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Economic growth, the high-tech sector, and the high skilled: Theory and quantitative implications☆

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ABSTRACT

Europe's "2020 Strategy" has the main goal of stimulating economic growth by increasing the weight of the high-tech sector and the share of high-skilled workers. However, cross-country European data suggests the relationship between economic growth and both the technology structure and the skill structure is statistically insignificant. We investigate an analytical mechanism that connects these facts by extending a directed-technical-change growth model and taking it to the data. Under high relative barriers to entry into the high-tech sector and scale effects we replicate the empirical relationships. We derive quantitative policy implications on the effects of a reduction of barriers to entry.

1. Introduction

Europe's "2020 Strategy" is motivated by the following diagnostics: "Europe's average growth rate has been structurally lower than that of our main economic partners, largely due to a productivity gap that has widened over the last decade. Much of this is due to differences in business structures combined with lower levels of investment in R&D and innovation, insufficient use of information and communications technologies, reluctance in some parts of our societies to embrace innovation, barriers to market access and a less dynamic business environment" (European Commission, 2010, p. 5). The "Strategy" rests on the conventional view that increases in the shares of high-skilled workers and of the high-tech sector are major intermediate goals to improve the economic growth rate of the European Union. One of the "headline targets" states that "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" by 2020 (European Commission, 2010, p. 3). Another major target is to reduce the gap over the relative importance of the high-tech sector as compared with the US (European Commission, 2010, p. 10).

However, cross-country data for Europe suggests that: firstly, the elasticity of the per capita GDP growth rate relative to the skill structure (the ratio of high- to low-skilled labour) is not significantly different from zero (the elasticity is −0.026, with a s.e. of 0.172; see Appendix A for details on the data); secondly, the elasticity of the growth rate relative to the technology structure, measured either as relative production or as the relative number of firms in the high- vis-à-vis the low-tech sector is also not significantly different from zero (e.g., the elasticity for production is −0.003, with

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a s.e. of 0.118);[1] thirdly, there is a significant positive elasticity of the technology structure with respect to the skill structure (e.g., the elasticity for production is 0.430, with a s.e. of 0.160); finally, the technology-skill elasticity is higher when the technology structure is measured by relative production than when it is measured by the relative number of firms, implying that relative firm size also exhibits a positive elasticity with respect to the skill structure.[2]

Thus, the conventional view underlying Europe's "2020 Strategy", based on the premise that improving the skill structure would induce an increase in the share of the high-tech sector together with an increase in the economic growth rate, contrasts with the data: indeed only the "right" relationship between the skill structure and the technology structure is observed. What can explain that puzzle? Are there any policy instruments that would allow for all the "right" correlations?

The available literature does not provide an answer if we consider all the three elasticities (and the two variants using the data on production and the number of firms). In order to give an answer, we adopt an agnostic approach by extending a benchmark model of endogenous growth and directed technical change with a very flexible structure. This allows us to identify the structural relationships between growth, technology structure and skill structure underlying those facts for a cross-section of European countries.

We assume that final goods can be produced with either one of two alternative technologies, high-tech or low-tech, which are characterised by using either high- or low-skilled labour-specific intermediate goods. Since the data shows that the high-tech sector is more intensive in high-skilled labour than the low-tech sector,[3] 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 in the data (e.g., Cozzi and Impullitti, 2010).

The skill structure is assumed to be exogenous, as usual in the literature of directed technical change, in order to isolate the impact of the observed differences in the proportion of high-skilled workers across countries through the technological-knowledge bias mechanism (e.g., Acemoglu and Zilibotti, 2001; Acemoglu, 2003).[4]

Moreover, empirically, there seems to be substantial barriers to mobility both between countries and between types of labour, which determines a segmentation of the labour market along those two dimensions. We address this segmentation by considering fixed skill endowments both intra- and inter-country.

R&D can be directed to either type of intermediate good. Here we introduce several ingredients allowing for an identification of the key structural relationships. Firstly, we assume there are two types of R&D, vertical and horizontal R&D, which can be sector specific. Firms can introduce a new high-tech or low-tech specific intermediate good or can improve the quality of the existing high-tech or low-tech intermediate goods. Secondly, there are several types of fixed and market-complexity R&D costs that are heterogeneous across sectors and/or R&D types. Thirdly, we assume domestic R&D can benefit from international technology linkages, e.g., channeled through foreign direct investment (FDI) flows.[5]

The model provides measurable relationships between the skill structure and the economic growth rate and the technology structure variables along the balanced-growth path (BGP). We quantify those structural (BGP) relationships by calibrating the model after the (indirect) estimation of key structural parameters using the available cross-country European data. We find consistency with the empirical relationships between the skill structure, the technology structure and growth if one allows for the simultaneous existence of scale effects on growth (associated with positive but small market-complexity costs in vertical R&D) and of high barriers to entry into the high-tech sector vis-à-vis the low-tech sector (associated with relatively large fixed R&D costs in the high-tech sector).

Thus, by taking a structural approach to the data, we are able to uncover the underlying mechanism linking the three sets of variables (growth, technology structure and skill structure). The weak cross-country elasticities between the growth rate and both the technology and the skill structure can be a consequence of the fact that large relative barriers to entry into the high-tech sector reduce the impact of the higher proportion of the high-skilled labour on a country's growth rate. These large barriers dampen the effect of the share of high-skilled labour on growth because the high-tech sector is the main employer of high-skilled labour.

Several robustness checks are performed 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). We also allow relative barriers to entry to comprise both homogeneous and country-specific components. Country-specific barriers do not affect our results, suggesting that the homogeneous component of relative barriers is the most relevant factor explaining the observed cross-country growth elasticities. As our data set comprises only European countries, this may be a consequence of the common, supranational, regulatory framework impinged on the EU production sectors.

Counterfactual policy exercises allows us to quantify the effect of a reduction in (vertical) relative barriers to entry on the growth-skill elasticity in our cross-section of European countries: those barriers must be reduced between 79% and 88% depending on the

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

[2] The data on the skill structure refers to manufacturing employment, because we want to relate the skill structure with the (manufacturing) technology structure. However, a similar weak growth-skill relationship arises if one considers the skill structure measured by total employment. More generally, the empirical growth literature presents disparate results concerning 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 et al., 1992; Benhabib and Spiegel, 1994; Pritchett, 2001; de la Fuente and Doménech, 2006; Cohen and Soto, 2007). In contrast, 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] 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).

[4] 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 data set). 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 et al., 2005).

[5] A modeling strategy that abstracts from international trade and focus on international technology linkages has been frequently adopted in the growth literature that looks into cross-country data (e.g., Borensztein et al., 1998; Dinopoulos and Thompson, 2000; Caselli and Coleman, 2006; Vandenbussche et al., 2006; Fadinger and Mayr, 2014). In our case, it seems particularly adequate since we are focusing on a cross-section of European countries, among which intrasectoral trade predominates and where the latter may be proxied by FDI flows.

scenario considered. In all cases, barriers to entry must become smaller in the high- than in the low-tech sector. The reduction in relative barriers 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 Ireland, the relative increase in the economic growth rate due to a given reduction in barriers to entry is, in the latter, about four times the relative increase in the former (if one allows for country-specific barriers, the gap increases to over five times). A policy implication suggests itself: education policy (or say measures to clamp down on brain-drain flows) and industrial policy aiming to reduce barriers to entry in the high-tech sector have complementary effects on economic growth. However, 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.

We run a second counterfactual exercise aiming at the determination of the impact on the European long-run growth rate if the average European entry costs were reduced to a point such that the share of the European high-tech sector is raised to the US level. A simultaneous reduction of vertical and horizontal relative barriers by, respectively, 34% and 61% increases the share of production and of the number of firms of the high-tech sector in Europe to about the US level, while it would increase the European economic growth rate by 0.22 p.p (relative increase of 7.4%). Alternatively, the same goal would be achieved by increasing the average European skill ratio by 94%, which would induce an increase of the European growth rate by 0.27 p.p. (relative increase of 8.9%). These results suggest that, as regards the impact on growth, the policy targeting relative barriers to entry would be more efficient than the one targeting relative supply of skills. In both cases, however, the predicted growth effects are modest relative to the size of the policy action.

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 et al. (2009) on growth, and Barseghyan (2008) on productivity levels. On the theoretical front, we single out Poschke (2010), Bento (2014), 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 et al. (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 data set 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 above empirical data could in principle be compatible with alternative theoretical explanations relating the skill structure to the technology structure. An apparent candidate would be the neoclassic Heckscher-Ohlinian approach. However, this relies on factor endowment abstracting from technological differences to explain *intersectoral* international trade, whereas the data highlights the relationship between factor endowment and technological differences among countries with relatively similar levels of technological development and, thus, among which *intrasectoral* trade dominates. Moreover, the Heckscher-Ohlinian approach cannot explain *per se* the differential behaviour between relative production and the relative number of firms vis-à-vis the skill structure, an also relevant feature of the data, whereas endogenous growth effects are typically absent in this framework. Therefore, we consider a directed technical change approach, which allows us to endogenously relate the skill structure to both measures of the technology structure and to economic growth in a natural and unified way, and to explore the connection between international technology linkages and intrasectoral trade.

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 the BGP. 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 Sections 4 and 5, we calibrate the model using the data on the skill structure and the technology structure, and quantify the key growth relationships of the model. Section 6 gives some concluding remarks.

2. The model

Two different types of labour, high and low skilled,[6] and factor-biased technical change are introduced in a dynamic general-equilibrium setup, as in Acemoglu and Zilibotti (2001). Moreover, the setup is augmented with vertical R&D, international technology linkages, and flexible scale effects. We consider that the world consists of many countries that have the same production structure and preferences but may differ as regards skill endowments. Countries are connected via technology linkages (channeled through, e.g., FDI or licensing), but we abstract from international trade and labour mobility. Empirically, the cross-border flows of labour are relatively small between European countries, while FDI flows may proxy for intrasectoral international trade, the predominant form of trade between these countries. Indeed, one can interpret FDI taking place between countries with roughly the same level of technological development as a reduced form of a mechanism of intrasectoral international trade.

