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An Empirical Note on the Long-Run Effects of Public and Private R&D on TFP

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Abstract

Several studies have examined the long-run effects of public and private R&D on TFP with mixed results. A common feature of these studies is that they measure public and private R&D activity using perpetual inventory stocks of public and private R&D capital, constructed under the assumption that the prices of GDP, public R&D, and private R&D move identically. This note argues that the results of these studies may be biased if the assumption of identical price movements is violated. The purpose and main contribution of this note is to estimate the long-run elasticities of TFP with respect to public and private R&D using both the stock of public/private R&D capital and an alternative measure of public/private R&D activity: the number of public/private sector researchers. In addition, this study contributes to the literature by developing a simple theoretical model that formalizes the intuition of how public and private R&D affect TFP, and by using both traditional and more recent panel methods. Contrary to previous studies, it is found—using numbers of researchers in the public and private sector—that there is strong evidence both of a significant positive long-run effect of both public and private R&D on TFP and of a greater effect of public R&D than private R&D. Consistent with the mixed evidence reported in the literature, it is also found that the use of public and private R&D stocks yields mixed results regarding the long-run effects of public and private R&D on TFP.

Keywords Public R&D · Private R&D · Total factor productivity · Panel cointegration

JEL Classification O30 · O47 · O11

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Introduction

Although industrial firms perform the bulk of applied research and development (R&D) that is necessary before introducing new products to the marketplace, the increase in academic patenting since the 1980s documents that researchers in universities and other public research organizations engage in applied commercial research and thereby *directly* contribute to the stock of applied technological knowledge—like their counterparts in industry. In addition, university researchers and other public scientists engage in basic scientific research. To the extent that basic scientific research in universities and other public research organizations enhances the productivity of applied R&D in industry, public R&D should also have an additional, *indirect* effect on the stock of applied technical knowledge. Thus, one would expect to find that both public and private R&D increase total factor productivity (TFP), with a greater long-run elasticity for public than private R&D. The evidence to support this expectation is, however, far from conclusive.

Guellec et al. (2004), using a panel of 16 OECD countries over the period 1980–1998, Luintel et al. (2014), employing panel data for 16 OECD countries between 1982 and 2004, and Pegkas et al. (2020), based on data from a panel of 19 Eurozone countries for the period 1995–2016, find a positive and significant effect of private R&D and public R&D on TFP, but their results provide no clear evidence of a greater long-run elasticity for public R&D: in Guellec et al.'s (2004) study, the long-run public R&D elasticity is greater than the long-run private R&D elasticity in one of two specifications; the results of Luintel et al. (2014) show a greater long-run elasticity for public R&D in two of three specifications, and in Pegkas et al.'s (2020) study, public R&D has a greater long-run elasticity than private R&D in three (and the same long-run elasticity as private R&D also in three) of eight specifications.[1]

Somewhat different evidence is provided by Soete et al. (2020a), who find, based on time series data for the Netherlands over the period 1968–2014, that both private and public R&D activities have a significant positive long-run effect on TFP and that the long-run elasticity for private R&D is greater than the long-run elasticity for public R&D.

This finding is partially consistent with that of Ziesemer (2020a), who performs separate time series analyses for Austria, Canada, France, Italy, and Portugal for the period 1963–2014, and finds for Austria and Italy that public R&D affects TFP only indirectly through its positive effect on private R&D. However, his results for Portugal suggest that while public R&D has a positive long-run effect on TFP, private R&D has no long-run effect on TFP. For Canada, in contrast, he finds positive effects of both public and private R&D, whereas he reports negative effects of both public and private R&D for France. And for Japan, he finds in another study, based

[1] In contrast to all other studies, which define public R&D as R&D performed by the government sector and the higher education sector, Pegkas et al. (2020) consider these sectors separately and find significant positive effects of public R&D on TFP only for R&D in the higher education sector, while R&D in the government sector is always insignificant.

on data for the period 1963–2017, that public R&D affects TFP indirectly (positively) through its positive effect on private R&D (Ziesemer, 2020b).

