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Ludovic RHEAULT
Department of Political Science
University of California, Riverside, USA
ludovic.rheault@ucr.edu

A recent stream of literature has challenged traditional views regarding the economic impact of population, on the ground that faster rates of population growth stimulate technological change, hence economic growth (see *e.g.* Kremer, 1993; Jones, 1995; Jones, Romer, 2010). This contrasts with the expectations stemming from neoclassical models. Production functions with decreasing returns in labour imply that a waxing working-age population boosts the total quantity of output, but adversely affects per capita outcomes such as wages or output per worker. Solow's growth model yields similar implications, from a dynamic perspective, by showing that a rise in the rate of population growth leads to a dilution of the capital-labour ratio (Mankiw *et al.*, 1992; Barro, 1998). However, under such a framework, the long-run rate of economic growth is unaffected by population, since the former depends on an exogenous rate of technological change. By placing people as the source of new ideas, models of endogenous innovation seem to have begotten a drastic revision of our knowledge regarding the economic role of demographic variables.

Even so, I show in this paper that considering population as a stimulus for innovation is misleading. My aim is to look at the implications of labour resource composition for business R&D[1] – the source of endogenous technological change. I consider a model along the lines of Grossman and Helpman (1991, ch.5), where intentional R&D activities take place within a high-technology sector, intensive in skilled labour compared to a low-technology sector. As long as factors are not close substitutes, the Rybczynski theorem implies that a relative increase in the supply of unskilled labour leads to an expansion of traditional activities, and to a dampening of research efforts. A disproportionate rise in the supply of skilled labour leads to the opposite

1. Although the term "R&D" without adjective is used in the text to increase readability, the paper focuses exclusively on R&D in the private sector.

impact. I then devise a panel data estimators allowing me to distinguish between scaling effects (resulting from proportional increases in factor supplies) and Rybczynski effects (resulting from disproportionate increases in a specific type of labour). Empirical data on OECD countries (1971-2003) yield support to the idea that skilled and unskilled labour supplies have opposite effects on the intensity of business R&D. Those findings raise an important qualification to the broader idea that population boosts innovation. In fact, population growth may actually slow down private research efforts, depending on the change it induces in the mix of labour resources.

It shall be noted that, from a theoretical perspective, the consequences of demography for endogenous technological change are contingent on assumptions regarding the factors used in the research sector. Authors concluding that innovation is positively related to the rate of growth of population consider labour as the input in research labs (Kremer, 1993; Jones, 1995; Jones, Romer, 2010). (In earlier models, the flow of new ideas produced through private R&D has also been modelled as an increasing function of labour supply per se (*e.g.* Romer, 1986); see also Boserup (1981) for an early argument). However, conclusions are affected whenever one distinguishes labour types. When skilled labour is considered as the main input in the R&D sector (as in Romer, 1990a, 1990b; Grossman, Helpman, 1991, ch. 5), it follows that a rise in the supply of unskilled labour may either have positive or negative consequences for the pace of technological progress, whereas increasing the supply of skilled labour would lead to benefits in terms of faster innovation[2]. Those last models build upon realistic assumptions, if one agrees with the idea that R&D requires specialized skills to begin with. Moreover, those implications seem a priori more congruous with the empirical fact that technologically advanced countries typically had relatively low rates of population growth in the past decades. As for the first generation of studies on endogenous innovation (induced innovation theory), it paid a great deal of attention to the impact of factor prices on incentives to invest in research (*e.g.* Samuelson, 1965; Drandakis, Phelps, 1966; Binswanger, Ruttan, 1978). Yet this line of research was often devoted to the resulting bias in technological change (for example, whether a relative increase in the price of labour induces labour-replacing innovation) rather than the impact of resource composition on total R&D outlays.

Following on the discussion above, making the distinction between skill levels appears crucial when studying the impact of labour supply on private R&D. Theoretical findings may be considerably altered by the underlying

2. See also Peretto (1998) for an account of the relationship between population growth and R&D under alternative assumptions.

assumptions regarding the inputs used in research. Empirical studies would also benefit from making this distinction. Furthermore, applied empirical studies have rarely considered synchronously both the scaling effects on R&D resulting from the growth in factor supplies (the effect of the size of the economy on R&D outlays), and the effects of changes in the intensity of a factor. While addressing the impact of resource composition on R&D, this paper considers not only the distinction between skilled and unskilled labour, but also the distinction between scale effects and relative endowment effects.

The paper is organized as follows. The following section develops the theoretical model. Afterwards, I introduce the data and methodology. Panel unit root and cointegration tests are then conducted, before presenting empirical estimates. Next, I discuss exogeneity issues and policy implications. A final section concludes.

THEORETICAL BACKGROUND

The purpose of this section is not to develop a new theory of endogenous technological change, but rather to rely upon existing models in order to stress expectations regarding the impact of labour supply on R&D. I consider a model along the lines of Grossman and Helpman (1991, ch.5, Section 3), which rests upon two key ideas. The first is that R&D is an activity requiring intensive use of skilled labour (in contrast with models in which labour in general is assumed to be the input in the research sector). The second idea is that not all industries or sectors of an economy contribute equally to the development of new technologies. In the lines that follow, a model is stressed in which a sector of the economy is assumed to enjoy favourable technological opportunities. The rest of the economy typifies the part of production in which prospects for technological advancements are absent. The two sectors are referred to as high- and low-technology, respectively.

The high-technology sector generates technological change endogenously, and is assumed to be intensive in skilled labour. Innovation is represented by an expansion of product variety[3]. The expanding variety of products means an increase in the number of intermediates used in the production of final goods, so that the model can be interpreted as depicting process

3. Other types of innovation could have been considered, such as quality-ladder models. However, Grossman and Helpman (1991) have shown how each type of innovation can lead to similar implications. The focus on expansion in the variety of products is therefore for simplicity of presentation.

innovation (*i.e.* improvements in the methods of production). The sector produces the final goods χ according to the function:

$$\chi = L_{\chi}^{\beta} H_{\chi}^{1-\alpha-\beta} \int_0^A x_j^{\alpha} dj \tag{1}$$

where L_χ is unskilled labour, H_χ skilled labour, and where $\int_0^A x_j^{\alpha} dj$ corresponds to an index of intermediate inputs. The intermediate inputs are capital goods, which are sold by R&D firms (*i.e.* firms whose purpose is to develop the blueprints for new varieties of capital goods). By extending the variety of intermediate inputs, final-good producers become more efficient, since the marginal product of each individual input is decreasing (assuming $\alpha < 1$) (see Barro and Sala-i-Martin, 2004, ch.6).

