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A dynamic Panel VECM Data Analysis for 14 OECD Countries

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Public R&D and Growth: A dynamic Panel VECM Data Analysis for 14 OECD Countries

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Abstract We start from five economic relations of research and development R&D driven growth for 14 OECD countries: GDP and technical change; technical change and private business R&D; domestic private and public R&D; domestic and foreign public R&D; foreign private and public R&D. Cointegration tests force us to go from these five pairs to four triples of these variables. We establish the four relations through (i) panel cointegration tests and (ii) a panel vector-error-correction model (VECM) with cross-section fixed effects in the differenced part and long-term relations from group mean versions of FMOLS and DOLS (fully modified and dynamic OLS) estimation (also with fixed effects), which are the current econometric standard for panel VECMs with homogenous adjustment coefficients and slopes in the differenced terms. Public R&D has positive long-run regression coefficients for direct effects on productivity and indirect ones via private R&D. Shocks on the intercepts of the public R&D growth equation of the VECM enhance private R&D, technical change, and GDP in a statistically significant way. Permanent changes of foreign public and private R&D have positive growth effects, which are transitional for foreign public R&D. Keywords: Growth; R&D; productivity; OECD; panel coinegration; panel VECM. JEL codes: O19; O47; O50.

1. Introduction

Van Elk et al. (2015, 2019) analyzed the rate of return for public R&D for a panel of OECD countries. When analyzing a Cobb-Douglas function for total factor productivity (TFP) with slope homogeneity, they find a negative or zero rate of return for public R&D. When moving to a translog function, international control variables, and some country-specific slope heterogeneity through interaction effects similar to Khan and Luintel (2006), they find more positive results especially in the augmented production function model, but overall, the authors remain sceptic about the effect of public R&D on TFP and see the value of public R&D in other aspects than TFP. Similarly, Donselaar and Koopmans (2016) find an output elasticity of public R&D of 0.03 in a meta-analysis for a small set of studies, but it is statistically insignificant.[1]

The standard approach used in the literature has a Cobb-Douglas output production function with a TFP variable and a Cobb-Douglas TFP production function depending on R&D stocks. Public R&D stocks are put directly into the TFP equation and thereby considers only direct effects of public R&D stocks on productivity (although van Elk et al. (2015, 2019) discuss indirect effects verbally). In contrast, Park (1998) models TFP only as a private stock variable

[1] Erken et al. (2008) find a positive effect of public R&D in a panel of 20 OECD countries. However, their method does not yield a t-value because they impose or estimate constrained coefficients. OECD (2017) surveys the literature on mainly aggregate R&D until 2014. We discuss more literature below in connection with our results but only to the extent that it is comparable in particular with respect to distinguishing between public and private R&D for home and foreign countries. In the literature reports we will not distinguish strictly between privately or publicly performed and financed R&D. It is conceivable that publicly performed R&D is productive whereas publicly financed R&D is less so, if the public finance means used in business are used less effectively; similar to measurement errors this may undermine statistical significance.

implying that direct effects of public R&D on productivity are excluded by assumption.[2] Public R&D goes only into the production of private knowledge and thereby only indirectly into TFP. This is motivated by finding a negative (positive) effect of public R&D when (not) controlling for private R&D in Park (1995) in the model without spillovers. We will show positive and statistically significant direct and indirect effects in the long-term relations estimated by DOLS and FMOLS and inserted into the panel VECM. This result is similar to that of Guellec and van Pottelsberghe de la Potterie (2002, 2004) who find positive direct effects and positive (negative) indirect effects from civilian (defence) R&D via an interaction term with private R&D in an unconstrained single-equation ECM.

Recent VECM models by Soete et al. (2020, 2022) and Ziesemer (2020, 2021a,b, 2022, 2023b) bring both effects together. These papers go more deeply into the analysis of slope heterogeneity by way of analyzing one vector-error correction model (VECM) per country. They go beyond Coe and Helpman (1995) and Luintel and Khan (2004) through splitting domestic and foreign R&D into private (business) and public (non-business) R&D, which Erken et al. (2008) do in a single equation panel regression. Soete et al. (2022) find that the most frequent constellation is the stylized result of five relations suggesting that (i) TFP drives GDP, (ii) private R&D drives TFP, (iii) public R&D drives private R&D, (iv) foreign public R&D drives domestic public R&D, (v) foreign private and foreign public R&D drive each other. Constellations of four or three long-term relations with three or four variables respectively are slightly less frequent. In line with van Elk et al. (2015, 2019) and the use of control variables by Erken et al. (2008) they find that national circumstances play a role. Public R&D may have differing direct effects on TFP, or indirect ones via private R&D, or indirect ones through the whole system.[3] However, the emphasis in VECMs is, in the first instance, not on direct or indirect effects but rather on normalizing three, four, or five long-term relationships (obtained from the Johansen trace and maximum eigenvalue tests) in a way that they are economically meaningful and statistically significant. In fact, the issue of renormalization leads to different versions of the cointegrating equations, but the interpretation of shocks is in line with the five relations indicated here. As a by-product of this normalization and the shock analysis, Soete et al. (2022) find positive (negative) indirect effects of public on private R&D for Austria, Denmark, France, Ireland, Italy, Japan, Norway, UK, (Belgium), and positive (negative) direct effects for the Netherlands, Norway, Portugal, Spain, (Belgium, Denmark, Ireland). The total effect from analysis of shocks (impulse response) on public R&D are positive for all countries except for Canada, France, and Ireland.[4] For some other countries, the rate of return for public R&D is only positive under the additional condition that the policy of enhancing public R&D is stopped before periods in which the gains get negative. Rates of return differ across countries. An in-depth

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[2] Formally, $dA_p = H_pF_p(A_p; A_g)$, $dA_g = H_gF_g(A_p; A_g)$. Only A_p enters the output production function in Park (1998), whereas in the standard model also A_g and the foreign R&D stock(s) would be included (see van Elk et al. 2015, 2019). Standard cost minimization considerations would have as R&D expenditure flow qH_p with q as factor price of H. A-terms and R&D stock variables then are equal and can replace each other: Summing dA and expenditure flows over time, A is equal to the R&D expenditure stock; for A_p this is only private R&D expenditure. For A_g this is public R&D expenditure which enters the production of A_p only as an externality, but A_g does not enter TFP directly as A_p does.

[3] In case of $K = 6$ variables, five (four, or three; $r = 5,4, or 3$) long-term relations can determine only five (four, three) variables depending on the other variables. Therefore, ultimately all values follow from the whole system and not from partial relations.

[4] For Canada, Loertscher and Pujolas (2023) attribute 20 years of TFP stagnation to high oil sector inputs.

analysis of the heterogeneity in the country-specific results shows, among other aspects, that total effects are mostly not positive if the indirect effect of public on private R&D does not work in the impulse response analysis. However, even if the indirect effect works, the direct effect and the system effect may work against it as in the case of Ireland.

Having results per country there is no econometric need for pooling (Hsiao 2022) other than having more observations. However, when seeing the extent of heterogeneity found for EU countries by Soete et al. (2022) (differences in numbers and normalizations of cointegrating equations, as well as results from shocks, and rates of return), at least some readers would like to see something simpler and more structured as under slope homogeneity. This may generate the desire for pooling similar countries.

In this paper we take Canada, France, and Ireland out of the OECD sample and do some panel analyzes for the remaining 14 OECD countries. We use two approaches.

(i) Cointegration tests show the relation for the pairs of variables mentioned above; three of the five pairs have no panel cointegration and therefore we go from five pairs to four triples of variables that do have cointegration.[5]

(ii) We use a vector-error-correction model with fixed effects, slope homogeneity in the differenced part, and four cointegrating equations from *group mean* versions of DOLS and FMOLS estimation with cross-section fixed effects as suggested in the econometric literature (Hsiao 2022, ch. 5.3.2.1). It allows us to run simulations of shock effects going through all six equations for growth of GDP, productivity, and the four R&D variables mentioned above.[6] We find positive direct and indirect effects of public R&D on productivity in the long-term relations obtained via DOLS and FMOLS, and also through the shocks on public R&D.

These approaches have three advantages in comparison to the standard procedure of OECD (2017), van Elk (2015, 2019), Donselaar and Koopmans (2016), and Erken et al. (2008).[7]

First, we do not impose having only one (cointegrating) equation for productivity, pressing all information for five or four relations into one equation; instead, we assume *four triple wise cointegrated relations*, which generates more and better information (Kilian and Lütkepohl 2017, p.103) typically shown through a higher log-likelihood for models with more cointegrating equations, provided they are economically plausible and statistically significant. This allows to deal explicitly with the suggestion of Park (1995) and Sveikauskas (2007), theoretically modelled in Park (1998), that public R&D works mainly through its effect on private R&D and thereby only indirectly on productivity.[8]

[5] Older panel time-series literature is occasionally criticized for not having taken into account issues of unit roots and cointegration (Hsiao (2022).

[6] This method is preferable to pairwise Granger causality analysis, which does not take into account the impact of other third variables (Lütkepohl 2005). Of course, Granger causality analysis can be useful for exploratory purposes.

[7] Abdih and Joutz (2006) suggest making TFP dependent on knowledge stocks in the form of research outputs like patents and having a patent production function depending on R&D stocks. However, the innovation studies community emphasizes that many research results are not patented. We follow this latter idea, also in the interest of keeping the number of variables low. In future work both approaches can perhaps be combined.

[8] Other reasons given in the literature for having no effect from public R&D are (i) being a substitute for private R&D (David et al. 2000), (ii) strengthening public consumption rather than investment, and (iii) a need for

Comparing the extended standard model of van Elk et al. (2015, 2019), modelling only direct effects of public R&D on productivity, and the extended Romer model of Park (1998), modelling only indirect effects via private R&D on productivity, suggests that van Elk et al. have tested only for the direct effects but not for the indirect effects of public R&D stocks working via the private R&D stock. The methods used in this paper tests for both effects. Similarly, foreign private R&D may have a direct effect on domestic business R&D in line with oligopoly theory (see Ziesemer 2022), and an indirect one via its effect on domestic public R&D. For the role of foreign R&D too, Park (1998) models only indirect effects and van Elk et al. (2015, 2019) model only direct effects on TFP.[9] Having several long-term relations allows us to treat the controversial effects of public and foreign R&D differently than those using only one long-term relation.

Second, *cointegrating equations* with a log-log specification do not use Cobb-Douglas or translog functions but are more closely related to the first-order conditions *related to the SMAC VES* (variable-elasticity of substitution) of Mukerji (1963),[10] which generalizes the CES function by way of giving the CES parameter an index of the related argument (see Ziesemer 2021a).[11] Otherwise, the setup is similar to the traditional model (see Guellec and Van Pottelsberghe de la Potterie 2004; OECD 2017, van Elk et al. 2015, 2019, Erken et al. 2008, 2018) that has a production function for GDP (here without capital and labour, which are replaced by time trend and constant and therefore free of the double counting bias discussed in Guellec and Van Pottelsberghe de la Potterie 2004), and one for TFP, and a perpetual inventory equation for R&D, in our case for four R&D variables.

Third, the use of a VECM allows to apply *shock or impulse response analysis to the solution* of the panel data VEC model and test whether good looking partial regression results also lead to plausible outcomes under a shock on public R&D and related variables in a multi-equation system.[12]

We tend to speculate that these three methodological issues, which we discuss in due course, are behind 'ambiguous results in the literature' (Erken et al. 2018) on public R&D (besides

longer lags than usually used in growth regressions (Bassanini 2001), and (iv) the possibility of full employment for top researchers resulting in mere wage effects (David and Hall 2000), and (v) disaggregation of publicly funded R&D may reveal that some parts are less effective (Elnasri and Fox 2017); (vi) public R&D may have inveretd u-shape effects in theory (Huang et al. (2023). There is a different literature for these aspects. Lags are considered well in the VECM models of Soete et al. (2022), which include direct and indirect effects of public R&D and give less pessimistic results.

[9] The statistical significance of both foreign R&D variables in the single-country papers by Soete et al. (2020, 2022), Ziesemer (2020, 2021a, b, 2022, 2023b) and this paper for the panel VECM-FM/DOLS approach reestablishes the result of Coe and Helpman (1995) and rejects the insignificance criticism of Kao et al. (1999) as van Pottelsberghe de la Potterie and Lichtenberg (2001) and Erken et al. (2008, 2018) do for the single equation approach, and Luintel and Khan (2004) do for the VECM approach for aggregated (private plus public) foreign R&D. The method of this paper is closer to that of Kao et al. (1999) than these other papers.

[10] SMAC abbreviates for the names of Solow, Minhas, Arrow, and Chenery and their paper Arrow et al. (1961) dealing empirically with the CES function.

[11] If first-order conditions are pairwise relations and cointegration requires having triples of variables, the two pairwise relations can be added up to form a triple.

