THEMA

théorie économique, modélisation et applications

THEMA Working Paper n°2025-09
CY Cergy Paris Université, France

R&D Tax Credits across the EU: Nonsense or Common Sense? A Dynamic Panel Data Approach

Laurence Jacquet, Stéphane Robin

June 2025

CERGY PARIS UNIVERSITÉ

cnrs

R&D Tax Credits across the EU: Nonsense or Common Sense? A Dynamic Panel Data Approach*†

Laurence JACQUET‡ Stéphane ROBIN§

June 23, 2025

Abstract

We re-examine the R&D - innovation - productivity nexus in 8 EU countries in the context of a possible EU-wide "super deduction" on R&D expenditures, using panels of industries with a long time dimension. We introduce dynamics in the innovation production function and extended production function models, taking the availability/unavailability of R&D tax credits (R&DTC) into account. Our benchmark estimates, obtained with panel ARDL models, yield positive long-run elasticities of innovation and productivity with respect to R&D intensity. R&D conducted under an R&DTC either reinforces an already-existing positive elasticity or makes it significantly positive if it was not before. Disentangling the respective effects of 'pure' business R&D and of government-supported R&D reveals a wider diversity of situations, however. The effect of R&DTC is less often significant, sometimes superseded by other forms of public support to R&D. The main policy implication of these results is that a harmonized "super-deduction" on R&D at the EU level may be slightly premature. Complementary analyses suggest that targeting specific industries may make such a policy more effective and accurate.

Keywords: Innovation, Productivity, Dynamic Panel Data Models, Public Support to R&D, European Science and Technology Policy

JEL codes: O30, O38, H25, H54

*This work was funded by CY Initiative, a programme supported by the French National Research Agency (ANR) under the French government grant: "Investissements d'avenir" #France2030 (ANR-16-IDEX-0008).

†We thank Robin Boadway, Rafael Morales-Guzman and other participants at the 2025 Canadian Economic Association (CEA 2025) Conference for their helpful comments and feedback on the latest version of this manuscript. We thank Cristiano Antonelli and an anonymous reviewer, as well as Ivan Ledezma, Jimmy Lopez, Francesco Venturini and other participants to the Innovation, Competition and Employment 2024 (ICE 2024) Workshop, June 13-15, 2024, Dijon, France, for their encouraging and helpful comments on its previous version. We also thanks participants to various conferences and seminars, in particular Marcel Gérard, Bertrand Koebel and Phu Nguyen-Van, for their welcome comments on its preliminary version. The usual disclaimers apply.

‡CY Cergy Paris Université, CNRS, THEMA, F-95000, Cergy, France. Email: laurence.jacquet@cyu.fr. Webpage https://sites.google.com/site/econlaurencejacquet

§Corresponding author, Université Paris 1 Panthéon-Sorbonne, PRISM-Sorbonne, Paris, France and BETA, University of Strasbourg. Email: stephane.robin@univ-paris1.fr. Webpage: https://www.pantheonsorbonne.fr/page-perso/strobin

I Introduction

Since the early 2000's, the European Union (EU) has been seeking to become "*the most competitive and dynamic knowledge-based economy in the world*".[1] This involves increasing investments in R&D up to 3% of the EU Gross Domestic Product (GDP). Although this objective has not been reached yet, it remains a "guiding light" for the current Horizon Europe programme.[2] So far, the main policy tools to achieve it have been national R&D tax incentives and, specifically, R&D tax credits (R&DTC). EU discussions on a harmonized corporate tax base – of which the latest outcome is the "Business in Europe: Framework for Income Taxation" (BEFIT) initiative – have evoked the implementation of a "super-deduction" that would allow EU-based firms to deduce more than 100% of their R&D expenditures from their tax base. This EU-wide deduction may supersede or complement existing national schemes. EU policy circles see this type of incentive as an obvious solution to boost R&D investment, hoping it will yield positive returns in terms of innovation and, ultimately, growth.

In this paper, we examine whether these expectations have strong foundations by re-investigating the R&D-innovation-productivity nexus in eight EU countries (Austria, Belgium, Czech Republic, France, the Netherlands, Italy, Spain and the UK[3]) from a macro-dynamic perspective. We also examine whether and how the availability of R&D tax incentives in a given country affect the dynamics of innovation and growth. From a policy perspective, we address two oft-mentioned challenges in the literature: (i) the dearth of cross-country comparisons on the one hand, and (ii) the fact that most studies limit themselves to the effect of tax incentives on R&D expenditures on the other. From a methodological perspective, we introduce dynamics, under the form of an autoregressive (AR) component, in econometric models derived from essentially static production function frameworks.

The first model is an adaptation of Mairesse and Mohnen (2002)'s "accounting framework" for innovativeness (also called "innovativity" in Mohnen et al. (2006)) and the second an adaptation of the CDM model (Crépon et al., 1998, Lööf et al., 2017). The former explicitly applies to various levels of analysis (from firm to country) and the latter, while primarily applied to firm-level data, has also proven worthy with industry-level data (Bourlès et al., 2013, Amable et al., 2016) and micro-aggregated data (Bartelsman et al., 2017). In order to introduce dynamics in the CDM model, though, we follow Bond and Guceri (2017) and focus on the productivity equation of the model, linking it directly to R&D (rather than to patents) in an "extended production function" approach à la Griliches (1979). In each country, we estimate these two models on industry-level panels that cover a period starting in the late 1970s / early 1980s (depending on the country) and ending in 2017.

We use panel autoregressive distributed lags (ARDL) specifications to estimate our econometric

[1] In the words of the EU Parliament (2000): http://www.europarl.europa.eu/summits/lis1_en.htm, Part I, Point 5.

[2] See for instance: https://sciencebusiness.net/framework-programmes/news/member-states-asked-sign-pact-higher-rd-investment.

[3] While the UK is not part of the EU anymore, it was a fully-fledged EU Member state over the period which we study. We discuss the implications of Brexit in Appendix A.

models on these heterogeneous panels, where the time dimension is longer than the individual one. We first run benchmark estimations in which we consider R&D intensity as a whole. We then conduct more detailed estimations in which we disentangle the respective effects of private R&D and of R&D that receives public support (with and without R&DTC). In our benchmark analysis, we identify positive long-run elasticities of innovation (measured by patenting intensity) and of productivity with respect to R&D intensity in almost all selected countries. The R&D conducted under an R&DTC either reinforces an already positive elasticity or makes it significantly positive if it was not before.

However, disentangling the respective effects of private and publicly-supported R&D reveals a wider diversity of situations. Purely private business R&D (hereafter, BRD) appears as the main driver of innovation and productivity in some countries, whereas government-supported R&D (hereafter, GRD) is the main driver in others. The availability of R&DTC is no longer systematically associated with more innovation or a higher productivity. Other public policy instruments embedded in GRD may prove as effective.

The main policy implication we derive from these results is that a "super-deduction" on R&D of the type proposed in BEFIT may be a little premature. Its effectiveness may depend more, in the end, on the taking into account of country-level industrial specialization than on the generosity of the scheme. A complementary analysis conducted within industries across countries suggest that targeting specific industries at the EU level may also be a good idea to improve the effectiveness and accuracy of such a policy.

The paper is organized as follows: In Section II, we present some economic justifications for the existence of R&DTC schemes as well as the rationale for the super-deduction proposed at the EU level. In Section III, we illustrate, using the selected EU countries, the complexity and sheer diversity of R&DTCs schemes. Readers already well versed in the intricacies of EU policy may want to directly go to Section IV where, after briefly replacing our study within the related literature, we present our data and econometric analysis. We summarize our findings and discuss their policy implications in Section V. We conclude in Section VI, the final section.

II R&DTC schemes in the EU

II.1 Economic justification for the existence of R&DTC

R&D tax incentives and related R&D policies are rooted in the belief that, in modern economies, innovation is the main source of growth, a belief largely grounded in endogenous growth theory (e.g., Romer (1990)). This belief has led to the widespread conviction, in EU policy circles, that innovation may be the only option to get the EU economy out of stagnation and back on the path of growth. The rationale is that innovation-induced economic growth will result in increased wealth, employment and well-being. EU policy makers are therefore searching for the conditions that are more likely to make firms increase their innovation effort. A widespread recommendation consists in creating the conditions of increased competition between firms (or in “letting the market decide"), as the increased competitive pressure would supposedly lead firms to innovate in order to survive or to gain advantages over their competitors.

A potential problem with this recommendation is that markets left to their own devices are likely to generate less R&D,[4] and therefore less innovation, than it would be desirable for the society as a whole (Arrow, 1962). Among economists, this is known as a “market failure". As far as investment in R&D is concerned, there are at least two reasons for such a failure.

One reason is that knowledge created through R&D, just like any type of knowledge, is largely immaterial and presents some characteristics of a “public good": It cannot be completely appropriated by its creators, and the related ideas can be - more or less rapidly, depending on their complexity - copied and used by other firms. Intellectual property rights (e.g., patents) may alleviate this problem, but do not completely solve it (e.g., a patent is effective only for a limited period of time and/or over specific geographical areas).

A second reason is that innovation is a very risky and uncertain endeavour, and that investment in R&D is not a safe investment. Firms may therefore face serious difficulties in finding financial support for their R&D projects, as banks and investors may be unwilling to lend money to projects that they cannot easily monitor (or the outcomes of which they cannot clearly see). This may result in the abandonment of projects that firms would be eager to pursue had they the required funds. If the assumption that innovation is conducive to economic growth and to social well-being is correct, then the two above-mentioned reasons call for public intervention in order to spur firms' R&D effort. This type of public intervention will generally take the form of R&D subsidies or of R&D tax incentives such as R&DTCs.

II.2 Towards a “super-deduction" on R&D in the EU?

So far, we have examined justification for the existence of R&DTCs in general. In practice, tax credits can take a multiplicity of forms, and may vary hugely across EU Member states. At one end of the spectrum, there are states where no tax credit exists (e.g., Germany) and, at the other, states where R&DTCs have been implemented for a long time (e.g., France), possibly experiencing changes along the way. The question of whether this variety should be harmonized at the EU level seems to have finally found, in EU policy circles at least, a positive answer with the proposal, in October 2016, of a revamped CCCTB (actually the re-launch of a 2011 proposal). This initiative, now superseded by the broader 2021 BEFIT proposal, suggested the implementation of a “super-deduction" on R&D

[4] Although alternative innovation channels do exist (see, e.g., Bozeman and Link (1983) for a thorough examination of these issues), R&D is generally considered as the primary input to the innovation process.

expenditures:[5]

"*To support innovation in the economy, this re-launch initiative will introduce a super-deduction for R&D costs into the already generous R&D regime of the proposal of 2011. The baseline rule of that proposal on the deduction of R&D costs will thus continue to apply; so, R&D costs will be fully expensed in the year incurred (with the exception of immovable property). In addition, taxpayers will be entitled, for R&D expenditure up to EUR [20 M], to a yearly extra super-deduction of 50%. To the extent that R&D expenditure reaches beyond EUR [20 M], taxpayers may deduct 25% of the exceeding amount.*" (European Commission (2016), pp. 9-10)

This super-deduction is, in effect, a very generous R&DTC scheme, as was clearly stated in the associated press release:[6] "*The CCCTB will support innovation in Europe by allowing the costs of R&D investment to be tax deductible. All companies that invest in R&D will be allowed to deduct the full cost of this investment plus an additional percentage of the costs, depending on how much they spend. The full cost of R&D will be 100% deductible, while an additional 50% deduction will be offered for R&D expenses of up to EUR* 20 *million. An additional 25% deduction will be allowed for R&D spending over EUR* 20 *million*".

The press release illustrated this scheme with the following example. An EU-based company that spends EUR 30 million on R&D in a given fiscal year will be allowed to deduct: (i) the full amount of its R&D expenditures (i.e., EUR 30 million) from its taxable income, plus (ii) an additional 50% of the first EUR 20 million (i.e., EUR 10 million) plus (iii) an additional 25% of the remaining R&D expenditures above the EUR 20 million threshold (i.e., EUR 2.5 million as 25% of the remaining EUR 10 million). In total, this hypothetical company will be able to deduct EUR 42.5 million from its CCCTB, which goes to show that "super-deduction" is indeed an appropriate term for this R&DTC scheme.[7]

The "super-deduction" seems to have been added to the 2016 CCCTB proposal to serve multiple objectives. The first was probably to make the proposal more appealing to reluctant Member states, as it offers them a channel through which they may maintain their international attractiveness– more specifically towards high-technology and innovative firms. Second, the variety of R&DTC regimes that currently prevails throughout the EU may result in a specific form of tax competition, geared towards R&D: high-tech and R&D intensive firms may be willing to settle down in countries/regions where the tax regime favours R&D more. This in turn could cause uneven increases in R&D investments across EU regions (with R&D expenditures rising in some States and stagnating in others), which plays against the "3% of GDP" objective for R&D investment in Europe. By introducing a certain degree of harmonization in R&DTCs, a "super-deduction" would lessen this threat.[8] Finally,

[5]The 2011 proposal already included a specific regime for R&D-conducting firms. The R&D regime in the 2016 proposal is more generous and constitutes a somewhat more radical proposal.

[6]http://europa.eu/rapid/press-release_MEMO-16-3488_en.htmtext

[7]The scheme is even more generous for "small starting companies" (i.e., start-ups, primarily), which will be allowed to deduct a further 100% of their R&D expenditures, within the limit of EUR 20 million. Thus, a start-up that invests EUR 5 million in R&D will be allowed to deduct EUR 10 million from its CCCTB.

[8]The super deduction would not totally rule out national R&D tax incentives, though. The principles stated in the 2011

the “super-deduction" could also be a way - insofar as tax credits are effective science and technology policy instruments - to foster higher investment in R&D despite post-pandemic budget cuts in the Horizon Europe programme.

The EU ECON committee adopted the report on the 2016 CCCTB proposal on February, 28th, 2018 (with some amendments), followed by the Parliament on March 15th, of the same year. The CCCTB, and its associated super deduction on R&D, was then submitted to the Council of the European Union for validation. On May 18th 2021, while the CCCTB was still waiting for validation, the European Commission (EC) adopted a new communication on business taxation in which it proposes a new framework dubbed BEFIT, destined to replace and extend the 2016 CCCTB proposal. At such, it will likely incorporate a (possibly updated) super-deduction on R&D. The BEFIT initiative is currently handled by the Economic and Monetary Affairs Committee of the European Parliament and under technical examination by the Council of the European Union.[9]

Whatever the outcome of this long legislative process, if a super-deduction on R&D expenditures is finally implemented as part of BEFIT, it will not make a clean slate - at least not in the short run - of all the R&DTCs that currently exist within EU Member states. This specific EU context therefore makes our projected empirical analysis on EU Member states, with harmonized industry-level data, particularly relevant. Before detailing the precise aims, scope and methodology of our empirical analysis, though, we need to further sketch and illustrate the sheer variety of R&D tax incentives that exist throughout Europe - variety to which we have only hinted at in the present section.

III The complexity of R&DTCs illustrated for selected EU Member states

We now turn to the examination of R&DTC schemes in eight EU Member states: Austria, Belgium, Czech Republic, France, Italy, The Netherlands, Spain and the United Kingdom. This selection was partly imposed by data constraints[10] (see Section IV) but nevertheless gives a fair representation of the EU, as it includes: (1) four members of the Inner Six (Belgium, France, Italy and the Netherlands), i.e. the founding members of the European Economic Community (EEC) in 1957, (2) two western European States that joined the European Community (successor to the EEC) in the 1970s (the United Kingdom, UK) and 1980s (Spain), (3) a western European State that joined the EU (successor to the European Community) in the 1990s (Austria) and (4) a former Communist State of Eastern Europe that joined the EU in 2004 (Czech Republic). The situation of the UK is unique among these

CCCTB proposal still prevailed in the 2016 proposal: “A company which does not qualify or does not opt for the system provided for by the CCCTB Directive remains subject to the national corporate tax rules, which may include specific tax incentive schemes in favour of Research & Development." (European Commission (2011), p. 6)

[9] See https://www.europarl.europa.eu/legislative-train/theme-an-economy-that-works-for-people/file-befit and https://www.europarl.europa.eu/legislative-train/carriage/befit/report?sid=8101 to follow the progress of the EU "legislative train" on BEFIT.

[10] These countries are those for which we were able to gather complete industry-level panel datasets, spanning a time period that goes from the mid-1970s/early 1980s to the late 2010s, and containing information on R&D, innovation and productivity.

countries: the UK was an EU Member state over the observation period (late 1970's to late 2010's) but has officially left the EU in January 2021, at the end of the 4-year process known as Brexit. The possible implications of Brexit for the R&DTC-innovation-productivity relationship are discussed in Appendix A.

In the present section, we highlight how the R&DTC schemes that exist in these countries may differ along multiples dimensions. We do not detail the specifics of each scheme, which would be beyond the scope of our study,[11] but focus instead on some key dimensions that we illustrate with some aspects of the above-mentioned schemes.

III.1 R&D expenditures

FIGURE 1 ABOUT HERE

Before comparing R&DTCs per se, it is useful to have a look at the state of investment in R&D in the EU. Figure 1 displays gross R&D expenditures as a percentage of GDP for each of our selected countries over the period 1981-2019. For the sake of comparison, Figure 1 also displays, as a benchmark, R&D expenditures in Germany (the only EU country that reached the 3% of GDP objective at the national level without implementing any R&DTC over the period) as well as the OECD average and the EU 27 average (the latter being available only from 1995 onwards). A first striking feature is that, across the whole period, R&D expenditures in Germany remain consistently above both the OECD average and the EU 27 average. They are also higher than in any of our selected countries for most of the period, being caught up by the Austrian ones from 2012 onwards. By 2017, both countries had reached the afore-mentioned "3% of GDP" objective, and even gone beyond this symbolic threshold, which was approached (but not attained) by Belgium in 2019. At that date, the remaining countries were all neatly below, and the EU27 average had only reached 2% of GDP. This may explain why Germany never felt the need to introduce an R&DTC. The question of whether Austria (and, to a lesser extent, Belgium) would have caught up with Germany in the absence of tax credit remains open, though. At the other end of the spectrum, R&D expenditures have remained consistently low (below 1.5% of GDP) throughout the period in Italy and Spain, both countries being far below the OECD average and the EU 27 average. Interestingly, Czech Republic (which is observed from 1995 onwards) started with a level of R&D expenditures akin to that of Italy and Spain, but managed to get close to the EU 27 average by the end of the period.

In the remaining countries, R&D expenditures more or less follow the OECD slowly ascending trend, while remaining below the OECD average throughout. Overall, they oscillate between the EU 27 average (which reached 2% of GDP in 2019) and the OECD average (which is higher than the EU average and around 2.5% of GDP in 2019). Among these countries, France is the one where

[11] For exhaustive comparisons, see Straathof et al. (2014), Deloitte (2014), Ernst&Young (2014). OECD (2010) also provides, for the year 2009, a useful comparative table that encompasses our selected countries.

R&D expenditures are the highest, going above the OECD average in the 1990s and remaining close in the 2000's and 2010's. Overall, Figure 1 suggests that our selected countries all have an interest (in the light of the Lisbon Agenda and subsequent Europe 2020 and Horizon Europe objectives) in raising their R&D expenditures. This may explain the reliance on R&DTCs as policy instruments to achieve this objective. Nevertheless, while all these countries have implemented R&DTC schemes, these differ widely in their timeline, tax rate and tax base. We will now provide a broad picture of these divergences, relying on factual information gathered by crossing the references mentioned in Footnote 11 : Deloitte (2014), Ernst&Young (2014), OECD (2010) and, last but not least, Straathof et al. (2014).