Clearly, the setup of this model is similar to the one proposed by Romer (1990a, 1990b), with the exception that χ represents one of two sectors in the aggregate economy. In the Romer model, a research sector produces new designs with *H*, skilled labour, as the sole input. In the lines that follow, I will instead represent R&D outlays as a constant fraction of final-goods' output (which leads to a setup similar to the Rivera-Batiz and Romer (1991) "lab-equipment" model). That is, the production of new varieties of intermediate goods has the same technology as the one introduced in (1). Notice that since the high-technology sector is intensive in skilled labour, it follows that research activities, being expressed in terms of the output of the whole sector, are themselves intensive in skilled labour. This is a desirable property to keep the model realistic, in the sense that producing new designs requires specialized skills that, by definition, skilled labour possesses. Considering R&D expenditures in terms of the output χ also implies that some physical capital and unskilled labour are used in the research lab (such as computers, machines, and support staff).

Let $\dot{R}$ denote R&D expenditures, conceptually defined as the fraction of resources devoted to R&D within the high-technology sector. Then

$$\dot{R} = s_R \chi \tag{2}$$

where s_R is the (constant) fraction of output invested in R&D. In turn, the creation of new varieties of capital goods is a function of $\dot{R}$, such that:

$$\dot{A} = B\dot{R}^{\gamma} \tag{3}$$

with *B* being a constant, and γ a productivity parameter (following the arguments in Jones, 1995).

The solutions for this type of model have been described in details several times before. For instance, Barro and Sala-i-Martin (2004, ch.6) provide a complete summary, as well as Rivera-Batiz and Romer (1991), Romer

(1990a, 1990b), and Grossman and Helpman (1991). R&D firms sell (or rent) the capital goods at a monopoly price, which is a markup above marginal cost.

Monopolistic competition ensures the existence of private research incentives (see the discussions in Dasgupta and Stiglitz, 1980; Romer, 1990b). The price of each intermediate x_j has been shown to correspond to $1/\alpha$ in equilibrium (or to $1/B$ in Rivera-Batiz and Romer (1991)), assuming a marginal cost equal to 1. The total quantity of physical capital used in the sector must in turn correspond to the sum of all intermediates, so that $x_j = K_\chi/A$. Substituting back into the production function, this yields the Cobb-Douglas function with labour-augmenting technological change:

$$\chi = (AL)_\chi^\beta (AH)_\chi^{1-\alpha-\beta} K_\chi^\alpha \tag{4}$$

Since the present model considers research expenditures as a fraction of χ, the magnitude of research activities, $\dot{R}$, is therefore linked to the fate of the high-technology sector.

In contrast, the low-technology sector is assumed to be relatively intensive in *unskilled* labour. This sector produces final goods Z according to the function:

$$Z = F(A_0, L_Z, H_{Z,} K_Z), \tag{5}$$

where L_Z, H_Z, and K_Z respectively refer to the quantity of unskilled labour, the quantity of skilled labour, and the stocks of physical capital used in the sector Z. Here, the technology level is held constant at an arbitrary value A_0, exogenously determined. Extensions to this model could permit the low-technology sector to experience some technological progress, but at a slower rate than the high-technology sector (for instance, one may consider that after some period of time, the new capital goods developed in the high-technology sector become available to the low-technology sector). For simplicity, I assume an absence of technological advancement (or, put another way, technological change is purely exogenous as in neoclassical theory)[4]. Thus, K_Z is the sole variety of capital good. The model implies that the aggregate endowments correspond to:

$$\alpha_{L\chi}\chi + \alpha_{LZ}Z = L_\chi + L_Z = L, \tag{6}$$

$$\alpha_{H\chi}\chi + \alpha_{HZ}Z = H_\chi + H_Z = H, \tag{7}$$

$$\alpha_{K\chi}\chi + \alpha_{KZ}Z = K_\chi + K_Z = K, \tag{8}$$

where α_{ij} are the input coefficients, and L, H, and K the aggregate factor supplies.

4. In fact, similar implications can be derived from models that do not make such a distinction between low- and high-technology industries. See for instance Romer (1990a).

A point emphasized by Grossman and Helpman (1991) is the need to distinguish the impact of a disproportionate change in the supply of one factor from equiproportional changes in all factors. First, if all factors increase proportionally, the model implies that the *intensity* of R&D remains unchanged. That is, the shares of industries expressed as a ratio of total output are expected to remain unaltered. In that case, however, the absolute level of R&D expenditures is increasing along with the size of the whole economy. I refer to this impact as a *scaling effect*. Second, when a factor increases disproportionally, at least in some circumstances, the Rybczynski (1955) theorem implies that the sector using that factor most intensively should expand, and the other sector contract. In other words, changes in factor intensities are expected to alter the intensity of R&D (the ratio of R&D outlays to aggregate output), because such changes affect unequally the size of the χ sector and that of the Z sector. I refer to this second impact as a *relative endowment effect*, or Rybczynski effect. Given the intensity rankings stressed above, the initial expectation is that increases in the relative endowment of L would contract private R&D, whereas increases in the relative endowment of H would expand private R&D.

Applying the Rybczynski theorem to this model implies several cautions. First, since $\dot{R}$ is by assumption proportional to χ, this amounts to a three-factor, two-good model. In general, previous studies have shown that the Rybczynski theorem may hold in this case, although with some caveats. The theorem has been transposed to the three-factor, two-good case by Chang (1979), Jones and Easton (1983), and Suzuki (1985). Suzuki (1985) shows that a relative increase in the endowment of a factor leads unambiguously to the expansion of the sector using this factor most intensively. Yet the impact on the second sector may be ambiguous. The ambiguity is related to the degree of substitutability between factors. For instance, if unskilled workers could easily substitute for engineers in the R&D sector, then the actual costs of research may not have increased following an augmentation in the intensity of unskilled labour (although in this example, such a substitution seems to a large extent implausible). Studies considering the possibility that increases in L negatively affect private R&D (*e.g.* Romer, 1990a; Grossman, Helpman, 1991, ch.5) agree on the idea that this effect is conditional on low substitutability. When addressing the hypothesis of Habakkuk (1962), who stressed that labour scarcity has historically fostered technical change in the U.S., Acemoglu (2002) also concludes that the result holds when there is a limited degree of factor substitution[5]. Second, the sector χ described above

5. Note that Acemoglu (2002) considers the possibility of intentionally directed technological change, in the sense that new technologies could be designed to augment the productivity of a specific factor. This issue is not addressed here.

implies overall increasing returns to scale (an assumption that could be relaxed), whereas the sector Z could have either decreasing or constant returns to scale. The Rybczynski theorem with variable returns to scale has also been shown to hold (Jones, 1968; Panagariya, 1980), yet not without implications regarding the expected magnitude of the effects. Sorting out whether the theoretical expectations hold given factor substitution and different levels of returns to scale is a matter probably best addressed empirically, which is the goal of the next section.

