Economic impact of public R&D: an international perspective

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Abstract

Despite the fact that research and development (R&D) activities are carried out in most countries in public research institutes such as universities and public research organizations, there have been few studies that attempted to estimate the economic impact of such public investment in R&D. In this paper, we analyze the relations between total factor productivity (TFP) and public and private R&D as well as gross domestic product for a set of 17 Organisation for Economic Cooperation and Development (OECD) countries using a vector-error-correction model. We find that for the period 1975–2014, investment in public R&D has had a clearly positive effect on TFP growth in the majority of countries analyzed. In simulations allowing for a permanent positive shock to public R&D, we observe a strong dynamic complementarity between the public and private (domestic) stocks of R&D for several countries. In countries where this complementarity is strong, the TFP effect of extra public R&D investments is also strong. A discriminant analysis shows that in countries with high complementarity between private and public R&D, the share of foreign funding of R&D performed in the business sector combined with a high business R&D intensity tends to be low. At the same time, the share of basic R&D in business R&D combined with a higher public R&D intensity tends to be higher in countries with strong complementarity.

JEL classification: O38, O30, H4

1. Introduction

The literature on the economic impact of investments in research and development (R&D) on economic growth and productivity focuses mostly on the R&D investments carried out by private firms (Hall et al., 2010). Although many public policies address these private R&D investments, e.g., through the provision of subsidies and tax credits, the largest part of Science and Technology policy consists of the provision of R&D by entities working in the public sector such as universities and (semi-)public research organizations (PROs). Surprisingly, this form of R&D support has received far less attention in the econometric literature, although there are a number of studies that have tried to estimate the economic impact of such public R&D investments.

In the current study, we provide new estimations of the economic impact of public R&D investments using a more comprehensive methodological approach that also includes private R&D investment. Our approach starts from the recognition that the institutional differences between countries in the provision of public R&D, reflected, e.g., in the “national innovation
systems” (Soete et al., 2010) concept, are significant, even in a set of developed countries such as the OECD countries. One may think of the importance given to military vs. civilian R&D or the institutional differences in the setup of public R&D, e.g., whether universities are fully autonomous or government-controlled (see Aghion et al., 2010), or the predominance and funding structure of PROs, which are likely to differ significantly between countries. Although one will not be able to estimate the effect of all these differences individually, the essence of the approach chosen here is to allow these country factors to have an impact on how public investment in R&D affects productivity and economic growth. We therefore adopt a time-series approach for individual countries to estimate the impact of public (and private) research investments. Contrary to most other econometric studies that pool data from various countries under the assumption that the estimated effects do not differ between countries, our approach ensures that the economic effects of R&D (public as well as private) that we estimate are specific to the institutional setting and economic structure of each country. Using this approach allows us also to focus more closely on the interaction between the various kinds of public, private, domestic, and foreign R&D allowing for a much richer kind of dynamics in the ways in which R&D affects productivity and gross domestic product (GDP) in a country.

In Section 2, we briefly review the literature, putting special emphasis on those studies that argue why a country-specific estimation methodology is particularly appropriate when attempting to measure the economic impact of R&D. In Section 3, we provide a broad empirical overview of national R&D systems across the global economy. Here, we use data on a much broader set of countries than the OECD countries subject to the detailed econometric analysis performed in Section 4. The purpose of Section 3 is to provide background information on the nature of the set of countries that will be used in the remainder of the paper.

Section 4 explains the econometric approach and the underlying data that are the basis of the country-level estimations on the relation between productivity and public R&D. Section 5 presents simulation effects for a permanent domestic shock in public R&D investment. These results represent the core of our findings about the impact of private and public R&D on productivity growth. The section also provides an interpretation of what drives the observed differences between countries in terms of the productivity effect of the public R&D policy shock. Section 6 summarizes the analysis and outcomes. Detailed model estimations by country are available in an online appendix.

2. A brief literature review

Only a small number of econometric studies have attempted to estimate the economic impact of public investment in R&D for different high-income countries such as the OECD. Until recently, a broad consensus, based largely on a study carried out by Guellec and van Pottelsberghe (2004), concluded that the rate of return to public R&D expenditures was high. Guellec and van Pottelsberghe’s (2004) study analyzed a panel of 16 OECD countries, using, among others, an error-correction model (ECM) to estimate the impact of public and private R&D on total factor productivity (TFP). The model they applied assumed identical coefficients for all 16 countries in the analysis.

Guellec and van Pottelsberghe obtained output elasticity for business (private) R&D in OECD countries over the period 1980–1998 equal to 13% and increasing over time. For public research, they found that the long-term elasticity of government and university-performed research was even higher: around 17%. Their study also highlighted the importance of “foreign” R&D activities for many countries, particularly the smaller OECD countries in their sample. The impact of received “cross-border” spillovers appeared, e.g., much higher for smaller countries than for larger ones, reflecting the higher shares of international co-publication and co-patenting of smaller nations. To achieve such benefits though, the smaller country would over time need to become more R&D-intensive and more specialized.

1 Within that, the effect of universities was again higher, possibly because in some countries, government laboratories had primarily non-economic objectives such as supporting defense.
A recent study by van Elk et al. (2019), also based on cross-country analysis but using R&D data going back to 1963, arrived at rather different conclusions on the economic returns to public R&D. Their results depended strongly on the specific model used in the estimations. They implemented three classes of econometric models: (i) a Cobb–Douglas production function, (ii) a translog production function, and (iii) an “augmented” production function as proposed by Khan and Luintel (2006). In the “raw” Cobb–Douglas estimations, none of the R&D measures appeared significant. In the ECM version of the Cobb–Douglas model, private R&D had a positive impact, but public R&D had a negative, often not significant impact. In the translog model, results varied widely depending on the exact implementation of the profit-maximization conditions. In the “augmented” model based on Khan and Luintel, the impact of public R&D appeared overall positive. Only in this latter “augmented” model that now allowed indirectly for different rates of return of public (and private) R&D between countries, did the impact of public R&D appear robustly positive. The estimates showed that public R&D had widely different impacts between countries.

