ISSN 1825-0211

LOOKING INTO THE BLACK BOX OF SCHUMPETERIAN GROWTH THEORIES: AN EMPIRICAL ASSESSMENT OF R&D RACES

Francesco VENTURINI

Quaderno n. 94 — Settembre 2011

QUADERNI DEL DIPARTIMENTO
DI ECONOMIA, FINANZA
E STATISTICA

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

Francesco Venturini*

September 2, 2011

Abstract

This paper assesses whether the most important R&D technologies at the roots of second-generation Schumpeterian growth theories are consistent with patenting and innovation statistics. Using US manufacturing industry data, we estimate various systems of simultaneous equations modeling the innovation functions underlying growth frameworks based on variety expansion, diminishing technological opportunities and rent protection activities. Our evidence indicates that innovation functions characterized by the increasing difficulty of R&D activity fit US data better. This finding relaunches the debate on the soundness of the new Schumpeterian strand of endogenous growth literature.

Keywords: R&D, patenting, Schumpeterian growth, US manufacturing.
JEL classification: O31, O41, O42.

*francesco.venturini@unipg.it. Department of Economics, Finance and Statistics, University of Perugia, Via Pascoli 20, 06123 Perugia (Italy). Tel.: +39 075 585 5291. I am grateful to Philippe Aghion, Antonio Minniti, Giulio Palomba, Carmelo Parello, Paul Segerstrom, Francesco Schettino and Thanasis Stengos for useful comments. I also wish to thank the seminar participants at the Scottish Economic Society Conference 2010, ZVI Griliches Summer School 2010, ICEEE 2011, ZEW SEEK Kick-off conference 2011, RCEA Workshop Advances in Business Cycles and Economic Growth Analysis 2011. The usual disclaimers apply.

1 Introduction

The critique formulated by Jones (1995a, 1995b), against the prediction of first-generation Schumpeterian growth models that productivity growth increases in the *level* of R&D resources (Figure 1), marked a change in the development of the endogenous growth theory. On a theoretical ground, alternative mechanisms have been suggested to eliminate what is known as the *scale effect* of R&D activity. On an empirical ground, the soundness of such theories has been assessed estimating one common reduced form of research technology using US industry or cross-country data; however, these studies do not offer adequate insights on some crucial issues of the underlying theories, i.e., how innovation process is exactly designed, its key forces, and consistency with R&D and patenting statistics. The present paper fills this lack by examining whether the innovation functions underlying the most important Schumpeterian growth theories are consistent with the real world of business research. Although this issue has been remained almost unexplored, it appears indispensable to both identify the most credible growth theory and help policy-makers tailor the most appropriate measures to promote economic development.

With the aim of removing the scale effect, a first body of theoretical studies emphasizes 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). Due to population growth, product varieties have to be expanded in order to satisfy consumer demand. This can be achieved by raising the volume of R&D resources, so to make research input per inhabitant stable over time. Along the steady-state growth path, the aggregate growth rate depends, among other things, on the R&D subsidy/tax rate. In the light of such properties, these are usually referred to as *fully-endogenous, scale-invariant* or *permanent effects on growth* models. A second direction has been explored by Jones (1995a), Kortum (1997) and Segerstrom (1998), who point out that a feature of modern innovation is the exhaustion of technological opportunities, which raises the difficulty of conducting research. Increasing resources are necessary to maintain a constant rate of innovation and a sustained economic growth. In such a framework, R&D policies affect growth only along transitional dynamics: for this reason, they are usually defined as *semi-endogenous, scale-invariant* or *temporary effects on growth* models. Lastly, research focus has recently shifted to rent protection activities, which incumbents undertake to reduce the technological opportunities of R&D activity by outside firms (Dinopoulos and Syropoulos, 2007). These activities consist of defensive patenting or expenses for specialized labor, lawyers and lobbyists, and are strategically aimed at lowering the probability for newcomers of introducing a frontier technology or a state-of-the-art product. Like the first strand of models, R&D policies can steadily fuel economic expansion in this set-up, and hence growth is *fully endogenous*.

As a result of competing views about the mechanism driving the growth process, several papers have assessed the soundness of the *fully-endogenous* growth models against *semi-endogenous* growth models. Using US manufacturing industry data, Zachariadis (2003) presents evidence in favor of the former theories. Research intensity is found to positively affect the rate of innovation, which in turn hastens technical progress. According to Laincz and Peretto (2006), data on US employment, R&D personnel and production establishments support the idea that the scale effect is sterilized by product proliferation. Examining the US macroeconomic performance, Ha and Howitt (2007) consistently show that semi-endogenous growth models do not behave as well as fully-endogenous growth theories. A similar conclusion is drawn by Madsen (2008b), applying to international data an extended framework which controls for technological catch-up and international technology spillovers.[1] Conversely, Madsen (2007) detects a stationary relationship between patent counts (research output) and R&D expenditure (research input) across OECD countries; this indicates that R&D activity may be characterized by constant returns to scale, confuting the hypothesis of either exhausting technological opportunities or product proliferation. Evidence in favor of semi-endogenous growth theory is sparse (Venturini, 2010 and, to some extent, Ang and Madsen, 2010 and Barcenilla-Visús *et al.*, 2010).

Using US manufacturing industry data for the period 1973-1996, this paper estimates various systems of simultaneous equations modeling the R&D technologies underlying the most important theories of Schumpeterian growth. Our evidence indicates that any growth framework has empirical foundations; however, the exhaustion of technological opportunities, which makes research less fertile over time, is the mechanism best matching the real dynamics of business innovation. The paper contributes to the literature in several respects. First, it directly looks into the black box of R&D-based endogenous growth models, by comparing various innovation functions on an empirical ground. Second, it overcomes the typical dichotomy between fully- and semi-endogenous scale-invariant Schumpeterian models, presenting a regression analysis based upon a more structured theoretical background. Third, it privileges cross-sectoral variation of data and focuses on the US, as most R&D-based growth theories are designed to describe innovation processes occurring at firm or industry level in a knowledge-based (frontier) economy.[2] Lastly, it is one of the first studies which joins patent quality statistics with traditional quantitative indicators of innovation output and research effort.

The outline of the work is as follows. Section 2 describes the analytical properties of the R&D technology at the basis of second-generation Schumpeterian growth theory. Section 3 develops the empirical set-up and illustrates the identification strategy. Section 4 describes innovation data for the US manufacturing sector. Section 5 presents the econometric results, and section 6 concludes.

2 R&D technology in Schumpeterian growth theory

Deliberate innovation activity, characterized by uncertain realization, is the milestone of R&D-based growth theory. The basic traits of R&D technology were originally developed by the first-generation Schumpeterian models of endogenous growth, following in the footsteps of the industrial organization literature on patent races (Aghion and Howitt, 1992; Segerstrom *et al.*, 1990; Grossman and Helpman, 1991, ch. 4). Such races play out at an economy-wide or industry level; they are assumed to be stochastic, memoryless processes characterized by free-entry conditions and exogenous probabilities of innovation. Firms target their research efforts to improve existing products, and do not benefit from cumulating unsuccessful research efforts; for this reason, newcomers can compete with incumbents in developing the next state-of-the-art product. The winner takes over industry leadership and earns monopoly profits up to the invention of the next state-of-the-art product. The probability that an innovation occurs is assumed to be independently distributed across firms, industries, and over time. The

[1] See also Zachariadis (2004), Bottazzi and Peri (2007), Ulku (2007a) and, in part, Ang and Madsen (2010). Sedgley (2006) develops (and) tests a scale-invariant growth model allowing for transitional dynamics and complementarities between knowledge and human capital.

[2] Aghion and Durleauf (2009, p. 22)

industry-wide rate of R&D success is defined as:[3]

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

where ω denotes industries and t time. λ (> 0) is the Poisson (instantaneous) rate of arrival, and $\ell(\omega, t)$ is the amount of specialized inputs devoted to R&D activities, typically labor (scientists and engineers) or research expenses. Since the most innovative ideas are patented, the rate of innovation is approximated by the rate of patenting.

The innovation function in equation (1) may be viewed as a re-parametrization of an ideas production function of the following form (Ha and Howitt, 2007):

$$\frac{\dot{i}(\omega, t)}{i(\omega, t)} = i(\omega, t)^{a-1} \lambda \big(\frac{\ell(\omega, t)}{V_t}\big)^b, \tag{2}$$

where $\dot{i}(\cdot)$ is the annual flow of new ideas; $i(\cdot)$ the stock of ideas available each year. $V_t = L_t^c$ captures the effect of product proliferation associated with population growth, L_t. c is the corresponding duplication parameter, ranging from 0 when all innovations are duplications, to 1 when there are no duplicating inventions. When $a = b = 1$ and $c = 0$, the expression for $\dot{i}(\omega, t)/i(\omega, t)$ boils down to equation (1). By empirically assessing innovation function (2), many works have sought to check the general validity of models based on variety expansion ($a = c = 1$, $b > 0$) against those based on exhausting technological opportunities ($a < 1$, $c = 0$, $b > 0$).

Variety expansion (VE). A first influential attempt to remove the scale effect from the endogenous growth framework is made by Aghion and Howitt (1998) and Howitt (1999). Such models are based on a research technology in which the industry-wide probability of introducing a new state-of-the-art product is generated by the following two-equation process:

$$\iota(\omega, t) = \lambda n(\omega, t) = \lambda \frac{r(\omega, t)}{A(t) m(\omega, t)} \tag{3}$$

$$\frac{\dot{a}(\omega, t)}{a(\omega, t)} = \sigma \iota(\omega, t). \tag{4}$$

λ is the productivity parameter of R&D activities performed to improve product quality; $n(\omega, t)$ is defined as ratio between research inputs devoted by each sector to vertical innovation, $r(\omega, t)$, and available product varieties multiplied by the total-economy leading-edge productivity level, $m(\omega, t)$ and $A(t)$. This type of correction is made to account for the forces of increasing complexity in production activities: the more product quality improvements, the more resource-intensive future technological advances. $n(\omega, t)$ may thus be thought as of a productivity-adjusted measure of research efforts. Another crucial insight of this framework is that, at an economy-wide level, leading-edge productivity, $A(t)$, grows at the same rate of industry productivity $a(\omega, t)$, as 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 the leading-edge productivity parameter, as well as in its industry counterparts, occurs as a result of the knowledge spillovers associated with R&D activities; the marginal impact of vertical innovation on knowledge stock is denoted by σ. This is the rationale behind equation (4). The main virtue of this

[3] In the following, a coherent notation across the parameters of the models taken into account is ensured by indicating industry-level variables in lower cases, and those pertaining to the overall economy (or manufacturing) in upper cases.

research technology is that of disentangling the effect of R&D activities on innovation output from that of innovation output on productivity, avoiding any mismeasurement due to the combination of knowledge and efficiency in Solow's residual (Ang and Madsen, 2010).

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 achievement of innovation. The rate of innovation is indeed hypothesized to be lowered by the difficulty associated with research activity, $x(\omega, t)$: researchers start off by pursuing the most promising projects and, if they fail, they try less promising projects. Higher values of $x(\omega, t)$ imply that research becomes less fertile: the same amount of R&D resources generates fewer inventions over time. To control for heterogeneity in innovation processes, Segerstrom (1998) assumes that the detrimental effect of research complexity is industry-specific; it contrasts with the formulation based on variety expansion shown above, where the rate of innovation is dampened by the frontier's productivity, which expands as a result of product proliferation. Moreover, in Segerstrom (1998), the rate at which $x(\omega, t)$ increases depends itself on the rate of research success according to parameter μ (> 0). The R&D race of this model is thus governed by the two following equations:

$$\iota(\omega,t) = \frac{Z\ell(\omega,t)}{x(\omega,t)} \tag{5}$$

$$\frac{\dot{x}(\omega,t)}{x(\omega,t)} = \mu\iota(\omega,t), \tag{6}$$

where Z (> 0) is an exogenous productivity parameter common to all sectors. According to equation (6), the rate of realization of current research efforts enhances the difficulty of introducing a patentable innovation in subsequent periods.

Li (2003) extends the previous innovation function in several respects. Two further explanatory factors of patenting are considered. First, he stresses the rise in innovation difficulty coming from past research successes. As products improve in quality and become more complex, the creation of the next state-of-the-art quality product becomes more difficult. The higher the quality of the state-of-the-art product, $q(j_\omega, \omega, t)$, the lower the rate of innovation $\iota(\omega, t)$. Second, innovating may 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-the-art products, $Q(t) = \sum_\omega q(j_\omega, \omega, t)$. ψ (> 0) is the corresponding parameter of externality. This kind of R&D race is investigated by following the formulation recently proposed by Minniti *et al.* (2008), in which product quality is hypothesized to evolve with random jumps of different magnitude drawn from a Pareto distribution, $\zeta = q(j_\omega + 1, \omega, t)/q(j_\omega, \omega, t) > 1$:

$$\iota(\omega,t) = \frac{Q(t)^\psi \ell(\omega,t)}{zx(\omega,t)q(j_\omega,\omega,t)} \tag{7}$$

$$\frac{\dot{x}(\omega,t)}{x(\omega,t)} = \mu\iota(\omega,t) \tag{8}$$

$$\dot{q}(j_\omega,\omega,t) = (\zeta-1)q(j_\omega,\omega,t)\iota(\omega,t), \tag{9}$$

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 state-of-the-art product and its predecessor (or follower) in the quality ladder which annually emerges in any industry. $\iota(\omega,t)q(j_\omega,\omega,t)$ may be thought as a quality-adjusted measure of the probability of innovating; it derives from the definition of quality improvement as the expected value between a positive jump $\dot{q}(j_\omega,\omega,t) = (\zeta-1)q(j_\omega,\omega,t) > 0$, 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 $1-\iota(\omega,t)$.[4] $\iota(\omega,t)q(j_\omega,\omega,t)$ determines the extent of the quality jump associated with the new state-of-the-art product.

Two important points on this innovation function are in order. First, it recognizes that knowledge spillovers originate from innovation quality, rather than from the amount of innovation output (patent counts) or, worse, of research inputs. Second, in comparison with the literature examining the relationship between innovation and productivity, equation (7) specifically identifies the channel through which firms (or industries) benefit from knowledge spillovers, i.e., a higher research fertility.