A last difficulty is the distinction between scaling effects and relative endowment effects. To isolate each of them, consider the following identity. R&D expenditures can be decomposed by multiplying the ratio of R&D outlays to aggregate output, by output (labeled Y):

$$\dot{R} = \frac{s_R X}{Y} Y = \frac{\dot{R}}{Y} Y \tag{9}$$

The right-hand term $\dot{R}/Y$ represents R&D intensity, and this ratio is expected to evolve according to the growth in relative factor supplies, since it measures to which extent the research sector (or high-technology sector) has grown at a different rate than the traditional sector. The additional term Y captures the scaling effect, in the sense that, for a given level of R&D intensity, the absolute level of $\dot{R}$ increases with the size of the economy. To isolate the total impact on $\dot{R}$, one may add the marginal effect of a factor on $\dot{R}/Y$ (relative endowment effect) to its marginal effect on output (scaling effect). Based on the model introduced above, for unskilled labour, the relative endowment effect is expected to be negative, and the scaling effect positive. As for skilled labour, both effects are expected to be positive. Empirical data can then be used to test those expectations. The disaggregation into two components should prove useful to understand how the influence of factor supplies on technological change actually operates.

EMPIRICAL ANALYSIS

This section introduces an empirical model that makes possible the distinction between scaling effects and relative endowment effects. In the following lines, I first discuss the baseline econometric specification, before presenting the data. Second, I address the issues of stationarity and cointegration. The main results are then discussed, before conducting exogeneity tests, which are used to assess the validity of statistical inference.

As a first step toward the estimation of the impact of factor supplies on business R&D, I consider the first right-hand side component of the identity discussed in (9): R&D intensity. The specification used to estimate relative endowment effects (or "Rybczynski effects") is akin to that used by Harrigan (1995, 1997), for instance, when measuring the impact of factor supplies on sectoral output and trade. Consider the following model:

$$\begin{aligned} \frac{\dot{R}}{Y} &= C\left(\frac{L}{K}\right)^{\theta_L}\left(\frac{H}{K}\right)^{\theta_H}, \\ \ln\frac{\dot{R}}{Y} &= \ln C + \theta_L \ln\frac{L}{K} + \theta_H \ln\frac{H}{K}, \end{aligned} \tag{10}$$

where the main variables are defined as before, C is a constant, and where θ_L, θ_H, and $-(\theta_L + \theta_H)$ measure the elasticities of R&D intensity with respect to unskilled labour, skilled labour, and capital. Since one factor is used as the denominator, by construction the three elasticities sum to zero. The reason why those parameters sum to zero should be straightforward. By imposing the restriction that proportional increases in the three factors leave the intensity of R&D unchanged, the model estimates only the effect of a disproportionate change in factor supplies, isolating the net relative endowment effects. Put another way, since output (Y) appears as the denominator on the left-hand side, θ_L measures the impact of a change in L on R&D expenditures after filtering out the effect of a change in the size of the economy, hence yielding the Rybczynski effet. Note that any factor could have been used as the denominator to construct the right-hand side ratios: in all cases, the estimates for all three factors are exactly the same, by construction.

As a next step, consider this second model:

$$\begin{aligned} \frac{\dot{R}}{K} &= D\left(\frac{L}{K}\right)^{\psi_L}\left(\frac{H}{K}\right)^{\psi_H}, \\ \ln\frac{\dot{R}}{K} &= \ln D + \psi_L \ln\frac{L}{K} + \psi_H \ln\frac{H}{K}. \end{aligned} \tag{11}$$

This time, one of the factors is the common denominator to all variables (again, D is some constant, which will later be treated as country-specific intercepts). ψ_L is the elasticity of *total* R&D expenditures with respect to L, ψ_H the elasticity with respect to H, and $-(\psi_L + \psi_H) + 1$ the elasticity with respect to K. This model implies that scaling effects (the effect of proportional changes in all factors) sum to one, which means an aggregate production function exhibiting constant returns to scale in those three factors. In sum, this second model estimates the net elasticity of total R&D expenditures, including both scaling effects and relative endowment effects.

Although an aggregate production function is not estimated per se, a property of this "two-step" approach is that the estimated productivity parameters of the production function are actually contained in the two sets of estimates. The difference $\psi_L - \theta_L$ (the total effect of the factor L minus its relative endowment effect), for instance, yields the scaling effect of L on R&D outlays.

This scaling effect, due to the construction of the model, corresponds to the estimated elasticity of total output with respect to unskilled labour. I do not impose any further restriction on the values of the parameters (for instance, by imposing that scaling effects correspond to factor shares as measured by some series from an external source). Therefore, the method used here avoids the need to specify some arbitrary type of aggregate production function.

To implement the empirical models, I consider panel data on 21 OECD countries, over a time-period ranging between 1971 and 2003[6]. The selection of countries is primarily determined by the availability of a key variable: business R&D expenditures ($\dot{R}$). This variable is derived from the Coe *et al.* (2009) data set, which covers 24 countries. From those 24 countries, three have been excluded here. First, some of the other required series for Iceland and Israel are missing. Second, some of the main variables for Germany suffer from inconsistencies due to German reunification (since population data prior to reunification refer to West Germany, whereas those after reunification to Germany as a whole). Thus, Iceland, Israel and Germany are absent, which leaves 21 countries.

The variables used to estimate (10) and (11) are the following. $\dot{R}$ corresponds to annual business enterprise R&D expenditures in constant 2000 prices, and in US dollars (using the 2000 purchasing power parity (PPP) exchange rates)[7]. K is a measure of physical capital stocks. It is created using the perpetual inventory method, based on the fixed capital formation series from the OECD Stats database (OECD, 2011). Output Y is measured as total gross domestic product (expenditures approach), again from the OECD Stats database. All those variables are expressed in constant 2000 prices, and in PPP-adjusted US dollars. Next, the inclusion of L and H proceeds as follows. The OECD working-age population series (*i.e.* population aged between 15 and 64) have been extracted, and skilled labour H is obtained by multiplying working-age population by the ratio of working-age population with a completed tertiary education degree. Since a number of issues have been raised over the years regarding the measurement of educational attainment, I consider two distinct sources: the Barro and Lee (2010) data set, version 1.2, and the International Institute for Applied Systems Analysis (World Population Program) data set (Lutz *et al.*, 2007). Both these sources provide detailed data

