R&D policy, Productivity Growth and Distance to Frontier

Antonio Minniti, University of Bologna
Francesco Venturini
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Abstract

Using data from 20 US manufacturing industries, we find strong evidence that a more generous tax treatment of R&D positively impacts on the growth rate of total factor productivity and that this effect is stronger for industries farther from the technological frontier. The estimates also suggest that the productivity growth effect of R&D tax policy is comparable in size to that induced by technology transfers.

1 Introduction

After half a century of research on R&D, economists still debate on the effectiveness of public policies in fostering business R&D, the breadth of their impact and the transmission of the related benefits from innovating firms to the rest of the economy. An extensive literature has investigated these issues, focusing on the additionality of R&D tax credits on research activities (see, e.g., [Wilson 2009 and Thomson 2015]) and on the effect of these instruments on economic growth ([Minniti and Venturini 2017]). However, two questions have not been explored thus far in the literature, namely whether R&D tax policy is able to raise total factor productivity (TFP) growth and whether the effectiveness of this policy depends on the technology conditions of the recipient firms. Although R&D tax policy is primarily targeted at raising R&D engagement, it is likely to stimulate complementary investments (human capital, intangibles, etc.), thereby fostering TFP growth. Moreover, the impact of fiscal incentives to R&D may be non-linear (i.e., stronger or weaker far from the frontier), despite these instruments are conceived as non-discretionary policy measures.

Using data from US manufacturing industries, we fill this gap in the literature showing that: i) a more generous fiscal treatment of R&D positively impacts on TFP growth and that ii) this effect is stronger for industries farther from the technological frontier.

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†Department of Economics, University of Perugia, Italy & NIESR (e-mail: francesco.venturini@unipg.it).
2 Empirical approach, estimation method and data

Empirical model

Following Bourlès et al. (2013), we study the effect of R&D tax policy on TFP growth with a panel Error Correction Model (\( i \) denotes industry, \( t \) year, \( F \) the frontier):

\[
\Delta \ln A_{it} = \alpha_1 \Delta \ln RD_{it-1} + \alpha_2 \Delta \ln A_{Fi} + \alpha_3 \ln DTF_{it-1} \\
+ \alpha_4 \ln RDTAX_{it-1} + \alpha_5 \ln DTF_{it-1} \times \ln RDTAX_{it-1} + \gamma_i + \gamma_t + \epsilon_{it}. \tag{1}
\]

Eq. (1) relates TFP growth (\( \Delta \ln A_i \)) to industry’s R&D effort (\( \Delta \ln RD_i \)), TFP growth at the frontier (\( \Delta \ln A_F \)), and technology transfers from the frontier (\( \ln DTF_i \)). A negative value for \( \alpha_3 \) implies that productivity grows faster closer to the frontier, a positive value that transfers are greater for laggards. R&D tax policy is assumed to have a direct effect on TFP growth and an indirect impact that changes with distance to frontier (DTF). As R&D tax policy variable, we use the tax price component of R&D capital user cost (inversely related to R&D tax credit). If fiscal incentives to R&D spur TFP growth, \( \alpha_4 \) should be negative. Consistently, R&D tax policy induces greater productivity gains far from the frontier if \( \alpha_5 \) is negative, and close to the frontier if \( \alpha_5 \) is positive. The effect of R&D tax policy on innovation effort is captured by \( \Delta \ln RD_i \), guaranteeing thus that \( \alpha_4 \) and \( \alpha_5 \) do not collect the productivity impact of the policy instrument via a greater research engagement. \( \gamma_i \) identifies the component of exogenous technical progress specific to each industry. \( \gamma_t \) captures time effects, and is modelled as a common dynamic process (described below). \( \epsilon_{it} = \lambda_i f_{it} + \epsilon_{it} \) is an error term that can be correlated across industries by means of time-varying unobservable common factors (\( f_{it} \)).