[12] This is done in addition to assuming effects of a hypothetically increased regressor in the interpretation of the long-term relations of PMG (pooled mean-group) or VECM estimation. The use of VAR methods with shocks alone is not a guarantee that all results will be plausible and homogenous. Estrada and Montero (2009) find effects of public R&D from a SVAR (structural vector autoregression) model that differs from country to country.

slope heterogeneity)[13]. They belong to the modern time-series and panel times-series methods, which are made possible by the availability of longer data series compared to the data bases of the literature surveyed in OECD (2017). The data are described in section 2 and the econometric methods in section 3. The major estimation results - presented in section 4, besides those on unit roots and panel cointegration - are that direct and indirect long-run effects of public R&D via private R&D always turn out to be positive when using FMOLS or DOLS estimation methods, the current standard for long-term relations in panel VECMs (Hsiao 2022). When using shock simulations including short term effects and adjustment processes towards the FM or DOLS based cointegrating equations, shown in section 5, effects of public R&D are also positive. Section 6 summarizes and concludes with suggestions for further research.

2. Data

We use data for 14 OECD countries. Data are an updated version of those in van Elk et al. (2015, 2019) and Soete et al. (2022), using more recent sources that extend the time period to 1963-2017.[14] GDP is from the Penn World Tables (version 9.1; Feenstra et al., 2015). We use the national accounts version for GDP (RGDPNA in PWT terminology). For technical change we use the data from Ziesemer (2023a) for labour-augmented technical change (not including human capital) derived from a CES function under the assumption of an elasticity of substitution of 0.7 denoted as TH07. R&D flow data come from the OECD MSTI (main science and technology indicators); and as in the case of van Elk et al. (2019) and Soete et al. (2022), 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).[15] We use a perpetual inventory method to construct the stocks: $S_t = (1 - 0.15)S_{t-1} + R_t$, where S is the stock and R is the current expenditure.[16] We apply this to both public and private R&D, yielding a stock for both types

[13] Khan and Luintel (2006), Luintel et al. (2014), and van Elk et al. (2015, 2019) mitigate the problem of slope homogeneity through the use of interaction effects.

[14] The rest of this section is a slightly modified version of two paras from Soete et al. (2022).

[15] It is not quite true that this value is chosen ad hoc. Several papers indicate that their authors have experimented with other rates. The volatility of R&D capital stocks is a bit lower if depreciation rates are lower (see Figure 5.1 in Shanks and Zheng (2006)). The reason is that a higher rate of depreciation brings us closer to using flow data, which are more volatile than stock data.

[16] Diewert (2008) and other parts of OECD (2008) read the PIM as a method pretending perfect future valuation, which they argue is more adequate for physical capital. In contrast, we would argue that machinery has similar problems of forecasting future values that are discussed for R&D. Uncertainty about future preferences and technologies, demand, and supply, is a fundamental problem for forecasting future valuations, and machinery can have a much longer expected lifetime than R&D when depreciated at the standard rate of 15% whereas the short-run uncertainties for the returns to R&D are perhaps higher than those for machinery. The R&D capital stocks from the PIM (perpetual inventory method) can perhaps better be seen as a rough knowledge indicator approximated by accumulated expenditure, similar to indicators in the learning-by-doing and learning-by-investment literature. Rates of return than have the interpretation as

of R&D, abbreviated as BERDST and PUBST. Private R&D expenditures are expenditures for R&D *performed* 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).[17] For details of constructing initial values see Soete et al. (2022). An *L* in the beginning of the variable name indicates the natural logarithm. An *F* indicates 'foreign'. 'Foreign' variables are obtained by adding the R&D flows from 17 OECD countries weighted by distance and then following again the aggregation procedure indicated above. Linking foreign R&D variables to domestic R&D variables is a way to take into account cross-unit cointegration.

3. Econometric methods

3.1 Unit roots in the presence of cross-section dependence

Panel unit root tests in the presence of cross-section dependence are based in the simplest case (Pesaran 2007) on the following equation (Baltagi 2021; Hsiao 2022)):

$$\Delta y_{i,t} = \alpha_i + \delta_i t + \gamma_i y_{i,t-1} + \sum_{l=1}^{p_i} \varphi_{il}\, \Delta y_{i,t-l} + c_i \bar{y}_{t-1} + \sum_{l=0}^{p_i} d_{il}\, \overline{\Delta y}_{t-l} + u_{it} \quad (1)$$

The first four terms on the right-hand side are known as the Dickey-Fuller equation for unit root tests. Because of the cross-section dependence (csd) of the residuals, Pesaran (2007) adds a common factor f_t assumed to cause the cross-section dependence to the first four terms. Averaging over the left-hand and right-hand sides of (1) allows solving for f_t in the form of the last two terms of (1), which are cross-section averages and can be used in the empirical work to take cross-section dependence into account. This is a special case of only one common factor where the unit root test is whether $\gamma_i = 0$ in (1), which would lead to having (1) in differences. The test is called CIPS (cross-sectionally augmented Im-Pesaran-Shin test). Bai and Ng (2004) have developed a method to get more common factors from models of factor analysis. Bai and Ng (2004) and Ahn and Horenstein (2013) have developed different approaches to finding the optimal number of common factors leaning on the most important principal components or on eigenvalue and growth ratios.

3.2 Cointegration testing linked to VECMs

As all variables are likely to have unit roots (reported in section 4 below), we need to test for the cointegration of the pairs of variables for the five central growth relations. For examples like the five relations presented in the introduction note that "the test[18] may lack the power to detect all cointegration relationships and, as a result, may understate the true cointegrating rank … . Hence, it is recommended to apply cointegration tests to all possible subsystems as well and to verify whether the results are consistent with those for the full model. For example, in a K-dimensional system where all variables are individually I(1) (integrated of order one meaning stationary after differentiating once), if all variables are cointegrated in

returns to investment in building experience. Building these indices for specific purposes, however, is a different task than integration of R&D expenditures into national accounts.

[17] I am grateful to Bart Verspagen for providing the R&D data.

[18] Johansen test consisting of the trace test and the maximum eigenvalue test for a single country.

pairs, the cointegrating rank must be $K - 1$. Cointegration for the bivariate subsystems may be easier to analyze than cointegration in the full K-dimensional system. This observation suggests that one should analyze the subsystems first and then assess whether the subsystem results are consistent with the results for the full system, ...” (Kilian and Lütkepohl 2017). Following this advice for our panel data set, we should test cointegration for all of the five relations as pairs of variables. If we do not find five cointegrating relations, $r = 5$, we should go to four triples of variables, $r = 4$, and again test for cointegration, proceeding this way until we find cointegration, or, in the end, no cointegrating relation for all the six variables together. This order of proceeding is the opposite of that in the trace test and maximum-eigenvalue test (see below). For each country and pair of variables there could be a vector-error-correction model as in (2) explained in detail in section 3.3.

$$dy_t = \alpha\beta' y_{t-1} + B_1 dy_{t-1} + B_2 dy_{t-2} + \cdots B_{p-1} dy_{t-(p-1)} + cX' + u_t \qquad (2)$$

The number of variables for each pair under consideration here is $K = 2$, and in case of rejection of cointegration for one of the pairs we go to $K = 3$, and so forth. α is the matrix of adjustment coefficients. β is the matrix of coefficients of the cointegrating equations. α and β are matrices of format (K,r), in the first instance $(2,r)$, implying that β' has format $(r, K) = (r, 2)$ and $\alpha\beta'$ has format $(K, K) = (2, 2)$. $\beta' y_{t-1} = u_{t-1}$, with format $(r,K)(K,1) = (r,1)$ are the r long-term, cointegrating equations. The trace test (and perhaps in addition the maximum eigenvalue test) is used to find the number of cointegrating equations or eigenvectors, r, by way of testing whether the corresponding eigenvalues are sufficiently different from zero. If $r = 0$, there are no eigenvectors and eigenvalues statistically different from zero, and therefore there is no cointegration and (2) is estimated in differences. If $r = 1$, we have one cointegrating equation and one unit eigenvalue. If $r = 2$, the matrix $\alpha\beta'$ has full rank, indicating that there are no unit eigenvalues, and the system of two equations could also be estimated as a VAR in levels. The p-values for the hypotheses ‘at most 0, 1, or 2 cointegrating equations’ for each country are then used to carry out the Johansen-Fisher test for the panel (Maddala and Wu 1999). The statistic $-2\sum_{i=1}^{N} ln p_i$ has a chi-square distribution with $2N$ degrees of freedom, where $N = 14$ is the number of countries in our case. Note that $ln\ p_i < 0$. For low p_i values for the hypothesis $r = 0$, the chi-square statistic is high, and the p-value of the chi-square test is low, leading to the rejection of the hypothesis $r = 0$. The test continues going to the hypothesis $r = 1$. If the p_i values for $r = 1$ are high, the chi statistic is low, the p-value for the panel hypothesis is high, and $r = 1$ is not rejected. If the hypothesis is rejected instead, the result is $r = K = 2$; there is no unit eigenvalue in the system and the estimation can be done in levels without combining them with differenced terms.

Kao’s (1999) panel cointegration test is also reported. It is residual (Engle-Granger) based, searching for a unit root in the residuals of the regression of interest. It has the null hypothesis ‘no cointegration’. From the seven tests of Pedroni (1999) we use the Group ADF test. It is evaluated positively by Wagner and Hlouskova (2009) in regard to providing good results in the presence of cross-setional correlation, cross-unit correlation and I(2) variables although the test does not take these aspects into account.

As the Johansen-Fisher test and Kao’s test do not take into account cross-section dependence, we also use the common correlated effects approach to testing cointegration of Pesaran (2006). It adds the averages of variables as in (1) to a correlation of the two or three variables. When residuals have no unit root, the variables are cointegrated.

3.3 A VECM with fixed effects, slope homogeneity in differenced terms and adjustment coefficients, and growth relations from DOLS and FMOLS

There is a broad literature for many areas in economics estimating *one* cointegrating panel relation using FMOLS or DOLS and inserting it into a panel VAR in differences.[19] Hsiao (2022), chapter 5.3.2.1, deals with the extension to several cointegrating equations suggesting the use of the within-estimator of FMOLS and DOLS (obtained with fixed effects) to get the cointegrating relations. Hsiao (2022) reports that Kao and Chiang (2000) find that DOLS is preferable in case of one cointegrating equation. Kao and Chiang (2000) end their paper by suggesting the investigation of the group mean DOLS estimator. Pedroni (2001a) finds that using the group mean estimator matters more than the choice between FMOLS and DOLS. Moreover, Pedroni (2001b) and Pesaran (2015, p.851) point out that DOLS is an adequate method to take care parametrically of nuisance parameters. Combining the results of Kao and Chiang (2000) and Pedroni (2001a, b) in line with Hsiao (2022) would therefore suggest using the group mean DOLS and FMOLS estimators. We use the group mean estimators of FMOLS and DOLS. This procedure yields new results for long-term relations with group mean versions of slopes for FMOLS or DOLS estimates with country-specific fixed effects in a panel VECM, which has cross-section fixed effects also in the differenced part.

The starting point for panel VECM and Johansen-Fisher tests is an underlying country-specific VAR for *K* variables denoted as *y*, with *p* lags shown in equation (3).

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots A_p y_{t-p} + cX + u_t \quad (3)$$

X consists of exogenous variables like the unit vector and a time trend and possibly others. The lag length *p* is obtained through tests. Model (3) can be rearranged to get (3').

$$dy_t = \Pi y_{t-1} + B_1 dy_{t-1} + B_2 dy_{t-2} + \cdots B_{p-1} dy_{t-(p-1)} + c\tilde{X} + u_t \quad (3')$$

$\tilde{X}$ indicates that *X* may be transformed or be the same as in (3). Π is a (*K, K*) matrix and (3) or (3') can be used for estimation only if there are *K* cointegrating equations of the variables y_t. If there are $r < K$ cointegrating relations, we can re-write (3') as

$$dy_t = \alpha\beta' y_{t-1} + B_1 dy_{t-1} + B_2 dy_{t-2} + \cdots B_{p-1} dy_{t-(p-1)} + cX' + u_t \quad (2)$$

α and β are matrices of format (*K,r*) implying that β' has format (*r, K*), and $\alpha\beta'$ has format (*K, K*). $\beta' y_{t-1} = u_{t-1}$ are disequilibrium terms or cointegrating equations, with format (*r,K*)(*K,1*) = (*r,1*). In equilibrium, $\beta' y_{t-1} = u_{t-1} = 0$ are the *r* long-term relations. In case of disequilibrium, $\alpha u_{t-1} \neq 0$ with format (*K,r*)(*r,1*) is the impact of disequilibrium on the left-hand side and therefore the coefficients α are called the adjustment coefficients.

The trace test is a method to determine the number *r* of cointegrating equations (see Enders 2015). If $r = K$ (full rank of Π) we can use the level equation (3) for estimation. If $r = 0$, the case of no cointegration, the first term on the right-hand side of (2) drops out and we estimate (2) in differences. The trace test starts with hypothesis of no cointegration, $r = 0$. If the p-value is above five or ten percent the hypothesis is accepted and the procedure stops; below five or ten percent, the hypothesis is rejected and replaced by the hypothesis $r = 1$. For $r = 1$, the p-value rule is used again, leading either to acceptance or to moving to $r = 2$. The

[19] An interesting paper in the economics of innovation is Castellacci and Natera (2013).

procedure goes on until $r = K\text{-}1$. If the hypothesis is rejected, we have $r = K$. If there are only two variables as in the case of pairwise cointegration testing, $K=2$, this implies $K = r = 2$, and the matrix Π has full rank leading to estimation of (3) in levels.