6. Those countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

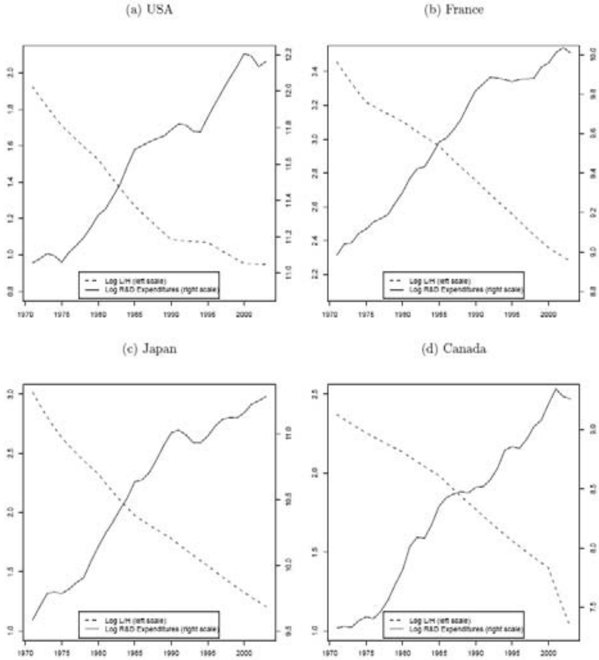
7. This variable relies upon the business R&D capital stocks series from the Coe *et al.* (2009) data set, converted into annual expenditures. The primary data source is OECD's ANBERD database. Further details regarding the definition and measurement of business R&D expenditures in OECD countries can be found in the Frascati Manual (OECD 2002).

on educational attainment by age groups, allowing to retrieve the share of working-age population with tertiary education. Unskilled labour L is measured as the stocks of working-age population without a completed tertiary education degree. Finally, I introduce an additional variable measuring the appropriability of R&D returns (which is a necessary condition for the presence of private incentives to invest in R&D), using the patent protection index devised by Park and Lippoldt (2005), and provided in the Coe *et al.* (2009) data set. This variable measures the extent of legal protection of intellectual property rights. Appendix A presents additional details regarding the data.

Before turning to a detailed estimation, Figure 1 shows the actual trends in R&D expenditures in four OECD countries (USA, France, Japan, and Canada). Those series are stacked against the ratio of L to H, a measure of unskilled labour intensity (with variables based on the Barro-Lee data set). The scale on the right y-axis measures the levels of R&D expenditures (in millions, converted to natural logs), whereas the scale of the left y-axis measures the levels of the log L/H ratios. The four panels illustrate one of the main points of this paper: the increase in the scope of R&D activities over time coincides with a fall in the relative intensity of unskilled labour (put the other way, with an increase in the relative intensity of skilled labour). A negative relationship can also be observed between the rate of growth of working-age population (without the distinction between skill levels) and total R&D expenditures. For instance, considering the 21 countries over the 1971-2003 period, the demeaned correlation coefficient between R&D expenditures and population growth is –0.42 (significant at the $p < 0.001$ level).

However, to confirm the existence of a genuine equilibrium relationship between factor supplies and R&D outlays, a number of issues must be addressed. First, I test each variable of the main models for trend stationarity, using panel unit root tests. This step is mandatory, to avoid spurious regression estimates under the form of biased t statistics. As emphasized by Hurlin and Mignon (2005), unit root testing has become the starting point of many empirical works involving a temporal dimension, and panel data help to improve the power of unit root tests when the number of time units is limited (see also Baltagi, Kao 2000). Depending on the presence of unit roots, panel cointegration tests would be required to confirm whether the stochastic trends in the variables are related. The choice of a consistent estimator will depend on the results of those tests. Second, fixed effects (*i.e.* country-specific intercepts to estimate the "within" dimension) represent a powerful econometric tool to account for the role of country-specific unobserved factors that may have an influence on R&D activities (*e.g.* the structure of competition). Finally, I address the issue of exogeneity of factor supply variables using an error-correction representation of the models, later in this section.

Figure 1 – Unskilled labour intensity and R&D expenditures in 4 countries, 1971-2003



Unit Roots and Cointegration

Table 1 reports the results of panel unit roots tests performed on each of the variables of the two models. I use the superscript *BL* when referring to variables constructed using the Barro-Lee data set on educational attainment, while the superscript *LU* indicates the use of the Lutz *et al.* data set. The variable *PP* is the above-mentioned patent protection index. The table shows the results of the Levin-Lin-Chu (Levin *et al.*, 2002) and the Im-Pesaran-Shin (Im *et al.*, 2003) panel unit root tests. Both have the null hypothesis of a unit root in all panels, but the latter takes into account the potential heterogeneity of autoregressive parameters under the alternative hypothesis (Hurlin and Mignon 2005, 266). Both these tests are performed with two lags, against the alternative of trend stationarity (an obvious choice based on the visual inspection of the series in Figure 1). As Table 1 shows, the tests suggest that all variables contain unit roots. Increasing lag length (for instance following the Newey and West (1994) rule of $4(T/100)^{2/9}$, where T is the number of time periods (in this case 32, suggesting 3 lags)) tends to reinforce the same conclusion. I therefore treat each of the variables as integrated of order one (*I(1)*) in the lines that follow.

The next step consists of testing for the existence of a cointegrating relationship in the two regression models introduced in (10) and (11), augmented to include the measure of appropriability as a control variable. Evidence of cointegration would entail a relationship between the stochastic trends of the variables under consideration, and the existence of a linear combination of those variables that is stationary. Given the format of the data, I make use of residuals-based panel cointegration tests, namely Pedroni's panel-ADF and group-ADF statistics (introduced as the parametric panel-*t* and group-*t* statistics in Pedroni (1999)), named after their similitude to the augmented Dickey-Fuller statistics. Wagner and Hlouskova (2010) compared the performance of several existing panel cointegration tests (including systems-based tests), and concluded that Pedroni's panel-ADF and group-ADF outperform the other tests. Moreover, they show that Pedroni's statistics are the most robust to cross-sectional correlation. The "group" version of the test corresponds to a group-mean aggregation of cointegration tests performed on individual panels, whereas the weighted "panel" statistics are pooled along the within-dimension (Pedroni, 1999). The two tests are performed for each of the two main models, but also for alternative specifications (*i.e.* after modifying the source of education data). All tests include individual intercepts and trends. They are computed with automatic lag length selection (based on the Schwarz information criterion) and bandwidth selection (based on Newey and West), the latter being used for the computation of long-run variances.