Rent protection activities (RPA). A mechanism alternative to the ones so far envisaged has been proposed by Dinopoulos and Syropoulos (2007). They identify in the rent-protection barriers that incumbent (innovating) firms erect to protect their positions the main impediment to the research of newcomers. RPA may involve excessive patenting, patent enforcement through litigation, practicing trade secrecy, lobbying the government to affect legislation, and corrupting the legal/political system. These activities enhance the difficulty which challengers face when entering an R&D race with the view of obtaining a new product (or technology).[5] Here, we employ the R&D technology proposed by Sener (2008). It combines the effect of RPA as formulated by Dinopoulos and Syropoulos (2007) with the baseline mechanism of DTO described above (see eqs. 5-6). This kind of R&D race assumes the following form:

$$\iota(\omega,t) = \frac{\ell(\omega,t)}{x(\omega,t)} \tag{10}$$

$$\frac{\dot{x}(\omega,t)}{x(\omega,t)} = \mu\iota(\omega,t) + \eta\frac{p(\omega,t)}{x(\omega,t)}. \tag{11}$$

Equation (10) closely corresponds to the rate of patenting devised by Segerstrom (1998), whereas equation (11) describes the evolution of R&D difficulty as dependent on two distinct forces. The former is the typical effect associated with the realization of innovation described by equation (6). The latter is the impact of rent protection activities performed at industry level, $p(\omega,t)$, scaled on the current level of R&D difficulty.[6] η captures the effectiveness of RPA on research difficulty; this parameter may either be interpreted as a proxy of the extent to which existing institutions protect intellectual property, or as the (time-invariant) productivity level of incumbents' lobbying outlays. Clearly, when $\mu > 0$ and $\eta = 0$, equation (11) boils down to the formulation of Segerstrom (1998). Conversely, when $\eta > 0$ and $\mu = 0$, equation (11) falls close to the RPA mechanism originally elaborated by Dinopoulos and Syropoulos (2007). The main discrepancy between the framework proposed by these authors and equation (11) is found in the assumption made on the nature of the rent-protection effect. R&D difficulty is modeled as a flow variable fully decaying at each instant in time in the original

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

[5]Grieben and Sener (2009) assess the RPA effect in a general-equilibrium North-South trade model.

[6]Equation (11) comes from rewording the law of motion for R&D difficulty proposed by Sener (2008) in terms of growth rates.

formulation, i.e., $x(\omega, t) = \eta p(\omega, t)$. By contrast, in equation (11) it is considered as a stock variable, to accommodate the possibility that RPA have persistent effects on the legislative and judicial system, or that the detrimental effects of R&D difficulty on technological advancements decrease slowly over time. As shown in an earlier version of this paper, the empirical counterpart of the system (10)-(11) outperforms the one originally conceived by Dinopoulos and Syropoulos (2007).

3 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 match notation with the standard practice of empirical literature, hereafter industries are indicated by i (in place of ω), and time and sectors are denoted as subscripts. The first point to be stressed is that log-linearization is implemented on the expression for the rate of innovation, ι. Any empirical specification is obtained from the theoretical counterpart by adding a deterministic part (fixed effects, time trends or time dummies). The equation for the rate of innovation, ι, includes both industry-specific intercepts, θ_i, and heterogenous time trends ϑ_i. θ_i should capture the time-invariant industry characteristics of the process underlying the probability of obtaining a patentable invention; ϑ_i should instead take the possible changes of the propensity to patent over time (Zachariadis, 2003, p. 580). Unless specified otherwise, all the specifications where the dependent variable is expressed as a percentage rate of change, or in first differences, omit time-invariant sectoral effects but include common time dummies to control for the impact of temporary shocks, TD (R&D policies, business cycle, changes in regulative frameworks, etc.).[7] 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 also include a set of control variables (C_{it}), to be introduced below, to assess the robustness of results.

We start by examining the R&D race at the basis of the variety expansion framework (Aghion and Howitt's technology) considering a productivity-adjusted measure of R&D input, $n_{it} = r_{it}/A_t m_{it}$ (Aghion and Howitt's technology, model A):

$$\ln \iota_{it} = \alpha_1 \ln n_{it} + \alpha_C \ln C_{it} + \theta_i + \vartheta_i T + \epsilon_{it} \quad (12)$$
$$\Delta \ln a_{it} = \beta_1 \iota_{it} + \beta_C C_{it} + \varepsilon_{it}. \quad (13)$$

According to theory, the predicted range of values for α_1 is $[0, 1]$, and $(0, +\infty)$ for β_1. $\alpha_1 = 0$ indicates that innovations are targeted to product duplication only, and $\alpha_1 = 1$ that they are truly novel (Ang and Madsen, 2010). However, we also estimate a more general innovation function that does not impose parameter restrictions for R&D input r_{it}, the frontier's productivity A_t, and product varieties m_{it} (Aghion and Howitt's technology, model B):

$$\ln \iota_{it} = \alpha_1 \ln r_{it} + \alpha_2 \ln A_t + \alpha_3 \ln m_{it} + \alpha_C \ln C_{it} + \theta_i + \vartheta_i T + \epsilon_{it} \quad (14)$$
$$\Delta \ln a_{it} = \beta_1 \iota_{it} + \beta_C C_{it} + \varepsilon_{it}, \quad (15)$$

$\alpha_1, \beta_1 > 0$, and $\alpha_2, \alpha_3 < 0$.[8] This specification has the advantage that it can be estimated safely with annual observations in place of long-differences or cointegration

[7] The appropriateness of the deterministic elements attached to each specification is confirmed by unreported F-test of significance.

[8] Common temporal controls are omitted from the specifications for $\Delta \ln a_{it}$ because of the procedure followed to build this technology indicator, which purges any systematic component from the dynamics of

equations, typically used with steady-state growth specifications (Ang and Madsen, 2010). Moreover, it better captures cross-sectional variation in the efforts made to generate new ideas as it rests upon *level* rather than *intensity* measures of research activity (Luintel and Khan, 2009); this issue will be discussed in-depth later.

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

$$\begin{aligned} \ln \iota_{it} &= \alpha_1 \ln \ell_{it} + \alpha_2 \ln x_{it} + \alpha_C \ln C_{it} + \theta_i + \vartheta_i T + \epsilon_{it} && (16) \\ \Delta \ln x_{it} &= \beta_1 \iota_{it} + \beta_C C_{it} + TD + \varepsilon_{it} && (17) \end{aligned}$$

where $\alpha_1, \beta_1 > 0$, and $\alpha_2 < 0$. As a second step, we estimate the system of three equations developed by Li (2003); in this set-up, the engine of innovation is represented by the (stochastic) qualitative evolution of state-of-the-art products, Δq, which is measured as the difference between the leader' s quality and that of the second most innovative product in the sectoral quality ladder (*Li's technology*):

$$\begin{aligned} \ln \iota_{it} &= \alpha_1 \ln Q_t + \alpha_2 \ln \ell_{it} + \alpha_3 \ln x_{it} + \alpha_4 \ln q_{it} + \alpha_C \ln C_{it} + \theta_i + \vartheta_i T + \epsilon_{it} && (18) \\ \Delta \ln x_{it} &= \beta_1 \iota_{it} + \beta_C C_{it} + TD + \varepsilon_{1,it} && (19) \\ \Delta q_{it} &= \gamma_1 q_{it} \iota_{it} + \gamma_C C_{it} + TD + \varepsilon_{2,it}. && (20) \end{aligned}$$

where $\alpha_1, \alpha_2, \beta_1 > 0$, $\gamma_1 > 1$, and $\alpha_3, \alpha_4 < 0$.[9]

In assessing the RPA set-up, we consider the empirical counterpart of the R&D technology designed by Sener (2008), as follows:

$$\begin{aligned} \ln \iota_{it} &= \alpha_1 \ln \ell_{it} + \alpha_2 \ln x_{it} + \alpha_C \ln C_{it} + \theta_i + \vartheta_i T + \epsilon_{it} && (21) \\ \Delta \ln x_{it} &= \beta_1 \iota_{it} + \beta_2 (p_{it}/x_{it}) + \beta_C C_{it} + +TD + \varepsilon_{it} && (22) \end{aligned}$$

with $\alpha_1, \beta_1, \beta_2 > 0$ and $\alpha_2 < 0$. In this framework, the main complication comes from the lack of adequate proxies for industry efforts in lobbying. For this reason, the impact of RPA is subsumed by adopting variables which on both theoretical and empirical grounds are argued to affect lobbying activities, and hence may raise research difficulty indirectly (*indirect identification*).[10] A similar strategy is followed by Comin and Hobijn (2009) to capture the effect of lobbying on cross-country technology diffusion. Since the effectiveness of lobbying is inversely related to its costs, and as these are higher in the presence of certain institutional characteristics, we can infer whether lobbying slows down the uptake of new technologies by looking at the relation between institutional factors and technology diffusion. Comin and Hobijn (2009) find that this effect is negatively significant, and stronger when a 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 by incumbents near the technological frontier. Accordingly, we hypothesize

the variable (Basu *et al.*, 2006). a_{it} is constructed as TFP growth net of the impact of non-technological effects (non-constant returns and imperfect competition, aggregation effects, varying utilization of capital and labor).

[9]The Pareto distribution, from which the theoretical parameter ζ $(= \gamma_1)$ is assumed to be drawn, may not have finite moments, and this condition may inhibit the use of traditional estimation techniques (Silverberg and Verspagen, 2007). However, the results of the current analysis do not depend on such distributional properties as holding for whatever type of distribution is imposed for ζ. For our purposes, a necessary condition to observe an improvement in the state-of-the-art products' quality is that ζ be greater than one $(\gamma_1 > 1)$.

[10]This amounts to assuming $\dot{x}/x = g\Big(p(u_1, u_2, ...)\Big)$, with $g'_p\Big(\cdot\Big) > 0$ and $p'_{u_j}(\cdot) > 0$, where u_j is an indirect indicator of RPA. In an earlier version of the work, we showed that the RPA impact cannot be identified through such *direct* measures as claimed priorities, blocking patents and total patent counts.

a relationship among the extent of technological market competition, product contiguity (denoted by h and c), and the RPA of the following form: $p_{it} = h_{it}^{\varphi} c_{it}^{\varsigma}$. In so doing, we keep the regression analysis as simple as possible by forcing factor elasticities φ and ς to take only two values, zero or one. This implies that three forms of indirect impact are admitted as regards research difficulty: 1) the impact of market concentration only ($\varphi = 1$, $\varsigma = 0$); 2) the impact of the technological closeness of competing products only ($\varphi = 0$, $\varsigma = 1$); and 3) a joint effect of both factors ($\varphi = \varsigma = 1$). This formulation admits the joint effect even when factors do not affect individually the dynamics of R&D difficulty.

In order to check the robustness of estimates, we consider numerous additional variables that might be shaping innovation performance (C). To exclude the possibility that technological laggards innovate more because they benefit from imitation, we include the distance to the innovation frontier (Acemoglu *et al.*, 2006); it is given by the ratio between the frontier and the industry value of research productivity, measured by the number of patent counts per real dollar spent on R&D. The sum of imports and exports over gross output is adopted to assess the benefits related to the trade openness of the sector (larger markets, cheaper inputs, induced changes in specialization; see Bloom *et al.*, 2010). We nonetheless consider the specific role of international technology spillovers by including the imports-weighted R&D capital of OECD partner industries; this is typically used to test whether knowledge diffuses across countries through the channel of trade (Coe and Helpman, 1995). As Aghion *et al.* (2005) point out, the degree of market power is another crucial characteristic that may shape innovation performance; for this reason, the profits-output ratio is introduced into the regression. According to Peretto (2007), firms more intensively take up innovation to find new growth opportunities when are subject to a heavier taxation; as a consequence, we also consider a proxy for the fiscal burden, defined as taxes on production and imports over gross output. The output share of skilled labour is instead introduced to circumvent the risk that estimates of theoretical parameters are plagued by the omission of human capital, given that high-tech industries employ more educated workers (Jorgenson *et al.*, 2005). The ratio between interests paid on loans and investment expenditure should instead identify the role of financial development. Structurally, R&D-intensive industries need more external funds which, however, are not always able to obtain because of a large share of intangible assets, difficult to collateralize. Due to this mismatch, financially developed industries are likely to be more prolific in patenting (Ilyina and Samaniego, 2010). Finally, the ratio between investment and capital service expenditure is used to filter out the effect of transitional dynamics; indeed, laggards may innovate at faster rates as they are at a lower stage of economic development, rather than for higher technological opportunities. Full details on control variables are given in the Appendix.

4 Data description

4.1 Sources and methodology

The analysis is performed on a panel of twelve US manufacturing industries: 1) Food, kindred products & tobacco; 2) Chemicals & allied products; 3) Petroleum, refining & extraction; 4) Rubber products & plastics; 5) Stone, clay & glass; 6) Primary metals; 7) Fabricated metal products; 8) Machinery, NEC; 9) Electrical equipment; 10) Transport equipment; 11) Professional & scientific instruments; 12) Others. The period covered spans from 1973 to 1996, that is the last year for which consistent series on patenting, R&D and productivity are available (see the Appendix for details). As in Zachariadis (2003), the rate of innovation, 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. Industry stocks of patented innovations are obtained from patent counts through the perpetual inventory method and geometrical depreciation (or obsolescence); unless otherwise specified, a standard decay rate of 15% is applied ($\delta = 0.15$). Patent data come from NBER USPTO database.

Research input is gauged by R&D employment (r_{it} and ℓ_{it}), i.e. full-time equivalent R&D scientists and engineers (source: National Science Foundation). As in Madsen (2008a), the productivity-adjusted measure of R&D engagement $n_{it} = r_{it}/A_t m_{it}$ uses total full-time equivalent employment as a proxy for variety expansion ($m_{it} \simeq e_{it}$): in most Schumpeterian growth models, the number of products is equal to the size of the population, and this ultimately determines occupational levels. Alternative proxies for m_{it} are real output, patent stocks and the interaction between the latter variable with employment (respectively indicated by y_{it}, k_{it} and $k_{it} \cdot e_{it}$). A_t is defined as the maximum value across industries of the pure technology index developed by Basu *et al.* (2006), taken as deviation from the mean of manufacturing.