Estimation procedure

We use the Augmented Mean Group (AMG) estimator developed by Eberhardt and Bond (2013). This estimator allows for fully heterogeneous parameters by estimating the model industry by industry, and filters out (strong) cross-sectional dependence, through the inclusion of a common dynamic process (CDP) term. The latter is derived from the coefficient vector of year dummies obtained by preliminarily estimating Eq. (1), expressed in first differences, with a pooled estimator. Here, we adopt the robust-to-outliers version of the AMG estimator.

Data

The analysis is performed on a sample of 20 US manufacturing industries observed between 1975 and 2000. DTF is measured as the yearly ratio of the frontier’s TFP to the TFP of the industry under consideration (source: Becker and Gray, 2009). As a proxy for R&D tax policy (RDTAX), we use the R&D tax component of R&D capital user cost; this reflects the fiscal treatment to R&D set at the federal and the US state level (source: Wilson, 2009). We infer the values of R&D tax price at industry level looking at the localization of innovators (source: NBER USPTO patent data). R&D input, RD, is measured as R&D capital stock (source: NSF).

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1See the Web Appendix for the analytical derivation of Eq. (1), a detailed data description and a sensitivity analysis to various controls.
3 Results

Table 1 presents estimates. Col. 1 considers the DTF framework without policy variables. It shows that TFP growth is driven by changes in the technology conditions at the frontier and related transfers, but not by the R&D investment. The latter finding is consistent with Eberhardt et al. (2013) who document that R&D spillover variables may be correlated with more general unobservable factors and turn out to be insignificantly related to productivity growth controlling for strong cross-sectional dependence. Col. 2 assesses the direct impact of R&D tax policy, showing that the tax component of the R&D user cost has strong negative effects, i.e., R&D fiscal incentives spur the rate of TFP growth. Col. 3 looks at whether the impact of R&D input is mediated by DTF, i.e., TFP grows as a result of R&D facilitating technology transfers from the frontier (ln DTF × Δ ln RD). Our data exclude this possibility. Finally, col. 4 includes the interaction between R&D tax policy variable and DTF. This term is negative and significant implying that a more favourable fiscal treatment to R&D delivers larger productivity gains far from the frontier. The finding that R&D tax policy favours industries with low productivity levels is in line with Castellacci and Lie (2015) who provide firm-level evidence on the heterogeneous impact of R&D fiscal policy on research engagement. The TFP growth effect of R&D tax policy is comparable in size to the impact estimated for technology transfers.

Table 1: Distance to frontier and R&D tax policy

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<th>(2)</th>
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<td>Dep.: ∆ ln A</td>
<td>0.761</td>
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<tr>
<td>Δ ln RD</td>
<td>0.483***</td>
<td>0.569***</td>
<td>0.561***</td>
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<td>(0.470)</td>
<td>(0.752)</td>
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<td>(0.024)</td>
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<td>Δ ln TFP</td>
<td>0.437***</td>
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<td>0.613***</td>
<td>0.962***</td>
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<td>(0.064)</td>
<td>(0.045)</td>
<td>(0.077)</td>
<td>(0.066)</td>
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<td>ln DTF</td>
<td>-2.669***</td>
<td>-2.106***</td>
<td>-1.555**</td>
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<tr>
<td></td>
<td>(0.437)</td>
<td>(0.445)</td>
<td>(0.650)</td>
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<tr>
<td>ln RDTAX</td>
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<tr>
<td></td>
<td>(0.471)</td>
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<tr>
<td>ln DTF × Δ ln RD</td>
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<td></td>
<td>-1.212***</td>
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<td>(0.322)</td>
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Notes: Robust-to-outliers AMG estimates. Obs. 480. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2 displays the direct and indirect effects estimated at level of individual industry, and the total (marginal) effect of R&D tax policy, computed as α_4i + α_5i × ln DTF_i, where the bar denotes the average log-distance of the industry from the frontier. There are a few industries which do not gain productivity benefits from the direct effect. These industries, however, experience quite large productivity gains through the indirect channel. As a result of the combination of these two effects, the total impact of R&D fiscal incentives is broadly positive for all industries.