It is van Elk et al.’s (2019) paper that inspired us to have a closer look at the ways in which public R&D has a different impact between a set of similar high-income countries. The paper that is methodologically closest to our approach is that by Luintel and Khan (2004). As we will do below, they applied a vector-error-correction model (VECM) and related TFP to foreign and domestic R&D, following an earlier paper by Coe and Helpman (1995). They did not consider public R&D explicitly but provided separate estimates for total (domestic) R&D and for private (domestic) R&D. In their results for 10 OECD countries, they found less significant effects for public R&D explicitly but provided separate estimates for total (domestic) R&D and for private (domestic) R&D. In their results for 10 OECD countries, they found less significant effects for business R&D than for total domestic R&D. One might interpret this as suggesting that non-business, i.e., public R&D, might play a strong role.

Bottazzi and Peri (2007) also used a VECM approach, but their interest focused primarily on the way R&D might explain the dynamics of patents as an indicator of ideas, rather than productivity (TFP). They also did not deal explicitly with the economic impact of public R&D expenditures. They used R&D employment rather than R&D expenditure data. We do not follow this approach as we believe that the broader measures of total R&D costs as reflected in the use of R&D expenditures and of TFP as the direct measure of productivity rather than the indirect one of patents appear more adequate and are also more in line with the empirical literature in this area (see Hall et al., 2010).

In Khan and Luintel’s (2006) article, no error-correction approach was followed. Instead, they adopted a generalized production function model in which the intercepts and slopes are allowed to differ between countries. To allow for variation in the slopes of the R&D variables per country, they constructed interaction terms of a range of variables such as foreign direct investment and the share of high-tech industries in exports, with the country-specific averages of the knowledge stock variables. The heterogeneity of country-specific regression coefficients that resulted from this exercise was then related to the variety of the interaction variables. In such an approach, it is, however, not possible to analyze potential feedbacks from productivity on the left-hand side of the equation to the knowledge stocks and the various dynamic interactions between the knowledge stocks, productivity, and output on the right-hand side. In short, this particular approach excludes indirect effects from the analysis, which is an important drawback.

The existence of complementarities between public and private R&D is a particularly crucial topic when trying to estimate the impact of public (or private) R&D. If public R&D stimulates private R&D, there are direct and indirect effects of such public R&D investments. Jaumotte and Pain (2005a, 2005b) analyzed, e.g., 19 OECD countries over a 20-year period up to 2001, and found evidence of significant complementarity between public sector and business sector R&D.

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2 This is rather crucial as Bottazzi and Peri (2007) support the semi-endogenous growth approach in line with Jones (1995), who emphasized the strong growth in the numbers of researchers to defend his semi-endogenous growth approach, whereas, e.g., Ha and Howitt (2007) emphasized the constancy of R&D expenditure (as a % of GDP) and TFP growth in favor of fully endogenous growth approaches.

3 This is important because it is well known from basic macroeconomics that impact effects may vanish after a system of equations has run through the various rounds of adjustment. The most well-known example is probably the ineffectiveness of fiscal policy in the Mundell–Fleming model under the special assumption of flexible exchange rates and perfect capital mobility. For our purpose here, this empirically controversial result is not important, but the theoretical possibility highlights the need for more empirical analyses of indirect and feedback effects in this area.
They argued that such complementarities more than offset any negative effect from the extra public R&D investments on the labor costs in the business R&D sector. They found that “an increase of one standard deviation in the share of non-business R&D in GDP (an increase of 0.06 percentage points for the average economy) raises business sector R&D by over 7% and total patenting by close to 4%” (Jaumotte and Pain, 2005b : 38). In a similar vein, Falk (2006) showed that the R&D of universities triggered additional business R&D in a panel of 21 OECD countries. In research presented by Cohen et al. (2002) using microeconomic data, it was shown that for US manufacturing firms the influence of public research on industrial R&D appeared disproportionately greater for larger firms as well as for start-ups.

One dimension of complementarity between public and private investment in research arises from the attraction it exerts on internationally mobile R&D, what could be called a domestic R&D “crowding-in” effect. Factors such as the prospect of high-quality collaborators, recruitment opportunities, and the presence of a local knowledge cluster, often accompanied by an infrastructure for knowledge and technology transfer, feature variously in such studies (Cassiman and Veugelers, 2002). The overall message is that particularly for small countries, a high-quality research base will attract international R&D. The same factors will encourage domestic companies to retain and expand their R&D investments domestically. A positive impact of foreign R&D on productivity has been confirmed through country-panel analyses by Luintel and Khan (2004) and Khan and Luintel (2006). More recent evidence on a large country such as the UK found that besides public sector–financed R&D, also foreign R&D had a significant impact on TFP growth (see e.g., Haskel and Wallis, 2013).

In summary, when estimating the economic impact of public R&D, it is rather important to account for the heterogeneity between countries and for the possible (indirect) effects of the interactions between the main variables involved (public R&D, private R&D, foreign R&D, and productivity). The VECM approach, when applied to a single country, incorporates these aspects. Because it exploits the time-series nature of the data rather than the cross-section, it will yield country-specific effects, and the modeling of interactions between the variables comes naturally with the approach because all variables are considered endogenous and impacting on each other.

To our knowledge, the present study following on from the pilot exercise carried out in 2019 on the Netherlands (Soete et al., 2020) is the first one to adopt this more appropriate VECM approach in trying to estimate the impact of public R&D at a broad internationally comparative level.

3. Research and development: a global outlook

Before presenting estimations on the economic impact of public R&D investment, we take a brief descriptive look at a few basic dimensions of what can be considered the national R&D “system” in a country (Freeman, 1995). Based on available national R&D data, a wide array of indicators exist for an increasingly large number of countries (41) as collected by the OECD. These include the absolute size or scale of the R&D performed in a country (small countries vs. large countries), the intensity of R&D activities (compared to GDP), the relative contributions of the private and public sectors, the relative importance of different kinds of actors in the public sector (universities and PROs), the interaction between the public and private sectors, and interactions with foreign actors (in terms of funding). We also add an indicator on patenting (triadic patent families as defined by OECD, and one on publications (only publications listed in the Science Citation Index are counted).

Table 1 presents the descriptive statistics (average and standard deviation) on the indicators that catch these dimensions. There is one observation per country, in most cases 2010. The table distinguishes also between the 41 countries and the 17 OECD countries for which time-series data are available and will be the subject of the econometric analysis presented in Section 4. Equality of averages between the 41 countries and the 17 sample OECD countries is tested with a t-test, and we observe significant differences (mostly at 1% level) for 10 of 14 indicators.

