Looking into the black-box of the Schumpeterian Growth Theories: An empirical assessment of R&D races

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Abstract

This paper assesses whether the most relevant R&D technologies at the roots of the new Schumpeterian theories of endogenous growth are consistent with patenting and innovation statistics. Using panel data for twelve US manufacturing industries, we estimate different systems of simultaneous equations drawn on the R&D races designed by the models of growth based on variety expansion, diminishing technological opportunities and rent protection activities. Although all the R&D technologies under examination are empirically grounded, our evidence indicates that those characterized by the increasing difficulty of innovation activities (i.e. diminishing technological opportunities) better fit US data.

Keywords: R&D technology, patenting, economic growth.
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1 Introduction

Recently, an increasing attention has been payed to the soundness of innovation-based growth theories and, in particular, to which of them better fits long-run data (Schumpeterian vs semi-endogenous growth models). The ambition of empirical studies is to identify the most credible Schumpeterian growth model, and hence help policymakers tailor actions able to promote innovation and sustained economic growth. Less interest has instead been shown to the consistency of the R&D technology at the basis of these models with the real world of scientific research. This should not be considered a trivial issue as such R&D races are the mainstay for the overall architecture of these theories; in steady-state, the parameters governing the process of innovation determine the rate of economic growth, irrespective of whether these models leave room for active R&D policies (fully- vs semi-endogenous models).

The inner mechanism of any typical quality-ladders growth model is that the discovery of new products occurs as result of a firm's engagement in uncertain R&D races. As prizes, winners gain the discounted stream of expected profits associated to the good with the state-of-the-art quality, with the possibility for new R&D comers to erode the monopoly power of incumbents owning the previous frontier product (or technology). In such models, the rate of success in R&D races is generally determined by the extent of research engagement; less univocal is instead which research inputs directly impact on the probability of obtaining an innovative output, and how these factors mutually influence each other.

Understanding whether the R&D technologies designed by new endogenous growth models properly describe the real dynamics of industrial research may help capture the forces of development in knowledge-based economies, and identify which Schumpeterian theory is better consistent with long-run data. Using US manufacturing industry data for the period 1973-1996, this paper estimates various systems of simultaneous equations modelling the R&D races designed by theoretical literature. We consider the innovation framework traced by the studies based on variety expansion, diminishing technological opportunities and rent protection activities. Albeit most of the examined R&D technologies appear empirically grounded, our evidence indicates that those characterized by the increasing difficulty of innovation activities (i.e. diminishing technological opportunities) better fit US data.

The outline of the work is as follows. Section 2 overviews the empirical literature developed around the new models of knowledge-based growth. The focus is placed upon the works living up the controversy on the presence of scale effects in economic growth, and on those assessing which model of Schumpeterian growth is consistent with long-run macro-economic data. Section 3 builds up the empirical setup starting from the main R&D races proposed by theoretical literature. Section 4 describes US manufacturing data used in the regression analysis and shows summary statistics. Section 5 presents the econometric results. Section 6 concludes after discussing the main findings of the paper.

2 Related literature

The critique formulated by Jones (1995a, and 1995b) against the prediction of the first generation of Schumpeterian growth models that the aggregate rate of growth increases in the *level* of R&D resources marked a revolutionary change on the development of this body of literature. A threefold direction has been taken in the attempt to remove such a *scale effect*.

A first, thriving body of studies has emphasized that R&D spreads thinly across product varieties as the economy grows (Aghion and Howitt, 1998, Dinopoulos and Thompson, 1998, Peretto, 1998 Howitt, 1999 and Young, 1998). Variety expansion takes the form of quality improvements or process innovations, and is related to demographic dynamics. As population grows, there is need to increase the volume of R&D resources to make the amount of research input per inhabitant stable the over time, and thus endogenously fuel the mechanism of economic expansion. Furthermore, in steady-state, the aggregate rate of growth depends on a large array of parameters, including the R&D subsidy/tax rate. In light of these properties, these are usually referred to as *fully-endogenous, scale-invariant growth* models, or equivalently *permanent effects on growth* models.

A second direction has been explored by Jones (1995a), Kortum (1997) and Segerstrom (1998). They point out that the modern processes of innovation are featured by the exhaustion of technological opportunities, that continuously raises the difficulty of conducting research activities. It means that increasing resources are necessary over time to maintain a stable rate of innovation and, consequently, a constant rate of economic expansion. In such frameworks, R&D policies affect growth only along the transitional dynamics, but not on the steady-state. As a consequence, they are usually defined as *semi-endogenous (or exogenous), scale-invariant growth* models, or equivalently *temporary effects on growth* models.

Finally, the focus of research has recently been shifted on rent protection activities that incumbents undertake to reducing the technological opportunities of R&D activity performed by outside firms (Dinopoulos and Syropoulos, 2007). These activities consist in defensive patenting or expenses for specialized labour, lawyers and lobbyists that are strategically aimed at lowering the probability for a new comer to introduce a frontier technology or a state-of-art product. Similarly to the first strand of models described above, in such a novel framework, R&D policies positively influence the long-run rate of economic expansion; accordingly, growth is fully endogenous.

As a result of the competing views about the mechanism behind the long-run process of growth (and the related welfare implications), a number of papers have attempted to assess the empirical plausibility of such theoretical contributions. Based on US manufacturing industry data, Zachariadis (2003) provides evidence in favor of the Schumpeterian endogenous growth framework without scale effects. The intensity of research engagement is found to positively affect the rate of innovation (or patenting). In turn, the rate of success in R&D races fastens the pace at which total factory productivity grows over time and, finally, this explains the rise in output per worker. Moreover, aggregate R&D intensity has a stronger impact on the rate of patenting than sectoral R&D, suggesting that technological spillovers may be at work across industries. Cross-country findings consistent with this type of conclusions have been reported by Zachariadis (2004) and Bottazzi and Peri (2007). Madsen (2007) examines instead the relationship between patent counts and R&D expenditure across OECD countries; the ratio between the levels of research input and research output is found to be stationary over the long-run, indicating that R&D activities are characterized by constant returns to scale. This contrasts against the wisdom of diminishing returns postulated by semi-endogenous growth theories, as well as against the idea that R&D efforts dilute across larger product varieties as the economy grows, as suggested by some models of the first strand of Schumpeterian theories. According to Laincz and Peretto (2006), however, aggregate statistics on US employment, R&D personnel and the number of establishments support the idea that the scale effect is sterilized by product proliferation. By examining the US aggregate performance over the second half of the 20th century, Ha and Howitt (2007) show that semi-endogenous growth models do not behave as well as fully endogenous theories. A similar conclusion is drawn by Madsen (2008) by applying to international data an extended framework that controls for technology catch-up, international technology spillovers, and adopting alternative measures of innovation activity/product variety. Finally, Sedgley (2006) develops a scale-invariant growth model characterized by transitional dynamics and complementarities between knowledge and human capital that is able to adequately replicate the US macro-economic performance over the Second Postwar.

3 Analytical framework

3.1 Theoretical background

Deliberate innovation activity, featured by uncertain realization, has become the milestone of the new R&D-based growth theory. The basic traits of R&D technology were originally developed by the first generation of Schumpeterian models of endogenous growth (Aghion and Howitt, 1992, Segerstrom *et al.*, 1990, Grossman and Helpman, 1991, ch. 4) following in the footsteps of the industrial organization literature on patent races.[1] Such races are assumed to be stochastic processes playing out at an economy-wide or at an industry level, where firms target their research efforts to improve existing products. They may occur either sequentially once at time staggered by long intervals, or simultaneously and involving many industries. R&D races are memoryless processes characterized by a free-entry condition and an exogenous probability of innovation. It implies that firms do not benefit from cumulating unsuccessful research efforts, and that new comers can compete with incumbents in developing the next state-of-art product without having been involved in previous races. The winner takes over industry leadership and earns monopoly profits up to the invention of the next state-of-art product. The probability that an innovation occurs is usually assumed to be independently distributed across firms, industries and over time; as a result, the industry-wide rate of R&D success amounts to:

$$\iota(\omega, t) = \lambda \ell(\omega, t), \tag{1}$$

where ω denotes industries, t time. λ (> 0) is the Poisson (instantaneous) rate of arrival, $\ell(\omega, t)$ is the amount of specialized inputs in R&D activities, typically labour (i.e. scientist and engineers) or research expenses. dt is the length of time interval of R&D engagement.

Variety expansion (VE). A first, influential attempt to remove the scale effect from the endogenous growth framework has been made by Aghion and Howitt (1998) and Howitt (1999). At the basis of such models, there is a research technology where the industry-wide probability of introducing a new state-of-art product is generated by the following two-equation process:[2]

$$\iota(\omega, t) \quad = \lambda n(\omega, t) \quad = \lambda \frac{1}{m} \frac{r(\omega, t)}{A(t)} \tag{2}$$

$$\frac{\dot{a}(\omega, t)}{a(\omega, t)} \quad = \sigma \iota(\omega, t). \tag{3}$$

λ is the productivity parameter of R&D activities performed to improve product quality. $n(\omega, t)$ denotes the ratio between research inputs devoted by each sector to vertical innovation, $r(\omega, t)$, and the total-economy leading-edge productivity parameter, $A(t)$. This type of correction is made to account for the

[1] Loury (1979), Lee and Wilde (1980) and Reinganum (1982).

[2] In what follows, a coherent notation across the parameters of the models taken into consideration is ensured by indicating with lower cases industry-level variables, and with upper cases those variables that pertain to the overall economy (manufacturing).

force of increasing complexity of innovation: the more technological improvements, the more resource-intensive they are. $n(\omega, t)$ can be then thought as of a productivity-adjusted measure of research effort, or more simply an indicator of their technological intensity. m is the number of product varieties annually available to consumers; as the economy develops an increasing number of specialized products, an innovation of a given size will have a smaller impact on the aggregate economy. However, during a R&D race, the number of product varieties is constant and firms undertake R&D projects to vertically improve existing technologies. Accordingly, without loss of generality, m can be normalized to unity (see Zachariadis, 2003). Another crucial insight of this framework is that, at an economy-wide level, the leading-edge productivity grows at the same rate of industry productivity as the ratio a_{it}/A_t converges monotonically to an invariant distribution, $\dot{a}(\omega, t)/a(\omega, t) = \dot{A}(t)/A(t)$. The rise in leading-edge productivity parameter, as well as in its industry counterparts, occurs as a result of the knowledge spillovers produced by R&D activities; the marginal impact of vertical innovation on the stock of public knowledge is denoted by σ. This is the rationale behind equation (3).

Diminishing technological opportunities (DTO). The R&D technology proposed by Segerstrom (1998) departs from the previous formulation for the channel through which technological complexity is assumed to thwart the realization of innovation. The rate of innovation is indeed hypothesized to be lowered by the difficulty associated with research failure, $x(\omega, t)$: researchers start off pursuing the most promising projects and, if they fail, they try less promising projects. Higher values of $x(\omega, t)$ imply that the same amount of R&D resources generates a lower growth in patentable innovation; $x(\omega, t)$ can be conceived as an inverse measure of total factor productivity in R&D activities. To control for the large degree of heterogeneity in the underlying process, the detrimental effect of technological complexity is assumed to be industry-specific; it contrasts with the formulation based on variety expansion where the rate of innovation is lowered by the productivity level of the economy-wide activities of final production. Moreover, in Segerstrom (1998) the rate at which $x(\omega, t)$ increases depends itself on the success rate of research activity according to the parameter μ (> 0). The R&D race of this model is then governed by the two following equations:

$$\iota(\omega, t) = \frac{Z\ell(\omega, t)}{x(\omega, t)} \tag{4}$$

$$\frac{\dot{x}(\omega, t)}{x(\omega, t)} = \mu\iota(\omega, t), \tag{5}$$

where Z (> 0) is an exogenous productivity parameter common to all sectors. According to the latter equation, the rate of realization of the current research efforts enhances the difficulty to introduce a profitable innovation in subsequent periods.