III.2 Differences in R&DTC schemes

Regarding **timeline**, France was first, among the selected countries, in introducing an R&DTC.[12] This was done in 1983. The credit was incremental, based on the yearly variation (increase) in R&D expenditures, and remained so until 1998, with various changes in rates and ceiling across the period, as well as a brief attempt at a co-existing volume-based tax credit from 1987 to 1990. In 1999, the R&DTC was renewed for a final period of five years, and it was made permanent in 2004, with a volume-based component introduced in parallel to the main incremental component. A major reform made the R&DTC completely volume-based in 2008. Compared to France, the remaining countries are latecomers: Spain introduced its first "real" R&DTC in 1995, Belgium and the Netherlands introduced theirs in 1998, Italy and the UK did so in 2000 and Czech Republic in 2005. Perhaps for this reason, these countries experimented less with their R&DTCs, and did not go through several phases with radical changes in their tax credit schemes. That said, in Italy, the R&DTC was introduced regionally at first, with a tax rebate varying across regions, and only became a harmonized national scheme in 2006. Last but not least, the case of Austria is rather specific, as an R&DTC co-existed with an "R&D tax allowance" (focusing on the outcome of R&D activities) from 1988 to 2010. In order to make the Austrian tax scheme simpler and more consistent, the tax allowance was suppressed in 2010, effectively leaving the tax credit as the sole instrument.

As mentioned earlier, eligibility conditions for an R&DTC may vary widely across countries, which results in tax bases (or, in the case of tax credit, the base for a tax rebate) varying along multiple dimensions. First, tax credits can be **incremental** (i.e., based on the yearly variation in R&D expenditures) or **volume-based** (i.e., based on the yearly volume of R&D expenditures, possibly with respect to a year of reference). The latter form of tax credit makes it easier for firms to obtain tax rebates, but whether it gives them a strong incentive to increase R&D expenditures remains doubtful. Nonetheless, R&DTCs are currently volume-based (or primarily volume-based) in all selected

[12] Giraud et al. (2014) present a detailed timeline of the French R&DTC in their report to the French Ministry of Higher Education and Research.

countries except in Italy, where an incremental tax credit prevails. The French R&DTC that existed between 1983 and 1999 was also primarily incremental[13] (it coexisted with a volume-based tax credit between 1987 and 1990). In the Czech Republic, a small incremental component may be added to the main R&DTC, which is volume-based. Overall, the current prevalence of volume-based tax credits would likely facilitate a possible harmonization, and indeed the super-deduction conceived in the 2016 CCCTB proposal is volume-based.

The tax base can also vary with **firm size** and with the **industry** in which a firm operates. Thus, the rate of the R&DTC in Italy during 2000-2014 was of 20 to 30% for SMEs (depending on regions), versus 15 to 25% for medium-sized firms and 10 to 20% for large ones. In the UK,[14] the R&DTC introduced in 2000 was originally available to SMEs only and a different regime for larger companies was introduced in parallel in 2002. The former could deduce 50% of their R&D personnel expenses from their taxable profit, whereas the latter could deduce 25%. In 2008, these amounts could be as high as 75% of R&D personnel expenses for SMEs and 30% for large firms. In the Netherlands, the amount of the 1998 tax credit was of 40% of "knowledge workers" wages in SMEs versus 17% in large firms. In 2004, it was raised to 42% for SMEs and reduced to 14% for large firms.

By contrast, in France, the current R&DTC does not formally distinguish between SMEs and large firms,[15] but the amount of the tax credit varies with respect to the investment in R&D. It is equal to 30% for investments below EUR 100 million and 5% for investments above this threshold. In effect, since SMEs typically invest lower amounts in R&D, they will benefit from the higher tax credit - but this scheme also let large firms benefit from the same rate (provided their investment remains below the threshold), which is not the case in the UK or in the Netherlands. Not only may this feature of the French tax credit give large firms an incentive to under-invest, it may also make harmonization more difficult.

R&DTC regimes may also be industry-specific, either targeting certain industries or excluding some industries. For instance, prior to 1992, agricultural and textile firms could not benefit from the French R&DTC. In the UK, since 2008, pharmaceutical firms doing vaccine research can deduce about 40 to 50% of their R&D personnel expenses from their taxable profit. This is, in effect, a specific regime, distinct from both the SME regime and the large company regime. In the super-deduction proposed with the 2016 CCCTB (and presumably with its successor), a specific regime for newly-created small firms would apply, as stated in Footnote 7.

Another dimension in which tax bases vary is the existence of a ceiling to the R&DTC. Most countries impose a ceiling, and among our selection all have, at some stage, imposed one, except for Czech

[13] For instance, from 1985 onwards, the tax rebate was equal to 50% of the variation of a firm's R&D expenditures between year t and $t-1$.

[14] See for instance https://forrestbrown.co.uk/rd-tax-credits-explained/ for a business-oriented presentation of the British R&DTC scheme

[15] In the sense that the applied rates and threshold are the same for SMEs and large firms. The main difference is that refund is immediate for SMEs, whereas it occurs after 3 years for large firms.

Republic. In France, the tax credit introduced in 1983 had a ceiling of FF 3 million (approximately EUR 0,9 million[16]), which was raised up to 5 million (about EUR 1.3 million) in 1985 and 10 million (about EUR 2.5 million) in 1987. A ceiling still existed in the early 2000's, but was finally suppressed in 2008, probably because it kept on rising (from EUR 8 million in 2004 to EUR 10 million in 2006 and EUR 16 million in 2007). The super-deduction included in the 2016 CCCTB proposal does not impose a ceiling: R&D expenditures are fully deductible from the consolidated corporate tax. A threshold of EUR 20 million exists, however, for additional deductions: an additional 50% deduction is available under the threshold, whereas the additional deduction is of "only" 25% beyond the threshold.

Last but not least, the contents of R&D expenditures that entitle firms to a tax rebate vary hugely across countries. In the Netherlands, the expense base for the R&DTC is restricted to R&D wages (and social contributions). In Belgium, it primarily consisted in R&D wages as well, but has been extended to include capital assets. Investments in R&D are eligible to the tax credit provided they have no harmful effect on the environment (a condition which does not exist in the other four countries). In the remainder of our selected countries, the expense base includes all R&D expenditures (reported as such in a firm's accounts). Of all these countries, France may be the one where the definition of R&D expenditures is the broadest. For instance, they include external R&D conducted in any European Economic Area (EEA) country. The expense base may also include items that are beyond the actual expenses. Thus, 200% of the wages (and overheads) of young Ph.D. graduates employed in a private firms are tax-deductible, provided that the firm hires them on long-term contracts. In the 2016 CCCTB proposal, the super-deduction was supposed to bear on all R&D costs incurred in a given year, with the exception of immovable property. Its precise form in the BEFIT proposal is still unclear a the time of this writing.

III.3 "L'exception française"

In all countries, there may sometimes be changes in R&DTC schemes, but they essentially correspond to minor adjustments (typically, a change in the share of R&D expenditures that can be claimed back by R&D-doing firms). By contrast, France has experimented, since the early 1980's, with several well-distinct sub-periods of R&DTC. They correspond to changes that may radically alter the design of the tax credit scheme. In this respect, France stands somewhat apart in our selection of EU Member states.

The French R&DTC was originally introduced in 1983 as an experiment. It was an incremental scheme (see Sub-Section III.2) set for a fixed period of time (five years), at the end of which its relevance was examined, and the decision to proceed or not with the scheme was taken. This lasted from 1983 to 1998, and the 1999-2003 period was the final five-year renewal period of the original

[16] We did all conversions of French francs to euros using the online tool of the French National Statistical Institute (INSEE) which takes long-term inflation into account.

R&DTC. In 2004, a new R&DTC scheme was introduced, on a permanent basis. This new scheme remained primarily incremental (as the original scheme had been), but now comprised a volume-based component. Finally, a major reform made the R&DTC completely volume-based in 2008. This comparatively tumultuous history was worth mentioning in a specific sub-section, since we will have to take it into account in our empirical analysis, to which we turn in the next section.

IV Empirical analysis

There exists a large literature on the evaluation of R&DTCs, the bulk of which uses micro-data to estimate the effect of specific tax credit schemes on R&D expenditures within countries. These studies rely primarily on structural approaches in IV settings and more rarely on quasi-experimental methods like differences-in-differences (DID). A detailed review of this literature would go far beyond the scope of the present paper. The interested reader will find a very thorough one in the 122 pages-long report on R&D tax incentives addressed by Straathof et al. (2014) to the EC and a less systematic but more recent one in Bloom et al. (2019).

Our study finds its own place in this already abundant literature, as we exploit panels of 11 to 13 industries observed for 22 to 37 years across our 8 selected EU countries to address two challenges highlighted in the above-mentioned reviews. The first is the dearth of cross-country comparisons on the effectiveness of R&D tax incentives. There are good reasons for this. On the one hand, harmonized innovation survey micro-data does not necessarily provide precise information on tax incentives, and cross-country comparisons that use this type of data ideally require an international team of researchers. These constraints explain why a comparative study like Czarnitzki and Lopes-Bento (2012) had to focus on a broad measure of public R&D subsidies (and not on tax incentives) and on an ad-hoc selection of countries (the Flanders region of Belgium, Germany, Luxembourg and South-Africa). On the other hand, macro-econometric studies like Bloom et al. (2002) generally rely on country-level data (a panel of 9 countries observed over 18 years, in the case of these authors), and can only estimate an averaged effect of R&DTCs across all countries.

Since our primary interest lies in comparing EU countries, we address this first challenge head-on. Industry-level panel data is particularly well suited to international comparisons, especially when the number of industries and/or years is large enough to allow for within-country estimations, as is the case with our panels, which we present in detail in Sub-Section IV.1.

The second challenge is that most studies focus on the impact of R&DTCs on R&D expenditures, and not on innovation, let alone productivity. Still, this would be the ultimate goal, given the abundant literature suggesting that growth is driven by innovation, which in turns depends on investment in R&D. Again, we are able to tackle this challenge head-on, because our panel provides us with a good proxy for innovation output (patenting intensity) and with a rigorously-constructed measure of productivity (an index of Total Factor Productivity growth).

An obvious shortcoming of industry-level data, compared for instance to firm-level data, is that it does not provide precise information on the specifics of a given tax credit scheme. However, we have collected precise information on the *timeline* of R&DTCs in each selected country, and we can use this information for econometric identification and statistical inference. Exploiting the rich time-series dimension of our panel, what we measure is thus the impact of doing R&D *when an R&DTC is available*, compared to doing R&D in periods when it is not. This is similar in spirit to measuring the effect of a time-varying event from a certain date onwards in pure time-series data. Our methodology is detailed in Sub-Section IV.2. The above-mentioned shortcoming is, in our opinion, more than offset by what our panel allows us to do, i.e., capture the long-run dynamics of R&D, innovation and productivity across a relevant selection of EU countries, with and without R&DTC, prior to the possible implementation of a harmonized R&DTC.

IV.1 Data and variables

Our primary data source was the EU-KLEMS database (Stehrer et al., 2019), originally compiled by the Groningen Growth and Development Centre (GGDC) and currently run by the Vienna Institute for International Economic Studies (WIIW). We exploit the latest update of the 2019 release,[17] which covers the years 1995 to 2017, matched with previous releases[18] to cover the period ranging from the late 1970s to 1995. We completed this data with information from linked OECD and EUROSTAT databases on patents and R&D. This compilation of data yielded, for every country covered in this study, a panel of 11 to 13 industries, the time dimension of which can vary from one country to the other. Within a given country, some variables are available over a longer period of time than others. However, constructing appropriate panels for the econometric analysis imposes a consistent time window, so our econometric models are *de facto* estimated over strongly balanced panels. We explain this balancing further at the end of this sub-section.

Our key variables are (i) R&D intensity, which can be decomposed into Business R&D intensity and Government R&D intensity, (ii) patenting intensity and (iii) Total Factor Productivity (TFP), which is sometimes called Multi-Factor Productivity (MFP) in the literature. We measure R&D intensity as the ratio of R&D capital stock[19] to the number of hours worked each year in each industry. Focusing on the stocks of R&D capital which corresponds, respectively, to strictly private investment and to publicly-supported R&D, we similarly compute Business R&D intensity (hereafter BRD) and Government R&D intensity (hereafter GRD).

Patenting intensity is defined as the number of patents divided by the number of hours worked. The number of patents is the number of patent applications to the European Patent Office (EPO) by sector of economic activity (EUROSTAT, Sciences & Technology database). A concordance matrix be-

[17] available at https://euklems.eu/

[18] available at http://euklems.net

[19] The stock of R&D capital is computed and provided by the EU-KLEMS linked database, derived from OECD ANBERD.

tween the International Patent Classification (IPC) and the NACE industry classification then allows patent applications to be distributed across industries for a given country (Schmoch et al., 2003). The division by hours worked yields a continuous aggregate indicator of innovation intensity. We use patenting intensity as a proxy for innovation broadly speaking. We are well aware that patents are not the only output of the innovation process, and that much innovation can occur without patenting. Our rationale for using patenting as a proxy for innovation is that we are conducting an industry-level (not a firm-level) analysis, and more innovative industries are likely to produce more patents on average. Thus, the intensity of patenting in an industry reflects the intensity of innovation, broadly defined, that occurs within this industry.

Finally, our measure of TFP is the TFP index computed at the industry level by the EUKLEMS team on the basis of VA and expressed in base 100 for the year 2010. As explained earlier, we will investigate the potential effect of R&DTCs by comparing periods without tax credits to periods that saw the implementation of an R&DTC. We therefore add to our main variables dummy variables that indicate whether an R&DTC is implemented in year t in the country to which industry i belongs. All of our selected countries except France have experienced a single phase of R&DTC that was still ongoing at the end of the observation period. Therefore, for all countries except France, a single dummy variable will suffice. France first introduced an R&DTC in 1983. The R&DTC scheme subsequently went through four well-distinct sub-periods (as explained in Sub-Section III.3). To take this into account, we will rely, in France, on four TC dummy variables instead of a single one.

Since our panels of industries all have a long time dimension, our variables of interest may display a behavior that is more typical of time series than of panel data. In particular, we need to check their stationarity, since non-stationary variables would lead to invalid econometric inference. To do so, we conduct unit root tests (adapted for panel data) on the natural logarithm of our raw variables, prior to the construction of the balanced panels. In the raw data, some variables are observed over a longer period of time than others, whereas the building of the estimation panels imposes a common time frame to all variables in a given country. In this context, it is generally wiser to perform unit root tests on the raw variables than after building the panels, because doing so lets the econometrician exploits the full time dimension of each variable to estimate the autoregressive models that yield the test statistic. We perform Im-Pesaran-Shin (IPS) tests (Im et al., 2003), the test statistic of which is built as the average of the usual Augmented Dickey-Fuller (ADF) test statistic computed for each time series in each x_{it} variable. We compute the ADF test statistics using Autoregressive Distributed Lags (ADL) models with drift and trend. We implement a version of the IPS test that allows the errors of the underlying ADL models to be serially correlated. To further account for possible cross-section dependence between individual time series in the panels, we also implements CIPS tests, i.e. IPS tests in which the ADF regressions are augmented with the cross-section averages of lags and lagged first-differences of the individual series (Pesaran, 2007). CIPS are especially useful before implementing

ARDL models (see Sub-Section IV.2).

The results of all these tests are displayed in Table 1, with the IPS tests in the upper panel and the CIPS tests in the lower panel. The IPS tests show that all our (log-)variables are at most I(1) in all countries, with the log of patenting intensity being I(0) in all countries. The more demanding CIPS tests lead us to the same conclusion. Overall, all panel unit root tests thus reveal that our variables are either I(0), i.e. stationary, or I(1). They therefore meet the prerequisite for the estimation of cointegrating relationships with panel ARDL models, which are at the heart of our econometric modeling, as will be explained in Sub-Section IV.2.

TABLE 1 ABOUT HERE

We further describe, in Appendix B, the construction and balancing of the panels that we will use for our econometric estimations. We first present the list of industries in Appendix B, Table A.1. We initially gathered information on 13 industries, namely 11 industries covering the whole of the manufacturing sector, plus the energy industry (E-D, "Electricity, Gas and Water Supply") and the construction industry (F, "Construction"). Unfortunately, the number of patents applications is not available in the latter two industries. Therefore, econometric models that involve the patenting intensity variable (see Sub-Section IV.2) can only be estimated on panels with the 11 manufacturing industries in the individual dimension. Models that do not involve patenting intensity, though, (again, see Sub-Section IV.2) can be estimated on the 13 industries (11 manufacturing industries plus the "Electricy, Gas and Water Supply" and "Construction" industries).

In addition, to ensure a consistent time windows for our econometric models, we have to define the starting year of a given panel as the first year in which all relevant variables are observed. In some countries, this may be as early as the late 1970's/early 1980's, whereas in other the starting year is in the mid-1990's. Furthermore, at the time of this writing, the number of patents applications is not available in the source dataset after 2014, which means that models involving patenting intensity have to be estimated on panels which end in that specific year, even though some variables (such as VA or TFP) are observed up to 2017. Taken together, these constraints make for strongly balanced panels of 11 to 13 industries, observed over 20 years for Austria, Belgium and Czech Republic and over 35 years for the remaining countries. We summarize the structure of these balanced panels in Appendix B, Table A.2, which also contains information about the timeline of R&DTC's in each selected country. We can notice that, once an R&DTC has been triggered in a given country, it lasts until the end of our observation period. Only in France does it undergo some significant formal changes over time, hence the use of four TC dummy variables in this country's models.

Last but not least, Table A.3 in Appendix B provides summary statistics (averaged over industries and time) for our variables. This table displays a sharp contrast, in terms of innovation effort and output, between Austria, Belgium, France, Netherlands and the UK on the one hand, and Italy and

Spain on the other, with Czech Republic standing somewhat in the middle. Countries in the first group all have both a high R&D intensity and a high patenting intensity. By contrast, Italy and Spain are lagging behind on both innovation indicators, although they display a higher level of productivity, which might explain their lower investment on innovation. Indeed, if their economies have been more dynamic (since the reference year of 2010) than those of the first group of countries, there was less need for sustaining growth through innovation. By contrast, the five aforementioned innovative countries all needed to invest in innovation (and to be innovative) in order to sustain an otherwise sluggish economy. In Czech Republic, we observe higher R&D intensities than in most other countries, but a lower patenting intensity. This may be explained by the fact that this country relied heavily on adaptive R&D in the catching-up process experienced during its transition from a former Communist state to an independent democratic country in 1993 and a new EU Member state in 2004. It relatively high average level of productivity over the period is probably further evidence of this catching-up process.

It is also worth noting that the high patenting intensity in the most innovative countries conceals a certain heterogeneity, as evidenced by the high dispersion (the standard deviation of the variable is much larger than its average value). Thus, innovation output in these countries is likely to be driven by a few innovative industries, with little patenting among the remaining industries. Conversely, the lower patenting intensity in Czech Republic may not reflect the situation of all industries in the country today. This observation will justify (in Sub-Section V.3) a cross-European, by-industry investigation to complement our main analysis.

In order to get a better grasp of the dynamics and heterogeneity of innovation within each of our selected countries, we also present the two most important innovation variables (R&D intensity as a whole and patenting intensity) by industry for each selected country in Figures A.1 and A.2 in Appendix B. In all countries except Czech Republic, we observe an increasing trend in R&D intensity. At the end of the period, R&D intensity is at its highest in Belgium, France, and the Netherlands closely followed by the UK. It is at its lowest in Czech Republic. Although the increasing trend concerns most industries, we notice that, in each selected country, a couple of industries are more R&D-intensive than the rest. These are primarily “Chemicals and Chemical products" and “Electric, Electronic and Optical Equipment", with some country-specific R&D champions like “Transport equipment" in France and Italy and “Coke, Petroleum and Nuclear fuel" in France, Spain and the UK.

Rather reassuringly for the R&D-innovation relationship, we observe that patenting intensity follows the same increasing trend as our measure of R&D intensity, although a slight decline may be observed in two UK industries (“Chemicals and Chemical products" and “Transport equipment"). At the end of the period, patenting intensity is at its highest in Belgium, the Netherlands and France, like R&D intensity was. We also notice that, in each country, the most R&D-intensive industries (such as the “Electric, Electronic and Optical Equipment" industry) are also the most patent-intensive ones, which, again, is reassuring for the R&D-innovation relationship that is at the heart of the Horizon Europe strategy.

IV.2 Methodology

IV.2.a Introducing dynamics in a static framework

To study the R&D - innovation - productivity nexus, there exist some canonical structural econometric models that all derive from a production function framework. Most of the time, these models are estimated on cross-sectional micro-data (such as innovation surveys data), or on panels with a short time dimension. Hence, they are usually specified as essentially static (i.e., without any AR component). We first present bare-bones versions of two of these static models, adapted to our research question and data, and build on them to introduce innovation dynamics.

