The Long-Run Growth Effects of R&D Policy

Antonio Minniti and Francesco Venturini*

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Abstract

We assess the long-run growth effects of public policies to business R&D using data for US manufacturing industries and taking Schumpeterian growth theory as guideline. Our analysis indicates that R&D policy in the form of R&D tax credits fosters the rate of productivity growth over the long-term horizon. This effect is quantitatively important: increasing R&D tax credits by 10 percent raises the growth rate of labor productivity by 0.4 percent per year. We show that our findings are robust to controlling for several policy instruments, growth determinants and econometric issues. The overall evidence is consistent with the predictions of second-generation fully-endogenous growth models.

Keywords: Schumpeterian growth theory; Productivity growth; R&D tax credits; US manufacturing industries

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1 Introduction

Do changes in public policies aimed at stimulating business R&D lead to higher growth rates of productivity? If any, are these effects long lasting? Taking Schumpeterian growth theory as guideline,

*Minniti: Department of Economics, University of Bologna, Piazza Scaravilli n. 2, 40126, Bologna (Italy), antonio.minniti@unibo.it. Venturini: Department of Economics, University of Perugia, Via Pascoli n. 20, 06123, Perugia (Italy), & NIESR London (UK), francesco.venturini@unipg.it.

this paper addresses these questions by providing econometric evidence on the long-run impact of R&D policy on productivity growth of the United States.

Early models of R&D-based growth postulate that the long-run growth rate of productivity is proportional to the *level* of research undertaken in the overall economy (see, e.g., Romer 1990, Grossman and Helpman 1991, and Aghion and Howitt 1992). In these models, any policy change affects permanently the growth rate of productivity. In the mid-1990s, the critique formulated by Jones (1995b) against the prediction of these models on the scale effect of R&D stimulated the development of an array of second-generation growth models without scale effects. A first strand of studies makes the assumption of diminishing returns to knowledge and predicts that the steady-state level of productivity is an increasing function of the economy's size (and hence of the amount of R&D), but not its growth rate. Accordingly, R&D policy has no impact on productivity growth in the long run, but only along the transition path. These models are referred to as of semi-endogenous growth as they contend that the growth rate of productivity is ultimately driven by the (exogenous) population growth rate (Jones 1995a; Kortum 1997; Segerstrom 1998). Another line of research known as fully-endogenous growth theory (see, e.g., Dinopoulos and Thompson 1998, Peretto 1998, Young 1998, and Aghion and Howitt 2008, ch. 12) builds upon the insight that, as an economy grows and new varieties are discovered, aggregate R&D effort becomes less effective because it spreads among a greater number of product lines. Productivity growth would depend on the R&D *intensity* at the firm level, explaining why growth can be stationary despite the increasing resources invested in R&D. Accordingly, any policy that affects R&D intensity has also an impact on the steady-state growth rate.

The present paper assesses empirically the long-run growth effect of public policies to business R&D in the US economy using a framework based on the latest strands of Schumpeterian growth theory. Our analysis is carried out in a dynamic panel data setting on twenty US manufacturing industries over the 1975-2000 period. Following the influential studies on tax changes and economic growth (see Lee and Gordon, 2005 and subsequent works), we estimate a growth equation which includes R&D policy instruments as explanatory variables, together with other growth determinants as suggested by the second-generation Schumpeterian growth models. We consider R&D tax credit and the proportion of direct (federal) funding on business R&D expenses as policy variables. The empirical model is estimated by means of a novel regression technique, the Cross-Sectionally Augmented Distributed Lags (CS-DL) estimator (Chudik *et al.*, 2016). This approach is based on a dynamic representation which provides consistent estimates for the long-run parameters and is robust along a number of important dimensions (namely, misspecification of dynamics, error serial correlation, cross-sectional dependence, etc.).

Our analysis indicates that R&D policy has a persistent, if not permanent, impact on the growth rate of productivity, which provides strong support to fully-endogenous growth theory. However, the growth effects of R&D policy vary with the type of instruments used. We find that R&D tax credits have a significant and positive impact on growth that persists over the long-term horizon. This effect is quantitatively important: increasing the generosity of R&D tax credits by 10% raises the growth rate of labor productivity by 0.4% per year. Conversely, direct funding to R&D does not appear to affect significantly productivity growth in the long run, indicating that at best this policy instrument has only temporary effects. Our findings are shown to be robust to including various tax policy and economic controls, as well as to various econometric issues.

Our paper does contribute to some important strands of the economic literature. First, it is related to a recent line of research evaluating whether semi-endogenous or fully-endogenous growth models are more empirically relevant (see the discussion in Dinopoulos and Thompson 1999). Our paper fills an important gap in the literature as prior work has assessed the consistency of the two competing growth frameworks with productivity and innovation statistics and, based on this evidence only, inferred whether innovation policies have permanent or temporary growth effects. Exploiting US manufacturing industry data, Zachariadis (2003) provides evidence in favor of the predictions of second-generation growth models, using a specification derived from a fully-endogenous growth setting. The subsequent empirical contributions have sought to discriminate between semi- and fully-endogenous growth theories. Ha and Howitt (2007) apply cointegration analysis to US macroeconomic data since the 1950s, finding strong support for fully-endogenous growth theory. This result appears to have general validity and is not limited to certain countries or certain stages of development. A similar conclusion is reached by Madsen *et al.* (2010) on the British transition to the post-Malthusian growth regime after the First Industrial Revolution, and by Madsen (2010) on the growth performance of OECD countries since the Second Industrial Revolution.[1] The present work makes a step forward in this literature by providing

[1] Other earlier works assessing the soundness of second-generation growth models using US industry data are Venturini

evidence in support of fully-endogenous growth theory through a direct estimation of the growth effects of R&D policies.

Second, our paper also relates to a large body of research inspecting the role of public support to R&D (direct public engagement, direct subsidies, tax credit, etc.). This literature has concentrated on two major questions: (1) the additionality issue, i.e., whether public support raises, or reduces, private R&D investment (crowding-in or crowding-out effect); and (2) whether R&D tax credits are more or less effective than direct subsidies in stimulating business R&D.[2] In the United States, with the diffusion of the R&D tax credit nationally and among the US states since the early 1980s, much of the debate has centered on evaluating whether tax credits are more effective than direct funding in stimulating business R&D. Using industry-level data, Mamuneas and Nadiri (1996) document that incremental R&D tax credit and the immediate deductibility provision of R&D expenditures have a significant impact on privately-funded R&D investment; on the other hand, publicly-financed R&D induces cost savings but crowds out privately-funded R&D investment. Guellec and van Pottelsberghe (2003) show that, in OECD countries, direct government funding spurs business-financed R&D (apart from when it is oriented towards defense), while tax incentives have short-lived effects. Bloom *et al.* (2002) quantify the impact of fiscal incentives on R&D investment by estimating an R&D demand equation for few OECD countries. They find that a 10% fall in the cost of R&D stimulates over a 1% rise in the R&D effort in the short run, and almost a 10% increase over the long run. Thomson (2015) performs an industry-level analysis for a large set of industrialized countries finding for business R&D a short-run responsiveness of 5% to a 10% increase in fiscal discounts. The present work extends this strand of literature by assessing the ability of public policies to business R&D in promoting productivity growth, drawing on the latest developments of Schumpeterian growth theory.

Finally, our work is also related to the vast literature on the relationship between taxation and economic growth. The seminal contributions by Easterly and Rebelo (1993) and Mendoza *et al.* (1997) showed that the effects of taxes on growth are difficult to isolate empirically (the so-called Harberger's

(2012a) and Venturini (2012b).

[2] See David *et al.* (2000) and Alonso-Borrego *et al.* (2014) for comprehensive surveys. Another important channel through which public policy can raise private R&D is through public procurement (see, e.g., Cozzi and Impullitti, 2010; Slavtchev and Wiederhold, 2015). Other valuable works on R&D tax incentives are those of Lokshin and Mohnen (2013) on the effect of these policy instruments on researchers' wages and Castellacci and Lie (2015) on their heterogeneous impact across industries and firms.

superneutrality conjecture). This issue has been further investigated by a number of subsequent studies which find a significant association between taxation and economic growth. The most recent contributions in this field focus on the design of growth-friendly tax policies and conclude that the corporate income tax is particularly detrimental for income growth (Kneller *et al.*, 1999, Lee and Gordon, 2005) and income levels (Arnold *et al.*, 2011). Gemmell *et al.* (2015) find that tax effects on GDP growth operate largely through changes in factor productivity, rather than via investment. This conclusion is in line with the view developed in Peretto (2003, 2007) and Lee and Gordon (2005) who stress the importance of innovation and entrepreneurship as transmission channels of taxation on GDP growth. We contribute to this literature by showing that, for a knowledge-based economy such as the United States, R&D activities represent an important transmission channel of the effects of taxation on productivity growth.