Once the number of cointegrating equations is obtained through the trace test the long-term relations have to be normalized to find economically meaningful and statistically significant relations. The problem that makes normalization necessary is that β is not unique, which can be seen as follows (see Pesaran 2015; Hsiao 2022). $\alpha\beta' = \alpha I\beta'$, where I is the (r,r) identity matrix, which can be written as $I = Q^{-1}Q$, where Q is any invertible (r,r) matrix. Using this we get $\alpha\beta' = \alpha I\beta' = \alpha Q^{-1}Q\beta'$. This implies that α and β are unique only after fixing the r x r elements of Q and thereby also its inverse. The Johansen default for this is $(I_{r,r}, \beta_{r,K-r})$, where $\beta_{r,K-r}$ is a matrix with r rows and $K\text{-}r$ columns. The extensive form of this for the case $r = 3$, $K = 5$, $K - r = 2$ is

$$\left(I_{r,r}, \beta_{r,K-r}\right) = \begin{bmatrix} 1 & 0 & 0 & \beta_{1,4} & \beta_{1,5} \\ 0 & 1 & 0, & \beta_{2,4} & \beta_{2,5} \\ 0 & 0 & 1 & \beta_{3,4} & \beta_{3,5} \end{bmatrix}$$

. The long-term relations then are

$$\left(I_{r,r}, \beta_{r,K-r}\right) \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix}_{t-1} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

. Each of the first three y-terms are a function of y_4 and y_5. Each of the three equations can be divided or multiplied by any (non-zero) value without changing the solution of the VECM. This is called re-normalization. However, the t-value will change with the coefficients. Whereas econometricians deal with the Johansen default, economists should try to find a re-normalization, which leads to economically meaningful and statistically significant equations (Jusélius 2006). Independent of the chosen normalization no causality direction is excluded; in the case of two variables this implies allowing for two-way causality. In the case of monetary macroeconomics these equations are the standard textbook equations like (uncovered) interests parity (UIP), PPP (purchasing power parity), and money demand. Therefore, the long-term relations show the theoretical core of the VECM and in similar cases it is false to say that a VECM is a tool without theory. For R&D variables, GDP and TFP, the link between theory and VECMs of Soete et al. (2022) is shown in Ziesemer (2021a).

Equation (2) now holds with $K = 14x6$, for 14 countries indexed i, with each $K_i = 6$ endogenous variables and equations leading to 84 equations with 84 variables on the left-hand side. The adjustment coefficients and the r_i long-term relations are the same for all countries and therefore α and β are matrices with format *(14x6, r)* but constrained to have the same *6 x r* adjustment coefficients in all 14 countries and no cross-unit cointegration except for the foreign R&D variables. The long-term relations, β'y, therefore, have format *(r, 14x6)(14x6, 1)*. The product of the long-term relations with the adjustment coefficients can be written in the form $\underbrace{\alpha\beta' y}_{(14x6,r)(r,14x6)(14x6,1)}$, which has format *(14x6, 1)* as the left-hand side of (2). Each differenced term Δy on the right-hand side is also *(14x6, 1)* for each lag l of each variable, and the matrices B_l are *(14x6, 14x6)*. Slope homogeneity turns this into having only *36 (6x6)* different coefficients for each lag of the differenced terms. Finally, the deterministic term at the end of the equations is the unit vector with unrestricted coefficient, which are

14x6 cross-section fixed effects. In short, we have 14 VECMs with each six equations, 84 fixed effects and slope homogeneity in the adjustment coefficients and differenced terms.[20]

Estimation of the coefficients of differenced terms, the fixed effects and adjustment coefficients with long-term relations given from separate estimations using DOLS and FMOLS entering the VECM with country-specific data, yields then new results. In order to take into account cross-section dependence in the residuals, we use the SUR (seemingly unrelated regression) method as originally suggested by PSS (1999), which is possible because we have more periods than countries and T is large compared to the number of 14 countries.[21] In the case of slope homogeneity where heterogeneity is limited to fixed effects (besides the group mean FMOLS and DOLS estimation of the long-term relations estimated separately), fixed effects in combination with lagged dependent variables lead to the Nickel bias, which is small though in our case of $T = 44$ (1973-2017, in terms of estimated residuals) and therefore does not require to eliminate them.

Ideally, we would also have liked to allow also for slope heterogeneity in the differenced terms and leaving only long-term relations with slope homogeneity as suggested by the PMG (pooled mean-group) estimator of PSS (1999) and by Breitung (2005). Groen and Kleibergen (2003), Breitung (2005) and Larsson and Lyhagen (2007) have proposed multi-country VECMs with identical long-term relations for all countries, but country-specific adjustment coefficients. The extension in the textbook version of Hsiao (2020), ch. 5.3.2.2, has slope heterogeneity in the differenced terms. However, this approach leads in our case to *14x6x4 = 336* adjustment coefficients (14 countries, each six equations with each four long-term relations), and with three lags in the differenced terms this would be *14x6x6x3 = 1512* coefficients for the differenced terms, whereas a package like EViews allows only for a maximum of *750* coefficients. In a panel VAR without long-term relation, we would still have 6x6x14 =504 slope coefficients for each lag. Curtailing lags to one would work technically, but cutting their number in an area that is prone to serial correlation issues like unit roots is not recommended and information on long-term relations would be missed. Therefore, besides reasons of length of the paper, these extensions to slope heterogeneity are not carried out here.

4. Estimation results from dynamic modelling

4.1 Unit roots results

Table 1 shows that panel unit roots cannot be ignored based on the Pesaran (2007) CIPS test. For public R&D there is a unit root only near the 5% level; all other variables have a probability of more than 10% for a unit root.

Table 2 reports country-specific information of unit roots based on the cross-sectional ADF (augmented Dickey-Fuller) unit root test. For the GDP variable, only Germany (DEU) has no unit root at the 10% level. The p-value is slightly larger than the 5% level as can be seen from comparing its t-value with the critical values in the notes to Table 2. For labour-augmenting

[20] The counterpart for stationary variables is discussed by Rebucci (2010).
[21] The GMM approach emphasized in the textbooks is for short panels.

Table 1 Panel unit root tests with cross-sectional dependence: Pesaran CIPS

Variable	t-value	p-value	Balanced observations	Total observations
LGDP	-1.97	>=0.10	54	756
LTH07	-2.056	>=0.10	54	756
LBERDST	-2.268	>=0.10	51	714
LPUBST	-2.77	< 0.10	48	672
LFPUBST	-1.4	>=0.10	54	756
LFBERDST	-2.073	>=0.10	54	756

Notes: Sample 1963-2017. 14 countries. Null hypothesis: Unit root. Critical values CIPS: 10% level is -2.67; 5% level is -2.78; 1% level is -2.96. All tests include constants and trends. Truncated values do not differ from the reported ones.

Table 2 Cross sectional ADF unit root tests for 14 OECD countries: Lags, t-values, and p-values

Country	LGDP	LTH07	LBERDST	LPUBST	LFPUBST	LFBERDST
AUT	6, -2.3, >=.10	7, -1.25, >=.10	6, -4.1, <0.05	7, -2.83, >=.10	6,-0.33, >=.10	7, -2.75, >=.10
BEL	3, -1.01, >=.10	1, -3.87, <0.05	5, -1.29, >=.10	7, -1.68, >=.10	6, -3.37, >=.10	1, -2.5, >=.10
DEU	7, -3.735, <0.10	2, -3.3, >=.10	7, -0.947, >=.10	1, -4.54, <0.01	7, -0.6, >=.10	6, -2.23, >=.10
DNK	1, -3.3, >=.10	7, 0.5357, >=.10	7, -2.98, >=.10	2, -4.07, <0.05	7, -0.77, >=.10	6, -1.0, >=.10
ESP	7, -1.323, >=.10	7,-1.888, >=.10	6, -3.9, <0.05	7, -3.256, >=.10	2, -1.916, >=.10	2, -1.86, >=.10
FIN	7,-2.47, >=.10	6, -2.02, >=.10	5, 0.625, >=.10	1, -2.64, >=.10	5, -1.45, >=.10	6, 0.51, >=.10
GBR	6, -2.265, >=.10	6, -2.78, >=.10	1, -2.72, >=.10	1, -1.96, >=.10	6, -1.176, >=.10	1, -4.464, <0.05
ITA	7, -2.08, >=.10	7,-1.55, >=.10	1, -2.4, >=.10	3, -3.62, <0.10	6, -0.127, >=.10	1, -4.03, <0.05
JPN	2, -1.13, >=.10	7, -3.04, >=.10	2, -3.13, >=.10	2, 0.175, >=.10	2, -0.22, >=.10	3, -1.69, >=.10
NLD	4, -2.1, >=.10	6, -2.07, >=.10	3, -3.56, <0.10	3, -1.717, >=.10	1, -1.57, >=.10	1, -3.22, >=.10
NOR	7, -0.457, >=.10	7, -2.446, >=.10	2, -0.88, >=.10	1, -2.93, >=.10	3, -2.57, >=.10	2, -1.27, >=.10
PRT	7, -0.77, >=.10	1, -2.95, >=.10	4, 1.05, >=.10	5, -3.97, <0.05	4, -1.85, >=.10	7,-1.335, >=.10
SWE	5, -2.29, >=.10	2, -0.84, >=.10	6, -2.03, >=.10	3, -4.2, <0.05	4, -1.35, >=.10	7, -0.74, >=.10
USA	6,-2.357, >=.10	3, -1.31, >=.10	7, -5.49, <0.01	2, -1.535, >=.10	3, -2.29, >=.10	7, -2.44, >=.10

Null hypothesis: Unit root for specified cross-section. Lag selection: AIC (Akaike information criterion) with maxlag=7. Critical values CADF (values in parentheses for LBERD and LPUBST deviate slightly): 10% level is -3.44 (-3.45); 5% level is -3.78 (-3.79); 1% level is -4.49 (-4.52). All tests include constants and trends. Truncated values do not differ from the reported ones.

technical change only Belgium has a probability below 5% for a unit root. There are low probabilities for unit roots in private R&D stocks for Austria, Spain, Netherlands, and USA.

Germany, Denmark, Italy, Portugal, and Sweden do have a probability lower than 10% for a unit root in public R&D. For foreign public R&D, t-values are negative indicating that roots are below unity, but not statistically significantly so at the 10 percent level. For foreign private R&D the UK and Italy have a probability below 5 percent for a unit root; all other countries have a higher probability than 0.1. Reading Table 2 from a country perspective, countries with two variables that have no unit root at the 10% level are DEU and ITA; countries with one variable that has no unit root at the 10% level are AUT, BEL, DNK, ESP, GBR, PRT, NLD, SWE, USA. FIN, JPN, and NOR have unit roots with high probabilities in all variables.

Whenever there is no unit root at the ten percent level, there can still be near unit roots, with coefficient values for the lagged dependent variables of 0.8-0.99 instead of unity (Enders 2015, p.236), causing similar problems as unit roots do. Table A.1 in the appendix shows similar results for the Bai/Ng unit root tests. Table 2 and Table A.1 both suggest that the problem of unit roots in the data cannot be ignored and thinking about cointegration is necessary.

4.2 Panel cointegration results

In this section we look at the pairs of variables, which constitute the five crucial relations mentioned in the introduction. Basically, the tests are for cointegration of I(1) variables. If in the pairs of variables considered next there would be any combination of I(0) and I(1) variables we should not find cointegration for them, because combinations of I(0) and I(1) variables are I(1) according to statistical theory.

Rows 1 and 2 in Table 3a are for the Fisher-Johansen test. The probability for no cointegration, except for the last column, is zero according to row 1. We find one panel cointegrating equation for each pair of variables with probabilities larger than the 10% level in row 2. Kao's test suggests probabilities below 8% for the hypothesis of 'no cointegration' in row 3. Pedroni's Group ADF test has similar low proabilities for 'no cointegration' except for the foreign R&D variables. The results of Table 3a mostly reject the hypothesis of 'no cointegration' under the tests assuming no cross-section dependence. However, the CIPS test shows that there is a unit root with more than 10% probability and therefore no cointegration for three of the pairwise relations.[22] Therefore, we go from pairs of variables to triples.

In line with VECM theory of section 3 we assume next having four cointegrating equations consisting of four triples of variables: The Johansen default for the long-term relations before re-normalization is $(I_{r,r}, \beta_{r,K-r})$, meaning that there are $r \times r = 4x4$ fixed coefficients in the form of the identity matrix and in each of the r cointegrating equations there are $K - r = 6 - 4$ free coefficients in each of the triples of variables, which have to be tested for cointegration.

[22] See appendix for other differences in the model with five pairwise cointegrated relations.