In each country, 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 (or L- or H-technology), 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 inter-

[6] The high-skilled type can be interpreted broadly as encompassing scientific, creative and entrepreneurial talents, which mainly meet the demand of high skills by knowledge-based industries. This view emphasises the relevance of diversity and creativity for innovation-based economic progress (see, e.g., Florida, 2002; Toner, 2011).

mediate goods. Horizontal R&D increases the number of industries, $N_m, m \in \{L, H\}$, in the m-specific intermediate-good sector,[7] 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. 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 $N_m(t)$, $m \in \{L, H\}$

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

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. The parameters $A > 0$ and $\alpha \in (0, 1)$ denote the total factor productivity and the labour share in production. The indexing of firms assigns a larger (smaller) n to firms holding a relative productivity advantage of using the H (L)-technology. For every t, there is an endogenous threshold $\bar{n}(t)$, at which a switch from one technology to the other becomes advantageous, so that every firm n produces exclusively with either the L- or the H-technology. The threshold $\bar{n}(t)$ follows from market clearing in the inputs markets, such that $\bar{n}(t) = \left[1 + \left(h/l\cdot H/L\cdot Q_H(t)/Q_L(t)\right)^{1/2}\right]^{-1}$, where $L = \int_0^{\bar{n}} L(n)dn$, $H = \int_{\bar{n}}^1 H(n)dn$, and

$$Q_m(t) = \int_0^{N_m(t)} q_m(\omega_m,t)d\omega_m, \quad q_m(\omega_m,t) \equiv \lambda^{j_m(\omega_m,t)\left(\frac{1-\alpha}{\alpha}\right)}, \quad m \in \{L, H\}, \quad (2)$$

is the aggregate quality index, or stock of knowledge, in the m-technology sector. 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 usual profit maximisation conditions, we determine the demand of L-specific (H-specific) intermediate good ω_m by firm $n \in [0, \bar{n}(t)]$ (firm $n \in [\bar{n}(t), 1]$). Also, it is convenient to define the price indices of final goods $P_L(t)$ and $P_H(t)$, which can be shown to relate with $P(n, t)$ and $\bar{n}(t)$, $P_L(t) = P(n,t)\cdot(1-n)^{\alpha} = \exp(-\alpha)\cdot\bar{n}(t)^{-\alpha}$ and $P_H(t) = P(n,t)\cdot n^{\alpha} = \exp(-\alpha)\cdot(1-\bar{n}(t))^{-\alpha}$.

The intermediate-good m-technology sector contains 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 $p_m(\omega_m, t)$ in face of an isoelastic demand curve, $X_L(\omega_L,t) = \int_0^{\bar{n}(t)} X_L(n,\omega_L,t)dn$ or $X_H(\omega_H,t) = \int_{\bar{n}(t)}^1 X_H(n,\omega_H,t)dn$. Intermediate goods are non-durable and entail a unit marginal cost of production in terms of the final good. 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 $p_m(\omega_m, t) \equiv p = 1/(1-\alpha) > 1$. From the markup, we find the optimal intermediate-good production, $X_m(\omega_m)$ and, thus, the optimal profit accrued by the monopolist in ω_m, $\pi_L(\omega_L,t) = \pi_0\cdot l\cdot L\cdot P_L(t)^{\frac{1}{\alpha}}\cdot q_L(\omega_L,t)$ or $\pi_H(\omega_H,t) = \pi_0\cdot h\cdot H\cdot P_H(t)^{\frac{1}{\alpha}}\cdot q_H(\omega_H,t)$, where $\pi_0 \equiv A^{\frac{1}{\alpha}}(1-\alpha)^{\frac{2}{\alpha}}\alpha/(1-\alpha)$ is a positive constant.

Aggregate productions of intermediate and final goods are, respectively

$$X_{tot}(t) = A^{\frac{1}{\alpha}}\cdot(1-\alpha)^{\frac{2}{\alpha}}\cdot\left(P_L(t)^{\frac{1}{\alpha}}\cdot l\cdot L\cdot Q_L(t) + P_H(t)^{\frac{1}{\alpha}}\cdot h\cdot H\cdot Q_H(t)\right) \quad (3)$$

and

$$Y_{tot}(t) = A^{\frac{1}{\alpha}}\cdot(1-\alpha)^{\frac{2(1-\alpha)}{\alpha}}\cdot\left(P_L(t)^{\frac{1}{\alpha}}\cdot l\cdot L\cdot Q_L(t) + P_H(t)^{\frac{1}{\alpha}}\cdot h\cdot H\cdot Q_H(t)\right). \quad (4)$$

where $X_{tot}(t) \equiv X_L(t) + X_H(t) \equiv \int_0^{N_L(t)} X_L(\omega_L,t)d\omega_L + \int_0^{N_H(t)} X_H(\omega_H,t)d\omega_H$ and $Y_{tot}(t) \equiv Y_L(t) + Y_H(t) \equiv \int_0^{\bar{n}(t)} P(n,t)Y(n,t)dn + \int_{\bar{n}(t)}^1 P(n,t)Y(n,t)dn$.

2.2. R&D

There are two types of R&D, one targeting vertical innovation and the other targeting horizontal innovation. Each new design (a new variety or a higher quality good) is granted a patent, and 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 et al., 2013). There is perfect competition among entrants and free entry into R&D activities. We model the latter by considering R&D costs as a function of an array of external factors: that is, as a positive function of complexity effects and of a flow fixed component (which later will be interpreted as a measure of barriers to entry), and a negative function of international technology linkages. In turn, the existing stock of knowledge determines the availability of resources to (potentially) allocate to innovation.

In this context, and in spite of the international linkages, the pace of innovation is mainly the result of the structural characteristics of the integrated innovation system at the country level. Thus, this approach allows us to address the diversity of country-level contexts in which the production of technological knowledge takes place and, ultimately, the persisting cross-country differences in the economic growth rate.[8]

Vertical R&D. A successful innovation will instantaneously increase the quality index in industry ω_m from $q_m(\omega_m, t) = q_m(j_m)$ to $q_m(j_m+1) = \lambda^{(1-\alpha)/\alpha} q_m(\omega_m, t)$, $m \in \{L, H\}$. 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 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

[7] Henceforth, we will also refer to the "m-specific intermediate-good sector" as "m-technology sector".

[8] In this sense, our model allows for path-dependent growth effects. A strand of the literature further analyses this issue in an endogenous technological knowledge setup where existing units of knowledge, being external to each agent, are identified, recollected and provisioned in order to be recombined and generate new technological knowledge. In an out-of-equilibrium context, this may give rise to pecuniary knowledge externalities, which reinforce path dependency (see, e.g., Antonelli, 2013).

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

$$I_m(j_m)=R_{v,m}(j_m)\cdot\frac{1}{\Phi_m(j_m)},\quad m\in\left\{L,H\right\}. \tag{5}$$

where $\Phi_m(j_m)=\zeta_m\cdot m^{\epsilon}\cdot q_m(j_m+1)/F_{v,m}$, with $\zeta_m>0$ and $\epsilon\in\mathbb{R}$. The flow $R_{v,m}(j_m)$ is measured in final-good units and, as such, also reflects the existing stock of knowledge in the economy (see Eq. (4)). Eq. (5) incorporates four types of effects. Firstly, there is an R&D complexity effect such that the larger the (next) quality level in an industry of sector m, $q_m(j_m+1)$, the costlier it is to introduce a further jump in quality (e.g., Howitt, 1999; Barro and Sala-i-Martin, 2004, chap. 7). Secondly, there is a (potential) market complexity effect, measured by m^{ϵ}: an increase in the market scale of the m-technology sector, measured by labour m, may imply say increasing coordination, organisational and transportation costs and thereby dilute the effect of R&D outlays on the innovation probability. 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, which accrue to the R&D successful firm. On the other hand, if $\epsilon<0$, 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, chap. 7). Thus, as shown later, there may be positive, null or negative net scale effects on industrial growth, as measured by $1-\epsilon$. Thirdly, the cost of vertical R&D also depends on a fixed flow cost specific to the m-complementary production technology targeted by vertical R&D, ζ_m. 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. Finally, we allow for a positive effect of international technology linkages on R&D performance, denoted by $F_{v,m}$ (this will be specified in Section 4.1).[9]

Under free-entry, one can derive the no-arbitrage conditions facing a vertical innovator,

$$r(t)+I_L(t)=\frac{\pi_0\cdot l\cdot L^{1-\epsilon}\cdot P_L(t)^{\frac{1}{\alpha}}}{\zeta_L/F_{v,L}}$$

$$,\quad r(t)+I_H(t)=\frac{\pi_0\cdot h\cdot H^{1-\epsilon}\cdot P_H(t)^{\frac{1}{\alpha}}}{\zeta_H/F_{v,H}}, \tag{6}$$

where r is the real interest rate. The above imply that the rates of entry are symmetric across industries, $I_m(\omega_m,t)=I_m(t)$.

Equating the effective rate of return for both sectors, in (6), another no-arbitrage condition obtains

$$I_H(t)-I_L(t)=\pi_0\left(\frac{h}{\zeta_H/F_{v,H}}\cdot H^{1-\epsilon}\cdot P_H(t)^{\frac{1}{\alpha}}-\frac{l}{\zeta_L/F_{v,L}}L^{1-\epsilon}\cdot P_L(t)^{\frac{1}{\alpha}}\right). \tag{7}$$

Solving Eq. (5) 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,

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

Horizontal R&D. Variety expansion emerges from R&D aimed at creating new intermediate goods. Let $\dot{N}_m^e(t)$ denote the contribution to the instantaneous flow of new m-specific intermediate goods by potential entrant e, $\eta_m(t)$ the R&D cost in units of the final good and $R_{hm}^e(t)$ the flow of resources devoted to horizontal R&D by e at time t. Then, aggregating across firms e, we get $R_{h,m}(t)=\sum_e R_{h,m}^e(t)$ and $\dot{N}_m(t)=\sum_e\dot{N}_m^e(t)$, implying

$$\dot{N}_m(t)=R_{h,m}(t)\frac{1}{\eta_m(t)},\quad m\in\left\{L,H\right\}, \tag{8}$$

where $\eta_m(t)=\phi_m\cdot m^{\delta}\cdot N_m(t)^{\sigma}/F_{h,m}$, with $\phi_m>0$, $\delta\in\mathbb{R}$, and $\sigma>0$. The flow $R_{h,m}(t)$ is measured in final-good units and, as such, also reflects the existing stock of knowledge in the economy (see Eq. (4)). Similarly to vertical R&D, Eq. (8) also incorporates four types of effects. Firstly, an R&D complexity effect arises through the dependence of η_m on N_m. That is, the larger the number of existing varieties, the costlier it is to introduce new varieties (e.g., Evans et al., 1998; Barro and Sala-i-Martin, 2004, chap. 6). Secondly, (8) 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, chap. 6), and, as made clear in Section 4, enables identification in our estimation exercise. Thirdly, for any given supply of labour and number of varieties, the cost of horizontal R&D also depends on a fixed flow cost, ϕ_m, 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. Finally, we consider a positive effect of international technology linkages on R&D performance, denoted by $F_{h,m}$ (this will be specified in Section 4.1).