Li (2003) extends the process underlying the probability to innovate described by equation (4) by introducing two further explanatory factors. Firstly, he emphasizes the increase in innovation difficulty coming from the past research successes. As products improve in quality and become more complex, the creation of the next state-of-art quality product becomes more difficult. The higher the quality of the state-of-art product, $q(j_\omega, \omega, t)$, the lower the rate of innovation $\iota(\omega, t)$. Secondly, innovating can become less difficult over time due to the possibility of positive cross-industry knowledge spillovers; the likelihood of research success is thus raised by the average quality of state-of-art products, $Q(t) = \sum_\omega q(j_\omega, \omega, t)$. ψ (> 0) is the corresponding parameter of externality. In what follows, this kind of R&D race is investigated following the formulation recently proposed by Minniti *et al.* (2008), where product quality is assumed to evolve with random jumps of different magnitude drawn from a Pareto distribution, $\lambda = q(j_\omega + 1, \omega, t)/q(j_\omega, \omega, t) > 1$. It models the idea of increasing difficulties in realizing innovations of greater size; it also fits the empirical distribution on the value of patented innovation which is highly skewed towards the low value side, with a very long tail into the high value side:

$$\iota(\omega, t) = \frac{Q(t)^\psi \ell(\omega, t)}{zx(\omega, t)q(j_\omega, \omega, t)} \tag{6}$$

$$\frac{\dot{x}(\omega, t)}{x(\omega, t)} = \mu\iota(\omega, t) \tag{7}$$

$$\dot{q}(j_\omega, \omega, t) = (\lambda - 1)\tilde{\iota}(\omega, t). \tag{8}$$

z (> 0) is a constant parameter. $\dot{q}(j_\omega, \omega, t) = q(j_\omega + 1, \omega, t) - q(j_\omega, \omega, t)$ is the quality difference (or jump) between the newest and the older state-of-art product annually arising in each industry. $\tilde{\iota}(\omega, t) = \iota(\omega, t) * q(j_\omega, \omega, t)$ is the quality-adjusted probability of innovation; it derives from the definition of quality improvement as expected value between the realization of a positive jump $\dot{q}(j_\omega, \omega, t) = (\lambda - 1)q(j_\omega, \omega, t) > 0$, occurring with probability $\iota(\omega, t)$, and the case of constant quality $\dot{q}(j_\omega, \omega, t) = 0$ whose rate of realization is obviously $1 - \iota(\omega, t)$.[3] $\tilde{\iota}(\omega, t)$ determines the extent of the qualitative growth associated with the new state-of-art product.

[3] In Li (2003) the quality jump is defined as $\lambda^{\epsilon(j_\omega+1)} - \lambda^{\epsilon(j_\omega)}$ where ϵ is a parameter depending on the consumer elasticity of substitution α, $\epsilon = \alpha/(1-\alpha)$. ϵ is assumed equal to zero by Minniti *et al.* (2008); this hypothesis considerably simplifies the parameter interpretation in the regression analysis.

Rent protection activities (RPA). A mechanism alternative to the ones so far envisioned has been proposed by Dinopoulos and Syropoulos (2007). They build up a two-equation technology of research that shares with Segerstrom (1998) the mechanism explaining the probability of innovation (eq. 4), but differs for the factors hindering research activity. The level of research difficulty is indeed shaped by the rent-protection barriers that incumbent (innovating) firms erect to protect their positions. These activities enhance the difficulty that challengers face when entering a R&D race with the view to obtaining a new product (or technology).

$$\iota(\omega,t) = \frac{\ell(\omega,t)}{x(\omega,t)} \tag{9}$$

$$x(\omega,t) = \eta p(\omega,t). \tag{10}$$

The level of innovation complexity is determined by the volume of rent-protection activities $p(\omega,t)$ performed at an industry-level (eq. 10). η captures the effectiveness of RPA on research difficulty; this parameter could be either interpreted as a proxy of the extent to which existing institutions protect intellectual property, or alternatively as the (time-invariant) productivity level of incumbents' lobbying outlays.

Sener (2008) combines the main characteristics of the models featured by RPA and DTO by drawing a R&D race of the following form:

$$\iota(\omega,t) = \frac{\ell(\omega,t)}{x(\omega,t)} \tag{11}$$

$$\frac{\dot{x}(\omega,t)}{x(\omega,t)} = \mu\iota(\omega,t) + \eta\frac{p(\omega,t)}{x(\omega,t)}. \tag{12}$$

In this model, the evolution of R&D difficulty is dictated by two distinct forces (equation 12). The former is the typical effect associated with the realization of innovation designed by Segerstrom (1998); the latter is the impact of rent protection activities, which is scaled on the current level of R&D difficulty.[4] Clearly, when $\mu > 0$ and $\eta = 0$, the formulation boils down to that of Segerstrom (1998); when $\eta > 0$ and $\mu = 0$, it captures the approach devised by Dinopoulos and Syropoulos (2007). The main discrepancy between (10) and (12) can be found in the assumption made on the nature of the rent-protection effect. In eq. (10), R&D difficulty is modelled as a flow variable fully decaying at each instant in time; in eq. (12), it is considered as a stock variable and this is done to accommodate the possibility that RPA have persistent effects on the legislative and judicial system,

[4] It comes from rewording the low of motion of the cumulative value of R&D difficulty in terms of growth rates.

or that the detrimental effects of R&D difficulty on technological advancements decrease slowly over time.

3.2 Empirical specification and identification strategy

In the regression analysis, we assess the empirical soundness of R&D races by estimating the discrete-time version of the equation systems introduced in the previous section. To conceal notation with standard practice of empirical literature, hereinafter industry are indicated by i (in place of ω), while time and sector arguments are denoted as subscript. The first point to be stressed is that a log-linearization is implemented on the expressions for the rate of innovation and the level of R&D difficulty, ι and x. The empirical specifications are obtained from the theoretical counterparts by adding a deterministic component (fixed effect, time trend or time dummies). The equation for the rate of innovation, ι, includes both industry-specific intercepts, θ_i, and time trend ϑ_i (either homogenous or heterogenous). θ_i should capture the time-invariant individual characteristics in the underlying process, whilst ϑ_i its deterministic evolution over time (Zachariadis, 2003, p. 580). Any specification where the dependent variable is expressed as percentage change of growth, or in first differences, does not consider time-invariant sectoral effects, but includes common time dummies, TD_t, to control for the impact of temporary shocks (R&D policies, business cycle, changes in regulative frameworks, etc.). The appropriateness of the deterministic elements attached to each specification is always checked by means of a test significance (F-test). Serial correlation is controlled for by adding a 2nd-order autoregressive error to the equations expressed in log-levels ($\epsilon_{it} = \rho_1 \epsilon_{t-1} + \rho_2 \epsilon_{t-2} + \xi_{it}$), and a 1st-order autoregressive error to those with dependent variables expressed as rate of change or first differences ($\varepsilon_{it} = \varrho \varepsilon_{it-1} + \upsilon_{it}$).

We shall start by examining the R&D race at the basis of the variety expansion framework (Aghion and Howitt's technology). Initially, we assess the steady-state specification previously estimated by Zachariadis (2003). It exploits the condition for which technology frontier and sectoral output, A_t and y_{it}, change at the same rate along the balanced growth path. Hence, the intensity of R&D activities can be approximated by the ratio between R&D expenses and gross output $n_{it} = r_{it}/A_t = r_{it}/y_{it}$ (*Aghion and Howitt's technology, model A*). It should be considered that the economy-wide level of leading-edge technology exceeds the economy-wide level of average technology by a time-invariant factor which depends on the size of innovations, implying that the former variable can be empirically approximated by the latter. the latter;

$$\ln \iota_{it} = \alpha_1 \ln n_{it} + \theta_i + \vartheta_i T + \epsilon_{it} \quad (13)$$

$$\Delta \ln a_{it} = \beta_1 \iota_{it} + \varepsilon_{it}. \quad (14)$$

According to the indications of the theory, α_1 and β_1 should be positive parameters.

Though, as Luintel and Khan (2009) point out, the most appropriate indicator of the effort made in the generation of new ideas is the *level* of research activities rather than their *intensity*, as the latter is far from fully revealing cross-sectional variation in research engagement. This issue will be extensively discussed below. For this reason, we estimate a second formulation for the Aghion and Howitt's technology where n_{it} is explicitly defined as ratio between the volume of sectoral R&D input and the leading-edge, economy-wide level of productivity, r_{it} and A_t (*Aghion and Howitt's technology, B*):

$$\begin{aligned} \ln \iota_{it} &= \alpha_1 \ln r_{it} + \alpha_2 \ln A_t + \theta_i + \vartheta_i T_i + \epsilon_{it} \qquad (15) \\ \Delta \ln a_{it} &= \beta_1 \iota_{it} + \varepsilon_{it}, \qquad (16) \end{aligned}$$

$\alpha_1, \beta_1 > 0$, and $\alpha_2 < 0$. A characteristics common to the previous sets of equations is the omission of temporal, along with fixed effects, from the specification for $\Delta \ln a_{it}$. It is due to the nature of the variable used as technology indicator (see Basu *et al.*, 2006) which is constructed as TFP growth net of the impact of non-technological effects, namely nonconstant returns and imperfect competition, aggregation effects, and varying utilization of capital and labor. By construction, this procedure purges out any systematic component from the dynamics of technology indicator, a_{it}.

The exploration of the DTO framework first considers the baseline technology of research proposed by Segerstrom (1998) (*Segerstrom's technology*):

$$\begin{aligned} \ln \iota_{it} &= \alpha_1 \ln \ell_{it} + \alpha_2 \ln x_{it} + \theta_i + \vartheta_i T_i + \epsilon_{it} \qquad (17) \\ \Delta \ln x_{it} &= \beta_1 \iota_{it} + TD_t + \varepsilon_{it} \qquad (18) \end{aligned}$$

where $\alpha_1, \beta_1 > 0$, and $\alpha_2 < 0$. The structure of the empirical model is close to the system (15)-(16) apart from the inclusion of time dummies in equation 2. As a second step, we estimate the system of three equations developed by Li (2003). In this setup, the engine of the entire process of innovation is represented by the (stochastic) qualitative evolution of state-of-art products, Δq, which reflects the inner nature of the R&D races of this class of models. A large number of firms participates to this type of competition each year; most fail in obtaining an innovation, but most succeed and demand for legal protection for them. However, these inventions are heterogenous in terms of innovation content and the leadership of the market is taken only by the product with the highest level of quality. This position is hold up to the next year when a new sequence of R&D races starts. The quality improvement (or quality jump) occurring at an industry-level is given by the difference between the leader quality and that of the secondly most innovative product. The dynamics of q is a erratic process, not following any deterministic path over time, but rather is shaped by strong technological (sectoral) specificities. As a consequence, equation (21) admits only industry fixed-effects as deterministic component (*Li's technology*):

$$\begin{aligned}
\ln \iota_{it} &= \alpha_1 \ln Q_t + \alpha_2 \ln \ell_{it} + \alpha_3 \ln x_{it} + \alpha_4 \ln q_{it} + \theta_i + \vartheta_i T_i + \epsilon_{it} && (19)\\
\Delta \ln x_{it} &= \beta_1 \iota_{it} + TD_t + \varepsilon_{1,it} && (20)\\
\Delta q_{it} &= \gamma_1 \iota_{it} + \nu_i + \varepsilon_{2,it}. && (21)
\end{aligned}$$

where $\alpha_1, \alpha_2, \beta_1$ and $\gamma_1 > 0$ should be positive parameters, whilst α_3 and α_4 negative.