The innovation production function

The first canonical model is that of the innovation production function, which gives a theoretical and empirical representation of the R&D - innovation relationship. As explained in Mairesse and Mohnen (2002), this model provides both an econometric and an interpretative (or “accounting") framework that can be applied to various spatial units (firms, industries, countries) and makes sense at each level of analysis. It allows researchers to assess “innovativeness" (or “innovativity") by relating a measure of innovation output (based for instance on the counting of patents) to a measure of R&D effort (e.g., stock of R&D capital or R&D intensity). In this respect, it can be linked to the empirical literature initiated by Hall et al. (1986), and pursued, e.g., in van Ophem et al. (2002) and Gurmu and Pérez-Sebastian (2008).

Adapted to our problematic, and applied to our industry-level panels within each of the eight selected EU countries, Hall et al. (1986)'s model could be specified, for industry i and year t, as:

$$\ln PI_{it} = \sum_{k=0}^{p} \beta_{1k} \ln RD_{it-k} + \sum_{k=0}^{p} \beta_{2k} (\ln RD_{it-k} \times TC_{t-k}) + u_i + v_t + w_{it} \qquad (1)$$

where PI denotes patenting intensity, RD denotes R&D intensity and TC_t is a dummy variable equal to 1 if an R&DTC exists in year t and to 0 otherwise. In interaction with the log-R&D intensity, it captures the effect of doing R&D when an R&DTC is available. The model also includes an industry-specific effect u_i, a time-specific effect v_t and a transitory error term w_{it}. Model (1) relates the log-patenting intensity to current and past log-R&D intensity. If $k = 0$, then Model (1) is a purely simultaneous specification of the innovation production function. If $k>0$, the model has one of more lags of log-R&D intensity alongside its current value. Models involving only lagged values (and no current value) of log-R&D intensity might also be considered.

CDM and the extended production function

The second canonical model is the structural model of the R&D - innovation - productivity relationship referred to as CDM (from the initials of Crépon et al. (1998), who first introduced the model).

This (generally) multiple-equation model can be thought of as an extension of the innovation production function to the full R&D - innovation - productivity nexus, with an additional equation dedicated to productivity. Its estimation involves methods that aims at controlling for the potential endogeneity of the innovation and R&D variables.

While most often applied to firm-level data, CDM has also been successfully applied to industry-level data (e.g., Bourlès et al. (2013); Amable et al. (2016)). Bourlès et al. (2013) estimate a reduced-form version of CDM, while Amable et al. (2016) estimate two- and tree-equations versions. Adapted from this literature to our problematic and data, this model, in its simplest static form, could be specified with one productivity equation and one patenting equation:

$$\begin{aligned} \ln TFP_{it} &= \alpha \ln PI_{it-1} + u_{1i} + v_{1t} + w_{1it} \\ \ln PI_{it-1} &= \sum_{k=2}^{p} \beta_{1k} \ln RD_{it-k} + \sum_{k=2}^{p} \beta_{2k} (\ln RD_{it-k} \times TC_{t-k}) + u_{2i} + v_{2t} + w_{2it} \end{aligned} \tag{2}$$

where TFP is the TFP index provided by EU-KLEMS. The upper equation (the "productivity equation") relates this index to the lagged value of patenting intensity, ln PI_{it-1}, thus taking into account possible delays between the introduction of an innovation and its payoff in terms of productivity (Amable et al. (2016)). The lower equation (the "patenting equation") similarly relates ln PI_{it-1} to lagged values of R&D intensity, again emphasizing the delay between investment in R&D and its outcome (Hall et al. (1986); Amable et al. (2016)). All in all, the patenting equation is quite similar to Model (1) without the current value of R&D intensity.[20]

It is worth noting that the productivity equation includes more implicit controls than meet the eye because, in the EU-KLEMS data, TFP is calculated following a classic growth accounting approach, using a VA-based measure of aggregate output and controlling for capital and labour aggregate inputs.[21] This approach ensures that our measure of productivity is net of the effect of the usual capital, materials and labour inputs, the influence of materials being taken into account through the use of a VA-based measure of output. In addition, the productivity equation includes an industry-specific effect u_{1i} and a time-specific effect v_{1t}.

For our purpose, it may be more interesting to consider the following reduced form of Model (2), obtained by substituting ln PI_{it-1} into the TFP equation, setting $\gamma_{jk} = \alpha \times \beta_{jk}$ with $j = 1, 2$:

$$\ln TFP_{it} = \sum_{k=2}^{p} \gamma_{1k} \ln RD_{it-k} + \sum_{k=2}^{p} \gamma_{2k} (\ln RD_{it-k} \times TC_{t-k}) + u_i + v_t + w_{it} \tag{3}$$

This model, which can be useful for instance if one lacks an appropriate measure of patenting or innovation output, corresponds to what is known since Griliches (1979) as the extended production function. Following Eberhardt et al. (2013) and Bond and Guceri (2017), we will rely on this extended

[20] Amable et al. (2016) introduce an AR component in the patenting equation, but not in the productivity equation. We will introduce dynamics later on, and therefore keep, for the time being, to a static version of the model.

[21] See, e.g., Adarov and Stehrer (2019), for details of the calculation.

production function specification to introduce dynamics. Hence, in what follows, we will focus on Models (1) and (3).

Our panels fall within the "small n, large t" category, since even in the shortest ones the maximum number of industries (13) is well below the minimum number of years (22). Their asymptotics are therefore quite different from those of panels with small t (Blackburne and Frank, 2007, Blackburne and Bumpass, 2014). In panels with large t, the assumption that the parameters of the models are homogeneous (and that only the FE differ across groups) is often found to be inappropriate (Pesaran and Smith, 1995, Pesaran et al., 1999, Im et al., 2003). The literature concerned with these panels (often refered to as "heterogenous panels") suggests relying on panel autoregressive distributed lags (ARDL) models to identify econometric relationships.[22] Besides allowing parameters to vary across groups, panel ARDL models present another practical advantage: their estimation does not call for instruments. Modifying the order of the ARDL model generally suffices to deal with endogenous regressors (Pesaran and Shin, 1999). There exist various consistent estimators, which can be tested against each other using Hausman tests. We now explain how we use these models to investigate the R&D - innovation - productivity relationship in the absence/presence of R&DTC in our study.

IV.2.b Implementing panel ARDL models: benchmark analysis

Panel ARDL models allow researchers to distinguish between long-run and short-run relationships between variables. Generally, the parameters of interest in a model are those that describe the underlying long-run relationship (if it exists) and the speed of adjustment to the long-run relationship. Following what is generally done in the literature, we first specify a long-run relationship for both our models. For the innovation production function, we start with the simplest possible specification of Model (1):

$$\ln PI_{it} = \theta_{1i} \ln RD_{it} + \theta_{2i}(\ln RD_{it} \times TC_t) + \omega_{it} \tag{4}$$

and for the extended production function, the simplest possible specification of Model (3):

$$\ln TFP_{it} = \theta_{1i} \ln RD_{it-2} + \theta_{2i}(\ln RD_{it-2} \times TC_{t-2}) + \omega_{it} \tag{5}$$

We then specify the dynamic relationships using ARDL(p, q) models in which p and q are determined using Akaike's Information Criterion (AIC). For the innovation production function, this yields

$$\ln PI_{it} = \sum_{j=1}^{p} \lambda_{ij} \ln PI_{it-j} + \sum_{j=0}^{q} \delta_{1ij} \ln RD_{it-j} + \sum_{j=0}^{q} \delta_{2ij}(\ln RD_{it-j} \times TC_{t-j}) + u_i + \pi_i.t + \epsilon_{it} \tag{6}$$

and for the extended production function, this leads to

$$\ln TFP_{it} = \sum_{j=1}^{p} \lambda_{ij} \ln TFP_{it-j} + \sum_{j=2}^{q} \delta_{1ij} \ln RD_{it-j} + \sum_{j=2}^{q} \delta_{2ij}(\ln RD_{it-j} \times TC_{t-j}) + u_i + \pi_i.t + \epsilon_{it} \tag{7}$$

[22] In Appendix C, we discuss issues that arise when one tries to introduce dynamics in Models (1) and (3) using techniques designed for (micro-level) homogeneous panels.

where all parameters are allowed to vary across industries and where u_i is an industry-specific constant. In practice, Model (7) will simplify somewhat because AIC will lead us to set $p = 1$, i.e. to specify Model (7) as an ARDL(1, q). Both models include a deterministic time trend $\pi_i.t$ because, as explained in sub-section IV.1, $lnPI_{it}$ is stationary around a deterministic time trend according to both IPS and CIPS tests, while $lnTFP_{it}$ is trend-stationary according to IPS tests and I(1) to CIPS tests. In fact, all of our variables are either stationary or I(1), as has been said in Sub-Section IV.1. The presence of some I(1) variables is not a limitation, because, just like their pure time series counterparts (Pesaran and Shin, 1999), panel ARDL models can accomodate both I(0) and I(1) variables (Pesaran and Smith, 1995, Pesaran et al., 1999, Blackburne and Frank, 2007).

When a panel ARDL model includes I(1) variables, researchers aim at identifying a cointegrating relationship, which is best evidenced by putting the ARDL models into their Error Correction Models (ECM) form. The cointegrating relationship can be interpreted as the underlying long-run relationship of the model. In our study, we write the ECM specification of the innovation production function as:

$$\begin{aligned}\Delta \ln PI_{it} &= \phi_i[\ln PI_{it-1} + \theta'_{1i} \ln RD_{it} + \theta'_{2i}(\ln RD_{it} \times TC_t)] \\ &+ \sum_{j=1}^{p} \alpha_{ij} \Delta \ln PI_{it-j} + \sum_{j=0}^{q} \gamma_{1ij} \Delta \ln RD_{it-j} + \sum_{j=0}^{q} \gamma_{2ij} \Delta(\ln RD_{it-j} \times TC_{t-j}) + u_i + \pi_i.t + \epsilon_{it}.\end{aligned} \tag{8}$$

Similarly, but keeping in mind, as stated above, that Model (7) will be specified as an ARDL(1, q) in our empirical application, we write the ECM specification of the extended production function as:

$$\begin{aligned}\Delta \ln TFP_{it} &= \phi_i[\ln TFP_{it-1} + \theta'_{1i} \ln RD_{it} + \theta'_{2i}(\ln RD_{it} \times TC_t)] \\ &+ \sum_{j=2}^{q} \gamma_{1ij} \Delta \ln RD_{it-j} + \sum_{j=2}^{q} \gamma_{2ij} \Delta(\ln RD_{it-j} \times TC_{t-j}) + u_i + \pi_i.t + \epsilon_{it}.\end{aligned} \tag{9}$$

Specifying the extended production function as an ARDL(1, q) implies that there is no lag of $\Delta lnTFP_{it}$ in the right hand-side of Model (9).

Models (8) and (9) constitute our benchmark models. In these models, the cointegrating relationship is featured between square brackets, θ'_{1i} and θ'_{2i} are the long-run parameters associated with R&D in the absence/presence of an R&DTC and ϕ_i is the speed-of-adjustment parameter. These three parameters are the primary parameters of interest, derived from the ARDL(p, q) specification[23] with:

$$\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}),\ \theta'_{1i} = \frac{\sum_{j=0}^{q} \delta_{1ij}}{-(1 - \sum_{j=1}^{p} \lambda_{ij})},\ \text{and}\ \theta'_{2i} = \frac{\sum_{j=0}^{q} \delta_{2ij}}{-(1 - \sum_{j=1}^{p} \lambda_{ij})}.$$

If a long-run relationship does exist, ϕ_i, written as above, is expected to be significantly negative. Often dubbed "speed-of-adjustment", it can be interpreted as a measure of how fast the model returns to the long-run relationship after deviating from it.

[23]The short-run parameters, i.e. the α_{ij}'s, γ_{1ij}'s and γ_{2ij}'s, also derive from the ARDL specification. The derivation can be found elsewhere with slightly different notation, e.g. in Blackburne and Frank (2007). For the sake of concision, we focus here on the parameters of interest.

Models (8) and (9) can be estimated either exactly as they are specified above, i.e. with an unrestricted trend, or in a specification that integrates the trend parameter in the cointegrating relationship (restricted trend). In our applications, we allow for both specifications (i.e. with unrestricted or restricted trend), carefully choosing the one where the trend is more significant and/or where the likelihood is higher (when relying on Maximum Likelihood.)

To estimate Models (8) and (9), we implement the three main estimators dedicated to panel ARDL models, i.e. dynamic fixed effects (DFE), Mean Group (MG) and Pooled Mean Group (PMG), using the xtpmg software component developed by Blackburne and Frank (2007). With the DFE estimator, all coefficients except u_i are held constant across industries. Due to the potential endogeneity between the FE and the lagged dependent variable, the DFE is prone to the same bias as the FE estimators reviewed in IV.2.a. With the MG estimator (Pesaran and Smith, 1995), all coefficients are allowed to vary across industries. MG consists in estimating as many separate time-series regressions as there are industries in the panel (i.e., 11 or 13) and in calculating the coefficient means (standard errors can be computed with the Delta method). The PMG estimator (Pesaran et al., 1999) occupies a middle ground between DFE and MG. With PMG, the long-run coefficients are held constant across industries, whereas ϕ_i and the short-run coefficients are allowed to vary. The model thus obtained is non-linear in its parameters and identification is ensured by Maximum Likelihood. In our empirical application, we implement all three estimators and select the most appropriate using Hausman tests, as recommended in the literature.

IV.2.c Disaggregating R&D into Business R&D and Government R&D

We estimate our benchmark models expecting to find a long-run relationship between R&D intensity and the relevant outcome variable (patenting intensity in Model (8) and TFP in Model (9)). However, even if we identify the expected relationship (e.g., a positive association between R&D and outcome, which may vary when an R&DTC is available), we still need to go beyond the benchmark. Indeed, relying only on R&D intensity as a whole may result in an aggregation problem if private investment in R&D (Business R&D) and publicly-supported R&D (Government R&D) have different effects. We therefore need to disentangle the respective effects of BRD and GRD (Business and Government R&D intensities, as defined in Sub-Section IV.1).

To take this further step, we could simply replace $\ln RD_{it}$ with $\ln BRD_{it}$ and $\ln GRD_{it}$ in our benchmark models, interacting each new variable with the TC_t indicator. We follow a subtler approach, in which the availability of an R&DTC comes in addition to other public support to R&D.[24] In this approach, one envisions the TC as an addition to public costs (which it actually is) rather than as a somewhat artificial addition to private R&D effort. Thus, the TC_t indicator will be introduced in interaction with $\ln GRD_{it}$ only, and not with $\ln BRD_{it}$. This leads to the following specification of the

[24] We are deeply indebted to an anonymous reviewer for directing us towards this subtler approach.

innovation production function:

$$\Delta \ln PI_{it} = \phi_i[\ln PI_{it-1} + \theta'_{1i} \ln BRD_{it} + \theta'_{2i} \ln GRD_{it} + \theta'_{3i}(\ln GRD_{it} \times TC_t)] + \sum_{j=1}^{p} \alpha_{ij} \Delta \ln PI_{it-j}$$
$$+ \sum_{j=0}^{q} \gamma_{1ij} \Delta \ln BRD_{it-j} + \sum_{j=0}^{q} \gamma_{2ij} \Delta \ln GRD_{it-j} + \sum_{j=0}^{q} \gamma_{3ij} \Delta(\ln GRD_{it-j} \times TC_{t-j}) + u_i + \pi_i.t + \epsilon_{it}. \tag{10}$$

The same holds for the extended production function, in which we also take into account the possibility that the knowledge generated by private investment in R&D may have both a direct effect on TFP and an effect that is mediated through patenting, which acts as a kind of multiplier.[25] So, BRD_{it} will be introduced on its own and in interaction with PI_{it}, which leads to the following generalization of the extended production function:

$$\Delta \ln TFP_{it} = \phi_i[\ln TFP_{it-1} + \theta'_{1i} \ln BRD_{it} + \theta'_{2i} \ln GRD_{it} + \theta'_{3i} \ln(BRD_{it} \times PI_{it})] + \theta'_{4i}(\ln GRD_{it} \times TC_t)]$$
$$+ \sum_{j=2}^{q} \gamma_{1ij} \Delta \ln BRD_{it-j} + \sum_{j=2}^{q} \gamma_{2ij} \Delta \ln GRD_{it-j} + \sum_{j=2}^{q} \gamma_{3ij} \Delta \ln(BRD_{it-j} \times PI_{it-j})$$
$$+ \sum_{j=2}^{q} \gamma_{4ij} \Delta(\ln GRD_{it-j} \times TC_{t-j}) + u_i + \pi_i.t + \epsilon_{it}. \tag{11}$$

As in our benchmark analysis, we allow for the possibility of an unrestricted or restricted time trend in both models, carefully basing our final choice on significance level and contribution to the likelihood (for likelihood-based estimators). Identifying distinct effects of BRD and GRD shall yield more nuanced policy implications.

V Findings and discussion

For the sake of clarity, all our tables of results follow the same structure, for both the innovation production function and the extended production function. We split each table in three parts: the first, indexed with the letter *a*, contains the results obtained on the shorter panels, in Austria, Belgium and Czech Republic. The second, indexed with the letter *b*, presents those obtained on the longer panels for countries with a single period of R&DTC, i.e. Italy, Netherlands, Spain and the UK. The third and final part, indexed with the letter *c*, presents the results obtained for France.

France had to be set apart from the other long panels because in this country, as explained in Sub-Sections III.3 and IV.1, we had to rely on four dummy variables to account for distinct sub-periods in the R&DTC scheme: *(i)* $TC1$ covers 1983-1998, which is the sub-period of the original incremental tax credit, renewed every five years; *(ii)* $TC2$ covers 1999-2003, the final five years of the original tax credit, with uncertainty regarding its renewal; *(iii)* $TC3$ covers 2004-2007, the sub-period in which the

[25]We are indebted to the same reviewer for suggesting this specification.

tax credit, now primarily incremental with a volume-based component, was made permanent; *(iv)* $TC4$ covers 2008 to the end of the panel, the sub-period in which the tax credit has become wholly volume-based. With these details in mind, we can now turn to our results.

V.1 Benchmark ARDL estimates

We first present the results obtained with our benchmark ARDL models, focusing our comments on the long-run parameters, θ_1' (associated with R&D intensity) and θ_2' (associated with R&D intensity when an R&DTC is available), as well as on the speed-of-adjustment parameter, ϕ_i. We provide estimates of the former in the upper part (labelled "Long run (ECT)") of each table of results, and an estimate of the latter (averaged over all cross-sections) in the lower part (labelled "Short run"), together with the averages of the other short-run coefficients. All tables feature a line for a restricted trend coefficient in the "Long run (ECT)" part and a line for an unrestricted trend coefficient in the "Short run" part. Depending on which type of trend is retained for a given country, we complete the corresponding line and fill in the other with a blank sign (''–"). The estimates obtained for the innovation production function are displayed in Tables 2a to 2c, while those obtained for the extended production function are displayed in Tables 3a to 3c. To obtain these estimates, we experimented with the three main estimators presented in IV.2.b and ran Hausman tests to retain the most appropriate one in each country.

V.1.a Benchmark estimates of the innovation production function

Looking first at the innovation production function, we identify a long-run relationship between R&D intensity and patenting intensity in all selected countries. The estimate of ϕ_i is always significantly negative, as expected, ranging from -0.24 in the UK (Table 2b) to close to -1 in the three countries with shorter panels (Table 2a).[26] The exact nature of the long-run relationship varies somewhat across countries, but it always entails some positive association between R&D and patenting.

In five countries out of eight (Austria, Italy, the Netherlands, Spain and the UK), the elasticity of patenting with respect to R&D, measured by θ_1', is significantly positive. In addition, the estimate of θ_2' reveals that the R&D conducted in an R&DTC period is positively associated with patenting in all five countries but Austria, where we observe a slightly negative association. Thus, the availability of an R&DTC tends to strengthen the positive association bewteen R&D and patenting, except in Austria where it has a dampening effect. In the later country, though, the TC_t dummy variable actually indicates a change in the tax credit that occurred in 2010 rather than the introduction of a tax credit. As explained in Sub-Section III.2, until 2010 the Austrian R&DTC co-existed with an "R&D tax allowance" that was conditioned on the outcome of R&D activities. This allowance was suppressed

[26] The estimate of about -1.49 obtained in Belgium should not be taken as face value. It is rather an econometric artifact stemming from the comparatively short time dimension of the panel, ϕ_i being also drawn close to -1 in the other two shorter panels.

in 2010, effectively leaving the tax credit as the sole instrument. The negative sign of θ_2' may then simply reflect the change from a more demanding scheme, partly conditioned on innovation output, to a less demanding one (a pure R&DTC with no incentive to achieve actual innovations).