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 $\bar{q}_m(t)=\int_0^{N_m(t)}q_m(\omega_m,t)d\omega_m/N_m(t)=Q_m(t)/N_m(t)$. Under free-entry, we can derive the no-arbitrage condition facing a horizontal innovator

$$r(t)+I_m(t)=\frac{\bar{\pi}_m(t)}{\eta_m(t)},\quad m\in\left\{L,H\right\}, \tag{9}$$

where $\bar{\pi}_L=\pi_0\cdot l\cdot L\cdot P_L^{\frac{1}{\alpha}}\cdot\bar{q}_L$ and $\bar{\pi}_H=\pi_0\cdot h\cdot H\cdot P_H^{\frac{1}{\alpha}}\cdot\bar{q}_H$.

We get total resources devoted to horizontal R&D by solving (8) with respect to $R_{h,m}$.

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 (6) and (9), we get the *intra-sector* no-arbitrage conditions

$$\bar{q}_m(t)=\frac{Q_m(t)}{N_m(t)}=\frac{\eta_m(t)}{\zeta_m\cdot m^{\epsilon}/F_{v,m}}=\frac{\phi_m}{\zeta_m}\frac{F_{v,m}}{F_{h,m}}\cdot m^{\delta-\epsilon}\cdot N_m(t)^{\sigma},$$
$$m\in\left\{L,H\right\} \tag{10}$$

[9] We do not consider technology catching-up effects of the traditional form, i.e., that technology is adopted and that the adoption cost is decreasing in the gap to the technology frontier (e.g., Nelson and Phelps, 1966). The assumption that countries do not invent technologies independently but rather adopt them from a technology frontier is especially plausible for developing countries, whereas international technology spillovers as enhancers of domestically-produced knowledge seem to be important also for industrialised countries (e.g., Coe and Helpman, 1995; Coe et al., 2009; Ang and Madsen, 2015). However, we do consider a multiplicative interaction between the flow fixed costs and the technology-knowledge stock (measured by quality level or number of varieties), which implies that the smaller the latter (and, hence, the *larger* the gap to the technology frontier), the *smaller* the impact of a given amount of flow fixed costs on R&D total costs.

These 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, $\bar{q}_m \cdot \zeta_m \cdot m^{\epsilon}/F_{v,m}$.

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. 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

$$U = \int_0^{\infty} \left(\frac{C(t)^{1-\theta} - 1}{1-\theta} \right) e^{-\rho t} dt, \tag{11}$$

where $\rho > 0$ is the subjective discount rate and $\theta > 0$ is the inverse of the intertemporal elasticity of substitution. Maximisation of (11) is subject to the flow budget constraint $\dot{a}(t) = r(t) \cdot a(t) + W_L(t) \cdot L + W_H(t) \cdot H - C(t)$, where a denotes households' real financial assets holdings, with a given initial level $a(0)$. The transversality condition is $\lim_{t\to\infty} e^{-\rho t} \cdot C(t)^{-\theta} \cdot a(t) = 0$, while the Euler equation for consumption is

$$\frac{\dot{C}(t)}{C(t)} = \frac{1}{\theta} \cdot (r(t) - \rho). \tag{12}$$

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 no-arbitrage condition between vertical and horizontal entry, and taking time derivatives, we find the aggregate flow budget constraint is equivalent to the final product market equilibrium condition, $Y_{tot}(t) = X_{tot}(t) + C(t) + R_h(t) + R_v(t)$, 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 $\left(\left\{X_m(\omega_m, t), p_m(\omega_m, t)\right\}, \omega_m \in [0, N_m(t)]\right)_{t\geq 0}$ and aggregate number of firms, quality indices and vertical-innovation rates $\left(\left\{N_m(t), Q_m(t), I_m(t)\right\}\right)_{t\geq 0}$ 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 Eq. (7), we derive an expression for P_H/P_L. Then, considering the threshold $\bar{n}$, we get the long-run technological-knowledge bias, $Q \equiv Q_H/Q_L$, as (henceforth a tilde over a symbol denotes BGP magnitudes)

$$\tilde{Q} = \frac{h}{l} \cdot \left(\frac{\zeta_H}{\zeta_L}\right)^{-2} \cdot \left(\frac{H}{L}\right)^{1-2\epsilon} \cdot \left(\frac{F_{v,H}}{F_{v,L}}\right)^2. \tag{13}$$

Assuming that the number of industries, N, is large enough to treat Q as time-differentiable and non-stochastic, we time-differentiate (2) 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 (12), together with the necessary condition (i), leads 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

$$\tilde{g} = \frac{1}{\theta}\left[\frac{\pi_0}{e}\left(\frac{l}{\zeta_L/F_{v,L}} L^{1-\epsilon} + \frac{h}{\zeta_H/F_{v,H}} H^{1-\epsilon}\right) - \rho\right]\left(1 - \frac{1}{1+\theta\mu}\right), \tag{14}$$

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 values are homogeneous across the H and L-technology sectors and are monotonically 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, Eq. (14) 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} exceeds 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.

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 (5) and (8)),[10] 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.

Importantly, Eq. (14) also allows us to account for the persisting differences in the economic growth rate across countries by considering country-specific levels of the skill endowments, H and L, and of the international technological linkages, $F_{v,m}$ (see Section 4).

[10] 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 $-(1+\sigma)$, $\sigma > 0$.

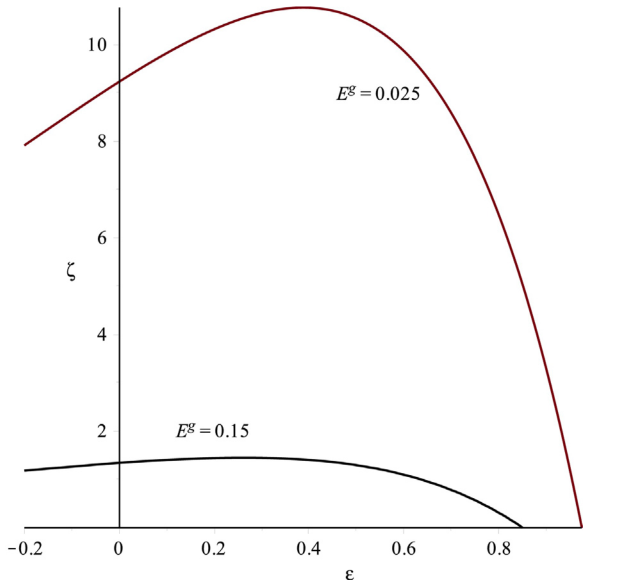

Fig. 1. Curves $\mathcal{E}^{\tilde g}_{H/L}(\epsilon,\zeta) = 0.025$ and $\mathcal{E}^{\tilde g}_{H/L}(\epsilon,\zeta) = 0.15$ for $h/l = 1.3$ and $H/L = 0.182$.

3. Growth, technology structure, and the skill structure

3.1. Growth and skill structure

The long-run economic growth rate, in Eq. (14), 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 Eq. (14), we find that the elasticity of the growth rate regarding H/L (i.e., the growth-skill elasticity) is

$$\mathcal{E}^{\tilde g}_{H/L} = \mathcal{E}^{\tilde g}_{H/L}(\epsilon,\zeta) \equiv \frac{\partial \tilde g}{\partial (H/L)}\,\frac{H/L}{\tilde g} = (1-\epsilon)\left(\frac{h/l\cdot(H/L)^{1-\epsilon}}{\zeta/F_v + h/l\cdot(H/L)^{1-\epsilon}}\right), \tag{15}$$

with $F_v \equiv F_{v,H}/F_{v,L}$ and $\zeta \equiv \zeta_H/\zeta_L$, which parametrise, respectively, the international technology linkages and the barriers to vertical entry in the H- relative to the L-technology sector (see (5)). 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.

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 at a point such that $1-\epsilon > \bar{\mathcal{E}}^{\tilde g}_{H/L}$. Fig. 1 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, we next 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 elasticities computed with the simulated and the observed 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 Eq. (13). From X_L and X_H, in Eq. (3), we get the relative intermediate-good production

$$\tilde X \equiv \left(\frac{\tilde X_H}{X_L}\right) = \frac{h}{l}\cdot\zeta^{-1}\cdot\left(\frac{H}{L}\right)^{1-\epsilon}\cdot F_v, \tag{16}$$

and, from N_L and N_H in Eq. (10), combined with (13), we get the relative number of firms

$$\tilde N \equiv \left(\frac{\tilde N_H}{N_L}\right) = Z_0\cdot\left(\frac{H}{L}\right)^{D_0}\cdot F_h^{\frac{1}{\sigma+1}}\cdot F_v^{\frac{1}{\sigma+1}}, \tag{17}$$

where

$$D_0 \equiv \frac{1-\epsilon-\delta}{1+\sigma} \tag{18}$$

$$Z_0 \equiv \left(\frac{h}{l}\right)^{\frac{1}{\sigma+1}}\cdot\phi^{\frac{-1}{\sigma+1}}\cdot\zeta^{\frac{-1}{\sigma+1}}, \tag{19}$$

with $F_h \equiv F_{h,H}/F_{h,L}$ and $\phi \equiv \phi_H/\phi_L$. Therefore, in addition to being a function of H/L (which sign depends crucially on the complexity-costs parameters ϵ and δ), the technology structure also depends on the relative productivity of high-skilled workers, h/l, on the relative barriers to entry into the H-technology sector, ζ and ϕ, and on the relative effect of international technological linkages, F_h and F_v.