Table 1 – Panel unit root tests

Variable	Levin-Lin-Chu t^*_δ	Im-Pesaran-Shin W_{tbar}
$ln(\dot{R}/Y)$	0.097	–0.627
$ln(\dot{R}/K)$	0.023	–1.132
$ln(L/K)^{BL}$	–0.012	2.390
$ln(H/K)^{BL}$	0.715	3.388
$ln(L/K)^{LU}$	–0.368	2.658
$ln(H/K)^{LU}$	2.348	7.009
$lnPP$	–0.140	–0.473

Notes: The Levin-Lin-Chu panel unit root test statistics t^*_δ is computed with two lags, using a Bartlett kernel with Newey-West automatic bandwidth selection, against the alternative of trend-stationarity (including individual intercepts and trends). The Im-Pesaran-Chin W_{tbar} is also computed with two lags against the alternative of trend stationarity. All statistics are non-significant, indicating the presence of unit roots in all panels.
***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

Focusing on the panel-*t* statistic, it can be observed from Table 2 that the null of no cointegration is clearly rejected in all cases, at the $p < 0.001$ level. Moreover, the group-*t* statistics are also significant at the $p < 0.001$ level. Overall, those results provide strong supporting evidence to the idea that there is a long-run equilibrium relationship between factor supplies and R&D outlays.

Table 2 – Panel cointegration tests

Response	Regressors	Panel-*t* (ADF)	Group-*t* (ADF)
$ln(\dot{R}/Y)$	$ln(L/K)^{BL}$, $ln(H/K)^{BL}$, $lnPP$	–3.698***	–3.918***
$ln(\dot{R}/K)$	$ln(L/K)^{BL}$, $ln(H/K)^{BL}$, $ln\ PP$	–3.649***	–4.698***
$ln(\dot{R}/Y)$	$ln(L/K)^{LU}$, $ln(H/K)^{LU}$, $lnPP$	–3.300***	–3.386***
$ln(\dot{R}/K)$	$ln(L/K)^{LU}$, $ln(H/K)^{LU}$, $lnPP$	–3.909***	–4.554***

Notes: The table reports Pedroni's parametric weighted panel-*t* and group-*t* cointegration test statistics of the null hypothesis of no cointegration. All tests are performed with automatic lag length selection based on the Schwarz information criterion (with maximum lag length of 6, based on the size of the sample), and using a Bartlett kernel for the estimation of long-run variances (with automatic bandwidth selection based on Newey-West). The tests are also performed while including individual intercepts and trends.
***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

Main Empirical Findings

Given the verdict of cointegration, I implement a dynamic OLS (DOLS) version of the main models. Early descriptions as well as discussions on the efficiency of the DOLS estimator can be found in Saikkonen (1991) and Stock and Watson (1993). Kao and Chiang (2001) discuss the implementation with panel data (see also Breitung and Pesaran, 2008). The DOLS model implies the inclusion of leads and lags of the difference operators for each of the *I(1)* explanatory variables. For example, the R&D intensity equation becomes:

$$\begin{aligned} \ln \frac{\dot{R}}{Y}_{i,t} &= \delta_i + \Phi_t + \theta_L \ln\left(\frac{L^{BL}}{K}\right)_{i,t} + \theta_H \left(\frac{H^{BL}}{K}\right)_{i,t} + \theta_p \ln PP_{i,t} \\ &+ \sum_{j=-1}^{1} \lambda_{L/K,j} \Delta \ln\left(\frac{L^{BL}}{K}\right)_{i,t+j} + \sum_{j=-1}^{1} \lambda_{H/K,j} \Delta\left(\frac{H^{BL}}{K}\right)_{i,t+j} \\ &+ \sum_{j=-1}^{1} \lambda_{pp,j} \Delta \ln PP_{i,t+j} + \varepsilon_{i,t} \end{aligned} \tag{12}$$

where the variables are defined as before. The country-specific and time intercepts (δ_i, Φ_t) imply that the model is estimated along the within dimension, using two-way fixed effects—a model without the time dummies is also investigated below. (12) presents only one variant of the two models discussed above, but the other one is constructed in a similar manner, modifying only the response variable. The DOLS estimator bears many interesting properties, since the inclusion of leads of the difference operators limits the concerns for the endogeneity of regressors, and since it produces consistent estimates in the presence of cointegrated series (see the references above for details). To palliate for serial auto-correlation and heteroskedasticity, all the statistics reported below are computed using HAC (heteroskedasticity and auto-correlation consistent) standard errors (Andrews, 1991), with degrees-of-freedom adjustment for panel data.

Table 3 shows the estimation results with labour supply variables created using the Barro-Lee data set as the source of educational data. I focus mainly on this variant of the models for simplicity, although the results using the alternative data source are also discussed below. The first two columns of Table 3 report the DOLS implementation of the models, without the inclusion of the measure of intellectual property rights[8]. The next two columns show the results after including this control variable, but without time dummies. The last two columns replicate the models while including time dummies as regressors (two-way fixed effects), to account for unobserved temporal shocks.

Table 3 – The impact of factor supplies on R&D expenditures (21 OECD Countries, 1971-2003)

Variable	Model 1 $ln(\dot{R}/Y)$	Model 2 $ln(\dot{R}/K)$	Model 1 $ln(\dot{R}/Y)$	Model 2 $ln(\dot{R}/K)$	Model 1 $ln(\dot{R}/Y)$	Model 2 $ln(\dot{R}/K)$
$ln(L/K)^{BL}$ *(ln L)*	–1.133***	–0.946***	–0.625***	–0.348**	–0.776***	–0.489**
	(0.082)	(0.075)	(0.140)	(0.132)	(0.168)	(0.161)
$ln(H/K)^{BL}$ *(ln H)*	0.448***	0.665***	0.122	0.296**	0.207	0.384***
	(0.085)	(0.081)	(0.095)	(0.092)	(0.113)	(0.109)
(ln K)	0.685***	1.281***	0.502**	1.051***	0.569***	1.105***
	(0.142)	(0.129)	(0.166)	(0.155)	(0.157)	(0.150)
lnPP			1.047***	1.215***	1.342***	1.529***
			(0.160)	(0.157)	(0.148)	(0.150)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	No	No	No	No	Yes	Yes
Adj.-R^2	0.93	0.94	0.94	0.95	0.95	0.96
N	651	651	651	651	651	651

Notes: The table shows estimates of DOLS models including one lead and one lag of the differences of the right-hand side *I(1)* variables, and computed with HAC standard errors (with a Bartlett kernel and a fixed bandwidth truncated after two lags), the latter being reported in parentheses. The response variables for Model 1 and Model 2 are indicated in the column headers. All models are estimated along the within dimension (*i.e.* including country-specific intercepts). See text for the interpretation of estimates.
***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

The columns labeled "Model 1" report the elasticity of R&D intensity with respect to relative factor supplies (*i.e.* the relative endowment effects), as explained in the introduction of this section. "Model 2" refers to

8. Note that cointegration tests similar to those reported above have been conducted for models without the control variable, and the verdict of cointegration holds in all cases as well.

the findings for the model estimating total effects (*i.e.* relative endowment effects plus scaling effects). Estimates can be interpreted straightforwardly. For instance, in Model 1, the estimate for the variable $ln(L/K)^{BL}$, labeled θ_L above, indicates the percent change in R&D intensity for a 1% increase in the value of (L/K), holding constant the ratio (L/K) (and the level of appropriability PP). Therefore, θ_L also indicates the impact of a 1% increase in the absolute level of L on R&D intensity, holding constant the other factors.

