantify the effect of a reduction in relative barriers to (vertical) entry into the high-tech sector on the elasticity of the growth rate with respect to the skill structure.

First, we calibrate A, in (30), as a country-specific parameter, such that the predicted and the observed growth rates match exactly for each individual country. This enables an exact matching to the observed cross-country growth-skill elasticity. Then, we compute the reduction of relative vertical R&D flow-fixed costs, $\zeta \equiv \zeta_H/\zeta_L$, that leads to an increase in the estimate of the growth-skill elasticity that excludes zero from the two-standard deviation confidence interval.

Table 4 depicts the main results. The estimate of the required reduction of relative barriers to entry varies between 75.6% and 88.3% across the eight scenarios considered

[20] But the estimation may be capturing some transitional-dynamics effects in this case, since we used trade openness in 1995, the first year of the sample period. We omit the latter estimation result from Table 5 for the sake of space, but it is available from the authors upon request.

$\sigma = 0.74$; $h/l = 1.3$				
ϵ	0.286		0.581	
ζ old	2.307	3.942	2.307	3.942
ζ new	0.530	0.650	0.350	0.460
chg in ζ	-77.0%	-83.5%	-84.8%	-88.3%
Avg $\tilde{\mathcal{G}}$	3.886%	3.817%	5.772%	5.369%
$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ (s.e.)	0.176 (0.174)	0.175 (0.173)	0.175 (0.175)	0.176 (0.175)
$\sigma = 0.74$; $h/l = 1.8$				
ϵ	0.286		0.581	
ζ old	2.827	4.832	2.827	4.832
ζ new	0.690	0.870	0.450	0.610
chg in ζ	-75.6%	-82.0%	-84.1%	-87.4%
Avg $\tilde{\mathcal{G}}$	3.914%	3.821%	5.892%	5.407%
$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ (s.e.)	0.175 (0.174)	0.174 (0.173)	0.175 (0.175)	0.175 (0.175)

Table 4: Counterfactual experiment by considering a reduction of relative barriers to (vertical) entry into the high-tech sector, $\zeta \equiv \zeta_H/\zeta_L$, that leads to a significant positive estimate of the elasticity of growth with respect to the skill structure. A is calibrated as a country-specific parameter, such that the observed and the (pre-shock) predicted growth rate match exactly for each individual country.

(among the 16 scenarios in Table 3; we did not consider all the scenarios here for the sake of space). This reduction leads to $\zeta < 1$ in all cases, i.e., barriers to entry into the high-tech sector must become smaller than those in the low-tech sector.

[Table 4 goes about here]

Our numerical results show that the impact of a reduction of barriers to entry on $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ is convex, i.e., for smaller initial barriers to entry, a given absolute reduction in those barriers produces a larger increase in $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$. For instance, under the first scenario in Table 4, a reduction of ζ from 2.307 to 0.53 increases $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ from 0.00001 to 0.175, whereas a reduction of ζ from 0.53 to 0.23 further increases $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ from 0.175 to 0.317. It can be shown that a similar outcome occurs under the other scenarios.

These results suggest that the effectiveness of industrial policy aiming at a reduction of barriers to entry in the high-tech sector is negatively related to the initial level of those barriers. Therefore, accordingly, not only should policymakers be aware of the well-known time lags between the timing of implementation of this type of policies and the production of impact (a dimension of analysis not considered here), but also of the fact that barriers must be brougth down to considerable low levels before they start producing significant results.

It is also noteworthy that the correlation coefficient obtained by regressing the economic growth rate on the skill structure increases as the barriers to entry decrease. Again, for example under the first scenario in Table 4, the correlation coefficient is 0.277, when $\zeta = 0.53$, and 0.465, when $\zeta = 0.23$, which suggests a monotonic improvement vis-à-vis the correlation coefficient of 0.000 obtained with the observed economic growth rate (see Table 5).