The degree of R&D difficulty, x, is the crucial force removing the scale effect from the DTO growth framework. We propose to measure x with the ratio between R&D expenses and gross output (taken at current prices). This choice follows Luintel and Khan (2009), who argue that the effort in generating new ideas is better captured by *level* rather than *intensity* measures of research input. The latter indicators are suited for revealing the 'congestion' of ideas production when increasingly larger resources are devoted to developing new goods or production techniques. Indeed, since its origins, patent literature has shown that innovation outcomes are related to the volume of R&D resources, not to their intensity (Wilson, 2002, p. 291). Moreover, by measuring R&D difficulty with the research expenses-output ratio, equation (19) is consistent with the findings of Ngai and Samaniego (2010) on the dominant role played by diminishing returns to scale of innovation in explaining cross-industry differentials in R&D intensity. Evidence on Schumpeterian growth theory where indicators of R&D intensity are negatively related to patenting or productivity performance can be found in Ulku (2007a, 2007b), Barcenilla-Visús *et al.* (2010), Madsen (2008a), among others.

Innovation quality is primarily measured by patent forward citations, adjusted for the effect of truncation (Hall *et al.*, 2001); alternatively, we also employ backward citations, claims, and a common quality factor extracted from these indicators (Hall *et al.*, 2007). Claims specify the building blocks (components) of an innovation over which the inventor asks for legal protection; their number is indicative of the extent of innovation. Citations reflect 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 application or grant date. The rationale for using citations is that the more frequently a patent is cited, the larger its effect on the creation of further innovation. However, according to Lanjouw and Schankerman (2004), these measures convey different pieces of information on the quality of a patented innovation, and it may be more appropriate to extract a synthetic indicator from them, in order to gain as much information as possible. 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 manufacturing mean of any quality indicator is used as a proxy for the cross-industry knowledge spillover, Q_t.

As an indirect proxy of rent protection, a concentration indicator of technological activity is constructed with patent citations. There is reason to believe that more effective barriers to prevent further entries in the sector are erected if the concentration is relatively high. Hence, for each individual application, we first compute a normalized Herfindahl index of the citations received, distinguished by the origin sector of the citing patent, and then take the average value of this indicator at industry level. This measure reveals the technological strength of a patent within the sector: the more concentrated the citations, the less pervasive the underlying technology across industries, and the higher the market power of patent assignee. Lastly, in order to gauge the technological closeness between the product leader and its close follower, we take the inverse of the quality jump between (adjusted) forward citations. This indicator approaches zero when the distance between the first two most frequently cited patents is indefinitely large, and grows with the rise of product similarity.

4.2 Descriptive statistics

Table 1 lists mean values of the explanatory variables. Between 1973 and 1996, the probability of patenting, ι, was of 16.9% in the US manufacturing sector. Productivity-adjusted R&D input, n, measured by R&D scientists and engineers over the product between the frontier's TFP and labor force, amounted to 3.1. If we look at the *level* of research engagement, (r and ℓ), it is possible to see that 41,800 specialized workers were on average employed in US research laboratories, rising from 30,000 in the early 1970s to over 50,000 in the mid-1990s. On the other hand, the *intensity* of R&D expenditure on gross output, which is our key measure of research difficulty (x), was of 2.8%. The dynamics of this variable reveals that the difficulty of conducting research rose at an annual rate of 0.4%, $\Delta \ln x$.[11]

Table 1 about here

Focusing on technological performance in final production (a and A), it emerges that the productivity index grew by 0.8%. The relative level of the economy-wide, leading-edge technology, A_t, assumes a value of 1.17, indicating that the technical frontier of the most advanced industry lied approximately one-fifth above the manufacturing mean. The quality of state-of-the-art products is inferred through the patent quality statistics, q. The maximum number of (un-adjusted) forward citations was 168, which is a value 20 times higher than sectoral mean citations (see series adjusted for truncation). The corresponding values of backward citations and claims are lower, respectively 114 and 139, for the common quality factor 2.5. Qualitative advances of frontier products were particularly erratic and heterogenous (Δq); on average, quality jump ranged from 42.9 for unadjusted forward citations (5.2 for adjusted series) to 0.33 for the common quality index. According to the indirect proxies of RPA, the degree of concentration was of 51% (i.e. half the citations received by a patent came from its own sector); the indicator of technological contiguity between the two first state-of-the-art products in the industry quality ladder was slightly higher than one (1.04).

[11]Notice that, apart from the technologically leading sectors (electrical and transport equipment), the distributions of R&D *intensity* and R&D *level* do not perfectly match, suggesting that such indicators may convey different pieces of information on innovation performed at industry level.

5 Empirical Results

5.1 Variety expansion (VE)

The regression analysis is performed with the estimator of three-stage least squares. For each specification, we report the Sargan-Hansen test of over-identifying restrictions, and the panel stationarity test robust to cross-sectional dependence of Hadri and Kurozumi (2009), applied to the residuals of each system equation.[12] Acceptance of the null hypothesis by the former statistics ensures that the instruments employed are sufficiently informative for parameter identification; in contrast, by failing to reject the null hypothesis, the latter test guarantees that our empirical model suitably describes an equilibrium (stationary) relationship.

Table 2 about here

We begin by assessing the set-up developed by Aghion and Howitt (1998, model A). The baseline regression is characterized by particularly low explanatory power, as all the stochastic regressors are not significant (column 1, Table 2). The insignificance of the productivity-adjusted research input, n, is compatible with the possibility that innovation fuels product duplication. However, it may also be that our estimates are plagued by the bias induced by the assumptions underlying the empirical framework. Therefore, we first assess the robustness of the results to the rate at which ideas are assumed to become obsolete (δ). This assumption determines the value of patent stocks, influencing the dynamics of the patenting rate; the related bias may reverberate through the system equations and undermine the consistency of estimates. The rate at which ideas depreciate reflects the creative destruction exerted by current innovation on older ideas (Caballero and Jaffe, 1993). As alternative values for δ, we adopt rates of 7 and 30%. The former is the average value over time estimated by the above authors using US patent citation data; the latter is adopted to control for the large cross-sectional variation they found in estimating the effect of creative destruction.[13] Hall (2010) extrapolates knowledge depreciation from estimates of R&D returns, finding for US manufacturing firms rates that range from below zero to 28 per cent, depending on the extrapolation method used.

By using a rate of 7% we find a negative effect of productivity-adjusted R&D input, n, on the achievement of innovation (col. 2), which is incompatible with any theoretical prediction. By imposing an annual decay of 30%, the results somewhat improve, as n is found to positively affect the rate of innovation (0.200); this finding is consistent with

[12] All the estimates of 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. The key results are confirmed by adopting the two-stage least squares estimator (the difference between 2SLS and 3SLS results is checked by a Hausman test) or weighting observations with industry size (approximated by patent counts, R&D expenditure or gross output, taken in logs). The panel stationarity test adopts a AR(1) specification; the method proposed by Sul *et al.* (2005) is used to build the long-run variance.

[13] The choice of the obsolescence parameter mirrors two opposite forces characterizing innovation, the so-called *standing-on-shoulders* effect and the *fishing-out* effect. On one hand, ideas flow freely across space and time, and contribute to the endowment of knowledge used for creating new ideas (δ low). On the other hand, patented ideas are continually displaced by new technological advances, suggesting a rapid decay for knowledge (δ high). If no obsolescence is assumed, older ideas fully concur to the creation of the current knowledge stock and, hence, to new inventions ($\delta = 0$); in this case, the standing-on-shoulders effect is dominant. Instead, assuming full decay nullifies the contribution of current ideas to the next technological advance ($\delta = 1$), thus maximizing the fishing-out effect. A given amount of technological knowledge reduces to less than one percentage of its initial level after 64 years from its introduction when it depreciates at an annual rate of 7%, after 29 years decaying at a 15% rate, and 14 years at 30%.

Zachariadis (2003) and Ulku (2007a). Conversely, in each specification, the patenting rate is far from being significant in explaining the industry technical change, $\Delta \ln a_{it}$. To understand whether this result is driven by the nature of technology indicator used (col. 4), we re-estimate the model using output per worker as a productivity measure, but the explanatory variable of the second equation remains ineffective. Therefore, the assessment of the R&D technology based on variety expansion proceeds considering an innovation framework where technological knowledge depreciates rapidly (30% per year).[14]

In columns (5) through (7), we adopt alternative adjustment factors for R&D effort, based on variables that more directly approximate innovation (or production) output; in this case, correction for product proliferation omits the effect of the frontier's productivity, $A = 1$ (Madsen, 2008a). When patent stock is used as a proxy for product varieties ($m \simeq k$), we have a common normalization for the dependent variable (patent counts) and the explanatory variable (research input), yielding a smaller coefficient for adjusted R&D input (0.078). The fall in parameter size is even more pronounced if the adjustment factor is given by the interaction between patent stock and employment (0.043, $m \simeq k \cdot e$), whilst it is modest when we use real output (0.072, $m \simeq y$).

The right-hand side of Table (2) reports estimates including control variables. We first introduce the distance to frontier; in the patenting equation, we consider how far an industry is from the innovation frontier, in the TFP growth equation how far it is from the productivity frontier. In column (8), the adjusted R&D input is ineffective in enhancing the rate of innovation, whilst the positive coefficient of the control variable signals a significant convergence in patenting rates between laggards and leaders (0.208); taken together, it means that imitation is the prevailing force of innovation (Madsen *et al.*, 2010). The impact of R&D effort on patenting is always identified in the following regressions, expect when we control for financial development (col. 14). Notice that the empirical model meets all the theoretical predictions when it includes controls for the fiscal burden or the endowment of human capital (cols. 12 and 13). The coefficient of tax rate is positive in both equations of regression (12), indicating that firms might rely more upon innovation when taxation is high in order to gain extensive margins, and this then translates into a faster growth of productivity. Moreover, the outward orientation is associated with a higher innovation capacity (0.480, col. 9); however, this effect is unrelated to international technology spillovers as foreign R&D capital has a negative impact on patenting (-0.275, col 10). The latter finding is consistent with the view that the US are a net loser in terms of technology transfers (Luintel and Khan, 2004). The irrelevance of transitional dynamics in both system equations might instead reflect the limited time span of data, which inhibits a proper identification of the effect of this variable.[15]

Table 3 about here

In Table (3) we re-assess the R&D race designed by Aghion and Howitt (1998) separating the effect of R&D input, r_{it}, from those of the frontier's productivity and product varieties, A_t and m_{it} (model B). In column (1) we use a standard rate of depreciation of 15%, finding that the probability of introducing a new (patentable) idea is unrelated to R&D effort. Leading-edge productivity plays instead a detrimental role, as

[14]The subsequent regressions are also estimated adopting slower rates of obsolescence, obtaining poor results.

[15]We also control for parameter heterogeneity between high- and low-tech industries. These checks are conducted for each R&D technology considered in the paper; results are unreported as no statistical difference is detected across industry groups.

probably raising the cost of further technological advances (-2.545); in contrast to expectations, our proxy for product proliferation is positively associated with innovation outcomes (0.740). From the second equation, again it can be observed the inconsistency of innovation arrival for productivity growth. These findings are reaffirmed assuming a slower depreciation for patented ideas (7%, col. 2), but not in the presence of a rapid obsolescence when estimates correctly reflect the theoretical predictions, except for the positive effect of the labour force (30%, col. 3). Less satisfactory results are obtained using either output per worker as a productivity measure or alternative indicators of product varieties; in the former regression, productivity growth and patenting are confirmed to be unrelated (col. 4); in the latter, inference is plagued by the particularly low power of instruments (Hansen-Sargan test p-value$<$0.10 in cols. 5-7).

In robustness checks, R&D input is not significant if we consider the distance to frontier or the labour share of skilled workers employed in the industry (cols. 8 and 13). It is worth noting that the arrival rate of innovation is found to drive productivity growth in most regressions. A relevant exception is the specification allowing for transitional dynamics (col. 15). As in Ang and Madsen (2010), the development stage towards the steady-state appears to matter for productivity growth (first equation), where this factor prevails over the effect of patenting, but it is ineffective in explaining industry differentials in innovation outcomes (second equation). Overall, regressions (8) through (15) suggest that TFP growth equation may be misspecified, and a larger array of determinants should be taken into account, both theoretically and empirically.

5.2 Diminishing technological opportunities (DTO)

Estimation results of the R&D race devised by Segerstrom (1998) are reported in Table (4). As the baseline specification shows (col. 1, $\delta = 0.15$), this type of R&D technology appears empirically grounded: the probability of success for a typical firm engaging in an R&D race, ι, rises with the volume of research resources but decreases with R&D difficulty, ℓ and x. The effect of the latter factor prevails over the positive one of R&D employment (-0.258 against 0.157): it implies that firms need increasingly larger volumes of R&D input to maintain innovation output constant over time. This effect is reinforced by the increasing returns of patenting on the dynamics of innovation difficulty, $\Delta \ln x$: a 1% increase in the rate of patenting speeds up the growth in research intensity by over 1.2% (significant at a 10% level), supporting the view advanced by Segerstrom (1998) that innovating is progressively harder and more complex.

Table 4 about here

As regression (2) shows, the baseline results do not find support assuming relatively slow obsolescence for patented ideas: when a depreciation rate of 7% is imposed neither the effect of R&D employment on the arrival rate of innovation, nor that of patenting on the change of R&D difficulty are identified. Corroborative evidence is apparently obtained by imposing a rapid rate of depreciation (30%, col. 3); however, this inference is compromised by the scarce information of the employed set of instruments (Hansen-Sargan test p-value=0.05). Therefore, robustness checks are conducted in the following using a standard rate of knowledge depreciation (15%).

One of the main motivations behind the removal of the scale effect from the Schumpeterian growth set-up is that, over the long run, TFP growth is stationary despite the upsurge in R&D resources. As discussed above, this fact is explained by the rising complexity of innovation. How innovation difficulty is measured is then crucial in assessing this innovation function. As an alternative to R&D intensity, regression (4) uses the amount of R&D expenses per each patent count (i.e. the inverse of research productivity). However, in our sample, this indicator is characterized by large cross-sectional variation, which inhibits identification of the effect of patenting on the dynamics of R&D difficulty.

By and large, the baseline DTO framework is validated by the regressions including control variables (cols. 5-12). The rate of patenting is higher for industries far from the innovation frontier (0.252), those more prone to international trade (0.227), gaining higher profit rates (0.040), which are subject to a heavier taxation (0.261) or are at the earlier stages of convergence towards the steady-state equilibrium (-0.122). Conversely, the dynamics of R&D difficulty turns out to be unrelated to each of these factors. Moreover, it should be noticed that the effect of additional regressors is not always consistent with the VE framework; indeed, in this type of DTO set-up, both profitability and convergence towards the steady state are found to explain differentials in innovation rates across sectors.