Consider Model 1 in the last section of Table 3, which includes time dummies. The estimates indicate that R&D intensity is negatively related to the supply of unskilled labour: a 1% increase in the supply of unskilled labour leads to an estimated –0.78% fall in the intensity of R&D, all else equals. This finding is consistent with the theoretical model, which stressed the idea that a relative increase in unskilled labour leads to the expansion of more traditional activities, and to the contraction of the research sector. This estimate is statistically significant at the $p < 0.001$ level. Besides, physical capital (rather than skilled labour) appears as the factor used most intensively in the research sector, as revealed by the unambiguously positive estimate. This finding lends initial credence to models of endogenous technological change in which capital is the main input in the research sector (*e.g.* Howitt and Aghion, 1998). Skilled labour appears as the "middle-factor", with a positive elasticity of 0.2, although short of being statistically distinguishable from zero. Finally, the patent protection index has an unsurprising positive effect on the intensity of R&D, suggesting that intellectual property rights stimulate private research.

When addressing the absolute levels of R&D expenditures, however, scaling effects must also be taken into consideration. Thus, the impact of an increase in L on R&D intensity may well be negative, but on the other hand, L contributes to making the economy larger. In other words, from the identity $\dot{R} = \frac{R}{Y} Y$, the effect of resource composition on the component $\frac{R}{Y}$ has been estimated in the previous step. Incorporating the contribution of each factor to the growth of output yields an estimate of the total effect of each factor on absolute levels of R&D.

Model 2 of Table 3 reports the elasticities for total R&D expenditures, including scaling effects. For instance, and still focusing on the last columns of Table 3, the elasticity of R&D with respect to L becomes –0.49. This implies that L has a scaling effect of ≈ 0.3 (–0.49 – (–0.78)). A 1% increase in unskilled labour is expected to depress R&D intensity by –0.78%, but to increase total output by 0.3%, hence scaling up the total amount of R&D expenditures by 0.3%. Overall, then, a 1% increase in L induces a change of about –0.5% in total R&D expenditures, all else equals. Notice that the approach used here avoids the flawed conclusions that may result when failing to disentangle the influence of factor supplies. The bivariate correlation between L and total R&D outlays is positive, but this correlation disguises the fact that the temporal rise in L occurs along with the increase in other factors (in fact, as discussed below, those other factors of production, H and K, happen to have increased much more rapidly than L have). By isolating the contribution of each factor, and with the distinction between relative endowment and scaling effects, the results presented here unveil a more detailed account of the impact of factors of production. Continuing with the results of Table 3, it can be seen that skilled labour has an overall positive and significant impact on total R&D outlays (with an elasticity of the order of 0.38). As for physical capital, it again turns out as the extreme factor in the R&D process. Notice that the appropriability variable is still included among the regressors in the second model, for consistency with the first model. Dropping this variable implies that each of the elasticities discussed so far becomes magnified, as can be observed in the first two columns of Table 3. Finally, when omitting time dummies, as in the middle columns, the substantive findings remain quite similar to those just discussed, albeit estimates of a slightly smaller absolute magnitude.

More generally, those findings are consistent with the following fact. As the countries under study experienced episodes of major technological improvements over the last decades, the stocks of physical capital and skilled labour have actually grown much more rapidly than unskilled labour. The compound annualized growth rate of capital, averaged across countries, has been 3.1% for the time-period 1971-2004. In contrast, the compound annual growth of unskilled labour has been 0.6% (five times lower than that of capital), while the annual growth of skilled labour has been 4.3%. Therefore, the findings suggest that a major source of technological change in OECD countries has been the divergence between those growth rates: the last decades are marked by the relatively slow rate of growth of unskilled labour, combined with an accelerated growth of capital and skilled labour. The above estimates indicate that precisely in such circumstances, R&D activities flourish, with an increasing portion of economic resources being devoted to research.

Some of the previous results are slightly altered when modifying the source of the educational data used to construct L and H. Table 4 reports the full set of elasticities, computed with two-way fixed effects. The models using the Lutz *et al.* data are estimated in a way similar to the ones that have been discussed in details above. When the factor variables are built using the Lutz *et al.* data, the factor endowment effect of skilled labour turns out to be larger. The new estimate is 0.7 (compared to 0.2), and skilled labour now appears as the extreme factor, whereas capital appears as the middle factor (as was initially assumed in the theoretical section). The scaling effects are rather similar, however, and the signs of the estimates remain consistent.

Table 4 – Elasticities of Business R&D Expenditures with Respect to Factor Endowments

Education Data	Factor	Rybczynski Effect	Scaling Effect	Total Effect
	Unskilled Labour	–0.78	+0.29	–0.49
Barro-Lee	Skilled Labour	+0.21ᵻ	+0.18	+0.38
	Physical Capital	+0.57	+0.54	+1.10
	Unskilled Labour	–0.95	+0.38	–0.57
Lutz *et al.*	Skilled Labour	+0.72	+0.10	+0.81
	Physical Capital	+0.23ᵻ	+0.52	+0.75

Notes: Summary of estimates from DOLS models similar to those reported in the last two columns of Table 3 (including the measure of appropriability as a control, individual intercepts and time dummies), but with variations in the source of educational data. Scaling effects are implied (see text). All estimates are statistically significant at the $p < 0.05$ level (using HAC standard errors), except those flagged with the ᵻ sign.

Exogeneity

An issue of concern to some may be the exogeneity of factor supplies. Although the reliance on a fixed effects estimator strongly reduces the risk of endogeneity bias under the form of omitted variables (by controlling for unit-level unobserved factors, and common temporal factors in the case of two-way fixed effects), and despite the robustness of the DOLS estimator to endogeneity with the inclusion of lead differences, one may shed theoretical doubt on the exogeneity of factor supplies. For instance, R&D, by inducing technological improvements and thus increases in per capita wealth, can also affect birth and schooling decisions. To address those concerns, I develop an error-correction implementation of the main models introduced above, in order to test both R&D and factor supply variables for weak exogeneity (see Engle *et al.*, 1983, for an extended discussion on concepts of exogeneity).