Table 3a Panel cointegration tests: p-values for five relations for growth (a)

Fisher-Johansen test. No. of CEs	LGDP-LTH07	LTH07-LBERD	LBERD-LPUB	LPUB-LFPUB	LFPUB-LFBERD
No ce (b)	0.0000	0.0000	0.0000	0.0000	0.0651
At most 1 (b)	0.279	0.293	0.460	0.323	1
Residual based tests					
Kao test (c)	0.0016	0.0710	0.0012	0.0387	0.0000
Pedroni Group ADF	0.0815	0.006	0.004	0.0094	0.494
CIPS (d)	< 0.01	> 0.1	> 0.1	> 0.1	< 0.01

(a)All variables in logs. Sample: 1963-2017. (b) Johansen-Fisher trace test assumptions: Linear deterministic trend in each relation; lag intervals are chosen in line with the automatic choice of PMG estimators (not shown). (c) Kao and Pedroni test assumptions: null hypothesis 'no cointegration'; lag length by the AIC; 'trend' included (in the list of regressors in Kao's test). (d) CIPS test construction: DOLS grouped cointegrating regression of two variables and their period-specific demeaned version with linear trend and constant; automatic leads and lags specification (based on AIC criterion, max=*); long-run variances (Prewhitening with lags from AIC maxlags = -1, Bartlett kernel, Newey-West automatic bandwidth, NW automatic lag length) used for individual coefficient covariances; saving residuals; Pesaran (2007) panel unit root test on residuals using constant and trend; null hypothesis: unit root (no cointegration for all countries.

Table 3b Panel cointegration tests: p-values for four growth relations (a)

Dependent variable	LGDP	LTH07	LBERDST	LPUBST
Regressors	LTH07, LBERDST	LBERDST, LPUBST	LPUBST, LFBERDST	LFPUBST, LFBERDST
None (b)	0.0000	0.0000	0.0000	0.0000
At most 1 (b)	0.0001	0.0000	0.0000	0.0359
At most 2 (b)	0.7230	0.5337	0.0067	0.9980
Kao test (c)	0.0018	0.1160	0.0012	0.0389
Pedroni Group ADF test (c)	0.0110	0.4236	0.0000	0.0000
Obs. In DOLS	714	708	702	702
s.e. of regress.	0.95	4.938	6.48	7.67
CIPS (d)	p < 0.05	p < 0.01	p < 0.05	p < 0.01 (e)
Obs. In CIPS	672	630	630	630

(a) – (d) As in Table 3a. (e) small p only for truncated value, avoiding 'undue influences of extreme outcomes' (Pesaran 2007).

The results for Fisher-Johansen cointegration tests assuming no cross-section dependence for triples of variables in Table 3b again reject the hypothesis of no cointegration, and also reject the hypothesis of one cointegrating equation in all columns; sub-systems of triples could be estimated by VARs in levels for column 3, but for the other three columns we get two cointegrating equations from the Fisher-Johansen test, which is in line with Table 3a, which supports pairwise cointegration when tests ignore cross-section dependence. The tests of Kao and Pedroni have low probabilities for the hypothesis of 'no cointegration'. For the CIPS test the hypothesis of unit roots (no cointegration) for all countries is rejected in all columns.

Unlike the tests for pairs of variables the CIPS test result does not go against the other tests. This can be taken as evidence of cointegration for the four triples of variables.

4.3 Results for a two-stage VECM with long-term relations from DOLS and FMOLS estimates

In this section we use the four triples of variables discussed above in a VECM in order to see whether the impact of public R&D on technical change and growth is also present in the form of an impact of accumulated shocks on the solution of a model and not only as an interpretation as partial regression results obtained so far in the panel literature and through cointegration tests in this paper.

The VECMs for each separate country analysis mostly have four lags according to the AIC criterium suggested by Kilian and Lütkepohl (2017), which is also their maximum suggested by Schwert's (1989) formula; this leads to three lags in differences. In case of using $r = 5$, the corresponding pairwise panel cointegration tests of Table 3a have unit roots and therefore no cointegration with $p > 0.1$ for three of the five pairs. Four cointegrating equations imply triple wise cointegration, which is supported by the CIPS test in Table 3b. Therefore, the number of cointegrating relations is imposed as $r = 4$, which is a frequent case in the country-by-country estimates in Soete et al. (2022); other frequent cases are $r = 3$ and $r = 5$.

The slope coefficients for the long-term relations can be obtained from cointegrating regressions, FMOLS and DOLS. FMOLS and DOLS estimations integrate constants and linear time trends in data transformations without presenting them in the regression output. Therefore, we use the slope coefficients from the cointegrating FMOLS and DOLS regressions and run a fixed effects regression with cross-section weights to find the coefficients for trends and intercepts for given slopes. If the time trend is highly insignificant, we drop it from both steps and rerun the procedure without time trend. These results for the long-term relations are shown in Table 4.

In the first relation, the results from FMOLS and DOLS show a positive effect of productivity on GDP; BERD sometimes is significant as well, but dropping it improves the goodness of fit indicators and is allowed because Table 2 shows that log-productivity and LGDP are cointegrated.

In the second relation, public and private R&D have a positive effect on labor productivity and therefore support the significantly positive direct effect of public R&D found by Guellec and Van Pottelsberghe (2004). A similar result was emphasized in the survey of OECD (2017) and found by Guellec and van Pottelsberghe de la Potterie (2002), and Luintel et al. (2014), who all also find positive effects of public R&D on productivity. Public R&D has a slightly negative direct effect in Bassanini et al. (2001); in Park (1995) it was insignificant at the 5% level when considering spillovers, and in van Elk et al. (2015, 2019) it appears with negative sign and statistical significance only in the regressions with the simplest production functions and limited control variables.

In the third relation in Table 4, the DOLS result for the effect of public on private R&D, has the same elasticity as a result for OECD industries and French firms and industries in a static panel data analysis by Moretti et al. (2023), saying that a 10% increase in publicly *financed*

R&D increases privately *financed* R&D, both performed by private firms, by 5 to 6% from IV (instrumental variable) estimation, but only 25% of this under OLS; our result is for

Table 4 Long-term relations from FMOLS and DOLS

Dependent variable	LGDP	LTH07	LBERDST	LPUBST
Regressors	LTH07, LBERDST	LBERDST, LPUBST	LPUBST, LFBERDST	LFBERDST, LFPUBST
Model 1	*Fully modified OLS (FMOLS) (b)*			
Slope (a)	0.895	0.2914	0.4036	-0.109
Slope (a)	-	0.2912	0.401214	3.528
Trend (e)	0.0127	-0.013	0.017849	-0.06
Constant (e)	11.0745	-3.529	0.334	-31.97
Adj. R-squared	0.997	0.899	0.986	0.99
Observations (g)	770	744	744	744
No csd p-val.(f)	0.0390	0.0608	0.1380	0.9504
Model 2	*Dynamic OLS (DOLS) (c)*			
Slope (a)	0.783	0.31	0.546	0.737
Slope (a)	-	0.174 (0.0014)	0.73	1.475
Trend (d)	0.014	-0.009	-	-0.029
Constant (e)	11.245	-2.67	-4.93	-17.985
Adj. R-squared	0.997	0.928	0.99	0.989
Observations (g)	770	744	744	744
No csd p-val.(f)	0.3416	0.3367	0.0004	0.0008
Model 3	*DOLS*		*FMOLS*	
Slope (a)	0.783	0.31	0.4036	-0.109
Slope (a)	-	0.174 (0.0014)	0.401214	3.528
Trend (d)	0.014	-0.009	0.017849	-0.06
Constant (e)	11.245	-2.67	0.334	-31.97
Adj. R-squared	0.997	0.928	0.986	0.99
Observations (g)	770	744	744	744
No csd p-val.(f)	0.3416	0.3367	0.1380	0.9504

(a) Slope of the variables in the pair of the second line obtained from FMOLS and DOLS dealing with endogeneity and serial correlation in variable transformations, with information as under (b), (c), (d). (b) Grouped estimation with linear trend; prewhitening: AIC; Bartlett kernel; Bandwidth: Newey-West automatic. (c) same assumptions as for FMOLS, with leads & lags using AIC. (d), (e) 14 countries; 55 periods. Panel EGLS regression with slopes fixed as from (a); cross-section weights in estimation of coefficients and covariance; Period SUR PCSE (panel corrected standard errors) & covariance (d.f. corrected). P-values 0.00 (rounded) unless indicated otherwise in parentheses. (f) Pesaran cross-section dependence test on the residuals of the equation. (g) Norway and Finnland have shorter R&D series compared to TH07 and GDP.

publicly and privately *performed* R&D though.[23,24] A positive effect of publicly *funded* on privately *funded* R&D was found for OECD countries by Guellec and van Pottelsberghe (2003),[25] who also point to a positive relation in earlier macroeconomic studies, and also by Jaumotte and Pain (2005a,b), Falk (2006) and Sveikauskas (2007), where Falk uses university R&D data. The third relation supports the results of Soete et al. (2020, 2022) mainly for EU countries, and Rehman et al. (2020) for a larger panel, regarding the effect of publicly performed on privately performed R&D.[26] Most recently, Ciaffi et al. (2023) find crowding in of private R&D expenditures through public R&D expenditures. Ziesemer (2021a) provides the related theory linking a VES function for TFP depending on R&D stocks to some country specific VECM estimates of Soete et al. (2022). Public R&D here has a positive direct effect on producitivty and an indirect effect on producitivty via private R&D in the third relation of Table 4. Huang et al. (2023) include public and private R&D in a second-generation endogenous growth model with vertical and horizontal innovation resulting in positive direct and indirect effects of public R&D on a Cobb-Douglas labour-productivity function at least in the long run, whereas in the short run the effect of public R&D may be negative as in some of the empirical studies mentioned above.

Private R&D reacts in the third relation positively to its foreign counterpart, which is plausible as an oligopolistic reaction (see Ziesemer 2022) and as coming from spillovers.

The fourth relation suggests that domestic public R&D reacts to foreign private and public R&D, because public R&D institutions follow and use international developments of R&D.

The statistical significance in all equations of Table 4 confirms the cointegration test results from Table 3b. As explained in section 3, Kao and Chiang (2000) prefer the DOLS method above OLS and FMOLS whereas Hsiao (2020) expresses no preference over DOLS or FMOLS for the case of several long-term relations, and Pedroni (2001a) prefers the group mean versions of DOLS and FMOLS above the within versions. We use only group mean versions. For the first two equations we use the DOLS version and for the third and fourth equation we use the FMOLS version, because these estimates are better in terms of cross-section dependence.[27] This combination is indicated as Model 3 in Table 4.

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[23] From a policy perspective it is not only important how much funding for R&D governments want to spend but also whether to give it to private business or to public institutions performing (executing, conducting) the R&D.

[24] In more formal terms, and for the corresponding R&D capital stocks, Moretti et al. define BERD = R+S and investigate the impact of S on R. We use GERD – BERD = PPR&D (publicly performed R&D flow) and investigate the impact of the stocks of PPR&D (LPUBST) on BERD (LBERDST). The theory of Huang et al. (2023) can be interpreted as seeing a log-log effect of S/BERD on the change or growth rate of BERDST.

[25] Subsidies have an inverted u-shape with a peak at 10% and negative values beyond 20%, and a negative effect for publicly performed R&D (which may have collinearity with publicly funded R&D) and negative effects for defense R&D shares all in terms of growth rate regressions with one lag using 3SLS (three stage least squares) for 17 OECD countries 1984-1996. Literature with data ending 1995 and earlier is surveyed in OECD (2017) and we do not repeat it here for reasons of space.

[26] Literature going beyond OECD samples or to the sector level or requiring a more sophisticated discussion is summarized in OECD (2017) and Ziesemer (2021c).

[27] To remove cross-sectional dependence, we could use principal component scores (if not correlated with the regressors) as Coakley et al. (2002) do or period-specific cross-section average values of the variables in a regression as in Pesaran (2007) assuming one common factor only. However, then these new variables have to be integrated into the VECM. This would be possible in the form of a weakly exogenous VAR in these factors.

We insert the group mean DOLS and FMOLS regression equations from Model 3 of Table 4 into the VAR in differences with *14x6* variables and equations as described in detail in section 3.3. Given the long-term relations from Table 4, the next interesting result is that for the adjustment coefficients shown in Table 5, which are by construct identical for all countries.

Table 5 Adjustment coefficients of the VECM cum DOLS and FMOLS (a)

Cointegrating equation → dependent variable↓	GDP, LTH07	LTH07, LBERDST, LPUBST	LBERDST, LPUBST, LFBERDST	LPUB, LFPUBST LFBERDST
D(LOG(GDP))	-0.079	-0.049	-0.0268	-0.00116 (b)
D(LOG(TH07))	-0.051	-0.057	-0.0229	-0.0099
D(LOG(BERDST))	-0.0035	-0.0195	-0.017	-0.0018
D(LOG(PUBST))	0.0077	0.00095 (c)	0.0017	-0.009
D(LOG(FBERDST))	-0.0033	0.00039	-0.001	0.002
D(LOG(FPUBST))	0.0052	0.003	0.0011	0.00078

(a) Period: 1967-2017; obs: 4128. Estimation Method: Seemingly Unrelated Regression for VECM; cointegrating equations from Table 4: group mean DOLS for first and second long-term relations and FMOLS for third and fourth cointegrating equations. Linear estimation after one-step weighting matrix. The determinant of the residual covariance matrix is 0.000000. P-values = 0.00 (rounded) unless indicated otherwise. (b) p = 0.0887; c) p = 0.1272.