Table 5 about here

In Table (5) we present estimates of the R&D technology designed by Li (2003). In regression (1), all the estimated parameters are statistically significant and consistent with the theory; the only exception is the quality of the state-of-the-art product (q), being unrelated to the rate of innovation (ι). The probability of introducing a patentable invention is raised by the across-industry quality spillover and the level of R&D input, Q and ℓ (0.077 and 0.212 respectively). As in Table (4), the difficulty of innovating, defined by the intensity of R&D expenses, is found to reduce the rate at which an innovation is generated (-0.300). The latter variable in turn speeds up the pace at which R&D difficulty grows over time (1.296). Finally, the quality-adjusted rate of innovation, $i \cdot q$, has a positive and statistically significant impact on the dynamics of the state-of-the-art quality (2.255); this effect is strong enough to stimulate significant quality improvements over time ($\Delta q > 0$), as witnessed by the rejection of the hypothesis that parameter γ_1 (or equivalently ζ) is equal to one (Wald test p-value=0.00).

The variant of Li's innovation function described by eqs. (18)-(20) is then evaluated by considering the two alternative obsolescence rates for patent stocks (cols. 2 and 3). If relatively slow obsolescence is assumed (7%), the dynamics of research difficulty turns out to be unrelated to patenting. By contrast, when a rate of 30% is imposed, there is no evidence of quality growth in the state-of-the-art products (Wald test p-value for γ_1 equal to one=0.21); this might explain the absence of evidence of the cross-industry quality externality in the first equation. As a further check for regression (1), we use R&D expenses per patent count as an alternative measure of research difficulty. In column (4), the detrimental effect of R&D difficulty, x, on the rate of innovation, ι, is definitively lower (-0.178). On the other hand, the patenting rate has a slightly stronger impact on the change in R&D difficulty (1.656), but the parameter still lies at the border of significance. Another limitation of this regression is that the average quality of state-of-the-art products, Q, loses significance in explaining the probability of winning an R&D race.

As an alternative to forward citations backward, citations and claims are used as patent quality indicators in regressions (5) and (6). These variables behave as inverse measures of the innovation content of state-of-the-art products, as indicating the presence of a negative externality among sectors. It may reflect the fact that most backward citations are inserted by examiners at USPTO,[16] and that claims are artificially added by the applicant to extend the breadth of legal protection as much as possible. When we use the common quality factor extracted from forward citations, backward citations and claims (col. 7), quality variables never reach a conventional level of significance, probably because of a relatively low power of instruments; in this case Li's technology collapses into that devised by Segerstrom.

It is worth pointing out implications of robustness checks reported on the right-hand side of Table (5). Most control variables play a role in the generation of new ideas (first equation), but they do not influence the dynamics of the forces underlying innovation processes, i.e. growth in R&D difficulty and product quality (second and third equation). These findings are not due to misspecification of the model, as they remain unchanged even when we introduce control variables expressed in logs or first differences. The absence of correlation between quality jumps and control variables appears reasonable in the light of the erratic evolution in product quality. Instead, the result for R&D difficulty closely follows Ngai and Samaniego (2010). Using US industry data, these authors calibrate a model where R&D intensity is assumed to depend on technological opportunities, appropriability and diminishing returns to R&D; they find that the latter factor completely explains industry differentials in research intensity. Looking at the determinants of patenting rate, it is interesting to observe that the across-industry quality spillover, Q, disappears when international knowledge flows are allowed for (col. 10). Following Luintel and Khan (2004), it may signal that technology transfers from the US mainly transit through dissemination of knowledge embodied in state-of-the-art products; in this sense, the coefficient of Q found in previous estimates might measure potential spillovers captured by foreign competitors.

5.3 Rent protection activities (RPA)

As a conclusive step of the work, we estimate the R&D technology featured by rent protection activities in the version proposed by Sener (2008). As described in section (3), the lack of an appropriate measure of RPA leads us to follow an indirect strategy of identification. In column (1), RPA are assumed to be inversely related to the across-industry dispersion of the received cites ($\varphi = 1, \varsigma = 0$). In this case, the effect of the variables identified by the theory as determinants of the rate of patenting is largely confirmed (0.140 for employment and -0.252 for research difficulty), as well as the role of the latter variable on the change in R&D difficulty (1.418). There is also evidence that the difficulty of innovating grows faster in technologically concentrated industries (0.300). Nevertheless, this inference has to be taken with extreme caution as instruments are not sufficiently informative (Sargan-Hansen p-value=0.02). Conversely, growth in research difficulty induced by RPA is not statistically significant when lobbying efforts are approximated by technological closeness (col. 2; $\varphi = 0, \varsigma = 1$). However, when an interactive effect between technological concentration and technological closeness is allowed for, it emerges that both the mechanisms elaborated by the Schumpeterian growth theory (DTO and RPA) may be behind the rise in research complexity (column 3; $\varphi = \varsigma = 1$). In terms of parameter size, the joint effect of RPA is found to fall between those yielded by using indirect indicators one at a time: ceteris paribus, a 1% increase in the lobbying activity raises research difficulty by over 0.016% (significant at a 10% level), and this reverberates through a lowering of patenting in the

[16] This result is consistent with Patel and Ward (2010), who find that the stock market value of US pharmaceutical firms decreases with backward cites made to patents of the same technological area.

industry (-0.257). The impact of RPA remains stable across the specifications using the alternative rates of obsolescence for patented ideas (cols. 4 and 5). As in Segestrom's technology, resorting to R&D expenses per patent as an empirical counterpart for R&D difficulty does not provide useful insights, as changes in this indicator cannot be predicted with the employed set of explanatory variables (col. 6). With regard to the forces driving the rate of patenting, the estimated coefficients are perfectly consistent with those found in the baseline DTO framework (see Table 4).

Table 6 about here

Inference on the detrimental effect of RPA for modern processes of innovation is partially supported by regressions including control variables. The interaction effect between technological concentration and technological contiguity is stronger and more significant when we consider the distance to innovation frontier (col. 7). The reverse occurs when profit rates are included into the specification: a larger profitability is associated with a higher probability to innovate and, consequently, to take over industry leadership; this makes difficult discerning the effect of the control variable from RPA, being the latter gauged by technological market concentration (and product contiguity). Finally, attention has to be paid to the role played by financial factors. Throughout the paper, financial development is not found to affect patenting, nor changes in productivity, research difficulty and product quality. It may occur as we look at cross-industry variation of data within the US; conversely, the majority of works use cross-industry, cross-country data where a large portion of variance is explained by international differentials in access to credit, the degree of external financial dependence, etc. (Ang, 2010). In such studies, financial development is found to contribute to innovation *directly*, but also *indirectly* by orienting funds towards innovative entrants and away from incumbents (Samaniego, 2010).

6 Concluding remarks

This paper has explored the soundness of the R&D technologies designed by the most recent Schumpeterian models of endogenous growth. The aim was to understand whether these models have solid foundations and can be used as guidelines for tailoring growth-oriented policies of innovation. The present work integrates the empirical literature inspired by the second-generation Schumpeterian growth theory, for which fully endogenous growth models replicate macroeconomic data better. Our evidence indicates that most characteristics of the R&D technologies designed by new endogenous growth theories are empirically grounded. However, the R&D race based on the mechanism introduced by Segerstrom, 1998 of diminishing technological opportunities fits US innovation statistics better, even when the change in state-of-the-art product quality is allowed for (Li, 2003). This effect is also found to interplay with barriers erected by incumbents to prevent the R&D competition of challengers, in the form described by Sener (2008). With regard to the R&D framework based on variety expansion of Aghion and Howitt (1998), corroborative evidence is obtained for an innovation framework where patentable knowledge becomes obsolete quite rapidly; mainly due to the increasing internationalization of knowledge, this scenario does not appear completely unrealistic, as the elapse of time during which research efforts are able to fuel own competitive advantage becomes progressively shorter.

In the light of such results, the main result of the literature that semi-endogenous scale-invariant growth models are empirically flawed should be reconsidered. Our conclusion should clearly be taken with the usual caution imposed by data limitation (industry disaggregation, time coverage, lobbying indicators, etc.). The legitimacy of the various forms of R&D technology will have to be re-examined in the near future by exploiting more adequate data and by considering the most recent years, when the global explosion of R&D and patenting activities triggered the take-off of knowledge economy. Nonetheless, we believe that the piece of evidence provided by this paper is a valuable starting point.

References

ACEMOGLU, D., AGHION, P. AND ZILIBOTTI, F. (2006). *Distance to Frontier, Selection and Economic Growth*. Journal of the European Economic Association, 4(1): 37–74.

AGHION, P., BLOOM, N., BLUNDELL, R., GRIFFITH, R. AND HOWITT, P. (2005). *Competition and Innovation: An Inverted-U Relationship*. Quarterly Journal of Economics, 120(2): 701–728.

AGHION, P., BLUNDELL, R., GRIFFITH, R., HOWITT, P. AND PRANTL, S. (2009). *The Effects of Entry on Incumbent Innovation and Productivity*. Review of Economics and Statistics, 91(1): 20–32.

AGHION, P. AND DURLEAUF, S. (2009). *From Growth Theory to Policy Design*. The International Bank for Reconstruction and Development/The World, Working paper No. 57.

AGHION, P. AND HOWITT, P. (1992). *A Model of Growth through Creative Destruction*. Econometrica, 60(2): 323–351.

— (1998). *Endogenous Growth Theory*. MIT Press, Cambridge.

ANG, J. B. (2010). *Financial Development, Liberalization and Technological Deepening*. European Economic Review, forthcoming.

ANG, J. B. AND MADSEN, J. B. (2010). *Can Second-generation Endogenous Growth Models Explain the Productivity Trends and Knowledge Production in the Asian Miracle Economies?* Review of Economics and Statistics, forthcoming.

BARCENILLA-VISÚS, S., LÓPEZ-PUEYO, C. AND SANAÚ, J. (2010). *Semi-endogenous Growth Theory versus Fully-Endogenous Growth Theory: A Sectoral Approach*. University of Zaragoza, mimeo.

BASU, S., FERNALD, J. G. AND KIMBALL, M. S. (2006). *Are Technology Improvements Contractionary?* American Economic Review, 96(5): 1418–1448.

BLOOM, N., ROMER, P. AND REENEN, J. V. (2010). *A Trapped Factors Model of Innovation*. LSE/Stanford mimeo.

BOTTAZZI, L. AND PERI, G. (2007). *The International Dynamics of R&D and Innovation in the Short and Long Run*. Economic Journal, 117(3): 486–511.

CABALLERO, R. J. AND JAFFE, A. B. (1993). *How High are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth*. NBER Macroeconomic Annuals, pp. 15–86.

COE, D. T. AND HELPMAN, E. (1995). *International R&D Spillovers*. European Economic Review, 39(5): 859–887.

COMIN, D. AND HOBIJN, B. (2009). *Lobbies and Technology Diffusion*. Review of Economics and Statistics, 91(2): 229–244.

DINOPOULOS, E. AND SYROPOULOS, C. (2007). *Rent Protection as a Barrier to Innovation and Growth*. EconomicTheory, 32: 309–332.

DINOPOULOS, E. AND THOMPSON, P. (1998). *Scale Effects in Schumpeterian Models of Economic Growth*. Journal of Evolutionary Economics, 9: 157–185.

GRIEBEN, W.-H. AND SENER, F. (2009). *Globalization, Rent Protection Institutions, and Going Alone in Freeing Trade*. European Economic Review, 53(8): 1042–1065.

GROSSMAN, G. M. AND HELPMAN, E. (1991). *Innovation and Growth in the Global Economy*. MIT Press, Cambridge, MA.

HA, J. AND HOWITT, P. (2007). *Accounting for Trends in Productivity and R&D: A Schumpeterian Critique of Semi-Endogenous Growth Theory*. Journal of Money, Credit and Banking, 39(4): 733–774.

HADRI, K. AND KUROZUMI, E. (2009). *A Simple Panel Stationarity Test in the Presence of Cross-Sectional Dependence*. Global COE Hi-Stat Discussion Paper Series 016.

HALL, B. H. (2010). *Measuring the Returns to R&D: The Depreciation Problem*. In *Contributions in Memory of Zvi Griliches* (edited by MAIRESSE, J. AND TRAJTENBERG, M.), pp. 341–381. National Bureau of Economic Research, Inc.

HALL, B. H., JAFFE, A. B. AND TRAJTENBERG, M. (2001). *The NBER Citations Data File: Lessons, Insights and Methodological Tools*. NBER Working papers 8498.

— (2005). *Market Value and Patent Citations*. Rand Journal of Economics, 36(1): 16–38.

HALL, B. H. AND MAIRESSE, J. (1995). *Exploring the Relationship between R&D and Productivity in French Manufacturing Firms*. Journal of Econometrics, 65: 263–93.

HALL, B. H., THOMA, G. AND TORRISI, S. (2007). *The Market Value of Patents and R&D: Evidence from European Firms*. NBER Working Paper No. 13426.

HOWITT, P. (1999). *Steady Endogenous Growth with Population and R&D Inputs Growing*. Journal of Political Economy, 107: 715–730.

ILYINA, A. AND SAMANIEGO, R. M. (2010). *Technology and Financial Development*. Journal of Money, Credit and Banking, forthcoming.

JONES, C. (1995a). *Time Series Tests of Endogenous Growth Models*. Quarterly Journal of Economics, 110: 495–525.

— (1995b). *R&D-based Models of Economic Growth*. Journal of Political Economy, 103: 759–784.

JORGENSON, D. W., HO, M. S. AND STIROH, K. J. (2005). *Information Technology and the American Growth Resurgence*. MIT.

KORTUM, S. (1997). *Research, Patenting and Technological Change*. Econometrica, 65: 1389–1419.

LAINCZ, C. AND PERETTO, P. (2006). *Scale Effects in Endogenous Growth Theory: An Error of Aggregation not Specification*. Journal of Economic Growth, 11(3): 263–288.

LANJOUW, J. O. AND SCHANKERMAN, M. (2004). *Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators*. Economic Journal, 114: 441–465.