Consider the following error-correction representation, leaving open the possibility that each variable is endogenous. For simplicity, let me focus again on the first variant of the models introduced above, where educational data are based on the Barro and Lee (2010) data set. For consistency with the previous subsection, I consider the measure of appropriability as part of the system. Also, let the two-way fixed effects represent the context within which the cointegration relationship takes place. The evidence of cointegration reported above implies that the residuals of the long-run equations,

$$\varepsilon_{1,i,t} = \ln \frac{\dot{R}}{Y_{i,t}} - \delta_i - \Phi_t - \theta_L \ln \frac{L^{BL}}{K_{i,t}} - \theta_H \ln \frac{H^{BL}}{K_{i,t}} - \theta_p \ln PP_{i,t}, \qquad (13)$$

$$\varepsilon_{2,i,t} = \ln \frac{\dot{R}}{K_{i,t}} - \delta_i - \Phi_t - \theta_L \ln \frac{L^{BL}}{K_{i,t}} - \theta_H \ln \frac{H^{BL}}{K_{i,t}} - \theta_p \ln PP_{i,t}, \qquad (14)$$

are stationary $I(0)$ processes.

The error-correction representation for the first model (with R&D intensity, yielding the Rybczynski effects) is then given by:

$$
\begin{aligned}
&\Delta \ln \frac{\dot{R}}{Y_{i,t}} = \pi_{10}\,\hat{\varepsilon}_{1,i,t-1} + \sum \pi_{11}(j)\Delta \ln \frac{\dot{R}}{Y_{i,t-j}} + \sum \pi_{12}(j)\Delta \ln \frac{L}{K_{i,t-j}} \\
&+ \sum \pi_{13}(j)\Delta \ln \frac{H}{K_{i,t-j}} + \sum \pi_{14}(j)\Delta \ln PP_{i,t-j} + \upsilon_{1,i,t}, \\
&\Delta \ln \frac{L}{K_{i,t}} = \pi_{20}\hat{\varepsilon}_{1,i,t-1} + \sum \pi_{21}(j)\Delta \ln \frac{\dot{R}}{Y_{i,t-j}} + \sum \pi_{22}(j)\Delta \ln \frac{L}{K_{i,t-j}} \\
&+ \sum \pi_{23}(j)\Delta \ln \frac{H}{K_{i,t-j}} + \sum \pi_{24}(j)\Delta \ln PP_{i,t-j} + \upsilon_{2,i,t}, \\
&\Delta \ln \frac{H}{K_{i,t}} = \pi_{30}\hat{\varepsilon}_{1,i,t-1} + \sum \pi_{31}(j)\Delta \ln \frac{\dot{R}}{Y_{i,t-j}} + \sum \pi_{32}(j)\Delta \ln \frac{L}{K_{i,t-j}} \\
&+ \sum \pi_{33}(j)\Delta \ln \frac{H}{K_{i,t-j}} + \sum \pi_{34}(j)\Delta \ln PP_{i,t-j} + \upsilon_{3,i,t},
\end{aligned}
\tag{15}
$$

where the last case (with $\Delta\ln(PP)$ as the response variable) is omitted for simplicity. Since the differenced variables are *I(0)* by construction, all the variables used in those equations are stationary. The *t*-statistics for π_{10}, π_{20}, and π_{30} (the estimates for the lagged error-correction terms) are of interest. A statistically significant value for π_{10} would confirm that there is a significant long-run effect of innovations in factor supplies and appropriability on R&D. Most importantly, non-significant statistics for π_{20} and π_{30} would imply that the response variables (in those cases, factor supplies) are *weakly exogenous* (Engle *et al.*, 1983; Enders, 2010, ch.6), hence confirming the validity of the statistical inferences stressed in the previous subsection. The error-correction equations for the alternative specifications are constructed in a similar way.

Table 5 reports the estimates for the error-correction terms, for each of the specifications used previously. In each case, the cointegrating regressions were first estimated, to obtain the residuals. The error-correction models are then estimated by OLS, with heteroskedasticity-robust standard errors (clustered by panel). All models are estimated with two lags of the differenced regressors. As can be observed from Table 5, for all of the specifications, there is solid evidence that factor supply variables are weakly exogenous, as revealed by the non-significant statistics when using factor supplies as the response variables. In contrast, R&D variables (no matter their form) consistently appear as endogenous, as was initially theorized in this paper. Overall, those results yield unambiguous support to the validity of inferences made previously, using Tables 3 and 4, concerning the relationship between factor supplies and private R&D.

Table 5 – ECM-Based Weak Exogeneity Tests

Model Type	Response	Education Data: Barro-Lee $\hat{\varepsilon}_{t-1}$	Education Data: Lutz et al. $\hat{\varepsilon}_{t-1}$
Model 1	*Δln* $(\dot{R}/Y)$	–0.0715**	–0.0777**
		(0.0208)	(0.0219)
	Δln L/K	–0.0017	–0.0013
		(0.0022)	(0.0020)
	Δln H/K	0.0021	–0.0016
		(0.0025)	(0.0027)
Model 2	*Δln* $(\dot{R}/K)$	–0.0814**	–0.0894**
		(0.0241)	(0.0242)
	Δln L/K	–0.0021	–0.0017
		(0.0023)	(0.0021)
	Δln H/K	0.0019	–0.0018
		(0.0026)	(0.0029)

Notes: The table shows estimates of the lagged error-correction terms for the ECM representation of the main models (including appropriability (*ln PP*) as a control variable, which is not reported for ease of presentation). A significant estimate indicates that the response variable is endogenous, and that innovations in the regressors have a significant long-run influence on the response variable. Non-significant estimates indicate that the response variable is weakly exogenous. The differenced equations are estimated with OLS, including two lags of each regressor, and using heteroskedasticity robust clustered standard errors (reported in parentheses).
***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

Policy Implications

The results of the last subsections may prove useful to derive policy implications. I consider two examples in this section, by contrasting immigration policies with education policies. Immigration policies are typically used by states to determine the number of residence permits granted to foreigners. When states are selecting foreigners according to their socio-demographic characteristics, immigration policies are by definition inducing a controlled modification to the supplies of unskilled and skilled labour in the recipient country. The elasticities provided in Table 4 can help to evaluate the impact of such policies, based on the assumption that immigrants and natives of the same skill level are interchangeable. As for education policies, they may affect the composition of labour resources, by increasing the ratio of working-age population with a tertiary degree. Yet, a caveat must be raised regarding point predictions. The use of alternative sources for educational data has shown that parameter constancy is not fully achieved. However, the estimated signs of the elasticities and the validity of inference are robust. For illustrative purposes, and keeping in mind the caveat just mentioned, I discuss in the following lines some stylized policy implications.