Figure 1 plots the coefficients estimated for the direct effect against the indirect effect estimated for R&D tax policy (α_4 along the x-axis and α_5 along the y-axis, respectively). The negative slope of the linear fit reveals that
Table 2: Industry-specific effects of R&D tax policy (estimated parameters and total marginal effect)

<table>
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<th>(1) Direct</th>
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<tr>
<td>FOO</td>
<td>2.480</td>
<td>-2.860</td>
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<tr>
<td>TEX</td>
<td>-2.496</td>
<td>-0.611</td>
<td>-3.655</td>
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<td>PUL</td>
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<tr>
<td>CHE</td>
<td>2.918</td>
<td>-2.243</td>
<td>-1.275</td>
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<td>PHA</td>
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<td>-2.756</td>
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<td>RUB</td>
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<td>-0.145</td>
<td>-4.174</td>
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<td>-2.992</td>
<td>-0.490</td>
<td>-3.695</td>
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<tr>
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<td>-0.291</td>
<td>-3.649</td>
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<tr>
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<td>-1.851</td>
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</tr>
<tr>
<td>MAC</td>
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<td>-1.070</td>
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<tr>
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<td>1.716</td>
<td>-1.473</td>
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<td>-2.830</td>
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<td>ELV</td>
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<td>-3.718</td>
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<td>-3.443</td>
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<tr>
<td>MOT</td>
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<tr>
<td>OTV</td>
<td>-3.276</td>
<td>-0.757</td>
<td>-3.645</td>
</tr>
<tr>
<td>OTM</td>
<td>0.330</td>
<td>-1.917</td>
<td>-5.364</td>
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</tbody>
</table>

Rob. Mean -1.555** -1.212*** -3.465***
Mean -2.069** -1.029** -3.554***
Median -2.053** -1.205 -3.588***

Notes: Col. 1 reports the value of $\alpha_4$ estimated in col. 4 of Table 1; col. 2 the estimate of $\alpha_5$, and col. 3 the total marginal effect ($\alpha_4 + \alpha_5 \times \ln DTF$).


There is an inverse relationship between these effects. This linkage is unrelated to DTF, as reflected by the relative size of industry markers (the dashed lines mark the robust mean of the parameters). In other words, industries with large productivity gaps fall at the tail of the distribution (i.e., they present large direct effects and small indirect effects, and vice-versa), whereas industries less distant from the frontier behave much similarly and fall around the mean.

Figure 2 plots the marginal effect of R&D tax policy at various percentiles of the DTF distribution in our benchmark specification ($\alpha_4 + \alpha_5 \times \ln DTF$) of col. 4, Table 1. The blue line is based on the robust mean estimates, the red line considers industry-specific parameters whilst the dotted lines represent the marginal impact estimated at the 5th and 95th percentile of the distribution of the direct impact of R&D tax policy (chemicals and office machinery, respectively). The marginal effect based on robust mean estimates perfectly fits the one arising using industry-specific parameters but corrects for the bias associated with the adverse indirect effects estimated.
Figure 1: Direct vs indirect effects of R&D tax policy and DTF

Notes: The value of $\alpha_4$ and of $\alpha_5$ estimated in col. 4 of Table 1 are plotted along the x-axis and the y-axis, respectively. See Table 2 for the industry list.

mainly for electronic valves and, to a smaller extent, for office machinery and other instruments (see Figure 1). At low levels of the DTF distribution, the overall benefit of R&D tax policy decreases more than proportionally with DTF, then it falls linearly with the widening of the productivity gap.
Figure 2: Marginal effects of total impact of R&D tax policy

Notes: The x-axis reports the percentiles of the DTF distribution. The y-axis reports the marginal effect of R&D tax policy on productivity growth based on estimates in col. 4, Table 1 ($\alpha_4 + \alpha_5 x \ln \text{DTF}_i$). The blue line uses robust mean estimates, the red line uses the underlying industry-specific parameters; the dotted lines use estimates for industries at the 5th and 95th percentile of the distribution of the direct impact of R&D tax policy (chemicals and office machinery).

References


This document describes the analytical framework underlying the DTF specification, the data used in the paper, and a series of robustness checks conducted for testing the consistency of our results.