The rest of the paper is organized as follows. Section 2 contrasts the main features of fully- and semi-endogenous growth theory and provides the theoretical background of the empirical analysis that follows. Section 3 describes the empirical specification and presents the data used. The econometric analysis is developed in Section 4 where we discuss the main results and a number of robustness checks. Finally, Section 6 concludes and outlines future research directions.

2 Second-generation endogenous growth models

The latest generation of Schumpeterian growth theories without scale effects, namely semi-endogenous growth theory and fully-endogenous growth theory, has opposite policy implications. This section reviews the two approaches and provides a brief background for the empirical analysis which follows. To focus on the mechanisms identified by second-generation endogenous growth models, following Jones (1999, 2005) and Laincz and Peretto (2006), we use a reduced form representation of the two classes of models.

2.1 Semi-endogenous growth theory

The semi-endogenous growth models developed by Jones (1995a), Kortum (1997) and Segerstrom (1998) contend that there are diminishing returns to R&D. According to this approach, policy changes do not affect the growth rate in the long run, but only along the transition path. To see this, let us consider a simplified framework where Y is aggregate output, A is productivity (or equivalently technological knowledge), L_y is labor used in producing output, L_A is labor engaged in R&D activities, and δ is a parameter governing R&D productivity:

$$Y = AL_Y,$$

$$\dot{A} = \delta L_A A^{\phi}, \quad \delta > 0, \quad 0 < \phi < 1.$$

The first equation is a standard output production function, whereas the second equation represents the knowledge production function. $\dot{A}$ measures the flow of new knowledge generated by employing L_A units of labor for an interval of time dt. This family of models makes the assumption that the parameter ϕ is strictly lower than one meaning that the knowledge production function exhibits decreasing returns. In equilibrium, both activities employ some fraction of labor. Let $s \equiv L_A/L$ denote the share of labor allocated to R&D with L being the size of the labor force. In steady state, s must be constant and, accordingly, the growth rate of output (or income) per capita, $y \equiv Y/L$, writes as:

$$g_y = g_A = \frac{n}{1-\phi}, \tag{1}$$

where $n > 0$ denotes the growth rate of the population. As one can see, the long-run growth rate of income per capita is proportional to the population growth rate and is independent of public policy to R&D.

2.2 Fully-endogenous growth theory

The fully-endogenous growth models developed by Young (1998), Peretto (1998), Dinopoulos and Thompson (1998) and Howitt (1999) posit proportionality of productivity growth to R&D inputs at the firm level, but not at the economy level as predicted by semi-endogenous growth theory. These models eliminate the scale effect by allowing for the expansion in the number of firms (or varieties of products). An increase in scale expands the number of product lines proportionally, leaving the amount of research per product unchanged. In such models, R&D intensity enters the rate of economic growth and, therefore, policies that are able to affect this share have an impact on the long-run rate of economic growth. To illustrate the mechanism, let us consider the following simplified framework:

$$Y = \left[\int_0^F Y_i^{1/\theta} di \right]^\theta, \quad Y_i = A_i L_{Yi}, \quad \theta > 1.$$

$$\dot{A}_i = \delta L_{Ai} A, \quad A = \int_0^F \frac{A_j}{F} dj, \quad \delta > 0.$$

The subscript i refers to firm i. The first line states that aggregate output Y is a CES composite of a variety of goods. F_t represents the number of varieties that are available at date t, Y_i is the output of variety i, A_i is firm i's stock of knowledge, L_{Yi} is labor used in producing firm i's output and $\theta/(\theta-1) > 1$ is the elasticity of substitution between products. The second line specifies the knowledge production function at the firm level. $\dot{A}_i$ measures the flow of new knowledge generated by an R&D project employing L_{Ai} units of labor for an interval of time dt and δ is a parameter governing R&D productivity. Each firm's stock of knowledge contributes to the pool of general knowledge A allowing the entire economy to grow through spillovers. We focus on the symmetric equilibrium and denote average variables without the subscript i. As each variety of output is produced in the same quantity, we can write aggregate production as:

$$Y = F_t^\theta A L_Y,$$

where A and L_Y stand respectively for the average levels of knowledge and employment used in production. Average knowledge, in turn, evolves according to:

$$\frac{\dot{A}}{A} = \delta L_A,$$

where L_A is average R&D. In steady state, the shares of the labor force engaged in R&D and production, namely $s \equiv L_A F/L$ and $1 - s \equiv L_Y F/L$, must be constant. Therefore, income per capita, $y \equiv Y/L$, writes as $y = F^{\theta-1}A(1-s)$. Differentiating this expression with respect to time yields:

$$g_y = (\theta-1)g_F + g_A = (\theta-1)g_F + \delta L_A = (\theta-1)g_F + \delta s\frac{L}{F}, \tag{2}$$

which says that the growth rate of income per capita, g_y, depends positively on the growth rates of product varieties and knowledge, namely g_F and g_A. As discussed more thoroughly in Jones (1999) and Laincz and Peretto (2006), a key property of this class of models is the proportionality between the number of product varieties (firms) and employment (population), i.e., $F = \eta L$.[3] By using this relation, Eq. (2) can be also written as:

$$g_y = (\theta-1)n + \delta s/\eta. \tag{3}$$

Eq. (3) shows that income per capita growth, g_y, is positively related to population growth, n, and R&D intensity, s. However, in this framework, dependence of g_y on population growth is not necessary. In fact, if the output aggregator Y did not feature the love-of-variety effect ($\theta = 1$), a positive rate of per capita income growth would persist in the long run. Moreover, the effect of policy on long-run growth is preserved as a permanent change in R&D intensity, s, would alter the steady-state growth rate. These two features are in stark contrast to semi-endogenous growth theory which, instead, predicts that income per capita growth depends solely on population growth.

3 Empirical analysis

Our empirical analysis is aimed at evaluating whether, and to what extent, R&D policy influences the long-run rate of productivity growth. In essence, we estimate a growth equation which includes the main determinants identified by the two strands of Schumpeterian growth theory, as described above. Our empirical specification is general enough to nest, under certain parameter conditions, either fully-endogenous growth or semi-endogenous growth and, hence, we are able to fully discriminate between these two classes of models.

[3] Laincz and Peretto (2006) make it clear that the relation $F = \eta L$ is not a "knife-edge" condition characterizing this class of models. On the contrary, it is the outcome of an economic mechanism driven by costly entry. Moreover, the authors provide empirical evidence lending support to the proportional relation between the number of firms and the size of the labor force by showing that either employees or R&D workers per establishment are stationary (trendless) variables.

The empirical model is estimated within a dynamic panel data setting on twenty US manufacturing industries over the 1975-2000 period. In what follows, we describe the econometric methodology and the data.

3.1 Estimation procedure and econometric issues

Following the extensive literature on tax policy and economic growth, we estimate an equation where the rate of productivity growth, g_y, is a function of the innovation policy variable, τ (Lee and Gordon, 2005; Gemmell *et al.*, 2011; Arnold *et al.*, 2011). We augment this specification with the set of variables identified by the two strands of Schumpeterian growth theory as drivers of long-run growth, i.e., the rate of population growth, n, and the rate of knowledge growth, g_A (or R&D intensity, s).

$$g_{y,it} = \mu_{0i} + \gamma \mathbf{z_{it-1}} + \epsilon_{it}, \tag{4}$$

where i denotes industries, t the year of observation, μ_{0i} are industry fixed effects, $\mathbf{z_{it}} = \{\tau_{it}, g_{F,it}, g_{A,it}\}$ is a matrix of regressors, γ is a vector of the corresponding long-run parameters. ϵ_{it} is an error term described below. Explanatory variables are one-year lagged with respect to g_y to mitigate reverse causality problems. Although the limited time span in this paper (25 years) might not be sufficient to understand whether the growth effect of R&D policy is permanent or transitory, the time interval should be nevertheless sufficient to understand whether this effect is or not persistent (Gemmell *et al.*, 2011).

