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HOW POWERFUL ARE NETWORK EFFECTS? A SKILL-BIASED TECHNOLOGICAL CHANGE APPROACH

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Even for the standard skill-biased technological change (SBTC) literature, the generic rise in the skill premium in the face of the relative increase in skilled workers since the 1980s seems a little puzzling. We develop a general equilibrium SBTC growth model that allows the dominance of either the *price channel* or the *market-size channel* mechanism through which network spillovers affect the technological-knowledge bias and, thus, the paths of intra-country wage inequality. The proposed mechanisms can accommodate facts not explained by the earlier literature.

Keywords: Network Effects, Technological-Knowledge Bias, Skill Premium, Economic Growth

1. INTRODUCTION

Using different proxies for skills, several studies document the rise in the relative wage of skilled workers (the skill premium) since the 1980s. For example, in the case of developed countries, Katz and Murphy (1992) report the increase of the relative wage of college graduates when compared to high-school graduates in the USA; Juhn et al. (1993) describe the rise in hourly and weekly wage differentials between the 90th wage percentile (skilled workers) and 10th wage percentile (unskilled workers) also in the USA; and Nickell and Bell (1996) illustrate the enlargement of the earnings differential between high- and low-educated males in Germany, the UK, and the USA—see also Machin and Van Reenen (1998), Acemoglu (2003), Goldin and Katz (2008), Autor et al. (2008), and Autor (2014), among others. The increase in the skill premium is also documented for some newly industrialized (developing) countries. Zhu and Trefler (2005) show that

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this occurred in Hong Kong, India, Thailand, and Uruguay, among other countries; Avalos and Savvides (2006) confirm the increase in wage inequality in Latin America and East Asia; and Brainerd (1998) verifies that the wage differential between the 90th and 10th wage percentiles widened in Russia.

In addition to these changes in wages, many developed countries have also experienced a steady increase in the relative supply of skilled workers over time. For example, Kranz (2006) shows that the share of workers with more than high-school education increased in Italy, Germany, the UK, and the USA; and Acemoglu (2003) attests that the same occurred in other developed countries (e.g. The Netherlands, Sweden, Norway, Belgium, and Finland)—see also, for example, He (2012). In developing countries the generic rise in the proportion of skilled workers is also observed [e.g. Zhu and Trefler (2005)].

The generic rise in the skill premium in many developed and developing countries since the 1980s seems, however, a bit puzzling. We would expect a fall in the skill premium in the face of the relative increase in the *scale or market size* of skilled workers. Concerning the related literature, the skill-biased technological change (SBTC) literature attempts to work out the contradiction between the rise in the skill premium and the relative increase in the supply of skills [e.g. Juhn et al. (1993), Acemoglu (1998), Acemoglu and Zilibotti (2001), Acemoglu (2002), Akerman et al. (2015), and McAdam and Willman (2018)]. In particular, Acemoglu (1998), Acemoglu and Zilibotti (2001), and Acemoglu (2002) consider that technological-knowledge change responds positively to shifts in labor supply, which, in turn, increases the demand. That is, when the supply of a type of labor increases, the market for technologies that complement it broadens (*scale or market size*), and this creates additional incentives for R&D aimed at those technologies. As a result, technological-knowledge change steers toward those technologies, which increases the demand for the complementary labor type. Hence, the SBTC literature interprets the rise in the skill premium as a direct consequence of the increase in the relative supply of skilled workers, which, by affecting the technological-knowledge change, induces an increase in the relative demand of skilled workers that exceeds the increase in the relative supply, thereby increasing the skill premium.

However, in theoretical terms, by stressing the *market-size channel* on technological-knowledge change, the SBTC literature contradicts the dominant literature on *scale effects* ever since Jones (1995a,b), who emphasized the (modern) evidence against *scale effects* on steady-state economic growth; indeed, growth rates have not always accelerated globally as population increased and bigger countries do not grow systematically at higher rates than smaller ones. In particular, *scale effects* arise through *market size*, measured by workers, and can be removed by considering a complexity effect in R&D, a *cost-of-market-size*, such that the difficulty of introducing new products and replacing old ones is proportional to the *market size*, often linked with population [e.g. Ha and Howitt (2007), Afonso (2012), and Ang and Madsen (2015)]: The greater the latter, the greater the costs to discover, develop, and market the associated technology

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(e.g. costs pertaining to the construction of prototypes and samples, new assembly lines and training of workers, and generic coordination, organizational, and transportation costs). These complexity costs, *cost-of-market-size*, offset the positive effect of scale on the (expected) profits of the successful innovator. In this way, the scale does not influence the steady-state growth rate because the probability of successful research is also independent of the scale [e.g. Dinopoulos and Thompson (1999, 2000), Barro and Sala-i-Martin (2004), and Afonso (2012)].

Moreover, in empirical terms, some evidence seems to contradict the explanation proposed by the SBTC literature. Acemoglu (2003), for example, documents a decline in the skill premium in the Netherlands between the early 1980s and the mid-1990s, in a scenario with relative increase of skills, and an increase in the skill premium in Canada between the late 1980s and the late 1990s, in a scenario with stable relative supply of skills. Moreover, data from developing countries reveal additional problematic evidence. For example, Crino (2005) shows that Hungary and the Czech Republic experienced an increase in the skill premium between 1993 and 2004, while at the same time the relative employment of skilled workers fell; Robertson (2004) detects that wage differential between the 90th and 10th wage percentiles decreased in Mexico between 1994 and 2002, even with the relative increase of skilled workers; and Zhu and Trefler (2005) reveal that the same situation occurred in Bolivia, South Korea, and the Philippines.

By paying special attention to the SBTC literature, we build a framework to address some new mechanisms that can accommodate the effective occurrences observed in different countries. It is closely related to the contributions of Acemoglu (1998), Acemoglu and Zilibotti (2001), Acemoglu (2002), Afonso (2006), and Afonso (2008), but it is built in order to:

- assess the implications arising from the total or partial removal of scale effects associated with the market size in the SBTC framework, then stressing fully or partially the price of goods (*price channel*) as determinant of the direction of technological knowledge since more expensive goods command higher profits for the producers of the respective inputs[1];
- include three additional findings observed in the literature, which by producing a *learning-by-interacting effect* in the R&D technology affect the direction of the technological-knowledge change—the complementarity between the intensity of R&D activity and (R&D) cooperations, the (R&D) cooperations as a mechanism to promote learning and knowledge diffusion and to internalize technological-knowledge spillovers, and the complementarity between R&D activity and skilled labor/technology.

Detailing a little more each one of these three findings, we observe that the positive link between R&D intensity and cooperations/alliances/connections/linkages has a very long tradition [Arrow (1962) and Spence (1984)]. Sectors in which R&D activity is relatively intense, such as pharmaceuticals, chemical, computer software, electronic components, and communication equipments, whose production is relatively intensive in skilled labor, have a relatively high number of cooperations and are intensively connected [Hagedoorn and Duysters (2002), Riccaboni and Pammolli (2002), Powell et al. (2005), and Roijakkers and Hagedoorn (2006)]. Firms in these sectors have thus formed R&D cooperation[2] that occurs among firms within the same market product and among firms from other sectors [König et al. (2014)], sharing knowledge and becoming more specialized in one technology [Weitzman (1998)]. Cooperation intensity is then an important mechanism through which spillovers flow and allows the propagation of learning, knowledge diffusion, and technological-knowledge spillovers through the network [König et al. (2014) and Tomasello et al. (2016)].[3] The non-internalization of technological-knowledge spillovers reduces R&D incentives, and learning and knowledge diffusion promote R&D. Hence, (R&D) cooperations arise as a mechanism to internalize spillovers and to emphasize learning and knowledge diffusion. Consequently, R&D cooperations also promote R&D activity [D'Aspremont and Jacquemin (1988), Kamien (1992), Kamien and Zang (2000), Bloom et al. (2013), and Tomasello et al. (2015)].

The complementarity between R&D activity and skills has been illustrated by the Industrial Organization literature, by Schumpeterian models, and by North–South models [Parello (2008) and Cozzi and Galli (2009)]. These different branches of the literature demonstrate that both applied and basic R&D investments are intensive in employed skilled workers. Firms that are intensive in skilled workers enjoy higher productivity, which can be interpreted as evidence of spillovers among firms. Even firms that do not make R&D investments benefit from higher productivity when they operate in the skill-intensive sector [Leiponen (2005) and O'Mahony and Vecchi (2009)]. This complementarity between skills and R&D is also observed for the firms' innovation rate [Mohnen and Röller (2005)] and for the internal and cooperative R&D absorptive capacity [Leiponen (2005) and Cohen and Frazzini (2008)]. Thus, the entire innovation organization (profitability of R&D cooperations, innovation rate, absorptive capacity, and knowledge spillovers) benefits from strong and positive skill effects.

To sum up, the literature has shown the importance of R&D cooperations in terms of R&D profitability due to the propagation of learning and knowledge diffusion effects as well as due to technological-knowledge spillovers through the network. Simultaneously, the literature demonstrates that these effects are positively related with the connectivity between firms and intensity of skills. In spite of the importance illustrated in the literature on the relationship between network connectivity, skills intensity, and knowledge spillovers, studies incorporating R&D collaboration network to analyze the impact on economic growth, technological-knowledge bias, and income inequality have not been developed. Exploring these relationships is an important objective of the paper.

In order to better understand the mechanism, we model a standard (in endogenous R&D-growth theory) economic structure. The production of perfectly competitive final goods uses labor together with quality-adjusted intermediate goods, which, in turn, use innovative designs under monopolistic competition. Each final good is produced by one of two technologies. One uses skilled labor together with a continuum set of skilled-specific intermediate goods (the skilled technology). The other brings together unskilled labor and a continuum set of unskilled-specific intermediate goods (the unskilled technology). This production function, with complementarity of inputs and substitutability between technologies, is adapted from Acemoglu and Zilibotti (2001), where the *market-size channel* is emphasized, and from Afonso (2006), where the *price channel* is stressed. Moreover, since innovation hardly ever takes place in isolation, we consider the literature on R&D intensity and collaboration network, and include in our SBTC context the importance of R&D cooperations owing to the propagation of learning and knowledge diffusion effects as well as due to technological-knowledge spillovers through the network (*learning-by-interacting effect*).

Bearing in mind the literature, we conjecture that the *learning-by-interacting effect* is positively related with the connectivity between firms and the intensity of skills[4]; that is, the increasing linkages favor learning and knowledge diffusion as well as the internalization of technological-knowledge spillovers reflected in the reduction of R&D costs, thus speeding up the technological-knowledge progress. In practice, the measure of the linkage/cooperation effects is captured by the network degree, which, in our case and in line with the literature [Leiponen (2005) and O'Mahony and Vecchi (2009)], is assessed in relative terms from the skilled to the unskilled technology. Hence, through the *learning-by-interacting effect*, the technological-knowledge progress is not balanced between technologies, with the bias leaning toward the skilled technology positively related with the number of final goods produced with this technology. Moreover, to meet this effect, we also follow Cohen and Levinthal (1989), Bloom et al. (2013), and Aghion and Jaravel (2015) and look at the input–output interconnections established between firms/sectors in the network structure.

For instance, in a case with complete removal of scale effects, by including a strong adverse *cost-of-market-size* in the R&D technology, the relative abundance of skilled labor increases the competitive price of goods produced by unskilled workers and, thus, the demand for R&D directed toward improvements in goods produced by unskilled labor (*price channel*). However, even when the *price channel* dominates the *market-size channel*, the rise in the skill premium can emerge due to the opportunities created by the *learning-by-interacting effect* in skilled technology, which, by capturing the relatively stronger benefits of productive cooperations/linkages in skilled technology, redirects technological knowledge in favor of intermediate goods used with skilled labor. We thus propose a framework in which the *learning-by-interacting effect* can have negative consequences on the unskilled wages and is capable of generating predictions compatible with the trend described above of the skill premium in all countries. To sum up, the more rapid rise in the demand for skills due to SBTC should be affected by the relatively stronger benefits of productive cooperations/linkages in skilled technology. The transmission of technological change intra-(skilled) technology through knowledge spillovers has important implications for our understanding of the innovation process in an economy, and we intend to analyze how these knowledge linkages affect the technological-knowledge bias, the skill premium, and the economic growth.