**Analytical framework**

Our framework of analysis starts from a standard production function ($i$ are industries, $t$ years):

$$Y_{it} = A_{it} F(K_{it}, L_{it}), \quad A_{it} = G(X_{it}),$$

where $Y$ is output, $A$ is Hicks-neutral technological progress measured by TFP, $K$ and $L$ are tangible factor inputs, whilst $X$ is a vector of determinants of TFP, namely industry’s R&D activities ($RD_{it}$), technology transfers from the frontier ($DTF_{it}$), R&D tax policy ($RDTAX_{it}$), and other control factors ($C_{it}$). Following Bourlès et al. (2013), $A_{it}$ is modelled as an autoregressive distributed lag model of order one, ARDL(1,1):

$$\ln A_{it} = \alpha_{1i} \ln A_{it-1} + \alpha_{2i} \ln X_{it} + \alpha_{3i} \ln X_{it-1} + \varepsilon_{it}.$$ 

Equivalently, this equation can be reformulated as an ECM model, assuming a long-run relationship between TFP levels and R&D tax policy. Making all the determinants of $A$ explicit (apart from controls, $C_{it}$), we have:

$$\Delta \ln A_{it} = \alpha_{1i} \Delta \ln RD_{it-1} + \alpha_{2i} \Delta \ln F_{it} + \alpha_{3i} \ln DTF_{it-1} + \alpha_{4i} \ln DTF_{it-1} \times \ln RDTAX_{it-1} + \gamma_{it} + \varepsilon_{it},$$

(A1)

where $\gamma_{i}$ and $\gamma_{t}$ identify the components of exogenous technical progress specific to each industry or time period. In the steady steady, all variables are constant and, hence, it is possible to express the equilibrium value of the technology gap
and TFP growth as follows:

\[ DTF_i = \frac{1}{\alpha_3 + \alpha_5 RDTAX_i} \times \left[ \alpha_4 (RDTAX_i - RDTAX_F) - (\gamma_i - \gamma_F) \right], \]

\[ \Delta \ln A_i = \Delta \ln A_F = \frac{\alpha_4}{1 - \alpha_2} RDTAX_F + \frac{\gamma_i + \gamma_F}{1 - \alpha_2}. \]

Two key features emerge in the long-run equilibrium. First, distance to the technological frontier is smaller, the larger are the gaps in i) the rates of exogenous technical progress, \( \gamma_i - \gamma_F \); and ii) R&D tax policies, \( RDTAX_i - RDTAX_F \) (provided that the fiscal discipline on R&D raises the rate of TFP growth, that is \( \alpha_4 < 0 \)). Second, TFP growth along and below the frontier is higher i) the larger are the rates of technical progress; and ii) the more favourable is the fiscal treatment of R&D in the frontier industry.

**Estimation procedure and econometric issues**

The regression analysis is based on the Augmented Mean Group estimator developed by [Eberhardt and Bond (2013)](https://doi.org/10.1093/ecta/ecta2003-0069). This procedure allows for fully heterogeneous parameters across panel individuals and accounts for the impact of unobserved variables. The latter may yield either to inconsistent or inefficient estimates depending on whether these factors are or not correlated with regressors. The AMG procedure estimates the regression model industry by industry and filters out cross-sectional dependence with the inclusion of a *common dynamic process* (CDP) term. Let us consider the following model:

\[ y_{it} = \beta_0 i + \beta_1 i x_{it} + \epsilon_{it}, \epsilon_{it} = \lambda_i f_{it} + \epsilon_{it}, \]

in which both intercepts and slope parameters are unit specific. \( \epsilon_{it} \) is an error term that is correlated among the units of the panel sample due to some latent (un-observable) factors, \( f_{it} \), \( \lambda_i \) is the loading parameter and \( \epsilon_{it} \) are spherical disturbs.