Estimation results for the VECM with cointegrating level equations from group mean DOLS and FMOLS estimation show that there is only one (of *24 = 6x4* statistically insignificant adjustment coefficients at the 10 percent level and one at the five percent level in Table 5. The adjustment coefficients are small and mostly negative. By implication, none of the variables is weakly endogenous (not affected by any disequilibrium) and none of the long-term relations is redundant (not affecting any dependent variable). We have simplified the model by leaving out labour and capital, which would lead us back into the area of large models. As a consequence, among the 84 equations the adjusted R-squared is very weak for the GDP and technical change equations, although the R-squared is doing reasonably well (see Table A.2). There are seemingly many lagged terms, which add very little to the explanation when coefficients are restricted. These terms may explain the good Durbin-Watson statistics though, which are important for avoiding serial correlation bias. Equations for R&D variables have very high adjusted R-squared values. Very similar results also hold when we use the FMOLS Model 1 and the DOLS Model 2 from Table 4 instead of Model 3; therefore, the results for Model 1 and Model 2 are shown in an appendix more briefly.

However, they may depend on the 84 variables of the model, and it is hard to explore how. Therefore, we do not pursue this route.

5 Public and private R&D changes

5.1 Effects from enhancing public R&D

A crucial question is whether a change of public R&D leads to more productivity and higher GDP and effects on other R&D variables in line with model 3 in Table 4 when taking into account all feedback effects from the VECM. In this section we show results from imposing a shock of 0.005 on each country's intercept of the growth rate equation for public R&D, which is equivalent to a repeated one-time random shock.[28] Figure 1 shows that the 14 countries gain up to 12.5% in labor-augmenting productivity in the 37 years between 1973 and 2020, which is 12.5/37 = 0.338 percent per year.

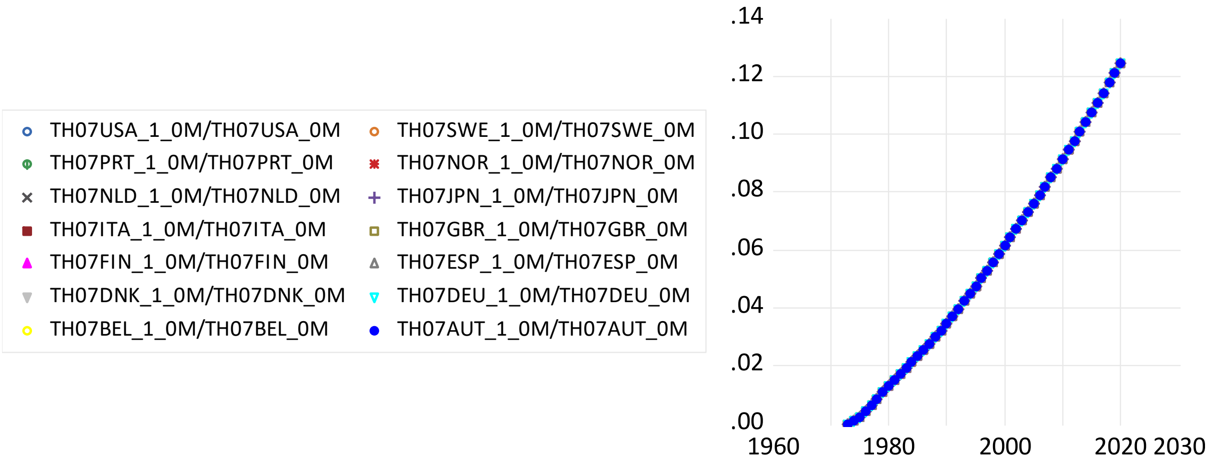

Figure 1 Effects of a shock of 0.005 on public R&D growth in 1973 on technical change (% TH07 baseline) for 14 OECD countries (14 lines visually on each other).

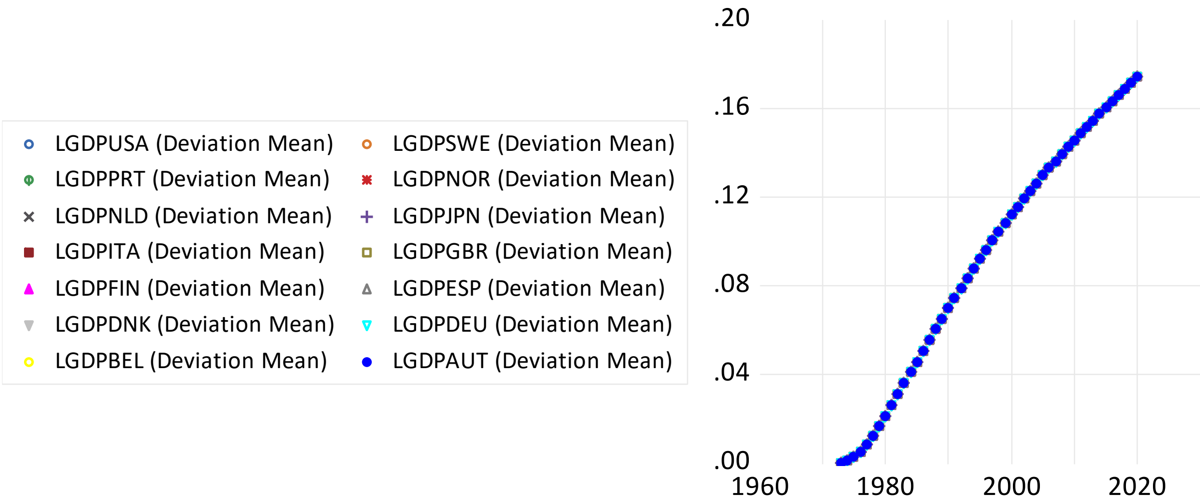

Figure 2 Effects of a shock of 0.005 on public R&D growth in 1973 on GDP (% GDP baseline). 14 OECD countries (14 very similar lines 'on' each other).

[28] For the econometrics of this approach see Lau (1997).

The percentage effect of a public R&D enhancement on GDP shown in Figure 2 is higher than that on technical change in Figure 1. This may be due to more inflow (less outflow) of capital and labor. In the case of using only FMOLS of Model 1 the effects on productivity and GDP are slightly larger, 26 and 28 percent; for pure DOLS of Model 2 they are 14 and 18 percent (see appendix), and here they are 12.5 and 17.4 percent. The choice of Model 3, emphasizing cross-section dependence, leads to the weakest effects.

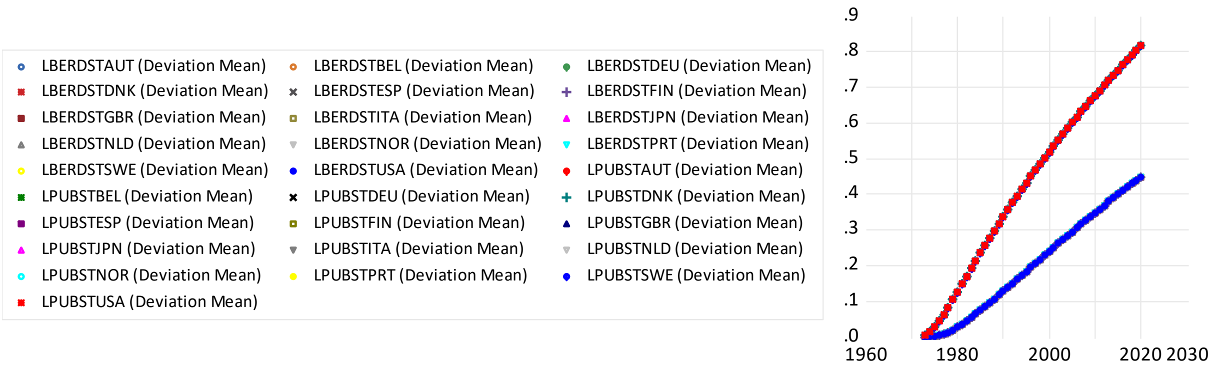

Figure 3 R&D stock changes from a 0.005 increase of the intercept of the public R&D growth equation with higher curves for public R&D and lower curves for private R&D, each for 14 countries. Public R&D runs up by about 80% above baseline and private R&D to 45%.

Public and private R&D stock increases by up to almost 80 and 45 percent of baseline values are shown in Figure 3, and almost 80% and 60% for the DOLS model 2 and slightly more than 100% and 55% for FMOLS model 1 above baseline in the appendix.

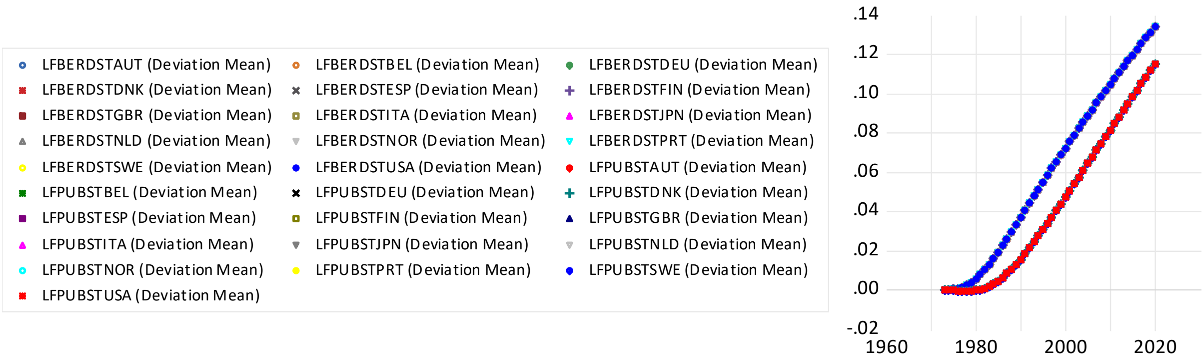

Figure 4 Foreign R&D reaction to a domestic public R&D enhancement. Higher curves for foreign private R&D (up to 13.4%); lower curves for foreign public R&D (up to 11.5%).

The results for Figure 1 to 3 have been obtained with feedback from what the other countries are doing in terms of foreign public and private R&D in each country's model. Figure 4 shows the (expected) foreign reactions, extending the result of Haskel and Wallis (2013) that domestic public R&D attracts foreign R&D to the UK, here for public and private foreign R&D separately for a panel of countries.[29]

This result suggests positively sloped reaction curves for public and private R&D from the perspective of the Cournot oligopoly model of Cabon-Dhersin and Gibert (2020) for which positive international spillovers of public to private R&D are required for positively sloped reaction curves.

In order to get a feeling whether the gains in terms of higher GDP outweigh the costs, we calculate the gains/GDP and the gains/cost ratio for every year. The yearly gross gains are the higher GDP of the policy scenario compared to baseline. The yearly costs are the differences in the domestic R&D stocks, requiring a higher net investment (plus higher depreciation a period later), again the scenario compared to the baseline. To approximate the costs roughly and in a simple manner, we take the percentage difference in the domestic public and private R&D stocks from Figure 3 and multiply them to the stock values of the baseline scenario resulting in the investment difference required to get the higher value; a factor of 1.15 adds the depreciation costs. The net gains are the gross gains minus the costs. We divide the net gains either by the GDP or by the costs, which is a different rate of return measure than those of the literature, which has estimated parameters of production functions (see Hall et al. 2010) or internal rates of return (Soete et al. 2020), which are discount rates that bring the sum of all discounted net gains to zero. If the flows of net gains are positive in all periods, internal rates of return are infinity. Therefore, utmost caution is required when comparing results for rates of return based on different concepts.

[29] The expected percentage reaction of foreign R&D variables in Figure 4 is weaker than the simulated one for domestic R&D variables in Figure 3. Moreover, public domestic R&D reacts stronger than private domestic R&D whereas for foreign R&D variables the opposite is the case. This is also the case for the pure DOLS model 2. For the FMOLS model private R&D variables are both higher than public R&D variables, but the foreign ones are very low and even negative for the early phase of foreign public R&D. As the aggregation from R&D flows to R&D stocks is not recalculated after the shock, these values for foreign R&D should be considered to be *expectations-compatible* recalculations. Although the ratio of domestic to foreign R&D variables for the 14 countries are between 45 and 115% in the data (also because of the distance weights), one might expect that in case of panel data analysis domestic and foreign R&D variables should be closer to each other in terms of percentage changes. One alternative could be to build foreign stocks from domestic stocks as in Park (1998) rather than building foreign flows and aggregating them as van Elk et al. (2015, 2019) do.

Figure 5 shows that net gains are between zero and 13% (zero and 21 percent of GDP for the FMOLS model 1 and the DOLS model 2; see appendices A and B.

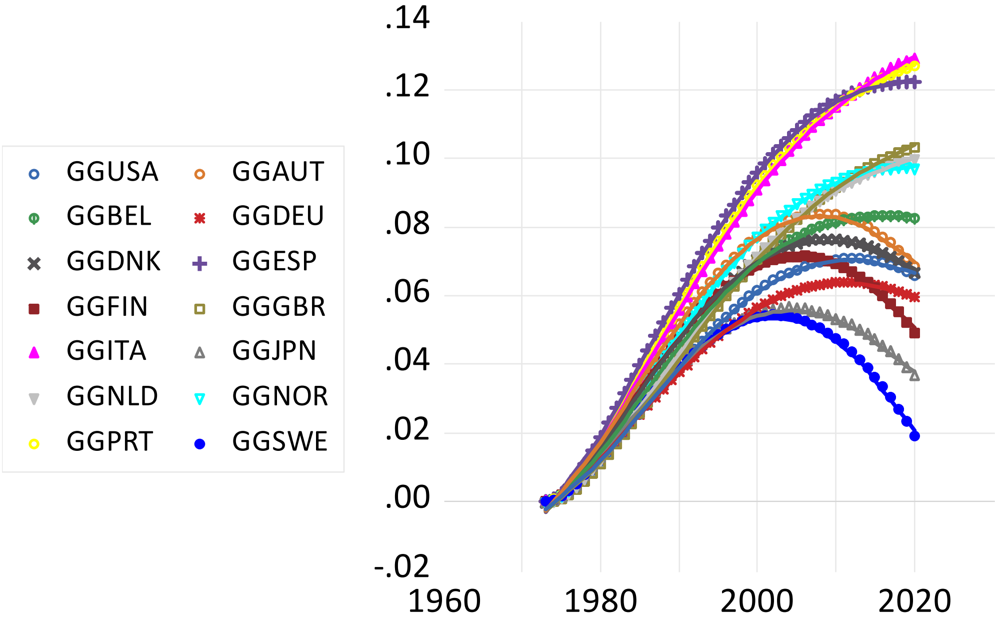

Figure 5 Yearly net gains as a percentage of GDP, all in terms of policy scenario compared to baseline.