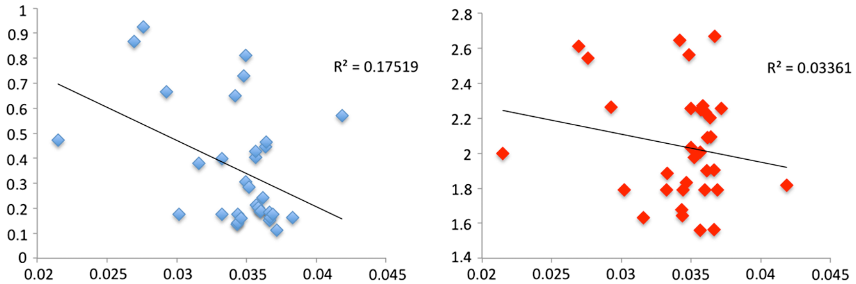
Although our model abstracts from important determinants of the skill premium in, for example, the US economy (including changes in the domestic supply of skills), it is consistent with the qualitative picture emerging from several decades of changes in the US wage structure. The first wave of strong cooperations/linkages in the 1980s, following the increase in skilled labor, coincides with a sharp increase in the skill premium, but as linkages continue to expand at decreasing rates in the late 1990s and 2000s, the skill premium rose smoothly and began stabilizing [Acemoglu and Autor (2011)].

Our analysis of transitional dynamics further shows that the process is basically governed by two conflicting channels/effects: The *price channel* due to the (partial) removal of scale effects and the *learning-by-interacting effect*, eventually helped by the *market-size channel*, which favors the capacity to internalize spillovers and benefit from the exchange of knowledge. For example, an increase in skilled labor implies that more final goods are produced with this technology, creating/reinforcing the *learning-by-interacting effect*, which, however, start to be sold at a relatively low price. The overall effect on the technological-knowledge bias and thus on the skill premium during the transitional phase depends on the magnitude of the contradictory channels/effects since, by reason of complementarity between inputs in the production of final goods, changes in the skill premium are closely related to the technological-knowledge bias.

After these introductory remarks the paper proceeds in Section 2 with some empirical motivation for the relationship between the relative skilled wage and the network intensity. Section 3 presents the setup of the theoretical model. In Section 4, the dynamic general equilibrium is derived and some transitional dynamics and steady-state growth effects are analyzed. Section 5 presents supportive quantitative results, discussing the calibration, and performing the transitional dynamics toward the steady state and the sensitivity analysis. Section 6 concludes the paper with an assessment of the current state of this research.

2. EMPIRICAL MOTIVATION

The literature reveals that (R&D) cooperations allow learning and knowledge diffusion as well as the internalization of technological-knowledge spillovers through the network, thus contributing to the intensification of R&D activity, which, in turn, is positively related with skilled labor. However, the effects of network intensity on technological-knowledge direction and on the skill premium have not been investigated and, as stated above, this is an important goal of the paper. Hence, our motivation stems from the gap observed in the aforementioned literatures as well as from the following empirical evidence.



Notes: The left panel plots relative skilled hours (y-axis) against the network distance (x-axis). The right panel plots the relative skilled wages (y-axis) against the network distance (x-axis).

FIGURE 1. Relative skilled wages and hours against network distance.

Our argument is supported by the empirical evidence shown in Figure 1, which plots the relative skilled wages and the relative skilled hours for the USA in 2007 against the network distance (x-axis) of each sector, at two-digit level (see Table C1 in Appendix C for detail), to every other sector in the network, where the relative skilled wages is the ratio between the hourly wage of skilled workers, that is, workers with college degree, or its vocational equivalent, and above, and the hourly wage of unskilled workers, that is, workers with education below a college degree. Similarly, the relative skilled hours is the ratio between the skilled and unskilled working hours. Remember that the network distance is the sum of the distance along the shortest path of a sector to every other sector of the network.[5] Thus, the higher is the network intensity, that is, the higher the connectivity or the closeness among agents, which captures the *learning-by-interacting effect*, the higher is the relative skilled wage and the higher are the relative skilled hours.

The sign of the relationship between the network intensity and the relative skilled wages, and between the network intensity and the skilled hours, is not a exclusive feature of the US economy or a year-specific feature. The same relationship is found in the US economy for the period 1995–2009, as well as for a representative set of 40 countries, 27 EU countries, and 13 major countries, that we test from 1995 to 2009 using the world input–output database (WIOD).[6] Thus, defining $\frac{w_H}{w_L}$ as the relative skilled wages, and reminding that D_i represents the network degree [equation (**A1**) in Appendix A] and Γ_i^{-1} the inverse of the network distance, that is, the network closeness [equation (**A2**) in Appendix A], we estimate the following equation:

$$\frac{w_H}{w_L}_{jit} = \beta_1 + \beta_2 NI_{jit} + \upsilon_{ji} + \delta_t + \mu_{jit}, \tag{1}$$

where NI_{jit} is the network intensity of sector i in country j and period t, which we approximate by D_{jit} or Γ_{jit}^{-1}, υ_{ji} is the i-sector, j-country fixed effect, δ_t is the time fixed effect. We also estimate an identical equation for the relative skilled hours. The estimation results are summarized in Table 1. The columns (1)–(2) and

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(5)–(6) of Table 1 show the relationship between the inter-sector network intensity and the relative skilled wages for the period 1995–2009. The columns (1)–(4) report the estimation results for the US economy, while the columns (5)–(9) report the estimation results for the 40 countries considered in our sample. Using either the network degree or the inverse of the network distance as measures of the network intensity [columns (1), (2), (5), and (6)], we observe a positive and significant effect of the network intensity on the relative skilled wages. The higher the sectors' connectivity (or network degree) and closeness (or inverse of the network distance) are, the higher is the skilled wage relative to unskilled. The columns (3), (5), and (7) of Table 1 show the network intensity effect on skilled hours relative to unskilled. The effect is also positive and significant, showing that the higher is the network intensity, the higher is the number of hours worked by skilled workers relative to unskilled. When we use the network degree as proxy of the network intensity, column (8), we find a negative relationship, but after introducing the squared degree, column 9 of Table 1, we conclude that there is a U-shaped relationship between network intensity and relative high-skilled hours for the set of 40 countries.[7] That is, after some degree level we also observe a positive relationship between the network degree and the relative high-skilled hours. Thus, both network measures favor our argument that the network intensity promote an intensification of the relative high-skilled hours.

3. THEORETICAL SETUP

This section describes the theoretical economic setup, which is based on Acemoglu and Zilibotti (2001), and the equilibrium analysis, stressing the law of motion of technological knowledge, the transitional dynamics, and the steady-state growth. A fixed number of infinitely lived households inelastically supply labor, maximize utility, and invest in firm's equity. The economy produces final goods in perfect competition and intermediate goods in monopolistic competition. Successful R&D activities result in innovations used by the intermediate goods sector, which drive the economic growth and the technological-knowledge bias, and thus the path of wage inequality. Labor and quality-adjusted intermediate goods are the inputs of final goods. The fraction of the aggregate final good that is not consumed is, in turn, used in the production of intermediate goods and in R&D.

3.1. Consumers

The economy is populated by a fixed number of infinitely lived households who consume and collect income from investments in financial assets and from labor. Households inelastically supply unskilled, L, or skilled labor, H. Total labor supply, $L + H$, is therefore exogenous and constant. We assume that consumers have perfect foresight concerning the technological change over time and choose the path of final good aggregate consumption $\{C(t), t \geq 0\}$ to maximize

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TABLE 1. Evidence of networks intensity on relative skilled wages and hours

	Relative skilled wages		Relative skilled hours		Relative skilled wages		Relative skilled hours		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Γ_{jit}^{-1}	0.041**		0.011***		0.03***		0.06***		
	(2.22)		(3.23)		(7.02)		(8.44)		
D_{jit}		0.086***		0.082**		0.0658***		−0.105***	−0.856***
		(2.62)		(2.56)		(11.76)		(−11.41)	(−34.39)
D_{jit}^2									0.355***
									(32.28)
Const.	1.841***	1.779***	0.087	0.257***	1.494***	1.497***	0.010	0.220***	0.547***
	(24.54)	(31.35)	(1.46)	(3.71)	(88.26)	(101.37)	(0.689)	(9.08)	(21.48)
Country FE					√	√	√	√	√
Time FE	√	√	√	√	√	√	√	√	√
No. of obs.	510	525	510	525	13,251	13,315	13,252	13,331	13,331
R^2	0.08	0.12	0.08	0.03	0.65	0.66	0.13	0.13	0.19

Notes: The columns (1)–(4) report the results for the USA, and the columns (5)–(9) report the results for the 40 countries specified in Table B1 in Appendix B. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. FE means Fixed Effects.

discounted lifetime utility. With a constant intertemporal elasticity of substitution instantaneous utility function, the infinite horizon lifetime utility is $U = \int_0^{\infty}(\frac{C(t)^{1-\theta}-1}{1-\theta})e^{-\rho t}dt$, where $\rho > 0$ is the subjective discount rate and $\theta > 0$ is the inverse of the intertemporal elasticity of substitution.

The maximization 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. The initial level of wealth $a(0)$ is given and the non-Ponzi games condition $\lim_{t\to\infty} e^{-\int_0^t r(s)ds} a(t) \geq 0$ is also imposed. The Euler equation for consumption is standard:

$$\frac{\dot{C}(t)}{C(t)} = \frac{1}{\theta} \cdot (r(t) - \rho)\,, \tag{2}$$

as is the transversality condition: $\lim\limits_{t\to\infty} e^{-\rho t} \cdot C(t)^{-\theta} \cdot a(t) = 0$.

3.2. Production, Price Decisions, and R&D Activity

Following Acemoglu and Zilibotti (2001), Afonso (2012), Gil et al. (2016), and Neto et al. (2017), each final good, indexed by $n \in [0, 1]$, is produced by one of two technologies. The L-technology uses L complemented with a continuum of L-specific intermediate goods indexed by $j \in [0, J]$. The H-technology's inputs are H complemented with a continuum of H-specific intermediate goods indexed by $j \in [J, 1]$. The constant returns to scale production function at time t is[8]

$$Y_n(t) = \begin{cases} \left[\int_0^J z_n(j,t)^{1-\alpha}dj\right] [(1-n)\, lL_n]^{\alpha}, & \text{if } n \leq \overline{n}(t) \\ \left[\int_J^1 z_n(j,t)^{1-\alpha}dj\right] (n\, h\, H_n)^{\alpha}, & \text{if } n > \overline{n}(t) \end{cases}. \tag{3}$$

By considering $z_n(j,t) = q^{k(j,t)}x_n(j,t)$ in equation (3), the integral terms are the contributions to production of quality-adjusted intermediate goods. The size of each quality upgrade obtained with each success in R&D is q, an exogenously constant greater than 1. The rungs of the quality ladder are indexed by k, with higher ks denoting higher quality. At time 0, the top-quality good in each intermediate good has a quality index $k = 0$. At t, the highest quality good produced by j has a quality index $k(j,t)$, which is used due to profit maximizing limit pricing by the monopolist producers of intermediate goods. The quantity $x_n(j,t)$ of j is used, together with its specific labor, to produce $Y_n(t)$. The term $(1-\alpha)$ is the intermediate-goods input share, and $\alpha \in (0, 1)$ is the labor share.

In equation (3), the labor terms include the quantities employed in the production of the nth final good, L_n and H_n, and two corrective, but important, factors accounting for productivity differentials. An absolute productivity advantage of skilled over unskilled labor is accounted for by assuming $h > l \geq 1$. A relative productivity advantage of either labor type is captured by the adjustment terms n and $(1-n)$. These adjustment terms transform the index n into an ordering index, meaning that final goods indexed by larger ns are relatively more

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intensive in skilled labor. Since $n \in [0, 1]$, there is a threshold final good, $\overline{n}(t)$, endogenously determined, at which the switch from one technology to another becomes advantageous. Hence, $\overline{n}(t)$ defines the structure of final-goods production—at each time t, there are $\overline{n}(t)$ final goods produced with the L-technology and $1-\overline{n}(t)$ final goods produced with the H-technology. Moreover, $\overline{n}$ is used to measure the network intensity in each technology and, as a result, the *learning-by-interacting effect*. Indeed, as emphasized by the literature, skill-intensive sectors (e.g. pharmaceuticals, computer software, electronic components, and communication equipment), thus produced with the H-technology, are relatively more intensive in network cooperations. Thus, to accommodate this result, we consider that the network intensity in each technology at each time t is measured by the respective (endogenous) average value of the ordering index n; that is, network intensity in the L-technology is evaluated by $\frac{\overline{n}}{2}$, while in H-technology is given by $(\frac{\overline{n}+1}{2})$. These measures will be used later in R&D activities carried out within each technology, L and H, to assess the spread and consequent internalization of technological-knowledge spillovers.