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4 We are grateful to an anonymous referee for suggesting this variable.
Table 1. Summary statistics on national R&D systems, 41 countries, approximately 2010

|                                | 41 countries         |          | 17 sample countries |          |
|--------------------------------|----------------------|----------|---------------------|----------|
|                                | Av.   | SD    | Av.   | t-Test  |
| Share of business sector in total R&D (perf.) | 0.569 | 0.142 | 0.617 | -2.086** |
| Share of HE in non-business R&D (perf.) | 0.600 | 0.169 | 0.689 | -3.280*** |
| Share of gov. sector in non-business R&D (perf.) | 0.361 | 0.183 | 0.270 | 3.176*** |
| Share of business funding in R&D perf. by HE | 0.067 | 0.065 | 0.051 | 1.453 |
| Share of gov. funding in R&D perf. by business | 0.099 | 0.106 | 0.068 | 1.821*  |
| Share of foreign funding in R&D perf. by business | 0.093 | 0.095 | 0.106 | -0.787 |
| Share of foreign funding in R&D perf. by HE | 0.062 | 0.055 | 0.051 | 1.141 |
| Natural log of R&D perf. by business | 8.421 | 1.782 | 9.364 | -3.289*** |
| Natural log of R&D perf. by non-business | 8.125 | 1.513 | 8.868 | -2.951*** |
| R&D perf. by business as a share of GDP | 0.012 | 0.008 | 0.014 | -2.085** |
| R&D perf. by non-business as a share of GDP | 0.007 | 0.002 | 0.008 | -3.510*** |
| Share of basic R&D in R&D perf. by business | 0.057 | 0.033 | 0.055 | 0.329 |
| Triadic patent families divided by GDP | 4.697 | 13.055 | 9.868 | -1.884*  |
| Science publications divided by GDP | 19.28 | 47.01 | 32.40 | -1.894*  |

\(t\)-Test indicates \(t\)-statistic for \(H_0\) that average of the variable are equal for countries in and not in the sample (not in sample average minus in sample average); the \(t\)-test assumes unequal variances between the groups; *, **, *** significance at 1%, 5%, and 10% in a two-sided test.

The 17 OECD countries are more R&D-intensive (R&D as a share of GDP) than the reference group of all countries: 2.2% for the sample countries vs. 1.9% for the total group. They also publish more and have more patents (both relative to GDP). Splitting R&D intensity into business and non-business, the sample countries are significantly higher in both categories. R&D performed by the business sector is the majority share in the total group and is somewhat larger (significantly so) in the sample group. Within the non-business sector, higher education (HE) is the largest share, in the total group, and again this share is significantly higher in the sample countries. The share of the government sector in non-business R&D is lower in the sample countries. The share of government funding in business R&D is lower in the sample group, although this is significant only at the 10% level. The scale of R&D (indicated by the log of R&D expenditures) is higher in the sample group than in the total group. This holds both for business R&D and for non-business R&D. In summary, our sample countries tend to be large and intensive R&D performers and have a relatively high importance in the HE sector.

4. Econometric model, data and estimation
4.1 The vector-error-correction model

The VECM represents a standard approach in the time-series econometric literature. It allows for non-stationarity in the data and incorporates multi-way interaction between all (endogenous) variables in the model. The models that we will apply here do not have any exogenous variables, except an intercept and a time trend in most cases. In formal terms, the VECM consists of two main parts that correspond to the long run and the short run. The long-run part consists of a number of so-called co-integrating equations, which take the general form

\[ \sum_{j} \beta_{jk} y_{t-j} + \mu_k t + c_k = 0, k = 1, \ldots, r \]

Here, \(y\) is an endogenous variable, \(t\) indicates the time period (in our case annual), and \(\mu\) and \(\beta\) are parameters that are estimated. Subscripts refer either to time \((t)\), to a variable index \((j)\), or to the specific co-integrating equation \((k)\), and \(c_k\) its intercept. We have to put restrictions on the \(\beta\)s, e.g., in each of the co-integrating equations one of the \(\beta\)s will be equal to (minus) unity, and some will be equal to zero. How many co-integrating equations a model of a certain dimension (number of endogenous variables) has is determined by empirical tests.
The short-run part of the model is a vector-autoregressive (VAR) model in first differences of the variables. This has one equation for each of the $M$ endogenous variables in the model, as follows:

$$
\Delta y_{it} = \sum_{\tau} \sum_{j} \gamma_{ijr} \Delta y_{it-\tau} + \sum_{k} \alpha_{ik} E_k + \varepsilon_{it} + c_i, i = 1, \ldots, M
$$

Thus, each equation in the VAR part has the first difference of an endogenous variable as the dependent variable and includes lagged endogenous variables as explanatory variables. $\varepsilon_{it}$ is a white noise error term added for estimation purposes. $E_k$ is a so-called error term (as before, $k = 1, \ldots, r$ is an index that points to the $k$th co-integrating equation), which is defined from the co-integrating equations in the following way

$$
E_k = \sum_{j} \beta_{jk} y_{t-1} + \mu_k t + c_k
$$

Thus, if co-integrating equation $k$ is in long-run equilibrium—i.e., it is satisfied exactly—the error term $E_k$ is equal to zero. Away from long-run equilibrium, the error term may either be negative or positive. The value of the parameters $\alpha$, together with $\gamma$ if lagged differences are present, determines whether the system is stable. For example, if all $\alpha$s are negative (but $>-1$), a state in which the endogenous variables overshoot their long-run equilibrium (positive $E_k$s) is more likely to revert to equilibrium.

The long-term relations are included in the model together with the differenced short-term parts. All parts are estimated simultaneously, and a change in one of these—adding or dropping lags or time trends or setting adjustment coefficients to zero—always affects all other parts as usual in a difference equation system. This leads adjustment to equilibrium to occur at different speed in each of the equations of this VCEM, and because the long-run equations may contain a variety of relationships between the variables ($\beta$s), the system may display very different dynamic adjustment paths between countries. Beyond the issue of whether or not the system is stable (which can be ascertained relatively easily), reporting the (estimated) parameter values in themselves gives very limited insight into the nature of these adjustment dynamics. This is why it is common to use simulation to explore the adjustment paths of the estimated models. We will also follow this approach below.