TABLE 2a ABOUT HERE

TABLE 2b ABOUT HERE

TABLE 2c ABOUT HERE

In the remaining three countries (Czech Republic, Spain and France), we do not find any significant association between R&D and patenting outside of the period of availability of an R&DTC. When an R&DTC is available, the association between R&D and patenting becomes significant and positive in all three countries. In France, this positive association endures throughout the various phases of the tax credit, captured by the four dummy variables described in the introduction to the present section.

Overall, our findings regarding the relationship between R&D and innovation (as measured by patenting intensity) are rather encouraging. First, we do find that more R&D (with or without the availability of an R&DTC) tends to be associated with more innovation, which is not always easy to ascertain with panel data. Second, we find that, leaving the specifics of Austria aside, the availability of an R&DTC either strengthens this association or make it become significant.

This is in line with the findings reviewed in Straathof et al. (2014), who consider that "[o]verall, studies on the effectiveness of R&D tax incentives tend to find a positive impact on innovation." (p.38). Indeed, Ernst and Spengel (2011) find that R&D tax incentives have a positive effect on patenting in Europe. However, they do not use cross-country comparisons, but relies on a database pooling patents applied for at the EPO level, from various European countries. Similarly, Westmore (2013), using a panel of OECD countries (with the country as the relevant unit of analysis) finds that R&D incentives are positively associated with patenting at the OECD level. But, again, the nature of the data precludes cross-country comparisons. Compared to these studies, the relationship between R&D and innovation may be more difficult to identify with industry-level panel data. This is why, without being unduly optimistic, we do find our results encouraging: not only do we identify the aforementioned relationship in several countries, we also observe that the availability of an R&DTC may actually consolidate it.

V.1.b Benchmark estimates of the extended production function

Moving on now to the extended production function, we find – in Tables 3a to 3c – results that are as unequivocal and encouraging as those found with the innovation production function. First, we identify a long-run relationship between R&D intensity and productivity growth in all countries. The estimate of ϕ_i is always significantly negative, as expected, ranging from -0.25 in the Netherlands to

-0.51 in Italy. Second, we find a positive association between R&D intensity and TFP in all countries except Czech Republic, i.e. in seven countries out of eight, with a long-run elasticity (θ'_{1i}) ranging from 0.08 in Spain and France to 0.69 in Italy. Third, θ'_{2i} is significantly positive in six of these seven countries, and non-significant in the seventh (the UK). In other words, the availability of an R&DTC reinforces the observed positive association between R&D and TFP.[27]

TABLE 3a ABOUT HERE

TABLE 3b ABOUT HERE

TABLE 3c ABOUT HERE

Standing as the only exception in our findings is Czech Republic, where we do not observe any significant association between R&D and TFP, and an unexpected negative effect of R&D conducted in a period of R&DTC. This may be due to structural reasons, and more specifically to the economic catching-up that followed the fall of the Iron Curtain and preceded the entry in the EU. Indeed, it is likely that the R&D conducted during that period was mostly adaptive, aiming at upgrading the country's economy, prior to any possible gain in productivity.

To put it in a nutshell, we find that R&D conducted when an R&DTC is available reinforces an already-existing positive association between R&D and TFP in six countries out of the eight we study. Interpreting this result as the sole effect of an R&DTC would certainly be stretching the truth, since other productivity-improving factors may co-occur. Nevertheless, it is reasonable to interpret it as evidence that R&DTC's may improve productivity in a majority of European countries. Our findings, and this conclusion, are in line with those reached by Minniti and Venturini (2017) for the USA, after conducting an ARDL-based analysis fairly similar to ours on a panel of US industries.

V.2 ARDL estimates with BRD and GRD

In the previous sub-section, we have identified a positive association between R&D intensity on the one hand, and innovation and productivity on the other. Availability of an R&DTC generally tends to strengthen this positive association. As stated in Sub-Section IV.2.c, we now disentangle the respective effects of private investment in R&D (measured by BRD) and publicly-supported R&D (measured by GRD). To achieve this, we now present the results obtained by estimating Models (10) and (11), which involve both BRD and GRD in the regressors, instead of a single measure of R&D intensity. Our tables of results follow the same structure as the one we adopted for our benchmark analysis. Tables 4a to 4c pertain to the innovation production function, while tables 5a to 5c refer to the extended production function. We indicate, in each table, to which variable each long-run coefficient θ'_{ji} refers.

[27] In France, this is true only during the second sub-period of the R&DTC, other sub-periods having no significant effect.

V.2.a Estimates of the innovation production function with BRD and GRD

As in our benchmark analysis, we start by commenting the estimates of Model (10), the innovation production function. Our main interest now lies in (i) identifying which channel (BRD, GRD or both) is conducive to more innovation and (ii) examining how the availability of an R&DTC affects publicly-supported R&D (GRD). As before, we successfully identify long-run relationships: The speed-of-adjustment coefficient, ϕ_i, is significantly negative in all countries, ranging from -0.28 in the UK to about -1 in Belgium (see Footnote 26). However, looking at Tables 4a to 4c reveals four distinct types of long-run relationships. First, in Austria, private R&D (BRD) is the only type of R&D associated with a higher level of patenting. The long-run coefficient of GRD, θ'_{2i}, is not significant, whereas its interaction with the TC dummy variable, captured by θ'_{3i}, is significantly negative, as in our benchmark analysis and presumably for the same reasons.

Second, there are two countries, the Netherlands and the UK, where the long-run elasticities of patenting intensity with respect to BRD and GRD, measured by θ'_{1i} and θ'_{2i} respectively, play in opposite directions: BRD is positively associated with patenting intensity, whereas GRD is negatively associated with this measure of innovation output. The positive effect of BRD seems to dominate the negative effect of GRD: The magnitude of θ'_{1i} is at least twice that of θ'_{2i} (in absolute value), which explains why we observe a positive elasticity of patenting with respect to R&D intensity as a whole in our benchmark analysis. The coefficient of the interaction between GRD and the TC dummy variable, θ'_{3i}, is significantly negative in the Netherlands (which increases the negative effect of GRD on patenting) and non significant in the UK. We may thus reasonably conclude that, according to our findings, private investment in R&D drives innovation in the Netherlands and the UK. The availability of an R&DTC has, at best, no significant influence on the innovation process and may have, at worst, a deterrant influence.

TABLE 4a ABOUT HERE

TABLE 4b ABOUT HERE

TABLE 4c ABOUT HERE

In a third group of countries, made up of Belgium, Italy and Spain, the long-run elasticities of patenting intensity with respect to BRD and GRD (θ'_{1i} and θ'_{2i}, respectively) again play in opposite directions, but this time BRD is negatively associated with patenting whereas GRD is positively associated with it. The magnitude of θ'_{2i} is slightly larger (in absolute value) than that θ'_{1i} in Italy and Spain, and is about the same in Belgium. Since our benchmark estimates display a positive elasticity of patenting intensity with respect to R&D as a whole in these three countries, we can reasonably conclude that the positive effect of GRD dominates here. The coefficient of the interaction term between GRD and the TC dummy variable, θ'_{3i}, is non significant in Belgium and Spain, but significantly positive in Italy, thus reinforcing the positive effect of GRD on patenting in this country. Overall, in this group of countries, we may conclude that R&D with public support is the main driver of innovation. The availability of an RDTC may reinforce this positive association.

To a certain extent, France is also part of this group of countries, as a positive elasticity of patenting with respect to GRD balances, and possibly dominates, a negative elasticity of patenting with respect to BRD. However, the existence of several phases of R&DTC (i.e., successive schemes), captured by four dummy variables instead of a single one, makes matters more complex and calls for a specific discussion. First, in order to avoid collinearity issues, we had to exclude $TC1$ from the model and to interact GRD with $TC2$, $TC3$ and $TC4$ exclusively. $TC2$ refers to the final incremental scheme proposed from 1999 to 2003. During those years, firms could reasonably believe that it would be the last opportunity to obtain tax rebates thanks to mere increments of their R&D expenditures. Thus $TC2$ can be interpreted as capturing the effect of this final opportunity with respect to those offered by the continuing incremental scheme that existed from 1983 to 1998.[28] $TC3$ refers to the 2004-2007 experimental scheme that combined a primarily incremental component with a volume-based component, while $TC4$ refers to the wholly volume-based scheme which existed from 2008 to the end of our observation period. $TC3$ and $TC4$ can be interpreted as capturing the respective effects of these schemes with respect to the above-mentioned continuing incremental scheme of 1983-1998.

Introducing $TC2$, $TC3$ and $TC4$ in interaction with GRD in the model leads to Specification (I) in Table 4c. With this specification, we observe, as previously mentioned, a positive elasticity of patenting with respect to GRD which balances, and possibly dominates, a negative elasticity of patenting with respect to BRD. The interaction terms involving GRD and the $TC2$ and $TC4$ dummy variables are significantly positive, adding to the positive elasticity of patenting with respect to GRD. The interaction between GRD and $TC3$, however, is not significant. We suspected that this was caused by the inclusion of several dummy variables in the model and estimated Specification (II) as a sensitivity analysis. In Specification (II), we merged $TC3$ and $TC4$ in a single $TC34$ dummy variable, which captures the availability of a partly or wholly volume-based scheme. With this alternative specification, the long-run elasticities of BRD and GRD both become non significant, but the interactions of GRD with $TC2$ and $TC34$ are both significantly positive. Based on all these findings, we may conclude that innovation in France is driven by publicly-supported R&D, especially when a (generous) R&DTC is available. In this respect, the situation in France is quite similar to the one observed in Belgium, Italy and Spain, despite the relative complexity of the French R&DTC history.

Finally, Czech Republic stands out with a fourth type of long-run relationship, in which patenting is not associated with BRD nor GRD, outside of the period when an R&DTC becomes available. When the R&DTC is available, a positive association between patenting and GRD appears, as evidenced by the sign and significance of θ'_{3i}, the coefficient of the interaction between GRD and the TC dummy.

[28] Since our observation period starts in 1980 in France, and since the ARDL model involves up to 3-year lags, the years preceding 1983, when there was no R&DTC, cannot be taken into account in the estimation.

This finding, which is consistent with our benchmark estimation, leads us to conclude that in Czech Republic, innovation is primarily driven by publicly-supported R&D conducted under an R&DTC. The existence of a tax credit seems to be a prerequisite for innovation.

V.2.b Estimates of the extended production function with BRD and GRD

We now turn to a commentary on the estimates of Model (11), the extended production function. We first want to determine whether TFP is primarily driven by BRD, GRD or both. When GRD appears as a driver of productivity, we will examine how the availability of an R&DTC affects this relationship. When BRD appears as a driver, we will examine the relative importance of its direct effect and of its effect mediated through patenting. As before, the speed-of-adjustment coefficient, ϕ_i, is significantly negative in all countries (ranging from -0.09 in France to about -0.43 in Austria), which allows us to focus on long-run relationships. The estimates displayed in Tables 5a to 5c reveal that the unequivocal relationship identified in our benchmark estimations (an overall positive elasticity of TFP with respect to R&D as a whole, strengthened by the existence of an R&DTC) actually conceals a diversity of situations.

TABLE 5a ABOUT HERE

TABLE 5b ABOUT HERE

TABLE 5c ABOUT HERE

In a majority of countries, consisting of Austria, Belgium, France, the Netherlands and Spain, we identify a positive long-run elasticity of TFP with respect to BRD (measured by θ'_{1i}) and a negative long-run elasticity of TFP with respect to GRD (measured by θ'_{2i}). The magnitude of θ'_{1i} is much larger than that of θ'_{2i} (in absolute value), which explains why we observe a positive long-run elasticity of TFP to R&D intensity as whole in our benchmark estimates. Looking further into this group reveals more diversity. First, Belgium is the only country among these five where we observe a multiplying effect of patents (i.e. where elasticity θ'_{3i} is significant and, in this case, positive). Second, and more importantly, we observe a positive association between TFP and GRD when an R&DTC is available (i.e., a significant effect of the interaction between GRD and the TC indicators) in Belgium, France and the Netherlands,[29] but neither in Austria nor in Spain. Overall, we can conclude that although private investment in R&D is the main driver of productivity in this group of countries, a certain diversity prevails as regards the use and effect of R&DTC.

Outside the above-mentioned five countries, we observe three distinct long-run relationships. In Italy (Table 5b), the long-run elasticity of TFP with respect to GRD (measured by θ'_{2i}) is significantly positive, and so is the interaction of GRD with the TC dummy (captured by θ'_{4i}). By contrast, the direct

[29]In France, to avoid multicollinearity issues, we used only two dummy variables, $TC2$ and $TC34$, rather than three, much like in Specification (II) of the innovation production function. Both their interactions with GRD are positively associated with TFP.

long-run elasticity of TFP with respect to BRD (measured by θ'_{1i}) is not significant, and neither is the indirect elasticity (which takes patenting into account), θ'_{3i}. We can therefore conclude that publicly-supported R&D is the primary driver of productivity in Italy, and that this positive relationship is reinforced when an R&DTC is available.

In the UK (also in Table 5b), the direct effect of BRD on TFP (measured by θ_{1i}) is significantly negative, but its interacted effect through patenting (measured by θ_{3i}) is significantly positive. In addition, the long-run elasticity of TFP with respect to GRD (measured by θ_{2i}) is significantly positive, but the interaction of GRD with the TC dummy variable (captured by θ_{4i}) has not significant effect. We may therefore conclude that in the UK, TFP is driven by a mix of patent-inducing private investment in R&D and of publicly-supported R&D without tax credit.

Finally, our findings for Czech Republic (Table 5a) confirm our benchmark estimates: we do not observe any significant association between TFP and BRD or GRD,[30] but we identify a negative effect of GRD conducted during a period of R&DTC. Again, this may be due to the economic catching-up already described in Sub-Section V.1.a.

V.3 Targeting innovative industries

Although our benchmark estimates suggest that R&D conducted when an R&DTC is available may favour innovation and productivity, disentangling the respective effects of public and private R&D reveals a certain diversity behind this apparent uniformity. We now discuss another possible deconstruction of our benchmark estimates. Indeed, the conclusions to which they point out may be driven by some industries more than others. This is an issue that sometimes arise in policy discussions, but that has not been formalized much in the literature. Among the welcome exceptions, Antonelli (2020) brings forwards theoretical arguments in favour of aiming R&DTC at firms or industries where "input additionality"[31] is larger than 1, i.e., firms or industries which use R&DTC not simply to maintain their R&D activities but also to generate new ones. In the same vein, Akcigit et al. (2022) develop a theoretical reasoning, complemented by empirical estimations, which leads them to conclude that there is indeed room for improvement in R&DTC policies. They suggest for instance conditioning R&D tax incentives on innovation performance (which may vary across industries, and even across firms).

Being aware of this literature, we thought that identifying which European industries are likely to make potential targets for conditional R&DTC would nicely complement our study. To do so, we needed long-run estimates of the innovation production function and/or of the extended production function by industry rather than by country. In our empirical analysis, the MG and PMG estimators

[30] Due to collinearity issues, we were not able to include BRD and GRD simultaneously in the Czech ARDL model. We included either one or the other, which led to Specifications (I) and (II) in Table 5a. As one can easily see in this table, both specifications yield similar results, and in particular identical estimates for the interaction between GRD and TC.

[31] Defined in Antonelli (2020) as the flow of additional R&D activities carried out by the recipient of public funding with respect to the amount of funding received.

let the short-run estimates of ARDL models vary across industries. In order to obtain the required long-run estimates by industry, we turned around the position of countries and industries, using panels of countries to estimate, within each industry, ARDL versions of the innovation production function and of the extended production function.

Using a balanced panel of 5 countries (France[32], Italy, Netherlands, Spain and UK) observed over 35 years,[33] we were able to estimate the ARDL innovation production function in 11 industries and the extended production function in 13 industries.[34] We were not able to identify a long-run relationship between R&D and patents with the innovation production function, because the speed of adjustment ϕ_i was systematically insignificant. In contrast, with the extended production function, ϕ_i was significant in every industry. Table A.4 in Appendix B displays these estimates of ϕ_i, as well as the estimates of θ_1' and θ_2', the long-run elasticities of R&D intensity and of R&D intensity interacted with the TC dummy variable, respectively.

Table A.4 reveals that the estimate of ϕ_i ranges from -0.33 in the "Food Products" industry to -0.56 in the "Rubber & Plastic" industry. We observe a significantly positive long-run elasticity of TFP with respect to R&D intensity in a majority of industries (10 out of 13). Regarding the effect of R&D conducted when an R&DTC is available, which is our main variable of interest in this experiment, we find a significantly positive estimate of θ_2' in only four industries: "Food Products", "Metals and Fabricated Metal Products", Machinery and equipment" and "Other Manufacturing". In three industries ("Textile, Apparel and Leather", "Chemicals and Chemical Products" and "Electricity, Gas and Water Supply" industries), the estimate is negative. In the remaining six industries, it is not significant.

While these estimates should be taken with great caution (due, in particular, to the short size of the panels), they point out to four industries where R&D conducted in an R&DTC period has a potentially positive effect on TFP growth. While the R&DTC may not be the sole factor that drives this results, it can be interpreted as evidence that these industries are the ones where an R&DTC would be likely to have most impact. There is of course a wide gap, which we do not intend to bridge, between this exploratory findings and any policy advice. Our rough estimates are not enough to justify targeting these industries rather than others. What they do suggest, though, is that some industries may do better than others with the extra R&D expeditures they derive from tax credits. In this respect, targeting some (carefully identified) industries rather than others, as suggested in Antonelli (2020) and Akcigit et al. (2022), makes sense and should be considered when implementing an R&DTC. At the EU level, this logic could be extended to serve the objectives of the European Green

[32]For the purpose of this analysis, the four sub-periods of the French R&DTC were all merged into one, obviously at the cost of some loss of information.

[33]We first experimented with a balanced panel involving all 8 countries during 20 years, but the estimations proved unfeasible on this panel, probably due to the short time dimension, in addition to the small n.

[34]As explained in Sub-Section IV.1, the patents variable is not available in the "Electricy, Gas and Water Supply" and "Construction" industries.

Deal, for instance by targeting industries where an R&DTC is most likely to generate eco-innovations. The recent project of rebuilding Europe's own defense capacity, evoked as a consequence of the war in Ukraine and of a possible disengagement of the USA, could also benefit from similar targeting.

V.4 Policy implications

At first glance, our benchmark estimates suggest that national R&DTC may be associated with more innovation and a higher level of productivity in almost all the countries covered in our study. However, disentangling the respective effects of private and public R&D reveals a greater diversity of situations: In some countries, innovation and productivity are primarily driven by Business R&D (BRD), whereas, in others, Government R&D (GRD) appears as the primary driver. In the latter case, the availability of an R&DTC may add to the baseline effect of GRD, but this is not systematic.

More specifically, regarding the effect on innovation, we find that GRD conducted during a period of R&DTC acts as a complement to baseline GRD in Italy, and as a substitute in Czech Republic and in France. In Belgium and Spain, where innovation is primarily driven by GRD, we do not observe any significant effect of R&DTC. In Austria and the Netherlands, where innovation is primarily driven by BRD, GRD coupled with an R&DTC has a deterring effect. Finally, in the UK, where BRD is also the primary driver of innovation, there is no significant effect of R&DTC.

As regards productivity, we observe a positive association with GRD conducted under an R&DTC scheme in Belgium, France and the Netherlands, three countries where BRD appears as the primary driver of TFP. This finding suggests that, in these countries, this specific form of public support adds to private R&D effort to sustain productivity. In Austria and Spain, where BRD is also the primary driver of productivity, we do not find any evidence of an influence of R&DTC. In Italy, where the primary driver of productivity is GRD, we observe a complementary positive effect of R&DTC. In the UK, where TFP is driven by a mix of BRD (mediated through patenting) and GRD, we do not observe any significant effect of R&DTC. Finally, in Czech Republic, the availability of an R&DTC is negatively associated with productivity, probably due to the reasons already detailed in Sub-Section V.1.b.