For example, an immigration policy causing a proportional increase in both unskilled labour and skilled labour would generate an aggregate impact on total R&D expenditures close to nil, whereas the effect on R&D intensity would be slightly negative. Depending on the source of educational data used, the estimated effect on total R&D outlays for a 1% increase in both L and H through immigration would range between –0.11% and +0.24%. To understand the meaning of this calculation, contrast the case of a 1% increase in skilled labour alone. This change induces an estimated increase between +0.38% and +0.81% in total R&D. By adding the growth in unskilled labour, the disproportionate increase that favours the research sector over the other economic activities is lost, reducing down the net effect that would have been obtained had skilled labour alone increased. The estimated effect of the same proportional policy on R&D intensity, on the other hand, would range between –0.6% and –0.2%. Thus, the findings of this paper imply that R&D intensity reacts acutely to changes in the supply of unskilled labour.

Policies that increase both the supplies of skilled and unskilled labour at the same rate may be quite close to what actually occurs in a typical OECD country in the recent years. For instance, according to OECD's DIOC-E database (described in Dumont *et al.*, 2010), which contains census-based cross-sectional information on the educational attainment of the foreign-born population in receiving countries, the average share of the foreign-born population with a completed tertiary degree in the countries under study is about one fourth. This value is quite close to the actual share in the native population, also around one fourth (both values are extracted from the same source). If one assumes that the mix of skilled/unskilled among new entrants is similar as well, which may or may not be valid, then the typical policy tends to fall close to the example just described, where both L and H grow at the same rate. That is, holding constant other sources of change in factor supplies, the typical immigration policy would generate little effect on the total quantity of private R&D expenditures, and a slight depressing effect on the intensity of R&D.

In contrast, the impact of a policy that would stimulate an increase in the tertiary graduation rate can be assessed as follows. Consider an initial state in which a working-age population of size N is composed of $hN = H$ skilled workers, and $(1 – h)N = L$ unskilled workers, where h is the ratio of the working-age population with a completed tertiary degree. Suppose that a policy is expected to produce the counterfactual state $h'N = H'$ and $(1 – h')N = L'$. Clearly, $h > h$ implies that $H > H$ and $L < L$, so that the direction of the estimated effect on business R&D is unambiguous, all else equals. For instance, let $h = 0.25$ and $h' = 0.255$. For N constant, a change from h to the counterfactual level h'

corresponds to a 2% increase in H, and a 0.7% fall in L. The estimated effect on absolute levels of business R&D expenditures, based on the elasticities of Table 4, would range between +1.1% and +2%. Note that such a calculation leaves aside temporal changes in factor supplies; it also assumes that the quality of the graduates remains the same under the two scenarios. In practice, manipulating the graduation rate through education policies may not be as straightforward as expanding labour supply through immigration, since the former may require a variety of policy instruments, the efficiency of which needing to be assessed. Nonetheless, this stylized example suggests that education plays an important role in the development of the private research sector, through its effect on labour resource composition.

CONCLUSION

This study sought to demonstrate how changes in the supplies of unskilled and skilled labour affect the scope of business R&D activities. The model incorporates three factors of production, and builds upon the idea that high-technology industries make intensive use of skilled labour (in contrast with traditional industries, intensive in unskilled labour). R&D intensity is expected to respond negatively to disproportionate increases in the supply of unskilled labour, and conversely following relative increases in the supply of skilled labour. On the other hand, proportional increases in the supply of all three factors are expected to generate scale effects, in the sense of higher absolute levels of expenditures in R&D. Empirical data on OECD countries have been found to be consistent with those expectations.

Based on an econometric specification distinguishing scale effects from relative endowment effects, the results suggest that a soaring supply of unskilled labour dampens private R&D expenditures, even after accounting for scale effects. The positive trends in R&D expenditures observed in OECD countries can be largely explained by the growth in the intensity of capital and skilled labour, rather than population growth per se, as was argued in recent publications. Indeed, capital and skilled labour have increased over five times more rapidly than unskilled labour during the last decades, while fertility rates have been declining. Thus, the results help to clarify the role of population for technological change. More people may well mean more ideas, but those ideas must also make it to the research lab. And a fast growing population can thwart R&D efforts if it augments the intensity of unskilled labour, since productive activities adapt to resource composition. Overall, by highlighting the role of factor intensities, the findings discussed in this paper rest upon an explanation of technological change that is quite consistent with empirical reality.

Moreover, the findings yield implications for policies. I have discussed two stylized examples. The empirical estimates were first used to illustrate the impact of immigration policies on the private research sector. This impact depends on the mix of unskilled and skilled migrants entering the labour market. An example realistically close to the situation in an average OECD country was considered, showing that the effects of skilled and unskilled immigration on absolute levels of business R&D expenditures tend to offset each other. On the other hand, the undermining impact of unskilled immigration on the intensity of R&D prevails. In contrast, an education policy increasing the ratio of working-age population with a tertiary degree has an unambiguous estimated impact on business R&D, insofar as it induces a net increase in the supply of skilled labour relative to unskilled labour. Although a full assessment of those implications falls beyond the scope of this paper, extensions to this study could further emphasize the role played by policies in changing the composition of labour over time, hence affecting the extent of private incentives to innovate.

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APPENDIX: ADDITIONAL INFORMATION ON EMPIRICAL DATA

Capital stocks (K) and output (Y). Both variables come from the OECD Stats database. Y is measured as total GDP (expenditure approach), and corresponds to the series B1_GE, in constant prices, and constant PPP-adjusted US dollars (base 2000). Gross fixed capital formation comes from the series B1_GE, P51. Capital stocks are computed using the perpetual inventory method. The depreciation rate δ is assumed to be 0.05, and the benchmark for 1970, for each country i, is computed as:

$$K_{i,1970} = \frac{\dot{K}_{i,1970}}{\delta + g_{K,i}},$$

where $g_{K,i} = \frac{\ln \dot{K}_{i,1985}/\dot{K}_{i,1970}}{15}$.

Unskilled labour (L) and *skilled labour* (H) *stocks*. Those variables are computed as:

$$L_{i,t} = N_{WA,i,t}(1 - h_{i,t});\ H_{i,t} = N_{WA,i,t}h_{i,t},$$

where $N_{WA,i,t}$ is working-age population in country i at year t (from OECD, 2011), and where $h_{i,t}$ is the share of working-age population with a completed tertiary degree. As mentioned in the text, two alternative sources for h are considered (Barro and Lee, 2010; Lutz *et al.*, 2007). The h series have been linearly interpolated within the five-year data points provided in the initial data sets.