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 $m=L$) $\mathfrak{X}_L = \int_0^{N_L}\int_0^{\tilde n}\lambda^{j_L(\omega_L)}\cdot X_L(n,\omega_L)\,dn\,d\omega_L = A^{\frac{1}{\alpha}}(1-\alpha)^{\frac{2}{\alpha}}P_L^{\frac{1}{\alpha}}\,lL\mathcal{Q}_L$, 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 $\mathcal{Q}_m$, $\hat{\mathcal{Q}}_m = Q_m^{\frac{1}{1-\alpha}}\cdot N_m^{-\left(\frac{\alpha}{1-\alpha}\right)}$ $m\in\{L,H\}$, and define $\hat{\mathfrak{X}}_m = X_m\cdot(Q_m/N_m)^{\frac{\alpha}{1-\alpha}}$ for $\mathfrak{X}_m$. Thus, bearing in mind (13), (16) and (17), we use, for conducting the empirical study, the following quality-adjusted measure of relative production,

$$\hat{\tilde{\mathfrak{X}}} = \tilde X\cdot\left(\frac{\tilde Q}{\tilde N}\right)^{\frac{\alpha}{1-\alpha}} = Z_1\cdot\left(\frac{H}{L}\right)^{D_1}\cdot F_h^{\frac{-\alpha}{(\sigma+1)(1-\alpha)}}\cdot F_v^{\left[1+\left(\frac{2\sigma+1}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]}, \tag{20}$$

where

$$D_1 \equiv \frac{\alpha\delta+1-\alpha+\sigma-\epsilon\left[1+(1+\alpha)\sigma\right]}{(1+\sigma)(1-\alpha)} \tag{21}$$

$$Z_1 \equiv \left(\frac{h}{l}\right)^{\left[1+\left(\frac{\sigma}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]}\cdot\phi^{\frac{\alpha}{(\sigma+1)(1-\alpha)}}\cdot\zeta^{-\left[1+\left(\frac{2\sigma+1}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]} \tag{22}$$

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

$$\tilde{\mathcal{G}} = \left(1+\frac{\alpha\sigma}{(1-\alpha)(1+\sigma)}\right)\cdot\tilde g. \tag{23}$$

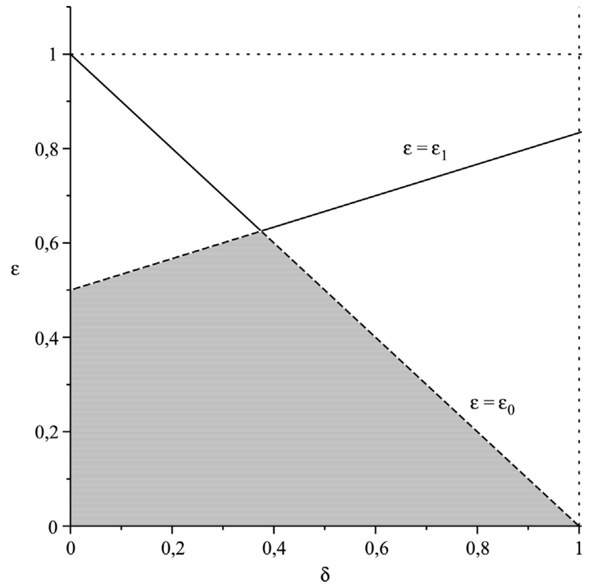

Fig. 2. Set of values for the market complexity-cost parameters (ϵ, δ) that are qualitatively consistent with the technology-structure elasticities found in the cross-country data (see Appendix A), i.e., that imply D_0, $D_1 > 0$ in (18) and (21). Example with $\alpha = 0.6$ and $\sigma = 0.5$.

In addition to its impact on the BGP economic growth rate (see (14)), the market complexity cost parameter associated to vertical R&D, ϵ, plays an important role in 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 of $D_0 > 0$ 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 $\bar{\epsilon}_0 = 1 - \delta$ and $\bar{\epsilon}_1 = \frac{1-\alpha+\sigma+\alpha\delta}{1+(1+\alpha)\sigma}$. 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 Fig. 2, where the values for ϵ and δ in the positive outhant are highlighted.

Additionally, the empirical evidence also suggests that the elasticity of the relative number of firms is smaller than the elasticity of relative production, which corresponds to $D_0 < D_1$. This will be satisfied if $\epsilon < \bar{\epsilon}_2 = \frac{\sigma+\delta}{\alpha+(1+\alpha)\sigma}$, and implies a positive relationship also between relative firm size and skill structure.

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.[11]

Proposition 2. Technology structure and skill structure. Let $\delta < \alpha/(1+\alpha)$ such that $\bar{\epsilon}_2 < \bar{\epsilon}_1 < \bar{\epsilon}_0$ for σ finite. If a country has a *higher* proportion of high-skilled labour, H/L, then it will have:

(i) A *larger* relative number of firms, production and firm size, if $0 \leq \epsilon < \bar{\epsilon}_2$;
(ii) A *larger* relative number of firms and production but a *smaller* relative firm size, if $\bar{\epsilon}_2 < \epsilon < \bar{\epsilon}_1$;
(iii) A *larger* relative number of firms but a *smaller* relative production and firm size, if $\bar{\epsilon}_1 < \epsilon < \bar{\epsilon}_0$;
(iv) A *smaller* relative number of firms, production and firm size, if $\epsilon > \bar{\epsilon}_0$.

[11] Henceforth, the $\sim$ is omitted for the sake of simplicity.

The results above derive from the different responses of the relative number of firms, N, and relative production, $\hat{\mathfrak{X}}$, 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 (17)), 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 $\hat{\mathfrak{X}}$ ($\partial D_1/\partial\delta > 0$, in (20)). 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 $\hat{\mathfrak{X}}$ 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 (i.e., $\partial D_0/\partial\sigma < 0$), whereas this cost has an indirect positive impact (substitution effect) on $\hat{\mathfrak{X}}$ (i.e., $\partial D_1/\partial\sigma > 0$).

4. Quantification

As reported in Section 1, there is a weak empirical relationship between the economic growth rate and both the skill structure and the technology structure but a significant positive relationship between the technology structure and the skill structure. As regards our theoretical model, the relationship between the market complexity cost parameter ϵ (where $1-\epsilon$ measures net scale effects on growth) and the barriers to entry parameter ζ that is consistent with low growth elasticities is non-linear (see Eq. (15) and Fig. 1). Thus, in order to quantify the structural parameters ϵ and ζ, we use the cross-country data for the technology structure and the skill structure and obtain the respective (indirect) empirical estimates. In particular, we take their confidence intervals as the range of empirically admissible values for ϵ and ζ in light of the available data (Section 4.1). Then, we use these values to compute the predicted value of each country's economic growth rate and relative production. Using these simulated data, we estimate the cross-country elasticity of economic growth regarding both the skill structure and relative production and compare them with the estimates of the cross-country elasticities obtained from the observed data (Section 4.2).

4.1. Scale effects and relative barriers to entry

Herein, we consider the BGP equations relating the technology-structure variables with the skill-structure variable, (17) and (20). Since these equations establish the endogenous variables (the technology-structure variables) as functions of the exogenous variables alone (the relative supply of skills, H/L, and the relative international technology linkages, F_h, F_v), then they can be seen as a reduced-form system of equations that can be estimated by standard OLS.

Moreover, bearing in mind the importance of economic openness (e.g., Edwards, 1992, 1998; Dinopoulos and Thompson, 2000; Ang and Madsen, 2015) and of foreign direct investment (FDI) (e.g., Coe and Helpman, 1995; Eaton and Kortum, 1996; Borensztein et al., 1998; Coe et al., 2009) for a country's ability to absorb ideas, we specify, in Eqs. (5) and (8), $F_{v,m} \equiv \kappa_{v,m}^{\upsilon_{1m}} \cdot \mathcal{O}^{\upsilon_{2m}}$, $\upsilon_{1m}, \upsilon_{2m} > 0$ and $F_{h,m} \equiv \kappa_{h,m}^{\gamma_{1m}} \cdot \mathcal{O}^{\gamma_{2m}}$, $\gamma_{1m}, \gamma_{2m} > 0$, where $\mathcal{O}$ is an economic openness indicator and $\kappa_{v,m}$ (respectively, $\kappa_{h,m}$) is the ratio of foreign entrant firms to the total number of entrants along the vertical (respectively, horizontal) margin in sector m. That is, there are two types of entrants/firms that innovate on intermediate goods: domestic firms and foreign firms that are undertaking a direct investment in the economy. This implies that: regarding vertical entry, $I_m = I_m^d + I_m^f$, with $I_m^d = \sum_{i \in \mathcal{D}} I_m^i(j_m)$, $I_m^f = \sum_{i \in \mathcal{F}} I_m^i(j_m)$, where $\mathcal{D}$ is the set of domestic firms and $\mathcal{F}$ the set of foreign firms, and thus, $\kappa_{v,m} \equiv I_m^f / I_m$; regarding horizontal entry, $\dot{N}_m = \dot{N}_m^d + \dot{N}_m^f$, with $\dot{N}_m^d = \sum_{e \in \mathcal{D}} \dot{N}_m^e$, $\dot{N}_m^f = \sum_{e \in \mathcal{F}} \dot{N}_m^e$, and, thus, $\kappa_{h,m} \equiv \dot{N}_m^f / \dot{N}_m$. The ratios $\kappa_{v,m}$ and $\kappa_{h,m}$ are constant along the BGP.[12]

Economic openness, $\mathcal{O}$, is measured by the ratio of exports plus imports of goods to GDP,[13] while the ratio of foreign entrant firms to the total number of entrants, κ, is measured by the ratio of FDI inflows to GDP. Since the available data on FDI inflows does not allow one to distinguish between either vertical/horizontal or low-tech/high-tech entry, we let $\kappa = \kappa_{v,m} = \kappa_{h,m}, \quad m \in \{L, H\}$, implying $F_v \equiv F_{v,H}/F_{v,L} = \kappa^{(\upsilon_{1H}-\upsilon_{1L})}\mathcal{O}^{(\upsilon_{2H}-\upsilon_{2L})}$ and $F_h \equiv F_{h,H}/F_{h,L} = \kappa^{(\gamma_{1H}-\gamma_{1L})}\mathcal{O}^{(\gamma_{2H}-\gamma_{2L})}$ in (17) and (20). The relative supply of skills, H/L, is measured as the ratio of college to non-college graduates among persons employed in manufacturing (see Appendix A for further details on the data).

Then, considering the BGP equations (17) and (20) and the specifications for $F_{v,m}$ and $F_{h,m}$, we run the regressions

$$\ln \tilde{N}_i = \ln Z_0 + D_0 \ln (H/L)_i + B_0^{\kappa} \ln \kappa_i + B_0^{\mathcal{O}} \ln \mathcal{O}_i + e_{0i}, \quad (24)$$

$$\ln \hat{\tilde{x}}_{\tilde{i}} = \ln Z_1 + D_1 \ln (H/L)_i + B_1^{\kappa} \ln \kappa_i + B_1^{\mathcal{O}} \ln \mathcal{O}_i + e_{1i}, \quad (25)$$

with e_{0i}, e_{1i} denoting the usual stochastic error terms for country i, to get the OLS estimates $\hat{D}_0$, $\hat{D}_1$, $\hat{\ln} Z_0$, and $\hat{\ln} Z_1$. We use a sample of 22 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. Columns (1b) and (2b) of Table 10, in Appendix A, report the OLS estimates of the coefficients in regressions (24) and (25). The estimates are all significant at the 1% or the 5% level, with an R^2 of, respectively, 0.34 and 0.42.[14]

According to Eqs. (18), (19), (21), and (22), the coefficients 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 (24) and (25). 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 (15), we see that the structural parameters

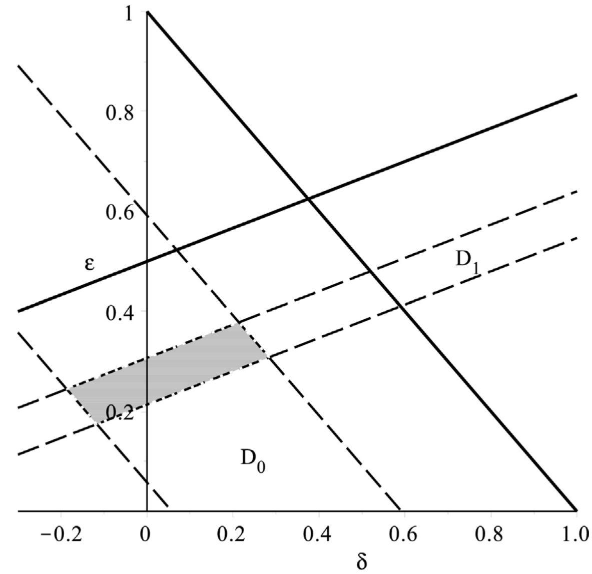

Fig. 3. Confidence intervals for the estimates of ϵ and δ (dashed lines) implicit in the two-standard-error confidence intervals for the estimates of the skill-structure coefficients of (24) and (25). Bold lines are the same as in Fig. 2. Example with $\alpha = 0.6$ and $\sigma = 0.5$.