The production function (3) combines complementarity between inputs and substitutability between the two technologies. The optimal choice of technology is reflected in the equilibrium (endogenous) threshold final good, $\overline{n}(t)$, obtained from profit maximization (by perfectly competitive final-goods producers and by intermediate-goods monopolists) and full-employment equilibrium in factor markets, given the labor supply and the current state of technological knowledge [e.g. Acemoglu and Zilibotti (2001), Afonso (2012), Gil et al. (2016), and Neto et al. (2017)]:

$$\overline{n}(t) = \left\{ 1 + \left[\frac{Q_H(t)\, h\, H}{Q_L(t)\, lL} \right]^{\frac{1}{2}} \right\}^{-1}, \tag{4}$$

where

$$Q_L(t) \equiv \int_0^J q^{k(j,t)\left[\frac{1-\alpha}{\alpha}\right]}\, dj \text{ and } Q_H(t) \equiv \int_J^1 q^{k(j,t)\left[\frac{1-\alpha}{\alpha}\right]}\, dj \tag{5}$$

are aggregate quality indexes of the technological-knowledge stocks and the ratio $B = \frac{Q_H}{Q_L}$ is the appropriate measure of the technological-knowledge bias.

Fact 1. *The threshold final good, $\overline{n}(t)$, is small, meaning that the fraction of final goods using the H-technology in equation (3) is large, when the technological knowledge, B, is highly H-biased, the relative supply of H, $\frac{H}{L}$, is large and the absolute advantage of the skilled labor, $\frac{h}{l}$, is strong. In this case, the relative network intensity in the H-technology is stronger.*

Proof. Directly from equation (4). ■

Thus, optimally only L-technology is used to produce final goods indexed by $n \leq \overline{n}(t)$, and only H-technology is used to produce goods with $n > \overline{n}(t)$; that is, in production function (3), $H_n(t) = x_n(j, t) = 0$, for $0 \leq j \leq J$, $\forall 0 \leq n \leq \overline{n}(t)$ and

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$L_n(t) = x_n(j,t) = 0$, for $J < j \leq 1$, $\forall \overline{n}(t) \leq n \leq 1$; and the demand for each j by the representative producer of nth final good is $x_n(j,t) = (1-n) l L_n [\frac{p_n(t)\cdot(1-\alpha)}{p(j,t)}]^{\frac{1}{\alpha}} q^{k(j,t)[\frac{1-\alpha}{\alpha}]}$ if $0 < j \leq J$, $\forall\, 0 \leq n \leq \overline{n}(t)$, and $x_n(j,t) = nhH_n[\frac{p_n(t)\cdot(1-\alpha)}{p(j,t)}]^{\frac{1}{\alpha}} q^{k(j,t)[\frac{1-\alpha}{\alpha}]}$ if $J < j \leq 1$, $\forall\, \overline{n}(t) \leq n \leq 1$, where $p_n(t)$ is the price of final good n, and $p(j,t)$ is the price of intermediate good j (prices given for the perfectly competitive producers of final goods). Plugging these demand functions into equation (3), the supply of n, Y_n, depends on Q_L, Q_H, parameters and exogenous variables:

$$Y_n(t) = \left[\frac{p_n(t)\,(1-\alpha)}{p(j,t)}\right]^{\frac{1-\alpha}{\alpha}} [(1-n)\, l\, L_n\, Q_L(t) + n\, h\, H_n\, Q_H(t)], \tag{6}$$

which clearly shows how final-production growth—the economic growth rate—is driven by the technological-knowledge growth/progress. The threshold $\overline{n}(t)$ can be implicitly expressed in terms of price indexes. This is achieved by considering that in the production of the threshold $n = \overline{n}(t)$ a firm that uses L-technology and a firm that uses H-technology should break even. This turns out to yield, at each time, the following ratio of index prices of goods produced with H and L technologies:

$$\frac{p_H(t)}{p_L(t)} = \left(\frac{\overline{n}(t)}{1-\overline{n}(t)}\right)^{\alpha}. \tag{7}$$

Fact 2. *The relative price of final goods produced with the H-technology, $\frac{p_H}{p_L}$, is low when the threshold final good, $\overline{n}$, is small; that is, when the relative network intensity in the H-technology is stronger. In this case, the demand for H-intermediate goods is low, which, as we see below, discourages (encourages) R&D activities aimed at improving their quality by the price channel (learning-by-interacting effect). Thus, by affecting the threshold final good, the labor structure influences the direction of R&D.*

Proof. Directly from equation (7). ■

Moreover, since the aggregate (or composite) final good is obtained by integration over final goods, "summing-up" homogenous physical quantities: $Y(t) = \int_0^1 p_n(t)\, Y_n(t)\, dn$ and equations (4) and (7), the price indexes of L and H final goods are, respectively, $p_L(t) = p_n\,(1-n)^{\alpha} = \exp(-\alpha)\overline{n}(t)^{-\alpha}$ and $p_H(t) = p_n n^{\alpha} = \exp(-\alpha)\,[1-\overline{n}(t)]^{-\alpha}$. The composite final good is the numeraire of the economy; that is, the appropriate price (index) is one by definition: $\exp \int_0^1 \ln p_n(t)\, dn = 1$. Economic resources measured in terms of Y can then be used in production of the intermediate goods, X, in the R&D sector, R, or consumed, C; that is, $Y(t) = X(t) + R(t) + C(t)$.

Full employment in the labor market, implicit in $\overline{n}$, yields the following equilibrium-skilled premium, measuring intra-country wage inequality (or the skill premium):

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$$\frac{w_H(t)}{w_L(t)} = \left(\frac{Q_H(t)}{Q_L(t)}\frac{h}{l}\frac{L}{H}\right)^{\frac{1}{2}}, \tag{8}$$

where $w_H(t)$ and $w_L(t)$ are, respectively, wages per unit of H- and L-type labors.

Fact 3. *The skill premium, $\frac{w_H}{w_L}$, is greater when the technological knowledge, $B = \frac{Q_H}{Q_L}$, is more skill biased, the absolute advantage of the skilled labor, $\frac{h}{l}$, is strong, and skilled labor, $\frac{L}{H}$, is relatively scarcer.*

Proof. Directly from equation (8). ■

Equations (4), (7), and (8) are useful in foreseeing the operation of the *price (of final goods) channel* and of the relative *network intensity* from the stocks (of labor and technological knowledge) to the flows of resources used in R&D and to wage inequality. For example, in a country relatively H-abundant and (or) with a large technological-knowledge bias, $\overline{n}(t)$ is small, that is, many final goods are produced with the H-technology and thus:

- On the one hand, final goods produced with the H-technology are sold at a relatively low price (Fact 2). Profit opportunities in the production of intermediate goods used by the relatively high-priced L-technology final goods induce a change in the direction of R&D against the technological-knowledge bias and in favor of unskilled wages, that is, there are stronger incentives to develop technologies when the final goods produced by these technologies command higher prices.[9]
- On the other hand, the *network intensity* in the H-technology is stronger, which, as will be clear further below, favors the capacity to internalize spillovers and benefit from the exchange of knowledge *learning-by-interacting effect*, which re-directs R&D toward designs that improve the quality of intermediate goods used together with skilled labor, increasing its relative demand and thus benefiting the skilled wages.

The overall effect on the technological-knowledge bias thus depends on the magnitude of the two contradictory channels—*price channel* and *learning-by-interacting effect*. To sum up, an increase in skilled labor causes an immediate steep drop in the skilled premium since its relative supply decreases its relative wage [see equation (8)], but this immediate effect is reversed in the transitional dynamics toward the (constant) steady-state skilled premium if the stimulus to the demand for skilled labor resulting from the technological-knowledge bias dominates, which occurs with a sufficiently strong *learning-by-interacting effect*.

In turn, firms in the intermediate-goods sector use one unit of aggregate output to obtain one unit of j and its marginal cost is thus one. Moreover, each quality of j is exclusively produced by the owner of its patent. This monopolist at t obtains a profit flow $\pi\,(j,t) = (p(j,t) - 1)\,X\,(j,t)$, where $X(j,t) = \int_0^1 x_n(j,t)\,dn$ represents the aggregate demand for the top quality, obtained from the demand by final-goods producers at each t. Since intermediate goods, bought by the producers of final goods, fully depreciate at the end of each t, the monopolist faces no dynamic constraints and every t chooses $p(j,t)$ so as to maximize π, obtaining: $p(j,t)=p=\frac{1}{1-\alpha}$, for all $j\in[0,1]$, which is a mark-up over the marginal cost, $0<\alpha<1$, constant across t, j, and k [e.g. Acemoglu and Zilibotti (2001)]. Whether or not a monopolist can price its output according to this price depends on the substitutability between qualities of j and on the value of q; following Barro and Sala-i-Martin (2004, Chapter 7), we assume that $q>\frac{1}{1-\alpha}$ and, thus, monopolists set $p=\frac{1}{1-\alpha}$.[10]

Firms in the intermediate-goods sector carry out R&D activities in order to improve their qualities. Let $I(j,t)$ denote the probability of the kth quality of j being introduced at t, thereby improving the quality level of that good from q^k to q^{k+1}, which is given by[11]

$$I(j,t)=y(j,t)\cdot\zeta^{-1}q^{-\alpha^{-1}k(j,t)}\cdot m^{-\xi}\cdot\beta q^{k(j,t)}\cdot f(\overline{n}(t)),\ \text{for all } j\in[0,1]\,, \tag{9}$$

where:

(i) $y(j,t)$ is the total amount of R&D spending (in terms of Y) aimed at improving j.

(ii) $\zeta^{-1}q^{-\alpha^{-1}k(j,t)}$ is an adverse *cost-of-complexity R&D effect*, since ζ is a positive constant [e.g. Afonso (2012)]. This effect reflects an increasing difficulty in improving the quality of intermediate goods [e.g. Barro and Sala-i-Martin (2004, Chapter 7)].

(iii) $m^{-\xi}$ is an adverse *cost-of-market-size*, which is measured by $m=L$ and $m=H$, due to the complementarity between inputs in equation (3). Given that scale effects are often considered implausible [e.g. Jones (1995a)], $m^{-\xi}$, $\xi\geq 0$, implies that an increase in market scale, measured by L or H, dilutes the effect of R&D outlays on the innovation rate, due to training, coordination, organizational, and transportation costs related to market size [e.g. Afonso (2012)], which can partially ($0<\xi<1$), totally ($\xi=1$), or over counterbalance ($\xi>1$) the scale benefits on profits, and thus allows us to remove scale effects on the economic growth rate. This contrasts with the usual knife-edge assumption that either $\xi=0$ or $\xi=1$ [e.g. Barro and Sala-i-Martin (2004, Chapter 7)].

(iv) $\beta q^{k(j,t)}$ is a positive *learning-by-past R&D effect*, which relates past successful R&D in j with the current probability of success [e.g. Afonso (2012)]. Through this effect we take into account that technological knowledge is non-rival and that the legal system gives protection only to production rights.[12] Thus, firms learn from past innovations in j (measured by $q^{k(j,t)}$) since the learning parameter β is greater than zero.

(v) $f(\overline{n}(t))$ is a positive *learning-by-interacting (R&D) effect*, capturing the benefits of network intensity due to allowed productive linkages. Thus, the probability of successful R&D in each intermediate good j is related to the existing network intensity in final goods sector which serves as input. We then introduce an absolute advantage of the H-technology over the L-technology; that is, we consider that there is a relatively high number of R&D network cooperations in the H-technology, which facilitates the access to a broader level of technological knowledge. This sharing of technological knowledge allows that the R&D activity aimed at improving intermediate goods used by the H-technology benefits relatively more from the internalization of technological-knowledge spillovers. To operationalize this idea, we consider the meaning of the index n in the production function (3) and, as already stated, we assume that the probability (9) in each j is positively related to the average value of the ordering index n in the respective technology, L and H, and thus with: (i) $\frac{\overline{n}}{2}$ if $j \in [0, J]$ belongs to L-technology, $n \leq \overline{n}(t)$; (ii) $\left(\frac{\overline{n}+1}{2}\right)$ if $j \in [J, 1]$ belongs to H-technology, $n > \overline{n}(t)$. Since $\overline{n}$ is a value between 0 and 1, we maintain the quality of the results by normalizing $\frac{\overline{n}}{2}$ to 1 and thus $(\frac{\overline{n}+1}{2})$ to $(1 + \frac{1}{\overline{n}(t)})$ in function $f(\overline{n}(t))$:

$$f(\overline{n}(t)) = \begin{cases} 1, & \text{if } n \leq \overline{n}(t);\ \text{i.e. } j \in [0, J] \\ \left(1 + \frac{1}{\overline{n}(t)}\right)^{\phi}, & \text{if } n > \overline{n}(t);\ \text{i.e. } j \in [J, 1] \end{cases}. \tag{10}$$

We also introduce the parameter $\phi \in [0, 1]$ to regulate how quickly the *learning-by-interacting R&D effect* increases as the threshold final good changes. The range of possible values for this parameter is limited, between 0 and 1, to obtain reasonable values for the main macroeconomic variables in our research; that is, $\overline{n}$, B, $\frac{w_H}{w_L}$ and the economic growth rate. In particular, the probability of successful R&D in intermediate goods $j \in [J, 1]$ increases when, *ceteris paribus*, skilled labor increases since, in this case, $\overline{n}$ decreases and, as a result, there are more network linkages, thereby speeding up the technological-knowledge bias.