To infer γ, we estimate the growth equation by means of a novel technique of regression, the CS-DL approach (Chudik *et al.*, 2016). This procedure considers a dynamic version of Eq. (4), expressed as an Auto-Regressive Distributed Lags (ARDL) model, and reformulates it in a way to avoid the bias in the long-run coefficients arising from the inconsistency in the parameter of the lagged dependent variable (Nickel effect). The main advantage of the CS-DL regression is that it yields more precise long-run estimates than ARDL when the time dimension of the data is not sufficiently long (less than 50 time observations).

To show how the CS-DL approach works, let us express Eq. (4) as an ARDL model assuming one lag of the variables ($p = 1$) and omitting deterministic elements for simplicity:[4]

$$g_{y,it} = \varphi g_{y,it-1} + \beta_{\mathbf{1}} \mathbf{z_{it-1}} + \beta_{\mathbf{2}} \mathbf{z_{it-2}} + \epsilon_{it}. \tag{5}$$

ϵ_{it} is a serially uncorrelated error term that, potentially, could be dependent across industries due to the presence of unobserved common factors. In this setting, the vector of long-run coefficients is usually inferred from the short-run coefficients of the explanatory variables (φ and $\beta_{\mathbf{i}}$), $\gamma = (\beta_{\mathbf{1}} + \beta_{\mathbf{2}})/(1 - \varphi)$. The CS-DL estimator abandons this approach and estimates directly the long-run parameters (γ) by rewording Eq. (5) as:

$$g_{y,it} = \gamma \mathbf{z_{it-1}} + \alpha \Delta \mathbf{z_{it-1}} + \tilde{\epsilon}_{it}, \tag{6}$$

where $\tilde{\epsilon}_{it} = \epsilon/(1 - \varphi)$ and $\alpha = \beta_{\mathbf{1}} + \beta_{\mathbf{2}}$.

To filter out the effect of cross-sectional dependence (unobserved factors), Eq. (6) is augmented with the cross-industry mean of the dependent variable and the regressors, taken at time t (Common Correlated Effects, hereinafter denoted as CCE; see Pesaran, 2006). Failing to control for strong cross-sectional dependence leads to inefficient estimates if unobserved factors are correlated with the dependent variable, but causes inconsistency in the estimates if such unobserved factors are correlated with the explanatory variables (Chudik and Pesaran, 2015).[5] Augmenting Eq. (6) with CCE terms allows us to exclude that our policy variable does capture the impact of federal fiscal policies, general technology shocks, as well as other un-observed factors that influence productivity growth at industry level.

Assuming no feedbacks from the lagged dependent variable onto the regressor (weak exogeneity), consistent estimates of the long-run parameters, γ, can be obtained by estimating Eq. (6) with least squares. This holds irrespective of whether or not, y and z are stationary; if not stationary, γ is a cointegrating vector. The CS-DL approach performs particularly well in small samples as compared to the panel ARDL and is applicable either with homogeneous or heterogeneous parameters. In the following, we estimate Eq. (6) assuming homogeneous parameters, weak exogeneity of the regressors, and

[4]In the regression analysis, we adopt a less parsimonious specification that includes three lags of the first-differenced regressors ($p = 3$). This corresponds to the integer part of the rule-of-the-thumb $p = T^{1/3}$ in which T are time observations.

[5]The CS-DL approach is robust to serial correlation, breaks in regressors/unobserved factors, and remains valid under weak cross-section dependence. This procedure has been recently used by Chudik *et al.* (2015) to assess the public debt-growth nexus using country-level data.

purging cross-sectional dependence through the contemporaneous cross-sectional mean of the variables. However, in the Online Appendix to this article, we assess the robustness of the results by relaxing such assumptions. In particular, i) we allow for heterogeneity in the impact of the explanatory variables (both in the short and the long run); ii) we admit reverse causality and estimate both an instrumental variable (IV) regression and a panel ARDL model that accounts for feedbacks of the lagged dependent variable onto the regressors (i.e. Eq. 5); and iii) we control more effectively for cross-sectional dependence by including higher order lags of the average variables into the specification.

3.2 Data

The empirical analysis uses data on twenty two-digit US manufacturing industries between 1975 and 2000, collected from several statistical sources.[6] The dependent variable g_y is measured by the annual rate of change of labor productivity, defined as the ratio between value added at 1995 prices and the number of employees (source: EU KLEMS, Release March 2007). We use the rate of patenting and, alternatively, the share of R&D workers on industry employment as a proxy for knowledge growth, g_A. The patenting rate approximates the rate at which new products or production modes (i.e. innovation output) come to the market. The rate of patenting is defined as the ratio between the annual number of granted patents at industry level (assigned to US firms on the basis of the application year) and their cumulative value up to the preceding year. The cumulative value of patents is determined by adopting the perpetual inventory method and a geometric depreciation rate of 15%. Each patent is weighted with the number of citations received; this quality indicator is adjusted for truncation, i.e., industry citations are scaled on the yearly manufacturing mean (Hall *et al.*, 2001). Patent data are taken from USPTO NBER Patent Data files. g_A is also measured in terms of research input and is proxied by the share of R&D scientists and engineers on total workers, expressed in full-time equivalent units (source: National Science Foundation). Following Ha and Howitt (2007) and Ang and Madsen (2011), we use the annual rate of change of industry employment as a proxy for population growth, n.

[6] Industry list (ISIC Rev 2): 1- Food, beverage & tobacco (15t16); 2- Textile (17t19); 3- Pulp, paper & printing (21t22); 4- Coke, refined petroleum and nuclear fuel (23); 5- Chemicals (24); 6- Pharmaceuticals (244); 7- Rubber and plastics (25); 8- Other non-metallic minerals (26); 9- Basic metals (27); 10- Fabricated metal (28); 11- Machinery, NEC (29); 12- Office, accounting and computing machinery (30); 13- Electrical machinery and apparatus, NEC (31); 14- Electronic valves and tubes (321); 15- Communication equipment (322t323); 16- Scientific instruments (331t3); 17- Other instruments (334t5); 18- Motor vehicles, trailers and semi-trailers (34); 19- Other transport equipment (35); 20- Manufacturing, NEC (36t37).

A large array of policy instruments can be adopted to foster industrial research (grants, tax credit, public procurement, public-private R&D partnerships, direct performance of research in public laboratories or universities, etc.). In this paper, we use two indicators offering large variation across industries and over time: R&D tax credit and federal funds to industrial R&D. The former (and main) indicator consists of the tax price component of the user cost of R&D, that is inversely related to the fiscal treatment of R&D outlays (source: Wilson, 2009).[7] The R&D tax price, ρ^P, varies with the federal- and state-level fiscal discipline on R&D expenditures and corporate income, ρ (below f denotes variables at the federal level, l at the state level).

Following Hall and Jorgenson (1967), the user cost of R&D capital is defined as:

$$\rho_{lt} = \frac{1 - \zeta_1(k_{lt} + k_{ft}) - \zeta_2(\vartheta_{lt} + \vartheta_{ft})}{1 - (\vartheta_{lt} + \vartheta_{ft})} \cdot (r_t + \delta) = \rho^P_{lt} \cdot (r_t + \delta), \tag{7}$$

where k_t denotes the effective R&D tax rate, ϑ_t is the effective corporate income tax rate, ζ_1 captures the fraction of qualified R&D expenses that are eligible for fiscal deduction, ζ_2 is the present discounted value of tax depreciation allowances, r_t is the real interest rate, and δ is the economic depreciation rate of R&D capital.[8] Higher tax deductions for R&D make the fiscal wedge on R&D capital lower (ρ^P_{lt}), reducing thus the user cost of these types of assets (ρ_{lt}). This stimulates research investment. Hall and Van Reenen (2000) describe extensively the properties of the R&D tax credit and discuss evidence on the effectiveness of this policy instrument to raise private research. The values of r_t and δ are assumed to be common across units and hence their effect is captured by the CCE terms and the deterministic elements of the empirical model. Since data on the tax price component of R&D capital user cost are available at the state level, following Bloom *et al.* (2013), we have re-attributed such values to manufacturing industries (denoted by i's) according to the spatial distribution of innovation (patent) activities (at each time t):

$$\rho^P_{it} = \sum_{l=1}^{50} \omega^a_{ilt-1} \cdot \rho^P_{lt},$$

where l indicates US states ($l = 1, ...50$) and ω^a_{ilt-1} is a percentage share indicating how US patentees

[7] This instrument is less affected by issues of arbitrariness and non-additionality and, often, is preferred to other policy instruments, such as R&D subsidies (David *et al.*, 2000).