Overall, an interesting policy implication arises from these results: industrial policy aiming to reduce barriers to entry in the high-tech sectors may effectively reinforce the effect of education policy (e.g., incentives for households to accumulate skills via improvement of the educational attainment level) on a country's growth. Given the cross-section nature of our study, with the implied hypothesis of homogeneous relative barriers to entry across countries, and the fact that our sample comprises countries belonging to the European Union, it seems particularly adequate to think of this policy implication as pertaining to EU supranational government intervention on industrial policies.

Nonetheless, it is also important to note that growth in a country that displays a more favourable skill structure (a higher proportion of high-skilled labour) benefits more from a given reduction in relative barriers to entry. For example, as shown in Figure 7, Belgium and Portugal have similar observed per capita GDP growth rates (1.9%), but the former has a larger proportion of high-skilled labour (29.5%) than the latter (4.2%). Then, e.g. under the first scenario of Table 4 (decrease of 77% in ζ), the model predicts a change in the growth rate of 0.33 p.p. (relative increase of 19%) in Portugal and of 1.19 p.p. (64%) in Belgium. In Finland, the country with the largest proportion of high-skilled labour in our sample (33.2%), the relative increase in the growth rate is of 69% under this scenario. A similar pattern is observed across the eight scenarios in Table 4. This mechanism is, of course, the reason why the growth-skill cross-country elasticity increases with a decrease in ζ. This also means that a country's education policy has the potential to leverage the effect of a barriers-reducing industrial policy on growth.

6. Concluding remarks

This paper builds an endogenous growth model of directed technical change with simultaneous vertical and horizontal R&D and scale effects to study an analytical mechanism that is consistent, for a feasible set of parameter values, with the observed cross-country pattern in the skill structure, the technology structure and economic growth. Our results indicate that the cross-country differences in the skill structure, combined with the existence of intermediate levels of market complexity costs, high relative fixed entry costs in the high-tech sectors and an absolute productivity advantage of the high-skilled workers, may be an important factor in explaining the observed pattern in the number of firms and production in high- versus low-tech sectors and hence the relationship between economic growth and the skill structure.

Furthermore, by linking the determinants of the technology structure to economic growth, our model and its estimation and calibration allow us to derive a set of policy implications: (i) the effects of a country's education policy (e.g., incentives for households to improve their educational attainment level) on economic growth may be effectively leveraged by industrial policy and vice versa; (ii) in particular, the latter should aim to reduce the fixed-entry costs pertaining to R&D activities, namely those originating relatively larger barriers to entry in the high-tech sectors (examples are the alleviation of the regulatory and IPR bureaucratic environment faced by technology-intensive firms, and the reduction of their information and management flow fixed costs, e.g. through the promotion of mentoring and business-angels activities), such that barriers to entry in the high-tech sector are brought below those in the low-tech sector; these forms of industrial policy should complement the direct subsidisation of R&D activities usually emphasised in the economic growth literature; (iii) the effectiveness of industrial policy aiming at a reduction of barriers to entry in the high-tech sector is negatively related to the initial level of those barriers.

Moreover, our estimates suggest that larger markets induce smaller costs as regards horizontal R&D activities but larger costs concerning vertical R&D. That is, in this regard, there is an apparent asymmetry between the introduction of new varieties of technological goods and the introduction of a further jump in quality of an existing variety.

It is also noteworthy the importance of distinguishing between the effects of industrial policies targeted at vertical R&D – which can be seen as pertaining to process innovation and incremental product innovation – and those targeted at horizontal R&D – pertaining to radical product innovation.[21] For instance, a reduction of the market complexity costs related to vertical R&D and of the R&D complexity costs related to horizontal R&D will have a similar, positive, impact on economic growth, but an asymmetric impact on the technology structure: for a given relative supply of skills below unity, a decrease of the first type of costs implies a smaller concentration of activity in high- vis-à-vis low-tech sectors in terms of the number of firms, production and firm size; a decrease of the second type implies a decrease of the proportion of high- versus the low-tech sectors in terms of the number of firms only.

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[21]The importance of analysing the impact of R&D policies separated this way has been emphasised by, e.g., Peretto (1998).