Even if we leave aside the UK, that is not a member of the EU anymore, this diversity of situations is enough to raise a doubt on the timeliness of a common EU R&DTC. Overall, when distinguishing between publicly-supported and private R&D, national schemes seem to be associated with an increase in innovation in three countries out of eight, and with an increase in productivity in four countries. Other national policy instruments – the effect of which is encompassed in GRD – may also play a significant role in fostering innovation and productivity. The divergences we observe within our group of eight countries may be an indication of even more contrast at the level of the EU 27. In the light of these findings, a common EU tax credit of the type included in the BEFIT proposal appears as a slightly premature suggestion.

Our tentative analysis on a panel of industries across countries reinforces this conclusion. Indeed, even when considering R&D intensity as a whole (i.e., without distinguishing R&D with public support from private R&D), we find a positive association between the existence of an R&DTC and productivity in only four industries out of thirteen. This finding is in line with the word of caution expressed in van Pottelsberghe de la Potterie (2008): Harmonized R&D policy rules at the EU level should take country-level industrial specialization into account. Thus, an EU-level R&DTC that would target industries where investment in R&D is likely to generate new R&D activities and actual innovations in several countries (in effect, the most innovative EU industries) may prove more effective than a general one, no matter how generous. Properly identifying these EU "innovation champions" and their reaction to an R&DTC calls for further investigation (probably at a more disaggregated level) and perhaps for some policy experimentation.

Before concluding, a remark on the UK is in order. This country was an EU Member state during the whole of our observation period (1980-2017) but left the EU in 2021, which places it in a rather unique situation. If an initiative like BEFIT were to become a reality, British firms would not benefit from the super-deduction on R&D, except for those firms that would choose to relocate in the EU. Therefore, the UK would have to rely on its own national R&D policies to spur its innovation effort. Since we find, in our empirical analyses, that innovation and productivity in the UK do not correlate with the existence of an R&DTC, this country should probably not rely on this type of policy instrument anyway for the future of its science and innovation policy. Public-private partnerships in research appear as credible alternatives, but probably imply sustained commitment to the EU Horizon programme (and its successors), as suggested in Appendix A. Other partnerships (with the USA, for instance) can be considered, but having one of the world's most research-intensive areas at one's doorstep and leaving it untapped would not be a sound strategy (Wellcome Trust, 2020).

VI Conclusion

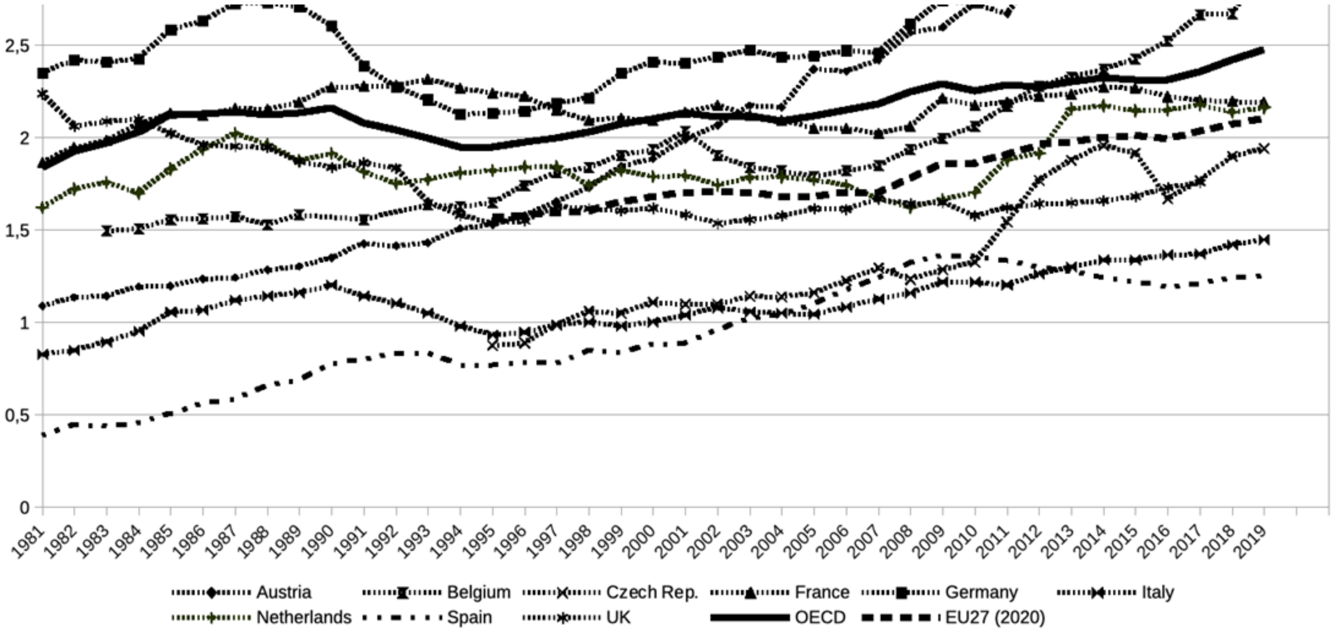
Using industry-level panel data for 8 EU countries (Austria, Belgium, Czech Republic, France, Italy, the Netherlands, Spain and the UK), we have re-examined the effect of R&D on innovation and productivity in the absence/presence of an R&DTC. To conduct this re-examination, which makes sense in the context of a proposed EU-wide “super deduction" on R&D expenditures, we implemented two canonical models: the innovation production function, linking R&D intensity to patenting intensity, and the extended production function, linking R&D intensity to productivity. While these models are primarily static in the existing literature, we introduced dynamics by including an AR component in each model.

Our panels having a long time dimension and a comparatively small number of industries we used ARDL specifications and relevant estimators to identify long-run relationships *(i)* between R&D intensity and patenting and *(ii)* between R&D intensity and TFP. Overall, we find R&D intensity as a whole to be positively associated with both innovation and productivity growth. The R&D specifically conducted when an R&DTC is available either reinforces an already-existing positive association or makes the positive association possible where none existed before.

These benchmark findings however conceal a diversity of situations which appear when we disentangle the respective effects of purely private business R&D (BRD) and government-supported R&D (GRD). The former appears as the main driver of innovation and productivity in some countries, whereas the latter is the main driver in others. The availability of R&DTC is no longer systematically associated with more innovation or a higher productivity. Other public policy instruments embedded in GRD may prove as effective.

The main policy implication we derive from these results is that a "super-deduction" on R&D of the type proposed in BEFIT may be a little premature. Its effectiveness may depend more, in the end, on the taking into account of country specifics, particularly industrial specialization, than on the generosity of the scheme. Targeting specific industries with a potentially high return on R&D in terms of productivity across the EU may be a good idea, as suggested by our complementary analysis conducted in 13 industries on a 5-country, 35-year panel.

Figure 1: **R&D expenditures in % of GDP for selected EU countries, 1981-2019**



Source: OECD

Table 1: **Unit root tests on all key variables, by country**

	Country							
	Austria	**Belgium**	**CZ**	**Italy**	**NL**	**Spain**	**UK**	**France**
IPS tests								
ln TFP	-2.10 (N = 13, T = 38)	-2.33 (N = 13, T = 38)	-1.78 (N = 13, T = 23)	-2.59[b] (N = 13 T = 46)	-2.32 (N = 13, T = 39)	-2.61 (N = 13, T = 37)	-2.31 (N = 13, T = 46)	-2.33 (N = 13, T = 38)
Δ ln TFP	-6.72[a]	-5.37[a]	-4.38[a]	-7.16[a]	-5.88[a]	-5.69[a]	-7.81[a]	-5.97[a]
ln patenting intensity	-3.88[a] (N = 11, T = 34)	-4.73[a] (N = 11, T = 34)	-3.92[a] (N = 11, T = 20)	-3.66[a] (N = 11, T = 35)	-6.78[a] (N = 11, T = 37)	-4.27[a] (N = 11, T = 35)	-9.00[a] (N = 11, T = 37)	-10.25[a] (N = 11, T = 37)
ln R&D intensity	-1.50 (N = 13, T = 23)	- 1.92 (N = 13, T = 24)	-2.09 (N = 13 T = 23)	-2.20 (N = 13, T = 38)	-1.39 (N = 13, T = 38)	-1.00 (N = 13, T = 48)	-1.68 (N = 13, T = 38)	-2.82[a] (N = 13, T = 40)
Δ ln R&D intensity	-3.45[a]	-3.79[a]	-3.23[a]	-4.02[a]	-3.75[a]	-3.69[a]	-4.22[a]	-2.91[a]
ln BRD intensity	-1.52	-2.00	-1.89	-2.04	-1.29	-1.93	-1.65	-3.01[a]
Δ ln BRD intensity	-3.41[a]	-4.02[a]	-3.51[a]	-5.17[a]	-4.46[a]	-4.02[a]	-4.22[a]	-4.19[a]
ln GRD intensity	-1.05	-1.47	-2.64	-2.84	-2.50	-2.24	-1.92	-2.72[a]
Δ ln GRD intensity	-2.82[a]	-3.96[a]	-4.07[a]	-6.28[a]	-6.87[a]	-5.89[a]	-5.99[a]	-7.41[a]
CIPS tests								
ln TFPG	-2.40	-2.39	-3.05[a]	-3.08[a]	-2.15	-2.21	-2.52	-3.01[a]
Δ ln TFPG	-5.50[a]	-5.21[a]	-4.23[a]	-5.81[a]	-5.56[a]	-5.37[a]	-5.68[a]	-5.91[a]
ln patenting intensity	-4.14[a]	-5.07[a]	-3.60[a]	-4.18[a]	-3.73[a]	-3.80[a]	-4.08[a]	-4.42[a]
ln R&D intensity	-1.74	- 2.24	-1.32	-2.58	-1.77	-1.97	-1.56	-1.74
Δ ln R&D intensity	-3.03[a]	- 3.28[a]	-3.33[a]	-3.98[a]	-3.67[a]	-4.21[a]	-4.25[a]	-3.59[a]
ln BRD intensity	-1.53	-2.01	-1.15	-2.27	-1.78	-1.05	-1.53	-2.57
Δ ln BRD intensity	-2.90[a]	-3.82[a]	-3.34[a]	-4.18[a]	-3.74[a]	-4.61[a]	-4.41[a]	-3.22[a]
ln GRD intensity	-2.22	-1.78	-1.82	-1.96	-1.96	-2.56	-1.77	-1.29
Δ ln GRD intensity	-4.14[a]	-3.55[a]	-4.04[a]	-4.13[a]	-3.50[a]	-5.98[a]	-4.21[a]	-3.12[a]

CZ: Czech Republic, NL: Netherlands, BRD: Business R&D, GRD: Government R&D

N: number of industries, T: years. In order not to overburden the table, N and T are not provided for: (i) first-differenced variables, as they are simply the N and T-1 of level variables; (ii) Business and Government R&D intensities, because they are identical to those of total R&D intensity; (iii) CIPS tests, as they are identical to the N and T featured in IPS tests.

In some countries, records of R&D stock start after records of productivity and patenting, which explains the shorter time dimension for the R&D intensity variables in these countries.

Significance levels: [a] p-value < 0.01, [b] p-value < 0.05, [c] p-value < 0.10.

Table 2a: **Innovation production function - benchmark ARDL estimates - Austria, Belgium and Czech Republic**

Dependent variable: Patenting Intensity (ln PI_{it})						
	AT		BE		CZ	
Long run (ECT)						
θ'_{1i}	1.26^{a}	*(0.23)*	0.02	*(0.26)*	-0.18	*(0.19)*
θ'_{2i}	-0.09^{a}	*(0.01)*	0.06^{a}	*(0.01)*	0.06^{c}	*(0.04)*
Restricted trend	0.16^{b}	*(0.08)*	0.15^{a}	*(0.05)*	0.07^{b}	*(0.03)*
Short run (averaged)						
ϕ_i	-0.91^{a}	*(0.17)*	-1.49^{a}	*(0.22)*	-1.12^{a}	*(0.15)*
$\Delta\ln PI_{it-1}$	0.03	*(0.07)*	0.21^{c}	*(0.11)*	0.17^{c}	*(0.08)*
$\Delta\ln RD_{it}$	-1.01	*(0.87)*	-1.72	*(3.24)*	-0.84	*(1.16)*
$\Delta\ln RD_{it-1}$	-0.68^{b}	*(0.32)*	-1.17	*(2.00)*	0.06	*(0.40)*
$\Delta\ln RD_{it}$ x TC_t	0.10^{a}	*(0.04)*	-0.22	*(0.18)*	-1.29	*(1.20)*
$\Delta\ln RD_{it-1}$ x TC_{t-1}	0.04	*(0.04)*	-0.04	*(0.17)*	0.56	*(0.54)*
Unrestricted trend	—		—		—	
Constant	4.39^{a}	*(0.97)*	8.42^{a}	*(1.52)*	-1.85^{b}	*(0.77)*
Observations	187		180		168	
Selected Estimator	PMG		PMG		PMG	
Hausman test	"H_0: PMG" vs "H_1: MG"		"H_0: PMG" vs "H_1: MG"		"H_0: PMG" vs "H_1: MG"	
(p-value)	(0.7884)		(0.9301)		(0.1709)	

AT: Austria, BE: Belgium, CZ: Czech Republic
Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficients θ'_{1i} and θ'_{2i} are the long-run coefficients of ln RD_{it} and ln RD_{it} x TC_t, respectively; ϕ_i is the speed-of-adjustment.
Hausman tests systematically discard the DFE estimator in favour of the PMG and MG estimators.

Table 2b: **Innovation production function - benchmark ARDL estimates - Italy, the Netherlands, Spain and the UK**

Dependent variable: Patenting Intensity (ln PI_{it})								
	IT		NL		SP		UK	
Long run (ECT)								
θ'_{1i}	2.19^a	*(0.10)*	2.67^a	*(0.22)*	0.35^b	*(0.14)*	5.41^a	*(0.86)*
θ'_{2i}	0.45^a	*(0.03)*	0.46^a	*(0.03)*	0.22^b	*(0.09)*	0.13^a	*(0.03)*
Restricted trend	—		—		0.04^a	*(0.01)*	—	
Short run								
ϕ_i	-0.59^b	*(0.23)*	-0.71^b	*(0.32)*	-0.45^a	*(0.10)*	-0.24^b	(0.10)
$\Delta\ln PI_{it-1}$	-0.16	*(0.16)*	-0.08	*(0.14)*	-0.39^a	*(0.12)*	-0.24^b	*(0.12)*
$\Delta\ln PI_{it-2}$	—		—		-0.09	*(0.06)*	—	
$\Delta\ln RD_{it}$	-1.01	*(0.78)*	-0.35	*(1.02)*	-0.03	*(0.27)*	-0.45	*(0.39)*
$\Delta\ln RD_{it-1}$	-2.14^b	*(0.85)*	-0.41	*(1.01)*	-0.62	(0.33)	-0.44	(0.41)
$\Delta\ln RD_{it-2}$	-0.80	*(0.78)*	-0.04	*(0.51)*	0.33	*(0.28)*	-0.57	*(0.56)*
$\Delta\ln RD_{it-3}$	-1.47^b	*(0.75)*	-0.22	*(0.49)*	-0.37	*(0.27)*	-1.00^b	*(0.51)*
$\Delta\ln RD_{it-4}$	-2.95^b	*(1.21)*	-0.89	*(0.72)*	-0.27	*(0.30)*	-0.53	*(0.35)*
$\Delta\ln RD_{it-5}$	-0.85	*(1.07)*	-0.45	*(0.41)*	-0.27	*(0.32)*	-0.42	*(0.40)*
$\Delta\ln RD_{it-6}$	-0.02	*(1.10)*	0.40	*(0.92)*	—		0.57^c	*(0.30)*
$\Delta\ln RD_{it-7}$	-1.21^c	*(0.68)*	-0.64	*(0.77)*	—		—	
$\Delta\ln RD_{it-8}$	-0.64^a	(0.64)	—		—		—	
$\Delta\ln RD_{it}$ x TC_t	-0.14	*(0.35)*	-0.08	*(0.14)*	-0.02	*(0.11)*	-0.11	*(0.11)*
$\Delta\ln RD_{it-1}$ x TC_{t-1}	0.09	*(0.51)*	-0.09	*(0.16)*	0.003	*(0.05)*	-0.31^c	*(0.19)*
$\Delta\ln RD_{it-2}$ x TC_{t-2}	-0.23	*(0.26)*	-0.06	*(0.07)*	0.03	*(0.04)*	-0.06	*(0.11)*
$\Delta\ln RD_{it-3}$ x TC_{t-3}	-0.08	*(0.71)*	-0.30	*(0.17)*	0.002	*(0.06)*	0.02	(0.08)
$\Delta\ln RD_{it-4}$ x TC_{t-4}	-0.34	*(0.27)*	-0.20	*(0.15)*	-0.13^a	*(0.03)*	-0.06	*(0.09)*
$\Delta\ln RD_{it-1}$ x TC_{t-5}	0.43	*(0.99)*	-0.11	*(0.09)*	-0.04	*(0.03)*	-0.14	*(0.14)*
$\Delta\ln RD_{it-2}$ x TC_{t-6}	-0.81	*(0.60)*	-0.11	*(0.13)*	—		0.05	*(0.10)*
$\Delta\ln RD_{it-3}$ x TC_{t-7}	0.61	*(1.03)*	-0.11	*(0.09)*	—		—	
$\Delta\ln RD_{it-4}$ x TC_{t-8}	-1.14	(0.77)	—		—		—	
Unrestricted trend	-0.01	(0.03)	-0.03	*(0.03)*	—		-0.03	*(0.02)*
Constant	2.69^c	*(1.69)*	2.08	*(1.49)*	1.60^a	*(0.39)*	-1.64	*(1.60)*
Observations	275		286		342		297	
Selected estimator	PMG		PMG		DFE		PMG	
Hausman test (p-value)	"H_0: PMG" vs "H_1: MG" (0.2668) DFE always discarded		"H_0: PMG" vs "H_1: MG" (0.3547) DFE always discarded		"H_0: DFE" vs "H_1: MG" (0.2738) PMG always discarded		"H_0: PMG" vs "H_1: MG" (0.8288) DFE always discarded	

IT: Italy, NL: Netherlands, SP: Spain, UK: United Kingdom
Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficients θ'_{1i} and θ'_{2i} are the long-run coefficients of ln RD_{it} and ln RD_{it} x TC_t, respectively; ϕ_i is the speed-of-adjustment.

Table 2c: **Innovation production function - benchmark ARDL estimates - France**

Dependent variable: Patenting Intensity (ln PI_{it})		
Long run (ECT)		
θ'_{1i} (long-run coefficient of ln RD_{it})	-0.05	*(0.21)*
θ'_{2i} (long-run coefficient of ln RD_{it} x $TC1_t$)	0.11^b	*(0.05)*
θ'_{3i} (long-run coefficient of ln RD_{it} x $TC2_t$)	0.16^a	*(0.05)*
θ'_{4i} (long-run coefficient of ln RD_{it} x $TC3_t$)	0.19^a	*(0.05)*
θ'_{5i} (long-run coefficient of ln RD_{it} x $TC4_t$)	0.14^a	*(0.05)*
Restricted trend	0.42^a	*(0.10)*
Short run		
ϕ_i	-0.45^a	*(0.08)*
Δln PI_{it-1}	-0.17^a	*(0.07)*
Δln PI_{it-2}	-0.07	*(0.06)*
Δln RD_{it}	-0.48	*(0.52)*
Δln RD_{it-1}	-1.00	*(0.48)*
Δln RD_{it} x $TC1_t$	-0.09	*(0.06)*
Δln RD_{it-1} x $TC1_{t-1}$	0.10	*(0.06)*
Δln RD_{it} x $TC2_t$	-0.22	*(0.21)*
Δln RD_{it-1} x $TC2_{t-1}$	0.37	*(0.30)*
Δln RD_{it} x $TC3_t$	0.01	*(0.28)*
Δln RD_{it-1} x $TC3_{t-1}$	0.55^c	*(0.30)*
Δln RD_{it} x $TC4_t$	0.16	*(0.38)*
Δln RD_{it-1} x $TC4_{t-1}$	0.50^b	*(0.33)*
Unrestricted trend	—	
Constant	2.75^a	*(0.44)*
Observations	374	
Selected estimator	PMG	
Hausman test (p-value)	"H_0: PMG" vs "H_1: MG"	(0.3584)

Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficient ϕ_i is the speed-of-adjustment.
Hausman tests systematically discarded the DFE estimator in favour of the PMG and MG estimators.