We estimate the VECM for each country using Eviews 10. The estimation procedure involves determining the number of lags in the VAR part (indicated by $\tau + 1$), and the number ($r \leq M$) of co-integrating equations (indicated by $k = 1, \ldots, r$ above), which appear in each equation $i$. These are determined by running the statistical tests available in Eviews, and we will report the values used in the estimations for each country below. Estimation also involves putting restrictions on the $\beta$s in the co-integrating equations and possibly on the $\alpha$s in the VAR part. Eviews will put necessary restrictions on the $\beta$s, but sometimes, we impose additional ones or different ones. The $\alpha$s are not restricted by default, but we do impose zero restrictions if they are statistically highly insignificant. We document the cases where such additional restrictions (to zero or unity) were used below and the models that are ultimately used, including the specific restrictions that were used, in an online appendix.

### 4.2 Variables and data

The model for each country includes a potential of six endogenous variables: TFP (denoted by $A$), GDP (denoted by $Y$), the domestic public R&D capital stock ($G$), the domestic private
R&D capital stock \( (P) \), the foreign public R&D capital stock \( (G^*) \), and the foreign private R&D capital stock \( (P^*) \).\(^6\) The foreign R&D capital stocks are included to represent (international) R&D spillovers. For some countries, where a six-variable model turns out to be unstable or where the fit of such a model is inferior, we exclude GDP and estimate the model with just five variables. All variables are specified as natural logs (log or ln), and TFP (non-log) is normalized to unity for 2011.

Our approach assumes that all variables in the model affect each other mutually and therefore are endogenous, going beyond the assumptions of Luintel and Khan (2004) where foreign R&D is weakly exogenous (receiving no feedback effects) and Haskel and Wallis (2013) where it is fully exogenous. This implies that we also assume that variables for each individual country, for which we estimate a model, may affect the foreign R&D stocks. In other words, we treat every country as a “large” country, as in imperfect competition theory.\(^7\) However, the estimations may still show that the effect of the variables in an individual country on the foreign R&D capital stocks is negligible, suggesting instead a “small country” effect.\(^8\)

Data are an updated version of those in van Elk et al. (2019), using more recent sources that extend the time period to 2014. GDP and TFP are from the Penn World Tables (version 9.0; Feenstra et al., 2015). We use the national accounts version (RGDPNA) for GDP; the TFP variable uses data on employment that is not augmented with the human capital index that is available in the Penn World Tables (PWT).

R&D data come from the OECD; and as in the case of van Elk et al. (2019), we use older versions of the OECD database kept at UNU-MERIT to extend the coverage of R&D data back into the 1960s. Gaps in the R&D data are filled by interpolating R&D intensity (R&D as a share of GDP) and using GDP data to recover the implied R&D expenditures. The time series for R&D expenditures are then converted into R&D capital stocks, to represent the idea that it is not only current R&D expenditures that influence productivity but rather the accumulated knowledge that results from present and past R&D expenditures. It is also assumed that this accumulated knowledge depreciates (we use a rate of 15% as common in the literature, Hall et al., 2010). We use a perpetual inventory method to construct the stocks:

\[
S_t = (1 - 0.15)S_{t-1} + R_t, \quad \text{where } S \text{ is the stock and } R \text{ is the current expenditure}.\(^9\)
\]

We apply this to both public and private R&D, yielding a stock for both types of R&D. Private R&D expenditures are expenditures by business enterprises, and public R&D expenditures are total domestic expenditures minus business enterprise expenditures (HE and public labs are the largest categories of public expenditures defined in this way).\(^10\)

The foreign R&D capital stocks, private and public, are inverse-distance-weighted averages of the stocks of all countries in our sample, plus Switzerland (a major global R&D performer for which we do not have sufficient data to estimate a full model), excluding the country for which the model is estimated. Using patent applications as weights instead, as Khan and Luintel (2006)

\(^6\) Variable descriptions draw on our earlier paper for the Netherlands (Soete et al., 2020).
\(^7\) According to basic microeconomics, under fixed costs and therefore imperfect competition, firms are price setters and there are no small countries in the sense of being price takers (Helpman and Krugman, 1989). In the literature on SMEs (small and medium enterprises) firms are defined as small in line with convenient statistical indicators (see Loveman and Sengenberger, 1991). Firms that are small according to these indicators will normally have some fixed costs and by implication they have to determine their prices; in other words, some firms, which are defined as small according to the SME literature, are not small according to the microeconomic definition. We use the definitions of microeconomics and international trade theory. In terms of examples, when Philips and Siemens both decide to specialize in health technology, they will observe each other irrespective of the geographical size of their countries of location.
\(^8\) Estimation results suggest that the foreign R&D stocks are endogenous in the model. However, we also estimated a model in which the two foreign R&D stock variables are considered as exogenous. In this model, which we do not document to save space, a permanent shock to public R&D (implemented in the in the same way as our scenario 1 below) has a positive impact on TFP, but additional private R&D (implemented in the same way as our scenario 3 below) has a slightly negative effect.
\(^9\) We also need to assume a value for the growth rate of the stock for the initial period. This is chosen to minimize the difference between the initial growth rate and the next one that results from the formula. In contrast, Khan and Luintel (2006) use the average growth rate over the sample of the flow variables, which is intuitively less likely to represent the initial rate required by the PIM. With little difference in the intensities noticed by the authors, stock differences (emphasized on p.12 of their paper) must be highly sensitive to the method constructing the initial value. As depreciation is also a common rate, the sensitivity comes from the chosen growth rate.
\(^10\) Lucas (1988) points out that even in the richest private universities in the United States, half of the money comes from governments.
Table 2. Summary characteristics of the estimated models

| Country     | GDP included? | Estimation period | # lags used¹ | # LR equations used |
|-------------|---------------|-------------------|--------------|---------------------|
| Austria     | Yes           | 1969–2014         | 2            | 5                   |
| Belgium     | Yes           | 1968–2014         | 1            | 4                   |
| Canada      | Yes           | 1971–2014         | 0            | 5                   |
| Denmark     | Yes           | 1968–2014         | 1            | 5                   |
| Finland     | Yes           | 1971–2014         | 1            | 5                   |
| France      | Yes           | 1964–2014         | 0            | 5                   |
| Germany     | Yes           | 1973–2014         | 2            | 4                   |
| Ireland     | No            | 1965–2014         | 1            | 3                   |
| Italy       | Yes           | 1966–2014         | 2            | 5                   |
| Japan       | Yes           | 1965–2014         | 1            | 3                   |
| Netherlands | Yes           | 1968–2014         | 0            | 4                   |
| Norway      | Yes           | 1971–2014         | 1            | 3                   |
| Portugal    | Yes           | 1965–2014         | 1            | 5                   |
| Spain       | Yes           | 1967–2014         | 0            | 5                   |
| Sweden      | Yes           | 1969–2014         | 1            | 3                   |
| United Kingdom | Yes      | 1966–2014         | 2            | 4                   |
| USA         | No            | 1966–2013         | 2            | 4                   |

¹Number of lags used in the VECM.