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Appendix

A. Data and empirical evidence: technology structure, skill structure and growth

The cross-country data with respect to the technology structure, measured by the number of firms and by production in high- vis-à-vis low-tech manufacturing sectors, was collected by considering the OECD high-tech low-tech classification (see Hatzichronoglou, 1997).[22] We also collected data on the skill structure, i.e., the ratio of high- to low-skilled workers or the relative supply of skills, measured as the ratio of college to non-college graduates among persons employed in manufacturing. "College graduates" refers to those who have completed tertiary education (corresponding to the International Standard Classification of Education [ISCED] levels 5 and 6), while "non-college graduates" refers to those who have completed higher-secondary education or less (ISCED levels from 0 to 4).

The data concerns the 1995-2007 average and covers 25, 16 and 29 European countries regarding, respectively, the number of firms, production,[23] and the supply of skills (educational attainment). The source is the Eurostat on-line database on Science, Technology and Innovation – tables "Economic statistics on high-tech industries and knowledge-intensive services at the national level" and "Annual data on employment in technology and knowledge-intensive sectors at the national level, by level of education" (available at `http://epp.eurostat.ec.europa.eu`).

At the aggregate level, we gathered data on the per capita real GDP growth rates for the same period and on 1995 trade openness covering 30 European countries (UE-27 plus EFTA countries), also from the Eurostat on-line database.

[22]High-tech industries are, e.g., aerospace, computers and office machinery, electronics and communications, and pharmaceuticals, while the low-tech industries comprise, e.g., petroleum refining, ferrous metals, paper and printing, textiles and clothing, wood and furniture, and food and beverages.

[23]According to our theoretical model, we should restrict our analysis to the production of intermediate and capital goods. However, we were not able to find data according to the OECD classification of high- and low-tech sectors detailed by type of good and thus focused on total production in each sector.