4. GENERAL EQUILIBRIUM

As the countries' economic structure has been characterized for given states of technological knowledge, we now proceed to include the equilibrium dynamics of the technological knowledge, which, in the absence of labor or human-capital accumulation, drives economic growth—see, for example, equation (6)—and wage dynamics—see equation (8). Bringing into consideration R&D activities, we first derive the aggregate spending in R&D and the law of motion of technological knowledge. Then, we use these results to characterize the dynamic general equilibrium in which it is embodied that households and firms are rational and solve their problems, free-entry R&D conditions are met, and markets clear. With this procedure we are able to depict the transitional dynamics and the steady-state growth.

4.1. R&D Equilibrium

Assuming that leader firms have no advantage over followers in R&D activities (as this is indifferent to our results), then, independently of j and the respective q^k, it is more profitable to introduce a new quality of j by a follower firm than by the current monopolist.[13] Indeed, follower/outside firms gain a one-rung quality advantage over their closest competitor and profits jump from zero (prior to the innovation) to $\pi\ (j,t)$ when the new quality is introduced. Let τ $(\tau+d)$ be the time when a firm introduces the quality q^k (q^{k+1}) for j. The firm that introduces q^k becomes the monopolist between τ and $\tau+d$ in j and earns a sum of profits given by $V\ (j,t)=\int_{\tau}^{\tau+d}\pi\ (j,t)\ e^{-r(t)}\ dt$. Since innovations arrive randomly, d is undetermined and the reward for introducing q^k, that is, the true value of $V\ (j,t)$ is unknown. However, if the interest rate is constant between τ and $\tau+d$, which will be the case in equilibrium, then $V\ (j,t)=\int_{t}^{\infty}\pi\ (j,t)\ e^{\left[-\int_t^s(r(\tau)+I(j,\tau))d\tau\right]}ds=\frac{\pi\,(j,t)}{r(t)+I(j,t)}$; that is, the expected value of introducing q^k in j depends positively on the dimension of the profits at each t, $\pi\ (j,t)$, and negatively on the interest rate, $r\,(t)$, and on the probability of successful innovation, $I(j,t)$, which captures the Schumpeterian idea of "creative destruction."

By considering free entry in R&D activities, free access to the R&D technology, and a proportional relationship between successful innovation and the share of R&D effort, the R&D spending aimed at improving j should equal the expected payoff generated by the innovation, that is, $y(j,t)=I(j,t)\cdot V(j,t)$. Then, using equation (9), the equilibrium probabilities of successful R&D, I_L and I_H, which are independent of j and k for each t: $I_m=\Re-r$, where $\Re\equiv\{\frac{\beta}{\zeta}\cdot(\frac{q-1}{q})\cdot\overline{m}\cdot(1-\alpha)^{\frac{1}{\alpha}}\cdot\underbrace{p_m(t)^{\frac{1}{\alpha}}}_{\text{Price channel}}\cdot\underbrace{m^{1-\xi}}_{\text{Market-size channel}}\cdot\underbrace{f(\overline{n}(t))}_{\text{Network-intensity channel}}\}$, $m=L$ or $m=H$, and $\overline{m}=l$ or $\overline{m}=h$, incorporate the three available channels if $0\leq\xi<1$. The equilibrium m-specific I_m turns out to be independent of j and k due to the removal of technological-knowledge scale effects—the positive influence of the quality rung on profits and on the *learning-by-past effect* is exactly offset by its influence on the *cost-of-complexity effect*. Additional scale effects could arise through market size, as has been discussed in the R&D endogenous growth literature since Jones (1995a,b) critique. Due to the technological complementarity in the production function (3), the size of the market for m-specific intermediate goods is the m-type labor. The scale effect is thus apparent in the size of the profits. The *cost-of-market-size* due to the scale difficulty of introducing new quality intermediate goods can be designed to offset the scale effect on profits by assuming $\xi=1$. Finally, the equilibrium can be translated into the path of technological knowledge, resulting in following expression—where the equilibrium m-specific probability of successful R&D, I_m, given r, p_m, and $\overline{n}$ is plugged in—for the equilibrium m-specific growth rate[14]:

$$\frac{\dot{Q}_m(t)}{Q_m(t)}=I_m(t)\cdot\left(q^{\frac{1-\alpha}{\alpha}}-1\right),\tag{11}$$

where $m=\{L,H\}$ and $\overline{m}=\{l,h\}$. The total equilibrium aggregate R&D spending is given by $R(t)=\int_0^J y(j,t)\,dj+\int_J^1 y(j,t)\,dj=f\ (Q_L(t),\ Q_H(t),\Omega_R)$.

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4.2. Transition Dynamics and Steady-State Growth

Since all macroeconomic aggregates (Y, X, R, C, and also, e.g. $\frac{w_H}{w_L}$) are multiples of Q_L and Q_H,[15] the path of all relevant variables outside the steady state relies on the single differential equation that governs the path of technological-knowledge bias, that is, $\frac{\dot{B}(t)}{B(t)} = \frac{\dot{Q}_H(t)}{Q_H(t)} - \frac{\dot{Q}_L(t)}{Q_L(t)}$. Thus, equation (11), we obtain the required expression:

$$\begin{aligned}\frac{\dot{B}(t)}{B(t)} = &\left[\frac{\beta}{\zeta}\left(\frac{q-1}{q}\right)\cdot(1-\alpha)^{\frac{1}{\alpha}}\cdot\exp(-\alpha)\right] \\ &\cdot\left\{h\cdot H^{1-\xi}\cdot\left(1+\frac{1}{\overline{n}(t)}\right)^{\phi}\cdot\left[1+\left(B(t)\frac{hH}{lL}\right)^{-1/2}\right]^{\alpha}\right. \\ &\left.-l\cdot L^{1-\xi}\cdot\left[1+\left(B(t)\frac{hH}{lL}\right)^{1/2}\right]^{\alpha}\right\},\end{aligned} \tag{12}$$

which can be used to quantitatively analyze the impact of some shocks—for example in β, ζ, α, ϕ, ξ, q, h, l, L, and H—on the technological-knowledge bias and consequently on the threshold final good and on the skill premium—indeed, equation (12) can be used in equations (4) and (8) to obtain the dynamics of those variables.

At the end of transitional dynamics, the economy reaches the steady state, which is unique and stable, and all relevant macroeconomic variables grow at the same constant rate. The steady-state growth rate, g^*, is

$$g^* \equiv \frac{\dot{Q}_L^*}{Q_L^*} = \frac{\dot{Q}_H^*}{Q_H^*} = \frac{\dot{Y}^*}{Y^*} = \frac{\dot{X}^*}{X^*} = \frac{\dot{R}^*}{R^*} = \frac{\dot{C}^*}{C^*} = \frac{r^*-\rho}{\theta}. \tag{13}$$

By equating equations (11) and (13), we can obtain the steady-state interest rate, r^*, which is unique and also ensures that the steady-state growth rate is unique. To prove that the steady state is stable, we start by noting that the dynamics of the economy can be represented by a two-dimensional dynamic system in detrended variables B and $D = C/Q_L$—see equations (11)–(13). This dynamic system has a recursive structure since the dynamic of B depends only on itself—see again equation (12). Hence, it suffices to show that equation (12) implies that $\frac{\dot{B}(t)}{B(t)} = Z(B(t))$, where $\dot{Z}(B^*(t)) < 0$; thus, the steady state is asymptotically stable.

To see the economic mechanism in more detail, let us consider that the economy is initially out of the steady state where, for example, $I_H > I_L$. From equation (11), this implies that $\frac{P_H}{P_L} > \frac{P_H^*}{P_L^*}$; that is, that $\overline{n} > \overline{n}^*$, meaning that $\frac{\dot{Q}_H}{Q_H} > \frac{\dot{Q}_L}{Q_L}$ and, since from equation (7) $\frac{P_H}{P_L} = \left(\frac{Q_H hH}{Q_L lL}\right)^{-\frac{\alpha}{2}}$, $\frac{\dot{p}_H}{P_H} - \frac{\dot{P}_L}{P_L} < 0$. Thus, $\frac{P_H}{P_L}$ (or $\overline{n}$) is decreasing toward $\frac{P_H^*}{P_L^*}$ (or $\overline{n}^*$). Notice that the decrease in $\frac{P_H}{P_L}$ (or $\overline{n}$) attenuates the rate at which the technological-knowledge bias is increasing. Thus, due to market incentives, while $\frac{\dot{Q}_H}{Q_H} > \frac{\dot{Q}_L}{Q_L}$, $\frac{\dot{Q}_H}{Q_H} - \frac{\dot{Q}_L}{Q_L}$ is decreasing until the unique and stable steady state is achieved, where $\left(\frac{\dot{Q}_H}{Q_H}\right)^* - \left(\frac{\dot{Q}_L}{Q_L}\right)^* = 0$. The argument to show that the economy starting with $I_H < I_L$ converges to $\frac{P_H^*}{P_L^*}$ is identical. Hence, the economy starting out at the steady state converges to this state and, without any exogenous disturbance, it remains there.

Moreover, from equations (11) and (7), $\left(\frac{\dot{Q}_H}{Q_H}\right)^*$ and $\left(\frac{\dot{Q}_L}{Q_L}\right)^*$ rise at the same rate if $\left(\frac{1+\overline{n}^*}{\overline{n}^*}\right)^{\phi} \frac{\overline{n}^*}{1-\overline{n}^*} = \left(\frac{L}{H}\right)^{1-\xi} \frac{l}{h}$, which, by using second-order Taylor expansion,[16] implies that[17]:

$$\overline{n}^* \simeq \frac{1}{6-2\phi} \cdot \left[2(\xi-1) \cdot \ln\left(\frac{H}{L}\right) - 2 \cdot \ln\left(\frac{h}{l}\right) - 3(\phi-1)\right]. \qquad \textbf{(14)}$$

PROPOSITION 1. *In steady state, the stable and unique endogenous threshold final good, $\overline{n}^*$, relies on specific parameters and exogenous variables: ϕ, ξ, $\frac{h}{l}$, and $\frac{H}{L}$. An increase in either ϕ, ξ, $\frac{h}{l}$, or $\frac{H}{L}$ for $0 \le \xi < 1$ decreases $\overline{n}^*$, strengthening the learning-by-interacting effect. The reinforcement of either of the other channels—price or market size—decreases $\overline{n}^*$: If ξ increases toward 1, the removal of scale effects is stronger and the price channel is reinforced; in turn, if $\frac{H}{L}$ increases and $0 \le \xi < 1$, the (skilled) market-size channel is reinforced; however, if $\frac{H}{L}$ increases and $\xi = 1$, the market-size channel is neutralized since scale effects are removed and there is no effect on $\overline{n}^*$.*

Proof. Directly from equation (14), bearing in mind that $\frac{H}{L} < 1$ and $\frac{h}{l} > 1$. ■

In addition, from the stable $\overline{n}^*$ we also find that final goods price indexes, p_H^*, p_L^*, and $\left(\frac{p_H}{p_L}\right)^*$ remain stable; that is, $\left(\frac{\dot{p}_H}{p_H}\right)^* = \left(\frac{\dot{P}_L}{p_L}\right)^* = \left(\frac{\dot{\overline{n}}}{\overline{n}}\right)^* = 0$. Hence, bearing in mind equations (11), (13), and (14), the steady-state growth rate is – considering $m = L$:

$$g^* = \frac{\exp(-1)\frac{\beta}{\zeta}\left(\frac{q-1}{q}\right)(6-2\phi)(1-\alpha)^{\frac{1}{\alpha}} L^{1-\xi} l\left(q^{\frac{1-\alpha}{\alpha}}-1\right) - \rho\left[2(\xi-1)\cdot\ln\left(\frac{H}{L}\right) - 2\cdot\ln\left(\frac{h}{l}\right) - 3(\phi-1)\right]}{\left[\theta\left(q^{\frac{1-\alpha}{\alpha}}-1\right)+1\right]\left[2(\xi-1)\cdot\ln\left(\frac{H}{L}\right) - 2\cdot\ln\left(\frac{h}{l}\right) - 3(\phi-1)\right]}, \qquad \textbf{(15)}$$

PROPOSITION 2. *In steady state, the stable and unique endogenous economic growth rate, g^*, relies on specific parameters and exogenous variables: ϕ, ξ, $\frac{h}{l}$, $\frac{H}{L}$, θ, ρ, β, ζ, q, and α.*

(i) As stated in Proposition 1, an increase in either ϕ, $\frac{h}{l}$, ξ, or $\frac{H}{L}$ for $0 \le \xi < 1$ decreases $\overline{n}^*$, strengthening in particular the learning-by-interacting effect and thus affecting positively g^*. When $\xi = 1$, scale effects are removed and changes in $\frac{H}{L}$ therefore have no effect on g^*. (ii) As to the R&D parameters, the higher the learning parameter, β, and the smaller the fixed cost parameter, ζ, the greater become the incentives to do R&D, and so the higher the growth rate. (iii) An increase of either ρ or θ decreases g^*: If present consumption is more highly valued than future consumption (following the properties of the utility function), then this will lead to less need for private investment and so to less dispersion over

time; in other words, the more patient—that is, the smaller the value of ρ—and the less keen the individuals are on consumption smoothing—that is, the smaller the value of θ—the higher is g^*. (iv) Finally, the labor share in the production function, α, has a negative impact on g^*.