In assessing the RPA framework, we consider the empirical counterpart of the R&D technology designed by Dinopoulos and Syropoulos (2007) that looks as follows:

$$\begin{aligned}
\ln \iota_{it} &= \alpha_1 \ln \ell_{it} + \alpha_2 \ln x_{it} + \theta_i + \vartheta_i + \epsilon_{1,it} && (22)\\
\ln x_{it} &= \beta_1 \ln p_{it} + \theta_i + TD_t + \epsilon_{2,it} && (23)
\end{aligned}$$

with $\alpha_1, \beta_1 > 0$ and $\alpha_2 < 0$. Although equation (23) is expressed in log-levels, it includes common time dummies in place of time trends to preserve the comparability across models of estimates concerning the explanation of research difficulty. It also turns out to provide more robust results. On the other hand, the empirical specification for the research technology conceived by Sener (2008) is defined as:

$$\begin{aligned}
\ln \iota_{it} &= \alpha_1 \ln \ell_{it} + \alpha_2 \ln x_{it} + \theta_i + \vartheta_i T_i + \epsilon_{it} && (24)\\
\Delta \ln x_{it} &= \beta_1 \iota_{it} + \beta_2 (p_{it}/x_{it}) + TD_t + \varepsilon_{it}. && (25)
\end{aligned}$$

with $\alpha_1, \beta_1 > 0$ and $\alpha_2, \beta_2 < 0$. For this type of framework, the main complication comes from the lack of adequate measures of the lobbying activities that are annually carried out at an industry level. This drawback leads us to follow a double strategy of identification. As a first step, we estimate the two previous kinds of research technology using some indicators more directly related to rent protection activities, and as such can be regarded as their proxy (*direct identification*). As a second step, the impact of RPA is subsumed by recurring to some indicators that, both on a theoretical and on an empirical ground, are argued to affect lobbying activities, and hence may raise research difficulty indirectly (*indirect identification*).[5] A similar strategy has recently been followed by Comin and Hobijin (2009) to examine the effect of lobbying on international technology diffusion. They find that the impact of institutional factors on the cost of erecting barriers is lower when the new technology has a technologically close predecessor or the degree of market competition is high. In the same vein, Aghion *et al.* (2009) show that the threat of technologically advanced entry encourages innovation of

[5]It amounts to assume $x = g\big(p(y_1, y_2, ...)\big)$, with $g'_p(\,\cdot\,) > 0$ and $p'_{y_j}(\cdot) > 0$, where y_j is an indirect indicator of RPA.

incumbents near to the technological frontier. Accordingly, in the second-step of the identification procedure, we hypothesize a relationship between RPA, market competition and technological contiguity among products (respectively denoted h and c) of the following form: $p_{it} = h_{it}^{\varphi} c_{it}^{\varsigma}$. However, to keep the regression analysis as simple as possible, factor elasticities are forced to take only two values, zero or one. It implies that only three forms of indirect impact are admitted on research difficulty: 1) a joint effect of both factors ($\varphi = \varsigma = 1$); 2) the impact of market concentration only ($\varphi = 1$, $\varsigma = 0$); and finally 3) the impact of products' technological closeness only ($\varphi = 0$, $\varsigma = 1$).

4 Data description

The empirical analysis is performed on a panel of twelve US manufacturing industries over the period 1973-1996. Table 1 reports summary statistics for the variables employed below; more details on data sources and on how variables have been constructed can be found in the Appendix. The rate at which an innovation occurs is approximated by the rate of patenting, ι. It is well-known that the most commercially exploitable innovations are patented, irrespective of they have an incremental or a drastic nature. A patent attributes a monopoly right over the innovation for a given time-span at the cost of disclosing the underlying knowledge. As in Zachariadis (2003), ι is defined as the ratio between the number of patent counts (ideas) applied each year and the stock of patented ideas (knowledge) accumulated up to that year. Based on NBER USPTO patent data files,[6] the analysis is restricted to all granted patents that have been applied from 1973 to 1996 (over one million of applications). Following the concordance SIC table alleged to the data set, patents have been assigned to twelve two-digit sectors according to their application year, as it is commonly considered the most relevant date for the commercial exploitation of the patented innovations. Because of the truncation affecting patent counts due to the lag between the application and the grant year (Hall *et al.*, 2005, p. 20), raw counts have been corrected by means of a weighting factor drawn from the empirical distribution of the mean difference between these two dates (see the Appendix). For each industry, the stock of patents is obtained from adjusted counts through the permanent inventory method and geometrical depreciation; unless differently specified, a standard decay rate of 15% is applied ($\delta = 0.15$). The rate of patenting amounts to a 16.9 percentage over the period considered, taken as simple cross-sectional mean. Electrical equipment is the most innovative sector in terms of probability of introducing new,

[6] Data are available at the Bronwyn Hall's homepage (http://elsa.berkeley.edu/ bhhall/patents.html).

patentable innovations (18.9%); on the other hand, the lowest propensity to patent is registered by primary metals and food (15.4%).

In the baseline regressions of the framework focused on variety expansion, the intensity of R&D activities, $n_{it} = r_{it}/A_t$, is approximated by the current prices ratio between total R&D expenses and gross output, r_{it}/y_{it}.[7] It exploits the condition for which technology frontier and sectoral output, A_t and y_{it}, change at the same rate along the balanced growth path. When considering n_{it} as ratio between the volume of sectoral R&D input and the economy-wide, leading-edge level of productivity, we use the cumulative value of R&D expenditure (in constant dollars) as proxy for r_{it}; A_t is instead defined as the maximum value across industries of the technology index developed by Basu *et al.* (2006), expressed as deviation from manufacturing mean. On average, the intensity of R&D expenditure amounts to 2.8% of gross output. At an industry-level, the largest intensities are shown by transport and electrical equipment (7.8 and 6.1% respectively); since this indicator can also be interpreted as a measure of R&D difficulty, it signals that the technological fields related to such sectors are characterized by a fiercer degree of competition in innovation activities. Looking at the dynamics of R&D intensity (row 4), the difficulty of conducting research has risen only by a half of percentage point on aggregate (0.4%, see row 4 of Table 1), as the significant surge in privately-funded R&D expenses has been offset by the severe reduction in public funds.[8] R&D intensity grows fast in the miscellaneous sector and professional instruments, whilst it decreases remarkably in rubber albeit starting from a moderately low value. If R&D capital is looked at, the largest volume of research inputs is still exhibited by transport (191 millions of 2000 dollars), and then by machinery and chemicals (around 70 millions of dollars). Over the period considered, technology index grew annually by less than one percent in manufacturing (0.8%). The pace of technological development has been particulary fast in food (3.4%), but a good performance is nonetheless shown by the miscellaneous sector and machinery; by contrast, a downgrading in the technological frontier is observed in petroleum (-0.3% annually). The relative level of the economy-wide, leading-edge technology, A_t, takes a value of 1.17, indicating that the technological frontier of the most advanced industry lies, on average, almost a fifth above the one of manufacturing.

In the setup characterized by diminishing technological opportunities or rent protection activities the volume of research resources is gauged by R&D employ-

[7] R&D statistics include both privately- and federally-funded expenses and are taken from National Science Foundation. Industry accounts series come from EUKLEMS data set.

[8] Due to public aids to defence and space, federal funds account for about a 5% of output in transport equipment; this share rose up to the mid-80s, but then reduced inexorably. The regression results are robust to the exclusion of this sector, as well to the usage of the intensity of privately-funded R&D expenses.

ment, ℓ_{it}, measured as full-time equivalent scientists and engineers (from National Science Foundation). About 42 thousands specialized workers are annually employed in the research labs of US manufacturing firms, rising from 30 thousands of the early 1970s to over 50 thousands of the mid-1990s. The largest base of R&D employment is exhibited by transport and electrical equipment (138 and 101 thousands), then followed by chemicals (67 thousands). On the other tail of the distribution, the lowest value is shown by stone, clay and glass where less than 6 thousands scientists and engineers have been occupied any year in research labs.

Following patenting literature, innovation quality is alternatively measured by claims, backward and forward patent citations (Hall *et al.*, 2001). Claims specify the building blocks (components) of an innovation over which the inventor asks for legal protection; their number is indicative of the width of innovation. Citations reflect pieces of previously existing knowledge upon which new patents build. Backward citations are those made to existing patents. Forward citations are those received by a patent from the date it has been applied (or granted). The rationale for using citations is that the more a patent is cited, the larger its effect on the creation of further innovation. According to Lanjouw and Schankerman (2004), though, these quality indicators convey different pieces of information on a patented innovation, and accordingly it may be more appropriate to use a synthetic indicator to extract the largest information possible. In the regression analysis below, we separately use all these measures of patent quality, as well as a residual common factor obtained from such series following the method devised by Hall *et al.* (2007) (see the Appendix). For each of these indicators, q_{it} is defined as the maximum value shown by a patent applied at year t in sector i. The (un-weighted) mean quality of manufacturing is reported in the last column of Table 1; it is used as proxy for the across-industry knowledge spillover, Q. A consistent technological ranking emerges from the full array of quality indicators used. Professional instruments, machinery, chemicals and electrical equipment stand out for the highest qualitative level of state-of-art products. In these sectors, the maximum number of cites received fluctuates between 260 and 280, while the average for manufacturing is 168;[9] backward citations and claims exhibit lower values, respectively 114 and 139 on aggregate. Looking at the common quality factor,[10] machinery and food fall in the opposite sides of the distribution with a (maximum) score of 3.1 and 2.0. Primary metals and food unequivocally arise as the least technically-advanced sectors also in terms of state-of-art products'

[9]In the regression analysis, forward citations are corrected for truncation by recurring to the non-structural, fixed-effects approach proposed by Hall *et al.* (2001). For sake of brevity, summary statistics on adjusted series are not reported in the main text, but are shown in the Appendix. Notice that the common quality factor is obtained using forward citations corrected for the year/sector effect of truncation.

[10]By construction, the common quality factor is distributed as a standard normal.

quality.[11]

Less univocal conclusions can be drawn on the evolution of quality, Δq, probably due to the erratic nature of advances in the technical frontier. Whereas the most pronounced quality jump is registered by chemicals if considering forward citations or claims (95 and 61), on the other side backward citations point to electrical equipment as the most dynamic sector (46) whilst, surprisingly, the common quality factor to primary metals (0.40).

Rent protection activities are approximated by such direct indicators as claims, blocking patents and patent counts. Claims track the legal borders of public protection and, by nature, defend innovations from imitation. However, more explicit strategies of 'patent blocking' are adopted by incumbents to avoid the circumvention of existing patents by challengers, as well as the market entry of competing innovations; a fence is usually constructed around a major invention by demanding protection for several other related secondary inventions, but with no intention to ever introduce them to the market (Dinopoulos and Syropoulos, 2007, p. 311). To this aim, an indicator of the blocking effort is built by considering, for each patent, all the applications made by its assignee in the same two-digit technological sub-class. As a further, direct measure of patent fence, we consider the amount of sectoral applications; it reflects the idea that at least a portion of patent counts are conceived for defensive goals. For each of these indicators (hereinafter denoted by d), we take the total sum of the variable at an industry-level. Rent protection activities, p, are hypothesized to linearly depend on patent fence, $p_{it} = f(d_{it}) = \chi_i \cdot \chi_t \cdot d_{it}$. d_{it} should explicitly capture the propensity of incumbents to erect barriers to protect their position, χ_i and χ_t the industry-specific and time-invariant profile of this process. Overall, US manufacturing firms issued (almost) 4 thousand annual applications between 1973 and 1996, for which they made 49 thousand claims, and cumulated about 66 thousand patents to block innovations by potential new comers. At an industry-level, there is small variation among these indicators, as they reflect the extent of industry engagement in patenting where, in absolute terms, machinery is the most active.