Figure 6 shows that net gains run up mostly from zero to between beyond 500 percent of the yearly costs ignoring the outliers of Spain (also for the FMOLS and DOLS models). The gains/cost ratios all start at a value of -1 because the first period has costs, but gains come only later.

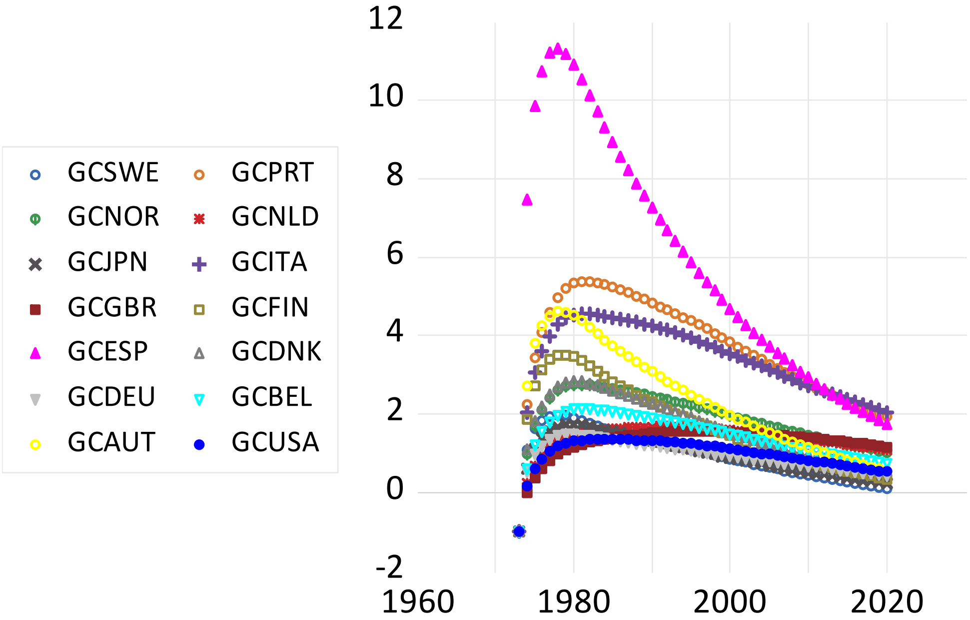

Figure 6 Yearly net gains as a percentage of yearly costs, all in terms of policy scenario compared to baseline.

Due to the nature of technical change, effects on GDP are accumulating over time. Similarly, the differences of the stocks are built through investment over several years. These rough and simple calculations suffice to indicate that additional public R&D is advantageous in the 14 OECD countries, but they do not compare to any form of rate of return because they just divide yearly gains and hypothetical costs or GDP by each other. Moreover, almost the same percentage changes in Figure 1 to 4 lead to different gains as percentages of cost or GDP for the countries because of different baseline levels.

5.2 Effects from enhancing domestic private R&D, foreign private and public R&D

A permanent change of the intercept of the equations for private R&D by 0.005 leads to negative effects on all variables (not shown) except private R&D itself up to 0.4, and a temporary small increase of foreign private (up to 0.0036) and domestic and foreign public R&D stocks (respectively not higher than 0.002 and up to 0.001) in spite of the long-run relations shown in Table 4. Technical change and GDP go down although long-term relations suggest that BERD should increase productivity and GDP. These partial long-term effects are outweighed by system feedback effects and show that positive partial effects in a long-term relation are not sufficient support for policy suggestions. The results are in line with the finding by Luintel and Khan (2004) that the effect of business R&D is weaker than effects of total R&D, pointing to a strong role of public R&D. Intuitively this could mean that private R&D is near its optimum and additional private R&D then is driving the economies away from the optimum to lower levels. Alternatively, this is a result where the slope homogeneity assumption introduces a heterogeneity bias, if the cross-section variance of the slope coefficients is large and persistence is not (Rebucci 2010) (perhaps together with end-of-sample bias through the 2007-2013 crises) with an impact on the simulation results. This alternative interpretation is more in line with the single country analyses for the Netherlands (Soete et al. 2020), USA and Japan in Ziesemer (2022, 2023b), where additional private R&D has positive effects, requiring that other countries have much less favourable results in separate analyses than these three.

In contrast, the same change for *foreign* private R&D drives up all variables for all countries (not shown): BERD and foreign BERD from zero to 160%, foreign public R&D to 92%, GDP to 82%, domestic public R&D by 240%, th07 by 216%. Percentages above 200 may seem unrealistic because they imply more than four percent for each year from 1973 to 2020. These numbers are very similar for DOLS model 2 and smaller in the case of FMOLS model 1.

The same change for foreign public R&D drives up (not shown) domestic public R&D up to 0.6 beyond baseline. Domestic and foreign private R&D go down. Foreign public R&D goes up to 35% beyond baseline, technical change goes up to 17.2% beyond baseline th07. GDP gets a positive effect running up to 10.4% of baseline. As domestic and foreign private R&D go down and productivity goes up there must be a positive effect from domestic and foreign public R&D although domestic and foreign public R&D here crowd out domestic and foreign private R&D.

6 Summary and conclusion

Our VECM approach of using four cointegrating equations shows favourable results for public R&D without resort to other variables than R&D, productivity, and GDP, whereas Khan and Luintel (2006) and van Elk et al. (2015, 2019) obtained similar results through adding control variables from international public and innovation economics. By implication, dependence of public R&D effects on national circumstances seems to be much lower for our approach for the 14 OECD countries. The four relations have support from (i) panel cointegration tests, (ii) cointegrating regressions using FMOLS and DOLS, (iii) shock (or impulse response) analysis for a panel VECM with four cointegrating equations. Distinguishing between direct and indirect effects of public R&D on productivity as done in these VECM models makes things economically a bit clearer and simpler.

In the long-term relations both, the direct effects of public R&D on productivity and the indirect ones via private R&D are positive when using group mean FMOLS or DOLS estimation.

Using the panel VECM with (i) DOLS long-term relations for the GDP and technical change equations and (ii) the FMOLS equations for the private and public R&D equations, shocks to public R&D enhance private R&D, technical change, and GDP growth. Shocks to foreign private and public R&D show that foreign private R&D has positive spillovers to technical change and all other variables, which are hard to distinguish from oligopolistic strategic reactions though (Ziesemer 2022). Foreign public and private R&D increase growth permanently. Using only DOLS or only FMOLS for the long-term relations changes some of these results but never the one for domestic public R&D (see appendix).

Slope homogeneity in VECMs in general may produce results with heterogeneity bias, and country-specific VECMs are most probably better in dealing with country-specific heterogeneity and policy, but they may suffer from low numbers of observations and thereby end of sample bias from recent crises. However, this does not affect the results of this paper regarding public R&D, whereas those for private R&D may be affected.

In future research, the issue of slope heterogeneity in adjustment coefficients may suggest that panel VECM methods could benefit from aligning the approaches of panel VECM with DOLS or FMOLS cointegrating equations lined up in Hsiao (2022) with those of the PMG single-equation estimator of Pesaran et al. (1999). Whereas the VECM with DOLS or FMOLS cointegrating equations has group mean slope estimation in the long-term relations and slope homogeneity in the differenced terms and adjustment coefficients, the PMG has the opposite: slope homogeneity in the estimation of only one long-term relation and mean-group estimation of differenced terms and adjustment coefficients. This raises the question, which of the methods suffers more from slope heterogeneity bias (and perhaps restriction of the number of long-term relations to only one). Estimating the long-term relations with the PMG method and putting them together to a simulation model is an interesting suggestion for further research.

For the time being, public R&D has positive direct and indirect (via private R&D) effects in DOLS and FMOLS estimates, and positive impulse response effects are shown when using the current standard of panel VECM with slope homogeneity, fixed effects, and long-term relations from DOLS and FMOLS group mean estimation.

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Table A.1

Bai/Ng unit root tests under cross-section dependence with two ways of factor selection

Variable	Bai/Ng (a): no unit root in	Bai/Ng (b): no unit root in	No of no-unit roots in CIPS test (Table 2)
LGDP	No country	*AUT*	1 (DEU)
LTH07	DEU, *JPN*	DEU, *JPN*	1 (DEU)
LBERDST	AUT, BEL, DEU, *FIN*	*AUT*, BEL, *DNK*, ESP, *FIN, ITA, NLD,* SWE	4 (*AUT, ESP*, NLD, *USA*)
LPUBST	All but … (c)	FIN, *GBR, ITA*, *PRT*, SWE	5 (*DEU, DNK*, ITA, *PRT, SWE*)
LFPUBST	DEU	No country	0
LFBERDST	*AUT, DEU, DNK, ITA, JPN, NLD*, NOR, *SWE*	*BEL, GBR, ITA*	*2 (GBR, ITA)*

(a) Bai/Ng options: constant and trend, MQC serial correlation correction, covariance lags: AIC; bandwidth: Newey-West automatic; factor selection in column 1: Bai/Ng, average, Schwert; cross and time demeaned and standardized. 10% level; countries in italics do not have a unit root at the 5% level. (b) Factor selection in column 2: Ahn/Horenstein; other aspects as in (a). (c) BEL, DEU, *DNK, ESP, ITA, JPN, NLD*, PRT, *USA*. Cross-unit cointegration in LBERDST, LPUBST, LFBERDST from Bai/Ng test.

The country-specific results from the Bai/Ng panel unit root test appear in Table A.1. In column 1, unit roots are likely for LPUBDST (9 countries, as in column 3 for the CIPS test); for LFBERDST (6 countries with unit root; 12 in CIPS) the Bai/Ng test is much less supportive for the hypothesis of a unit root than the CIPS tests; for LBERDST we have (8 countries with unit roots; 8 in CIPS). For LGDP, LTH07, and LFPUBST both column 1 for Bai/Ng tests and column 3 for the CIPS test show no more than two exceptions from the unit root result. When the Ahn/Horenstein factor selection procedure is used there is often only one common factor (not shown) as assumed in Pesaran (2007). Results therefore are also close to those of the Bai/Ng and CIPS/CADF tests. In sum, column 2 differs for LBERD from the other columns, and column 1 differs for LPUBST and LFBERDST from the other ones. Overall, the differences in the results do give us little confidence about the absence of unit roots. Even when the *numbers* of countries with no unit root are equal or similar in columns 1 to 3, the countries are sometimes different ones.

Table A.2 VECM with country fixed effects: R-squared, Adj. R-squared, Durbin-Watson for six equations in each of 14 countries (a)

Equation Country	D(LGDP)	D(LOG(TH07))	D(LBERDST)	D(LPUBST)	D(LFBERDST)	D(LFPUBST)
AUT	R^2: 0.299 (b): -0.316 DW:2.31	0.115 -0.664 2.04	0.696 0.428 2.20	0.827 0.675 1.965	0.894 0.80 2.165	0.94 0.888 1.731
BEL	0.06 -0.767 2.75	0.251 -0.41 2.56	0.827 0.675 2.239	0.794 0.613 1.266	0.897 0.807 2.065	0.94 0.888 1.53
DEU	0.126 -0.56 1.885	0.248 -0.342 1.39	0.927 0.87 1.83	0.943 0.898 2.22	0.886 0.797 1.70	0.924 0.866 1.993
DNK	0.103 -0.687 2.247	0.019 -0.844 2.404	0.907 0.825 1.224	0.678 0.396 2.45	0.892 0.797 2.085	0.944 0.894 1.564
ESP	0.468 0.0001 1.129	0.37 -0.184 1.47	0.845 0.71 2.54	0.797 0.62 2.445	0.883 0.78 2.003	0.93 0.869 1.54
FIN	0.336 -0.3 1.567	0.336 -0.299 1.531	0.92 0.843 1.74	0.919 0.841 2.175	0.893 0.792 1.959	0.947 0.895 2.008
GBR	0.045 -0.705 2.184	0.141 -0.534 2.433	0.613 0.308 2.31	0.67 0.41 1.646	0.907 0.834 2.182	0.967 0.942 1.856
ITA	0.234 -0.368 2.04	0.302 -0.247 1.807	0.88 0.787 1.781	0.865 0.76 2.298	0.94 0.894 1.91	0.941 0.894 1.94
JPN	0.633 0.345 2.198	0.445 0.0092 1.835	0.946 0.903 2.216	0.972 0.95 1.56	0.908 0.836 2.019	0.937 0.888 1.756
NLD	0.462 0.039 1.55	0.206 -0.417 2.06	0.681 0.43 2.092	0.619 0.319 2.445	0.913 0.845 2.076	0.955 0.919 2.096
NOR	0.447 -0.106 1.697	0.178 -0.644 2.12	0.901 0.802 1.91	0.842 0.683 2.31	0.886 0.772 1.937	0.921 0.842 1.853
PRT	0.457 0.0298 1.995	0.31 -0.232 1.90	0.863 0.756 1.597	0.897 0.817 1.393	0.895 0.812 1.973	0.95 0.91 1.942
SWE	0.16 -0.58 2.168	0.265 -0.383 1.712	0.884 0.782 2.10	0.914 0.838 1.555	0.905 0.821 1.954	0.944 0.895 1.552
USA	0.023 -0.744 1.861	-0.202 (c) -1.146 1.644	0.863 0.755 1.575	0.859 0.747 1.19	0.926 0.867 1.998	0.898 0.818 2.106

(a) Slope homogeneity in VECM. Estimation Method: Seemingly Unrelated Regression (SUR, cointegrating equations from group mean DOLS and FMOLS from Table 4, model 3, imposed). Sample: 1967 2017; included observations per country: 51; total system (unbalanced) observations: 4128. Linear estimation after one-step weighting matrix. Determinant residual covariance: 0.000000. (b) adjusted R-squared. (c) R-squared can be negative when residuals are weighted such as in IV estimation (see Wooldridge 2013, page 523); SUR estimation uses just a different weighting.