Proof. Directly from equation (15). In particular, the negative impact of α on g^* is because it increases the size of each quality upgrade, $q = \frac{1}{1-\alpha}$, which requires more resources to obtain each successful research and this acts as a disincentive to R&D activities. But, a greater q also increases the size of profits. Thus, the intuition is the following: Intermediate-good firms take into account the probability of losing the monopoly, and so discount profits at a rate higher than the interest rate. The discount rate is higher when α is greater, which discourages R&D activities and thereby influences negatively the growth rate. ■

Then, from equations (4) and (14), the stable steady-state technological-knowledge bias is

$$B^* \simeq \left(\frac{hH}{lL}\right)^{-1} \left[\frac{6-2\phi}{2(\xi-1)\cdot \ln\left(\frac{H}{L}\right) - 2\cdot \ln\left(\frac{h}{l}\right) - 3(\phi-1)} - 1\right]^2. \qquad \textbf{(16)}$$

PROPOSITION 3. *In steady state, the stable and unique endogenous technological-knowledge bias also depends on ϕ, ξ, $\frac{h}{l}$, and $\frac{H}{L}$. An increase in either ϕ, $\frac{h}{l}$, ξ, or $\frac{H}{L}$ with $\xi \to 0$ increases B^*.*

Proof. Directly from equation (16). Indeed, an increase in: (i) ϕ starts by increasing the *learning-by-interacting effect* (Proposition 1), which improves the relative profitability of skilled technological knowledge and thus biases the technological knowledge in favor of H-intermediate goods; (ii) $\frac{h}{l}$ starts by decreasing the threshold final good (Fact 1), which reinforces the *learning-by-interacting effect* (Proposition 1) and decreases the relative price of final goods produced with H-technology—equation (7). The former effect dominates the latter and becomes more profitable to improve the skilled technological knowledge, thus biasing the technological knowledge in favor of H-intermediate goods; (iii) ξ starts by increasing the *cost-of-market-size*—equation (9)—thus reinforcing the *price channel* through which there are stronger incentives to improve technological knowledge embodied in goods produced with higher prices; that is, the technological knowledge embodied in goods produced with the scarce labor—equation (7) and note that $\frac{H}{L} < 1$—biasing the technological knowledge in favor of H-intermediate goods; (iv) $\frac{H}{L}$, with $\xi \to 0$, starts by decreasing the threshold final good (Fact 1), which reinforces the *learning-by-interacting effect* (Proposition 1) and decreases the relative price of final goods produced with H-technology—equation (7). The former effect dominates the latter and becomes more profitable to improve the skilled technological knowledge, thus biasing the technological knowledge in favor of H-intermediate goods—the chain of effects is dominated by the *learning-by-interacting effect* and there is also influence of the *market-size channel*, by which technologies that use the more abundant type of labor are favored. (v) $\frac{H}{L}$, with $\xi \to 1$, starts by decreasing the threshold final good (Fact 1), reinforcing the *learning-by-interacting effect* (Proposition 1), and by decreasing the relative price of final goods produced with H-technology—(7)—as well as by increasing the *cost-of-market-size*—equation (9). By removing the scale effects, the *price channel* dominates the *market-size channel* and, *ceteris paribus*, the demand for H-intermediate goods decreases, which discourages R&D activities aimed at improving their quality; that is, B^* decreases since the technological knowledge that uses the decreasing type of labor is favored. ∎

Moreover, from equations (8) and (16), the stable steady-state wage premium is

$$\left(\frac{w_H}{w_L}\right)^* \simeq \left(\frac{H}{L}\right)^{-1}\left[\frac{6-2\phi}{2(\xi-1)\cdot\ln\left(\frac{H}{L}\right)-2\cdot\ln\left(\frac{h}{l}\right)-3(\phi-1)}-1\right]. \tag{17}$$

PROPOSITION 4. *In steady state, the stable and unique endogenous skill premium also depends on ϕ, ξ, $\frac{h}{l}$, and $\frac{H}{L}$. An increase in ϕ, $\frac{h}{l}$, or ξ increases $(\frac{w_H}{w_L})^*$, since in each one of these cases there is an increase in B^*—see Proposition 2. In turn, an increase in $\frac{H}{L}$ has an immediate negative effect on $\left(\frac{w_H}{w_L}\right)^*$—see (8)—which can positively affect B^* over the transitional dynamics toward the new steady state; the final effect on $\left(\frac{w_H}{w_L}\right)^*$ can be positive or negative, depending on the magnitude of the two effects: If $\xi \to 0$, the final effect on $(\frac{w_H}{w_L})^*$ is positive (the latter effect dominates the former one); if with $\xi \to 1$, the final effect on $\left(\frac{w_H}{w_L}\right)^*$ is negative as both the immediate effect and the effect on B^* are negative.*

Proof. Directly from equation (17). ∎

Thus, $\left(\frac{\dot{w}_H}{w_H}\right)^* - \left(\frac{\dot{w}_L}{w_L}\right)^* = 0$ and wages rise steadily in line with the technological-knowledge progress; that is, $\left(\frac{\dot{w}_H}{w_H}\right)^* = \left(\frac{\dot{w}_L}{w_L}\right)^* = \left(\frac{\dot{Q}_H}{Q_H}\right)^* = \left(\frac{\dot{Q}_L}{Q_L}\right)^*$. From the previous analysis, it is also worth noting that an increase in ϕ, $0 < \xi < 1$, $\frac{h}{l}$, and β as well as a decrease in θ, ρ, ζ, and α increases g^* and increases or has no impact on $\left(\frac{w_H}{w_L}\right)^*$. Hence, any change in these parameters in the sense referred to implies that all workers will earn higher wages in the new steady state (i.e. welfare gains emerge). The variation in the opposite direction of each of these parameters slows down the economic growth rate and can be used to align with Gordon (2012) who anticipates scenarios of long anemic economic growth or even stagnation in the 21st century. This slowdown can be more or less pronounced depending, for example, on the parameterization of the complexity parameter, ζ, and the regulator of network effects, ϕ. This is in line with, for example, Kasparov et al. (2012), who emphasize the secular stagnation in innovations, with Fernald (2015), who presents evidence in favor of the slowdown in the pace of progress in information technologies after the mid-1990s, and with Gordon (2012), who also argues that the slowdown stems from the features of the innovations (computers, web, and mobile phones) of the late 20th century, the spillovers of which were less long-lasting than those of the innovations of the second industrial revolution.

TABLE 2. Parameter values

Description	Parameter	Value
Labor share	α	0.60
Subjective discount rate	ρ	0.02
Inter-temporal elasticity of substitution	θ	2
Fixed cost of innovation	ζ	2
Learning-by-past parameter	β	1.4
Learning by interacting parameter	ϕ	0.14
Relative skilled-labor supply	$\frac{H}{L}$	0.64
Relative skilled productivity	$\frac{h}{l}$	1.3
Scale effects	ξ	0.45

5. QUANTITATIVE RESULTS

In this section, we calibrate the model results to today's equilibrium, having as reference the current levels of R&D, networks intensity, and labor-market features. This allows us to compute the transitional dynamics toward the steady-state ratios and to perform comparative static and dynamic analysis in face of changes in parameters—β, ζ, α, ϕ, and ξ—and in the relative labor supply, $\frac{H}{L}$, and relative labor productivity, $\frac{h}{l}$.

5.1. Calibration

The calibrated values for parameters and exogenous variables in the baseline case, which are summarized in Table 2, were chosen bearing in mind standard values in the literature, model assumptions, estimated values, and a steady-state growth rate of around 2%, which approximately matches the average per capita growth rate of the USA in the postwar period [e.g. Jones (1995b)].

The subjective discount rate, ρ, and the inverse of the inter-temporal elasticity of substitution, θ, are set equal to 0.02 and 2, respectively, as in Jones and Williams (2000), Afonso (2006), and Grossmann et al. (2013). The technology parameter α, which under our assumptions, has two interpretations (the labor share, α, and the mark-up ratio, $q = \frac{1}{1-\alpha}$) and is set to 0.6, such that the size of quality improvement, q, makes it equal to 2.5, which is in line with the mark-up estimates given by Hall et al. (1986) and Kwan and Lai (2003).

The relative supply of skilled labor, $\frac{H}{L}$, and the relative supply of skilled-labor productivity, $\frac{h}{l}$, are defined equal to 0.64 and 1.3, respectively. The former value is obtained from the OECD's Education at Glance 2014 data for the US economy in the period 2000–2010, in which skilled labor means individuals who have at least some tertiary education.[18] The relative skilled-labor productivity is in line with Acemoglu and Zilibotti (2001) and Afonso (2006).[19]

TABLE 3. Effects of the network intensity in R&D activity

Specification	(1) OLS	(2) OLS	(3) OLS	(4) Newey–West	(5) Tobit	(6) Tobit	(7) Tobit
S_i	0.139	0.143	0.139	0.099	0.142	0.146	0.090
	(2.438)	(2.423)	(2.171)	(2.475)	(2.491)	(2.607)	(2.571)
Const.	−0.017	−0.017	−0.018	−0.060	−0.019	−0.021	−0.052
	(−0.566)	(−0.515)	(−0.473)	(−2.142)	(−0.655)	(−0.583)	(−0.208)
Time FE		√	√			√	√
Sector FE			√				√
No. of obs.	213	213	213	213	213	213	213

Notes: Dependent variable is the share of R&D spending in the value-added output of each sector. Independent variable is the network in-strength. Standard errors are robust and allow for the first-order serial correlation in model (4). For the network metrics distance we also obtain an estimate of around 0.14. OLS means Ordinary Least Squares.

Concerning the measure of the strength of network intensity in R&D activity, $\phi \in [0, 1]$, we follow Cohen and Levinthal (1989), Bloom et al. (2013), and Aghion and Jaravel (2015) to estimate the *learning-by-interacting parameter*. We identify this *parameter* by the input–output interconnections established between firms and sectors in the production network structure. By definition, *learning-by-interacting effects* are proportional to the interconnections between firms that we measure using social network metrics as, for example, the network in-strength, S_i, which gives us the intensity of the inward connections of each firm/sector—see Appendix A.[20] Given the straight and direct relationship between the probability of innovating in the intermediate-goods sector and the R&D spending, see equation (9), we use the share of R&D spending of each sector/firm in terms of the sector's value added, $\frac{R\&D_i}{VA_i}$, as proxy of the probability of successful innovation. Thus, one can estimate the *learning-by-interacting effects* in R&D by the equation: $\frac{R\&D_i}{VA_i} = \alpha_o + \alpha_1 S_i + \epsilon_i$, for each sector/firm i. Table 3 contains the estimate results for the impact of the strength of network intensity in R&D activities for the US economy[21] over the period 1995–2009. Bearing in mind the literature concerning the heteroscedasticity and serial correlation problems [e.g. Cohen and Levinthal (1989) and Bloom et al. (2013)], different estimation methods are presented in Table 3 in order to check the results' robustness. Since the estimates α_1 are quite robust, we set $\phi = 0.14$ in line with the result proposed in Table 3.

Finally, to calibrate the regulator of the *cost-of-market-size*, $\xi \geq 0$, we use the US data and equation (17). We take the US average values of $\frac{H}{L} = 0.64$ and $\frac{w_H}{w_L} = 1.98$ for the period 2000–2010,[22] and the calibrate value of $\frac{h}{l} = 1.3$, as corresponding to the steady-state value, and then by using equation (17) we obtain the value of $\xi = 0.45$. This value is an interesting result that emerges from the calibration of the model, pointing to a significant but not total removal of scale effects, in line with the dominant evidence against (large) scale effects on growth [e.g. Alesina et al. (2005)].