As indirect proxy of rent protection, a concentration indicator of technological activity is constructed using patent citations. For each individual application, we compute a normalized Herfindahl index of the cites received by sector of origin, and then take the average value of this indicator at an industry level. It should reveal the technological strength of a patent within the sector: more concentrated the citations, the less pervasiveness the underlying technology across industries; it

[11] By comparing the extent of research engagement with the maximum quality of innovative output, it can be observed the relatively poor performance of transport equipment. It may alternatively signal the low research productivity in this sector, the scarce pervasiveness of innovation in the related technological fields, or the drastic nature of industry-specific technical change that may be characterized by a continuous sequence of radical breakthroughs.

implies that the market power of patent assignees is higher and effective barriers may be erected to prevent further entries in the sector. Moreover, as measure of technological closeness between the product leader and its followers, we take the inverse of quality jump computed on (adjusted) forward citations. This indicator approaches to zero when the distance from them is indefinitely large, while it rises with the technological similarities. Information provided by indirect indicators of rent protection completes the outline on lobbying effort. Over the period 1973-1996, the concentration index of technical knowledge amounts to 51% for manufacturing; it means that, on average, about a half of citations received come from the same sector of the patent; this value ranges from 60% of chemicals and electrical equipment to less than 30% of stone, rubber and primary metals. On the one hand, rubber and chemical exhibit the lowest level of technological closeness (around 0.3-0.4) whilst, one the other, food and primary metals are characterize by a vis-a-vis competitiveness (1.9 and 1.7). For manufacturing, the indicator of technological closeness amounts to 1.

5 Empirical Results

5.1 Variety expansion (VE)

The regression analysis begins by assessing the steady-state set-up developed by Aghion and Howitt (1998) that has previously been estimated by Zachariadis (2003) (model A). Unless differently indicated, all estimates shown throughout the paper are obtained using as instruments from two- to four-year lagged values of the right-hand side (endogenous) variables as well as the deterministic elements of the empirical model (industry-specific intercepts, time-trend, common time dummies, etc.). For any specification estimated, we report the Sargan-Hansen test of over-identifying restrictions, and the panel stationarity test devised by Shin and Snell (2006) applied to the residuals of each system equation. The acceptance of the null hypothesis by the former statistics ensures that the instruments employed are sufficiently informative for parameter identification; on the other hand, by failing to reject the null hypothesis, the latter guarantees that our empirical model suitably describes an equilibrium (stationary) relationship.[12]

[12]This statistics, denoted by τ_{NT}, consists in the panel-based mean group value of the stationarity test (η_i) devised by Kwiatkowski *et al.* (1992)

$$\tau_{NT} = 1/\sqrt{N}\sum_{i=1}^{N}(\frac{\eta_{iT} - \mu}{\omega})$$

where $\mu = 1/6$ and $\omega^2 = 1/45$. τ_{NT} admits the null hypothesis of stationarity against the alternative of unit roots in the presence of both heterogeneity across cross-section units and serial

The baseline specification of model A uses a homogenous time-trend in the equation for the rate of innovation (column 1, Table 2). This regression is characterized by a low explanatory power as neither regressor is significant. If compared to the evidence provided by Zachariadis (2003) for the period 1963-1988, our findings seem to indicate that a deep change might be occurred in the fundamentals of US economy in more recent years, and that the drivers of growth identified by the Schumpeterian models might not be as effective as in the past. Another plausible explanation could be found in estimation bias potentially induced by the assumptions at the basis of the empirical framework.

As a first control, a larger degree of heterogeneity is admitted in the patenting process by including industry-specific time trends into equation 1 (col. 2). In this case, the negative effect of R&D intensity on the rate of innovation, ι, is significant (-0.102), while the rate of patenting is confirmed to be unrelated to technology growth, $\Delta \ln a$. The F-statistic test rejects the null hypothesis of homogenous time trends across sectors ($\chi^2(11)$=417.9, p-value$<$0.001).

Secondly, we assess the robustness of results to the rate at which ideas are assumed to become obsolete (δ). This assumption determines the value of patent stock, and thus influences the dynamics of the rate of patenting, ι. The bias related to such a measurement error might reverberate through the system equations, undermining the consistency of estimates. The rationale of imposing an intermediate value of 15% for the decay parameter derives from the presence of two opposite forces in innovation activity, the so-called *stand-on-shoulders* effect and the *fishing-out* effect. On the one hand, ideas flow freely across space and time, and contribute to the knowledge endowment used for creating new ideas, implying a low value for δ. On the other hand, patented ideas are continually displaced by new technical advances, leading to suppose a high value for δ. If no obsolescence was assumed, older ideas would fully concur to the creation of the current knowledge stock and to new inventions ($\delta = 0$); in this case, the stand-on-shoulders effect would be dominant. Assuming a full decay would instead nullify the contribution of current ideas to the next technological advances ($\delta = 1$), maximizing the fishing-out effect.

To assess the sensitivity of estimates, the two subsequent sets of regressions adopt two alternative (intermediate) values for the rate of depreciation, respectively 7 and 30%. Using a rate of 7% exacerbates the detrimental effect of R&D

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correlation across time periods. τ_{NT} is distributed as one-sided standard normal. Following Shin and Snell (2006, p. 131), we apply a small-sample adjustment based on a correction factor of 0.5

$$\widetilde{\tau}_{NT} = (\omega/\hat{\omega})^{0.5}\tau_{NT} \qquad \hat{\omega} = 1/(N-1)\sum_{i=1}^{N}(\eta_{iT} - \overline{\eta})^2$$

where $\overline{\eta}$ is the cross-section mean of Kwiatkowski *et al.* (1992) statistics.

intensity on the realization of innovation, especially in the specification with heterogenous trends (col. 3 and 4). By contrast, imposing an annual decay of 30% completely reverses the results. Indeed, in regressions (5) and (6), the ratio between R&D expenses and gross output is found to enhance the rate at which patentable innovations are introduced (0.053 and 0.086 respectively). Furthermore, when heterogenous trends are used (col. 6), technology (or productivity) growth is positively and significantly affected by the rate of innovation (0.133).[13] Comparing column (6) with the baseline results of Zachariadis (2003), our estimates are one third smaller.[14] Overall, the present empirical set-up appears suitable to describe innovation performance of US firms only by explicitly acknowledging a larger (deterministic) heterogeneity in the patenting process and a more rapid obsolescence for patented ideas. It may reflect the emergence in more recent years of a fiercer R&D competition that is highly differentiated across sectors.

As discussed in section (3.1), the effort in the generation of new ideas is likely to be better captured by the *level* of research activities. In this connection, using a global sample of countries, Luintel and Khan (2009) show that the volume of R&D resources has an effect on patenting consistent with the predictions of growth theory, while R&D intensity (defined in occupational terms) presents diminishing returns. This may in part explain the negative coefficient for r/y found in regressions (2) through (4). To tackle this issue we re-estimate the original version of the R&D race designed by Aghion and Howitt (1998) by considering research effort, n_{it}, as ratio between the volume of sectoral R&D input and the economy-wide level of leading-edge productivity, r_{it} and A_t (model B). In Table 3, regressions (1) through (3) use the stock of real R&D expenditure as proxy for r_{it},[15] while the second part of the table adopts R&D employment. Both sets of regressions are estimated using heterogenous trends and the entire array of values for the depreciation rate considered above. The picture arising from Table 3 is consistent with one provided by the former results. When the cumulative value of research expenses is used, R&D input is confirmed not to enhance the rate of innovation. On the other hand, the level of leading-edge productivity raises the cost of further technological advances, lowering the probability to introduce of a new

[13]The relatively low value of the Sargan-Hansen test for the specifications based on heterogenous trends reveals the good explanatory power of such variables as instruments.

[14]See Zachariadis (2003, col. I, Tab. 2, 1S, 2S). Our analysis departs from this work as we also include Petroleum and Other manufacturing sectors; nevertheless, all the results of the paper are robust to the exclusion of such two sectors

[15]The cumulative value of R&D expenses is constructed with the same procedure followed for the stock of patent counts (see the Appendix). Using the annual flow of R&D expenditure as proxy for r_{it} yields consistent results; this variable is however characterized by less powerful instruments. Adopting heterogenous rates for the depreciation of patent and R&D stocks delivers qualitatively similar outcomes.

patentable idea; the impact of this factor ranges from -3.424 to -1.135.[16] Looking at the specification for technology growth, the rate of patenting is found to exert a positive effect only when we admit a fast decay for the cumulative value of patent counts and R&D expenses (see column 3).

Table 3 about here

The research technology designed by Aghion and Howitt (1998) is then re-estimated using research employment as proxy for r_{it} (columns 4-6). In this case, the volume of R&D resources exhibits a negative effect on the rate of innovation only when adopting a rate of depreciation of 7% (regression 4); this finding is however plagued by the low power of instruments (Sargan-Hansen test p-value=0.06). Interestingly, if a faster rate of obsolescence is allowed for, the estimates of the extended specification are consistent with both the theoretical expectations (col. 6). The coefficient of R&D input amounts to 0.109, while the detrimental effect of innovation complexity on the rate of patenting, as proxied by leading-edge productivity parameter, is of -1.455. In turn, the rate of innovation is still confirmed to speed up technology growth, showing a double effect with respect to one found in Table 2 (0.239 against 0.133).

5.2 Diminishing technological opportunities (DTO)

In assessing the R&D race devised by Segerstrom (1998) innovation engagement is measured by R&D occupation, ℓ. On the other side, the degree of R&D difficulty, x, which is the crucial force to remove the scale effect from the Schumpeterian growth framework, is approximated by the ratio between R&D expenses and gross output. Indeed, albeit intensity measures are unfit to reveal cross-sectional disparities in research levels, they may nonetheless be capturing the 'congestion' that arises in ideas production when increasingly larger resources are devoted to developing new goods or production technique (Luintel and Khan, 2009). This explantation is also borne out by the evidence illustrated in section (5.1).

Table 4 about here

Column (1) of Table (4) displays the results for the baseline DTO specification (equations 17-18). The R&D technology under examination appears empirically well-grounded: the probability of success for a typical firm engaging a R&D race, ι, rises with the volume of research resources, ℓ. On the other hand, ι is lowered by the degree of R&D difficulty, x. It should be pointed out that the negative

[16] In terms of magnitude order, the estimates of A_t obtained through the indicator of relative productivity described in the main text fall between those yielded by the technology index of aggregate manufacturing and those yielded by the highest value of sectoral technology index.

effect of the latter factor largely prevails on the positive one of R&D employment (-0.258 against -0.157). It implies that increasingly larger volumes of R&D inputs are needed to maintain constant over time the capacity to obtain some output from innovation activity. This effect is reinforced by the increasing returns of patenting activity on the dynamics of innovation difficulty, $\Delta \ln x$: a 1% increase in the rate of patenting speeds up the rise in the intensity of research effort by over a 1.2%.[17] It strongly supports the view advanced by Segerstrom (1998) that innovating is progressively harder and complex. To a broad extent, this evidence is consistent with Schettino (2009) who considers a reduced form of Segerstrom's technology where the change in R&D difficulty is driven by research employment, and the corresponding coefficient is interpreted as an inverse measure of the scale effect.