Similarly, Soete et al. (2020b) find in simulations based on separate time series analyses for 17 countries for the period 1975–2014 that the effect of public R&D is positive in 12 and negative in 5 cases (including Canada, France, Ireland, Spain, and the UK) and that this effect acts mainly through private R&D.[2]

Bengoa et al. (2017), using a panel of 17 Spanish regions over the period 1980–2007, and Voutsinas and Tsamadias (2014), employing time series data for Greece for the period 1981–2007, however, detect a positive and significant long-run effect only for public R&D. In contrast, Coe et al. (2009) find, based on regressions for a 24-country OECD panel for the period 1971–2004, that while public R&D is not robustly significant, private R&D is positive and significant. This latter finding is partially consistent with that of van Elk et al. (2019), who find, in a panel study of 20 OECD countries for the period 1971–2002, that private R&D is consistently positive and mostly significant, whereas their results for public R&D are mixed, ranging from negative to positive effects. Finally, Erken et al.'s (2009) panel study of 20 OECD countries over the period 1971–2002 shows a significant positive long-run relationship between private R&D and TFP and a significant negative long-run relationship between public R&D and TFP.[3]

Thus, the existing literature regarding the effects of public and private R&D on TFP is conflicting, and no studies provide conclusive evidence that both public and private R&D drives TFP growth and that public R&D has a greater long-run effect on TFP than private R&D.

However, a potential problem with the existing literature is that all studies, whether using time series or panel data, measure public and private R&D activity using real stocks of public and private R&D capital, constructed from deflated public and private R&D expenditure data based on the GDP deflator. The R&D data underlying these studies are thus based on the assumption of identical price deflators for GDP, public R&D expenditures, and private R&D expenditures. Since this

[2] Unfortunately, the authors do not provide simulation results for the effect of private R&D on TFP.

[3] Three other related studies should be mentioned. Lichtenberg (1993) finds that private R&D investment (measured as a percentage of GNP) is positive and significant in cross-country regressions for a sample of 53 countries for the (log) level of GDP per adult in 1985 and GDP per adult growth in the period 1960–1985, while public R&D investment is insignificant or even negative. Park (1995) examines the relationship between the growth rates of public and private R&D capital per hour and the growth rate of output per hour using panel data for 10 OECD countries over the period 1973–1987. He finds a positive and significant relationship between the growth rate of private R&D capital per hour and the growth rate of output per hour; the growth rate of public R&D capital per hour is significantly positive only when the growth rate of private R&D capita is not included in the model (i.e., when the growth rate of private R&D capita is included, the growth rate of public R&D capital becomes insignificant). Bassanini et al. (2001) examine the long-run effects of public and private R&D expenditures (measured as percentages of GDP) on GDP per capita in a panel of 15 OECD countries between 1971 and 1998 and find a positive effect for private R&D expenditures and a negative effect for public R&D expenditures. Since these studies account for physical and human capital in explaining labor productivity (growth), they indirectly capture the effects of (growth in) public and private R&D on TFP (growth).

assumption is likely to be violated in many years,[4] changes in public and private R&D expenditures/stocks may, in part, reflect measurement error rather than real changes in public and private R&D activity, and this measurement error may lead to biased estimates of the long-run elasticities of TFP with respect to public and private R&D. Thus, it is possible that some of the conflicting and counterintuitive findings in the literature reflect biases associated with the use of stocks of public and private R&D capital.

An additional potential problem with the existing literature is that the panel studies use so-called first-generation panel unit root and cointegration methods, which assume cross-sectional independence of the error terms and thus that there are no unobserved common factors in the error terms.[5] If this assumption is violated, these methods may produce biased results. Some studies, therefore, account for error cross-sectional dependence using time dummies (Guellec et al., 2004; Erken et al., 2009; Bengoa et al., 2017). However, the implicit assumption behind the use of time dummies is that the effects of the common factors are homogeneous across the cross-sectional units. If this assumption does not hold, then the use of time dummies may be ineffective in eliminating error cross-sectional dependence (e.g., Pedroni, 2007). Thus, some of the results in the literature may be biased because of failure to (adequately) account for potential cross-sectional dependence.