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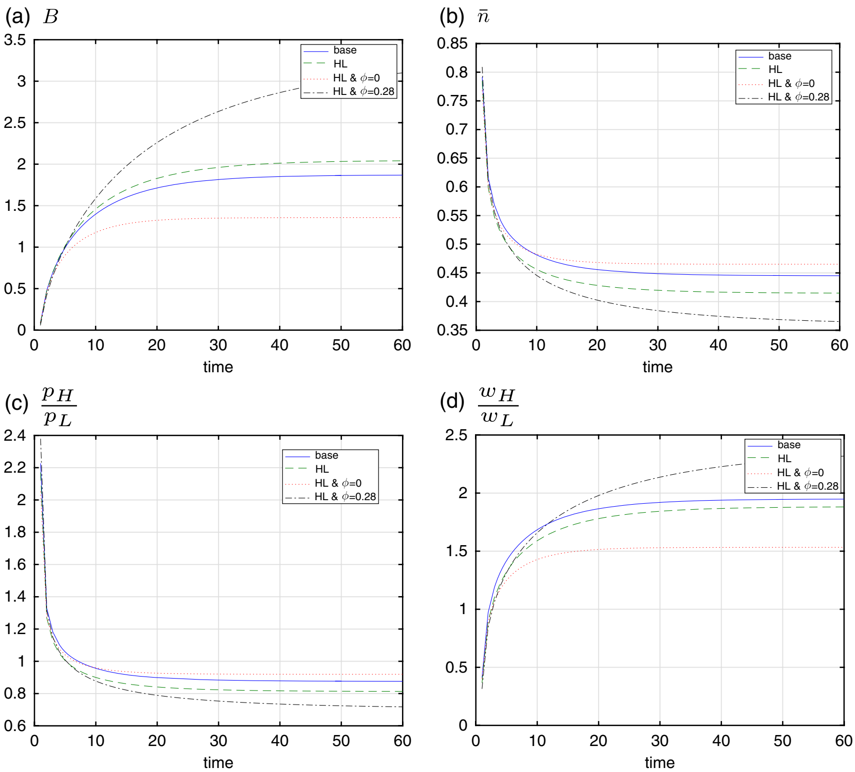

Notes: The solid line describes the transitional dynamics for the baseline parameter and labor endowment values. The dashed, dot, dash-dot lines describe the transitional dynamics for an increase in $\frac{H}{L}$ with $\phi = 0.14$, $\phi = 0$, and $\phi = 0.28$, respectively.

FIGURE 2. The transitional dynamics to the steady state.

5.2. Transitional Dynamics

To analyze the transitional dynamics of the technological-knowledge bias and its repercussions in the threshold final good, $\bar{n}$, the relative price of final goods produced with the H-technology, $\frac{p_H}{p_L}$, and the skill premium, $\frac{w_H}{w_L}$, we use the differential equation of the technological-knowledge bias, equation (12), and then characterize the behavior of the remaining variables using equations (4), (7), and (8), respectively.

Figure 2 summarizes the variables' transitional time path for: (i) the baseline values of the parameters and labor endowments (solid line); and (ii) an increase, at time $t = 0$, in the skilled-labor supply from 0.64 to 0.75: (ii.a) $\phi = 0.14$ (baseline, dashed line); (ii.b) $\phi = 0$ (dot line); (ii.c) $\phi = 0.28$ (dash-dot line).

As explained in Proposition 3, due to an increase in the skilled-labor supply, from $\frac{H}{L} = 0.64$ to $\frac{H}{L} = 0.75$, with partial removal of scale effects, $\xi = 0.45$,

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three immediate effects emerge: The threshold final good decreases—see equation (4)—which reinforces the *learning-by-interacting effect*; the skilled market size widens then operating the *market-size channel*; the relative price $\frac{p_H}{p_L}$ decreases then operating the *price channel*—see equation (7). The operation of the set of the effects/channels during the transitional dynamics toward the new steady state implies that the technological-knowledge bias, B^*, changes from 1.87 to 2.05 in case (ii.a), from 1.87 to 1.36 in case (ii.b), and from 1.87 to 3.28 in case (ii.c). That is, cases (ii.a) and (ii.c) favor the technological-knowledge bias toward H-technology. During the transition dynamics, the set of effects/channels continue to coexist so that $\bar{n}$ and $\frac{p_H}{p_L}$ are changing at decreasing rates until the new steady state; $\bar{n}$ has changed from 0.44 to 0.41 in case (ii.a), to 0.47 in case (ii.b), and to 0.36 in case (ii.c); $\frac{p_H}{p_L}$ from 0.88 to 0.81 in case (ii.a), to 0.92 in case (ii.b), and to 0.71 in case (ii.c).

The skill premium falls instantly from 0.41 to 0.36 due to the rise in the relative supply of skilled labor without new endogenous technological-knowledge progress, and thus without change in the technological-knowledge bias. By reason of complementarity between inputs in the production of final goods—see equation (3)—changes in the skill premium are thus closely related to the technological-knowledge bias, as equation (8) clearly shows. When the increase in the supply of skilled labor induces technological-knowledge bias due to the set of effects/channels, as in cases (ii.a) and (ii.c), the immediate effect on the level of the skill premium ends up being reversed in the transition toward the steady state. That is, in cases (ii.a) and (ii.c), the stimulus to the demand for skilled labor arising from the technological-knowledge bias increases the skill premium. Once in steady state, with a constant technological-knowledge bias, the skill premium remains constant. Moreover, we must highlight that if:

- the effects/channels are not strong enough to reverse the initial effect, as in case (ii.a), the steady-state skill premium is smaller than that which prevailed under the baseline case: $\frac{w_H}{w_L}$ has changed from 1.95 to 1.88;
- the *learning-by-interacting effect* is neutralized, as in case (ii.b), B^* decreases, which also negatively affects the skill premium that is then given by 1.53;
- the *learning-by-interacting effect* is reinforced, as in case (ii.c), the increase of B^* is also reinforced and, as a result, the skill premium is positively affected and given by 2.38.

5.3. Sensitivity Analysis

In this subsection, we analyze the sensitivity of the threshold final good, $\bar{n}^*$, the economic growth rate, g^*, the relative technological-knowledge bias, B^*, and the skill premium, $\frac{w_H}{w_L}^*$ to changes in parameters α (labor share), β (*learning-by-past parameter*), ζ (fixed *cost-of-complexity parameter*), ϕ (*learning-by-interacting parameter*), and ξ (regulator of *cost-of-market-size*), as well as to changes in skilled-labor supply, $\frac{H}{L}$, and skilled productivity, $\frac{h}{l}$.

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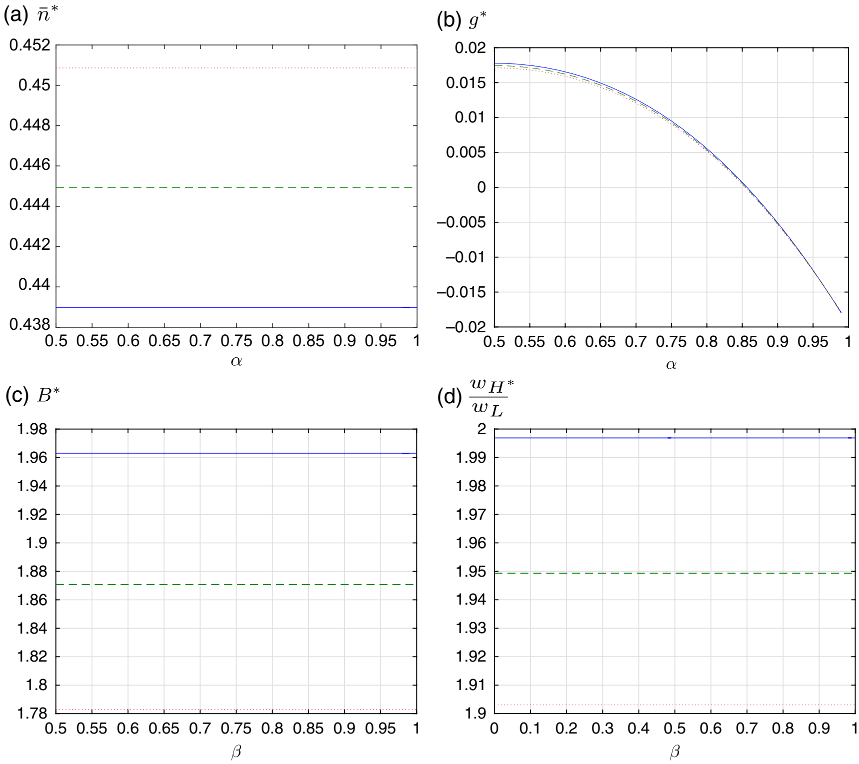

Notes: The dashed, solid, and dot lines denote the baseline ξ value, the two-times standard deviation increase of ξ, and the two-times standard deviation decrease of ξ, respectively.

FIGURE 3. The impact of labor share, α, and scale effects, ξ.

5.3.1. Impact of labor share, α, and cost-of-market-size*, ξ, parameters.* We start by analyzing the sensitivity of the model results to variations of the labor share in the interval $\alpha \in (0.5, 1)$ and variations of the regulator of *cost-of-market-size* in the interval of two standard deviation from the baseline value of ξ.[23]

Figure 3 presents the model results in steady state for: (i) the baseline parameters (dashed line), (ii) a two-times standard deviation increase of ξ (solid line), and (iii) a two-times standard deviation decrease of ξ (dot line). The first observation is that the labor share, α, has no impact on $\bar{n}^*$, B^*, or $\frac{w_H}{w_L}^*$, as directly shown by equations (14), (16), (17), and Propositions 1, 3, and 4, respectively. The only effect of the labor share is the negative impact on g^*. An increase of α makes the size of each quality upgrade greater, $q = \frac{1}{1-\alpha}$, requiring more resources in order to obtain successful research, which discourages R&D activities. On the other hand, the greater is q, the greater are the profits. Thus, intermediate-goods firms take into account the probability of losing profits and discount profits at a higher rate than the interest rate decreasing R&D and, consequently, g^*—see equation (15) and Proposition 2.

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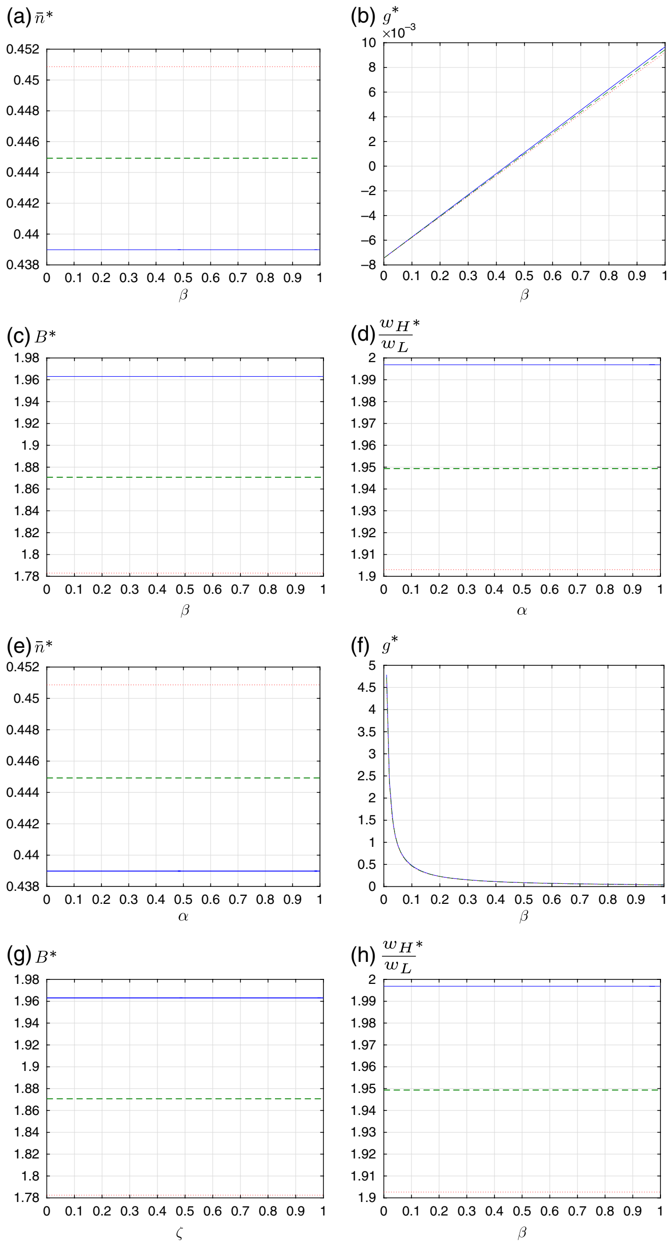
As for the effects of scale, an increase in ξ (solid line), for $0 < \xi < 1$, that is, a decrease of the scale effects' importance, reduces $\bar{n}^*$, reinforcing the *learning-by-interacting effect* and slightly increasing g^* as shown by equation (14) and Proposition 1, and by equation (15) and Proposition 2, respectively. As ξ increases, it raises the *cost-of-market-size*, raising the relative probability of successful R&D of H-intermediate goods type (note that $\frac{H}{L} < 1$)—see equation (9), biasing technological knowledge in favor of H-technology, that is, raising B^*, as shown by equation (16) and Proposition 3, and thus the skill premium, as shown by equation (17) and Proposition 4.