[8] The parameter ζ_1 is set to 0.5, whereas ζ_2 is set to 1 (see Wilson, 2009).

of industry i distribute across states. These weights are one-year lagged with respect to tax prices to reduce possible simultaneity between innovation output and innovation policies.[9]

Federal funds to industrial R&D are measured as a share of total R&D expenditure performed by private firms in the industry (ν_{it}). Federal funds to R&D are managed by several agencies (NASA, Departments of Defense, Energy, Agriculture, National Institute of Health, NSF, etc.) and cover eight broad scientific fields (life sciences; psychology; physical sciences; environmental sciences; mathematics and computer sciences; engineering; social sciences; and other sciences). In the early 2000s, companies administered about 10-15% of federal budget to research and 50% of federal grants to development projects (CBO, 2007). Universities and other research institutions managed the rest. Federal funds include the cost of R&D performed within the company in the 50 US states and the District of Columbia funded by federal R&D contracts, subcontracts, R&D portions of federal procurement contracts and subcontracts, grants, or other arrangements. They exclude R&D expenses supported by the federal government but contracted to outside organizations such as research institutions, universities and colleges, non-profit organizations, or other companies. Federal funds are not eligible for the R&D tax credit.[10]

3.2.1 Control variables

We perform a battery of robustness checks, including both *tax policy* and *economic controls*, in order to avoid omitted variables' problems.

Tax policy controls

We use various indicators of tax policy to exclude the possibility that the estimated impact of R&D policy variables captures the effect of other policy instruments. Following the literature on the relationship between tax structure and economic growth, we construct a set of variables gauging the taxation on sales, corporate income, individual income and property income. These variables are defined as average (effective) taxation rates, i.e., they are determined by the ratio between tax revenues and taxable

[9] Using industry data at the economy-wide level, rather than industry-by-state information, is less subject to simultaneity bias occurring whether, for instance, firms change the settlement of their R&D labs (or impute research expenses to their establishments localized) in those US states in which they expect larger R&D tax deductions. As Wilson (2009) documents, there is a crowding-out effect across states in the effect of state-level fiscal deduction for R&D (i.e. more generous fiscal benefits in a state reduce private firm's R&D effort in the surrounding states). Using data at the economy-wide level, we capture the net effect of R&D tax incentives on industrial growth.

[10] See also <http://www.nsf.gov/statistics/nsf09301/>.

income. As for R&D tax price, we exploit state-level variation in tax policies and re-attribute such taxation rates to manufacturing industries on the basis of how industry's taxable income distributes across states (i.e., we apply the same formula as in Eq. 7).

First, we consider taxes on sales, defined as the average tax rate on production and imports, AST. This category comprises primarily non-personal property taxes, licenses, and sales and gross receipts taxes. Taxes on production and imports consist of taxes payable on products when they are produced, delivered, sold, transferred, or otherwise disposed of by their producers (i.e. VAT). Such tax receipts are divided by the state value added. Second, we construct the average tax rate on corporate income, defined as the ratio between corporate tax revenues and gross operating surplus, ACT. Third, a measure of individual income tax rate is obtained taking the ratio between tax revenues from net labor income and special types of income (interest, dividends, income from intangible property, etc.) and personal income, AIT. Finally, we include an average tax rate on property income, e.g., real property (land and structures), personal tangible property (automobiles and boats) and personal intangible property, APT (bank accounts and stocks and bonds). The last two tax policy measures are assigned to manufacturing industries on the basis of the distribution across states of labor compensation and gross operating surplus.[11]

Wilson (2009) documents that, due to competition in R&D policies across US states, the impact of own-state R&D tax credit is reduced by the generosity of innovation policies implemented by the neighbors. For this reason, we include a proxy for external R&D policies, based on averaging ρ^P of other industries with weights reflecting the technological distance between pairs of sectors. The matrix of technological distances is computed tracing citations between industries, as the higher is the number of (backward) citations made, the more technologically contiguous are the US companies:

$$\rho_{it}^{P,W} = \sum_{j=1}^{20} \omega_{ij}^{c} \cdot \rho_{jt}^{P},$$

where $\omega_{ij}^{c} = BC_{ijt}/BC_{it}$ $(i \neq j)$ is the share of (backward) citations made by US patentees of industry i to US firms operating in industry j, over total patent citations made by industry i. These weights are

[11] Tax revenues come from the Database on Historical State Tax Collection: <http://www.census.gov/govs/statetax/historical_data.html>. Taxable income come from the Bureau of Economic Analysis (BEA), Regional data: <http://www.bea.gov/iTable/index_regional.cfm>.

time invariant, i.e., they are built considering all patents applied for through the 1975-2000 period.[12]

Economic controls

We extend our growth equation to include some standard determinants of labor productivity growth. We first consider the rate of change in the ratio between capital stock and employees (capital deepening), KL (source: Becker and Gray, 2009), and, then, the labor share of high-skilled workers, HS (source: KLEMS, 2008). We also assess whether our main explanatory variables covariate with other important industry characteristics. We control for the average mark-up set by the firms in each industry. This is constructed as the ratio between undistributed corporate profits and sales (Aghion *et al.*, 2005). The former variable is defined as difference between gross operating surplus and financial costs of firm activity; the latter is measured as gross output (source: BEA Regional accounts). The degree of technological concentration is gauged by the Herfindahl-Hirschman index of patent citations at the industry level. This variable is time-varying and excludes self-cites:

$$HHI = \sum_{a=1}^{N} (FC_{ait}/FC_{it})^2,$$

where a indicates US patentees (from 1 to N), FC are (forward) citations received by each US innovator from US patenting firms of the same industry.[13] We adopt two measures related to the industry dependence on external finance. The former consists in the share of capital expenditure which is not self-financed, provided by Von Furstenberg and Von Kalckreuth (2006), FD. The latter is the proportion of undistributed profits, SF (source: BEA Regional accounts). Finally, we allow for knowledge spillovers across industries, using alternatively as control variables the technological distance-weighted value of the rate of patenting, the stock of patents and the stock of R&D expenses of the other industries (see above for further details on the construction of such variables). The R&D stock is constructed using the perpetual inventory method as for the patent stock.

Summary statistics of the main variables used in the analysis are shown in Table 1.

[12] We limit our analysis to the external measure of R&D tax price as we show below that the proportion of federal funds to R&D has no (persistent) effects on growth.

[13] HHI is rescaled in order to vary between zero and one.

4 Empirical results

4.1 Baseline estimates

Table 2 reports baseline estimates of Eq. (6), based on homogeneous parameters. Col. 1 considers only R&D policy instruments as explanatory variables, namely the R&D tax price and the share of federally-funded R&D. The subsequent columns add the proxies for the growth rates of knowledge and population. Cols. 2 through 4 use the rate of patenting as a proxy for g_A, cols. 5 through 7 adopt the share of R&D workers on total employment; the latter specification corresponds to the stochastic version of Eq. (3).

Col. 1 shows that productivity growth has been spurred by R&D tax credit but not by federal funds to R&D. This may be due to the fact that federal funds collect grants both to basic and applied research, spread through a variety of fields (and industries) and that are managed by several agencies. Most funds were targeted to defense and aerospace, and these grew significantly up to the late 1980s but fell sharply then on. The concentration in few sectors and the bell-shaped pattern may explain why this policy instrument did not affect significantly the rate of economic growth in the long run. More generally, federal funds may not have been awarded to innovation projects with the highest potential because of the discretionary nature of the administrative procedure for granting and for the problems of asymmetric information between the applicant and the agency. Federal funds may also have crowded out privately funded research expenses, leaving unchanged the overall R&D engagement (David *et al.*, 2000). Moreover, direct public funding and R&D tax incentives are likely to serve as substitutes so that the increased generosity of one may reduce the effect of the other on business R&D (Guellec and van Pottelsberghe, 2003). All this could explain the reason why the effect of federal funds on productivity growth is irrelevant in the long run.