Appendix A

Results for VECM with cointegrating equations from FMOLS (Table 4, Model 1)

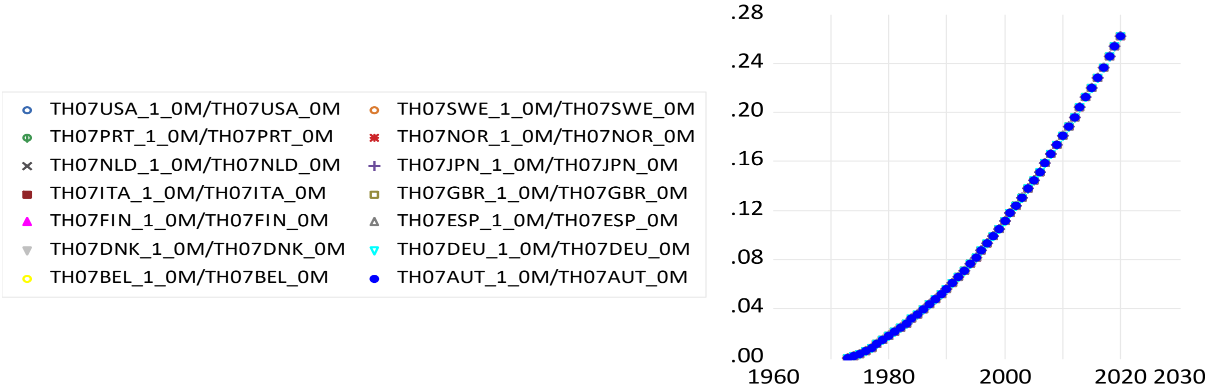

Figure A.1 Effects of a shock of 0.005 on public R&D growth in 1973 on technical change (% TH07 baseline) for 14 OECD countries (14 lines visually on each other).

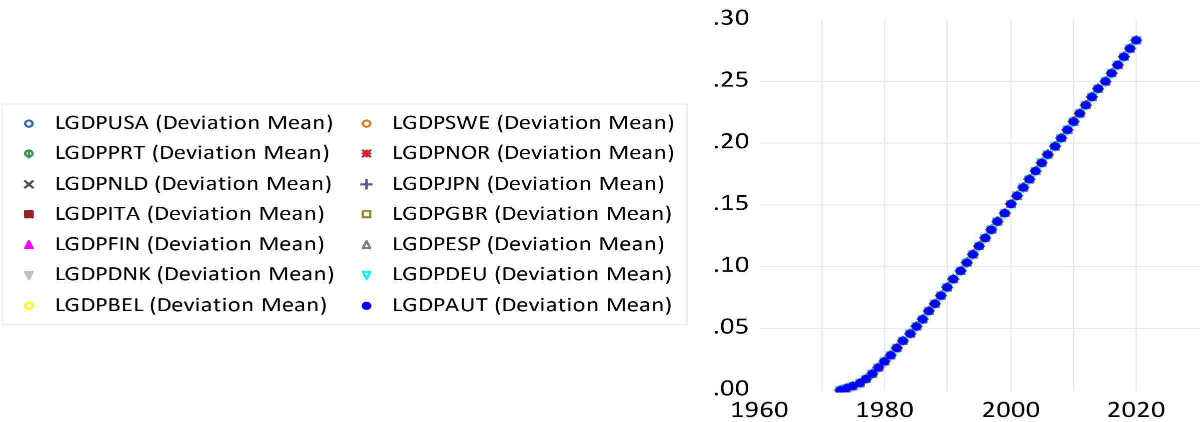

Figure A.2 Effects of a shock of 0.005 on public R&D growth in 1973 on GDP (% GDP baseline). 14 OECD countries (14 very similar lines 'on' each other).

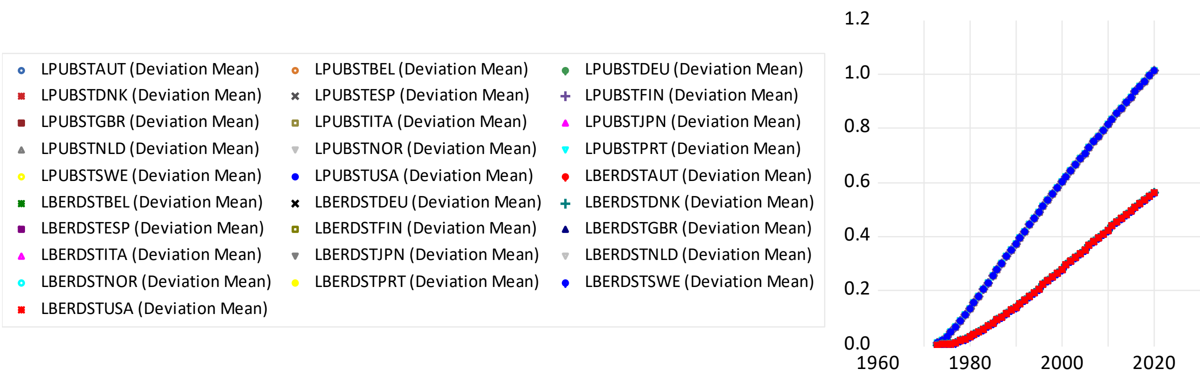

Figure A.3 R&D stock changes from a 0.005 increase of the intercept of the public R&D growth equation with higher curves for public R&D and lower curves for private R&D, each for 14 countries. Public R&D runs up to almost 100% above baseline and private R&D to almost 60% above baseline.

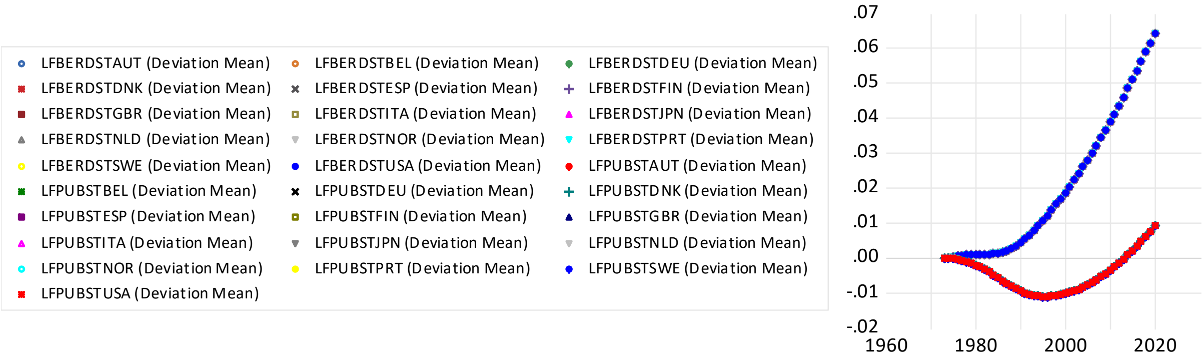

Figure A.4 Foreign R&D reaction to a domestic public R&D enhancement. Higher curves for foreign private R&D; lower curves for foreign public R&D.

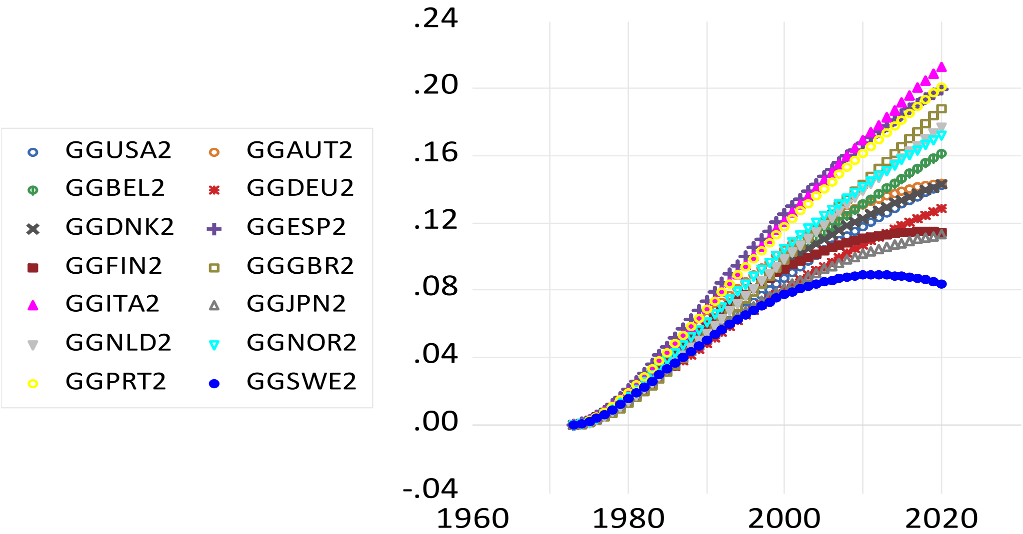

Figure A.5 Yearly net gains as a percentage of GDP, all in terms of policy scenario compared to baseline.

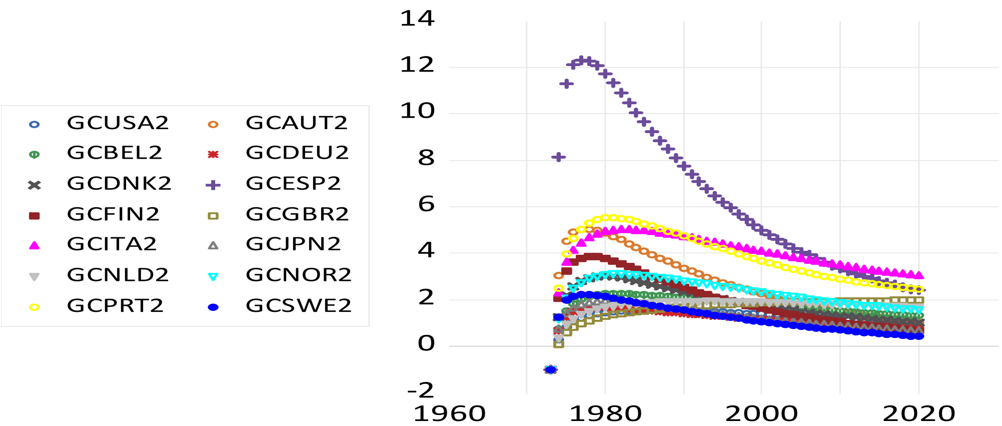

Figure A.6 Yearly net gains as a percentage of yearly costs, all in terms of policy scenario compared to baseline.

In the FMOLS variant, a permanent change of the intercept of the equations for private R&D by 0.005 leads to a rise of private R&D itself up to 0.29 before it declines again. It has zero or negative effects for GDP, public R&D, and technical change in spite of the long-run relations shown in Table 4, a small 30 years increase by up to 0.15 percent of foreign private R&D, 13 years increase by up to 0.13% of foreign public R&D.

In contrast, the same change for foreign private R&D drives up all variables for all countries (not shown): BERD by more than 50% of baseline, Foreign BERD by 86%, foreign public R&D 45%, GDP 28%, domestic public 71%, th07 54%.

The same change for foreign public R&D (not shown) has the following effects. Domestic and foreign private R&D are zero for five years and then go down. Foreign public R&D goes up by up to 65% beyond baseline, domestic public R&D by 20%, technical change goes up to 11.36% of th07 in 2008, which is larger than under DOLS and then goes down. GDP gets a positive effect running up to 10.9%. As domestic and foreign private R&D go down and productivity goes up there must be a positive effect from domestic and foreign public R&D. Overall, foreign public R&D has positive but small effects.

Appendix B

Results for VECM with cointegrating equations from DOLS (Table 4, Model 2)

Figure B.1 shows that 14 countries gain up to 16% in labour-augmenting productivity in the 37 years between 1973 and 2020, which is 16/37 = 0.43 percent per year.