The augmentation of the regression model with the CDP term is implemented in three steps. In the first step, a pooled regression model, expressed in first differences, is estimated with year dummies (TD); the coefficients of year dummies are collected to form the CDP term, that is:

\[ \Delta y_{it} = \eta \Delta x_{it} + \sigma_t T D_t + \epsilon_{it}, CDP_t = \sigma_t. \quad \text{(STEP 1)} \]

In the second step, group-specific regressions, based on least squares, are estimated augmenting the specification with the CDP term:

\[ y_{it} = \beta_0 i + \beta_1 i x_{it} + CDP_t + \epsilon_{it}. \quad \text{(STEP 2)} \]

Finally, in the third step, group-specific parameters are averaged across the panel on the basis of the mean robust to outliers as in [Bond et al. (2010)](https://doi.org/10.1086/590355):  

\[ \bar{\beta}_1 = \omega_i \hat{\beta}_1 i, \quad \text{(STEP 3)} \]
where $\omega_i$ are weights that are inversely related to the observations’ residual and are chosen with the Huber weight/bi-
weights iteration procedure.

**Data**

The analysis is performed for a sample of 20 manufacturing industries from the US over the period between 1975 and 2000. Details on the sample composition can be found in Minniti and Venturini (2017). Data on industry accounts (value added, employment, capital) come from Becker and Gray (2009) and updates. TFP levels are obtained assuming a Cobb-Douglas value-added production function with constant returns to scale. DTF is measured on a yearly base as ratio of the level of the frontier’s TFP to the TFP of the sector under consideration. Income share of factor inputs are taken from EU KLEMS dataset (release March 2007).

We use a measure of R&D policy reflecting the tax price component of R&D user cost. The fiscal treatment to R&D changes at the federal and the US state level. Following Bloom et al. (2013), data on the tax price component of the user cost of R&D have been re-attributed to manufacturing industries exploiting information on the geographic localization of US innovating firms (patentees) across states, extrapolated from NBER USPTO patent data files. R&D input, $RD$, is measured as R&D capital stock, which has been built with the perpetual inventory method from research expenses (the depreciation rate is set to 15% annually). R&D expenses at current prices are taken from National Science Foundation (NSF); these series are converted on a constant prices base by means of industry deflator for value added. A similar procedure has been followed to build the industry level stock of patent applications. The latter are taken from USPTO NBER data file (see Hall et al. 2001 for data description). The concordance table between IPC classes and SIC categories has been implemented following Schmock et al. (2003).

The rate of union membership, defined as proportion of total employment, is taken from Hirsch and MacPherson (2003). The index of upstream regulation is extracted from the OECD regulation impact dataset (Conway and Nicoletti 2006). It measures the knock-in effects of service regulation on downstream industries that use services as intermediate inputs. The intensity of the use of such intermediate inputs is approximated by the inter-industry intermediate input share, taken from OECD input tables (benchmark year 2000). The share of high skilled workers on total number of hours worked is taken EU KLEMS dataset. External financial dependence is inferred from Von Furstenberg and Von Kalckreuth (2006); missing data are interpolated. The stringency of legal protection on intellectual property rights (IPRs) at industry level is obtained by multiplying the index developed by Ginarte and Park (1997), which is available at country level at 5-year intervals (intermediated years are interpolated), by the industry share of total manufacturing patent applications. This share should reflect the extent of enforcement of IPRs rules in relation to the industry propensity to patenting. These weights are taken as averages between 1975 and 1980 to mitigate reverse causality problems. Trade figures (import and export series) come from Feenstra et al. (2002). The profit share and the corporate tax rate are computed as the ratio to industry value added of gross operating surplus and taxes revenues, respectively. These data are available at the US state level and then attributed i according to the distribution of industry value added across states. Tax revenues come from the Database
Robustness checks