In the estimation for Sweden, the first difference of the domestic private R&D stock is used.

do, would have meant that one had to deal with the strong structural change in the data for the period 2000–2010.¹¹ The broad discussion of this issue in Hall et al. (2010) does not lead to any better alternative than our choice.

4.3 Summary of the estimated models

Table 2 documents the summaries of the models that we estimated, as well as the countries in the analysis. The fully detailed documentation of all models is given in the online appendix to the paper. Of the 17 countries, there are two for which we exclude GDP from the analysis, Ireland and the USA. When GDP is included, we get a very low adjusted $R^2$ for the growth equation of the USA and instability of the VECMs for Ireland. A reason for this may lie in the fact that much of the R&D in these countries is offshore, e.g., R&D by US firms in Ireland is counted as Irish R&D, whereas it does not have an effect on Ireland’s TFP growth, and it is not counted as R&D of the USA.¹² Disequilibria then may not feed back into the growth of the USA, and the coefficients for Ireland’s R&D variables may be too low, making the autoregressive coefficients too high leading to instability. In these cases, the model contains five endogenous variables. In all other cases, the model contains six endogenous variables. The periods for which we estimate the model depend on data availability. We always start in the mid- to late 1960s or early 1970s, and the final observation is 2014, except for the USA where it is 2013 (because of data availability).

We determine the number of lags to use by estimating a VAR and testing for optimal lag length. The number of lags used in the VECM, shown in Table 2, is equal to the number of lags in the VAR minus one. This varies between 4 and 0. The VAR with the optimal lag length is tested for stability. If the VAR is unstable, we exclude the lag length and carry out a new lag length test. In one case (Sweden), we use the first difference of the domestic private R&D stock, because the variable is integrated of order two, I(2), and without differencing this variable the VAR is unstable for alternatively chosen lags one to five. Therefore, the well-justified approach of applying the Johansen model to I(2) (Jusélius, 2006: eq. 16.5) does not work here. Finally, we also test the VECM that has a certain number of co-integrating or long-term equations for stability.

¹¹ For example, UK applications by nonresidents dropped by 20% in 2005/2006. They do so even more strongly for Croatia and several other countries in connection with changes in their relation to the European Patent Office (EPO).

¹² We thank an anonymous referee for pointing this out.
The minimum number of co-integrating equations is three, the maximum is five, but never six, and thus always smaller than the number of variables. This variety in the number of co-integrating relations underlines the importance of the country-by-country estimation and analysis, as suggested by Banerjee et al. (2004). We also impose additional or alternative restrictions in all models. In case of restrictions in the co-integrating equations, this is either because we find three to five long-term relations or to exclude statistically insignificant variables and because one of the coefficients can be normalized to unity.\textsuperscript{13} In case of restrictions on the adjustment coefficients, this is done to exclude statistically insignificant feedbacks from disequilibrium error terms. It never happens that in one equation all adjustment coefficients are insignificant, and by implication, all variables get disequilibrium feedback. All variables are endogenous. Weak exogeneity is not obtained for any variable for any of the 17 countries.

Table 3 presents an overview of the long-term relations (the co-integration equations), as documented in full in the online appendix. The table distinguishes three groups, according to the number of long-term relations found (using the trace and maximum-eigenvalue tests). In the top part of the table, we document all co-integration equations with just two variables (these are cases where the number of co-integration equations is found to be equal to the number of variables minus one, and/or where we impose additional restrictions in these equations). The other parts of the table document the co-integration equations with either three or four variables (these are found in models where the number of co-integration relationships is smaller than the number of variables minus one).

Because of the systems nature of the country models, these co-integration relationships are difficult to interpret in isolation of each other or in terms of the value of the coefficients found in them. All relations (coefficients) indicate multi-directional causality, i.e., instead of a single dependent variable “explained” by several independent variables, causality in these models is always in either direction. In cases where the maximum number of co-integration equations appears in the model (this is usually five in our case because we have six variables), the entire model (i.e., all co-integration relationships together) can be represented relatively simple, as in the left pane of Figure 1. Here, each arrow represents one co-integration equation, and the sign indicates the nature of the bi-directional relation (i.e., either both variables move in similar directions, a + sign, or in opposite directions, a – sign). In this example, the sign that goes along with each co-integration equation is positive, which is the case if the two variables have opposite signs in the equation. For example, the \( \log Y - \log A \) relation for Austria has a positive sign because, in Table 3, this equation is \( \log Y(+) \), \( \log A(-) \). If the signs of two variables in a co-integration equation are the same, we have a negative relationship between the two variables.

The right-hand-side pane of Figure 1 shows two individual co-integration relationships: one with three variables (top) and one with four variables (bottom). Also in these cases, the rule about the signs of the variables in the equations corresponding to signs in the figure holds. It can clearly be seen that in the case of more than two variables in the co-integration equation, the signs in the figure can never be all the same. For example, the two positive signs in the top-right figure imply that the third sign must be negative (the two positive signs imply that \( \log G \) and \( \log P \) have the same sign in the equation).\textsuperscript{14}

A model that involves the co-integration equations with three or four variables must therefore be inherently complex. It consists of multiple triangles or squares as found in the right-hand-side pane of Figure 1, and these triangles or squares would be connected to each other. Judging what the effect of a shock in public R&D would be is very difficult. This is why we apply, in line with the standard approach in VECM analysis, simulation analysis to analyze the impact of specific scenarios on exogenous shocks in public R&D to obtain an idea about the impact of such shocks.\textsuperscript{15}

\textsuperscript{13} In addition, if there are \( r \) long-term relations, identification requires that there are \( r \) constraints in each of the \( r \) long-term relations; see also footnote 4. In the standard version, one variable has a unit coefficient and \( r - 1 \) has a zero constraint. In the case of \( M \) variables, there are only \( M - r \) variables for which we get an estimate of the coefficient and the standard error. This limits the freedom of adding control variables in the specification. It is a major difference between long-term relations in VECMs and other forms of regression analysis.