Cols. 2 and 5 include the growth determinants identified by the latest strands of Schumpeterian growth theory. Our proxy for population growth (i.e. employment growth) does not seem to affect the rate of productivity growth, g_y. Conversely, knowledge growth is found to significantly spur g_y showing an impact quite similar when using the patenting rate or the share of R&D workers as a proxy for g_A (1.182 or 1.464 respectively). Notice that the parameter of the share of R&D workers declines, remaining significant at a 10% level, when R&D policy variables are introduced into the model (cols. 6 and 7). This is due to the fact that public support to R&D is aimed at raising firms' research effort. Conversely, the coefficient of the rate of patenting remains highly significant and does increase in magnitude in the extended specification (cols. 3 and 4). Quantitatively, the parameter estimated for g_A indicates that a 1% increase in innovation activities has raised the rate of labor productivity growth by over 1%. The impact of innovation on the rate of growth is slightly larger than that found by Zachariadis (2003) for the US manufacturing sector for an earlier period of time.[14]

This first set of results illustrates that the tax price component of the R&D user cost has a significant and negative impact on output growth over the long-term horizon, implying that R&D tax credit has a positive effect on the rate of productivity growth that persists over time. The estimated impact of R&D tax price has to be interpreted as a unit impact. Expressed in terms of elasticity, our estimates indicate that a 10% decrease (increase) in R&D tax price (credit) generates a permanent increase in the rate of growth of labor productivity of around 0.4%.[15] The result that the R&D tax policy variable is significant for labor productivity growth in the long run can be explained in different ways. R&D policy may indeed promote reallocation of resources away from stagnant industries toward R&D intensive, high growth sectors. However, as long as R&D tax credits generate increases in R&D scientists and engineers' wages (see Lokshin and Mohnen, 2013), R&D policy may either stimulate the effort (and productivity) of these workers, or stably expand the aggregate demand as a larger share of income is allocated to labor compensation. Our findings also indicate that, over the long-term horizon, productivity growth is related to the patenting rate or the share of R&D workers, meaning that knowledge growth is an important growth determinant and is independent of R&D tax policy. This finding, along with the significance of R&D policy variables, provides strong confirmation of fully-endogenous growth models. Conversely, our proxy for population growth, namely employment growth, does not significantly influence productivity

[14] Extrapolating the output growth effect of patenting from col. I, Table 2, in Zachariadis (2003), we obtain an approximate value of 0.4 (=0.083/0.206).

[15] A unit decrease in the R&D tax price from the sample mean of 1.333 to 0.333 corresponds to a rate of change of 139% (in natural logs). Dividing the coefficients in Table 2 by this value yields the elasticity. In the period under assessment, the statutory federal tax credit rate to R&D averaged around 20%, the state-level rate around 2.5%. It implies that, on the basis of Eq. 7, the overall R&D tax credit would have to increase approximately from 22.5 to 32.5% (as ζ_1 is equal to 0.5; see Wilson 2009, p. 432) in order to observe a permanent increase of 0.4% per year in the rate of labor productivity growth. Notice that the resulting statutory rate of tax discounts for R&D would be comparable with the new discipline adopted in France since 2008 (see Mulkay and Mairesse, 2013, p. 751).

growth.[16] As semi-endogenous growth models predict that population growth is the sole determinant of the long-run economic growth rate, the lack of statistical significance of employment growth casts some doubts on the empirical relevance of this class of models.[17]

4.2 Sensitivity analysis: tax policy controls

Our previous estimates concentrate on the impact of the R&D policy on productivity growth without considering the general effect of fiscal policy. In what follows, we introduce several tax rates to exclude the possibility that the estimated impact for R&D policy captures the impact of other forms of taxation.

Col. 1 of Table 3 considers as a benchmark the specification based on the patenting rate as a proxy for knowledge growth, and R&D tax price as innovation policy variable, as reported above. In cols. 2 through 5 we add control variables one by one to the growth regression. Taxation has quite heterogeneous effects on economic growth (see Arnold *et al.*, 2011 for a discussion on the "tax and growth ranking"). Property income taxes are argued to promote economic growth by shifting investment out of housing into more productive activities. Consumption taxes, such as VAT, increase consumer goods' prices and can affect labor supply by reducing the real reward for working. However, consumption taxes do not discourage saving and investment and, hence, they may have little (or negative) impact on economic growth. Personal income taxes are seen as more harmful to economic growth than consumption taxes for several reasons. First, they are generally progressive, in contrast to consumption taxes. Second, they typically tax the return to savings (interest and/or dividends), thus discouraging investment. Third, high income taxes reduce the entrepreneurial rate or lead to people staying on social benefits rather than work. Corporate income taxes are expected to be the most harmful for growth as they impact negatively on the entrepreneurial activity by reducing firm entry and discouraging investment in capital and in productivity improvements. However, very recently, these findings have been questioned by a few works that have re-examined the taxation-growth nexus by addressing various econometric concerns, namely strong cross-sectional dependence, parameter heterogeneity, etc. (see Xing, 2012 and Arachi

[16] As pointed out above, in fully-endogenous growth models, exponential growth in per capita outcome can be sustained even in the absence of population growth. This is not the case for semi-endogenous growth models which, instead, identify the rate of population growth as the only driver of the long-run growth rate.

[17] In the Online Appendix, we provide unit roots and panel cointegration tests for the variables used in the baseline regressions. We show that such variables are I(1) and that there is a long-run stationary (cointegration) relationship between dependent variable and the regressors in accordance with the results of Table 2.

et al., 2015). The latter issues are discussed extensively in the econometric checks displayed in the Online Appendix.

In col. 2, we use the average tax rate on production and imports, which mostly reflects VAT levied at the state level. Including this fiscal policy variable leaves unchanged the magnitude and the significance of R&D policy instrument, as well as those of the other explanatory variables. This control variable reveals a positive and statistically significant impact on growth.[18] In col. 3, we use the average tax rate on corporate income. The impact of this control variable on productivity growth is negative as expected, although it is not statistically significant. This may reflect the fact that the corporate income tax also enters the R&D user cost formula (i.e., ϑ in Eq. 7), indicating that at best the fiscal discipline on corporate profits is relevant for economic growth as long as it reduces the effective cost of research.

Finally, we use personal income and property income taxes in cols. 4 and 5 respectively. The effect of both variables is positive but never reaches significance. Overall, our results are in line with the recent evidence provided by Gale *et al.* (2015) who show that the average levels of taxation did not significantly affect state-level per capita income growth in the US.[19] As average tax rates potentially suffer from endogeneity and may not capture the entire effect of fiscal policy along the tax schedule, we have also used marginal tax rates, inferred by preliminarily regressing taxation revenues on taxable income –both expressed at current prices– along with deterministic elements (Koester and Kormendi, 1989, Padovano and Galli, 2001, Reed *et al.*, 2011). Our results for Eq. (6) do not change using these alternative taxation rates. Compared to earlier studies based on international data (Gemmell *et al.*, 2011 and Arnold *et al.*, 2011 among others), the lack of significance for our set of tax policy variables may depend on a smaller variation in tax rates across US states than across countries, probably because of a fiercer tax competition or a similar institutional setting. As Chirinko and Wilson (2013) document, another possibility is that state-level taxation responds similarly to unobserved common factors (business cycle, technology shocks, etc.) whereby tax policy variables turn out to be insignificant when accounting for the effect of strong cross-sectional dependence. Although our estimates indicate that tax policies have no impact on the long-run rate of productivity growth, it cannot be excluded that their effect is

[18]The coefficient size of production taxes appears oversized; however, this variable turns out to be insignificant in a regression admitting all fiscal controls and R&D tax price (unreported).

[19]However, in contrast with Gale *et al.* (2015) who found that tax changes do matter for growth, expressing tax variables in rates of change does not remarkably modify our findings (unreported).

temporary. In this case, tax policy would have a *level effect* on income, as found by Arnold *et al.* (2011).

Next, we evaluate whether the growth effect of R&D policy is strictly related to the fiscal discipline of the sector, ρ^P, or rather reflects the firms' response to the changes in R&D tax deductions of the other industries, ρ^W (see cols. 6 and 7). The external measure of R&D tax price is insignificant either when considered alone (col. 6) or together with own-industry R&D tax price (col. 7). Notice that the latter variable loses significance, due to the large correlation between ρ^P and $\rho^{P,W}$. Furthermore, we have also investigated whether R&D tax price has a own direct effect on growth or, rather, the impact of this variable is mediated by its effect on the research effort (unreported). To this aim, in Eq. (6) we have introduced the amount of R&D expenses per worker induced by innovation policies. Following Bloom *et al.* (2013), this value has been predicted by estimating an R&D demand equation in which, along with deterministic elements, privately-financed R&D expenses are assumed to depend on (internal) R&D tax price, the share of company R&D financed with federal funds, and valued added which is a predictor for future sales. Including the predicted value from this auxiliary specification into Eq. (6), our main result remains unaffected. In other words, R&D tax price is confirmed to have a direct effect on the rate of change of valued added per worker over the long run.