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, we focus on the extreme values of the implicit confidence intervals for the parameters $(\epsilon, \delta, \zeta, \phi)$ to carry out our quantification exercise.[16] These intervals are shown in Figs. 3 and 4 and reported in Table 10.

Fig. 3 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 (24) and (25) (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 Fig. 2. Fig. 4 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 (24) and (25).

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 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 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 (although, as shown below, they bear no impact on the estimates of ϵ and ζ), while, following Acemoglu and Zilibotti (2001), we consider 1.8 as an alternative value for h/l.

[12] This is a flow version of the specification in Borensztein et al. (1998).

[13] See, e.g., Dinopoulos and Thompson (2000) for references and a developed discussion on the choice of proxy for a country's ability to absorb ideas connected to openness.

[14] Table 10, in Appendix A, also shows that the sign of the OLS estimates of the coefficients of economic openness and of FDI inflows to GDP are, respectively, positive and negative in regressions (24) and (25). Interestingly, these results suggest that the effect of international technology linkages captured by economic openness (respect., FDI inflows) is relatively stronger in the high-tech (low-tech) sector.

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

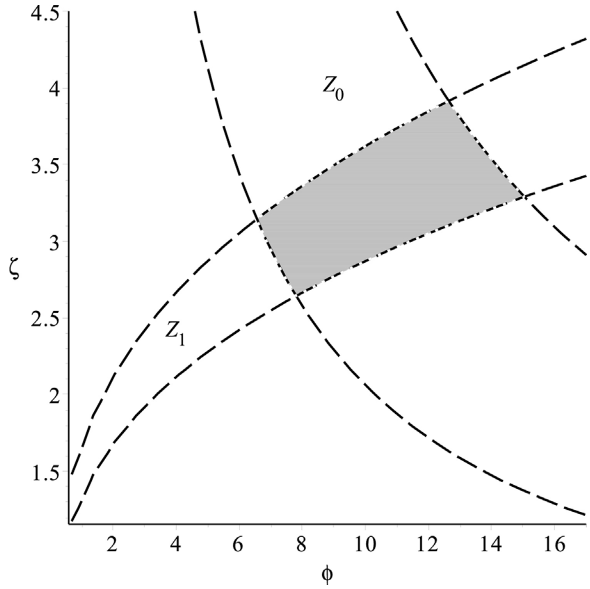

Fig. 4. Confidence intervals for the estimates of $\phi \equiv \phi_H/\phi_L$ and $\zeta \equiv \zeta_H/\zeta_L$ implicit in the two-standard-error confidence intervals for the estimates of the intercepts of (24) and (25). Example with $\alpha = 0.6$, $\sigma = 0.5$ and $h/l = 1.3$.

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 10, columns (1b) and (2b). Computation with $\alpha = 0.6$.

	$\sigma = 0.74$		$\sigma = 0.5$		$\sigma = 1.0$	
δ	0.149	−0.267	0.214	−0.117	0.078	−0.430
ϵ	0.378	0.175	0.378	0.175	0.378	0.175

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 10, columns (1b) and (2b). 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	22.602	12.128	12.628	7.795	42.464	19.579	25.535	13.703
ζ	3.915	2.642	3.915	2.642	3.915	2.642	4.798	3.238

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 no implication to the quantification of that elasticity (see (15)).

As regards (ii), ϵ smaller than unity implies that net scale effects on growth are positive, although relatively small.[17] 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 (10) 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. 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.[18],[19]

4.2. Growth elasticities

Now, we use the above values for the structural parameters ϵ and ζ to compute the predicted economic growth rate, $\tilde{\mathcal{G}}$, for each country. Then, we use these simulated data for the growth rate, together with the observed skill structure for each country, to compute the OLS estimate of the cross-country growth-skill elasticity, $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$, and compare with the OLS estimate of the elasticity of the observed economic growth rate (the slope of regression (5) in Table 10). We also compute the predicted relative production, $\hat{\tilde{\mathfrak{X}}}$, for each country and the OLS estimate of the cross-country elasticity of the predicted economic growth rate with respect to the predicted relative production, $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{\mathfrak{X}}}}$, and compare with the OLS estimate of the elasticity obtained from the observed data.

Substituting in Eqs. (23) and (20) 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),[20] as well as the observed country data on H, L, $\mathcal{O}$, and κ, we compute the predicted economic growth rate and relative production for each country. As we have 8 different scenarios, we obtain 8 simulated sets of country growth rates and production ratios. This allows us to find 8 distinct OLS estimates of the cross-country growth-skill and growth-production elasticities $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ and $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{\mathfrak{X}}}}$.

[17] Several empirical studies uncover the existence of scale effects of human capital on growth using cross-section or panel data: e.g., Backus et al. (1992), Benhabib and Spiegel (1994), Hanushek and Kimko (2000), Vandenbussche et al. (2006), and Hanushek and Woessmann (2012).

[18] 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 being more aggressively pursued; they also rely more heavily on formal planning activities, on customer support and on superior product warranties, and face environments where regulation more frequently plays a structuring role (e.g., the biotech industry) (e.g., Covin et al., 1990; Qian and Li, 2003; Tunzelmann and Acha, 2005).

[19] 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. 18). To the best of our knowledge, there are no direct measures of the barriers to entry separated by high- and low-tech sectors in the literature. However, Bento (2014) computes countrywide entry costs for a cross section of 136 countries and finds a ratio of 51 to 1 between the highest and the lowest decile of entry costs. A similar ratio is found by Djankov et al. (2002) for a cross section of 85 countries (46 to 1). As shown in Table 2, our estimates suggest that the entry-cost ratio between the high- and the low-tech sectors may be as high as 4.8 to 1 for vertical entry and 42.5 to 1 for horizontal entry.

[20] Since the estimates of ϵ and ζ are independent of σ, as shown above, we only consider the baseline value for σ.

Table 3
Simulation results for the cross-country growth-skill and growth-production elasticities. $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ and $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{x}}}$ denote the OLS estimate of the elasticity of the predicted growth rate, $\tilde{\mathcal{G}}$, with respect to, respectively, the observed skill structure and predicted relative production, $\hat{\tilde{x}}$ (heteroskedasticity-consistent s.e. in brackets). Values for $\hat{\tilde{x}}$ and $\tilde{\mathcal{G}}$ 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 weighted average of the observed growth rate (2.024% for the 22 countries); values for ϵ and ζ are set in accordance to the estimation exercise in Tables 1 and 2. For comparison: the estimate of the elasticity of the observed economic growth rate with respect to the observed skill structure and observed relative production is, respectively, −0.026 (s.e. of 0.172) and −0.003 (s.e. of 0.118).

ϵ	ζ	A	$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ (s.e.)	$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{x}}}$ (s.e.)
$\sigma = 0.74$; $h/l = 1.3$				
0.175	2.642	0.2434	−0.0786 (0.283)	−0.0915 (0.330)
	3.915	0.2517	−0.1051 (0.284)	−0.1225 (0.331)
0.378	2.642	0.6488	−0.0384 (0.210)	−0.0663 (0.362)
	3.915	0.6772	−0.0627 (0.211)	−0.1081 (0.365)
$\sigma = 0.74$; $h/l = 1.8$				
0.175	3.238	0.2403	−0.0687 (0.283)	−0.0800 (0.329)
	4.798	0.2494	−0.0977 (0.284)	−0.1138 (0.331)
0.378	3.238	0.6384	−0.0296 (0.209)	−0.0510 (0.362)
	4.798	0.6693	−0.0558 (0.211)	−0.0963 (0.364)

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 growth-skill elasticity. 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.

$\sigma = 0.74$; $h/l = 1.3$				
ϵ	0.175		0.378	
ζ old	2.642	3.915	2.642	3.915
ζ new	0.520	0.615	0.380	0.470
Change in ζ	−80.3%	−84.3%	−85.6%	−88.0%
Average $\tilde{\mathcal{G}}$	4.789%	4.678%	6.522%	6.135%
$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$	0.171	0.171	0.170	0.170
$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{x}}}$	0.200	0.199	0.293	0.293
$\sigma = 0.74$; $h/l = 1.8$				
ϵ	0.175		0.378	
ζ old	3.238	4.798	3.238	4.798
ζ new	0.680	0.815	0.480	0.610
Change in ζ	−79.0%	−83.0%	−85.2%	−87.3%
Average $\tilde{\mathcal{G}}$	4.824%	4.701%	6.732%	6.255%
$\hat{E}^{\tilde{\mathcal{G}}}_{H/L}$	0.171	0.170	0.171	0.170
$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{x}}}$	0.199	0.199	0.294	0.293

Table 3 presents the results. The point estimates of the growth-skill elasticity computed with the simulated data are negative in all scenarios, replicating the sign of the elasticity estimated with the observed data.[21] The magnitude is also well approximated in particular in the scenarios with the largest admissible value of ϵ (i.e., the smallest net scale effects of high-skilled labour through vertical R&D) and the smallest admissible value of ζ. Like in the observed data, the estimates are not significantly different from zero. The upper limit of the two-standard-error confidence interval for the estimate obtained from the simulated data lies between 0.148 and 0.214 across the 8 scenarios, while we find an upper bound of 0.146 for the elasticity in the observed data.

In turn, the point estimates of the growth-production elasticity computed with the simulated data are also negative in all scenarios, while the elasticity estimated with the observed data is roughly zero. The estimates are not significantly different from zero both in the case of the simulated data and of the observed data, but the former exaggerates the standard deviations. The upper limit of the two-standard-error confidence interval for the estimate obtained from the simulated data lies between 0.209 and 0.311, the elasticity in the observed data displays an upper bound of 0.115.

Bearing in mind the possible simultaneity bias issue regarding the regressor in (24) and (25), 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 both the skill structure and the technology 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), and (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 (24) and (25)), 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 elasticities. The two factors impact this cross-country elasticities with opposite signs, with the positive impact of scale effects being offset by the negative effect of relative barriers to entry. This result 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 (see elasticity (15)).