\textsuperscript{14} The special case where sign and value of constants and trend generate an exception does not appear in the six cases which we have with three variables in each of four cointegrating equations.
Table 3. A summary of the long-run relations in the estimated models for all countries

| LR relationship (signs) | Found in models for country |
|-------------------------|-----------------------------|
| Two variables           |                             |
| \( \log Y(+) \), \( \log A(-) \) | AUT(5), CAN(5), FIN(5), FRA(5), ITA(5), NLD(4), PRT(5), ESP(5) |
| \( \log Y(-) \), \( \log G(+) \) | CAN(5), FIN(5) |
| \( \log A(+) \), \( \log P(-) \) or \( \log P(+) \), \( \log A(-) \) | AUT(5), CAN(5), FRA(5), ITA(5), ESP(5), USA(4*) |
| \( \log A(+) \), \( \log P(+) \) | PRT(5) |
| \( \log A(+) \), \( \log G(-) \) or \( \log A(-) \), \( \log G(+) \) | PRT(5), ESP(5) |
| \( \log A(-) \), \( \log G(+) \) | USA(4*) |
| \( \log P(+) \), \( \log P(-) \) or \( \log P(+) \), \( \log P(-) \) | FIN(5) |
| \( \log P(+) \), \( \log G(-) \) | AUT(5), FRA(5), ITA(5) |
| \( \log P(+) \), \( \log P(-) \) | BEL(4) |
| \( \log P(+) \), \( \log P(+) \) | FIN(5), ESP(5) |
| \( \log P(+) \), \( \log P(-) \) | PRT(5) |
| \( \log G(+) \), \( \log P(-) \) | CAN(5), FRA(5), ITA(5), SWE(3) |
| \( \log G(+) \), \( \log G*(-) \) | AUT(5) |
| \( \log G(+) \), \( \log G(+) \) | BEL(4), USA(4*) |
| \( \log P(+) \), \( \log G*(-) \) or \( \log G(+) \), \( \log P(-) \) | AUT(5), CAN(5), ITA(5), PRT(5), USA(4*), ESP(5), FIN(5) |
| \( \log P(+) \), \( \log G(+) \) | FRA(5) |
| Three variables         |                             |
| \( \log Y(+) \), \( \log A(-) \), \( \log G(-) \) | BEL(4), GBR(4), DNK(4) |
| \( \log Y(+) \), \( \log A(-) \), \( \log P(+) \) | DEU(4) |
| \( \log Y(-) \), \( \log P(+) \), \( \log G(-) \) | DNK(4) |
| \( \log Y(-) \), \( \log G(+) \), \( \log P(-) \) | DEU(4) |
| \( \log A(+) \), \( \log P(-) \), \( \log G(+) \) | GBR(4) |
| \( \log A(-) \), \( \log P(+) \), \( \log G(-) \) | IRL(3*) |
| \( \log A(+) \), \( \log P(-) \), \( \log G(-) \) | NLD(4) |
| \( \log A(+) \), \( \log P(-) \), \( \log G(+) \) | BEL(4) |
| \( \log A(+) \), \( \log P(-) \), \( \log G(+) \) | DEU(4) |
| \( \log A(+) \), \( \log P(-) \), \( \log G(-) \) | IRL(3*) |
| \( \log A(+) \), \( \log G(+) \), \( \log G(-) \) | DNK(4), GBR(4) |
| \( \log A(-) \), \( \log G(+) \), \( \log G(-) \) | DEU(4) |
| \( \log P(+) \), \( \log G(-) \), \( \log P(-) \) | GBR(4) |
| \( \log P(+) \), \( \log P(+) \), \( \log G(-) \) | NLD(4) |
| \( \log G(+) \), \( \log P(+) \), \( \log G(+) \) | IRL(3*), DNK(4) |
| \( \log G(+) \), \( \log P(-) \), \( \log G(+) \) | NLD(4) |
| Four variables          |                             |
| \( \log Y(+) \), \( \log A(-) \), \( \log G(-) \), \( \log G(+) \) | NOR(3) |
| \( \log Y(+) \), \( \log P(+) \), \( \log G(-) \), \( \log P(+) \) | JPN(3) |
| \( \log Y(-) \), \( \log P(+) \), \( \log P(+) \), \( \log G^*(+) \) | JPN(3) |
| \( \log Y(-) \), \( \Delta \log P(+) \), \( \log P(+) \), \( \log G^*(-) \) | SWE(3) |
| \( \log A(+) \), \( \log P(-) \), \( \log G(-) \), \( \log P^*(+) \) | NOR(3) |
| \( \log A(-) \), \( \log P(+) \), \( \log P^*(-) \), \( \log G^*(+) \) | JPN(3) |
| \( \log A(-) \), \( \Delta \log P(+) \), \( \log G^*(-) \), \( \log P^*(+) \) | SWE(3) |
| \( \log P(+) \), \( \log G(-) \), \( \log P^*(-) \), \( \log G^*(+) \) | NOR(3) |

Signs between brackets after variable names indicate the sign of the variable in the co-integration equation; numbers between brackets after country acronyms represent the number of co-integration equations in the model for the country, a star after such a number indicates countries where GDP was excluded from the model (and hence the number of variables is five).

In each of the countries. The impact of these hypothesized policy changes is impossible to see or analyze by looking only at the estimation results. This is also why we put less emphasis on the specific econometric output (see the online appendix).

In the top part of Table 3, (a positive) long-term relation between GDP and TFP is most frequently found. There is, of course, heterogeneity in the form of different numerical sizes of the slope coefficients, which we document only in the online appendix. The table also does not
5. Economic impact of public R&D

We now proceed to analyze the economic effects of public and private R&D in the 17 countries under analysis. This is done by simulations that analyze the effects of an exogenous shock to the R&D capital stock variables. When these variables are shocked, they will invoke deviations from long-run equilibrium (the co-integrating equations in the model). These deviations will lead to adjustment dynamics in the short run (non-zero error terms and their repercussions in the VAR part of the models). Given that the estimated models are all stable, the economy will, over
time, show an adjustment path that ultimately leads to a new long-run equilibrium, in which the shock may have caused some changes relative to the original equilibrium state. Coming close to a new equilibrium may take long periods (decades), and therefore, we look at the adjustment paths rather than the equilibria in isolation of the adjustment path. These adjustment paths are considered as the (causal) effects of the original shocks, i.e., as the economic effects of public or private R&D (depending on which variables were shocked in the first place).