4.3 Sensitivity analysis: economic controls

Table 4 shows estimates with economic controls. Col. 1 displays our benchmark specification (i.e., col. 3, Table 2). Col. 2 allows for capital deepening, whilst col. 3 accounts for the impact of high-skilled labor. The coefficients of these control variables are insignificant; the same holds when we express these regressors in levels rather than in rate of change (unreported results). Col. 4 indicates that the degree of monopoly power defined in terms of firms' ability to charge a mark-up over costs is unrelated to the growth rate of productivity. Conversely, those sectors in which there are technologically leading firms, identified on the basis of the citation rate of their innovation by their competitors, are likely to grow faster (col. 5). This probably occurs because there are knowledge spillovers across firms within the industry originating from R&D activities performed by the leader, favoring the expansion of the sector. Notice that the inclusion of the Herfindahl-Hirshman index of citations within the sector reduces the impact of both the patenting rate and the R&D policy variable, which is now significant at 10% level of significance.

Col. 6 indicates that the degree of dependence on external finance is not related to growth and, more importantly, that fiscal incentives for R&D act neither as a substitute nor as a complement to external funds. Consistently, self-financing turns out to be positively and significantly related to growth but, overall, the impact of our main regressors remain unchanged (col. 7). The last columns of the table report the estimates obtained including proxies for knowledge spillovers across industries, i.e., the technological distance-weighted measure of patenting rate, patent and R&D stocks. Still, these variables are insignificant and their inclusion does not affect any of our key results. In the Online Appendix we perform a sensitivity analysis to numerous econometric issues and find strong confirmation for the persistent growth effects of R&D tax policies.

5 Discussion

5.1 Second-generation growth models

Our paper is strictly related to a recent line of empirical research testing the soundness of the latest Schumpeterian growth theories. Using US manufacturing industry data, Zachariadis (2003) provided, as first, evidence in favor of the predictions of second-generation growth models, albeit based on a fully-endogenous growth model only. The subsequent contributions have discriminated between semi- and fully-endogenous growth theories, mostly using cross-country or cross-industry data on innovation and productivity growth. Ha and Howitt (2007) test the two growth theories by applying cointegration analysis to US data since the Fifties, finding strong support for fully-endogenous growth theory.[20] This conclusion appears to have general validity and is not limited to certain countries and certain stages of development. Madsen *et al.* (2010) model the transition to the post-Malthusian growth regime induced by the First Industrial Revolution in the British economy. They find that a crucial role in this process is played by innovation, and the impact of this factor reflects the pattern of fully-endogenous growth theory. Consistent results are obtained by Madsen (2010) in a growth-regression analysis conducted on

[20]Further studies, building on the empirical specification proposed by Ha and Howitt (2007), provide evidence that fully-endogenous growth theory better fits macroeconomic and industrial data (see, e.g., Ang and Madsen, 2011 and Venturini 2012b). Madsen (2008) obtain similar findings applying a framework of analysis which controls for technological catch-up and international technology spillovers to data on patents, trademarks, and R&D expenditure.

a sample of OECD countries since the Second Industrial Revolution onwards.

Our paper fills an important gap of the literature which has assessed the consistency of these two competing growth frameworks with productivity and innovation statistics without testing their policy implications. Our findings indicate that R&D policy has a persistent, if not permanent, impact on the rate of productivity growth, providing further evidence in support of fully-endogenous growth theory.

5.2 Tax incentives and direct funding to R&D

The present work also relates to a large body of research inspecting the role of public support to R&D (direct public engagement, direct subsidies, tax credit, public procurement, etc.). This literature has concentrated on two major questions: (1) the additionality issue, i.e., whether public support raises, or reduces, private R&D investment (crowding-in or crowding-out effect); and (2) whether R&D tax credits are more or less effective than direct subsidies in stimulating business R&D.

The evidence on these points is very extensive but, nevertheless, remains quite controversial. In the United States, with the diffusion of the R&D tax credit nationally and among the US states since the early 1980s, much of the debate has centered on evaluating whether tax credits are more effective than direct funding in stimulating business R&D.[21] Using industry-level data, Mamuneas and Nadiri (1996) document that incremental R&D tax credit and the immediate deductibility provision of R&D expenditures have a significant impact on privately-funded R&D investment; on the other hand, publicly-financed R&D induces cost savings but crowds out privately-funded R&D investment. Guellec and van Pottelsberghe (2003) show that, in OECD countries, direct government funding spurs business-financed R&D (apart from when it is oriented towards defense), while tax incentives have short-lived effects. Bloom *et al.* (2002) quantify the impact of fiscal incentives on R&D investment by estimating an R&D demand equation for few OECD countries. They find that a 10 percent fall in the cost of R&D stimulates over a 1 percent rise in the R&D effort in the short run, and almost a 10 percent increase over the long run. Thomson (2015) extends this type of analysis to a larger set of industrialized countries finding for business R&D a short-run responsiveness of 5% to a 10% increase in fiscal discounts.[22]

[21] For the sake of brevity, we mostly concentrate on the evidence based on industry- and country-level data. The interested reader may refer to David *et al.* (2000) and Alonso-Borrego *et al.* (2014) for more comprehensive surveys.

[22] Another important channel through which public policy can raise private R&D is through government procurement (see, e.g., Cozzi and Impullitti, 2010). Slavtchev and Wiederhold (2015) document that the rising government demand

Our findings indicate that only market-based incentives such as R&D tax credits have a positive growth effect that is long lasting and statistically robust. Conversely, the growth effect of federal funds to R&D does not appear to be established and statistically robust. Our estimates indicate that a 10 percent increase in R&D tax credit would bring the growth rate of labor productivity to increase approximately by 0.4 percent per year, i.e., from an (un-weighted) average of 5.3 to 5.7 percent. This impact is comparable to the growth effect of marginal tax rates on personal and corporate income estimated by Gemmell *et al.* (2015) for industrialized countries. The impact that we estimate for R&D policies should be considered as an upper bound value, given that we are looking at a knowledge-based economy such as the United States where the discipline on fiscal incentives to R&D is broadly consolidated. Using industry-level data for OECD countries, Vartia (2008) finds an elasticity of TFP growth to R&D tax policy much smaller.

5.3 Taxation and economic growth

Another strand of literature to which our paper is related is that looking at the nexus between taxation and economic growth.

On the theoretical ground, there is an extensive literature on the interaction between tax policy and economic growth, mostly based on the neoclassical growth model with physical capital (King and Rebelo 1990; Rebelo 1991; Jones *et al.* 1993; Pecorino 1993; Devereux and Love 1994; Stokey and Rebelo 1995; Milesi-Ferretti and Roubini 1998, among others). The growth effects of taxation have been recently re-examined by Zeng and Zhang (2002) and Peretto (2003) within a fully-endogenous Schumpeterian growth framework. Zeng and Zhang (2002) show that consumption and labor-income taxes do not affect long-run growth, as product proliferation nullifies the scale effect associated with the expanding labor force induced by such policies. Instead, capital-income taxes are harmful for growth as discouraging saving and, thus, capital investment. Peretto (2003) observes that, as a consequence of market fragmentation, policy variables that work through the size of the aggregate market do not affect steady-state growth, whereas fiscal variables working through the interest rate channel do have long-run growth effects. As a result, although they expand the demand, labor and consumption taxes do not

for high-tech goods during the 2000s in the US states has considerably stimulated private firms' R&D effort.

affect long-run growth, whereas taxes on household asset income or corporate income do.[23]