[21] In Section 3.1, we have shown that the theoretical growth-skill elasticity is always positive when $1 - \epsilon > 0$ (see (15)). This will imply a positive cross-country growth-skill elasticity if the structural parameters in (15) 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.

4.3. 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 growth elasticities. First, we calibrate A, in (14), 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 respective two-standard deviation confidence interval. This amounts to increase the point estimate of the growth-skill elasticity to about 0.17.

Table 4 depicts the main results. The estimate of the required reduction of relative barriers to entry varies between 79% and 88% across the eight scenarios considered. 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. The growth-production elasticity increases somewhat more than the growth-skill elasticity, to about 0.2 to 0.3.

Our numerical results show that the impact of relative barriers to entry on the growth elasticities is convex, i.e., for smaller initial

Table 5
Counterfactual experiment by considering a reduction of relative barriers to entry into the high-tech sector, $\zeta \equiv \zeta_H/\zeta_L$ and $\phi \equiv \phi_H/\phi_L$, or an increase in the relative supply of skills, H/L, such that the average European share of the high-tech sector (22 countries) is raised to the US level (0.440 for relative production and 0.215 for the relative number of firms, 1995–2007 average). Computation for the scenario with $\sigma = 0.74$, $h/l = 1.3$, where the initial values for ζ and for ϕ are indirect estimates based on the point estimates of the intercept coefficients in Table 10, columns (1b) and (2b). 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.

	Observed	Predicted		
		$\phi = 16.557$; $\zeta = 3.216$ $H/L = 0.178$ (avg)	$\phi = 6.480$; $\zeta = 2.135$ $H/L = 0.178$ (avg)	$\phi = 16.557$; $\zeta = 3.216$ $H/L = 0.345$ (avg)
Relative production	0.310	0.273	0.440 [targeted]	0.440 [targeted]
Relative number of firms	0.105	0.099	0.215 [targeted]	0.133
GDPpc growth rate	2.993%	2.993% [targeted]	3.213%	3.260%

barriers to entry, a given absolute reduction in those barriers produces a larger increase in $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ and $\hat{\mathcal{E}}^{\hat{\mathcal{G}}}_{\hat{x}}$. For instance, under the first scenario in Table 4, a reduction of ζ from 2.642 to 0.52 increases $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ from −0.026 to 0.171, whereas a reduction of ζ from 0.52 to 0.20 further increases $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ from 0.1715 to 0.322. 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 relative 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 brought down to considerable low levels before they start producing significant results.

Overall, an interesting policy implication arises from these results: industrial policy aiming to reduce relative 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 and the implied assumption of homogeneous relative barriers to entry across countries, as well as 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, as made clear by the elasticity (15). For example, Belgium and Portugal have similar observed per capita GDP growth rates (1.9%), but the former has a larger proportion of high-skilled labour (0.295) than the latter (0.042). Then, e.g., considering a reduction of 84% in ζ (as an average of the upper-panel four scenarios depicted by Table 4), the model predicts a change in the growth rate of 0.59 percentage points (relative increase of 30%) in Portugal and of 1.97 p.p. (102%) in Belgium. In Ireland, the country with the largest proportion of high-skilled labour in our sample (0.33), the relative increase in the growth rate is of 128% (see column (3) in Table 6). 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.

European politicians have also emphasised the need to increase the share of the high-tech sector, with a view to reducing the gap with the US, as part of the European growth strategy. Therefore, as a second counterfactual exercise, we decrease the relative entry costs into the high-tech sector such that the average European share of the high-tech sector is raised to the US level and compute the impact in the European long-run economic growth rate. Table 5 summarises the results for the scenario with $\sigma = 0.74$ and $h/l = 1.3$. A simultaneous reduction of ζ and ϕ by, respectively, 34% and 61% increases the share of the production of the high-tech sector in Europe (22 countries average) by 0.167 points and the share of the number of firms by 0.116 points (relative increase of, respectively, 61% and 117%) to about the US level, while it increases the European economic growth rate by 0.22 p.p (relative increase of 7.4%).

However, the small relative production and number of firms vis-à-vis de US also reflects the different skill structure in Europe (0.178, for the 22-countries average) versus the US (0.398). In order to account for this, alternatively we consider the counterfactual exercise of an increase in the average European skill ratio such that the share of the high-tech sector is raised to the US level. According to our exercise (in this case we only target relative production), the average European skill ratio must be increased to 0.345 (relative increase of 94%), inducing an increase of the average economic growth rate by 0.27 p.p. (relative increase of 8.9%). By comparing the relative change in the policy variables, H/L or ζ and ϕ, in modulus, with the relative change in the predicted growth rate, we get a ratio of, respectively, 10.5 or 4.6 and 8.3. In other words, an increase of the European growth rate by 0.1 percentage points requires a change in H/L or ζ and ϕ of, respectively, 35.1% or −15.4% and −27.7%. In light of these results, we conclude it is more efficient for policy to target relative barriers to entry than the supply of skills. However, importantly, whatever the chosen policy variables, the predicted growth effects are modest relative to the size of the policy action.

5. Country-specific relative barriers to entry

A recent literature has found a significant relationship between the cross-country variability of (countrywide) entry costs and the observed dispersion of per capita output levels across countries (e.g., Bento, 2014). Motivated by these findings, we now check whether allowing for cross-country variability of relative barriers to entry in the high-tech sector (i.e., relaxing the assumption that all countries face the same relative barriers) affects our results relating the per capita output growth rate and the skill structure.

To be specific, we now assume that the level terms in (17) and (20), Z_0 and Z_1, comprise both an homogeneous component across countries, $\bar{Z}_0$ and $\bar{Z}_1$, and a country-specific component, Z^c_{0i} and Z^c_{1i}. Thus, we re-write Eqs. (17), (19), (20), and (22), considering now that, for each country i,

$$\tilde{N}_i = Z_{0i} \cdot \left(\frac{H}{L}\right)_i^{D_0}, \tag{26}$$

where

$$Z_{0i} \equiv \underbrace{(h/l)^{\frac{1}{\sigma+1}} \cdot \bar{\phi}^{\frac{-1}{\sigma+1}} \cdot \bar{\zeta}^{\frac{-1}{\sigma+1}}}_{\equiv \bar{Z}_0} \cdot \underbrace{\left(\phi_i^c\right)^{\frac{-1}{\sigma+1}} \cdot \left(\zeta_i^c\right)^{\frac{-1}{\sigma+1}}}_{\equiv Z^c_{0i}}, \tag{27}$$

Table 6
Columns (1)–(2): indirect estimates of structural parameters $\bar{\phi}$ and $\bar{\zeta}$ (the homogeneous components of relative barriers to entry), and ϕ_i^c and ζ_i^c (country-specific components), based on the point estimates of the intercept coefficients in Table 10, columns (1b) and (2b), and the estimation residuals of those regressions (not shown); computation for the scenario with $\sigma = 0.74$, $h/l = 1.3$. Columns (3)–(4): relative effect on a country's growth rate of a counterfactual reduction of relative barriers to entry (ζ in column (3) and $\zeta_i = \bar{\zeta} \cdot \zeta_i^c$ in column (4)) that leads to a significant positive estimate of the cross-country growth-skill elasticity; A is calibrated such that the observed and the (pre-shock) predicted growth rate match exactly for each individual country.

Country	(1) $\bar{\phi} = 16.557$ ϕ_i^c	(2) $\bar{\zeta} = 3.216$ ζ_i^c	(3) Relative impact of a reduction in ζ on a country's growth rate: Homogeneous case ($\Delta\zeta = -84\%$)	(4) Country-specific case ($\Delta\zeta_i = -85\%$)
Austria	0.8468	0.8758	59%	68%
Belgium	1.3298	1.2359	102%	88%
Bulgaria	0.7563	1.0009	52%	53%
Czech Republic	0.9304	0.9510	60%	64%
Denmark	0.7981	0.9744	88%	93%
Finland	1.6172	1.1142	115%	108%
France	1.0031	0.7497	76%	99%
Germany	0.5231	0.8138	102%	123%
Greece	2.0633	1.7093	59%	37%
Hungary	1.0354	0.8867	82%	93%
Ireland	1.3493	0.9634	128%	135%
Italy	0.5144	0.7065	38%	54%
Netherlands	0.8716	1.0205	87%	88%
Norway	1.1566	1.2374	81%	69%
Poland	0.5656	0.9996	65%	67%
Portugal	2.7977	1.2352	30%	25%
Romania	2.0179	1.6686	59%	38%
Slovak Republic	0.4940	0.7734	49%	63%
Slovenia	0.9977	1.0797	75%	72%
Spain	1.6942	1.3308	89%	72%
Sweden	0.7196	0.6632	71%	102%
United Kingdom	0.6497	0.7409	88%	115%

and

$$\tilde{\hat{x}}_i = Z_{1i} \cdot \left(\frac{H}{L}\right)_i^{D_1}, \quad (28)$$

where

$$Z_{1i} \equiv \underbrace{(h/l)^{\left[1+\left(\frac{\sigma}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]} \cdot \bar{\phi}^{\frac{\alpha}{(\sigma+1)(1-\alpha)}} \cdot \bar{\zeta}^{-\left[1+\left(\frac{2\sigma+1}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]}}_{\equiv \bar{Z}_1} \cdot \underbrace{\left(\phi_i^c\right)^{\frac{\alpha}{(\sigma+1)(1-\alpha)}} \cdot \left(\zeta_i^c\right)^{-\left[1+\left(\frac{2\sigma+1}{\sigma+1}\right)\left(\frac{\alpha}{1-\alpha}\right)\right]}}_{\equiv Z_{1i}^c}, \quad (29)$$

and $\phi_i = \bar{\phi} \cdot \phi_i^c$ and $\zeta_i = \bar{\zeta} \cdot \zeta_i^c$. Observe that $\bar{\phi}$ and $\bar{\zeta}$ denote the homogeneous components of relative barriers to entry (which, in Section 4, were denoted by ϕ and ζ), while ϕ_i^c and ζ_i^c denote the country-specific components. The elasticities D_0 and D_1 are the same as in Section 3.2.