A final critique is that the literature does not provide theoretical models of the effects of public and private R&D on TFP.[6] Indeed, the literature provides possible explanations for (i) why private R&D may have an insignificant effect on TFP, such as low levels of private R&D activity or low power of statistical tests with small samples (e.g., Voutsinas & Tsamadias, 2014); (ii) why public R&D may have an insignificant or even negative effect on TFP, such as crowding out of private R&D by public R&D or collinearity between the public and private R&D variables (e.g., Erken et al., 2009); and (iii) why public R&D may have a positive effect on TFP,

[4] Two well-known facts are (1) more than half of R&D expenditures are labor costs (e.g., Becker 2015) and (2) the growth rate of salaries of researchers in the public sector differs (sometimes substantially) from the growth rate of salaries of researchers in the private sector (e.g., Hansen and Guidugli 1990). These facts indicate that it is problematic to assume identical price deflators for public and private R&D expenditures (or to use shares of public and private R&D expenditures in GDP as measures of the shares of public and private R&D activities in total economic activity).

[5] Cross-sectional dependence may be due to unobserved common factors. Unobserved common factors can be divided into two categories: "strong" factors that affect all countries (but not necessarily with the same magnitude) and "weak" factors that produce spatial spillover effects across subsets of countries (e.g., Chudik and Pesaran 2015). The presence of weak factors does not affect the consistency of conventional panel data estimators, but the standard errors may be biased. In contrast, strong factors, if not adequately controlled, can lead to biased coefficient estimates. First-generation panel unit root and cointegration tests (developed in the 1990s) suffer from size distortions in the presence of error cross-sectional dependence.

[6] Park (1998) presents a Romer-type growth model in which it is assumed that the stock of private sector knowledge is equal to TFP and that the production of new knowledge in the private sector (and thus the change in TFP) depends on research effort in the private sector and on the stocks of private and public knowledge, but he does not model the effects of public and private research effort on TFP. Ziesemer (2020a) develops a semi-endogenous growth model in which it is assumed (ad hoc) that TFP depends (positively) on public and private R&D. However, he does not specify exactly how public and private R&D might affect TFP.

such as direct and/or indirect TFP effects (e.g., Soete et al., 2020b), but these explanations would be more convincing if they were supported by a theoretical model that formalizes the effects of public and private R&D on TFP and provides a framework to predict these effects.

Given these limitations and the conflicting findings in the current literature, further examination of the impact of public and private R&D on TFP is warranted. Clarification of this issue is important for two related reasons. First, TFP is a measure of the stock of technological knowledge, and most growth models predict that the accumulation of technical knowledge (technological progress), rather than factor accumulation, is the main cause of economic growth. This is supported by a growing body of evidence suggesting that TFP, rather than factor accumulation, accounts for most of the income and growth differences across countries and over time (e.g., Easterly & Levine, 2001; Hall & Jones, 1999; Hsieh & Klenow, 2010). It is therefore important to know what determines TFP. Second, semi-endogenous growth models suggest that TFP is determined in the long run by R&D effort (e.g., Jones, 1995, 2002).[7] Although these models generally assume that R&D is performed only by the private sector, an integral part of a nation's research system is the public sector, which performs research in various institutions, including universities. It is thus of considerable interest to policymakers to know how specifically public R&D, as an active policy variable, affects TFP—particularly at a time of increasing pressure on public finances. Therefore, the purpose of this study is to provide further evidence on the long-run effects of public and private R&D on TFP, based on a theoretical framework and using an alternative measure of public/private R&D activity and a number of different estimation approaches.

Specifically, this study makes three contributions to the literature. First, it is the first to present a theoretical model to formalize the intuition that both the long-run TFP elasticity with respect to private R&D and the long-run TFP elasticity with respect to public R&D are positive and that the latter is greater than the former. The theoretical model also provides a formal justification of the empirical model used to estimate the long-run TFP elasticities of public and private R&D. Second, we are the first to use first- and second-generation panel unit root and cointegration techniques to examine the long-run TFP effects of public and private R&D; second-generation panel unit root and cointegration methods explicitly account for potential error cross-sectional dependence. It should, perhaps, be noted here that our decision to use panel methods is guided by the fact that hypothesis tests based on panel data have higher power than that based on time series data and that the data availability does not allow us to perform separate, meaningful time series analyses. Third, and our main contribution, we are the first to use numbers of public and private researchers as measures of public and private R&D activity to estimate the long-run elasticities of TFP with respect to public and private R&D. The advantage of using the

[7] Schumpeterian growth models, in contrast, predict that the growth rate of the stock of knowledge (or TFP), and thus, the growth rate of output per capita depends on R&D intensity (the amount of resources devoted to R&D relative to the scale of the economy). For a review of semi-endogenous and Schumpeterian growth models, see Herzer (2020).

number of public/private sector researchers is that this measure does not depend on prices and is thus more likely to reflect real public/private R&D activity and thus to yield more intuitively plausible results than the perpetual inventory stock of public/private R&D capital. To support this argument, we also employ stocks of public and private R&D capital to estimate the long-run TFP elasticities with respect to public and private R&D and to compare the estimates based on the stocks with those obtained from using the numbers.