On the empirical ground, evidence on the effects of taxation on economic growth does vary with the growth setting analyzed, the nature of the data used (nation-wide, industry-level, etc.) and the econometric issues addressed (endogeneity, heterogeneity, dynamics, cross-sectional dependence, etc.). Easterly and Rebelo (1993) and Mendoza *et al.* (1997) first showed that these effects are difficult to isolate empirically (the so-called Harberger's superneutrality conjecture).[24] This issue has been further investigated by a number of subsequent studies which find a significant association between taxation and growth (see, e.g., Kneller *et al.*, 1999, Arnold *et al.*, 2011, and Gemmell *et al.*, 2011, 2015). Kneller *et al.* (1999) find that distortionary taxation has a negative impact on growth, while non-distortionary taxation does not. Lee and Gordon (2005) find that corporate income taxes are particularly detrimental for economic growth, whereas personal income taxes are not significantly associated with economic growth. Arnold *et al.* (2011) draw attention to a growth-friendly design of tax structures, suggesting that the most harmful policy instruments for income levels are corporate income taxes, followed by personal income taxes, consumption taxes and, finally, property taxes. Gemmell *et al.* (2011) disentangle the short- from the long-run effects but nonetheless show that the growth effects of fiscal policy are achieved quickly. Gemmell *et al.* (2015) identify the mechanism behind the negative impact of corporate income taxation: tax effects on GDP growth operate largely through changes in factor productivity, rather than via investment. This mechanism is consistent with the view developed in Peretto (2003, 2007) and Lee and Gordon (2005) who stress the importance of innovation and entrepreneurship as transmission channels of taxation on GDP growth. As previously discussed in the paper, the latest empirical evidence based on novel techniques of regression warns against the results of the papers surveyed above (Xing, 2012; Arachi *et al.*, 2015; Gale *et al.*, 2015). Our paper contributes to this debate by showing that, even after accounting for the main econometric issues plaguing earlier studies, R&D tax credit proves to be a key policy tool for promoting long-run growth in a knowledge-based economy such as the United

[23] Peretto (2007, 2011) extend this kind of analysis to study transitional dynamics. Peretto (2007) assumes that the government has no access to lump-sum taxes or public debt and shows that the dividend income tax raises economic growth and welfare. As a result, subsidizing R&D, eliminating corporate taxes or reducing consumption or labor taxes are welfare improving because the endogenous increase in the tax on dividends necessary to balance the budget has a positive effect on growth. Peretto (2011), instead, explores the case in which the government finances tax changes with debt and, calibrating the model with US data, shows that a dividend tax cut reduces economic growth with considerable welfare losses.

[24] Harberger (1964) shows that changes in the mix of direct and indirect taxes in the US economy had negligible growth effects, as they left almost unchanged the labor income share, labor supply, and the rates of saving and investment.

States.

6 Conclusions

The present paper has provided econometric evidence on the effects that public policies targeted to business R&D produce on the rate of productivity growth over the long-term horizon. Using industry-level data for the United States between 1975 and 2000, we have estimated a specification relating the growth rate of labor productivity to R&D policy instruments, namely R&D tax credit and federal funds to R&D, and to other growth determinants as suggested by the latest Schumpeterian growth theories. The analysis has been carried out using a novel regression procedure that provides consistent estimates for the long-run parameters within a dynamic panel data setting.

Our findings indicate that only market-based incentives such as R&D tax credits have a positive growth effect that is long lasting and statistically robust. Conversely, the growth effect of federal funds to R&D does not appear to be established and statistically robust. These results have been shown to be robust to including various tax policy and economic controls, as well as to various econometric issues.

Our estimates indicate that a 10% increase in R&D tax credit would bring the growth rate of labor productivity to increase approximately by 0.4% per year, i.e., from an (un-weighted) average of 5.3 to 5.7%. This impact is comparable to the growth effect of marginal tax rates on personal and corporate income estimated by Gemmell *et al.* (2015) for industrialized countries. The impact that we estimate for R&D policies should be considered as an upper bound value, given that we are looking at a knowledge-based economy such as the United States where the discipline on fiscal incentives to R&D is broadly consolidated. Using industry-level data for OECD countries, Vartia (2008) finds an elasticity of TFP growth to R&D tax policy much smaller.

Our analysis is nonetheless subject to some caveats. First, we have used industry-level data from a frontier economy, and hence a more thorough analysis would require exploitation of cross-country (and cross-industry) data. This extension may be implemented within an open-economy framework, so to account for the impact of R&D policy competition across countries and quantify the net effects of these measures. Second, the relatively limited time span of the data may have somehow influenced the identification of the growth effects of R&D policies. Specifically, the lack of significance of federal funds to R&D may be explained with the fact that this policy measure is devoted to basic R&D projects, which are more general in scope, subject to a higher uncertainty and whose commercial exploitation occurs only after decades. Both of these represent areas worthy of further investigation.

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Table 1: **Summary statistics**

		Obs.	Mean	SD	Median	Min	Max
Labor productivity growth	g_y	375	0.053	0.186	0.029	-1.616	1.061
Patenting rate	g_A	375	0.150	0.043	0.029	0.065	0.348
Share of R&D workers	g_A	375	0.044	0.056	0.013	0.001	0.237
Employment growth	n	375	0.002	0.043	0.005	-0.225	0.129
R&D tax price	ρ^P	375	1.334	0.137	1.298	1.157	1.525
R&D federal funds	ν	375	0.103	0.184	0.023	0.000	0.775
FISCAL CONTROLS							
Sales tax	AST	375	0.010	0.010	0.006	0.001	0.075
Corporate income tax	ACT	375	0.012	0.005	0.011	-0.021	0.052
Individual income tax	AIT	375	0.033	0.006	0.034	0.017	0.045
Property income tax	APT	375	0.016	0.015	0.014	-0.047	0.134
ECONOMIC CONTROLS							
Capital/Labor (log-change)	KL	375	0.035	0.052	0.032	-0.111	0.431
High-skilled labor share (change)	HS	375	-0.001	0.017	0.029	-0.103	0.121
Mark-up	MUP	375	0.050	0.050	0.029	-0.009	0.238
Tech. concentration	HHI	375	0.324	0.261	0.235	0.010	1.000
External finance dependence	FD	375	0.227	0.012	0.406	0.159	0.270
Self-financing	SF	375	-0.146	11.45	0.228	-219.3	9.768
Knowledge spillovers (patenting rate)	KS	375	0.158	0.025	0.159	0.114	0.256
Knowledge spillovers (patent stocks, thousands)	KS	375	23.01	4.494	22.62	12.97	38.81
Knowledge spillovers (R&D stock, USD billions)	KS	375	25.89	7.586	24.56	11.30	57.68

Table 2: **Long-run estimates of growth equation**

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Knowledge growth	g_A		1.182***	1.391***	1.393***	1.464***	1.170*	1.168*
			(0.381)	(0.416)	(0.426)	(0.551)	(0.602)	(0.610)
Employment growth	n		0.073	0.281	0.293	0.441	0.602	0.594
			(0.343)	(0.362)	(0.369)	(0.376)	(0.396)	(0.405)
R&D tax price	ρ^P	-5.037**		-4.606**	-4.606**		-4.748**	-4.648**
		(1.991)		(2.046)	(2.077)		(2.146)	(2.184)
R&D federal funds	ν	-0.106			-0.013			-0.072
		(0.132)			(0.132)			(0.135)
g_A proxied by:				Patenting rate			Share of R&D employment	
Observations		420	400	400	400	400	400	400
R-squared		0.090	0.111	0.137	0.139	0.087	0.101	0.102
No. of industries		20	20	20	20	20	20	20

Notes: CS-DL estimates of Eq. (6). Dependent variable = Rate of change of value added per worker. Each regression includes industry-specific fixed effects, three-year lags of first-differenced regressors and contemporaneous cross-sectional mean value of the dependent variable and regressors (in level). *,**,*** significant 10, 5 and 1%. Standard errors in parentheses.

Table 3: **Long-run estimates with tax policy controls**

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Knowledge growth	g_A	1.391***	1.229***	1.159***	1.447***	1.353***	1.227***	1.419***
		(0.416)	(0.416)	(0.439)	(0.439)	(0.420)	(0.462)	(0.472)
Employment growth	n	0.281	0.331	0.346	0.136	0.310	0.220	0.277
		(0.362)	(0.362)	(0.374)	(0.379)	(0.376)	(0.365)	(0.368)
R&D tax price	ρ^P	-4.161**	-4.691**	-5.579***	-4.324**	-5.404**		-5.485
		(2.046)	(2.027)	(2.138)	(2.060)	(2.142)		(3.652)
Taxes on production and imports	AST		13.695					
			(3.823)					
Corporation income tax	ACT			-6.703				
				(4.109)				
Individual income tax	AIT				7.260			
					(11.407)			
Property income tax	APT					1.841		
						(1.389)		
External R&D tax price	$\rho^{P,W}$						-7.977	0.493
							(5.368)	(8.069)
Obs.		400	400	400	400	400	400	400
R-squared		0.137	0.174	0.145	0.151	0.144	0.130	0.149
Number of industry		20	20	20	20	20	20	20

Notes: CS-DL estimates of Eq. (6). Dependent variable = Rate of change of value added per worker. Each regression includes industry-specific fixed effects and three-year lags of first-differenced regressors. Cross-sectional dependence is purged out by including contemporaneous cross-sectional mean value of the dependent variable and regressors (in levels). *,**,*** significant 10, 5 and 1%. Standard errors in parentheses.