In order to quantify the new structural parameters ϕ_i^c and ζ_i^c, we allow the country-specific terms Z_{0i}^c and Z_{1i}^c to be random variables uncorrelated with each country's skill structure and then, by applying logs to (26) and (28), run the regressions

$$\ln \tilde{N}_i = \ln \bar{Z}_0 + D_0 \ln (H/L)_i + B_0^{\kappa} \ln \kappa_i + B_0^{\mathcal{O}} \ln \mathcal{O}_i + \ln Z_{0i}^c, \quad (30)$$

$$\ln \hat{\tilde{x}}_{\tilde{i}} = \ln \bar{Z}_1 + D_1 \ln (H/L)_i + B_1^{\kappa} \ln \kappa_i + B_1^{\mathcal{O}} \ln \mathcal{O}_i + \ln Z_{1i}^c, \quad (31)$$

where $\ln Z_{0i}^c$ and $\ln Z_{1i}^c$ stand for the respective stochastic error terms. Except for the (now) structural definition of the error terms, regressions (30) and (31) are similar to regressions (24) and (25), and, thus, the OLS estimates of their intercepts and slopes (from which we recover $\delta, \epsilon, \bar{\phi}$ and $\bar{\zeta}$, for given α, σ and h/l) are unchanged. However, we are also able to use the regression residuals, together with the analytical expressions for Z_{0i}^c and Z_{1i}^c in (27) and (29), to recover ϕ_i^c and ζ_i^c.[22]

Our results show that the country-specific component of relative barriers to entry varies considerably across countries (see Table 6, columns (1) and (2)), with a variation coefficient of 0.273 (vertical entry) and 0.529 (horizontal entry) versus 0.393 for the economic growth rate. Nevertheless, there is a roughly null correlation between our estimates of country-specific barriers and both the observed economic growth rate and the skill structure, as depicted by Table 7. We find that the consideration of country-specific barriers does not affect the predicted growth elasticities; see Table 8, for the case of $\sigma = 0.74$ and $h/l = 1.3$. Thus, these results suggest that the role of relative barriers to entry in explaining the observed cross-country growth elasticities relies on the interaction of the homogeneous component of relative barriers with each country's skill structure, instead of on the variability of the country-specific component of relative barriers across countries.

Some authors interpret the country-specific component of barriers to entry as pertaining to regulatory costs and its homogeneous component as non-regulatory costs (see, e.g., Bento, 2014). If we allow for this interpretation in our case, then our results further suggest that the regulatory costs are of little importance for the growth-skill and growth-production relationships across the

[22] See, e.g., Caselli and Coleman (2006) for a similar procedure, applied to the quantification of country-specific technology frontiers.

Table 7
Correlation of the country-specific relative barriers to entry (Table 6, columns (1) and (2)) with the per capita GDP growth rate and the skills structure in a cross-section of European countries, 1995–2007 average (t-statistic in brackets).

	ζ_i^c	ϕ_i^c
ϕ_i^c	0.772 (5.432)	–
pc GDP growth rate	0.114 (0.512)	−0.016 (−0.073)
Skills structure	−0.039 (−0.174)	−0.044 (−0.196)

Table 8
Simulation results for the cross-country growth-skill and growth-production elasticity: homogeneous case (relative barriers to entry are assumed homogeneous across countries) versus country-specific case (relative barriers to entry have an homogeneous and a country-specific component). $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ and $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{x}}}$ denote the OLS estimate of the elasticity of the predicted growth rate, $\tilde{\mathcal{G}}$, with respect to, respectively, the observed skill structure and predicted relative production, $\hat{\tilde{x}}$. Values for $\hat{\tilde{x}}$ and $\tilde{\mathcal{G}}$ are obtained as in Table 3. Values for $\zeta_i = \bar{\zeta} \cdot \zeta_i^c$ (country-specific case) are set in accordance to the estimation exercise in Table 6, column (2). Values for ζ (homogeneous case) and for ϵ are indirect estimates based on the point estimates of the intercept and slope coefficients in Table 10, columns (1b) and (2b).

	ϵ	ζ	A	$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$	$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{x}}}$
	σ = 0.74; h/l = 1.3				
Homogeneous	0.277	3.216	0.4075	−0.0703	−0.0980
Country-specific	0.277	3.323 (avg)	0.3988	−0.0708	−0.0987

European countries. An alternative conjecture is that both the non-regulatory and the regulatory components tend to constitute homogeneous barriers to entry across these countries, possibly as an effect of the process of European integration in terms of regulatory framework. This, of course, strengthens the pertinence of the view laid out in Section 4.3 of a barriers-reducing industrial policy set at the EU supranational level.

We have re-run the counterfactual policy experiment of Section 4.3, for the case of country-specific relative barriers to entry, where $\phi_i = \bar{\phi} \cdot \phi_i^c$ and $\zeta_i = \bar{\zeta} \cdot \zeta_i^c$, and found that the results are similar to the case of homogeneous barriers. The proportional reduction in (average) relative barriers that leads to a significant positive estimate of the cross-country growth-skill elasticity is roughly the same in the homogeneous and in the country-specific case (change of −84% and −85%, respectively; see Table 6, columns (3) and (4)). However, if we take the analysis to the individual country level, we find that when barriers are assumed homogeneous across countries, the model over(under)-estimates the impact on the growth rate of those countries that actually have above(below)-average relative barriers to entry, i.e., that have a country-specific component ζ_i^c larger (smaller) than unity. This is due to the already noted non-linear impact of relative barriers to entry on growth, implying that the lower the relative barriers to entry, the larger the impact of a further reduction in those barriers on a country's growth rate. On the other hand, the larger the proportion of high-skilled labour in a country, the more intense the described over(under)-estimation effect. For instance, in the homogeneous case, the countries that benefit the most from a given proportional reduction in relative barriers are Ireland and Finland, the countries with the largest share of high-skilled labour in the sample. In the country-specific case, those countries are Ireland and Germany, whose below-average relative barriers to entry combine with a fairly large, above-average, high-skilled labour ratio. Portugal is the country that benefits the least in both cases, since it boasts the smallest share of high-skilled labour in the sample, combined with quite large (vertical) relative barriers to entry (the 4th largest in the sample).

By the same token, as regards the second counterfactual experiment, we analyse the growth effect of a decrease in the entry costs into the high-tech sector such that the share of the high-tech sector in each individual country is raised to the US level. We focus our attention on the countries that display a share of the high-tech sector that is simultaneously smaller than in the US and the 22-European country average: Bulgaria, Greece, Italy, Norway, Poland, Portugal, Romania, and Spain. Table 9 summarises the results. By comparing the relative change in the policy variable (H/L, or ζ and ϕ) with the relative change in the predicted growth rate in each country, we find that the ratio is larger for H/L in all selected countries, showing that it is more efficient for policy to target relative barriers to entry than the supply of skills. However, whatever the chosen policy variables, the predicted growth effects are modest relative to the size of the policy action, as in the case of homogeneous relative barriers across countries. The countries with worst performance are Portugal, Italy, Romania and Greece, reflecting a

Table 9
Counterfactual experiment by considering a reduction of relative barriers to entry into the high-tech sector, $\phi_i = \bar{\phi} \cdot \phi_i^c$ and $\zeta_i = \bar{\zeta} \cdot \zeta_i^c$, or an increase in the relative supply of skills, H/L, such that the share of the high-tech sector in each country is raised to the US level (0.440 for relative production and 0.215 for the relative number of firms, 1995–2007 average). Computation for the scenario with σ = 0.74, h/l = 1.3, where the initial values for ζ_i and for ϕ_i are indirect estimates based on the point estimates of the intercept coefficients in Table 10, columns (1b) and (2b), and the estimation residuals of those regressions (not shown). A is calibrated such that the observed and the (pre-shock) predicted growth rate match exactly for each individual country. We present in parentheses the ratio between the relative change in the policy variable (ϕ_i and ζ_i, or H/L), in modulus, and the relative change in the predicted growth rate.

	Predicted GDPpc growth rate (%)		
Italy	ϕ_i = 8.52; ζ_i = 2.27; $\frac{H}{L} = 0.053$ 1.164% [targeted]	ϕ_i = 4.43; ζ_i = 1.49; $\frac{H}{L} = 0.053$ 1.225% (9.2; 6.6)	ϕ_i = 8.52; ζ_i = 2.27; $\frac{H}{L} = 0.151$ 1.298% (16.2)
Norway	ϕ_i = 19.15; ζ_i = 3.98; $\frac{H}{L} = 0.217$ 2.217% [targeted]	ϕ_i = 6.20; ζ_i = 2.06; $\frac{H}{L} = 0.217$ 2.484% (5.6; 4.0)	ϕ_i = 19.15; ζ_i = 3.98; $\frac{H}{L} = 1.010$ 2.806% (13.7)
Poland	ϕ_i = 9.37; ζ_i = 3.21; $\frac{H}{L} = 0.136$ 4.656% [targeted]	ϕ_i = 5.87; ζ_i = 1.90; $\frac{H}{L} = 0.136$ 5.057% (4.3; 4.7)	ϕ_i = 9.37; ζ_i = 3.21; $\frac{H}{L} = 0.775$ 6.112% (15.0)
Portugal	ϕ_i = 46.32; ζ_i = 3.97; $\frac{H}{L} = 0.042$ 1.943% [targeted]	ϕ_i = 3.48; ζ_i = 1.27; $\frac{H}{L} = 0.042$ 2.137% (9.2; 6.8)	ϕ_i = 46.32; ζ_i = 3.97; $\frac{H}{L} = 0.277$ 2.209% (40.3)
Spain	ϕ_i = 28.05; ζ_i = 4.28; $\frac{H}{L} = 0.294$ 2.585% [targeted]	ϕ_i = 6.35; ζ_i = 2.05; $\frac{H}{L} = 0.294$ 2.964% (5.3; 3.6)	ϕ_i = 28.05; ζ_i = 4.28; $\frac{H}{L} = 1.260$ 3.224% (13.3)
Greece	ϕ_i = 34.17; ζ_i = 5.50; $\frac{H}{L} = 0.124$ 3.302% [targeted]	ϕ_i = 5.32; ζ_i = 1.77; $\frac{H}{L} = 0.124$ 3.783% (5.8; 4.6)	ϕ_i = 34.17; ζ_i = 5.50; $\frac{H}{L} = 1.880$ 4.716% (33.2)
Bulgaria	ϕ_i = 12.52; ζ_i = 3.22; $\frac{H}{L} = 0.146$ 3.975% [targeted]	ϕ_i = 3.66; ζ_i = 1.44; $\frac{H}{L} = 0.146$ 4.463% (5.8; 4.5)	ϕ_i = 12.52; ζ_i = 3.22; $\frac{H}{L} = 1.141$ 5.323% (20.1)
Romania	ϕ_i = 33.41; ζ_i = 5.37; $\frac{H}{L} = 0.093$ 3.734% [targeted]	ϕ_i = 6.08; ζ_i = 1.95; $\frac{H}{L} = 0.093$ 4.195% (6.6; 5.2)	ϕ_i = 33.41; ζ_i = 5.37; $\frac{H}{L} = 1.000$ 4.936% (30.4)

particularly unfavourable combination of initial larger relative barriers to entry into the high-tech sector and low skills ratio in these countries.