Table 3a: **Extended production function - benchmark ARDL estimates - Austria, Belgium and Czech Republic**

	Dependent variable: log TFP (ln TFP_{it})					
	AT		BE		CZ	
Long run (ECT)						
θ'_{1i}	0.78[a]	*(0.16)*	0.35[a]	*(0.08)*	0.10	*(0.08)*
θ'_{2i}	0.13[a]	*(0.03)*	0.08[a]	*(0.02)*	-0.34[a]	*(0.03)*
Restricted trend	—		—		—	
Short run (averaged)						
ϕ_i	-0.37[a]	*(0.07)*	-0.48[a]	*(0.08)*	-0.27[a]	*(0.09)*
$\Delta\ln RD_{it-2}$	0.28	*(0.45)*	-0.14	*(0.12)*	0.19[b]	*(0.09)*
$\Delta\ln RD_{it-3}$	-0.41	*(0.28)*	-0.11	*(0.13)*	-0.05	*(0.08)*
$\Delta\ln RD_{it-4}$	—		-0.20	*(0.12)*	0.05[c]	*(0.03)*
$\Delta\ln RD_{it-2}$ x TC_{t-2}	-0.16[c]	*(0.09)*	0.004	*(0.04)*	0.02	*(0.03)*
$\Delta\ln RD_{it-1}$ x TC_{t-3}	-0.11[c]	*(0.06)*	0.003	*(0.04)*	-0.01	*(0.02)*
$\Delta\ln RD_{it-2}$ x TC_{t-4}	—		-0.01	*(0.02)*	-0.01	*(0.02)*
Unrestricted trend	-0.02[a]	*(0.01)*	-0.01[a]	*(0.003)*	0.01[b]	*(0.006)*
Constant	1.70[a]	*(0.41)*	2.06[a]	*(0.39)*	1.11[a]	*(0.36)*
Observations	247		228		216	
Selected estimator	PMG		PMG		PMG	
Hausman test (p-value)	"H_0: PMG" vs "H_1: MG" (0.6651)		"H_0: PMG" vs "H_1: MG" (0.9354)		"H_0: PMG" vs "H_1: MG" (0.5587)	

AT: Austria, BE: Belgium, CZ: Czech Republic

Significance levels: [a] p-value < 0.01, [b] p-value < 0.05, [c] p-value < 0.10.

Coefficients θ'_{1i} and θ'_{2i} are the long-run coefficients of ln RD_{it} and ln RD_{it} x TC_t, respectively; ϕ_i is the speed-of-adjustment.

Hausman tests systematically discard the DFE estimator in favour of the PMG and MG estimators.

Table 3b: **Extended production function - benchmark ARDL estimates - Italy, the Netherlands, Spain and the UK**

Dependent variable: log TFP (ln TFP_{it})	IT		NL		SP		UK	
Long run (ECT)								
θ'_{1i}	0.69[a]	*(0.03)*	0.43[a]	*(0.04)*	0.08[a]	*(0.02)*	0.60[a]	*(0.03)*
θ'_{2i}	0.13[a]	*(0.01)*	0.44[a]	*(0.03)*	0.04[a]	*(0.01)*	-0.02	*(0.02)*
Restricted trend	0.50[a]	*(0.03)*	0.95[a]	*(0.19)*	0.14[a]	*(0.03)*	0.18	*(0.03)*
Short run								
ϕ_i	-0.51[a]	*(0.11)*	-0.25[a]	*(0.10)*	-0.37[a]	*(0.07)*	-0.43[a]	*(0.10)*
$\Delta\ln RD_{it-2}$	-0.35[a]	*(0.13)*	-0.21[b]	*(0.09)*	0.001	*(0.07)*	-0.02	*(0.08)*
$\Delta\ln RD_{it-3}$	-0.29[a]	*(0.11)*	-0.08	*(0.09)*	-0.01	*(0.07)*	-0.15[b]	*(0.06)*
$\Delta\ln RD_{it-4}$	-0.10	*(0.13)*	-0.12	*(0.10)*	-0.07	*(0.14)*	-0.08	*(0.06)*
$\Delta\ln RD_{it-5}$	0.02	*(0.16)*	-0.15[b]	*(0.06)*	0.05	*(0.08)*	0.06	*(0.06)*
$\Delta\ln RD_{it-6}$	-0.24[a]	*(0.09)*	0.15	*(0.19)*	-0.16[a]	*(0.06)*	-0.08	*(0.07)*
$\Delta\ln RD_{it-7}$	-0.28	*(0.19)*	0.06	*(0.10)*	0.23[b]	*(0.11)*	-0.09	*(0.07)*
$\Delta\ln RD_{it-8}$	-0.21[b]	*(0.09)*	-0.30[b]	*(0.16)*	-0.11	*(0.07)*	—	
$\Delta\ln RD_{it-2}$ x TC_{t-2}	-0.02	*(0.10)*	-0.02	*(0.04)*	-0.04	*(0.03)*	-0.01	*(0.02)*
$\Delta\ln RD_{it-3}$ x TC_{t-3}	-0.03	*(0.06)*	-0.11[a]	*(0.03)*	0.03	*(0.04)*	0.002	*(0.01)*
$\Delta\ln RD_{it-4}$ x TC_{t-4}	0.002	*(0.08)*	-0.07	*(0.04)*	-0.06	*(0.06)*	0.04	*(0.02)*
$\Delta\ln RD_{it-5}$ x TC_{t-5}	0.01	*(0.06)*	-0.08	*(0.04)*	-0.03	*(0.06)*	0.01	*(0.02)*
$\Delta\ln RD_{it-6}$ x TC_{t-6}	-0.001	*(0.14)*	-0.02	*(0.03)*	-0.01	*(0.03)*	0.06	*(0.04)*
$\Delta\ln RD_{it-7}$ x TC_{t-7}	0.01	*(0.08)*	-0.04[c]	*(0.03)*	-0.07[c]	*(0.04)*	0.01	*(0.02)*
$\Delta\ln RD_{it-8}$ x TC_{t-8}	0.01	*(0.04)*	-0.003	*(0.02)*	-0.03	*(0.03)*		
Unrestricted trend	—		—		—		—	
Constant	2.60[a]	*(0.55)*	1.25[a]	*(0.48)*	1.87[a]	*(0.43)*	1.66[a]	*(0.38)*
Observations	377		377		455		390	
Selected estimator	PMG		PMG		PMG		PMG	
Hausman test (p-value)	"H_0: PMG" vs "H_1: MG" (0.1704)		"H_0: PMG" vs "H_1: MG" (0.1096)		"H_0: PMG" vs "H_1: MG" (0.8447)		"H_0: PMG" vs "H_1: MG" (0.3470)	

IT: Italy, NL: Netherlands, SP: Spain, UK: United Kingdom
Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficients θ'_{1i} and θ'_{2i} are the long-run coefficients of ln RD_{it} and ln RD_{it} x TC_t, respectively; ϕ_i is the speed-of-adjustment.
Hausman tests systematically discard the DFE estimator in favour of the PMG and MG estimators.

Table 3c: **Extended production function - benchmark ARDL estimates - France**

Dependent variable: log TFP (ln TFP_{it})			
Long run (ECT)			
θ'_{1i} (long-run coefficient of ln RD_{it})	0.08^{a}	*(0.02)*	
θ'_{2i} (long-run coefficient of ln RD_{it} x $TC1_{t}$)	0.01	*(0.01)*	
θ'_{3i} (long-run coefficient of ln RD_{it} x $TC2_{t}$)	0.06^{a}	*(0.01)*	
θ'_{4i} (long-run coefficient of ln RD_{it} x $TC3_{t}$)	-0.02	*(0.02)*	
θ'_{5i} (long-run coefficient of ln RD_{it} x $TC4_{t}$)	-0.02	*(0.02)*	
Restricted trend	0.21^{a}	*(0.03)*	
Short run			
ϕ_i	-0.28^{a}	*(0.07)*	
Δln RD_{it-2}	0.06	*(0.05)*	
Δln RD_{it-2} x $TC1_{t-2}$	-0.03	*(0.02)*	
Δln RD_{it-2} x $TC2_{t-2}$	-0.04	*(0.03)*	
Δln RD_{it-2} x $TC3_{t-2}$	-0.01	*(0.04)*	
Δln RD_{it-2} x $TC4_{t-2}$	0.03	*(0.04)*	
Unrestricted trend	—		
Constant	1.21^{a}	*(0.30)*	
Observations	481		
Selected estimator	PMG		
Hausman test (p-value)	“H_0: PMG” vs “H_1: MG”		(0.8379)

Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficient ϕ_i is the speed-of-adjustment.
Hausman tests systematically discarded the DFE estimator in favour of the PMG and MG estimators.

Table 4a: **ARDL estimates of innovation production function with Business and Government R&D (Austria, Belgium and Czech Republic)**

Dependent variable: Patenting Intensity (ln PI_{it})						
	AT		**BE**		**CZ**	
Long run (ECT)						
θ'_{1i} (coef. of ln BRD_{it})	1.44^{a}	*(0.37)*	-1.09^{a}	*(0.21)*	0.67	*(0.68)*
θ'_{2i} (coef. of ln GRD_{it})	0.06	*(0.05)*	0.93^{a}	*(0.16)*	-0.07	*(0.43)*
θ'_{3i} (coef. of ln GRD_{it} x TC_t)	-0.10^{b}	*(0.05)*	-0.02	*(0.05)*	0.13^{b}	*(0.06)*
Restricted trend	—		0.04^{a}	*(0.01)*	0.05^{c}	*(0.03)*
Short run (averaged)						
ϕ_i	-0.80^{a}	*(0.14)*	-1.15^{a}	*(0.20)*	-0.64^{a}	*(0.14)*
Δln PI_{it-1}	-0.001	*(0.08)*	-0.02	*(0.17)*	-0.16^{b}	*(0.08)*
Δln PI_{it-2}	—		—		-0.24^{a}	*(0.06)*
Δln BRD_{it}	-0.96	*(0.86)*	1.77	*(2.18)*	-1.05	*(0.68)*
Δln BRD_{it-1}	—		0.34	*(1.43)*	—	
Δln GRD_{it}	0.02	*(0.10)*	-0.08	*(1.81)*	0.31	*(0.20)*
Δln GRD_{it-1}	—		-1.91^{c}	*(1.01)*	—	
Δln GRD_{it} x TC_t	0.52	*(0.55)*	-0.04	*(1.62)*	*-0.11*^{a}	*(0.04)*
Δln GRD_{it-1} x TC_{t-1}	—		1.70	*(1.27)*	—	
Unrestricted trend	-0.05	*(0.01)*	—		—	
Constant	4.27^{a}	*(0.74)*	9.46^{a}	*(1.85)*	0.67	*(1.15)*
Observations	180		180		168	
Selected Estimator	PMG		PMG		PMG	
Hausman test	"H_0: PMG" vs "H_1: MG"		"H_0: PMG" vs "H_1: MG"		"H_0: DFE" vs "H_1: MG"	
(p-value)	(0.2769)		(0.9899)		(0.9997)	
	DFE always discarded		DFE always discarded		PMG always discarded	

AT: Austria, BE: Belgium, CZ: Czech Republic
Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficient ϕ_i is the speed-of-adjustment.

Table 4b: **ARDL innovation production function estimates with Business and Government R&D (Italy, The Netherlands, Spain and the UK)**

	Dependent variable: Patenting Intensity (ln PI_{it})							
	IT		**NL**		**SP**		**UK**	
Long run (ECT)								
θ'_{1i} (coef. of ln BRD_{it})	-0.28^{b}	*(0.12)*	1.68^{a}	*(0.41)*	-0.29^{c}	*(0.15)*	0.63^{a}	*(0.14)*
θ'_{2i} (coef. of ln GRD_{it})	0.34^{a}	*(0.11)*	-0.62^{a}	*(0.12)*	0.36^{a}	*(0.09)*	-0.32^{b}	*(0.14)*
θ'_{3i} (coef. of ln GRD_{it} x TC_t)	0.15^{a}	*(0.03)*	-0.13^{b}	*(0.05)*	-0.06	*(0.04)*	-0.04	*(0.04)*
Restricted trend	0.08^{a}	*(0.01)*	-0.02^{c}	*(0.01)*	0.05^{a}	*(0.01)*	—	
Short run								
ϕ_i	-0.36^{c}	*(0.19)*	-0.44^{a}	*(0.10)*	-0.54^{a}	*(0.09)*	-0.28^{b}	*(0.14)*
Δln PI_{it-1}	-0.06	*(0.07)*	-0.06	*(0.07)*	-0.15	*(0.09)*	-0.18^{b}	*(0.07)*
Δln PI_{it-2}	—		—		—		—	
Δln BRD_{it}	0.52^{a}	*(0.19)*	0.35	*(0.28)*	0.12	*(0.33)*	0.53^{b}	*(0.14)*
Δln BRD_{it-1}	0.09	*(0.27)*	0.53^{c}	*(0.28)*	-0.58	*(0.55)*	-0.10	*(0.11)*
Δln BRD_{it-2}	0.29	*(0.21)*	-0.14	*(0.45)*	1.03	*(0.69)*	—	
Δln BRD_{it-3}	-0.19	*(0.18)*	-0.32	*(0.45)*	-0.58^{b}	*(0.27)*	—	
Δln BRD_{it-4}	-0.28	*(0.29)*	—		—		—	
Δln GRD_{it}	0.01	*(0.09)*	0.26	*(0.10)*	-0.33^{a}	*(0.11)*	-0.23^{b}	*(0.11)*
Δln GRD_{it-1}	0.07	*(0.07)*	0.31	*(0.09)*	-0.03	*(0.15)*	0.06	*(0.05)*
Δln GRD_{it-2}	0.12	*(0.08)*	0.08	*(0.07)*	-0.23	*(0.16)*	—	
Δln GRD_{it-3}	0.08^{c}	*(0.04)*	0.26	*(0.07)*	-0.42^{a}	*(0.13)*	—	
Δln GRD_{it-4}	0.07	*(0.07)*	—		—		—	
Δln GRD_{it} x TC_t	-0.09^{a}	*(0.03)*	-0.04	*(0.04)*	0.45	*(0.33)*	-0.01	*(0.02)*
Δln GRD_{it-1} x TC_{t-1}	-0.21	*(0.14)*	-0.05	*(0.07)*	-0.20	*(0.13)*	0.03^{c}	*(0.02)*
Δln GRD_{it-2} x TC_{t-2}	-0.18	*(0.14)*	0.07^{c}	*(0.04)*	0.06	*(0.11)*	—	
Δln GRD_{it-3} x TC_{t-3}	-0.07	*(0.05)*	-0.08	*(0.07)*	0.53^{c}	*(0.33)*	—	
Δln GRD_{it-4} x TC_{t-4}	-0.05	*(0.05)*	—		—		—	
Unrestricted trend	—		—		—		0.002	*(0.004)*
Constant	1.11^{c}	*(0.83)*	1.33^{a}	*(0.19)*	1.86^{a}	*(0.37)*	-1.34^{b}	*(0.63)*
Observations	319		330		321		341	
Selected estimator	PMG		PMG		PMG		DFE	
Hausman test (p-value)	"H_0: PMG" vs "H_1: MG" (0.8508) "H_0: PMG" vs "H_1: DFE" (0.9999)		"H_0: PMG" vs "H_1: MG" (0.2082) DFE always discarded		"H_0: PMG" vs "H_1: MG" (0.6064) "H_0: PMG" vs "H_1: DFE" (0.9999)		"H_0: DFE" vs "H_1: MG" (0.9999) PMG always discarded	

IT: Italy, NL: Netherlands, SP: Spain, UK: United Kingdom
Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficient ϕ_i is the speed-of-adjustment.

Table 4c: **ARDL estimates of innovation production function with Business and Government R&D (France)**

Dependent variable: Patenting Intensity (ln PI_{it})				
	(I)		(II)	
Long run (ECT)				
θ'_{1i} (long-run coefficient of ln BRD_{it})	0.61^{a}	*(0.18)*	0.12	*(0.14)*
θ'_{2i} (long-run coefficient of ln GRD_{it})	-0.67^{a}	*(0.18)*	-0.08	*(0.10)*
θ'_{3i} (long-run coefficient of ln GRD_{it} x $TC2_t$)	0.11^{b}	*(0.06)*	0.07^{b}	*(0.03)*
θ'_{4i} (long-run coefficient of ln GRD_{it} x $TC3_t$ in (I),	-0.05	*(0.08)*	—	
long-run coefficient of ln GRD_{it} x $TC34_t$ in (II))	—		0.08^{b}	*(0.04)*
θ'_{5i} (long-run coefficient of ln GRD_{it} x $TC4_t$ in (I))	0.16^{c}	*(0.10)*	—	
Restricted trend	-0.17^{a}	*(0.03)*	-0.66^{a}	*(0.17)*
Short run				
ϕ_i	-0.35^{a}	*(0.13)*	-0.45^{a}	*(0.11)*
Δln PI_{it-1}	-0.10^{c}	*(0.06)*	-0.003	*(0.08)*
Δln PI_{it-2}	-0.08	*(0.06)*	-0.03	*(0.07)*
Δln BRD_{it}	-0.31	*(0.46)*	0.10	*(0.26)*
Δln BRD_{it-1}	-0.42	*(0.27)*	-0.75^{a}	*(0.26)*
Δln GRD_{it}	0.13^{b}	*(0.07)*	-0.03	*(0.03)*
Δln GRD_{it-1}	-0.11^{c}	*(0.06)*	-0.24^{a}	*(0.07)*
Δln GRD_{it} x $TC2_t$	0.08^{c}	*(0.04)*	0.08	*(0.07)*
Δln GRD_{it-1} x $TC2_{t-1}$	0.02	*(0.04)*	0.06	*(0.04)*
Δln GRD_{it} x $TC3_t$	0.03	*(0.07)*	—	
Δln GRD_{it-1} x $TC3_{t-1}$	0.02	*(0.02)*	—	
Δln GRD_{it} x $TC4_t$	-0.14	*(0.10)*	—	
Δln GRD_{it-1} x $TC4_{t-1}$	-0.11	*(0.12)*	—	
Δln GRD_{it} x $TC34_t$	—		-0.05	*(0.09)*
Δln GRD_{it-1} x $TC34_{t-1}$	—		-0.01	*(0.07)*
Unrestricted trend	—		—	
Constant	1.76^{b}	*(0.74)*	2.65^{a}	*(0.64)*
Observations	341		341	
Selected estimator	PMG		PMG	
Hausman test (p-value)	“H_0: PMG” vs “H_1: MG” (0.9999) “H_0: PMG” vs “H_1: DFE” (0.9999)		“H_0: PMG” vs “H_1: MG” (0.9999) “H_0: PMG” vs “H_1: DFE” (0.9999)	

Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficient ϕ_i is the speed-of-adjustment.