Table 4: **Long-run estimates with economic controls**

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Knowledge growth	g_A	1.391***	1.449***	1.391***	1.375***	0.961**	1.262***	1.315***	1.189**	1.483***	1.552***
		(0.416)	(0.419)	(0.421)	(0.422)	(0.466)	(0.426)	(0.403)	(0.542)	(0.542)	(0.455)
Employment growth	n	0.281	0.192	0.450	0.378	0.359	0.307	0.171	0.356	0.393	0.339
		(0.362)	(0.508)	(0.377)	(0.411)	(0.367)	(0.367)	(0.352)	(0.371)	(0.383)	(0.403)
R&D tax price	ρ^P	-4.606**	-5.308**	-4.808**	-4.557**	-3.865*	-4.042*	-4.420**	-4.149*	-5.334**	-4.616**
		(2.046)	(2.140)	(2.055)	(2.127)	(2.063)	(2.065)	(1.977)	(2.226)	(2.530)	(2.265)
Capital/Labor	KL		0.050								
			(0.459)								
High-skilled labor share	HS			0.246							
				(1.361)							
Mark-up	MUP				-0.150						
					(0.631)						
Tech. concentration	HHI					0.137**					
						(0.058)					
External finance dependence	FD						2.720				
							(2.020)				
Self-financing	SF							0.004**			
								(0.002)			
Knowledge spillovers (patenting rate)	KS								1.497		
									(1.696)		
Knowledge spillovers (patent stocks)	KS									-0.104	
										(0.126)	
Knowledge spillovers (R&D stock)	KS										0.022
											(0.114)
Observations		400	400	400	400	400	400	400	400	400	400
R-squared		0.137	0.154	0.151	0.150	0.16	0.160	0.211	0.143	0.142	0.142
Number of industries		20	20	20	20	20	20	20	20	20	20

Notes: CS-DL estimates of Eq. (6). Dependent variable = Rate of change of value added per worker. Each regression includes industry-specific fixed effects and three-year lags of first-differenced regressors. Cross-sectional dependence is purged out by including contemporaneous cross-sectional mean value of the dependent variable and regressors (in level). *,**,*** significant 10, 5 and 1%. Standard errors in parentheses.

Table 5: **Sensitivity analysis to econometric issues**

		(1)	(2)	(3)	(4)	(5)
Knowledge growth	g_A	1.391***	1.531***	-0.339	1.218**	2.016*
		(0.416)	(0.427)	(0.415)	(0.474)	(1.220)
Employment growth	n	0.281	0.421	0.075	0.218	-0.755
		(0.362)	(0.396)	(0.225)	(0.287)	(0.703)
R&D tax price	ρ^P	-4.606**	-4.052*	-4.259**	-4.911*	-10.32**
		(2.046)	(2.133)	(2.125)	(2.773)	(4.191)
First-step results						
External R&D tax price	$\rho^{P,W}$				1.588***	
					(0.149)	
External Finance dependence	FD				-0.074***	
					(0.026)	
Joint F-test					57.85	
[p-value]					[0.000]	
Estimation procedure		CSDL	CSDL	ARDL	CSDL-IV	CSDL
Econometric issue			Cross-sectional dependence	Reverse causality	Reverse causality	Hetero-geneity
Observations		400	400	420	400	400
R-squared		0.137	0.150	0.198	0.130	0.294
No. of industries		20	20	20	20	20

Notes: CS-DL estimates of Eq. (6). Dependent variable = Rate of change of value added per worker. Cols. 1-4 are based on homogeneous parameter estimation. Col. 5 is based on heterogeneous parameter estimation and reports the cross-section mean value of coefficients obtained on industry-specific specifications, obtained with a robust-to-outlier mean estimation. Each regression includes industry-specific fixed effects and three-year lags of first-differenced regressors. Cross-sectional dependence is purged out by including contemporaneous cross-sectional mean value of the dependent variable and regressors (in level) in all regressions expect than col. 2 which uses three-year lags. Cols 4 uses the predicted value of R&D tax price obtained by a first-step regression. In the second step of such estimation all standard errors are bootstrapped with 1000 replications. Joint F-test assesses the null hypothesis that the coefficients of regressors in the first step are jointly significant. First-step results are obtained with a panel static specification based on standard errors robust to heteroskedasticity and three-year order serial correlation. *,**,*** significant 10, 5 and 1%. Standard errors in parentheses.

Appendix

Panel unit roots and cointegration tests

This section describes the methodology followed to assess whether the variables used in estimating the growth equation contain unit roots and whether there is a long-run stationary relationship between the dependent variable and the regressors.

Non-stationarity

We use the statistic test devised by Pesaran (2007) to assess non-stationarity of panel time series. This test assumes the null hypothesis that all individual series contain unit roots, against the alternative hypothesis that a non-vanishing fraction of the series are stationary. Such a statistic relaxes the assumption of independence by modelling cross-sectional dependence as one latent factor model, which is accounted for by including the cross-section averages of lagged levels and first-differences of the variable into an Augmented Dickey Fuller (ADF) specification. The panel statistic consists of a cross-industry average of ADF-type regressions; therefore, it preserves parameter heterogeneity and can be used when either the time or the panel dimension (T and N) of the dataset are similar. The test has a non-standard one-side limit distribution. Below, we report the p-value associated with this test statistic. As Table 6 shows, the test cannot reject the null hypothesis using a relatively rich lag structure to control for serial correlation (three- and four-year lags).

Cointegration

The existence of a long-run stationarity relationship is checked using the set of four panel cointegration tests developed by Westerlund (2007). These procedures test the absence of cointegration in the growth equation modelled as an ECM regression framework. More specifically, these four statistics assess the significance of the adjustment parameter (ECM term), determining whether there exists error correction for individual panel members or for the panel as a whole. Ga and Gt consist respectively in the group mean statistics of the ECM coefficient and related t-statistics, computed considering singly the potentially cointegrated relationship for each individual industry. For these tests, the null hypothesis is that the ECM term is not significant for all panel individuals ($H0: a_i = 0$ for all i) against an alternative hypothesis that the ECM term is significant and negative for a few panel individuals ($H0: a_i < 0$ for some i). By rejecting $H0$, Ga and Gt indicate that there is cointegration for one or more industries. Conversely, Pa and Pt are pooled statistics exploiting information over all the cross-sectional units. They assume the null hypothesis that the ECM term is not significant for all panel individuals ($H0: a_i = 0$ for all i), against the alternative hypothesis that it is significant for all industries ($H1: a_i < 0$ for all i). In other words, rejecting $H0$, Pa and Pt provide evidence of cointegration for the panel as a whole. As the covariance matrix of such statistics may be affected by small sample bias in the presence of cross-sectional dependence (modelled as a common latent factor), we apply the bootstrap procedure devised by Westerlund (2007) to get consistent standard errors (based on 100 replication). Below, we report the associated p-values of significance.

Table 6: Panel unit root test

	Labor productivity growth	R&D tax price	R&D federal funds	Patenting rate	Share of R&D workers	Employment growth
lags	g_y	s_1	s_2	g_A	g_A	n
1	0.000	0.071	0.045	0.082	0.699	0.114
2	0.009	0.023	0.041	0.325	0.935	0.196
3	0.511	0.196	0.509	0.127	0.822	0.520
4	0.962	0.967	0.997	0.978	1.000	0.989

Notes: The hull hypothesis is that all individual series contain unit roots, H0=I(1). P-values reported.

Table 7: Panel cointegration tests for Table 2 (Westerlund, 2007)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Knowledge growth	g_A		Yes	Yes	Yes	Yes	Yes	Yes
Employment growth	n		Yes	Yes	Yes	Yes	Yes	Yes
R&D tax price	ρ^P	Yes		Yes	Yes		Yes	Yes
R&D federal funds	ν	Yes			Yes			Yes
g_A proxied by:			Patenting rate			Share of R&D employment		
Ga		0.000	0.000	0.010	0.190	0.000	0.010	0.230
Gt		0.000	0.000	0.000	0.150	0.000	0.000	0.180
Pt		0.020	0.010	0.150	0.470	0.040	0.170	0.230
Pa		0.000	0.000	0.010	0.200	0.000	0.010	0.100

Notes: The hull hypothesis is that there is no cointegration. Bootstrapped p-values reported.