5.3.2. Impact of learning-by-past R&D*, β,* cost-of-complexity R&D*, ζ, and* cost-of-market-size*, ξ, parameters.* Figure 4 presents the model results' sensitivity to variations of the *learning-by-past R&D parameter*, β, and *cost-of-complexity*, ζ, parameters for the three values of the scale-effects parameter considered previously. Again, the dashed line denotes the effects for the baseline parameters and the solid and dot lines denote the two times standard deviations increase and decrease of ξ, respectively.

The steady-state values of $\bar{n}^*$, B^*, or $\frac{w_H}{w_L}^*$ are not affected by changes in β or ζ, as directly shown by equations (14), (16), (17), and Propositions 1, 3, and 4, respectively. The only effect is the positive (negative) impact in β (ζ) in g^*: The steady-state growth rate increases with β and decreases with ζ since the former encourages and the latter discourages R&D activities—see equation (15) and Proposition 2. An increase in β, for example, raises the *learning-by-past R&D effect* and thus the current probability of success—see equation (9)—since technological knowledge is non-rival (and partly excludable). As the *learning-by-past R&D parameter* and the *cost-of-complexity parameter* are offset in equilibrium, no impact arises in B^* or $\frac{w_H}{w_L}^*$.

5.3.3. Impact of learning-by-interacting*, ϕ, and* cost-of-market-size*, ξ, parameters.* In this subsection we analyze the model results' sensitivity to variations of ϕ in the interval $(0, 0.5)$, considering again the previously defined three different values for ξ. As illustrated in Figure 5, an increase in the regulator of the *learning-by-interaction effect*, ϕ, reinforces the effect and thus raises the profitability of skilled technological knowledge. The bias in technological knowledge, favoring H-intermediate goods (i.e. B^* increases), reduces $\bar{n}^*$ and affects positively the skill premium, $\frac{w_H}{w_L}^*$, and the growth rate, g^*—see equations (15)–(17), and Propositions 2–4.

5.3.4. Impact of relative skilled-labor supply, $\frac{H}{L}$, and relative skilled productivity, $\frac{h}{l}$, and cost-of-market-size*, ξ, parameters.* In this subsection, we analyze the model results' sensitivity to variations in the relative skilled-labor supply, $\frac{H}{L}$, and skilled-labor productivity, $\frac{h}{l}$, again for the previously defined three different scale values of ξ. These results are shown in Figure 6.



Notes: (a)–(d) present the sensitivity to β and (e)–(h) present the sensitivity to ζ. The dashed, solid, and dot lines denote the baseline ξ value, the two-times standard deviation increase of ξ, and the two-times standard deviation decrease of ξ, respectively.

FIGURE 4. The impact of *learning-by-past R&D*, β, *cost-complexity*, ζ, and scale effects, ξ, parameters.

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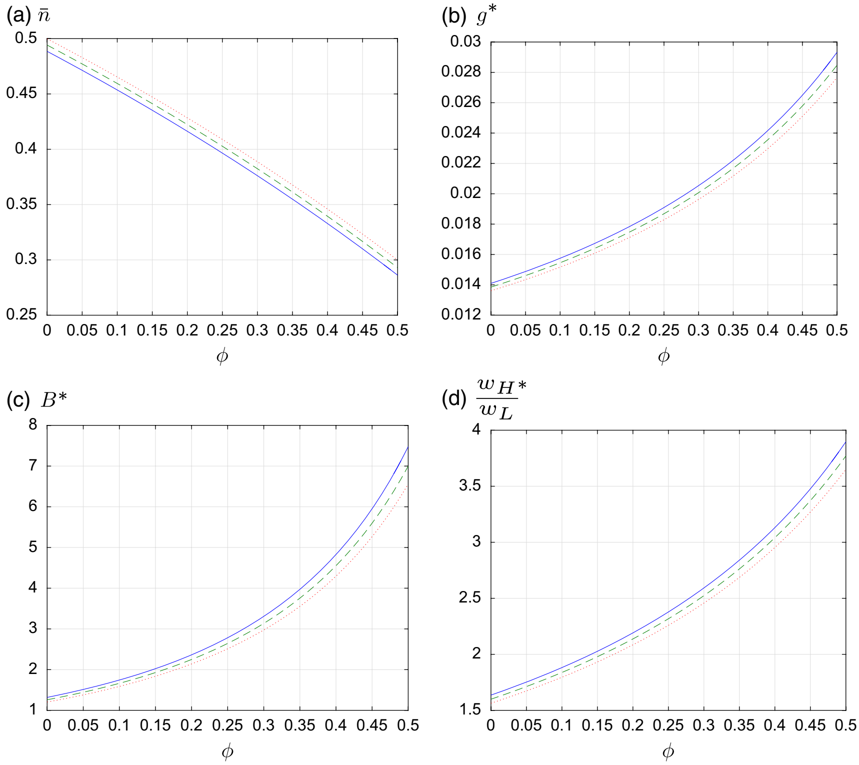
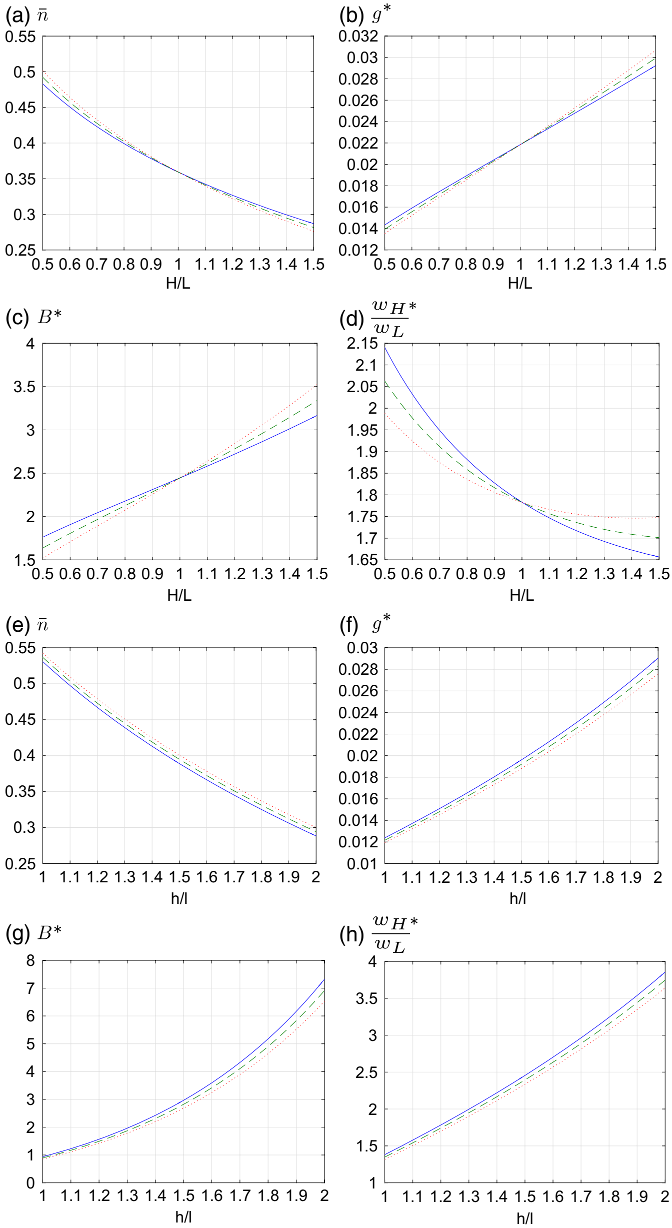


Notes: The dashed, solid, and dot lines denote the baseline ξ value, the two-times standard deviation increase of ξ, and the two-times standard deviation decrease of ξ, respectively.

FIGURE 5. The impact of learning by interacting, ϕ, and scale effects, ξ, parameters.

Concerning the relative labor supply, an increase in $\frac{H}{L}$ raises the probability of successful R&D via the *market-size channel* and, by decreasing $\bar{n}^*$, via the *learning-by-interacting effect*, and consequently increases g^*—see equations (9), (14), (15), and Propositions 1 and 2. As $\bar{n}^*$ decreases, the relative price of final goods produced with H-technology diminishes—see equation (7). However, the *learning-by-interacting effect* and the *market-size channel* dominate the *price channel* and, thus, the profitability of skilled technological knowledge is improved. This technological-knowledge bias in favor of H-intermediate goods improves the skill premium. Nevertheless, despite the bias in favor of the H-technology, the effect of the initial increase in the relative skilled-labor supply on the skill premium is stronger and thus $\frac{w_H}{w_L}^*$ decreases—see equations (16) and (17), and Propositions 2–4. It is also worth mentioning that as $\xi \to 1$, the scale effects are less and the *price channel* dominates the *market-size channel*, discouraging R&D activities toward the H-technology and decreasing B^*.



Notes: (a)–(d) present the sensitivity to $\frac{H}{L}$ and (e)–(h) present the sensitivity to $\frac{h}{l}$. The dashed, solid, and dot lines denote the baseline ξ value, the two-times standard deviation increase of ξ, and the two-times standard deviation decrease of ξ, respectively.

FIGURE 6. The impact of relative skilled-labor supply, $\frac{H}{L}$, relative skilled productivity, $\frac{h}{l}$, and scale effects, ξ, parameters.

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Concerning the skilled-labor productivity, $\frac{h}{l}$, also reduces $\bar{n}^*$, reinforcing the *learning-by-interaction effect*, increases g^*, and reduces the relative price of final goods produced with H-technology—see equation (7). The *learning-by-interaction effect* dominates the *price-channel effect* and the profitability of the skilled technological knowledge rises, biasing the technological knowledge in favor of H-intermediate goods. As a consequence, the skill premium goes up—see equations (16) and (17), and Propositions 2–4.

6. CONCLUDING REMARKS

In this paper we have proposed an endogenous SBTC growth model: individuals decide between consumption and savings on income allocation and two productive technologies of perfectly competitive final goods are used. One combines unskilled labor with unskilled-specific (complementary) quality-adjusted intermediate goods and the other uses skilled labor complemented with a continuum of skilled-specific quality-adjusted intermediate goods. Intermediate goods, which are improved in the R&D sector, are as usual produced in monopolistic competition.

The model is closely related to the contributions of Acemoglu and Zilibotti (2001) and Afonso (2006). However, by considering complementarity between R&D intensity and R&D cooperations, which, in turn, emerge as a mechanism to internalize technological-knowledge spillovers (through the network) and to learn with shared knowledge (in the network), as well as complementarity between R&D activity and skilled labor, we propose a new mechanism (*learning-by-interacting effect*) that affects the direction of technological-knowledge change and thus the relative demand of skilled labor and the skill premium. Labor endowments are linked with the intensity of network cooperations/linkages to evaluate a *learning-by-interacting effect*. Hence, the firms' benefit per amount of R&D spending rises with the network intensity and, consequently, the respective technological-knowledge progress rises as well. This increase in technological-knowledge progress induces an increase in the relative demand of skilled workers that *ceteris paribus* increases the skill premium.

To sum up, we argue that the greater the firms' network intensity, the greater is the capacity to internalize and benefit from others' knowledge and, consequently, the higher is the relative demand for labor. Since skilled-intensive sectors have a relative high number of R&D network cooperations, the skilled labor tends to be increasingly demanded and better paid. Moreover, the parameterization of the regulator of the *learning-by-interacting effect*, governed by network effects, can also contribute to the explanation of the economic growth and skill-premium slowdown that seem to characterize the current generation.