Table 5a: **ARDL estimates of extended production function with Business and Government R&D (Austria, Belgium and Czech Republic)**

Dependent variable: log TFP (ln TFP_{it})								
	AT		BE		CZ			
					(I)		(II)	
Long run (ECT)								
θ'_{1i} (coef. of ln BRD_{it})	0.21^{b}	*(0.10)*	1.35^{a}	*(0.09)*	-0.04	*(0.07)*	—	
θ'_{2i} (coef. of ln GRD_{it})	-0.12^{a}	*(0.04)*	-0.76^{a}	*(0.06)*	—		0.01	*(0.03)*
θ'_{3i} (coef. of ln $(BRD_{it} \times PI_t)$)	0.07	*(0.05)*	0.14^{a}	*(0.02)*	-0.02	*(0.02)*	-0.03	*(0.02)*
θ'_{4i} (coef. of ln $GRD_{it} \times TC_t$)	-0.02	*(0.03)*	0.32^{a}	*(0.02)*	-0.28^{a}	*(0.04)*	-0.28^{a}	*(0.04)*
Restricted trend	0.003	*(0.01)*	—		—		—	
Short run (averaged)								
ϕ_i	-0.43^{a}	*(0.07)*	-0.23^{c}	*(0.13)*	-0.38^{a}	*(0.09)*	-0.31^{a}	*(0.07)*
Δln BRD_{it-2}	-0.09	*(0.11)*	0.09	*(0.35)*	0.17^{c}	*(0.09)*	—	
Δln BRD_{it-3}	—		-0.10	*(0.21)*	—		—	
Δln GRD_{it-2}	0.09	*(0.11)*	0.14	*(0.11)*	—		0.06^{b}	*(0.03)*
Δln GRD_{it-3}	—		0.11	*(0.14)*	—		—	
Δln $(BRD_{it} \times PI_t)_{it-2}$	-0.01	*(0.02)*	-0.01	*(0.03)*	0.01^{c}	*(0.02)*	0.01	*(0.02)*
Δln $(BRD_{it} \times PI_t)_{it-3}$	—		0.003	*(0.02)*	—		—	
Δln $GRD_{it-2} \times TC_{t-2}$	0.01	*(0.01)*	-0.19	*(0.15)*	0.09	*(0.02)*	0.11	*(0.03)*
Δln $GRD_{it-2} \times TC_{t-3}$	—		-0.03	*(0.10)*	—		—	
Unrestricted trend	—		-0.01	*(0.01)*	0.02^{a}	(0.005)	0.02^{a}	(0.005)
Constant	1.52^{a}	*(0.33)*	-0.19	*(0.15)*	1.66^{a}	*(0.41)*	1.29^{a}	*(0.33)*
Observations	180		198		168		168	
Selected estimator	DFE		PMG		PMG		PMG	
Hausman test (p-value)	H_0: DFE vs H_1: MG (0.9999)		H_0: PMG vs H_1: MG (0.5623)		H_0: PMG vs H_1: MG (0.2510)		H_0: PMG vs H_1: MG (0.5789)	
	H_0: PMG vs H_1: MG (0.0494)		H_0: PMG vs H_1: DFE (0.9999)		H_0: PMG vs H_1: DFE (0.9999)		H_0: PMG vs H_1: DFE (0.9999)	

AT: Austria, BE: Belgium, CZ: Czech Republic
Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficient ϕ_i is the speed-of-adjustment.

Table 5b: **ARDL estimates of extended production function with Business and Government R&D (Italy, the Netherlands, Spain and the UK)**

	Dependent variable: log TFP (ln TFP_{it})							
	IT		**NL**		**SP**		**UK**	
Long run (ECT)								
θ'_{1i} (ln BRD_{it})	-0.01	*(0.04)*	0.33^{a}	*(0.09)*	0.13^{a}	*(0.02)*	-0.57^{b}	*(0.24)*
θ'_{2i} (ln GRD_{it})	0.05^{b}	*(0.03)*	-0.14^{a}	*(0.04)*	-0.04^{a}	*(0.01)*	0.23^{a}	*(0.09)*
θ'_{3i} (ln $(BRD_{it} \times PI_t)$)	-0.01	*(0.04)*	-0.08	*(0.07)*	-0.08^{a}	*(0.02)*	0.45^{a}	*(0.13)*
θ'_{4i} (ln $GRD_{it} \times TC_t$)	0.02^{b}	*(0.01)*	0.21^{a}	*(0.03)*	-0.004	*(0.01)*	-0.02	(0.03)
Restricted trend	-0.06^{a}	*(0.02)*	0.01^{b}	*(0.01)*	0.07^{a}	*(0.01)*	—	
Short run								
ϕ_i	-0.40^{a}	*(0.06)*	-0.18^{a}	*(0.07)*	-0.41^{a}	*(0.08)*	-0.19^{a}	*(0.04)*
Δln BRD_{it-2}	-0.07	*(0.06)*	-0.12	*(0.09)*	-0.11	*(0.09)*	0.11	*(0.10)*
Δln BRD_{it-3}	0.13^{a}	*(0.05)*	0.05	*(0.11)*	-0.10	*(0.06)*	0.01	*(0.09)*
Δln GRD_{it-2}	-0.02^{c}	*(0.01)*	0.004	*(0.02)*	-0.08^{c}	*(0.05)*	0.02	*(0.02)*
Δln GRD_{it-3}	-0.02	*(0.03)*	0.02	*(0.02)*	0.05^{c}	*(0.02)*	-0.02	*(0.03)*
Δln $(BRD_{it} \times PI_t)_{it-2}$	0.01	*(0.02)*	0.07^{a}	*(0.03)*	0.02^{a}	*(0.02)*	-0.08^{a}	*(0.02)*
Δln $(BRD_{it} \times PI_t)_{it-3}$	-0.04^{b}	*(0.02)*	-0.004	*(0.01)*	0.02	*(0.01)*	-0.07	*(0.04)*
Δln $GRD_{it-2} \times TC_{t-2}$	-0.02^{c}	*(0.01)*	-0.002	*(0.02)*	0.05^{a}	*(0.02)*	-0.02	*(0.02)*
Δln $GRD_{it-2} \times TC_{t-3}$	0.05^{c}	*(0.03)*	-0.03	*(0.03)*	-0.05	*(0.05)*	0.01	*(0.01)*
Unrestricted trend	—		—		—		-0.002^{c}	*(0.001)*
Constant	1.95^{a}	*(0.26)*	0.73^{a}	*(0.26)*	1.87^{a}	*(0.36)*	0.45^{a}	*(0.11)*
Observations	352		352		339		341	
Selected estimator	PMG		PMG		PMG		PMG	
Hausman test (p-value)	H_0: PMG vs H_1: MG (0.9997)		"H_0: PMG" vs "H_1: MG" (0.1484)		H_0: PMG vs H_1: MG (0.9998)		H_0: PMG vs H_1: MG (0.9324)	
	H_0: PMG vs H_1: DFE (0.9999)		H_0: PMG vs H_1: DFE (0.9999)		H_0: PMG vs H_1: DFE (0.9999)		H_0: PMG vs H_1: DFE (0.9999)	

IT: Italy, NL: Netherlands, SP: Spain, UK: United Kingdom
Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficient ϕ_i is the speed-of-adjustment.

Table 5c: **ARDL estimates of extended production function with Business and Government R&D (France)**

Dependent variable: log TFP (ln TFP_{it})			
Long run (ECT)			
θ'_{1i} (long-run coefficient of ln BRD_{it})	2.37[a]	*(0.64)*	
θ'_{2i} (long-run coefficient of ln GRD_{it})	-0.77[a]	*(0.20)*	
θ'_{3i} (long-run coefficient of Δ ln (BRD_{it} x PI_t))	-0.30	*(0.18)*	
θ'_{4i} (long-run coefficient of Δ(ln GRD_{it} x $TC2_t$))	0.17[b]	*(0.08)*	
θ'_{5i} (long-run coefficient of Δ(ln GRD_{it} x $TC34_t$))	0.26[b]	*(0.12)*	
Restricted trend	—		
Short run			
ϕ_i	-0.09[c]	*(0.05)*	
Δln BRD_{it-2}	0.01	*(0.11)*	
Δln BRD_{it-3}	-0.36[b]	*(0.14)*	
Δln GRD_{it-2}	0.04	*(0.04)*	
Δln GRD_{it-3}	-0.06	*(0.05)*	
Δln (BRD_{it-2} x PI_{t-2})	0.05	*(0.03)*	
Δln (BRD_{it-3} x PI_{t-3})	0.03	*(0.02)*	
Δln GRD_{it-2} x $TC2_{t-2}$	0.02	*(0.03)*	
Δln GRD_{it-3} x $TC2_{t-3}$	0.06	*(0.08)*	
Δln GRD_{it-2} x $TC34_{t-2}$	-0.01	*(0.04)*	
Δln GRD_{it-3} x $TC34_{t-3}$	0.06	*(0.07)*	
Unrestricted trend	-0.01[c]	*(0.01)*	
Constant	0.54[c]	*(0.29)*	
Observations	341		
Selected estimator	PMG		
Hausman test (p-value)	"H_0: PMG" vs "H_1: MG"		(0.9997)

Significance levels: [a] p-value $<$ 0.01, [b] p-value $<$ 0.05, [c] p-value $<$ 0.10.
Standard errors in parentheses.
Coefficient ϕ_i is the speed-of-adjustment.
Hausman tests systematically discard the DFE estimator in favour of the PMG and MG estimators.

References

Adarov, A. and R. Stehrer, "Tangible and Intangible Assets in the Growth Performance of the EU, Japan and the US ," WIIW Research Report 442, 2019.

Akcigit, U., D. Hanley, and S. Stantcheva, "Optimal taxation and R&D policies," *Econometrica*, 2022, *90* (2), 153–91.

Amable, B., I. Ledezma, and S. Robin, "Product market regulation, innovation, and productivity," *Research Policy*, 2016, *45* (10), 2087–2104.

Antonelli, C., "Knowledge exhaustibility public support to business R&D and the additionality constraint," *The Journal of Technology Transfer*, 2020, *45*, 649–663.

Arellano, M. and O. Bover, "Another Look at the Instrumetal-Variable Estimation of Error-Components Models," *Journal of Econometrics*, 1995, *68*, 29–51.

Arrow, K., "Economic welfare and the allocation of resources for invention," The rate and direction of inventive activity: Economic and social factors, NBER Chapters 1962.

Bartelsman, E., G. van Leeuwen, and M. Polder, "CDM using a cross-country micro moments database," *Economics of Innovation and New Technology*, 2017, *26* (1-2), 168–182.

Blackburne, Edward F. and Donald L. Bumpass, "Estimation of Consumption Elasticities for OECD Countries: Testing Price Asymmetry with Alternative Dynamic Panel Data Techniques," *Journal of Business Strategies*, 2014, *31*, 263–280.

_ and Mark W. Frank, "Estimation of nonstationary heterogeneous panels," *Stata Journal*, 2007, *7*, 197–208.

Bloom, N., R. Griffith, and H. William, "A Toolkit of Policies to Promote Innovation," *Journal of Economic Perspectives*, 2019, *33*, 163–184.

_ , _ , and J. Van Reenen, "Do R&D tax credits work? Evidence from a panel of countries 1979-1997," *Journal of of Public Economics*, 2002, *85*, 1–31.

Blundell, R. and S. Bond, "GMM Estimation With Persistent Panel Data: An Application to Production Functions," *Econometric Reviews*, 2000, *19*, 321–340.

Blundell, Richard and Steven Bond, "Initial Conditions and Moments Restrictions in Dynamics Panel Data Models," *Journal of Econometrics*, 1998, *87*, 115–143.

Bond, S. and I. Guceri, "R&D and productivity: evidence from large UK establishments with substantial R&D activities," *Economics of Innovation and New Technology*, 2017, *26* (1-2), 108–120.

Bourlès, R., G. Cette, J. Lopez, J. Mairesse, and G. Nicoletti, "Do product market regulations in upstream sectors curb productivity growth? Panel data evidence for OECD countries," *Review of Economics and Statistics*, 2013, *95* (5), 1750–1768.

Bozeman, B. and A.N. Link, *Investments in Technology: Corporate Strategies and Public Policy Alternatives*, New York: Praeger Publishers, 1983.

Broadbent, B., F. Di Pace, T. Drechsel, and R. Harrison, "The Brexit Vote, Productivity Growth, and Macroeconomic Adjustments in the U.K.," *Review of Economic Studies*, 2024, *91.*

Bui, H., I. Dwesar, S. Patel, D. Seymour, and T. To, "London's economy after Brexit: Impacts and impications," Technical Report 48 p., Cambridge Econometrics 2023.

Craft, N., "Brexit: Lessons from history ," VOXEU Column, VOXEU / CEPR 2016.

Crépon, B., E. Duguet, and J. Mairesse, "Research, innovation and productivity: an econometric analysis at the firm level," *Economics of Innovation and New Technologies*, 1998, *7*, 115–158.

Czarnitzki, D. and C. Lopes-Bento, "Evaluation of public R&D policies: A cross-country comparison," *World Review of Science, Technology and Sustainable Development*, 2012, *9* (2), 254–282.

Deloitte, "2014 Global Survey of R&D Tax Incentives," Technical Report 2014. 85p.

Eberhardt, M., C. Helmers, and H. Strauss, "Do Spillovers Matter When Estimating Private Returns to R&D? ," *Review of Economics and Statistics*, 2013, *95* (2), 436–448.

Ernst, C. and C. Spengel, "Taxation, R&D tax incentives and patent application in Europe," ZEW Discussion Papers 11-024, ZEW - Leibniz Centre for European Economic Research 2011.

Ernst&Young, "Worldwide R&D incentives reference guide," Technical Report 2014. 252p.

European Commission, "Proposal for Council Directive on a Common Corporate Tax Base," Technical Report 2011.

_ , "Proposal for Council Directive on a Common Corporate Tax Base," Technical Report 2016.

Faccini, R. and E. Palombo, "News Uncertainty in Brexit United Kingdom," *American Economic Review: Insights*, 2021, *3.*

Giraud, L., Miotti, J. Quéméner, M. Rosa, and F. Sachwald, "Développement et impact du crédit d'impôt recherche: 1983-2011," Report, Ministère de l'Education Nationale, de l'Enseignement Supérieur et de la Recherche, Service de l'Innovation, du Transfert de technologie et de l'Action régionale 2014.

Griliches, Z., "Issues in Assessing the Contribution of Research and Development to Productivity Growth," *Bell Journal of Economics*, 1979, *10* (1), 92–116.

Griliches, Z. and J. Mairesse, "Production Functions: The Search for Identification," in "Essays in Honor of Ragnar Frisch, S. Strøm (Ed)," Cambridge University Press, Cambridge, 1998, p. Econometric Society Monograph Series.

Gurmu, S. and F. Pérez-Sebastian, "Patents, R&D and lag effects: evidence from flexible methods for count panel data on manufacturing firms," *Empirical Economics*, 2008, *35*, 507–526.

Hall, B., Z. Griliches, and J. Hausman, "Patents and R and D: Is There a Lag?," *International Economic Review*, 1986, *27* (2), 265–283.

Im, K.S., M.H. Pesaran, and Y. Shin, "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics*, 2003, *115*, 53–74.

Jones, R. A.L., "Science and innovation policy for hard times: an overview of the UK's Research and Development landscape," The Productivity Institute - Productivity Insight Paper 14, 2022.

Lööf, H., J. Mairesse, and P. Mohnen, "CDM 20 years after," *Economics of Innovation and New Technology*, 2017, *26* (1-2), 1–5.

Mairesse, J. and B. Hall, "Estimating the Productivity of Research and Development in French and US Manufacturing Firms: An Exploration of Simultaneity Issues with GMM methods," in "International Productivity Differences and Their Explanations, Wagner K. and B. Van Ark (Eds)," Elsevier Science, 1996, pp. 285–315.

Mairesse, J. and P. Mohnen, "Accounting for innovation and measuring innovativeness: an illustrative framework and application," *American Economic Review*, 2002, *92* (2), 226–230.

Millard, S., A. Nicolae, and M. Nower, "Understanding the effects of Brexit on UK Productivity," *National Institute Economic Review*, 2024, *268.*

Minniti, A. and F. Venturini, "The long-run growth effects of R&D policy," *Research Policy*, 2017, *46.*

Mohnen, P., J. Mairesse, and M. Dagenais, "Innovativity: a comparison across seven European countries," NBER Working Paper Series, Working Paper 12280 2006.

OECD, "Worldwide R&D incentives reference guide," https://www.oecd.org/sti/ind/46352862.pdf 2010.

Pesaran, M. Hashem, "A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence," *Journal of Applied Econometrics*, 2007, *22*, 265–312.

Pesaran, M.H. and R.P. Smith, "Estimating long-run relationships from dynamic heterogeneous panels," *Journal of Econometrics*, 1995, *68.*

_ and Y. Shin, "An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis," in "Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium, Cambridge University Press, Steinar Strøm (Ed)," Palgrave Macmillan, London, 1999, pp. 371–413.

_ , _ , and R.P. Smith, "Pooled mean group estimation of dynamic heterogeneous panels," *Journal of the American Statistical Association*, 1999, *94*, 621–634.

Portes, J., "The impact of Brexit on the UK economy: Reviewing the evidence," VOXEU Column, VOXEU / CEPR 2023.

Romer, P., "Endogenous Technological Change," *Journal of Political Economy*, 1990, *98* (5), S71–S102.

Roodman, D.M., "How to do xtabond2: An introduction to difference and system GMM in Stata," *The Stata Journal*, 2009a, *9* (1), 86–136.

_ , "A note on the theme of too many instruments," *Oxford Bulletin of Economics and Statistics*, 2009b, *71*, 135–158.

Schmoch, U., F. Laville, P. Patel, and R. Frietsch, ",Linking Technological Areas to Industrial Sectors," Final Report to the European Commission, DG Research (77p.) 2003.

Semykina, Anastasia and Jeffrey M. Wooldridge, "Estimating panel data models in the presence of endogeneity and selection," *Journal of Econometrics*, 2010, *157*, 375–380.

Stehrer, R., A. Bykova, K. Jäger, O. Reiter, and M.Schwarzhappel, "Industry level growth and productivity data with special focus on intangible assets. Report on methodologies and data construction for the EU KLEMS Release 2019," WIIW Research Report 8, 2019.

Straathof, B., E. Gaillard-Ladinska, H. Kox, R. Mocking, I. Goldberg, C. Jensen, P. Lindholm, M. Sobolewski, B. Berg-Andersson, H. Kaseva, P. Rouvinenand, T. Valkonen, R. Sellner, K. Schönpflug, and I. Paterson, "A Study on R&D Tax Incentives - Final Report," European Commission Taxation Papers, Working Paper 52 2014.

van Ophem, H., E. Brouwer, A. Kleinknecht, and P. Mohnen, "The Mutual Relation between Patents and R&D," in "Innovation and Firm Performance, Palgrave Macmillan, Kleinknecht A. and P. Mohnen (Eds)," Palgrave Macmillan, London, 2002, pp. 56–70.

van Pottelsberghe de la Potterie, B., "Europe's R&D: Missing the wrong targets?," *Intereconomics*, 2008, *43* (4), 220–225.

Wellcome Trust, "The UK's role in global research: How the UK can live up to its place in the world," Wellcome Trust report, 28p. 2020.

Westmore, B., "R&D, Patenting and Growth: The Role of Public Policy," Technical Report 1047, OECD Economic Department Working Papers 2013.

Appendices

A Implications of Brexit

Well before the June 2016 referendum on Brexit, a panel of 150 leading academic economists (including 12 Nobel laureates) had warned that leaving the EU would likely result in a drop of investment in the UK, harming both innovation and job growth.[35] Nearly a decade after the referendum, and four years after the Brexit became effective, the economic situation of the UK certainly does not appear as catastrophic as it could have been. Where most economists expected, in accordance with the academic literature, a V-shaped recession (i.e. a short and brutal contraction followed by a slower recovery), what has been observed is a slow decline in production (Faccini and Palombo, 2021). This pattern has been shown to arise when uncertainty concerns future (rather than current) fundamentals, such as future productivity growth (Faccini and Palombo, 2021, Broadbent et al., 2024).

Regarding the magnitude of this decline, Millard et al. (2024) estimate that the long-run GDP level of the UK is 4% below the level it would have reached had Brexit not happened, while Portes (2023) estimate the negative impact of Brexit on current UK GDP at around 2 or 3%. Millard et al. (2024) link this decline in GDP to negative productivity effects entailed by the increased costs of trading between the UK and the EU post-Brexit. Recent studies such as Jones (2022) and Bui et al. (2023) indeed document a post-Brexit stagnation or decline in productivity in the UK. Bui et al. (2023) specify that the decline in productivity concerns the UK outside London – in their study, the productivity in London remains similar to what it would have been without Brexit, but the productivity gap between London and the rest of the UK is widening. Jones (2022) examine the possibilities to find a remedy for this predicament in innovation.