In column (2), this type of R&D race is re-estimated through two-stage least squares, 2SLS. By exploiting contemporaneous cross-equation correlation, the three-least squares (3SLS) estimator is more efficient than 2SLS but, contrarily to the latter estimator, is inconsistent when the empirical model is mis-specified. However, in our case, results are similar. Ax expected, parameters are estimated less precisely by 2SLS, and now the effect of ι on the change of R&D difficulty is significant at a 10% only. The statistical difference between three- and two-least squares results has then been checked by means of the Hausman test; the failure to reject the null hypothesis ensures that the three-least squares estimator is preferable for our empirical set-up as being more efficient ($\chi^2(37)$=14.7, p-value=1.00).

A further concern in this kind of estimation is the wide across-industry variation in the dynamics of variables; since this source of bias is often related to the level of data aggregation, it may be appropriate to weight observations with industry size (Kahn and Jong-Soo, 1998). To this aim, regression (3) uses as weights the (contemporaneous) amount of patent counts (taken in logs), here considered as proxy of innovation capacity. These findings do depart from the baseline estimates of column (1) only for a stronger impact of R&D difficulty on the rate of innovation (-0.304).[18]

One of the main motivations behind the removal of the scale effect from the Schumpeterian growth setup is that, over the long-run, TFP growth is stationary in most countries despite the upsurge in R&D resources. This fact is explained with the rising complexity of innovation featuring the modern market competition. How innovation difficulty is measured turns out to be a crucial issue for our analysis. For this reason, as alternative to the intensity of R&D expenditure, regression (4) uses the amount of R&D expenses per each patent, which is another

[17]Diagnostic tests confirm the good informative capacity of the instruments used, as well as the appropriateness of the specification employed as equilibrium framework.

[18]Results do not change either by adopting weights based on counts taken at the beginning year, or when an alternative measure of innovation capacity (R&D expenditure) or industry size (gross output) is used.

typical (inverse) measure of research productivity.[19] In this case, the negative effect of research difficulty on ι is smaller than in regression (1), -0.179 against -0.258. On the other side, the dynamics of R&D difficulty appears more heavily affected by the capacity to introduce innovations (-1.574), even though a large cross-sectional variation limits the significance of this regressor to a 10% level.

The last two regressions of Table (4) assess the robustness of this form of R&D technology to the depreciation rate used to build patent stocks. When a rate of 7% is adopted, R&D employment is insignificant for the probability of patenting, whilst the impact of R&D difficulty is stronger (-0.322); furthermore, the effect of the rate of innovation on the dynamics of research difficulty is weaker (and significant at a 10% only). Specularly, the baseline results of column (1) are broadly confirmed when an obsolescence rate of 30% is assumed for patented ideas (col. 6). As a whole, the R&D technology designed by Segerstrom (1998) appears more robust to the assumptions at the roots of the empirical model than shown by the framework based on variety expansion.

Table 5 about here

As an extension of the DTO setup so far considered, Table (5) displays the estimates of the R&D technology designed by Li (2003).[20] Regressions (1) adopts the maximum amount of unadjusted cites received by a patent as quality indicator. All the estimated parameters are statistically significant and coherent with the hypotheses of theoretical models. The only exception can be found in the quality of the state-art product, q, that turns out to be unrelated to the rate of patenting, ι. The probability of introducing a patentable innovation is raised by the across-industry quality spillover Q (0.152), and by the amount of resources devoted to R&D activities, ℓ (0.092). The difficulty to perform innovation, as proxied by the intensity of R&D expenses, is confirmed to reduce the patenting probability, ι (-0.341). The rate at which an innovation is generated is still proved to promote the pace at which R&D difficulty rises over time (1.296); finally, the quality jump, Δq, is found to be determined by the quality-adjusted rate of innovation, $\tilde{\iota}$ (1.775). Diagnostic tests stress the validity of the instruments employed (Sargan-Hansen test p-value=0.99), as well as the residuals' stationarity in each equation (Shin-Snell test p-value=0.43, 0.57 and 0.62).

Next, we re-estimate the Li's technology by controlling for the effect of truncation that affects forward citations. In column (2), the number of cites received by any individual patent has been normalized to the yearly mean of manufacturing citations; it amounts to eliminating the year-effect of truncation. In column

[19]Real R&D expenses (per patent) are preferred to research employment as R&D input indicator to limit the degree of collinearity between ℓ and x in the equation for the patenting rate.

[20]For sake of brevity, only 3SLS results are reported, since they are largely confirmed by the alternative procedures of estimation employed above (results available upon request).

(3), individual citations are instead scaled on industry average in order to purge the year/sector distortion. These two regressions deliver a similar picture. The sole exception can be identified in the process underlying quality jump, Δq, that appears unrelated to $\tilde{\iota}$ when the adjustment to manufacturing mean is applied, suggesting that type correction may be unfit to adequately describe the evolution of q. In comparison to column (1), the rate of innovation benefits from a lower spillover, while the effect of both R&D employment and R&D difficulty is reinforced. With respect to the Segerstrom's technology (col. 1, Table 4), the impact of ℓ and x on the patenting rate, and that of ι on R&D difficulty are larger in absolute terms. It may have two possible explanations. On a theoretical ground, it may reflect a better formulation of the true technology of research provided by this model; on a statistical ground, it may derive from the usage of a more powerful set of instruments.

In alternative to forward citations, regressions (4) and (5) employ backward citations and claims as indicators of patent quality. In both cases, there is evidence of a negative across-industry externality. These variables seem to behave as inverse measures of innovation contained in state-of-art product once one controls for the deterministic profile of their evolution over time;[21] indeed, backward citations are sometime inserted by the examiner, whilst claims are artificially added by the applicant to extend as much as possible the breadth of legal protection. It should also be emphasized that when we use the common quality factor extracted from (adjusted) forward citations, backward citations and claims (col. 6), quality variables are never significant and, as a consequence, the Li's technology collapses into the one devised by Segerstrom; it is caused by the low power of the lagged values of residual quality indicator as instruments. In light of these results, the analysis proceeds by considering forward citations adjusted for the year/sector effect of truncation as quality indicator.

In order to control the robustness of estimates reported in column (3), we use R&D expenses per patent count as alternative measure of research difficulty. In column (7), the detrimental effect of x on the rate of innovation is sensibly lower (-0.174), whilst that of ι on the change of R&D difficulty is strengthened (1.630). Surprisingly, the average quality of state-of-art products, Q, turns out to be insignificant for the rate at which firms introduce innovations, while quality jump is affected by $\tilde{\iota}$ to a smaller extent.

As a final check, we evaluate this type of R&D race by considering the two alternative rates of depreciation for patent stocks adopted above. These findings largely bear out those of columns (3), even though diverging indications come

[21] R&D employment is insignificant for explaining the rate of innovation when backward citations are used; the value of the Sargan-Hansen test however points out the partial inadequacy of the instruments employed in this regression. Using claims, ℓ and q show a positive impact on ι, while $\tilde{\iota}$ is not significant for quality jump.

from regressions (8) and (9) concerning the forces driving the rate of innovation. If one assumes a slow rate of obsolescence (7%) research difficulty arises as key determinant of the probability to succeed in a R&D race, as the negative impact of this factor exceeds those of quality spillover and research employment (-0.369 against 0.107 and 0.131). By contrast, when the rate of depreciation is fixed to 30%, the cumulated effect of Q and ℓ prevail on that of x (0.053 and 0.236 against -0.168). These checks confirm the appropriateness of using an intermediate rate of 15% for the decay parameter, as yielding coefficients that fall between those obtained with the two other measures adopted.

5.3 Rent protection activities (RPA)

The R&D technology proposed by Dinopoulos and Syropoulos (2007) departs from the baseline DTO framework analyzed above as considering the *level* of rent protection activities, p, as determinant of the *level* of difficulty to perform R&D, x. As described in section (3.2), the absence of an appropriate measure of RPA induces us to follow a double identification strategy. In both types of regressions, the set of instruments employed includes only four-year lagged explanatory variables, along with the deterministic elements of the empirical model.[22] The left-hand side of Table (6) shows the results yielded by the direct procedure of identification. In column (1), RPA are measured by the total amount of priorities claimed at an industry level. This variable turns out to be flawed to explaining R&D difficulty, whereas the patenting probability is borne out to be explained by R&D employment and R&D difficulty. A similar result is obtained by considering blocking patents, i.e. the total sum of applications made by the assignees within the same technological subclass of the original patent (column 2). The non-stationarity of residuals in the equation for R&D difficulty indicates that the results of column (1) and (2) should be taken with caution. Inference improves at a first sight when the number of patent counts are used as proxy of RPA. In column (3), lobbying activity is found to raise innovation complexity (-0.178), even though only at a 10% level of significance. A closer inspection nonetheless reveals that this finding is not robust; indeed, when innovation difficulty is approximated by R&D expenses per patent count the coefficient of RPA becomes negative, -0.977 (col. 4). It strongly contrasts with the results for the DTO framework where the parameters remained stable across the specifications considered, independently of how R&D difficulty was measured. By selecting a different rate of obsolescence for patented ideas (see column 5 and 6), coefficients resemble those observed in column (3). Two noteworthy points are however in order. On the one hand, in column (5) the

[22]Findings do marginally change by recurring to a different set of instruments; these however are affected by a very low explanatory power.

size of rent protection effect is relatively low, and now this variable lies at the border of the significance region. One the other hand, the validity of estimates reported in column (6) is severely undermined by the weakness of instruments (Sargan-Hansen test p-value=0.06), as well as by the unit roots contained in the residuals of the equation for innovation difficulty (Shin-Snell test p-value=0.04).

Table 6 about here

The indirect strategy of identification hinges on technological concentration and closeness as indicators of RPA; they are respectively defined by Herfindal index of citations (h) and the inverse of the quality distance between the two mostly cited patents (c). These findings are displayed in the right-hand side of Table 6. If considered together (col. 7), both variables appear significant, but the rejection of the null hypothesis by the Sargan-Hansen test warns against the statistical robustness of this finding (p-value=0.02). The same occurs when the Herdindal index is employed as sole explanatory variable of R&D difficulty (col. 8). Instead, taken alone, technological closeness is positively and significantly related to the level of research complexity (0.041). Whereas regression (9) suffers the weakness of instruments to a lesser extent (Sargan-Hansen test p-value=0.08), estimates do not achieve a satisfactory degree of statistical robustness, exactly as occurring for patent counts. Indeed, the coefficient of RPA completely loses significance when R&D difficulty is measured by research expenses per application. Moreover, as diagnostic tests denote, the regressions based on the alternative rates of ideas' obsolescence do not rely upon sufficiently informative instruments (col. 11), or fail to meet the stationarity condition in the residuals of the equation for R&D difficulty (col. 12).[23]

Table 7 about here

In conclusion, we assess the R&D race traced by Sener (2008) combining the main features of the RPA and DTO approaches. These estimates are reported in Table (7) and follow a two-step strategy of analysis identical to the one adopted above.[24] As illustrated by the left panel of the table, the results yielded by the direct procedure of identification are doubtlessly poor. A moderate improvement is observed following the second strategy of identification. If we admit an interactive effect between technological concentration and closeness, and scale it on

[23]Compared to Segerstrom's technology, the effect of the determinants of the rate of innovation is overstated due to the different set of instruments used.