To preview our main results, we find, using numbers of researchers in the public and private sector, that there is strong evidence of significant positive long-run effects of public and private R&D on TFP and that, consistently across all estimation methods employed in this study, the long-run elasticity of TFP with respect to public R&D is greater than that with respect to private R&D. In contrast, we find mixed results regarding the long-run effects of public and private R&D on TFP using public and private R&D stocks.

The structure of this note is as follows. The "Theoretical Framework" section presents the theoretical framework that guides the empirical analysis. The empirical methodology, including the estimation equation and data, is discussed in the "Empirical Methodology" section. The "Empirical Results" section presents the results, and the final section presents implications and conclusions.

Theoretical Framework

Suppose that the total output of country i at time t, Y_{it}, is given by a Cobb–Douglas production

$$Y_{it} = A_{Tit} K_{it}^{\alpha} (L_{it} n_{it} h_{it})^{1-\alpha} \; 0 < \alpha < 1 \tag{1}$$

where K_{it} denotes the stock of physical capital, α is the elasticity of output with respect to capital, L_{it} is the number of workers, n_{it} and h_{it} represent hours and human capital per worker, respectively, $1–\alpha$ is the elasticity of output with respect to human capital augmented labor, and A_{Tit} is the stock of applied technical knowledge relevant to the development of new and better products and production processes, measured by TFP.

The empirical literature generally specifies TFP as an ad hoc function of the multiplicative form

$$A_{Tit} = c_i PRS_{it}^{\varphi} PUS_{it}^{\psi} e_{it} \tag{2}$$

where c_i is a country-specific constant, PRS_{it} is the private R&D capital stock, PUS_{it} is the public R&D capital stock, and e_{it} represents all other factors that determine the level of TFP. As is well known, φ and ψ can be interpreted as the long-run elasticities of TFP with respect to PRS_{it} and PUS_{it}, respectively, if the logs of the variables in Eq. (2) are non-stationary and cointegrated.

Equation (2) can also be derived formally from two knowledge production functions: a production function for applied technical knowledge,

$$\dot{A}_{Tit} = \delta_{Ti} PR_{it}^{\lambda} PU_{it}^{\lambda} A_{Tit}^{\phi} A_{Sit}^{\beta} \tag{3}$$

and a production function for basic scientific knowledge,

$$\dot{A}_{Sit} = \delta_{Si} PU_{it}^{\gamma} A_{Sit}^{\phi} \tag{4}$$

where $\dot{A}_{Tit}$ represents the flow of new technical knowledge, $\dot{A}_{Sit}$ is the flow of new basic scientific knowledge, A_{Sit} denotes the stock of basic scientific knowledge, δ_{Ti} and δ_{Si} are constants of proportionality, PR_{it} is a private research effort, and PU_{it} stands for the public research effort.

Equation (3) is based on the fact (mentioned in the "Introduction" section) that researchers in both industry and public organizations engage in applied commercial research and therefore assumes that the emergence of new technological knowledge depends on research effort in industry and in the public sector.[8] In addition, Eq. (3) assumes that the emergence of new technological knowledge depends on both the stock of technological knowledge and the stock of scientific knowledge. In contrast, Eq. (4) assumes that new basic scientific knowledge is only a function of the research effort of universities and other public research organizations and of the existing stock of scientific knowledge.

The parameters λ and γ, where $0 < \lambda \leq 1$ and $0 < \gamma \leq 1$, capture the possibility of duplication in research (i.e., the possibility that doubling the number of researchers less than doubles the production of new knowledge because of duplication). For simplicity, we assume the same duplication parameter for public and private research effort in Eq. (3), although it could be that there is less duplication of research effort in the public research sector since universities might have less incentive to try to keep research secret (which would imply that the duplication parameter for public research effort is greater than the duplication for private research effort).