LI, C.-W. (2003). *Endogenous Growth without Scale Effects: Comment*. American Economic Review, 93(3): 1009–1017.

LICHTENBERG, F. R. AND VAN POTTELSBERGHE, B. (1998). *International R&D Spillovers: A Comment*. European Economic Review, 42(8): 1483–1491.

LUINTEL, K. B. AND KHAN, M. (2004). *Are International R&D Spillovers Costly for the United States*. Review of Economics and Statistics, 86(4): 896–910.

— (2009). *Heterogeneous Ideas Production and Endogenous Growth: An Empirical Investigation*. Canadian Journal of Economics,, 42(3): 1176–1205.

MADSEN, J. B. (2007). *Are There Diminishing Returns to R&D?* Economics Letters, 95(2): 161–166.

— (2008a). *Economic Growth, TFP Convergence and the World Export of Ideas: A Century of Evidence*. Scandinavian Journal of Economics, 110(1): 145–167.

— (2008b). *Semi-endogenous versus Schumpeterian Growth Models: Testing the Knowledge Production Function using International Data*. Journal of Economic Growth, 12(1): 1–26.

MADSEN, J. B., ISLAM, M. R. AND ANG, J. B. (2010). *Catching up to the Technology Frontier: The Dichotomy between Innovation and Imitation*. Canadian Journal of Economics, 43(4): 1390–1411.

MINNITI, A., PARELLO, C. P. AND SEGERSTROM, P. S. (2008). *A Schumpeterian Growth Model with Heterogenous Firms*. Dipartimento di Scienze Economiche, Universita' di Bologna, Working paper n. 645.

NGAI, L. R. AND SAMANIEGO, R. M. (2010). *Accounting for Research and Productivity Growth across Industries*. Review of Economic Dynamics, forthcoming.

PATEL, D. AND WARD, M. R. (2010). *Using Patent Citation Patterns to Infer Innovation Market Competition*. University of Texas at Arlington, mimeo.

PERETTO, P. (1998). *Technological Change and Population Growth*. Journal of Economic Growth, 3: 283–312.

— (2007). *Corporate Taxes, Growth and Welfare in a Schumpeterian Economy*. Journal of Economic Theory, 137: 353–382.

SAMANIEGO, R. M. (2010). *Financial Development and Creative Destruction: Evidence and Theory*. MRPA Working Paper 22348, Revision November 2010.

SEDGLEY, N. H. (2006). *A Time Series Test of Innovation-Driven Endogenous Growth*. Economic Inquiry, 44(2): 318–332.

SEGERSTROM, P. S. (1998). *Endogenous Growth without Scale Effects*. American Economic Review, 88(5): 1290–1310.

SEGERSTROM, P. S., ANANT, T. C. A. AND DINOPOULOS, E. (1990). *A Schumpeterian Model of the Product Life Cycle*. American Economic Review, 80(5): 1077–1091.

SENER, F. (2008). *R&D Policies, Endogenous Growth and Scale Effects*. Journal of Economic Dynamics & Control, 32(12): 3895–3916.

SILVERBERG, G. AND VERSPAGEN, B. (2007). *The Size Distribution of Innovations Revisited: An Application of Extreme Value Statistics to Citation and Value Measures of Patent Significance*. Journal of Econometrics, (139): 318–339.

SUL, D., PHILLIPS, P. C. B. AND YO.CHOI, C. (2005). *Prewhitening Bias in HAC Estimation*. Oxford Bulletin of Economics and Statistics, 67(4): 517–546.

ULKU, H. (2007a). *R&D, Innovation, and Growth: Evidence from Four Manufacturing Sectors in OECD Countries*. Oxford Economic Papers, 59(3): 513–535.

— (2007b). *R&D, Innovation, and Output: Evidence from OECD and non-OECD Countries*. Applied Economics, 39: 291–307.

VENTURINI, F. (2007). *ICT and Productivity Resurgence: A Growth Model for the Information Age*. The B. E. Journal of Macroeconomics (Contributions), 7(1). Article 31.

— (2010). *Product Variety, Product Quality, and Evidence of Schumpeterian Endogenous Growth*. University of Perugia, mimeo.

WILSON, D. J. (2002). *Is Embodied Technology the Result of Upstream R&D? Industry-level Evidence*. Review of Economic Dynamics, 5: 287–317.

YOUNG, A. (1998). *Growth without Scale Effects*. Journal of Political Economy, 106(1): 41–63.

ZACHARIADIS, M. (2003). *R&D, Innovation, and Technological Progress: A Test of the Schumpeterian Framework without Scale Effects*. Canadian Journal of Economics, 36(3): 566–586.

— (2004). *R&D-induced Growth in the OECD?* Review of Development Economics, 8(3): 423–439.

Figure 1: R&D employment and Productivity Growth in US manufacturing (1973-1996)

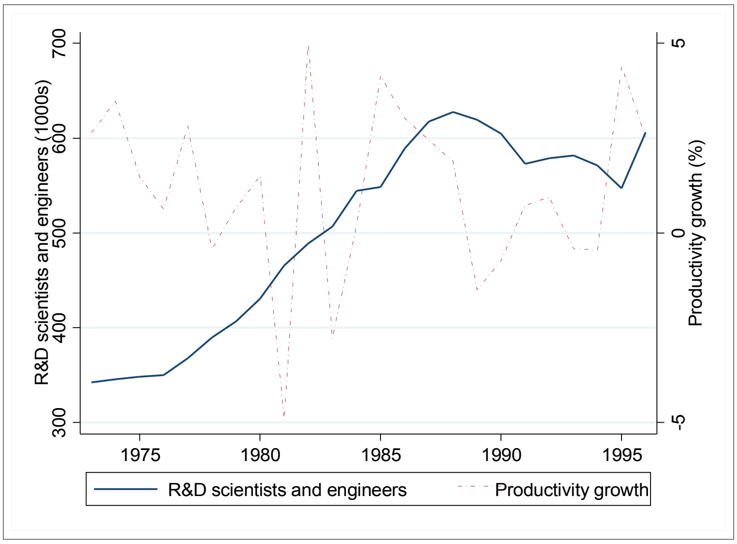

Table 1: **Summary statistics**, average 1973-1996

	VARIABLE	DESCRIPTION	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
ι	Rate of patenting (%)	Patent counts/patent stock	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
n	Adjusted R&D input (%)	R&D scientists and engineers/ (max productivity $\times$ total employment)	0.4	5.8	5.4	1.3	0.8	0.7	0.5	4.8	4.6	5.7	7.0	0.3	3.1
ℓ	R&D input (thousands)	R&D scientists and engineers	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
m	Product varieties (thousands)	Total employment	1,727	1,017	173	739	588	838	1,751	1,412	1,917	2,082	608	6,106	1,581
x	R&D difficulty (%)	R&D expenses/output	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
$\Delta \ln x$	R&D difficulty (%) growth	R&D expenses/output	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
$\Delta \ln a$	Technology growth (%)	BFK productivity index	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
q, Q	State-of-the-art product quality	Forward citations	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
q, Q	State-of-the-art product quality	Adjusted forward citations	7.9	37.5	9.5	26.2	12.3	10.3	17.1	33.8	25.2	14.7	24.7	23.7	20.2
q, Q	State-of-the-art product quality	Backward citations	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
q, Q	State-of-the-art product quality	Claims	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
q, Q	State-of-the-art product quality	Quality factor	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
Δq	Change in state-of-the-art product quality	Forward citations	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
Δq	Change in state-of-the-art product quality	Adjusted forward citations	1.2	11.9	1.7	9.2	2.7	1.9	4.5	8.1	5.9	4.1	5.1	6.4	5.2
Δq	Change in state-of-the-art product quality	Backward citations	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
Δq	Change in state-of-the-art product quality	Claims	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
Δq	Change in state-of-the-art product quality	Common factor	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
h	Technological concentration (%)	Herfindal index of forward cites	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
c	Technological contiguity	Inverse in change of forward cites	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. Eqs. 12-13)

	BASELINE SPECIFICATIONS							REGRESSIONS WITH CONTROL VARIABLES (C)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) Distance to frontier	(9) Trade openness	(10) International technology spillovers	(11) Profitability	(12) Taxation	(13) Human capital	(14) Financial development	(15) Transitional dynamics
$eq.1 : \ln \iota$															
$\ln n$	0.075	-0.116**	0.200**	0.406**	0.078**	0.043*	0.072**	0.019	0.157**	0.392**	0.139*	0.200**	0.189**	0.010	0.193**
	(0.048)	(0.051)	(0.043)	(0.081)	(0.026)	(0.024)	(0.035)	(0.081)	(0.046)	(0.084)	(0.072)	(0.054)	(0.087)	(0.128)	(0.051)
$\ln C$								0.208**	0.480**	-0.275**	-0.114	0.302**	0.367	0.336	-0.028
								(0.095)	(0.161)	(0.098)	(0.084)	(0.106)	(0.403)	(0.241)	(0.145)
$eq.2 : \Delta \ln a$															
ι	0.129	0.058	0.218	-0.406	0.177	0.197	0.213	0.218	0.228	0.203	0.211	0.242*	0.277*	0.238	0.189
	(0.161)	(0.209)	(0.143)	(0.266)	(0.144)	(0.143)	(0.143)	(0.145)	(0.170)	(0.156)	(0.145)	(0.137)	(0.163)	(0.146)	(0.143)
C								-0.001	-3.57e-06	1.05e-07	0.062	0.839**	-0.028	0.011	-0.033
								(0.001)	(2.77e-05)	(9.34e-07)	(0.156)	(0.357)	(0.034)	(0.010)	(0.025)
Obs.	240	240	240	240	240	240	240	240	240	240	237	240	240	237	240
Log-likelihood	720.6	695.4	752.4	485.5	753.1	759.5	732.8	702.2	731.5	679.3	675.9	717.8	704.8	630.8	753.2
Hansen-Sargan overidentification statistic χ^2 [p-value]															
	24.5	25.6	21.9	8.03	19.8	21.9	18.0	17.2	17.9	15.6	16.9	16.4	19.7	13.7	22.0
	[0.65]	[0.59]	[0.78]	[0.99]	[0.87]	[0.78]	[0.92]	[0.90]	[0.87]	[0.94]	[0.91]	[0.92]	[0.80]	[0.97]	[0.68]
Hadri-Kurozumi statistic on residuals' stationarity [p-value]															
	[0.97]	[0.96]	[0.97]	[0.78]	[0.78]	[0.78]	[0.29]	[0.99]	[0.99]	[0.99]	[0.88]	[0.99]	[0.99]	[0.99]	[0.97]
	[0.25]	[0.27]	[0.19]	[0.37]	[0.22]	[0.19]	[0.20]	[0.21]	[0.18]	[0.21]	[0.21]	[0.25]	[0.16]	[0.15]	[0.24]
Ideas depreciation (δ)	0.15	0.07	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
Productivity (a and A)	TFP	TFP	TFP	ALP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Adjustment factor for R&D input (n)	$A \cdot e$	$A \cdot e$	$A \cdot e$	$A \cdot e$	k	$k \cdot e$	y	$A \cdot e$	$A \cdot e$	$A \cdot e$	$A \cdot e$	$A \cdot e$	$A \cdot e$	$A \cdot e$	$A \cdot e$

Notes: Standard errors reported in parentheses. Equation 1 includes industry-specific intercepts and time trends, as well as AR(2) errors; equations 2 AR(1) errors. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. The Hansen-Sargan test checks the null hypothesis that there are no overidentification restrictions, the Hadri-Kurozumi test checks that each equation's residuals are panel stationary under cross-sectional dependence. P-value in square brackets.

Dependent variables. EQ. 1 ι: rate of patenting. EQ. 2 $\Delta \ln a$: productivity growth. *Explanatory variables*. n: adjusted R&D input. ι: rate of patenting. *Control variables* (C). Distance to frontier: ratio between the frontier and industry's research productivity. Trade openness: imports plus exports over output. International technology spillovers: imports-weighted R&D stock of OECD partner industries. Profitability: profits over output. Taxation: taxes on production and imports over output. Human capital: high-skilled labour share. Financial development: interests and other payments over investment expenditure. Transitional dynamics: investment over capital service expenditure. *Productivity indicators* (a *and* A). TFP: Basu *et al.* (2006) pure technology index. ALP: Output per worker. *Adjustment factor for* n ($n = r/(A \cdot m)$, *with* $m \simeq e$, k *or* y). A: leading-edge, total economy productivity. e: total FTE employment. k: patent stock. y: real output.