[24]The results of Table (7) are obtained using as instruments from two- to four-year lags of the explanatory variables, as well as the deterministic elements of the model. In the left-hand side of the table, the variables used as proxy for RPA are expressed in millions to reduce the discrepancy in the scale order of regressors.

the degree of innovation difficulty, there is indication that both mechanisms elaborated by the Schumpeterian growth theory may be operating in the growth of research complexity (column 7). The role of the forces identified within the DTO setup, as quantified in Table (4), is largely confirmed. On the other side, the join effect of RPA indicators is found to amount to 0.016. Though, when the focus is placed upon any single indirect measure of lobbying, only technological closeness arises as determinant of the change in innovation difficulty (0.007); indeed, from a statistical point of view, regression (9) satisfies all the desirable properties, in contrast to what occurs to the specification based on the Herfindahl index of citations (see col. 8). Albeit this conclusion is not supported by the results obtained with to R&D expenses per patent as empirical counterpart of R&D difficulty (col. 10), a strongly favorable indication comes from the regressions using the alternative rates of decay for patent stocks, where the coefficient of p/x is always statistically significant and stable in magnitude. These findings in part restore the legitimacy of the rent protection mechanism devised by Dinopoulos and Syropoulos (2007), crediting it as source of innovation complexity to the same extent of exhausting technological opportunities.

6 Concluding remarks

This paper has explored the soundness of the R&D technologies designed by the main Schumpeterian models of endogenous growth. The aim was of understanding whether these models hinge on solid foundations and can be used as guidelines for tailoring growth-oriented policies of innovation. Thus far, econometric works have mainly looked for whether the reduced form of Schumepeterian growth models adequately replicates the main macroeconomic facts; on the other hand, calibration studies have assessed the normative implications of such models, i.e. whether it is better to tax or subsidize R&D activities. In this sense, the paper should be considered a valuable attempt to fill a relevant lack of literature.

The strategy of the work was of estimating the most popular forms of R&D technology developed by the branches of Schumpeterian growth theory based on variety expansion, diminishing technological opportunities and rent protection activities. The R&D races incorporated within the theories featured by diminishing technological opportunities seem to behave better, as proved by the results for the research technology thought up by Segerstrom (1998) and for the one devised by Li (2003) allowing for the effect of product quality. With regard to the R&D framework based on variety expansion traced by Aghion and Howitt (1998), corroborative evidence is found only under relatively restrictive conditions. On the other hand, the barriers erected by incumbents to enhance the innovation complexity of challengers, as introduced by Dinopoulos and Syropoulos (2007), are effective only when interacting with exhausting technological opportunities in the manner described by Sener (2008). The robustness of results has been checked by approximating theoretical variables with a large array of empirical indicators, and by changing the assumptions underlying the regression framework. Though, it should not be concluded that the latter types of research technology are less relevant on a empirical ground. Indeed, the scope of the analysis has clearly been limited by data availability in terms of industry disaggregation, time coverage and appropriate indicators of lobbying activity. The legitimacy of these alternative forms of R&D race may be restored by using more adequate data, or extending the analysis to the most recent years, when the explosion of patenting activity and R&D engagement has triggered the take-off of the knowledge economy. This will be object of further research.

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Table 1: **Summary statistics**, average 1973-1996

			Food, Kindred, Tobacco	Chemicals, Allied Products	Petroleum, refining, extraction	Robber products	Stone, Clay, Glass	Primary metals	Fabricated metal products	Machi-nery	Electrical equip.	Transport equip.	Professional Scientific instruments	Other	Total
1)	Rate of patenting (%)	ι	15.4	16.6	16.3	16.8	16.8	15.4	16.3	17.5	18.9	16.5	18.3	17.7	16.9
2)	R&D intensity (%)	n, x	0.3	3.9	1.2	1.2	1.0	0.6	0.5	5.2	6.1	7.8	5.7	0.3	2.8
3)	R&D capital (billions)	r	7.1	71.2	5.6	6.3	4.3	7.1	5.3	72.4	27.8	191.2	35.9	11.8	37.1
4)	R&D intensity growth	$\Delta \ln x$	2.1	1.9	-2.1	-3.1	-1.8	0.1	1.3	1.4	-1.5	0.0	2.6	4.3	0.4
5)	Technology growth (%)	$\Delta \ln a$	3.4	0.6	-0.3	0.2	0.3	0.4	0.2	1.4	0.8	1.1	0.2	1.7	0.8
6)	R&D employment (thousands)	ℓ	8.0	67.4	10.6	11.5	5.6	6.6	9.1	77.6	101.9	138.4	48.1	17.5	41.8
7)	Forward citations	q, Q	68.5	279.0	73.1	217.8	101.4	65.8	103.0	279.9	266.2	96.8	283.0	181.1	168.0
8)	Backward citations	q, Q	74.6	172.6	81.2	125.3	88.3	65.0	101.0	135.4	156.5	66.4	156.3	146.5	114.1
9)	Claims	q, Q	88.3	235.5	103.8	125.0	112.7	91.7	124.3	201.7	179.2	104.1	176.7	124.8	139.0
10)	Quality factor	q, Q	2.0	2.9	2.1	2.6	2.3	2.1	2.4	3.1	2.9	2.3	2.9	2.7	2.5
11)	Change in forward cites	Δq	11.3	94.5	12.7	70.8	22.2	12.2	26.8	68.4	59.2	26.8	58.4	51.4	42.9
12)	Change in backward cites	Δq	11.3	40.3	21.5	17.3	11.9	22.1	24.6	17.8	46.4	7.9	14.3	37.1	22.7
13)	Change in claims	Δq	23.0	61.4	22.3	26.1	34.6	19.7	26.4	49.3	32.5	29.0	51.4	20.0	33.0
14)	Change in quality factor	Δq	0.19	0.23	0.21	0.34	0.24	0.40	0.26	0.31	0.34	0.29	0.25	0.26	0.28
15)	Total claims (thousands)	p	5.0	89.7	7.5	32.2	7.7	4.8	41.4	139.4	121.0	15.5	72.1	48.1	48.7
16)	Blocking patents (thousands)	p	2.4	151.6	18.2	19.0	5.5	4.8	13.7	240.7	238.1	9.4	78.6	12.6	66.2
17)	Patent counts (thousands)	p	0.4	6.8	0.5	2.8	0.6	0.4	3.8	11.2	9.1	1.4	5.2	4.2	3.9
18)	Concentration index (%)	h	54.3	62.8	38.6	25.9	22.1	27.7	35.0	54.0	61.6	44.2	51.7	48.2	51.4
19)	Technological contiguity	c	1.9	0.4	1.0	0.3	1.4	1.7	1.0	0.9	0.6	1.4	0.7	0.9	1.0

Table 2: Estimates of R&D technology by Aghion and Howitt (1998) (model A)

	(1)	(2)	(3)	(4)	(5)	(6)
eq. 1: $\ln \iota$						
$\ln r/y$	-0.049	-0.102**	-0.146**	-0.298**	0.051*	0.086**
	(0.032)	(0.039)	(0.033)	(0.040)	(0.028)	(0.035)
trend	0.011**		0.012**		0.007**	
	(0.001)		(0.001)		(0.001)	
eq. 2: $\Delta \ln a$						
ι	0.075	0.045	-0.001	-0.033	0.164	0.133**
	(0.029)	(0.097)	(0.152)	(0.123)	(0.120)	(0.085)
Sargan-Hansen test [p-value]						
	21.7	24.1	23.1	26.1	19.6	21.1
	[0.30]	[0.77]	[0.23]	[0.67]	[0.42]	[0.88]
Shin-Snell test [p-value]						
eq. 1	[0.17]	[0.71]	[0.13]	[0.62]	[0.16]	[0.69]
eq. 2	[0.40]	[0.50]	[0.32]	[0.46]	[0.47]	[0.54]
trend	homo-genous	hetero-genous	homo-genous	hetero-genous	homo-genous	hetero-genous
depreciation rate used for stocks (δ)	0.15	0.15	0.07	0.07	0.15	0.15

Notes: Three-stage least squares estimates. Heteroskedasticity-robust standard errors reported in rounded parentheses. Equation 1 includes industry fixed-effects, time-trends, and AR(2) errors. Equation 2 includes AR(1) errors. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. Sargan-Hansen test checks the null hypothesis that there are no over-identification restrictions. Shin-Snell test checks the null hypothesis that each equation's residuals are panel stationary. P-value in squared brackets. **, * significant at 5 and 10% respectively.

Table 3: Estimates of R&D technology by Aghion and Howitt (1998) (model B)

	(1)	(2)	(3)	(4)	(5)	(6)
eq. 1: $\ln \iota$		R&D capital			R&D employment	
$\ln r$	-0.304**	-0.112**	0.020	-0.158**	0.007	0.109**
	(0.068)	(0.038)	(0.023)	(0.057)	(0.048)	(0.032)
$\ln A$	-3.424**	-2.503**	-1.135**	-2.900**	-2.555**	-1.448**
	(0.308)	(0.236)	(0.184)	(0.325)	(0.269)	(0.205)
eq. 2: $\Delta \ln a$						
ι	0.083	0.118	0.190**	0.100	0.146	0.239**
	(0.122)	(0.096)	(0.084)	(0.122)	(0.096)	(0.085)
Sargan-Hansen test: $\chi^2(35)$ [p-value]						
	45.9	41.0	44.5	49.0	40.2	40.9
	[0.10]	[0.22]	[0.13]	[0.06]	[0.25]	[0.23]
Shin-Snell test [p-value]						
eq. 1	[0.69]	[0.67]	[0.64]	[0.66]	[0.68]	[0.70]
eq. 2	[0.55]	[0.60]	[0.63]	[0.52]	[0.57]	[0.60]
depreciation rate used for stocks (δ)	0.07	0.15	0.30	0.07	0.15	0.30

Notes: Three-stage least squares estimates. Heteroskedasticity-robust standard errors reported in rounded parentheses. Equation 1 includes industry fixed-effects, time-trends, and AR(2) errors. Equation 2 includes AR(1) errors. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. Sargan-Hansen test checks the null hypothesis that there are no over-identification restrictions. Shin-Snell test checks the null hypothesis that each equation's residuals are panel stationary. P-value in squared brackets. **, * significant at 5 and 10% respectively.

Table 4: Estimates of R&D technology by Segerstrom (1998)

	(1) 3sls	(2) 2sls	(3) weighted 3sls	(4) 3sls (x=R&D exp. per count)	(5) 3sls (δ =0.07)	(6) 3sls (δ=0.30)
eq. 1: $\ln \iota$						
$\ln \ell$	0.157**	0.171**	0.170**	0.135**	0.050	0.211**
	(0.041)	(0.053)	(0.042)	(0.036)	(0.046)	(0.034)
$\ln x$	-0.258**	-0.274**	-0.304**	-0.179**	-0.322**	-0.145**
	(0.034)	(0.042)	(0.035)	(0.025)	(0.038)	(0.029)
eq. 2: $\Delta \ln x$						
ι	1.236**	1.354*	1.226**	1.574*	1.135*	1.330**
	(0.606)	(0.790)	(0.610)	(0.846)	(0.646)	(0.608)
Sargan-Hansen test: χ^2 [p-value]						
	64.1	56.7	62.8	59.6	57.3	69.7
	[0.12]	[0.30]	[0.15]	[0.78]	[0.71]	[0.95]
Shin-Snell test [p-value]						
eq. 1	[0.50]	[0.47]	[0.47]	[0.71]	[0.40]	[0.60]
eq. 2	[0.50]	[0.53]	[0.58]	[0.59]	[0.50]	[0.55]

Notes: Heteroskedasticity-robust standard errors reported in rounded parentheses. Equation 1 includes industry-specific intercepts and time trends, as well as AR(2) errors, equation 2 common time dummies and AR(1) errors. Regression (3) uses patent counts (in logs) as weights. Unless differently specified, R&D difficulty is measured by the ratio between R&D expenditure and gross output, and a depreciation rate of 15% is used to build patent stocks. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. Sargan-Hansen test checks the null hypothesis that there are no over-identification restrictions. Shin-Snell test checks the null hypothesis that that each equation's residuals are panel stationary. P-value in squared brackets. **, * significant at 5 and 10% respectively.