In terms of transition dynamics, suppose that there is an increase in skilled labor. This increase causes an immediate steep drop in the skill premium since its relative supply decreases its relative wage. However, this immediate effect can be reversed in the transitional dynamics toward the (new) constant steady-state skill premium, due to the stimulus to the demand for skilled labor resulting from the technological-knowledge bias. Moreover, with a sufficiently strong *learning-by-interacting effect*, the steady-state skill premium can be greater than the previous one.

Finally, we have estimated the *learning-by-interacting parameter* by the input–output interconnections established between firms/sectors in the production network structure, and we have used the US data to calibrate the regulator of scale effects. The value of this regulator points to a significant, but not total, removal of scale effects.

NOTES

1. In the SBTC literature two standard forces can determine the direction of the technological-knowledge change. The (dominant) *market-size channel*: a larger market for a technology, measured for workers who use it, leads to more innovations. The (neutralized) *price channel*: there will be more innovations for more expensive goods. *Ceteris paribus*, the former (latter) force encourages innovations for the more abundant (scarce) type of labor.

2. We distinguish between R&D cooperation and R&D network. In the latter case firms cooperate with respect to their innovative activities [e.g. Hagedoorn and Duysters (2002), Powell et al. (2005), and Roijakkers and Hagedoorn (2006)] and will not been explicitly considered.

3. For additional details on the theoretical insight of the networks literature see Appendix A.

4. The importance of the interconnections between different technologies on the technological-knowledge progress has long been recognized by economic historians [e.g. Landes (1969), Rosenberg (1982), and David (1990)].

5. See Appendix B for details on data source and construction of the variables of wages and hours; and see Appendix A and equation (**A2**) for details on definition of network distance and its construction.

6. See Table B1 in Appendix B for the full list of countries. These 40 countries produce 85% of the world GDP.

7. This U-shaped suggests the presence of a threshold level for the degree of sector connectivity. As this threshold value is around 1.2 and almost all sectors have at least two connections, we can state that the positive relationship between network degree and demand for relative skilled labor is also positive for the 40 countries of our sample.

8. It could be considered a positive exogenous variable A, common to both technologies, representing the productivity level dependent on the country's domestic institutions, namely property rights, tax laws, and government services. However, it would not affect the results and thus we have decided, for simplicity, not to consider it.

9. This *price channel* shows up in various papers by Acemoglu (2002), although always dominated by the market-size channel, which, in our case, can be removed through the *cost-of-the-market size*—see the equilibrium R&D in Subsection 4.1.

10. An additional assumption underlying this result is that the monopolist of the top-quality good has a one-rung quality advantage over its closest competitor—see Subsection 4.1.

11. This is an adaptation of the probability function for R&D success proposed by Afonso (2006, 2012).

12. That is, no protection is given to the technological knowledge.

13. This *replacement effect* is a common feature of Schumpeterian quality-ladder models [e.g. Aghion and Howitt (1992) and Barro and Sala-i-Martin (2004, Chapter 7)].

14. Following Barro and Sala-i-Martin (2004, Chapter 7), for example, the introduction q^k in j implies a change in the respective aggregate quality index, resulting in equation (11).

15. Please note that $X(t) = \int_0^1 \int_0^1 x_n(j, t)\, dndj = f\,(Q_L(t),\ Q_H(t), \Omega_X)$,

16. That is, $\phi[\ln(1+\overline{n}) - \ln \overline{n}] + \ln \overline{n} - \ln(1-\overline{n}) = (1-\xi) \cdot \ln\left(\frac{L}{H}\right) + \ln\left(\frac{l}{h}\right)$ and, since $0 < \overline{n} < 1$, it results $\ln(1+\overline{n}) = \sum_{k=1}^{\infty}(-1)^{k+1}\frac{\overline{n}^k}{k}$, $\ln \overline{n} = \sum_{k=1}^{\infty}(-1)^{k+1}\frac{(\overline{n}-1)^k}{k}$ and $\ln(1-\overline{n}) = \sum_{k=1}^{\infty}\frac{-\overline{n}^k}{k}$.

17. As a result of this second-order Taylor expansion, all the propositions abstract from third- and higher-order effects.

18. For example, for the OECD countries the relative skilled supply is 0.55.

19. From the definition of h, the absolute advantage of H over L in production is smaller when h is near 1. Considering that intra-country h is likely to be structural, this advantage of H over L can be proxied by the ratio between the share of computer users in H and in L. The value 1.3 is compatible with data on computer usage in, for example, Katz et al. (1998).

20. Bloom et al. (2013) also recognize that firms benefit from other firms "close" to them and measure this closeness effect through the "knowledge weighting matrix," where the knowledge spillovers from firms' interactions are proportional to weights measured by distances.

21. The US input–output table and the R&D intensity data were collected from the WIOD database and the STAN indicators database (OECD), respectively, for the time period 1995–2009. From the input–output tables we compute the network (in)strength and distance for each sector and year.

22. The skill-premium $\frac{w_H}{w_L}$ is obtained from the Socio-Economic Accounts from the WIOD.

23. To obtain the standard deviation of ξ we use equation (17) and the estimated results obtained for ϕ—see Table 3.

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APPENDIX A: THEORETICAL INSIGHT ON NETWORKS

The network concept was introduced in Economics by studies of effects of social networks on economic activity, namely on the transmission of information about jobs, diffusion of new products or technologies, and transmission of political opinions [Jackson (2011,

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2016)]. This concept rapidly expanded to business and political interactions that are also networked, as, for example, the network of relationships among firms, countries, and political organizations that affect R&D, trade patterns, political alliances, and economic growth [Hausmann and Hidalgo (2011), Acemoglu et al. (2012), and Fadinger et al. (2016)].

Formally, a network can be defined by the graph $\mathcal{G}_n = (\mathcal{V}_n, E_n, \mathcal{W}_n)$, with vertex (or node) set $\mathcal{V}_n$, edge set E_n, and edge weighted matrix $\mathcal{W}_n$. Moreover, $(i, j) \in E_n$ takes the value 1 if vertices i and j are connected and 0 otherwise, and the weight of edge $(i, j) \in E_n$ is equal to w_{ij}; that is, the intensity of the relationship between the vertices i, j at time t. The directed edges are ordered from i to j and called arcs in graph theory [Graph theory is used to describe network properties and their formation. For an introduction to this theme applied to social sciences and economics we refer to Jackson (2008)]. Consequently, the weighted link $w_{i,j}$ is different from $w_{j,i}$. The $\mathcal{W}_n$ matrix is also called an adjacency matrix.

The importance of network analysis in economics relies on the potential of the network tools in analyzing the network formation and the network structure features. Network metrics such as network degree/strength and distance are frequently used by economic researchers as features that provide important information about the strength of connections between agents and their proximity. The degree of a vertex (or node), D_i, is the number of links/neighbors that a vertex (or node) has to other network vertices (or nodes),

$$D_i = \sum_{j}^{n} d_{ij}, \tag{A1}$$

where $d_{ij} = 1$ if $w_{ij} > 0$ and $d_{ij} = 0$ otherwise. Similarly, the network strength of a vertex is the sum of weights w_{ij} of a vertex, $S_i = \sum_j^n w_{ij}$—that we use in Subsection 5.1 to estimate the regulator of the network intensity in our theoretical model. In directed networks, we can distinguish between incoming and outgoing degree/strength for each vertex i accounting the former for the inward links/weights and the latter for the outward links/weights. The distance of a vertex (or node) is the sum of the distances along the shortest path of a vertex i to every vertex of the network:

$$\Gamma_i = \sum_{j} \gamma_{ij}, \tag{A2}$$

where γ_{ij} is the geodesic distance between i and j. In weighted networks, the network distance is obtained using the Dijkstra (1959) algorithm. It takes into account the length of the path (the minimum number of steps between i and j) and the weight of each step. In the same way as the network degree, we can also distinguish between incoming and outgoing distance in directed networks if we consider the links' directions between vertices [For definition of additional network metrics, see, for example, Jackson (2008) as the pioneering study on this subject].

The above network metrics provide information about the features of the network structure and agents' position within and relative to the network. Simultaneously, theoretical and empirical research have shown that these features help to understand how the network structure affects the macroeconomic outcomes, the propagation of shock through the network, the technology diffusion, the knowledge spillover diffusion, and the economic growth [Montresor and Marzetti (2009), Atalay et al. (2011), Jackson (2011), Antras et al. (2012), Acemoglu et al. (2012), Carvalho (2014), Chaney (2014), Bertolotti et al. (2015), Guan et al. (2016), and Magalhães (2018)].

TABLE B1. WIOD countries, regional aggregation, and income classification

Euro-zone		Non-Euro EU	NAFTA	China	East Asia	BRIIAT
Austria[d]	Italy[d]	Bulgaria[a,b]	Canada[d]	China[a,b,c]	Japan[d]	Brazil[a,b]
Belgium[d]	Luxembourg[d]	Czech Republic[b,d]	Mexico[b]		Korea	Russia[a,b]
Cyprus[d]	Malta[b,d]	Denmark[d]	USA[d]		Taiwan	India
Estonia[b,d]	Netherlands[d]	Hungary[b,d]			Indonesia	
Finland[d]	Portugal[d]	Latvia			Australia[d]	
France[d]	Slovakia[b,d]	Lithuania			Turkey[a,b]	
Germany[d]	Slovenia[d]	Poland[b,d]				
Greece[d]	Spain[d]	Romania[a,b]				
Ireland[d]		Sweden[d]				
		UK[d]				

Notes: The countries classification is based on World Bank Atlas method and during the sample period some countries moved from one income group to another. [a]Denotes low middle income. bDenotes upper middle income. [c]Denotes low income. [d]Denotes high income.

APPENDIX B: DATA AND VARIABLES

This appendix describes data used in Figure 1 and Table 1. Data are collected from the world input–output database (WIOD). WIOD provides input–output tables for 40 countries classified into 35 industries from 1995 to 2011. The countries included in the database are 27 EU countries and 13 other major countries (see Table B1 for details). These 40 countries produce 85% of world GDP. From the input–output tables, we set the production network structure for each country. Each sector is a note and each input–output relationship is a weighted direct arc linking two nodes. Then, using the definitions of network distance and degree provided in Appendix A, we calculate the network distance and degree for each sector.

The WIOD also computes the Social Economic Accounts (SEA) that contain industry-level data on employment (workers and educational attainment) capital stocks, gross output, and value added. The industry classification is the same as for the world input–output tables. From the SEA we collect the following variables: high-skilled labor compensation (share in total labor compensation); medium-skilled labor compensation (share in total labor compensation); low-skilled labor compensation (share in total labor compensation); hours worked by high-skilled persons engaged (share in total hours); hours worked by medium-skilled persons engaged (share in total hours); hours worked by low-skilled persons engaged (share in total hours); total hours worked by persons engaged (millions); and labour compensation (in millions of national currency). The skill is measured by schooling, using the International Standard Classification of Education (ISCED). High-skilled workers are workers below completed upper secondary; medium-skilled workers are workers who completed upper secondary and some tertiary, but below a college degree; and high-skilled workers are workers with 2–4 year college degree, or its vocational equivalent, and above.

To compute wages, we calculate the labor compensation by skills and divide it by number of hours worked by each skill group. Afterwards, we reduce the three WIOD skill categories to two as in Timmer et al. (2014), by joining low skilled and medium skilled

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into unskilled. Thus, the relative skilled wage is the ratio between the high-skilled labor compensation per hour worked and the unskilled labor compensation per hour worked. The relative skilled hours is the ratio between the high-skilled working hours and the unskilled working hours.

APPENDIX C: SECTORS

TABLE C1. List of sectors at two-digit level

c1: Agriculture, hunting, forestry, and fishing	c2: Mining and quarrying	c3: Food, beverages, and tobacco
c4: Textiles and textile products	c5: Leather, leather and footwear	c6: Wood and products of wood and cork
c7: Pulp, paper, printing, and publishing	c8: Coke, refined petroleum, and nuclear fuel	c9: Chemicals and chemical products
c10: Rubber and plastics	c11: Other non-metallic mineral	c12: Basic metals and fabricated metal
c13: Machinery, Nec	c14: Electrical and optical equipment	c15: Transport equipment
c16: Manufacturing, Nec; Recycling	c17: Electricity, gas, and water supply	c18: Construction
c19: Sale, maintenance, and repair of motor vehicles	c20: Wholesale trade and commission trade	c21: Retail trade
c22: Hotels and restaurants	c23: Inland transport	c24: Water transport
c25: Air transport	c26: Other supporting and auxiliary transport activities	c27: Post and telecommunications
c28: Financial intermediation	c29: Real estate activities	c30: Renting of M&Eq and other business activ.
c31: Public admin and defense	c32: Education	c33: Health and social work
c34: Other community, social, and personal services	c35: Private households with employed persons	

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