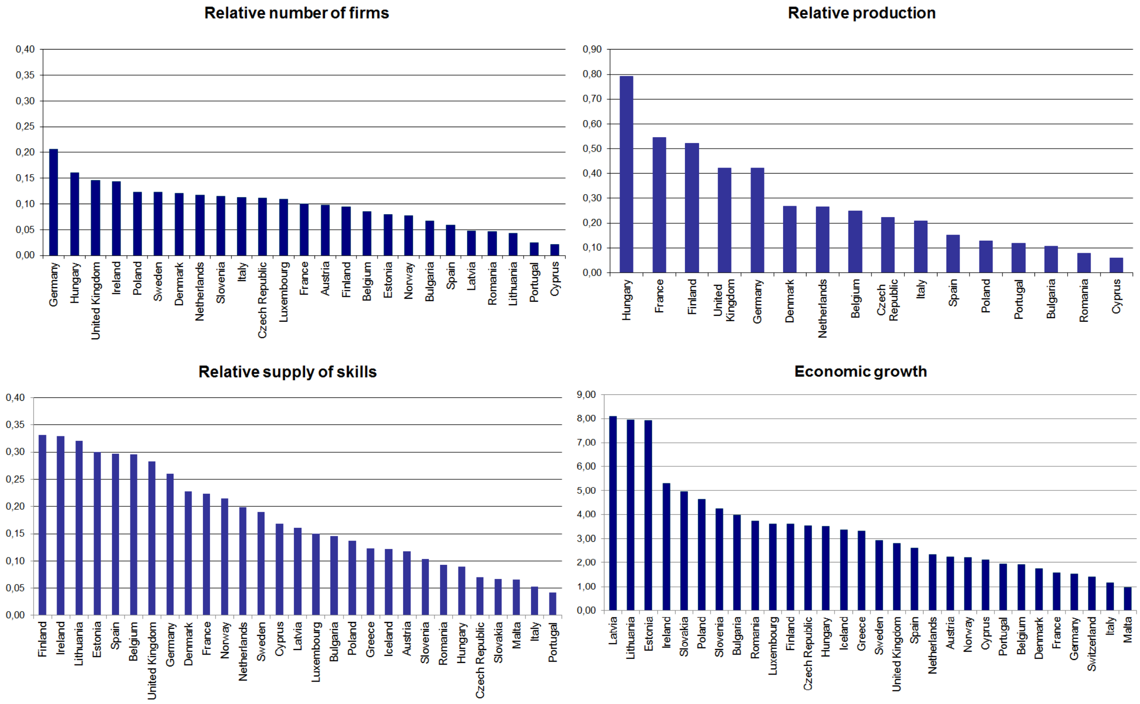

Figure 7: The technology-structure variables (the relative number of firms and relative production), the relative supply of skills (i.e., the ratio of high- to low- skilled labour) and economic growth (per capita real GDP growth rate, %) in European countries, 1995-2007 average.

[Figure 7 goes about here]

Table 5 reports the details on the OLS regressions run on the data depicted by Figure 7.[24] Notice that, even though the goodness of fit of the regressions in Table 5 might most likely increase if we added explanatory variables, the bivariate approach followed therein anticipates the fact that the log-log linear relationships between the technology-structure variables and the relative supply of skills have an exact analytical counterpart in terms of the BGP equilibrium of the model developed in Sections 2 and 3. We take advantage of this fact to pursue an identification strategy for the technology parameters of the model in Section 4 and thereby to estimate it using the data on the technology-structure

[24] In the regressions of columns (4)-(5) of Table 5, we could have used the growth rate of the production volume in manufacturing instead of the growth rate of per capita GDP. However, there are a number of countries in the Eurostat database that display a negative annual growth rate of production for the 1995-2007 average. Thus, in order to estimate the log-log relationship between the growth rate and the relative supply of skills, the total number of countries we can use in the sample falls to 25. If we only consider the countries that have available data for both technology-structure variables, then the number of countries in the sample falls to 13. The OLS point estimate of the elasticity of the growth rate (s.e.) is 0.175 (0.776) with 25 countries, and -0.598 (0.816) with 13 countries.

Dependent variable	ln Relative number of firms				ln Relative production			ln GDPpc growth rate	
	(1)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4)	(5)
Constant	-2.133	-1.936	-1.930	-1.860	-0.855	-0.841	-0.932	-3.231	-3.697
(s.e.)	(0.396)	(0.457)	(0.477)	(0.544)	(0.387)	(0.337)	(0.417)	(0.365)	(0.310)
ln Relative supply of skills 1995-2007	0.181	0.279	0.279	-	0.349	0.349	-	0.163	0.000
(s.e.)	(0.229)	(0.257)	(0.266)		(0.205)	(0.207)		(0.185)	(0.176)
ln Relative supply of skills 1995	-	-	-	0.289	-	-	0.278	-	-
(s.e.)				(0.288)			(0.199)		
ln Trade 1995	-	-	0.010	-	-	0.020	-	-	-
(s.e.)			(0.323)			(0.410)			
Observations	25	16	16	16	16	16	16	30	16
Correl. coefficient	0.190	0.289	0.290	0.289	0.312	0.313	0.240	0.178	0.000

Table 5: OLS regressions of the technology-structure variables (the relative number of firms and relative production) and the economic growth rate on the relative supply of skills (i.e., the ratio of high- to low- skilled labour) and 1995 trade openness, in logs. Regressions in columns (1), (3) and (4) were run using samples with the maximum number of countries with available data for each case among the 30 European countries comprising the EU-27 plus EFTA. Regressions in columns (2) and (5) were run using the common sample of 16 European countries with available data on the economic growth rate, relative production and the relative number of firms (thus, this sample of countries coincides with the one used in column (3)). Standard errors (s.e.) are are heteroskedasticity consistent.

variables presented in Table 5. This allows us to uncover the effect of the skill structure on economic growth by studying how the former affects the technology structure of the economy.