**,* significant at 5 and 10% respectively.

Table 3: Estimates of R&D technology by Aghion and Howitt (1998) (model B. Eqs. 14-15)

	BASELINE SPECIFICATIONS							REGRESSIONS WITH CONTROL VARIABLES (C)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) Distance to frontier	(9) Trade openness	(10) International technology spillovers	(11) Profitability	(12) Taxation	(13) Human capital	(14) Financial development	(15) Transitional dynamics
$\frac{eq.1 : \ln \iota}{\ln r}$	0.036	-0.087	0.139**	0.116**	0.055	0.118**	0.153**	0.054	0.133**	0.106**	0.158**	0.122**	0.036	0.129**	0.139**
	(0.063)	(0.066)	(0.042)	(0.042)	(0.049)	(0.050)	(0.044)	(0.057)	(0.042)	(0.049)	(0.051)	(0.0514)	(0.077)	(0.056)	(0.046)
$\ln A$	-2.545**	-2.742**	-1.662**	-0.203**	-1.088**	-1.650**	-1.272**	-1.411**	-1.521**	-1.779**	-1.503**	-1.840**	-1.944**	-1.719**	-1.501**
	(0.345)	(0.364)	(0.235)	(0.034)	(0.186)	(0.210)	(0.249)	(0.296)	(0.238)	(0.258)	(0.259)	(0.385)	(0.384)	(0.251)	(0.290)
$\ln m$	0.740**	1.397**	0.433**	0.383**	-0.143**	-0.032	-0.313**	0.500**	0.327**	0.576**	0.396**	0.414**	1.026**	0.544**	0.651**
	(0.271)	(0.287)	(0.137)	(0.119)	(0.060)	(0.051)	(0.108)	(0.155)	(0.135)	(0.187)	(0.149)	(0.152)	(0.439)	(0.169)	(0.215)
$\ln C$								-0.146**	0.376**	0.078	0.028	-0.078	0.724*	0.076	-0.120
								(0.057)	(0.133)	(0.054)	(0.028)	(0.118)	(0.374)	(0.076)	(0.077)
$\frac{eq.2 : \Delta \ln a}{\iota}$	0.145	0.0897	0.248*	-0.294	0.137	0.130	0.242*	0.227*	0.273*	0.247*	0.209	0.275**	0.294**	0.269**	0.187
	(0.149)	(0.196)	(0.130)	(0.243)	(0.139)	(0.124)	(0.134)	(0.131)	(0.152)	(0.141)	(0.133)	(0.126)	(0.146)	(0.132)	(0.130)
C								-0.001	-1.03e-05	-8.05e-11	0.141	0.914**	-0.028	0.012	-0.047**
								(0.001)	(2.57e-05)	(8.72e-07)	(0.129)	(0.336)	(0.032)	(0.009)	(0.023)
Obs.	240	240	240	240	240	240	240	240	240	240	237	240	240	237	240
Log-likelihood	661.4	643.3	764.7	608.1	755.9	763.7	769.9	743.5	764.6	750.2	751.0	760.3	667.6	750.2	747.2
Hansen-Sargan overidentification statistic χ^2 [p-value]															
	35.6	46.5	48.0	48.8	63.2	59.8	51.1	38.9	40.5	44.7	45.4	44.8	31.8	44.2	41.7
	[0.58]	[0.16]	[0.12]	[0.11]	[0.01]	[0.01]	[0.08]	[0.34]	[0.27]	[0.15]	[0.13]	[0.14]	[0.66]	[0.16]	[0.23]
Hadri-Kurozumi statistic on residuals' stationarity [p-value]															
	[0.99]	[0.99]	[0.97]	[0.99]	[0.64]	[0.66]	[0.64]	[0.98]	[0.94]	[0.98]	[0.98]	[0.97]	[0.99]	[0.97]	[0.98]
	[0.23]	[0.26]	[0.15]	[0.13]	[0.25]	[0.26]	[0.25]	[0.21]	[0.13]	[0.15]	[0.27]	[0.35]	[0.13]	[0.13]	[0.29]
Ideas depreciation (δ)	0.15	0.07	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
Productivity (a and A)	TFP	TFP	TFP	ALP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Product varieties (m)	e	e	e	e	k	$k \cdot e$	y	e	e	e	e	e	e	e	e

Notes: Standard errors reported in parentheses. Equation 1 includes industry-specific intercepts and time trends, as well as AR(2) errors; equations 2 AR(1) errors. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. The Hansen-Sargan test checks the null hypothesis that there are no overidentification restrictions, the Hadri-Kurozumi test that each equation's residuals are panel stationary under cross-sectional dependence. P-value in square brackets.

Dependent variables. EQ. 1 ι: rate of patenting. EQ. 2 $\Delta \ln a$: productivity growth. *Explanatory variables*. r: R&D employment. A: leading-edge, total economy productivity. m labour force (product varieties). ι: rate of patenting. *Control variables* (C). Distance to frontier: ratio between the frontier and industry's research productivity. Trade openness: imports plus exports over output. International technology spillovers: imports-weighted R&D stock of OECD partner industries. Profitability: profits over output. Taxation: taxes on production and imports over output. Human capital: high-skilled labour share. Financial development: interests and other payments over investment expenditure. Transitional dynamics: investment over capital service expenditure. *Productivity indicators* (a *and* A). TFP: Basu *et al.* (2006) pure technology index. ALP: Output per worker. *Proxies for product varieties* (m). e: total FTE employment. k: patent stock. y: real output.

**,* significant at 5 and 10% respectively.

Table 4: Estimates of R&D technology by Segerstrom (1998) (Eqs. 16-17)

	BASELINE SPECIFICATIONS				REGRESSIONS WITH CONTROL VARIABLES (C)							
	(1)	(2)	(3)	(4)	(5) Distance to frontier	(6) Trade openness	(7) International technology spillovers	(8) Profitability	(9) Taxation	(10) Human capital	(11) Financial development	(12) Transitional dynamics
***eq 1*: $\underline{\ln \iota}$**												
$\ln \ell$	0.157**	0.051	0.211**	0.135**	0.106*	0.146**	0.182**	0.172**	0.287**	0.156**	0.125*	0.195**
	(0.056)	(0.061)	(0.047)	(0.048)	(0.061)	(0.055)	(0.054)	(0.061)	(0.064)	(0.057)	(0.065)	(0.063)
$\ln x$	-0.258**	-0.322**	-0.145**	-0.179**	-0.395**	-0.249**	-0.256**	-0.210**	-0.391**	-0.286**	-0.267**	-0.326**
	(0.042)	(0.046)	(0.036)	(0.023)	(0.054)	(0.043)	(0.044)	(0.048)	(0.048)	(0.049)	(0.043)	(0.049)
$\ln C$					0.252**	0.227*	-0.021	0.044*	0.261**	0.162	0.030	-0.122**
					(0.049)	(0.122)	(0.046)	(0.024)	(0.054)	(0.131)	(0.061)	(0.046)
***eq. 2*: $\underline{\Delta \ln x}$**												
ι	1.236*	1.135	1.330*	1.574	1.324*	1.540*	1.538**	1.038	1.328*	1.390*	1.407*	1.118
	(0.711)	(0.815)	(0.688)	(1.078)	(0.728)	(0.797)	(0.760)	(0.711)	(0.771)	(0.773)	(0.790)	(0.714)
C					0.000	-6.90e-05	-2.97e-06	0.218	0.528	-0.063	0.020	-0.092
					(0.001)	(9.30e-05)	(3.10e-06)	(0.507)	(1.310)	(0.121)	(0.039)	(0.083)
Hansen-Sargan overidentification statistic χ^2 [p-value]												
	64.0	57.2	69.6	59.5	48.0	58.6	52.7	64.7	50.9	58.5	62.5	61.2
	[0.12]	[0.28]	[0.05]	[0.21]	[0.55]	[0.18]	[0.36]	[0.07]	[0.43]	[0.19]	[0.10]	[0.13]
Hadri-Kurozumi statistic on residuals' stationarity [p-value]												
	[0.95]	[0.98]	[0.88]	[0.63]	[0.86]	[0.95]	[0.98]	[0.98]	[0.96]	[0.89]	[0.96]	[0.97]
	[0.45]	[0.50]	[0.35]	[0.60]	[0.61]	[0.35]	[0.37]	[0.63]	[0.48]	[0.53]	[0.59]	[0.68]
Obs.	240	240	240	240	240	240	240	237	240	240	237	240
Log-likelihood	433.2	411.6	469.5	349.6	403.1	434.1	436.1	420.0	409.7	427.5	417.1	402.4
Ideas depreciation (δ)	0.15	0.07	0.30	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
R&D difficulty	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses per patent	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio

Notes: Standard errors reported in parentheses. Equation 1 includes industry-specific intercepts and time trends, as well as AR(2) errors; equations 2 common time dummies and AR(1) errors. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. The Hansen-Sargan test checks the null hypothesis that there are no overidentification restrictions, the Hadri-Kurozumi test that each equation's residuals are panel stationary under cross-sectional dependence. P-value in square brackets.

Dependent variables. EQ. 1 ι: rate of patenting. EQ. 2 $\Delta \ln x$: rate of change in R&D difficulty. *Explanatory variables*. ℓ: R&D employment. x: R&D difficulty. ι: rate of patenting. *Control variables* (C). Distance to frontier: ratio between the frontier and industry's research productivity. Trade openness: imports plus exports over output. International technology spillovers: imports-weighted R&D stock of OECD partner industries. Profitability: profits over output. Taxation: taxes on production and imports over output. Human capital: high-skilled labour share. Financial development: interests and other payments over investment expenditure. Transitional dynamics: investment over capital service expenditure.

**,* significant at 5 and 10% respectively.

Table 5: Estimates of R&D technology by Li (2003)-Minniti *et al.* (2008) (Eqs. 18-20)

	BASELINE SPECIFICATIONS							REGRESSIONS WITH CONTROL VARIABLES (C)							
								Distance to frontier	Trade openness	International technology spillovers	Profitability	Taxation	Human capital	Financial development	Transitional dynamics
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
eq.1: $\underline{\ln\iota}$															
$\ln Q$	0.077*	0.101**	0.043	0.025	-0.116**	-0.155**	-0.091	0.079*	0.086**	0.041	0.104**	0.050	0.095**	0.088*	0.108**
	(0.045)	(0.045)	(0.037)	(0.041)	(0.049)	(0.064)	(0.142)	(0.047)	(0.043)	(0.045)	(0.049)	(0.047)	(0.047)	(0.046)	(0.053)
$\ln\ell$	0.212**	0.125**	0.234**	0.139**	0.036	0.166**	0.091*	0.153**	0.194**	0.220**	0.242**	0.330**	0.217**	0.155**	0.258**
	(0.057)	(0.062)	(0.048)	(0.046)	(0.055)	(0.063)	(0.055)	(0.062)	(0.058)	(0.056)	(0.064)	(0.066)	(0.060)	(0.062)	(0.067)
$\ln x$	-0.300**	-0.368**	-0.171**	-0.178**	-0.271**	-0.226**	-0.209**	-0.427**	-0.285**	-0.293**	-0.265**	-0.402**	-0.343**	-0.314**	-0.382**
	(0.045)	(0.049)	(0.037)	(0.024)	(0.042)	(0.049)	(0.040)	(0.054)	(0.045)	(0.047)	(0.053)	(0.050)	(0.052)	(0.045)	(0.054)
$\ln q$	-0.003	-0.030	0.017	0.021	-0.001	0.130**	0.076	-0.026	-0.033	-0.001	-0.020	0.013	-0.018	0.002	-0.006
	(0.043)	(0.050)	(0.034)	(0.041)	(0.043)	(0.065)	(0.104)	(0.045)	(0.045)	(0.042)	(0.046)	(0.043)	(0.045)	(0.044)	(0.045)
$\ln C$								0.262**	0.255*	-0.00965	0.047**	0.190**	0.238*	0.052	-0.146**
								(0.051)	(0.142)	(0.046)	(0.024)	(0.049)	(0.137)	(0.062)	(0.045)
eq. 2: $\underline{\Delta\ln x}$															
ι	1.296**	1.137	1.466**	1.656	1.068	1.237*	1.124*	1.407**	1.596**	1.564**	1.077	1.357*	1.449**	1.455**	1.190*
	(0.657)	(0.755)	(0.637)	(1.007)	(0.678)	(0.682)	(0.597)	(0.673)	(0.735)	(0.703)	(0.665)	(0.712)	(0.714)	(0.725)	(0.659)
C								0.000	-6.91e-05	-2.70e-06	0.418	0.463	-0.060	0.020	-0.087
								(0.001)	(8.63e-05)	(2.89e-06)	(0.469)	(1.218)	(0.112)	(0.036)	(0.076)
eq. 3: $\underline{\Delta q}$															
ι	2.255**	3.690**	1.300**	2.252**	0.414	1.050**	-0.0195	2.278**	2.652**	2.389**	1.990**	2.256**	2.533**	2.382**	2.263**
	(0.442)	(0.778)	(0.441)	(0.452)	(0.306)	(0.390)	(0.213)	(0.458)	(0.503)	(0.456)	(0.483)	(0.490)	(0.494)	(0.478)	(0.463)
C								0.005	-0.008	-0.001	41.97	-1.296	-8.695	1.856	-0.139
								(0.021)	(0.005)	(0.001)	(29.95)	(74.13)	(6.862)	(2.073)	(4.727)
Obs.	240	240	240	240	240	240	240	240	240	240	237	240	240	237	240
Log-likelihood	-401.7	-426.8	-362.5	-491.1	-834.1	-841.6	461.5	-433.1	-402.0	-398.0	-414.7	-420.3	-411.0	-405.2	-435.8
Test on positive quality jump ($\zeta = 1$): χ^2 [p-value]															
	8.06	11.9	1.51	7.66	3.67	0.02	23.0	7.58	10.8	9.27	4.21	6.57	9.61	8.35	7.45
	[0.00]	[0.00]	[0.21]	[0.01]	[0.06]	[0.90]	[0.00]	[0.01]	[0.00]	[0.00]	[0.04]	[0.01]	[0.00]	[0.00]	[0.01]
Hansen-Sargan overidentification statistic χ^2 [p-value]															
	78.7	71.8	88.8	85.4	106.	80.6	122.	67.4	75.3	67.0	77.4	72.0	71.6	78.4	75.7
	[0.97]	[0.99]	[0.88]	[0.92]	[0.46]	[0.96]	[0.13]	[1.00]	[0.98]	[0.99]	[0.97]	[0.99]	[0.99]	[0.96]	[0.97]
Hadri-Kurozumi statistic on residuals' stationarity [p-value]															
eq. 1	[0.95]	[0.97]	[0.86]	[0.53]	[0.97]	[0.55]	[0.88]	[0.65]	[0.91]	[0.65]	[0.98]	[0.96]	[0.95]	[0.98]	[0.97]
eq. 2	[0.63]	[0.69]	[0.54]	[0.40]	[0.61]	[0.35]	[0.55]	[0.68]	[0.47]	[0.66]	[0.68]	[0.59]	[0.64]	[0.78]	[0.77]
eq. 3	[0.26]	[0.32]	[0.26]	[0.37]	[0.00]	[0.00]	[0.30]	[0.28]	[0.38]	[0.21]	[0.12]	[0.24]	[0.30]	[0.26]	[0.15]
Ideas depreciation (δ)	0.15	0.07	0.30	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
R&D difficulty	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses per patent	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-
Quality (q and Q)	forward citations	forward citations	forward citations	forward citations	backward citations	claims	common factor	forward citations	forward citations	forward citations	forward citations	forward citations	forward citations	forward citations	forward citations

Notes: Standard errors reported in parentheses. Equation 1 includes industry-specific intercepts and time trends, as well as AR(2) errors; equations 2 and 3 common time dummies and AR(1) errors. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. The Hansen-Sargan test checks the null hypothesis that there are no overidentification restrictions, the Hadri-Kurozumi test that each equation's residuals are panel stationary under cross-sectional dependence. P-value in square brackets.