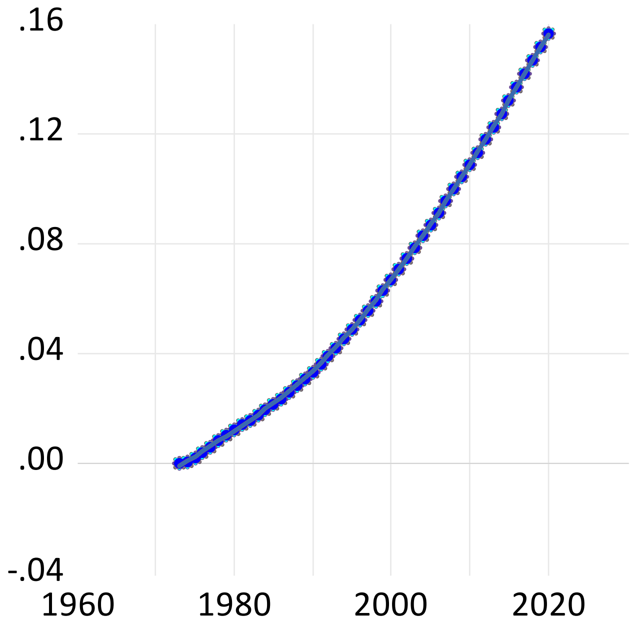

Figure B.1 Effects of a shock of 0.005 on public R&D growth in 1973 on technical change (% TH07 baseline) 14 OECD countries (14 lines visually on each other).

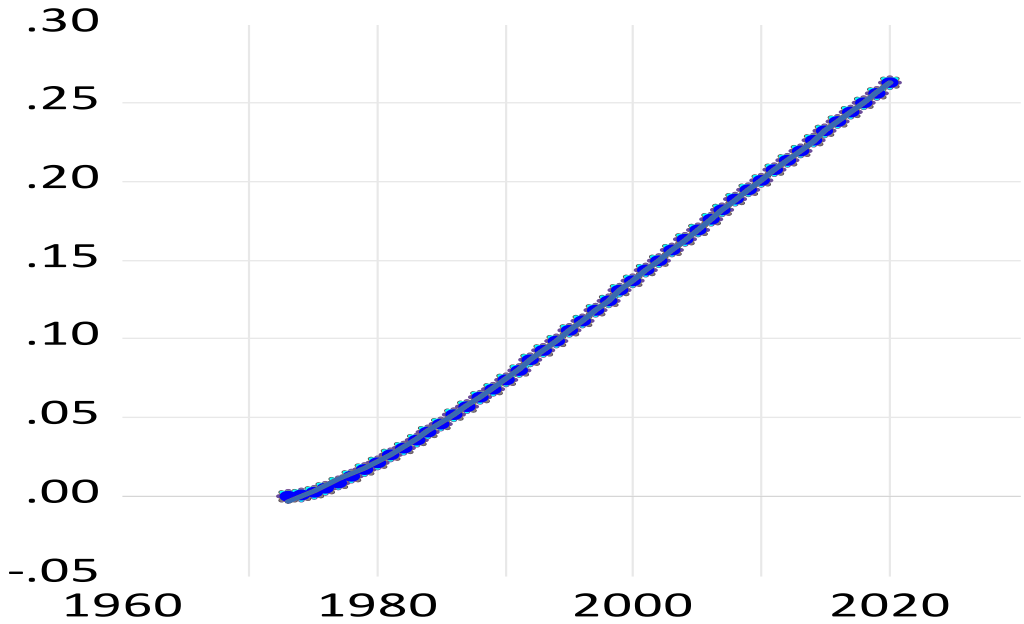

Figure B.2 Effects of a shock of 0.005 on public R&D growth in 1973 on GDP (% GDP baseline). 14 OECD countries (14 very similar lines 'on' each other).

The percentage effect of a public R&D enhancement on GDP shown in Figure B.2 is higher than that on technical change in Figure B.1. This may be due to a greater inflow (less outflow) of additional foreign capital and labour.

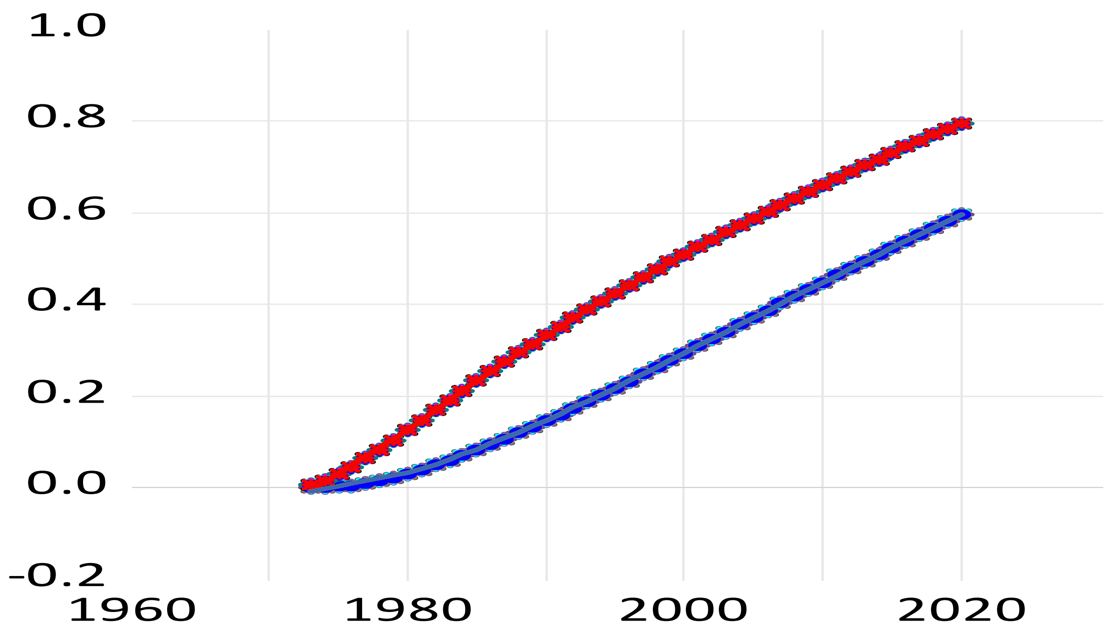

Figure B.3 R&D stock changes from a 0.005 increase of the intercept of the public R&D growth equation with higher curves for public R&D and lower curves for private R&D, each for 14 countries. Public R&D runs up to 80% above baseline and private R&D to 60% above baseline.

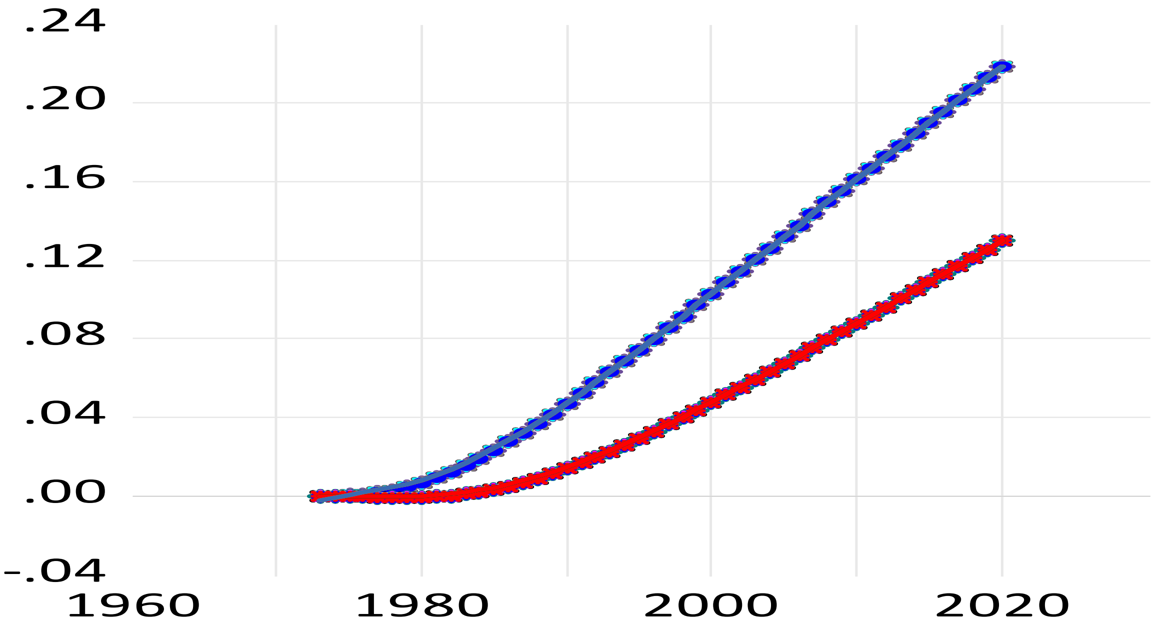

Figure B.4 Foreign R&D reaction to a domestic public R&D enhancement. Higher curves for foreign private R&D; lower curves for foreign public R&D.

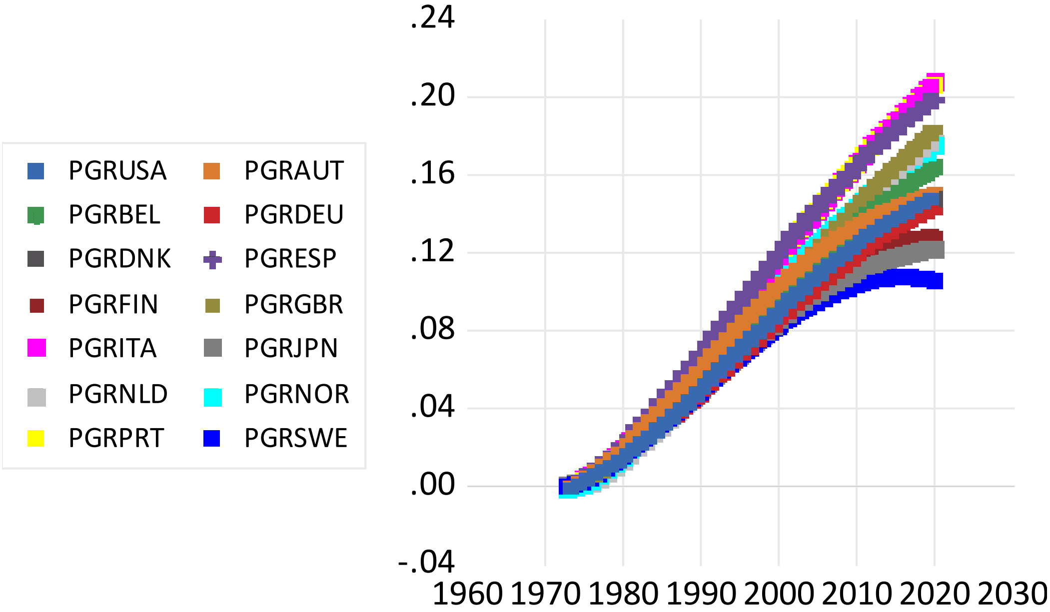

Figure B.5 Yearly net gains as a percentage of GDP, all in terms of policy scenario compared to baseline.

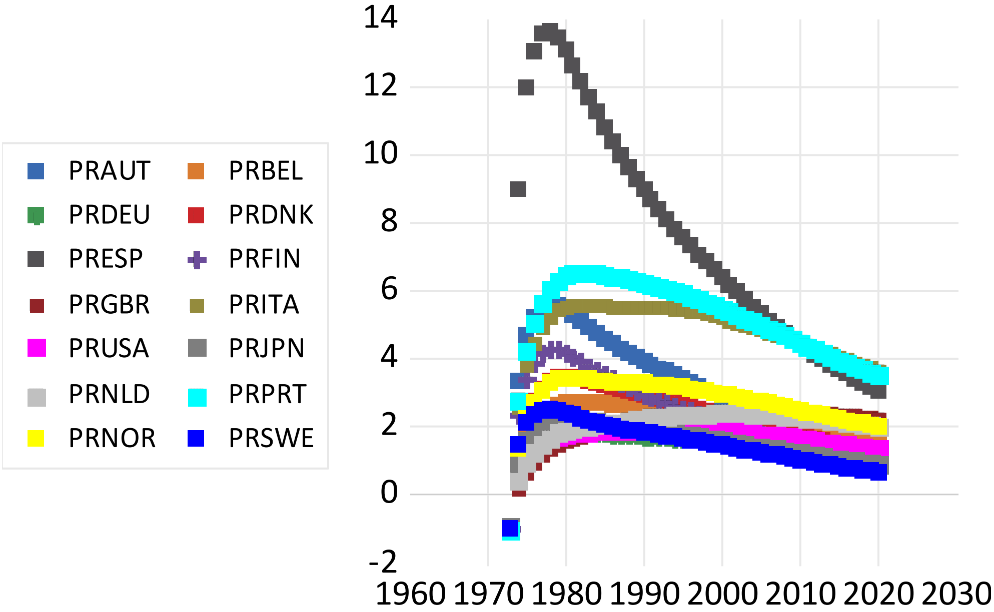

Figure B.6 Yearly net gains as a percentage of yearly costs, all in terms of policy scenario compared to baseline.

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