6. Discussion and 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 and high relative fixed entry costs in the high-tech sectors, are consistent with the observed pattern in the number of firms and production in high- versus low-tech sectors and with the relationship between economic growth and the skill structure.

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.[23] 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.

By linking the determinants of the technology structure to economic growth, our model allows us to derive a set of policy implications. Firstly, the effects of a country's education policy (e.g., incentives for households to improve their educational level), or say of measures to enhance qualified immigration or revert brain-drain flows, on economic growth may be effectively leveraged by industrial policy and vice versa. Furthermore, we notice that set of policies aimed at improving the skill structure gains relevance in the observed context of high barriers to mobility in the labour market. Secondly, industrial policy should aim to reduce the fixed-entry costs originating relatively larger barriers to entry in the high-tech sectors (e.g., the alleviation of the regulatory and IPR bureaucratic environment faced by technology-intensive firms or the reduction of their information and management flow fixed costs at firm creation, say through the promotion of mentoring and business-angels activities), such that barriers to entry in the high-tech sector are brought down 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. Finally, 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. Exploratory (reduced-form) estimations also suggest that a reduction of overall regulatory costs to create a business (e.g., Djankov et al., 2002) or an increase in a country's financial development (e.g., Cihák et al., 2013) may be associated with the reduction of relative barriers to entry into the high-tech sector. This is a topic that deserves further investigation in future work.

In a context of increasing globalization, it is pertinent to discuss its potential effects in terms of factor cost equalisation and possibly also factor endowment equalisation (with inter-country factor mobility). For instance, under trade and even without factor mobility, the Heckscher-Ohlian theory predicts factor cost equalisation: imports of goods produced by low-skilled labour reduce low-skilled wages in the high-skilled abundant country and vice versa (Stolper-Samuelson theorem). Therefore, trade ultimately generates the same result as factor mobility, even in a context of neutral technical change. In light of our model, these forces would tend to dampen the effects arising from the labour market segmentation and from the mechanism of directed technical change. This, in turn, would attenuate the differences in the long-run economic growth rate across countries. This issue gains further relevance in a context of apparent diverse degrees of directed technological knowledge among countries (e.g., Germany versus the UK and the US). This is also an interesting avenue for further research.

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).[24] 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).[25] The data concerns the 1995–2007 period and covers 22 European countries regarding,[26] respectively, the number of firms, production,[27] and the supply of skills (educational attainment). The sources are the OECD STAN Database for Structural Analysis, the OECD SDBS Structural Business Statistics (available at www.stats.oecd.org), and 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 country data on the per capita real GDP growth rates for the same period and on economic openness in 1995, measured as the ratio of exports plus imports of

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

[24] 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.

[25] Herein, we abstract from the division of high-skilled workers into, e.g., scientific, creative and entrepreneurial talents (Toner, 2011) and focus, instead, on education levels due to data availability in our sample of countries.

[26] The 22 countries are: Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Slovak Republic, Romania, Slovenia, Spain, Sweden, and the United Kingdom.

[27] 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.

Table 10
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), 1995–1997 FDI inflows to GDP and 1995 trade openness, in logs. Regression in column (3a) was run for the 30 European countries comprising the EU-27 plus EFTA. Regressions in the other columns were run using the common sample of 22 European countries with available data on relative production and the relative number of firms. Standard errors (s.e.) are heteroskedasticity consistent.

Dependent variable	ln Relative number of firms			ln Relative production			ln GDPpc growth rate		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Constant	−1.894	−2.134	−2.182	−0.584	−0.816	−0.929	−3.231	−3.637	−3.427
(s.e.)	(0.287)	(0.292)	(0.290)	(0.346)	(0.348)	(0.404)	(0.365)	(0.298)	(0.355)
ln Relative supply of skills 1995–2007	0.242	0.450	–	0.430	0.719	–	0.163	−0.026	0.033
(s.e.)	(0.169)	(0.178)		(0.160)	(0.140)		(0.185)	(0.172)	(0.142)
ln Relative supply of skills 1995	–	–	0.332	–	–	0.502	–	–	–
(s.e.)			(0.198)			(0.190)			
ln FDI/GDP 1995–1997	–	−0.234	−0.196	–	−0.323	−0.254	–	–	−0.060
(s.e.)		(0.064)	(0.070)		(0.08)	(0.09)			(0.060)
ln Trade/GDP 1995	–	0.520	0.428	–	0.883	0.732	–	–	0.592
(s.e.)		(0.239)	(0.214)		(0.263)	(0.272)			(0.232)
Observations	22	22	22	22	22	22	30	22	22
R^2	0.092	0.340	0.248	0.144	0.419	0.282	0.032	0.002	0.241

goods over the GDP, also from the Eurostat on-line database, while the data on the FDI inflows for 1995–1997 was taken from the IMF on-line database (http://www.imf.org/external/data.htm).

Table 10 reports the details on the OLS regressions run on the data described above.

Appendix 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:

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

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 $\mathcal{Q}_m=\sum_i^{N_m}\mathcal{K}_{mi}$, $m\in\left\{L,H\right\}$. Then, for a given N_m, we get

$$\mathbb{E}(Q_m)=N_m e^{-I_m t(1-\lambda^{\frac{1-\alpha}{\alpha}})}, \tag{32}$$

$$\mathbb{E}(\mathcal{Q}_m)=N_m e^{-I_m t(1-\lambda^{\frac{1}{\alpha}})}. \tag{33}$$

Using $\ln(v+1)\approx v$ for v small enough, (32) and (33) can be rewritten as follows

$$\mathbb{E}(Q_m)=N_m e^{I_m t\left(\frac{1-\alpha}{\alpha}\right)\ln\lambda}=N_m\lambda^{I_m t\left(\frac{1-\alpha}{\alpha}\right)}, \tag{34}$$

$$\mathbb{E}(\mathcal{Q}_m)=N_m e^{I_m t\left(\frac{1}{\alpha}\right)\ln\lambda}=N_m\lambda^{I_m t\left(\frac{1}{\alpha}\right)}. \tag{35}$$

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 (34) and (35), we also have

$$\left(\mathbb{E}(Q_m)\right)^{\left(\frac{1}{1-\alpha}\right)}N_m^{-\left(\frac{\alpha}{1-\alpha}\right)}=N_m\lambda^{I_m t\left(\frac{1}{\alpha}\right)}=\mathbb{E}(\mathcal{Q}_m). \tag{36}$$

Since, in our model, Q_m is treated as a continuous deterministic variable, we consider the following proxy, $\hat{\mathcal{Q}}_m$, as a deterministic version of (36)

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

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

Appendix C. Acemoglu and Zilibotti's (2001) 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 Zilibotti's (2001) 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

$$\tilde{N}\equiv\left(\frac{\tilde{N}_H}{N_L}\right)=\left(\frac{h}{l}\right)\cdot\phi^{-2}\cdot\left(\frac{H}{L}\right)^{1-2\delta}\cdot F_h^2, \tag{37}$$

$$\tilde{X}\equiv\left(\frac{\tilde{X}_H}{X_L}\right)=\frac{h}{l}\cdot\phi^{-1}\cdot\left(\frac{H}{L}\right)^{1-\delta}F_h. \tag{38}$$

Let $D_0\equiv 1-2\delta$, $Z_0\equiv\left(h/l\right)\cdot\phi^{-2}$, $D_1\equiv 1-\delta$, and $Z_1\equiv\left(h/l\right)\cdot\phi^{-1}$, and consider the reduced-form system (24) and (25) as a log-log stochastic representation of the BGP equations (38) and (37), to get the OLS estimates $\hat{D}_0$, $\hat{D}_1$, $\hat{\ln}Z_0$, and $\hat{\ln}Z_1$. 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.[28]

As shown in the text, extending the Acemoglu and Zilibotti's (2001) 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 $\hat{D}_0$, $\hat{D}_1$, $\hat{\ln}Z_0$, and $\hat{\ln}Z_1$, 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.

[28] Alternatively, this model could be used to test some over-identification hypothesis regarding the key structural parameters. From Eqs. (38) and (37), we see that the Acemoglu and Zilibotti's (2001) model imposes the restriction $D_0=2D_1-1$. Bearing in mind the slope estimates in Table 10, columns (1b) and (2b), we find that, under that restriction, the point estimate of D_1 of 0.719 implies a value of 0.438 for D_0, whereas the point estimate of D_0 is 0.450. The ILS estimate of δ is 0.281, which nearly matches the ILS point-estimate of ϵ in the text, 0.277. However, as regards the intercepts, Acemoglu and Zilibotti's (2001) model imposes the restriction $Z_0=Z_1^2/(h/l)$ and, thus, the point estimate of Z_1 of −0.816 implies a value of 0.512 for Z_0, whereas the point estimate of Z_0 is −2.134. Given the s.d. reported in Table 10, we find that this restriction is not satisfied not even within the 95% confidence interval.

Appendix D. Quantification with 1995 skill structure

In this Appendix, we reiterate the steps followed in the text to quantify the key structural parameters and calibrate the model, but now using the 1995 proportion of high- to low-skilled workers instead of the 1995–2007 average. Tables 11 and 12 depict the results. As can be seen, they are similar to the ones obtained in Section 4.

Table 11
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 10, columns (1c) and (2c).

	$\sigma = 0.74$; $h/l = 1.3$; $\alpha = 0.6$				
δ	0.269	−0.176	ϕ	23.071	12.796
ϵ	0.497	0.253	ζ	4.154	2.731

Table 12
Simulation results for the cross-country growth-skill and growth-production elasticity. $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ and $\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{x}}}$ denote the OLS estimate of the elasticity of the predicted growth rate, $\tilde{\mathcal{G}}$, with respect to, respectively, the observed skill structure and predicted relative production, $\hat{\tilde{x}}$ (heteroskedasticity-consistent s.e. in brackets). Values for $\tilde{\mathcal{G}}$ are obtained as in Table 3, in the text. Values for ϵ and $\zeta \equiv \zeta_H/\zeta_L$ are set in accordance to the estimation exercise in Table 11. For comparison: the estimate of the elasticity of the observed economic growth rate with respect to the observed skill structure and observed relative production is, respectively, −0.026 (s.e. of 0.172) and −0.003 (s.e. of 0.118).

ϵ	ζ	A	$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{H/L}$ (s.e.)	$\hat{\mathcal{E}}^{\tilde{\mathcal{G}}}_{\hat{\tilde{x}}}$ (s.e.)
$\sigma = 0.74$; $h/l = 1.3$; $\alpha = 0.6$				
0.253	2.731	0.3596	−0.0660 (0.256)	−0.0953 (0.370)
	4.154	0.3726	−0.0925 (0.257)	−0.1335 (0.371)
0.497	2.731	1.1596	−0.0240 (0.169)	−0.0772 (0.545)
	4.154	1.2163	−0.0463 (0.170)	−0.1492 (0.549)

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