We analyze the effect of permanent shocks to the R&D stock variables. We will implement this by adding 0.005 to the intercept of the short-run equation for an R&D stocks, $c_i$, in the model above, either the domestic public or the domestic private stock. For example, in the model for Canada, the intercept of the VAR equation for the domestic public R&D stock is estimated at 0.022, and we add 0.005 to this. By doing this, we effectively increase the growth rate of this stock by half a percent annually. This is implemented for all years from 1975 onwards. We then stochastically solve the model with this new intercept, for the same period as was used in the estimation, and compare the time paths that were generated to the baseline simulation. Deviations from the baseline will occur from 1975 onwards, when the shock is first implemented. We document these deviations in Figure 2 below. What we document in the graphs is deviations from the baseline where both the baseline and the alternative scenario have all variables specified in logs. Therefore, the deviations can be interpreted as percent deviations from the baseline.

In interpreting the results of the shocks in public and private R&D stocks, we may expect both negative and positive effects on productivity. This is in line with the analysis in, e.g., Jones and Williams (1998), who apply a theoretical “new growth” approach that is based on a knowledge production function with various types of externalities. In this knowledge production function, knowledge is measured in terms of the number of “ideas.” New ideas are generated with two inputs: R&D and existing knowledge (again measured in terms of ideas). There are various kinds of externalities that are involved in the knowledge production process, some of them negative and some positive. One externality is the fact that knowledge itself is an input in the generation of new knowledge. This is a positive externality and is an important factor in enabling endogenous growth.

Negative externalities may arise from duplication of research efforts, from a “fishing out” effect, and from “creative destruction.” Duplication arises because firms, universities, and other research organizations may chase the same research goals, without pooling resources or cooperating otherwise. The private benefits to such competing research projects will fall to whoever reaches the goal first, while the investment of the other contestants in the race will be (largely) lost. Fishing out refers to the notion that some ideas are easier to develop than others, and that over time, the harder to implement ideas remain the ones to be discovered, thus requiring higher R&D effort. Finally, creative destruction refers to the idea that new ideas may make older ones obsolete and hence may destroy rents that previous innovators are collecting.

As is well known from new growth theory (e.g., Jones and Williams, 1998), if positive externalities dominate, there will be a tendency for the economy to underperform in terms of R&D and growth, while if the negative externalities dominate, there will be a tendency for too much investment in R&D. Although the distinction between private and social rates of return is not our main concern in this paper, the existence of negative spillovers (outweighing the positive ones) also opens the possibility of R&D investments that reduce productivity rather than enhance it.

Spillovers may also run through the labor market. If researchers are well allocated to public and private R&D, additional (public) R&D expenditure will drive up the wages of researchers. This may affect private R&D (which could even decline if wages increase strongly), leading to unpredictable net effects on productivity.

5.1 A permanent shock to domestic public R&D

In our policy simulations experiments, we look at the effects of the permanent shock in $G$, the domestic public R&D stock. Figure 2 documents the simulation results for the 17 countries in the analysis. These figures show the deviations from baseline for all (five or six) variables in the analysis. We report these results in pairs of variables (TFP and GDP; domestic private and public
Figure 2. Effects of a permanent shock to public domestic R&D (deviations from baseline scenario), 17 countries
Figure 3. Relation between effect on private R&D and effect on TFP

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R&D; and foreign private and public R&D), and each pair of variables has its own small piece of the horizontal axis, which implies that this axis in its entirety is not a linear sequence of time.

There are 12 countries (i.e., a large majority in the set of 17) in which there is a positive effect on TFP but also 5 countries in which the effect on TFP is negative. These five countries are the UK, Spain, Ireland, France, and Canada. In France, it is not only TFP that falls below the baseline but also the public R&D stock itself is negatively affected. Norway, Finland, Japan, Germany, and Portugal have the highest TFP effect: in these countries, the average yearly effect is larger than 0.1.

The figures also show the effects of the policy shock to the foreign R&D stocks. This captures strategic interaction between R&D in the countries under consideration and R&D in foreign countries. We see mixed results in terms of the sign of these interactions: in 10 out of 17 cases, the effect on the foreign private R&D stock is positive, and in 13 out of 17 cases, it is positive for the foreign public R&D stock.

A likely explanation for the negative effect of the public R&D shock to TFP in five countries can be found in the effect that increasing public R&D has on domestic private R&D. This is negative in the long run in all five cases, as well as in Sweden, which has a small positive TFP effect. Thus, increasing the growth rate of the stock of domestic public R&D seems to disincentivize firms in these countries to invest in their own R&D, possibly through higher wages for researchers, and this has a negative effect on productivity growth, compared to the baseline scenario.

The strong relationship between the effect of public R&D on TFP and on private R&D also extends beyond the effects of negative TFP effects. Figure 3 shows the cross-country relation between the average annual effects on private R&D and on TFP. This is strongly positive, with a correlation of 0.72. Table 4 documents correlations between the all simulation effects, again in terms of average annual effects. The correlation coefficient between TFP and domestic private R&D is even slightly higher than the correlation between TFP and domestic public R&D. Correlations to the GDP effect tend to be higher than for TFP.

With respect to the foreign R&D stocks, we observe a strong correlation between the foreign private and foreign public R&D effects (0.65). This is in line with the strong complementarity between domestic public and private R&D stocks that we already noted. The correlations between foreign R&D stocks and the other variables, shown in Table 4, are much weaker (0.35–0.56), including those with (domestic) TFP. Interestingly, public R&D, G, and foreign private R&D are positively correlated with all variables.
Table 4. Correlations of the average annual deviation from baseline with a shock in domestic public R&D

|     | A   | G   | P   | G*  | P*  | Y   |
|-----|-----|-----|-----|-----|-----|-----|
| A   | 1   | 0.667 | 0.720 | -0.112 | 0.041 | 0.850 |
| G   | 1   | 0.524 | 0.232 | 0.151  | 0.214 | 0.771 |
| P   | 1   | -0.151 | 0.648 | 0.046  | 0.395 |
| G*  | 1   | 0.648 | 0.224 | 0.734  |
| P*  | 1   | 0.395 |
| Y   | 1   |

The conclusion from these country-level results is that there is a large variety of results between countries in terms of how public R&D affects productivity. The effect of a permanent shock to domestic public R&D is positive for the majority of countries but not for all of them. This raises the question whether there is any way in which we can interpret and better understand the variety of results obtained. Why is it that some countries have large positive effects, and others are characterized by effects that are close to zero or even slightly negative?