Dependent variables. EQ. 1 ι: rate of patenting. EQ. 2 $\Delta\ln x$: rate of change in R&D difficulty. EQ. 3 Δq: quality jump in state-of-the-art products. *Explanatory variables*. Q: across-industry quality spillover. ℓ: R&D employment. x: R&D difficulty. q quality of state-of-the-art product. ι: rate of patenting. *Control variables* (C). Distance to frontier: ratio between the frontier and industry's research productivity. Trade openness: imports plus exports over output. International technology spillovers: imports-weighted R&D stock of OECD partner industries. Profitability: profits over output. Taxation: taxes on production and imports over output. Human capital: high-skilled labour share. Financial development: interests and other payments over investment expenditure. Transitional dynamics: investment over capital service expenditure.

**,* significant at 5 and 10% respectively.

Table 6: Estimates of R&D technology by Sener (2008) (Eqs. 21-22)

	BASELINE SPECIFICATIONS						REGRESSIONS WITH CONTROL VARIABLES (C)							
							Distance to frontier	Trade openness	International technology spillovers	Profitability	Taxation	Human capital	Financial development	Transitional dynamics
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
***eq. 1*: $\ln \iota$**														
$\ln \ell$	0.140**	0.155**	0.152**	0.056	0.207**	0.124**	0.115**	0.141**	0.178**	0.167**	0.258**	0.149**	0.121**	0.181**
	(0.054)	(0.053)	(0.053)	(0.058)	(0.045)	(0.047)	(0.057)	(0.053)	(0.052)	(0.057)	(0.060)	(0.054)	(0.062)	(0.059)
$\ln x$	-0.252**	-0.258**	-0.257**	-0.327**	-0.144**	-0.174**	-0.398**	-0.237**	-0.255**	-0.211**	-0.370**	-0.282**	-0.267**	-0.315**
	(0.041)	(0.040)	(0.040)	(0.044)	(0.034)	(0.023)	(0.052)	(0.041)	(0.041)	(0.045)	(0.044)	(0.046)	(0.041)	(0.046)
$\ln C$							0.245**	0.250**	-0.021	0.041*	0.257**	0.157	0.034	-0.116**
							(0.048)	(0.115)	(0.045)	(0.023)	(0.053)	(0.129)	(0.060)	(0.045)
***eq. 2*: $\underline{\Delta \ln x}$**														
ι	1.418**	1.578**	1.502**	1.577*	1.431**	1.209	1.666**	1.526*	1.724**	1.264*	1.282	1.542**	1.592**	1.347*
	(0.698)	(0.752)	(0.731)	(0.855)	(0.696)	(1.104)	(0.752)	(0.820)	(0.773)	(0.726)	(0.784)	(0.785)	(0.803)	(0.733)
h/x	0.030*													
	(0.018)													
c/x		0.007												
		(0.005)												
$(h \times c)/x$			0.016*	0.017*	0.016*	0.044	0.018**	0.016*	0.015*	0.014	0.019*	0.016*	0.016*	0.014
			(0.009)	(0.009)	(0.009)	(0.027)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.009)
C							0.000	-4.11e-05	-2.23e-06	0.139	-1.148	-0.017	0.013	-0.069
							(0.001)	(0.002)	(3.17e-06)	(0.508)	(1.644)	(0.125)	(0.039)	(0.084)
Obs.	240	240	240	240	240	240	240	240	240	237	240	240	237	240
Log-likelihood	443.3	431.5	433.1	410.7	469.3	348.4	403.2	433.8	436.2	423.2	415.1	428.7	418.6	407.2
Hansen-Sargan overidentification statistic χ^2 [p-value]														
	79.6	64.8	64.8	57.1	71.0	61.9	49.8	61.7	53.8	66.4	55.5	60.0	60.1	63.6
	[0.02]	[0.22]	[0.22]	[0.46]	[0.10]	[0.30]	[0.67]	[0.24]	[0.51]	[0.13]	[0.45]	[0.29]	[0.29]	[0.19]
Hadri-Kurozumi statistic on residuals' stationarity [p-value]														
eq. 1	[0.97]	[0.95]	[0.95]	[0.97]	[0.89]	[0.60]	[0.90]	[0.61]	[0.97]	[0.97]	[0.95]	[0.89]	[0.98]	[0.96]
eq. 2	[0.53]	[0.26]	[0.27]	[0.30]	[0.19]	[0.40]	[0.33]	[0.00]	[0.19]	[0.51]	[0.29]	[0.33]	[0.43]	[0.55]
Rent protection indicator (p)	concentration	closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness	concentration/ closeness
Ideas depreciation (δ)	0.15	0.15	0.15	0.07	0.30	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
R&D difficulty	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses per patent	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio	R&D expenses-output ratio

Notes: Standard errors reported in parentheses. Equation 1 includes industry-specific intercepts and time trends, as well as AR(2) errors; equations 2 common time dummies and AR(1) errors. 2-4 year lagged values of the explanatory variables, as well as the deterministic components, are used as instruments. The Hansen-Sargan test checks the null hypothesis that there are no overidentification restrictions, the Hadri-Kurozumi test that each equation's residuals are panel stationary under cross-sectional dependence. P-value in square brackets.

Dependent variables. EQ. 1 ι: rate of patenting. EQ. 2 $\Delta \ln x$: rate of change in R&D difficulty. *Explanatory variables*. ℓ: R&D employment. x: R&D difficulty. ι: rate of patenting. h: technological concentration. c: technological contiguity in state-of-the-art products. *Control variables (C)*. Distance to frontier: ratio between the frontier and industry's research productivity. Trade openness: imports plus exports over output. International technology spillovers: imports-weighted R&D stock of OECD partner industries. Profitability: profits over output. Taxation: taxes on production and imports over output. Human capital: high-skilled labour share. Financial development: interests and other payments over investment expenditure. Transitional dynamics: investment over capital service expenditure.

**,* 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 Bronwyn Hall's homepage; release March 2006);

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

3. EUKLEMS Industry Accounts (release March 2007), OECD STAN (2005) and BEA Historical series on GDP-by-Industry, SIC data 1947-1997 (*GDP-by-Ind-VA-SIC*);

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 patents 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 of industry i is defined as the ratio between counts of patent applications at year t (w_{it}), and the cumulative value of counts up to that year (k_{it}). k_{it} is built through the perpetual inventory method and geometrical depreciation from series on patent counts. The rate of depreciation, δ, is assumed to be constant among sectors and over time; it is set at 15% in baseline regressions, while rates of 7 and 30% are used in robustness checks. The initial value k_{i0} is computed by means of Hall and Mairesse (1995)'s formula:

$$k_{it} = w_{it} + (1-\delta)k_{it-1}, \quad k_{i0} = \frac{w_{i0}}{\delta + g_i},$$

where w_{i0} is the amount of patent counts at 1973, g_i the average annual rate of change of w_{it} between 1973 and 1996.

The number of patent counts is corrected for the truncation due to the time lag existing between the application date and the grant date (on average, 1 year and 11 months in our sample). This lag leads the number of observed applications to be underestimated for the period before 1975 (i.e., the first available granting year for cited/citing patents) with respect to the true distribution of applications. 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 came to an end for 95% applications, implying that a patent applied in 1970 was highly probable to be issued by 1975. Following Hall *et al.* (2005), the applications before 1975, $\widetilde{w}_{it}$, are corrected with a factor defined by the inverse of cumulative probabilities of the application-grant time lag (Pr_s), calculated on the overall sample: $cf_s = (\sum_{s=1}^{2} Pr_{1975-s})^{-1}$, $s = 1, \ldots, 2$. The correction factor is slightly higher than 1 for patents applied in 1974, whereas amounts to 1.5 for those of 1973. For these years, adjusted patent counts are given by $w_{it} = cf_t * \widetilde{w}_{it}$. Based on the application year, patents are assigned to twelve manufacturing industries according to their first SIC code reported in the NBER USPTO data set. The SIC classification is also used to consistently aggregate data on R&D employment, R&D expenses and control variables.

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 federally- and privately-funded research expenses. It is important to remark that NSF does not disclose publicly-funded R&D resources for the entire time-span, as it does for privately-financed R&D expenses. Hence, missing values are calculated by first interpolating the ratio between total and privately-funded R&D expenses and, then, applying the resulting mark-up to the private research expenditure. As an alternative indicator of R&D difficulty, we also use the ratio between R&D expenses and patent counts, which also consists in the inverse measure of research productivity. R&D expenses are converted into 1995 constant dollars by applying industry deflators for 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 some missing values, these series are completed by following a two-step procedure similar to that adopted for R&D expenditure. For missing years, we first interpolate the share of S&E on total employment of firms undertaking R&D activities; we then apply the interpolated shares to the total employment of R&D-performing firms.

Data on technology index are available for detailed 21 manufacturing sectors for the period 1973-1996 (Basu *et al.*, 2006). 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):

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

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. In the light of the number index nature of this variable, the economy-wide level of leading-edge technology is defined as deviation of the maximum value of the industry technology index from the aggregate (manufacturing) value. The contribution of technologically advanced industries to the dynamics of manufacturing technology index is constantly increasing, as $\overline{s}_{it}$ is relatively stable over time with respect to technology growth, $\Delta \ln a_{it}$ (see the discussion in Venturini, 2007); this ensures that the largest deviation between sectoral and aggregate (manufacturing) levels of the technology index is a good proxy for the relative production frontier.

As a quality measure of state-of-the-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: the volume of their cites reduces with approaching the end of the period under examination (the year 1996), as the time window to be cited is shorter than for older applications. This aspect is controlled for by applying the quasi fixed-effect correction proposed by Hall *et al.* (2001). We scale the citations received by any individual patent (one million and over observations) on the yearly citation mean of reference industry (year/sector-effect correction). This type of correction removes the annual effect of truncation which is specific to each sector.

Lanjouw and Schankerman (2004) point out that the above reported quality indicators are likely to convey different pieces of information about the true value of patent quality. As a consequence, by assuming q_j to be a latent factor common among such observable features, the process underlying the quality endowment of each 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 among the different observable indicators. e_{kj} is a well-behaving error term that is typically associated with this process; μ_k is 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 (application year and IPC technological sub-class of the patent), and a 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 for q_j; the quality level of the state-of-the-art products is defined as the highest score assigned any year to a patent in each sector.

As an indirect measure of rent protection, we compute a normalized Herfindahl-Hirsh index of forward citations, where the total cites received by a patent j in the sector i, N_{ji}, are distinguished by the origin of citing industries, s (time subscripts omitted):

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

In the regression analysis, we use the industry average of the patent concentration index: $h_i = \sum_{j=1}^{J} \widetilde{HI}_{ji}$/J, where J is the total number of patents counted in each sector. As an indicator of technological closeness (or contiguity), we take the inverse of the quality jump between the two most frequently cited patents, $1/\Delta q$, using data on adjusted forward citations.

The control variables are constructed as follows:

Distance to frontier: Ratio between industry-level and and the maximum sample value of research productivity. For each year, a TFP-type index of research productivity is calculated as the ratio between innovation output (patent counts) and innovation input (research expenses at constant prices). In the TFP growth equation of the VE framework, distance to productivity frontier is used.

Trade openness: Sum of industry imports and exports over gross output (in current prices). Trade data are taken from OECD Bilateral Trade 1998.

International technology spillovers: Imports-weighted R&D capital of the OECD partner industries (Australia, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Spain, Sweden and UK, hereafter denoted by f, $f = 1, ..., F$). The weighting scheme follows Lichtenberg and van Pottelsberghe (1998):

$$FRD_{it} = \sum_{f=1}^{F} \frac{mx_{ift}}{y_{ift}} RDS_{ift}, \quad t = 1973, ..., 1996.$$

RDS_{ift} is the R&D stock of sector i at time t in country f, mx_{ift} the export flow of this industry towards the US, and y_{ift} is gross output of the exporting industry; mx and y are expressed at current prices. For each partner country, R&D capital is built with the perpetual inventory method described above ($\delta = 0.15$), from R&D expenditure series expressed at US PPP of 1995 (source: OECD Anberd database, 2002 and 2009).

Profitability: Current prices ratio between profits and gross output. We consider corporate profits before tax without inventory valuation adjustment and capital consumption adjustment, extracted from BEA Historical series on GDP-by-Industry. Due to the presence of some negative values (losses), profit rate has been scaled on the minimum value.

Taxation: Taxes on production and imports over gross output, at current prices (source: BEA Historical series on GDP-by-Industry).

Human capital: Output share of skilled labour (source: EU KLEMS database, March 2007).

Financial development: Current prices ratio between interest payments and gross fixed capital formation. Interest payments come from BEA Historical series on GDP-by-Industry; investment expenditure series from OECD STAN 2005.

Transitional dynamics: Investment expenditure over capital service expenditure (in nominal terms); these series are taken respectively from OECD STAN 2005 and EU KLEMS, March 2007.