Table 5: Estimates of R&D technology by Li (2003)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
eq. 1: $\ln \iota$									
$\ln Q$	0.152**	0.109**	0.087**	-0.115**	-0.116*	-0.006	0.039	0.107**	0.053**
	(0.032)	(0.032)	(0.035)	(0.041)	(0.059)	(0.042)	(0.032)	(0.042)	(0.027)
$\ln \ell$	0.092**	0.213**	0.217**	0.035	0.182**	0.103**	0.140**	0.131**	0.236**
	(0.042)	(0.045)	(0.044)	(0.044)	(0.059)	(0.044)	(0.037)	(0.048)	(0.035)
$\ln x$	-0.341**	-0.296**	-0.298**	-0.272**	-0.240**	-0.216**	-0.174**	-0.369**	-0.168**
	(0.031)	(0.035)	(0.035)	(0.034)	(0.042)	(0.032)	(0.025)	(0.038)	(0.028)
$\ln q$	-0.017	-0.013	0.009	-0.003	0.136**	0.010	0.027	-0.012	0.020
	(0.032)	(0.037)	(0.038)	(0.039)	(0.060)	(0.033)	(0.033)	(0.045)	(0.028)
eq. 2: $\Delta \ln x$									
ι	1.296**	1.330**	1.304**	1.179**	1.241**	1.153**	1.630**	1.148*	1.476**
	(0.561)	(0.561)	(0.555)	(0.574)	(0.559)	(0.520)	(0.765)	(0.589)	(0.567)
eq. 3: Δq									
$\tilde{\iota}$	1.775**	0.459	1.099**	0.757**	0.065	0.099	1.007*	1.672*	0.784**
	(0.443)	(0.600)	(0.540)	(0.130)	(0.276)	(0.184)	(0.542)	(0.928)	(0.335)
Sargan-Hansen test: χ^2 [p-value]									
	83.4	94.6	100.4	127.0	95.5	155.1	108.4	94.2	110.0
	[0.99]	[0.76]	[0.61]	[0.07]	[0.74]	[0.00]	[0.39]	[0.77]	[0.35]
Shin-Snell test [p-value]									
eq. 1	[0.43]	[0.63]	[0.61]	[0.50]	[0.49]	[0.58]	[0.73]	[0.57]	[0.66]
eq. 2	[0.57]	[0.56]	[0.56]	[0.16]	[0.49]	[0.11]	[0.58]	[0.38]	[0.58]
eq. 3	[0.62]	[0.45]	[0.15]	[0.12]	[0.18]	[0.41]	[0.16]	[0.15]	[0.15]
Quality (q and Q)	forward citations	for. cites adjusted for year effect	for. cites adjusted for year/sector effect	backward citations	claims	common latent factor	for. cites adjusted for year/sector effect	for. cites adjusted for year/sector effect	for. cites adjusted for year/sector effect
Difficulty index (x)	R&D intensity	R&D intensity	R&D intensity	R&D intensity	R&D intensity	R&D intensity	R&D exp. per patent	R&D intensity	R&D intensity
Depreciation rate (δ)	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.07	0.30

Notes: Three-stage least squares estimates. Heteroskedasticity-robust standard errors reported in rounded parentheses. Equation 1 includes industry-specific intercepts and time-trends, and AR(2) errors. Equation 2 comprises common time dummies and AR(1) errors, Equation 3 industry fixed-effects and AR(1) errors. Unless differently specified, R&D difficulty is measured by the ratio between R&D expenditure and gross output, and a depreciation rate of 15% is used to build patent stocks. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. Sargan-Hansen test checks the null hypothesis that there are no over-identification restrictions. Shin-Snell test checks the null hypothesis that each equation's residuals are panel stationary. P-value in squared brackets. **, * significant at 5 and 10% respectively.

Table 6: Estimates of R&D technology by Dinopoulos and Syropoulos (2007)

	direct identification						indirect identification					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
eq. 1: $\ln \iota$												
$\ln \ell$	0.405**	0.405**	0.405**	0.265**	0.298**	0.416**	0.368**	0.366**	0.399**	0.214**	0.303**	0.395**
	(0.109)	(0.106)	(0.109)	(0.095)	(0.121)	(0.085)	(0.102)	(0.102)	(0.108)	(0.088)	(0.118)	(0.083)
$\ln x$	-0.426**	-0.407**	-0.441**	-0.246**	-0.553**	-0.275**	-0.398**	-0.396**	-0.418**	-0.176**	-0.549**	-0.250**
	(0.082)	(0.078)	(0.081)	(0.057)	(0.086)	(0.067)	(0.078)	(0.079)	(0.081)	(0.061)	(0.088)	(0.065)
eq. 2: $\ln x$												
$\ln r$	0.011	0.002	0.178*	-0.977**	0.163*	0.180*						
	(0.088)	(0.032)	(0.099)	(0.139)	(0.099)	(0.099)						
$\ln h$							0.613**	631**				
$\ln c$							(0.212)	(0.215)				
							0.050*		0.041*	0.046	0.040*	0.041*
							(0.028)		(0.022)	(0.031)	(0.022)	(0.022)
Sargan-Hansen test: χ^2 [p-value]												
	32.2	36.5	32.6	30.6	25.7	40.2	47.4	45.7	39.3	35.2	33.4	47.7
	[0.27]	[0.13]	[0.25]	[0.33]	[0.59]	[0.06]	[0.02]	[0.02]	[0.08]	[0.68]	[0.22]	[0.01]
Shin-Snell test [p-value]												
eq. 1	[0.42]	[0.39]	[0.42]	[0.73]	[0.36]	[0.49]	[0.31]	[0.33]	[0.41]	[0.73]	[0.36]	[0.49]
eq. 2	[0.05]	[0.04]	[0.16]	[0.15]	[0.15]	[0.04]	[0.30]	[0.12]	[0.14]	[0.14]	[0.09]	[0.60]
Rent protection indicator (r)	claims	blocking patents	patent counts	patent counts	patent counts	patent counts	concentration, closeness	concen-tration	compe-tition	compe-tition	compe-tition	compe-tition
Difficulty index (x)	R&D in-tensity	R&D in-tensity	R&D int. tensity	R&D exp. per count	R&D in-tensity	R&D in-tensity	R&D in-tensity	R&D in-tensity	R&D in-tensity	R&D exp. per count	R&D in-tensity	R&D in-tensity
Depreciation rate (δ)	0.15	0.15	0.15	0.15	0.07	0.30	0.15	0.15	0.15	0.15	0.07	0.30

Notes: Three-stage least squares estimates. Heteroskedasticity-robust standard errors reported in rounded parentheses. Equation 1 includes industry-specific intercepts and time-trends, and AR(2) errors. Equation 2 includes industry fixed-effects, common time dummies, and AR(1) errors. Unless differently specified, R&D difficulty is measured by the ratio between R&D expenditure and gross output, and a depreciation rate of 15% is used to build patent stocks. 4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. Sargan-Hansen test checks the null hypothesis that there are no over-identification restrictions. Shin-Snell test checks the null hypothesis that each equation's residuals are panel stationary. P-value in squared brackets. **, * significant at 5 and 10% respectively.

Table 7: Estimates of R&D technology by Sener (2008)

	direct identification						*indirect identification*					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
eq. 1: $\ln \iota$												
$\ln \ell$	0.089**	0.172**	0.091**	0.119**	-0.020	0.167**	0.152**	0.140**	0.155**	0.126**	0.061	0.207**
	(0.037)	(0.040)	(0.036)	(0.034)	(0.041)	(0.030)	(0.038)	(0.038)	(0.039)	(0.034)	(0.043)	(0.032)
$\ln x$	-0.205**	-0.235**	-0.211**	-0.166**	-0.270**	-0.120**	-0.257**	-0.252**	-0.258**	-0.175**	-0.330**	-0.143**
	(0.030)	(0.034)	(0.030)	(0.025)	(0.034)	(0.025)	(0.032)	(0.031)	(0.032)	(0.024)	(0.036)	(0.027)
eq. 2: $d \ln x$												
ι	0.860	0.821	0.939	1.191	0.770	1.028*	1.502**	1.418**	1.578**	1.487*	1.688**	1.506**
	(0.591)	(0.631)	(0.589)	(0.796)	(0.646)	(0.581)	(0.650)	(0.592)	(0.666)	(0.866)	(0.737)	(0.642)
p/x (X 1000)	0.001**	0.000	0.006**	0.002	0.006**	0.006**						
	(0.000)	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)						
$(h \cdot c)/x$							0.016*					
							(0.009)					
h/x								0.030**				
								(0.011)				
c/x									0.007*	0.011	0.008*	0.007*
									(0.004)	(0.007)	(0.005)	(0.004)
Sargan-Hansen test: χ^2 [p-value]												
	74.9	75.8	73.1	64.3	66.7	77.4	64.8	79.7	64.8	61.3	57.0	71.2
	[0.06]	[0.03]	[0.07]	[0.16]	[0.15]	[0.03]	[0.22]	[0.03]	[0.22]	[0.33]	[0.47]	[0.10]
Shin-Snell test [p-value]												
eq. 1	[0.57]	[0.53]	[0.56]	[0.72]	[0.48]	[0.64]	[0.50]	[0.48]	[0.49]	[0.71]	[0.39]	[0.59]
eq. 2	[0.09]	[0.59]	[0.12]	[0.67]	[0.53]	[0.12]	[0.49]	[0.50]	[0.56]	[0.11]	[0.44]	[0.12]
Rent protection indicator (r)	claims	blocking patents	patent counts	patent counts	patent counts	patent counts	concentration, closeness	concen- tration	compe- tition	compe- tition	compe- tition	compe- tition
Difficulty index (x)	R&D in- tensity	R&D in- tensity	R&D int. tensity	R&D exp. per count	R&D in- tensity	R&D in- tensity	R&D in- tensity	R&D in- tensity	R&D in- tensity	R&D exp. per count	R&D in- tensity	R&D in- tensity
Depreciation rate (δ)	0.15	0.15	0.15	0.15	0.07	0.30	0.15	0.15	0.15	0.15	0.07	0.30

Notes: Three-stage least squares estimates. Heteroskedasticity-robust standard errors reported in rounded parentheses. Equation 1 includes industry-specific intercepts and time-trends, and AR(2) errors. Equation 2 includes common time dummies and AR(1) errors. Unless differently specified, R&D difficulty is measured by the ratio between R&D expenditure and gross output, and a depreciation rate of 15% is used to build patent stocks. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. Direct proxies of RPA are expressed in millions. Sargan-Hansen test checks the null hypothesis that there are no over-identification restrictions. Shin-Snell test checks the null hypothesis that each equation's residuals are panel stationary. P-value in squared brackets. **, * significant at 5 and 10% respectively.

Appendix

The work employs data for the period 1973-1996 taken from the following data sets:

1. NBER USPTO patent data files (from the Bronwyn Hall's homepage; release March 2006);

2. R&D expenses and employment, National Science Foundation (NSF);

3. EUKLEMS Industry Accounts (release March 2008);

4. Basu *et al.* (2006) technology index.

The NBER data file set contains information on individual granted patent applied from 1963 up to 2002. Citations are available only for those issued since 1975 onwards, while statistics on claims end in 1998. We consider all cited/citing patents applied by US residents (firms, individual inventors or non-profit organization) between 1973 and 1996 for which a SIC code was available (1,101,104 observations).