Similarly, it is assumed that the ϕ parameter is the same for the technical knowledge stock and its scientific counterpart and thus that the magnitude of the (positive or negative) externality in the production of new technical knowledge from the stock of technical knowledge is equal to the magnitude of the externality in the production of new scientific knowledge from the stock of scientific knowledge. Following Jones (1995), we impose $\phi < 1$ so that technical/scientific ideas still become either easier ($\phi > 0$) or harder ($\phi < 0$) to find as the stock of technical/scientific ideas increases.

Finally, β parameterizes the extent to which the productivity of applied technical research depends upon the stock of basic scientific knowledge. Since it is reasonable to assume that opportunities for commercial technological innovation are contingent on the stock of basic scientific knowledge, we assume $\beta > 0$.

Rewriting Eqs. (3) and (4) as

[8] PR_{it} enters the equation multiplicatively with PU_{it}, which can be justified by university-industry interactions in the innovation process (so that neither private nor public research substitutes perfectly for the other).

$$\frac{\dot{A}_{Tit}}{A_{Tit}} = \delta_{Ti} PR_{it}^{\lambda} PU_{it}^{\lambda} A_{Tit}^{\phi-1} A_{Sit}^{\beta} \tag{5}$$

and

$$\frac{\dot{A}_{Sit}}{A_{Sit}} = \delta_{Si} PU_{it}^{\gamma} A_{Sit}^{\phi-1} \tag{6}$$

and assuming that both stocks grow at a constant rates in the long run (which is a reasonable assumption given that the growth rate of TFP is typically found to be stationary), the above equations can be solved for the stock of technical knowledge and the stock of scientific knowledge, respectively,

$$A_{Tit} = \left(\frac{\delta_{Ti}}{g_{Ti}}\right)^{\frac{1}{1-\phi}} PR_{it}^{\frac{\lambda}{1-\phi}} PU_{it}^{\frac{\lambda}{1-\phi}} A_{Sit}^{\beta} \tag{7}$$

$$A_{Sit} = \left(\frac{\delta_{Si}}{g_{Si}}\right)^{\frac{1}{1-\phi}} PU_{it}^{\frac{\gamma}{1-\phi}} \tag{8}$$

where $g_{Ti} \equiv \frac{\dot{A}_{Tit}}{A_{Tit}}$ and $g_{Si} \equiv \frac{\dot{A}_{Sit}}{A_{Sit}}$ represent the constant growth rate of technical knowledge and the constant growth rate of scientific knowledge, respectively. Substituting (8) into (7) and adding e_{it} yields the equation that corresponds to Eq. (2) when the public/private R&D capital stock is used as a measure of public/private research effort:

$$A_{Tit} = c_i PR_{it}^{\varphi} PU_{it}^{\psi} e_{it} \tag{9}$$

where $c_i \equiv \left(\frac{\delta_{Ti}}{g_{Ti}}\right)^{\frac{1}{1-\phi}} \left(\frac{\delta_{Si}}{g_{Si}}\right)^{\frac{\beta}{1-\phi}}$, $\varphi \equiv \frac{\lambda}{1-\phi}$, and $\psi \equiv \frac{\lambda}{1-\phi} + \frac{\gamma\beta}{1-\phi}$.

Thus, since the number of researchers is also a commonly used measure of research effort, our simple theoretical framework justifies the use of the number of researchers in the private sector, PRR_{it}, and the number of researchers in the public sector, PUR_{it}, for examining the long-run effects of private and public R&D on TFP. In addition, the model predicts three testable hypotheses:

H1: *The long-run elasticity of TFP with respect to private R&D, φ, is positive (since $\lambda > 0$ and $\phi < 1$).*

H2: *The long-run elasticity of TFP with respect to public R&D, ψ, is positive (since $\lambda > 0$, $\phi < 1$, $\beta > 0$, and $\gamma > 0$).*[9]

[9] In the short run, where the supply of researchers is inelastic, or fixed, increases in the number of researchers in the public sector, resulting from higher wages in the public R&D sector, necessarily reduce the number of researchers in the private sector and increase their wages. In other words, public R&D necessarily crowds out private R&D in the short run. Under the (unrealistic) assumptions that public R&D contributes little or not at all to the production of new technological knowledge (which would imply that the duplication parameter for public research effort in Eq. (3) is smaller than the duplication