However, this raises a next question: why does the specific interaction between public and private R&D lead to a positive productivity impact in one country and to a lack of impact or even negative impact in another country. We try to provide an answer to this question by going back to the indicators of the R&D systems in our sample countries that we introduced in Section 3.

5.2 What drives the differences in productivity effects of public R&D?

Our core hypothesis is that the differences in productivity and other effects that result from the country-level estimations are related to unobserved characteristics of the innovation systems in the countries analyzed. Although unobserved in a direct sense, we can learn something about these differences by observing some of the key correlation coefficients in Table 4 and relating them back to the R&D indicators used in Section 3.

Figure 4 presents scatterplots between three main outcome variables in the simulations: the effects of the policy shocks on public R&D, on private (business) R&D, and on TFP. These effects are measured as average log differences over the simulation time period. The top part of the figure shows the relation between the public R&D effect and the private R&D effect. These effects are both positive in 10 countries and both negative in 1 country, France. This indicates that in these countries, public and private R&D are complementary: a positive shock to public R&D leads to more private R&D. However, in the six other countries, public and private R&D appear as substitutes: a positive shock to public R&D leads to a decline of the private R&D stock. These six countries are colored red in Figure 4.

In the bottom panel of the figure, we see the relation between the two R&D effects and the TFP effect. On the left, it can clearly be seen that countries with complementarity between public and private R&D tend to have a positive TFP effect. There are five countries with a negative TFP effect in the simulations, and four of those are countries where private and public R&D appear as substitutes. France is the only country with complementarity that also has a negative TFP effect, but this seems to be related to the result that the effect of the policy shock to public R&D is negative in France. A reason for this may be that the public R&D stock is too high and crowding out private R&D. A negative shock to public R&D in simulations leads to higher public R&D anytime soon after the shock (not shown). In current French practice, this goes together with refocussing R&D into other areas. All other countries (than France) with complementarity have a positive TFP effect.

This suggests that whether public and private R&D appear as complementary is an important indicator of whether the public R&D shock will have a positive productivity effect. Hence, we conclude our analysis by investigating the relationship between complementarity (of public and private R&D) and the indicators mentioned in Table 1. We use canonical discriminant analysis to analyze this relationship. In this method, we formulate a weighted sum of the R&D-system

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We are grateful to Jan van den Biesen for pointing this out to us.
Table 5. Canonical discriminant analysis for complementarity between public and private R&D

| Variable                                                      | Standardized canonical coefficients |
|---------------------------------------------------------------|------------------------------------|
| Share of foreign funding in R&D performed by business         | Model 1: -1.22                     |
| Share of basic R&D in R&D performed by business               | Model 2: -1.27                     |
| R&D performed by business as a share of GDP                    | Model 1: 1.12                      |
| R&D performed by non-business sector as a share of GDP         | Model 2: 1.04                      |
| Canonical correlation (eigenvalue)                            | Model 1: 0.799 (1.768)             |
| F (P-value)                                                   | Model 2: 5.304 (0.010)             |
| Number of countries mis-classified (“leave-out-one”)          | Model 1: 0.153 (0.001)             |

This means one canonical function, the number of dimensions must be smaller than the number of groups, and we have two groups (complementary or not).
correlated strongly to the ratio of these two variables). Instead of these last two scale variables, we included a single scale variable, defined as the natural log of total R&D in the country. All variables were z-scored.

As it turns out, dropping variables in this way, up to where we have only two variables left, improves, or leaves unaffected, the ability of the estimated model to correctly classify the data. This ability is assessed using the so-called “leaving-one-out” classification table. Each observation (country) is, in turn, left out of the estimation, and then, the estimated model is used to classify the country that was left out. We document two final models, one with four variables and one with just two variables. Both models mis-classify two (of 17) countries. Models that include five or more variables mis-classify at least three countries, while a model with just one variable mis-classifies five countries. In the ultimate models, the two countries that are mis-classified are Norway (shows complementarity and is classified as substitution) and Spain (shows substitution and is classified as complementarity).

Table 5 shows the results for the canonical discriminant analysis. In both models in the table, the share of foreign funding of R&D performed in the business sector has a negative impact on a country being classified complementary, and the share of basic R&D in R&D performed by business has a positive impact. Both of these variables correspond to basic intuition. A higher share of foreign funding in business R&D makes domestic R&D more “footloose” and disconnects it from the domestic public R&D institutions. Firms performing basic R&D makes them more compatible with public R&D performers, which also tend to do much basic R&D.

The two other variables in the table are the intensity (share of GDP) of public and private R&D. These variables do not add much to the classification (their canonical coefficients are small, and the model with two variables classifies just as well as the model with four variables). Nevertheless, public R&D intensity leads to complementarity, while business R&D intensity has the reverse effect.

6. Summary and conclusions

We presented individual country estimations of an econometric times-series model (a VCEM) for the impact of public R&D investment on TFP. Our choice to look (in first instance) at individual countries rather than at a pooled dataset was motivated by the expectation (based on previous econometric results such as in Khan and Luintel, 2006) that the effects of especially public R&D would be highly country-specific and cannot be estimated by a single effect in a pooled dataset. Our approach also has the advantage of allowing for multi-directional endogeneity between the variables, thus allowing for a richer dynamics based on various types of feedback between R&D and other variables.

The simulation results of a permanent shock to public R&D suggest that this will increase the growth rate of TFP (and GDP) in a majority of countries, but that there are also countries in which such extra public R&D investment has small effects or leads even to lower productivity. We attribute this variety in results by the different importance of positive vs. negative externalities of R&D in the different countries. There is a relatively strong effect on productivity of the complementarity between public and private domestic R&D investments: i.e., when the public R&D shock leads to extra private R&D, the effect on productivity is stronger. This works through the incentives that public R&D gives to firms to increase their own R&D investment.

The results suggest that national R&D systems have an impact on the nature of the economic effects of investment in public (and private) R&D. Specifically, we find that the more firms are involved in basic research, the higher complementarity between private and public R&D is, and the higher complementarity, the higher the productivity effect of public R&D. Similarly, the more foreign funding of private R&D, the weaker complementarity, and the weaker the productivity effect of public R&D.

18 Higher values of the canonical functions in the table lead countries to be classified as complementary.
Supplementary data

Supplementary materials are available at Industrial and Corporate Change online.

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