The rate of patenting at year t is defined as ratio between new patent counts, I_{it}, and the cumulative value of counts up to that year (K_{it}). K_{it} is built through the permanent inventory method and geometrical depreciation from the industry series of patent counts. The rate of depreciation, δ, is assumed to be constant among sectors and over time; it is fixed to 15% in baseline regressions, while values of 7 and 30% are used in robustness checks (see Zachariadis, 2003 and Hall *et al.*, 2005). The initial value K_{i0} is computed by means of the Hall and Mairesse (1995)'s formula:

$$K_{it} = I_{it} + (1-\delta)K_{i,t-1}, \quad K_{i0} = \frac{I_{i0}}{\delta + g_i},$$

where I_{i0} is the amount of patent counts at 1973, g_i the average annual rate of change of I_{it} between 1973 and 1996. This procedure has also been followed to build the cumulative value of total research expenditure, expressed in 1995 dollars.

The original number of patent counts is corrected for the truncation due to the time lag existing between the application and the grant date (on average 1 year and 11 months in our sample). It implies that the amount of applications is underestimated for the period before 1975, i.e. the first available granting year for cited/citing patents. During the 1970s, the probability for an application to be accepted within one year from the application date was of 25%, within two years of 77%, and 89% within three. After four years, the granting process of the 95% of applications came to an end, implying that a patent applied in 1970 was highly likely to be issued by 1975. Following Hall *et al.* (2005), the amount of pre-1975 applications, $\widetilde{I}_{it}$, has been corrected with a factor defined by the inverse of the cumulative probability of application-grant time lag, p_s, calculated on the overall sample, $C_s = (\sum_{s=1}^{2} p_{1975-s})^{-1}$, $s = 1, ..., 4$. The correction factor amounts to roughly 1 for patent applied in 1974 and to 1.5 for those of 1973. For these years, adjusted counts are given by $I_{it} = C_t * \widetilde{I}_{it}$.[25] Based on the application year, patents have been assigned to twelve manufacturing industries according to their first SIC code reported in the NBER USPTO data set. This classification is used to consistently aggregate statistics on R&D employment and R&D expenses as well.

The intensity of R&D expenditure is defined by total funds devoted to research activities over gross output, both taken at current prices. Total R&D expenditure is the sum of federal and private funds research activities. It is important to remark that NSF does not disclose publicly-funded R&D resources for the entire time-span. Hence, missing values are calculated by first interpolating the ratio between total and privately-funded R&D expenses and, then, applying this mark-up to private research expenditure. As an alternative indicator of R&D difficulty, we also use the ratio between R&D expenses and patent counts; the former variable is expressed in 1995 dollars and has been obtained by applying industry deflators of gross output to current prices expenditure.

The number of full-time equivalent R&D scientists and engineers (S&E) is utilized as a measure of R&D employment. Due to presence of some missing values; these series are completed by following a two-step procedure similar to that adopted for R&D expenditure: 1) for missing years, we interpolate the share of S&E on total employment of firms undertaking R&D activities, and then 2) we apply the interpolated shares to total employment of R&D-performing firms.

Data on technology index are available for detailed 21 manufacturing sectors. They are aggregated up to twelve industries, and then to total manufacturing, using the Divisia-Tornqvist index formula based on Domar weights, i.e. the current prices ratio between industry gross output and aggregate value added (respectively indicated with GO_{it} and VA_t):

$$\Delta \ln A_t = \sum_{i=1}^{12} \overline{s}_{it} \Delta \ln a_{it}$$

[25] The adoption of a similar correction for patents applied after 1996 (the last year considered in this analysis) is prevented from the availability of patent statistics up to 2002.

where $\overline{s}_{it}$ is a two-year average of the GO_{it}/VA_t ratio. A_t and a_{it} are then indexed to 100 in 1995. For each year, the economy-wide level of leading-edge technology is defined as deviation of the maximum value of industry technology index from the aggregate (manufacturing) value. The contribution of technologically advanced industries is constantly increasing over time since $\overline{s}_{it}$ is relatively stable with respect to technology growth, $\Delta \ln a_{it}$ (see the discussion in Whelan, 2003 and Venturini, 2007); this ensures that the largest deviation between sectoral and aggregate (manufacturing) levels of technology indicators is a good proxy of the relative technology frontier.

As a quality measure of state-of-art products, for each industry we consider the maximum number of forward citations, backward citations or claimed shown by a patent, q_j. It is well known that the most recently applied patents are affected by citation truncation. Indeed, the volume of their cites reduces with approaching to the end of the period under exam (the year 1996) as the time window to be cited is shorter than for older applications. This aspect is controlled for by applying the fixed-effect correction proposed by Hall *et al.* (2001). It amounts to scaling the citations received by any individual patent (one million and over observations) either on the mean of overall manufacturing or on that of reference industries. The former type of correction removes the (year) effect of truncation common to the whole patent sample, the latter the one which is specific to each sector.

As Lanjouw and Schankerman (2004) point out, however, these indicators are likely to convey different pieces of information about the true value of patent quality. By assuming q_j to be a latent factor common among such observable features, the process underlying the quality endowment of a patent can be formulated as a multiple-indicator model:

$$y_{kj} = \mu_k + \beta \mathbf{X}_j + \lambda_k q_j + e_{kj}.$$

y_{kj} is the log-value of the k indicator (adjusted forward citations, backward citations and claims) concerned with the jth patent. y_{kj} is hypothesized to be determined by some observable (exogenous) features, $\mathbf{X}_j$, and by the latent common factor, q_j. Such a quality variable is assumed to be distributed as a standard normal; λ is the loading factor denoting the degree of correlation existing between the different observable indicators. e_{kj} is a well-behaving error term that is typically associated with this process, μ_k a constant term. The key assumption of the multiple-indicator model is that the variability of each observable quality measure is generated by the common factor and the residual disturbance. q_j is estimated on the overall sample of individual applications through the two-step procedure proposed by Hall et al. (2007). Firstly, we build a system where each observable indicator of patent quality is regressed on the two (observable) exogenous characteristics (the application year and the technological sub-class (out of 36) of the patent), and the constant term:

$$y_{kj} = \mu_k + \beta_1 appyear_j + \beta_2 techclass_j + \epsilon_{kj}.$$

Secondly, the common quality factor is extracted from the residuals of such auxiliary regressions (so-called first-step residuals) by means of the method of maximum likelihood:

$$\hat{\epsilon}_{kj} = \lambda_k q_j + e_{kj}.$$

The score assigned to each patent is treated as a proxy of q_j; for each industry, the quality level of state-of-art products is defined by highest score assigned any year.

Table A.2 reports the correlation among the observable quality indicators (expressed in logs), the first-step residuals, and the estimated value of the latent quality, q_j. Looking at the original values, the strongest relationship arises between claims and backward citations (0.1800); however, one removed the effect of exogenous characteristics and of the constant term , as shown by first-step residuals, the highest degree of correlation is registered by adjusted forward citations and backward citations (0.1580). The loading factors show that the largest contribution to the variance of common quality factor, q_j, is given by forward citations (0.414), followed by claims and backward cites.

Along with total amount of claims and patent counts, as direct measure of rent protection we employ an indicator of patent blocking activities. It is built by considering for each individual patent, j, applied at year t, the amount of applications by its assignee in the same sub-technological class in that year. These values are then aggregated at an industry level according to the SIC code of patent j.

In the indirect identification, to measure the degree of technological concentration of a sector, we compute a normalized Herfindahl-Hirsh index on forward citations. N cites received by a patent, j in the sector i, are therefore distinguished by the origin of citing industries, s (time subscripts omitted):

$$\widetilde{H}_{ji} = \frac{N_{ji} \cdot H_{ji} - 1}{N_{ji} - 1} \qquad H_{ji} = \sum_{s=1}^{12} (\frac{N_{jis}}{N_{ji}})^2.$$

In the regression analysis, we use the industry average of patent concentration index: $h_i = \sum_{j=1}^{J} \widetilde{H}_{ji}$, where J is the total number of patents counted in each sector. Finally, as indicator of technological closeness, we take the inverse of the quality jump between the mostly cited patents, $1/\Delta q$ using data on forward citations corrected for the year/sector effect.

Table A.1: **Definition of variables**

	Label	**Definition**
ι	Rate of patenting	Patent counts / Stock of Patent counts
n	Research intensity	Total R&D expenses / Gross output
r	Research effort	Stock of R&D expenses
A	Economy-wide level of leading-edge technology	Maximum deviation of industry technology from manufacturing index
a	Technology growth	Change in sectoral technology index
ℓ	R&D Employment	Full-Time Equivalent Scientists and Engineers
x	Difficulty index	R&D expenses / Gross output; real R&D expenses patent counts
q $(Q = \sum_{i=1}^{12} q_{it})$	State-of-art product quality	Max number of forward cites, backward cites, claims and common quality factor
p	Rent protection activities	
	Direct:	
		Total claims
		Total blocking patents
		Total patent counts
	Indirect:	
h	Concentration	Normalized Herfindahl index of forward cites
c	Closeness	Inverse of the distance between the two mostly cited patents

Table A.2: **Correlation matrix among observable quality variables and latent common factor model, and values of related factor loadings**

	Original values (in logs)			
	Adjusted forward cites	*Backward citations*	*Claims*	*Quality factor*
Adjusted forward cites	1			
Backward cites	0.1166*	1		
Claims	0.1567*	0.1800*	1	
Quality factor	0.7090*	0.5638*	0.6375*	1

	First-step residuals			
	Adjusted forward cites	*Backward citations*	*Claims*	*Quality factor*
Adjusted forward cites	1			
Backward cites	0.1386*	1		
Claims	0.1580*	0.1322*	1	
Quality factor	0.7107*	0.5948*	0.6550*	1

	Factor loading		
	Adjusted forward cites	*Backward citations*	*Claims*
	0.4140	0.3465	0.3816

* significant at 5.

Table A.3: **Supplementary summary statistics**

	Rate of patenting ($\delta = 0.07$)	Rate of patenting ($\delta = 0.30$)	Relative technology level	R&D expenses per count	Forward cites adjusted for year effect	Forward cites adjusted for year/sector effect	Change in forward cites adjusted for year effect	Change in forward cites adjusted for year/sector effect
Food	7.5	30.4	0.82	3.4	8	8	1.3	1.2
Chemicals	8.6	31.5	1.00	1.9	31	37	10.0	11.9
Petroleum, refining	8.7	30.8	1.03	2.6	8	10	1.4	1.7
Rubber	8.9	31.6	1.09	0.4	25	26	8.3	9.2
Stone,	9.0	31.5	1.07	1.1	11	12	2.5	2.7
Primary metals	7.5	30.3	1.07	2.8	7	10	1.4	1.9
Fabricated	8.5	31.1	1.08	0.2	12	17	3.1	4.5
Machinery	9.7	32.2	0.93	1.1	33	34	8.6	8.1
Electrical eq.	11.2	33.3	1.01	0.7	30	25	6.5	5.9
Transportation eq.	8.6	31.4	1.07	23.4	11	15	3.0	4.1
Professional instruments	10.5	32.8	1.16	1.4	32	25	6.2	5.1
Other	10.0	32.3	0.99	0.5	21	24	5.7	6.4
Total	9.0	31.6	1.03	3.3	19	20	4.8	5.2