[Table 5 goes about here]

B. Proxy for quality-adjusted production

Assume that j follows a Poisson distribution with parameter $I \cdot t$, $j \sim Po(I \cdot t)$ over $[0, t]$. Then $\mathbb{E}\left(\lambda^{\beta j}\right) = e^{-(1-\lambda^{\beta})It}$. Proof:

$$\begin{aligned}
\mathbb{E}\left(\lambda^{\beta j}\right) &= \mathbb{E}\left(\left(\lambda^{\beta}\right)^{j}\right) = \sum_{j=0}^{\infty}\left(\lambda^{\beta}\right)^{j}\frac{e^{-It}(It)^{j}}{j!} = \\
&= e^{It\lambda^{\beta}}e^{-It}\sum_{j=0}^{\infty}\frac{e^{-It\lambda^{\beta}}\left(It\lambda^{\beta}\right)^{j}}{j!} = e^{It\lambda^{\beta}}e^{-It} = e^{-It(1-\lambda^{\beta})}.
\end{aligned}$$

Next, consider the random variables $\mathcal{Z} \equiv \lambda^{j\frac{1-\alpha}{\alpha}}$ and $\mathcal{K} \equiv \lambda^{j\frac{1}{\alpha}}$, as well as the sum of the random variables $\mathcal{Z}_i$, i.i.d. of $\mathcal{Z}$, in $Q_m = \sum_i^{N_m}\mathcal{Z}_{mi}$, and $\mathcal{K}_i$, i.i.d. of $\mathcal{K}$, in $\mathcal{Q}_m = \sum_i^{N_m}\mathcal{K}_{mi}$, $m \in \{L, H\}$. Then, for a given N_m, we get

$$\mathbb{E}(Q_m) = N_m e^{-I_m t(1-\lambda^{\frac{1-\alpha}{\alpha}})}, \tag{45}$$

$$\mathbb{E}(\mathcal{Q}_m) = N_m e^{-I_m t(1-\lambda^{\frac{1}{\alpha}})}. \tag{46}$$

Using $\ln(v+1) \approx v$ for v small enough, (45) and (46) can be rewritten as follows

$$\mathbb{E}(Q_m) = N_m e^{I_m t\left(\frac{1-\alpha}{\alpha}\right)\ln\lambda} = N_m \lambda^{I_m t\left(\frac{1-\alpha}{\alpha}\right)}, \tag{47}$$

$$\mathbb{E}(\mathcal{Q}_m) = N_m e^{I_m t\left(\frac{1}{\alpha}\right)\ln\lambda} = N_m \lambda^{I_m t\left(\frac{1}{\alpha}\right)}. \tag{48}$$

Thus, $\mathbb{E}(\mathcal{Q}_m)/\mathbb{E}(Q_m) = \lambda^{I_m t\left(\frac{1}{\alpha}-\frac{1-\alpha}{\alpha}\right)} = \lambda^{I_m t}$, which goes to ∞ as $t \to \infty$. However, given (47) and (48), we also have

$$\left(\mathbb{E}(Q_m)\right)^{\left(\frac{1}{1-\alpha}\right)} N_m^{-\left(\frac{\alpha}{1-\alpha}\right)} = N_m \lambda^{I_m t\left(\frac{1}{\alpha}\right)} = \mathbb{E}(\mathcal{Q}_m). \tag{49}$$

Since, in our model, Q_m is treated as a continuous deterministic variable, we consider the following proxy, $\widehat{\mathcal{Q}}_m$, as a deterministic version of (49)

$$\widehat{\mathcal{Q}}_m = Q_m^{\frac{1}{1-\alpha}} \cdot N_m^{-\left(\frac{\alpha}{1-\alpha}\right)}.$$

It can then be shown that $\mathcal{Q}_m/\widehat{\mathcal{Q}}_m = \text{constant}$.

C. Acemoglu and Zilibotti (2001)'s model of horizontal R&D

In this Appendix, we present the system of equations pertaining to the BGP relationship between the technology structure and the skill structure in the case of the Acemoglu and

	$\sigma = 0.74$; $h/l = 1.3$				
δ	0.393	-0.294	ϕ	20.955	5.844
ϵ	0.605	0.289	ζ	4.065	2.195

Table 6: Indirect estimates of structural parameters δ, ϵ, $\phi \equiv \phi_H/\phi_L$, and $\zeta \equiv \zeta_H/\zeta_L$ based on the extreme values of the two-standard-error confidence intervals for the estimates of the slope and intercept coefficients in Table 5, columns (2c) and (3c). Computation with $\alpha = 0.6$.