Table A.1 shows how our key estimates are robust to an array of economic and institutional control factors. These are included within the specification one by one given that each regression is estimated industry by industry and each is based on 24 year point observations. For ease of comparison, we reproduce in col. 1 the results of our main specification, whilst col. 2 displays the results obtained using the rate of change of total R&D stock as for $\Delta \ln RD$. It should be observed that similar findings on direct and indirect effects of R&D tax policy arise even when we use a measure of R&D capital, obtained considered only privately funded research expenses. As col. 3 shows, similar findings arise when the impact of R&D input on TFP growth is expressed in terms of rate of return and, hence, R&D intensity over value added is used as a proxy for $RD$ (see Griffith et al. 2004). Surprisingly, the coefficient of R&D intensity is negative. According to second-generation fully-endogenous growth theory (see e.g., Young 1998, Peretto 1998, Dinopoulos and Thompson 1998 and Howitt 1999), as the economy expands, the number of product varieties increases and this may offset the expansive effect of R&D. Our finding can therefore be justified on this basis as the negative effect of $Y$ on productivity growth may prevail over the expansive impact associated with $RDEXP$ (for a similar result, see Ang and Madsen 2011. In col. 4, we approximate the innovation effort of the industry in terms of patenting output, and, hence, we use the rate of change in the stock of patent applications at the USPTO as control variable. Financial dependence is accounted for in col. 5, whereas the degree of exporting and importing intensity (as a ratio to value added) are considered in cols. 6-7. The logged ratio between capital and labour and the labour share of high-skilled workers are then inserted in cols. 8 and 9. These economic controls do not modify substantially the results. The negative and significant coefficient for high-skilled labour share may reveal that the assumption of perfectly competitive markets, which implies that factors are paid to their marginal productivity, may not hold (at least for a sub-sample of industries). Cols. 10 through 14 account for the role of the strength of IPRs protection, the regulation in service input market (upstream product market regulation), the share of profit (used as a proxy of entry barriers in the sector), the rate of union density, and the proportion of corporate tax on taxable income (a proxy of the tax burden). Finally, our results continue to hold if the regression includes the share of federal funds to R&D, intended as a proxy of public direct funding to research (unreported); indeed, this variable is insignificant either taken alone or interacted with DTF. As a further robustness check, we have also assessed the sensitivity of our estimates to the assumption of constant returns to scale by including employment as control variable (taken either in level or rate of change). Also in this case, our results are largely confirmed.
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<td>Δ ln TFP_F</td>
<td>0.525***</td>
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<td>ln DTF</td>
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<td>(0.059)</td>
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</tr>
<tr>
<td></td>
<td>(0.650)</td>
<td>(0.744)</td>
<td>(0.600)</td>
<td>(0.652)</td>
<td>(0.615)</td>
<td>(0.673)</td>
<td>(0.780)</td>
<td>(0.508)</td>
<td>(0.611)</td>
<td>(0.542)</td>
<td>(0.480)</td>
<td>(0.673)</td>
<td>(0.564)</td>
<td>(0.661)</td>
</tr>
<tr>
<td>ln DTF × ln RDTAX</td>
<td>-1.213***</td>
<td>-1.083***</td>
<td>-0.728**</td>
<td>-0.871**</td>
<td>-1.067***</td>
<td>-0.920**</td>
<td>-1.198***</td>
<td>-1.059***</td>
<td>-0.811**</td>
<td>-1.381***</td>
<td>-1.243***</td>
<td>-1.190***</td>
<td>-1.309***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.322)</td>
<td>(0.325)</td>
<td>(0.301)</td>
<td>(0.355)</td>
<td>(0.332)</td>
<td>(0.302)</td>
<td>(0.360)</td>
<td>(0.380)</td>
<td>(0.331)</td>
<td>(0.271)</td>
<td>(0.320)</td>
<td>(0.380)</td>
<td>(0.320)</td>
<td>(0.370)</td>
</tr>
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Controls:
- R&D stock growth
- R&D exp./Y
- Patent stock growth
- External finance dependence
- Import/Y
- Export/Y
- K/L (logs)
- High-skilled labour share
- IPR protection
- Upstream regulation
- Profit rate
- Union membership
- Corporate tax

Notes: Obs. 480 (20 groups). Augmented Mean Group (AMG) estimates. Robust mean coefficients. Standard errors in parentheses. NS=Not significant. NEG=negative and significant. POS=positive and significant. *** p<0.01, ** p<0.05, * p<0.1
References