ISSN 1825-0211

QUADERNI DEL DIPARTIMENTO DI ECONOMIA, FINANZA E STATISTICA
Università degli Studi di Perugia

1	Gennaio 2005	Giuseppe CALZONI Valentina BACCHETTINI	Il concetto di competitività tra approccio classico e teorie evolutive. Caratteristiche e aspetti della sua determinazione
2	Marzo 2005	Fabrizio LUCIANI Marilena MIRONIUC	Ambiental policies in Romania. Tendencies and perspectives
3	Aprile 2005	Mirella DAMIANI	Costi di agenzia e diritti di proprietà: una premessa al problema del governo societario
4	Aprile 2005	Mirella DAMIANI	Proprietà, accesso e controllo: nuovi sviluppi nella teoria dell'impresa ed implicazioni di corporate governance
5	Aprile 2005	Marcello SIGNORELLI	Employment and policies in Europe: a regional perspective
6	Maggio 2005	Cristiano PERUGINI Paolo POLINORI Marcello SIGNORELLI	An empirical analysis of employment and growth dynamics in the italian and polish regions
7	Maggio 2005	Cristiano PERUGINI Marcello SIGNORELLI	Employment differences, convergences and similarities in italian provinces
8	Maggio 2005	Marcello SIGNORELLI	Growth and employment: comparative performance, convergences and co-movements
9	Maggio 2005	Flavio ANGELINI Stefano HERZEL	Implied volatilities of caps: a gaussian approach
10	Giugno 2005	Slawomir BUKOWSKI	EMU – Fiscal challenges: conclusions for the new EU members
11	Giugno 2005	Luca PIERONI Matteo RICCIARELLI	Modelling dynamic storage function in commodity markets: theory and evidence
12	Giugno 2005	Luca PIERONI Fabrizio POMPEI	Innovations and labour market institutions: an empirical analysis of the Italian case in the middle 90's
13	Giugno 2005	David ARISTEI Luca PIERONI	Estimating the role of government expenditure in long-run consumption
14	Giugno 2005	Luca PIERONI Fabrizio POMPEI	Investimenti diretti esteri e innovazione in Umbria
15	Giugno 2005	Carlo Andrea BOLLINO Paolo POLINORI	Il valore aggiunto su scala comunale: la Regione Umbria 2001-2003
16	Giugno 2005	Carlo Andrea BOLLINO Paolo POLINORI	Gli incentivi agli investimenti: un'analisi dell'efficienza industriale su scala geografica regionale e sub regionale

17	Giugno 2005	Antonella FINIZIA Riccardo MAGNANI Federico PERALI Paolo POLINORI Cristina SALVIONI	Construction and simulation of the general economic equilibrium model Meg-Ismea for the italian economy
18	Agosto 2005	Elżbieta KOMOSA	Problems of financing small and medium-sized enterprises. Selected methods of financing innovative ventures
19	Settembre 2005	Barbara MROCZKOWSKA	Regional policy of supporting small and medium-sized businesses
20	Ottobre 2005	Luca SCRUCCA	Clustering multivariate spatial data based on local measures of spatial autocorrelation
21	Febbraio 2006	Marco BOCCACCIO	Crisi del welfare e nuove proposte: il caso dell'unconditional basic income
22	Settembre 2006	Mirko ABBRITTI Andrea BOITANI Mirella DAMIANI	Unemployment, inflation and monetary policy in a dynamic New Keynesian model with hiring costs
23	Settembre 2006	Luca SCRUCCA	Subset selection in dimension reduction methods
24	Ottobre 2006	Sławomir I. BUKOWSKI	The Maastricht convergence criteria and economic growth in the EMU
25	Ottobre 2006	Jan L. BEDNARCZYK	The concept of neutral inflation and its application to the EU economic growth analyses
26	Dicembre 2006	Fabrizio LUCIANI	Sinossi dell'approccio teorico alle problematiche ambientali in campo agricolo e naturalistico; il progetto di ricerca nazionale F.I.S.R. – M.I.C.E.N.A.
27	Dicembre 2006	Elvira LUSSANA	Mediterraneo: una storia incompleta
28	Marzo 2007	Luca PIERONI Fabrizio POMPEI	Evaluating innovation and labour market relationships: the case of Italy
29	Marzo 2007	David ARISTEI Luca PIERONI	A double-hurdle approach to modelling tobacco consumption in Italy
30	Aprile 2007	David ARISTEI Federico PERALI Luca PIERONI	Cohort, age and time effects in alcohol consumption by Italian households: a double-hurdle approach
31	Luglio 2007	Roberto BASILE	Productivity polarization across regions in Europe
32	Luglio 2007	Roberto BASILE Davide CASTELLANI Antonello ZANFEI	Location choices of multinational firms in Europe: the role of EU cohesion policy
33	Agosto 2007	Flavio ANGELINI Stefano HERZEL	Measuring the error of dynamic hedging: a Laplace transform approach

34	Agosto 2007	Stefano HERZEL Cătălin STĂRICĂ Thomas NORD	The IGARCH effect: consequences on volatility forecasting and option trading
35	Agosto 2007	Flavio ANGELINI Stefano HERZEL	Explicit formulas for the minimal variance hedging strategy in a martingale case
36	Agosto 2007	Giovanni BIGAZZI	The role of agriculture in the development of the people's Republic of China
37	Settembre 2007	Enrico MARELLI Marcello SIGNORELLI	Institutional change, regional features and aggregate performance in eight EU's transition countries
38	Ottobre 2007	Paolo NATICCHIONI Andrea RICCI Emiliano RUSTICHELLI	Wage structure, inequality and skill-biased change: is Italy an outlier?
39	Novembre 2007	The International Study Group on Exports and Productivity	Exports and productivity. Comparable evidence for 14 countries
40	Dicembre 2007	Gaetano MARTINO Paolo POLINORI	Contracting food safety strategies in hybrid governance structures
41	Dicembre 2007	Floro Ernesto CAROLEO Francesco PASTORE	The youth experience gap: explaining differences across EU countries
42	Gennaio 2008	Melisso BOSCHI Luca PIERONI	Aluminium market and the macroeconomy
43	Febbraio 2008	Flavio ANGELINI Marco NICOLOSI	Hedging error in Lévy models with a fast Fourier Transform approach
44	Febbraio 2008	Luca PIERONI Giorgio d'AGOSTINO Marco LORUSSO	Can we declare military Keynesianism dead?
45	Febbraio 2008	Pierluigi GRASSELLI Cristina MONTESI Paola IANNONE	Mediterranean models of Welfare towards families and women
46	Marzo 2008	Mirella DAMIANI Fabrizio POMPEI	Mergers, acquisitions and technological regimes: the European experience over the period 2002-2005
47	Marzo 2008	Bruno BRACALENTE Cristiano PERUGINI	The Components of Regional Disparities in Europe
48	Marzo 2008	Cristiano PERUGINI Fabrizio POMPEI Marcello SIGNORELLI	FDI, R&D and Human Capital in Central and Eastern European Countries
49	Marzo 2008	Cristiano PERUGINI	Employment and Unemployment in the Italian Provinces
50	Marzo 2008	Sławomir I. BUKOWSKI	On the road to the euro zone. Currency rate stabilization: experiences of the selected EU countries
51	Aprile 2008	Bruno BRACALENTE Cristiano PERUGINI Fabrizio POMPEI	Homogeneous, Urban Heterogeneous, or both? External Economies and Regional Manufacturing Productivity in Europe

52	Aprile 2008	Gaetano MARTINO Cristiano PERUGINI	Income inequality within European regions: determinants and effects on growth
53	Aprile 2008	Jan L. BEDNARCZYK	Controversy over the interest rate theory and policy. Classical approach to interest rate and its continuations
54	Aprile 2008	Bruno BRACALENTE Cristiano PERUGINI	Factor decomposition of cross-country income inequality with interaction effects
55	Aprile 2008	Cristiano PERUGINI	Employment Intensity of Growth in Italy. A Note Using Regional Data
56	Aprile 2008	Cristiano PERUGINI Fabrizio POMPEI	Technological Change, Labour Demand and Income Distribution in European Union Countries
57	Aprile 2008	Simona BIGERNA Paolo POLINORI	L'analisi delle determinanti della domanda di trasporto pubblico nella città di Perugia
58	Maggio 2008	Simona BIGERNA Paolo POLINORI	The willingness to pay for Renewable Energy Sources (RES): the case of Italy with different survey approaches and under different EU "climate vision". First results
59	Giugno 2008	Simona BIGERNA Paolo POLINORI	Ambiente operativo ed efficienza nel settore del Trasporto Pubblico Locale in Italia
60	Ottobre 2008	Pierluigi GRASSELLI Cristina MONTESI Roberto VIRDI	L'interpretazione dello spirito del dono
61	Novembre 2008	Antonio BOGGIA Fabrizio LUCIANI Gianluca MASSEI Luisa PAOLOTTI	L'impatto ambientale ed economico del cambiamento climatico sull'agricoltura
62	Novembre 2008	Elena STANGHELLINI Francesco Claudio STINGO Rosa CAPOBIANCO	On the estimation of a binary response model in a selected population
63	Dicembre 2008	Gianna FIGÀ-TALAMANCA	Limit results for discretely observed stochastic volatility models with leverage effect
64	Maggio 2009	Mirella DAMIANI Andrea RICCI	Factors behind performance-related pay: evidence from Italy
65	Giugno 2009	Alessandra RIGHI Dario SCIULLI	The Timing of the School-to-Permanent Work Transition: a Comparison across Ten European Countries
66	Settembre 2009	Fabrizio LUCIANI	Economia agraria e pianificazione economica territoriale nel Parco nazionale del Sagarmatha (Everest, Nepal)
67	Settembre 2009	Valentina TIECCO	I regimi di protezione dell'impiego

68	Ottobre 2009	Gianna FIGÀ-TALAMANCA	Path properties of simulation schemes for the Heston stochastic volatility model
69	Ottobre 2009	Cristina MONTESI	A comparative analysis of different business ethics in the perspective of the Common Good
70	Ottobre 2009	Luisa FRANZINI Margherita GIANNONI	Determinants of Health Disparities in Italian Regions
71	Novembre 2009	Flavio ANGELINI Stefano HERZEL	Evaluating Discrete Dynamic Strategies in Affine Models
72	Novembre 2009	Giuseppe ARBIA Michele BATTISTI Gianfranco DI VAIO	Institutions and geography: Empirical test of spatial growth models for European regions
73	Gennaio 2010	Mirella DAMIANI Andrea RICCI	Performance-Related Pay, Unions and Productivity in Italy: evidence from quantile regressions
74	Febbraio 2010	Davide CASTELLANI Fabio PIERI	The Effect of Foireign Investments on European Regional Productivity
75	Luglio 2010	Guglielmo M. CAPORALE Davide CIFERRI Alessandro GIRARDI	Time-varying spot and futures oil price dynamics
76	Settembre 2010	Mirella DAMIANI	Labour regulation, corporate governance and varieties of capitalism
77	Settembre 2010	Dario SCIULLI Marcello SIGNORELLI	University-to-work transitions: the case of Perugia
78	Ottobre 2010	Olga DEMIDOVA Marcello SIGNORELLI	The Impact of Crises on Youth Unemployment of Russian Regions: An Empirical Analysis
79	Ottobre 2010	Misbah T. CHOUDHRY Enrico MARELLI Marcello SIGNORELLI	The Impact of Financial Crises on Youth Unemployment Rate
80	Novembre 2010	Marco BELLUCCI	Fusioni ed acquisizioni: determinanti ed effetti in un confronto europeo
81	Dicembre 2010	Silvia MICHELI	Learning Curve and Wind Power
82	Dicembre 2010	Leonardo BECCHETTI Stefano CASTRIOTA Elena GIACHIN RICCA	Beyond the Joneses: inter-country income comparisons and happiness
83	Gennaio 2011	Davide CASTELLANI Fabio PIERI	Foreign Investments and Productivity Evidence from European Regions
84	Febbraio 2011	Stefano HERZEL Marco NICOLOSI Cătălin STĂRICĂ	The cost of sustainability on optimal portfolio choices
85	Marzo 2011	Pierluigi GRASSELLI Cristina MONTESI	Politiche orientate al bene comune e politiche attive del lavoro
86	Marzo 2011	Massimo DE FELICE Franco MORICONI	Un'estensione stocastica del modello "Fisher-Lange"
87	Marzo 2011	Mirella DAMIANI Fabrizio POMPEI Andrea RICCI	Temporary job protection and productivity growth in EU economies

88	Aprile 2011	Gaetano MARTINO Paolo POLINORI	Productive process innovation as sequential adjustment of the hybrid governance structure: the case of the poultry sector
89	Aprile 2011	Stefano CASTRIOTA Marco DELMASTRO	Inside the black box of collective reputation
90	Maggio 2011	Roberto BASILE Luigi BENFRATELLO Davide CASTELLANI	Spatial clustering and nonlinearities in the location of multinational firms
91	Giugno 2011	Andrea RICCI Robert WALDMANN	Job Security and Training: the Case of Pareto Improving Firing Taxes
92	Giugno 2011	Francesca PIERRI Alberto BURCHI Elena STANGHELLINI	La capacità predittiva degli indicatori di bilancio: una verifica sulle aziende umbre
93	Luglio 2011	Francesco VENTURINI	Product variety, product quality, and evidence of Schumpeterian endogenous growth: a note
94	Settembre 2011	Francesco VENTURINI	Looking into the black box of Schumpeterian Growth Theories: an empirical assessment of R&D races

ISSN 1722-618X

I QUADERNI DEL DIPARTIMENTO DI ECONOMIA
Università degli Studi di Perugia

1	Dicembre 2002	Luca PIERONI:	Further evidence of dynamic demand systems in three european countries
2	Dicembre 2002	Luca PIERONI Paolo POLINORI:	Il valore economico del paesaggio: un'indagine microeconomica
3	Dicembre 2002	Luca PIERONI Paolo POLINORI:	A note on internal rate of return
4	Marzo 2004	Sara BIAGINI:	A new class of strategies and application to utility maximization for unbounded processes
5	Aprile 2004	Cristiano PERUGINI:	La dipendenza dell'agricoltura italiana dal sostegno pubblico: un'analisi a livello regionale
6	Maggio 2004	Mirella DAMIANI:	Nuova macroeconomia keynesiana e quasi razionalità
7	Maggio 2004	Mauro VISAGGIO:	Dimensione e persistenza degli aggiustamenti fiscali in presenza di debito pubblico elevato
8	Maggio 2004	Mauro VISAGGIO:	Does the growth stability pact provide an adequate and consistent fiscal rule?
9	Giugno 2004	Elisabetta CROCI ANGELINI Francesco FARINA:	Redistribution and labour market institutions in OECD countries
10	Giugno 2004	Marco BOCCACCIO:	Tra regolamentazione settoriale e antitrust: il caso delle telecomunicazioni
11	Giugno 2004	Cristiano PERUGINI Marcello SIGNORELLI:	Labour market performance in central european countries
12	Luglio 2004	Cristiano PERUGINI Marcello SIGNORELLI:	Labour market structure in the italian provinces: a cluster analysis
13	Luglio 2004	Cristiano PERUGINI Marcello SIGNORELLI:	I flussi in entrata nei mercati del lavoro umbri: un'analisi di cluster
14	Ottobre 2004	Cristiano PERUGINI:	Una valutazione a livello microeconomico del sostegno pubblico di breve periodo all'agricoltura. Il caso dell'Umbria attraverso i dati RICA-INEA
15	Novembre 2004	Gaetano MARTINO Cristiano PERUGINI	Economic inequality and rural systems: empirical evidence and interpretative attempts
16	Dicembre 2004	Federico PERALI Paolo POLINORI Cristina SALVIONI Nicola TOMMASI Marcella VERONESI	Bilancio ambientale delle imprese agricole italiane: stima dell'inquinamento effettivo