According to our findings, R&DTC are not the best tool to spur innovation and productivity in the UK. Our findings are in line with the conclusions reported in Jones (2022), which suggests that the UK R&DTC has been ineffective in fostering innovation. Worse, being untargeted, this form of public support to R&D also prevents the successive British governments to align the spending with their strategic priorities, should they decide to set some.[36] These findings and conclusions suggest that post-Brexit UK should not be overly concerned with the loss of the possibility to benefit from an EU-wide R&DTC, should it come into being.

Our findings suggest that, in order to spur innovation and regain productivity, the UK should rather turn to other forms of public support to R&D, such as public-private cooperation in research. This is where Brexit may have harmful consequences, if the UK fails to remain associated with EU institutions such as the European Research Council and the EU Horizon programme (the way Norway and Switzerland do), as these were until recently the main source of funding for such cooperation

[35] See Craft (2016) for a summary of their argument.
[36] This is, in a nutshell, an application of the argument developed in Antonelli (2020)

(Wellcome Trust, 2020, Jones, 2022). This issue is all the more serious since alternative strategies appear sketchy at best (Jones, 2022).

B Additional tables and figures

Table A.1: **List of industries (NACE, 2 digits)**

Code	**Description**
10-12	Food products, Beverages and Tobacco
13-15	Textiles, Wearing apparel, Leather and related products
16-18	Wood and paper products; Printing and reproduction of recorded media
19	Coke and refined petroleum products
20-21	Chemicals and chemical products
22-23	Rubber and plastic products, Other non-metallic mineral products
24-25	Basic metals and Fabricated metal products
26-27	Electrical, electronic and optical equipment
28	Machinery and equipment, n.e.c.
29-30	Transport equipment
31-33	Other manufacturing; repair and installation of machinery and equipment
D-E	Electricity, Gas and Water Supply
F	Construction

Table A.2: **Balanced panel construction**

	# of industries in balanced panel	Years in balanced panel	Pre-RDTC years	Post-RTDC years
Austria	N = 11 or 13	1995-2014/2017	1995-2010	2011 to end
Belgium	N = 11 or 13	1994-2014/2017	1994-1997	1998 to end
Czech Republic	N = 11 or 13	1995-2014/2017	1995-1999	2000 to end
Italy	N = 11 or 13	1980-2014/2017	1980-1999	2000 to end
Netherlands	N = 11 or 13	1980-2014/2017	1980-1997	1998 to end
Spain	N = 11 or 13	1980-2014/2017	1980-1994	1995 to end
UK	N = 11 or 13	1980-2014/2017	1980-1999	2000 to end
France	N = 11 or 13	1980-2014/2017	1980-1982	1983 to end, in 4 phases

Note: The starting year of each balanced panel is the year in which all variables first become available together in the source dataset. The end year may go up to 2017 for models that do not involve patenting (although missing values in some variables in the latter years may constrain it in practice to 2016 or 2015). For models that involve patenting, the end year is constrained to 2014 (the "patents" series are not available in the source dataset after 2014 at the time of this writing). The time span of each panel is constrained by the variable with the shortest time span and may thus vary in practice from 20 to 35 years. Similarly, the number of industries is 13 for models that do not involve patenting, and 11 for models that involve patenting, because the "patents" variable is not available in industries D-E ("Electricity, Gas and Water Supply") and "F" ("Construction"). Finally, in France, the years following the introduction of the first RDTC are divided into 4 well-distinct phases.

Table A.3: **Summary statistics (averaged over industries and years).**

	Total R&D intensity	Business R&D intensity	Government R&D intensity	Patenting intensity	TFP index
Austria	15.87	13.91	1.96	978.50	84.23
	(*18.83*)	(*16.21*)	(*2.74*)	(*1186.52*)	(*33.67*)
Belgium	22.91	21.50	1.41	994.34	94.70
	(*33.81*)	(*31.77*)	(*2.10*)	(*1603.45*)	(*25.11*)
Czech Republic	46.99	41.40	5.59	73.38	92.31
	(*63.04*)	(*55.61*)	(*8.17*)	(*121.96*)	(*23.32*)
Italy	5.87	5.18	0.69	426.01	125.87
	(*9.24*)	(*8.38*)	(*1.03*)	(*559.86*)	(*129.86*)
Netherlands	20.11	18.74	1.37	1689.63	91.30
	(*32.15*)	(*30.17*)	(*2.27*)	(*3028.57*)	(*24.56*)
Spain	3.90	3.51	0.46	190.43	111.30
	(*6.65*)	(*6.81*)	(*0.91*)	(*346.80*)	(*78.65*)
UK	16.74	14.44	2.46	732.89	76.94
	(*30.05*)	(*25.55*)	(*5.25*)	(*1033.24*)	(*37.90*)
France	17.03	16.00	2.21	1397.53	95.41
	(*25.20*)	(*25.48*)	(*2.89*)	(*2040.53*)	(*39.40*)

Standard errors in parentheses. TFP index is measured in base 100 for year 2010.

Table A.4: **ARDL long-run estimates of extended production function by industry (over panels of 5 countries and 35 years)**

Dependent variable: TFP (ln TFP_{it})						
	Food Products		**Textile, Apparel, Leather**		**Wood & Paper, Printing**	
Long run (ECT)						
θ_{1i}	-0.17	*(0.15)*	0.31^{a}	*(0.06)*	0.07	*(0.08)*
θ_{2i}	0.25^{a}	*(0.04)*	-0.15^{b}	*(0.06)*	0.03	*(0.11)*
ϕ_i	-0.33^{a}	*(0.12)*	-0.49^{b}	*(0.21)*	-0.51^{a}	*(0.16)*
Observations	153		153		169	
Estimator	PMG		PMG		MG	
	Coke & Refined Petroleum		**Chemicals**		**Rubber & Plastic**	
Long run (ECT)						
θ_{1i}	0.55^{a}	*(0.12)*	0.34^{a}	*(0.05)*	0.18^{a}	*(0.02)*
θ_{2i}	0.03	*(0.04)*	-0.07^{a}	*(0.01)*	0.05	*(0.06)*
ϕ_i	-0.46^{a}	*(0.08)*	-0.47^{c}	*(0.26)*	-0.56^{a}	*(0.14)*
Observations	169		153		153	
Estimator	PMG		PMG		PMG	
	Metal & Metal Products		**Electrics & Electronics**		**Machinery & Equipment**	
Long run (ECT)						
θ_{1i}	0.54^{a}	*(0.07)*	0.32^{a}	*(0.07)*	0.72^{a}	*(0.04)*
θ_{2i}	0.19^{a}	*(0.04)*	0.001	*(0.02)*	0.15^{a}	*(0.01)*
ϕ_i	-0.45^{a}	*(0.16)*	-0.52^{b}	*(0.21)*	-0.49^{c}	*(0.29)*
Observations	153		153		153	
Estimator	PMG		PMG		PMG	
	Transport Equipment		**Other Manufacturing**		**Electricity, Gas & Water**	
Long run (ECT)						
θ_{1i}	0.51^{a}	*(0.11)*	-0.06	*(0.06)*	0.61^{a}	*(0.05)*
θ_{2i}	0.04	*(0.04)*	0.08^{a}	*(0.03)*	-0.10^{c}	*(0.05)*
ϕ_i	-0.53^{b}	*(0.07)*	-0.38^{b}	*(0.12)*	-0.40^{b}	*(0.18)*
Observations	153		153		153	
Estimator	PMG		PMG		PMG	
	Construction					
Long run (ECT)						
θ_{1i}	0.12^{a}	*(0.04)*				
θ_{2i}	0.02	*(0.01)*				
ϕ_i	-0.30^{b}	*(0.13)*				
Observations	165					
Estimator	PMG					

Significance levels: ^{a} p-value < 0.01, ^{b} p-value < 0.05, ^{c} p-value < 0.10.
Standard errors in parentheses.
Coefficients θ_{1i} and θ_{2i} are the respective long-run coefficients of $lnRD_{it}$ and $\Delta(lnRD_{it}xTC_t)$, ϕ_i is the speed-of-adjustment.
"Estimator" indicates which estimator was selected by the Hausman tests.

Figure A.1: **R&D intensity by industry for each selected EU country**

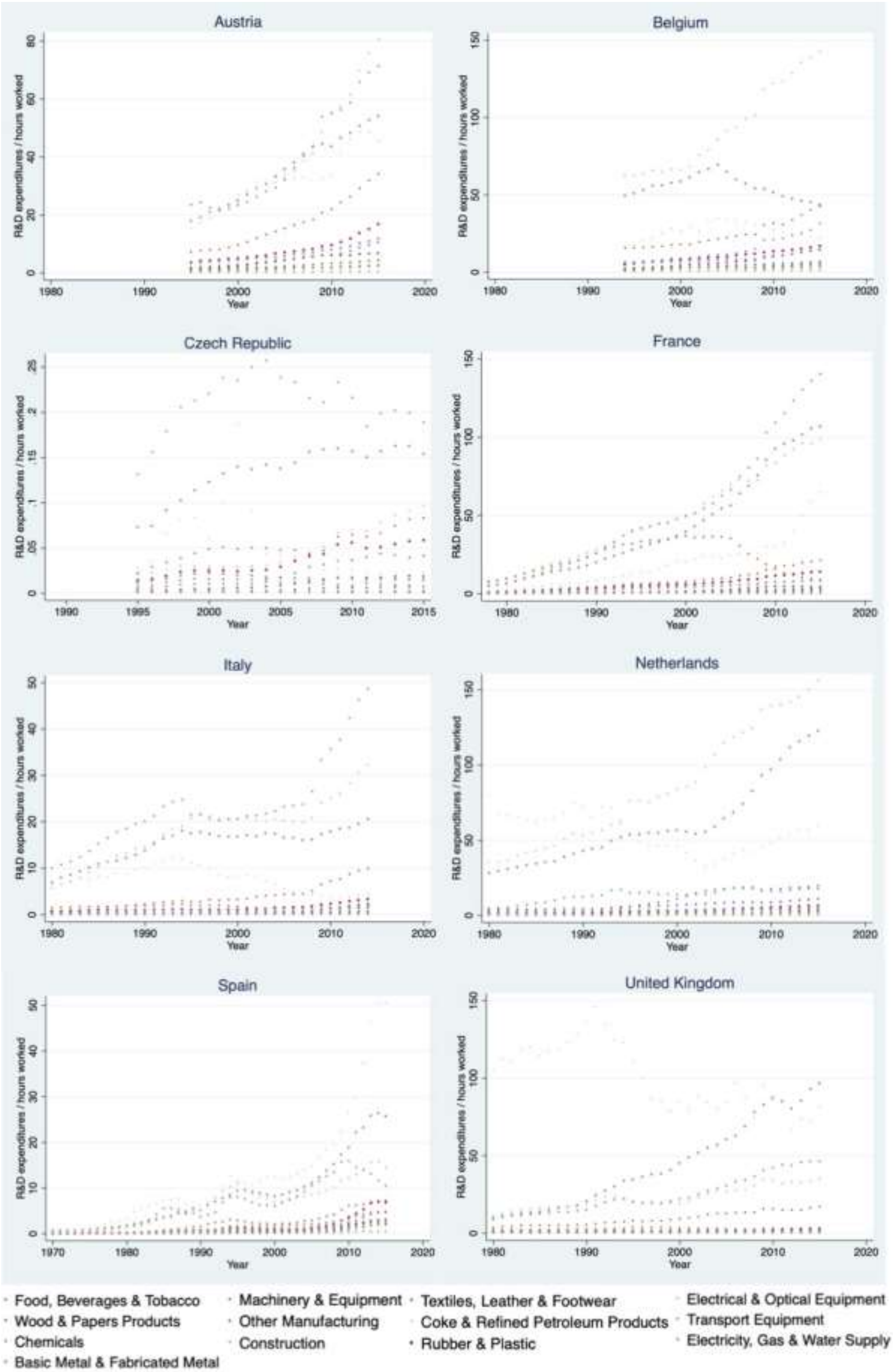
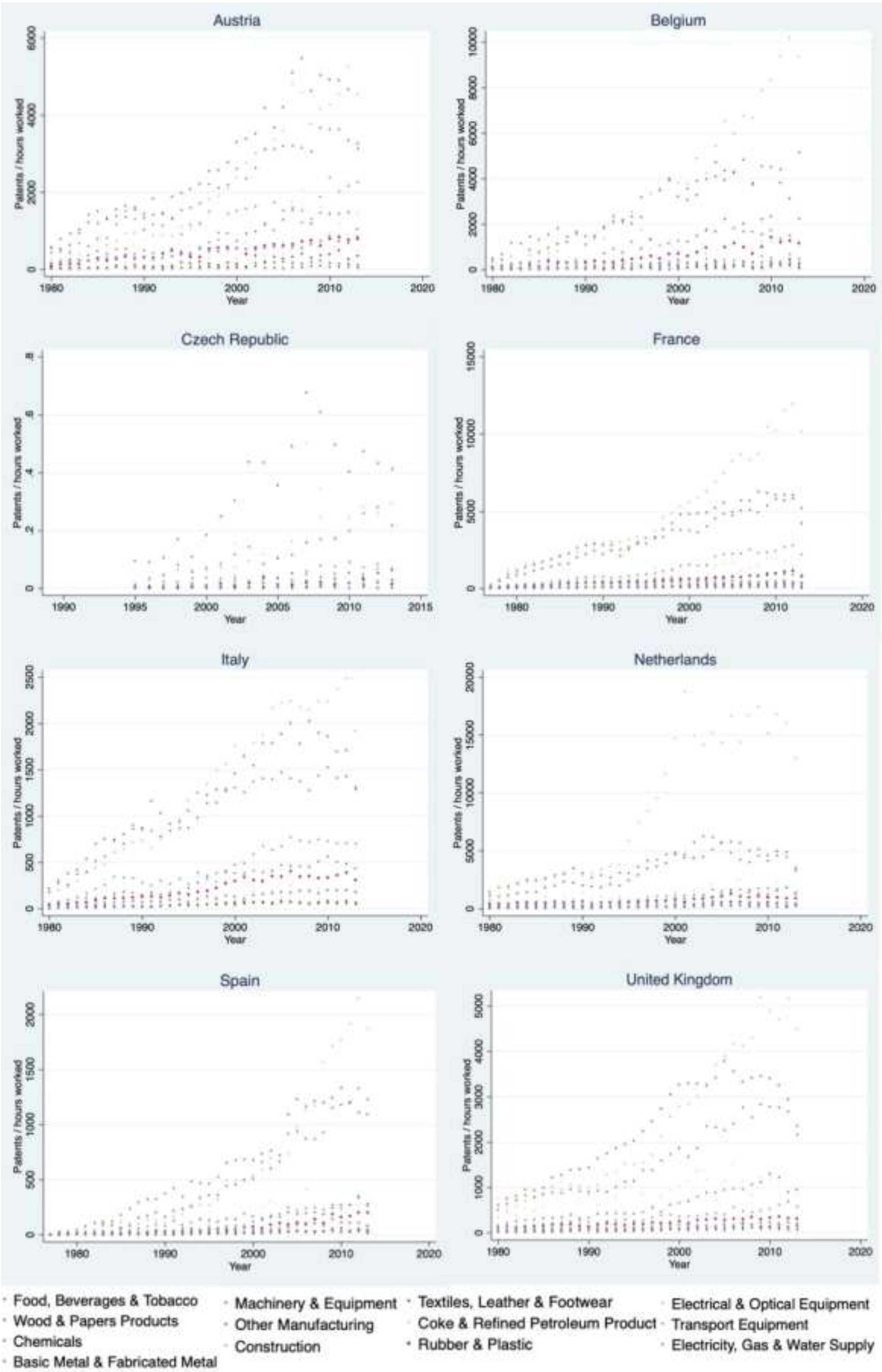


Figure A.2: **Patenting intensity by industry for each selected EU country**



C Alternative econometric approaches and their weaknesses

Estimating Models (1) to (3) in Section IV.2.a, where there is no dynamics yet, is not as straightforward as it seems, if only because R&D intensity may be endogenous. Specifying the industry effects as fixed effects (FE) and using the within estimator to estimate Models (1) and (3) may correct for unobserved heterogeneity, but not for endogeneity. Moreover, the within estimator is likely to yield the type of "unsatisfactory" results highlighted in Griliches and Mairesse (1998). Implementing the FE-2SLS estimator, using the lags of the R&D variables as instruments, could be a possible solution to address both heterogeneity and endogeneity (Semykina and Wooldridge, 2010). However, when applied to production function models, this estimator is likely to yield very unsatisfactory results, just like the first-differenced GMM estimator (Mairesse and Hall, 1996).

Blundell and Bond (2000) provide a sensible explanation for this (level variables are weak instruments for differenced variables) and suggest to rely instead on the system GMM (SGMM) estimator, which has since then become the go-to solution to circumvent the above-mentioned issues. In addition, SGMM allows researchers to explicitly model dynamics, which is what we are aiming to do here. Thus, we could simply add an AR(p) component in Model (1) to capture the dynamics of patenting:

$$\ln PI_{it} = \sum_{k=1}^{p} \alpha_k \ln PI_{it-k} + \sum_{k=0}^{q} \beta_{1k} \ln RD_{it-k} + \sum_{k=0}^{q} \beta_{2k} (\ln RD_{it-k} \times TC_{t-k}) + u_i + v_t + w_{it} \quad (12)$$

Similarly, a dynamic version of the extended production function could be obtained by adding the lagged dependent variable in Model (3):[37]

$$\ln TFP_{it} = \alpha_1 \ln TFP_{it-1} + \sum_{k=2}^{q} \gamma_{1k} \ln RD_{it-k} + \sum_{k=2}^{q} \gamma_{2k} (\ln RD_{it-k} \times TC_{t-k}) + u_i + v_t + w_{it} \quad (13)$$

In both dynamic models, the error term w_{it} can further be split into two components, $w_{it} = \mu_{it} + m_{it}$, where μ_{it} is allowed to be AR(1):

$$\mu_{it} = \rho \mu_{it-1} + \epsilon_{it} \quad (14)$$

In Model (12) (Model (13)), the coefficients of primary interest are the β_{1k}'s and $\beta_2 k$'s (the γ_{1k}'s and $\gamma_2 k$'s), which provide a measure of the elasticity of patenting (TFP) with respect to R&D intensity, in the absence/presence of an R&DTC.

Although the estimation of Models (12) and (13) with SGMM is possible in theory, it faced, in the context of our study, a number of practical hurdles which led us to abandon this path of research after some preliminary investigations. First, the comparatively small size of our panels, together with the fact that the SGMM estimator relies on generated instruments, seriously limits the number of regressors that can be included in Models (12) and (13). As explained in Blundell and Bond (2000, 1998)

[37] Including only one lag of the dependent variable, instead of several as we did in Model (12), follows what is usually done in the literature (Bourlès et al., 2013, Bond and Guceri, 2017). It also has empirical relevance: when we implement the extended production function as an ARDL model (see IV.2.b), the information criterion for lags selection point out to models with one lag of $lnTFPG$.

and Arellano and Bover (1995), the SGMM estimator consists in *(i)* adding a differenced equation to tackle FE, thus building a system of equations, and *(ii)* using the lagged differences as instruments for the variables in levels in addition to the lagged levels as instruments for the differenced equation. The number of generated instruments can be quite large if one uses all the available lags offered in a panel, which can be a problem in finite samples, and specifically in relatively small panels such as the ones considered in the present study. In the absence of clear guidance from the literature, it is not uncommon to estimate the models with the full set of generated instruments, gradually restricting it to a minimal number of lags. Even then, the variance matrix of the moments may become singular, which makes the Hansen overidentification test unreliable (a rather frequent problem according to Roodman (2009a,b)).

Second, it is well known from the literature that the SGMM estimator is most appropriate - and performs well - on "large n, small t" panels, i.e. panels with a large individual dimension and a short time dimension (Blundell and Bond, 2000, Roodman, 2009a). In heterogeneous macro panels with large t such as ours, the long time dimension may result in overfitting and the assumption of parameter homogeneity, required for instrumentation in SGMM, becomes an issue (Pesaran and Smith, 1995). In addition, SGMM require stationary variables whereas panel ARDL can handle I(1) variables, as mentioned in Section IV.2.b. Last but not least, SGMM assume cross-section independence, which is not required in ADRL models, provided that appropriate tests (such as the CIPS tests we implement in Section IV.1) are performed beforehand.