H3: *The long-run elasticity of TFP with respect to public R&D is greater than the long-run elasticity of TFP with respect to private R&D (since* $\frac{\lambda}{1-\phi} + \frac{\gamma\beta}{1-\phi} > \frac{\lambda}{1-\phi}$*).*

Empirical Methodology

Taking logs of Eq. (9) yields the equation that is the basis for our empirical analysis:

$$\log A_{Tit} = c_i + \varphi \log PR_{it} + \psi \log PU_{it} + \vartheta F_t + \varepsilon_{it} \tag{10}$$

where $\vartheta F_t + \varepsilon_{it} \equiv \log e_{it}$, and the process F_t represents unobserved common factors (such as global technological progress and global crises) that, if not controlled, can induce error cross-sectional dependence and lead to inconsistent estimates.

Following common practice, we calculate A_{Tit} as the residual from the production function (1), assuming $\alpha = 1/3$. All data used to calculate TFP are from the Penn World Tables (PWT) version 9.1 (available at https://www.rug.nl/ggdc/productivity/pwt/).[10]

The source of our R&D data is the OECD Main Science and Technology Indicators (MSTI) database (available at https://stats.oecd.org/Index.aspx?DataSetCode=MSTI_PUB#). Our first measure of private (public) research effort, the stock of private (public) R&D capital, is constructed from R&D expenditures by the business sector (government and the higher education sectors) in constant dollars using the perpetual inventory equation $S_{it} = E_{it} + (1-\delta)S_{it-1}$,[11] where S_{it} is the stock of R&D expenditures, E_{it} denotes R&D expenditures, and δ is the depreciation rate. Consistent with the literature, we set the initial value of the R&D stock equal to $E_{i0}/(g+\delta)$, where E_{i0} is the value of the expenditure series the first year it is available, and g is the average growth rate of expenditures over the estimation period. Following the literature, we use a depreciation rate of $\delta = 15\%$.

Footnote 9 (continued)
for private research effort or even zero) and that the stock of basic scientific knowledge has no or little effect on the production of new technological knowledge (which would imply that β in Eq. (3) is small or even zero), public R&D can negatively affect TFP by crowding out private R&D. However, there is no reason to assume that in the long run, where the labor supply of scientists and engineers is not fixed, the number of private sector researchers should decline with an increasing number of public sector researchers and thus that public R&D should have a negative long-run effect on TFP.

[10] The Penn World Tables 9.0 contains its own measure of TFP, which is based on a translog production function in which the labor share varies across countries and across time. However, as argued by Jones (2016), such a measure is problematic because it implies that countries and years with the same inputs and the same level of TFP will have different outputs. In fact, it is still debated whether the labor share is approximately constant across time and space (with a value of about 2/3). While Karabarbounis and Neiman (2014) document a secular decline in the labor share in most advanced countries since the early 1980s, Cette et al. (2020) challenge this finding and demonstrate that, when corrected for measurement error, the labor share of advanced economies does not follow a secular trend. Therefore, we follow the common practice of assuming $\alpha = 1/3$.

[11] The existing official OECD estimates of real R&D expenditures are based on the GDP deflator.

Our second and primary measure of PR_{it} (PU_{it}), the number of researches in the private (public) sector, is defined as the number of full-time equivalent researchers in the business sector (government and the higher education sectors).[12] To ensure consistency, we use a common sample for both measures.

Given that the MSTI data start in 1981 and end in 2017, the sample covers the period between 1981 and 2017. We include all countries with complete time series and at least 20 time-series observations, resulting in an unbalanced panel of 577 observations from 20 OECD countries (Belgium, Canada, the Czech Republic, France, Germany, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Netherlands, Poland, Portugal, Slovak Republic, Slovenia, South Korea, Spain, Turkey, and the UK).[13]

Equation (10) assumes that, in the long run, permanent changes in $\log PR_{it}$ and $\log PU_{it}$ are associated with permanent changes in $\log A_{Tit}$. Empirically, this implies that when $\log PR_{it}$, $\log PU_{it}$, and $\log A_{Tit}$ are stochastically non-stationary, these variables must be cointegrated for our model to be valid; if $\log PR_{it}$, $\log PU_{it}$, and $\log A_{Tit}$ are non-stationary and not cointegrated, then Eq. (10) is a spurious regression.[14] Thus, our empirical methodology consists of three steps: first, we check whether our variables are stationary or non-stationary; second, we test whether the variables in Eq. (10) cointegrate, and third, we estimate Eq. (10).