Zilibotti (2001)'s model of horizontal R&D, extended only with a flexible degree of scale effects and heterogeneous flow fixed costs to (horizontal) R&D across the $H-$and the $L-$technology sector. Retaining the notation from Section 2, we get

$$\tilde{N} \equiv \left(\frac{\tilde{N_H}}{N_L}\right) = \left(\frac{h}{l}\right) \cdot \phi^{-2} \cdot \left(\frac{H}{L}\right)^{1-2\delta}, \tag{50}$$

$$\tilde{X} \equiv \left(\frac{\tilde{X_H}}{X_L}\right) = \frac{h}{l} \cdot \phi^{-1} \cdot \left(\frac{H}{L}\right)^{1-\delta}. \tag{51}$$

Let $D_0 \equiv 1 - 2\delta$, $Z_0 \equiv (h/l) \cdot \phi^{-2}$, $D_1 \equiv 1 - \delta$, and $Z_1 \equiv (h/l) \cdot \phi^{-1}$, and consider the reduced-form system (43)-(44) as a log-log stochastic representation of the BGP equations (51) and (50), to get the OLS estimates $\hat{D}_0$, $\hat{D}_1$, $\widehat{\ln Z_0}$, and $\widehat{\ln Z_1}$. It is clear that there is an over-identification of the structural parameter δ and, thus, its indirect (ILS) estimation is not feasible. The same applies to ϕ, if, as in Section 4, we previously calibrate h/l.

As shown in the text, extending the Acemoglu and Zilibotti (2001)'s model by considering simultaneous horizontal and vertical R&D allows us to add two more structural parameters, ϵ and ζ, to be (indirectly) estimated. Therefore, given the OLS estimates $\hat{D}_0$, $\hat{D}_1$, $\widehat{\ln Z_0}$, and $\widehat{\ln Z_1}$, we get exact identification of the (now four) structural parameters and hence are able to compute their ILS estimates, as laid out in Section 4.

D. Estimation and calibration with 1995 skill structure

In this Appendix, we reiterate the steps followed in the text to compute the (indirect) estimates of the key structural parameters, but now using the 1995 proportion of high- to low-skilled workers instead of the 1995-2007 average.

Tables 6 and 7 depict the results. As can be see, they are similar to the ones obtained in Section 4.

[Table 6 goes about here]

[Table 7 goes about here]

ϵ	ζ	A	avg $\tilde{\mathcal{G}}$	$\mathcal{R}^2$	$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ (s.e.)
$\sigma = 0.74$; $h/l = 1.3$					
0.289	2.195	0.697	2.671%	0.312	-0.0605 (0.266)
	4.065	0.727	2.672%	0.322	-0.0982 (0.266)
0.605	2.195	2.794	2.672%	0.664	0.0008 (0.148)
	4.065	2.983	2.672%	0.668	-0.0324 (0.148)

Table 7: Simulation results for the economic growth rate and its cross-country elasticity with respect to the skill structure. $\mathcal{R}^2$ measures the goodness of fit of *predicted* vis-à-vis *observed* economic growth rate. $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ denotes the OLS estimate of the elasticity of the *predicted* growth rate, $\tilde{\mathcal{G}}$, with respect to the observed skill structure (White s.e. in brackets). Values for $\tilde{\mathcal{G}}$ are obtained as in Table 3, in the text. The values for ϵ and $\zeta \equiv \zeta_H/\zeta_L$ are chosen in accordance to the estimation exercise in Table 6. For comparison: the estimate of the elasticity of the *observed* economic growth rate is 0.00001 with a standard error of 0.176.

Although not shown here, the estimation and calibration strategy carried out with the 1995 skill structure is robust to the consideration of (possible) effects of international linkages on R&D performance, proxied by trade openness, as carried out in Section 4.3.