Empirical Results

We examine the (non-)stationarity of the variables by testing for unit roots using the tests suggested by Im et al. (2003) and Pesaran (2007). The former is a first-generation panel unit root test that assumes cross-sectionally independent residuals and suffers from size distortions in the presence of error cross-sectional dependence due to common factors. To account for cross-sectional dependence, we apply this test to demeaned data $x_{it} - N^{-1}\sum_{i=1}^{N} x_{it}$ in place of the original data x_{it}.[15] The implicit assumption behind the use of demeaned data (or time dummies) is that the responses to the common factors do not differ across the units. However, if this assumption does not hold, the demeaning procedure may be ineffective in eliminating error cross-sectional dependence. Therefore, we also use the Pesaran (2007) panel unit

[12] The total number of researchers is the sum of the number of researchers in four sectors: business, government, higher education, and the private non-profit sector. Due to the lack of data on the number of higher education researchers for the period 1999–2004 for the UK, we construct the number of UK researches in the public sector for this period by subtracting the number of business researchers from the total number of researchers; this should not be a problem since the number of UK researchers in the private non-profit sector is very small or even zero (in 1998, for example).

[13] It should perhaps be noted explicitly that sufficiently long time series on the number of business, government, and higher education researchers are not available for the USA from the MSTI, so that we are forced to exclude the USA from our sample.

[14] As shown by Kao (1999), the tendency for spuriously indicating a relationship may even be stronger in panel data regressions than in pure time series regressions.

[15] The use of demeaned data is equivalent to using the residuals from regressions of each variable on time dummies and serves to account for potential error cross-sectional dependence. The implicit assumption behind the use of demeaned data is that the responses to the common factors do not differ across the

Table 1 Panel unit root tests

	Im et al. (2003)	Pesaran (2007)
$\log A_{Tit}$	0.433	0.282
$\log PRS_{it}$	0.108	0.937
$\log PUS_{it}$	0.943	0.763
$\log PRR_{it}$	0.523	0.755
$\log PUR_{it}$	0.828	0.763

Reported values are *p*-values. To account for potential error cross-sectional dependence in the Im et al. (2003) test, we used demeaned data. The Pesaran (2007) test accounts for error cross-sectional dependence via the use of (weighted) cross-sectional averages. Two lags were used in the tests. Both tests include country-specific intercepts

root tests, which is a second-generation panel unit root test that follows the so-called common correlated effects (CCE) approach and allows for heterogeneous responses to the common factors by using weighted cross-sectional averages of the variables. This test, which explicitly accounts for potential error cross-sectional dependence, is applied to the original data. The results of both tests are presented in Table 1. Both panel unit root tests show that all variables are stochastically non-stationary.

Table 2 presents the results of several first- and second-generation tests for panel cointegration between $\log A_{Tit}$, $\log PRS_{it}$ ($\log PRR_{it}$), and $\log PUS_{it}$ ($\log PUR_{it}$). For the (first generation) tests that assume error cross-sectional independence, such as the Pedroni (1999) and Westerlund (2005) tests, we report results based on the demeaned data. For the (second generation) tests that account for error cross-sectional dependence (via the use of weighted cross-sectional averages), such as the Gengenbach et al. (2016) tests, we report results based on the raw data. In sum, these tests suggest that there is a long-run relationship between $\log A_{Tit}$, $\log PRS_{it}$, and $\log PUS_{it}$ and a long-run relationship between $\log A_{Tit}$, $\log PRR_{it}$, and $\log PUR_{it}$, though the evidence is stronger for the latter.

To estimate the long-run elasticities of TFP with respect to private and public R&D based both on stocks of private and public R&D capital and on numbers of private and public researchers, we use seven different estimators: the panel DOLS (PDOLS) estimator of Kao and Chiang (2000), the group mean panel DOLS (GMDOLS) estimator suggested by Pedroni (2001), the pooled mean-group (PMG) estimator of Pesaran et al. (1999), the pooled CCE (PCCE) estimator of Pesaran (2006), Pesaran's (2006) CCE mean group (CCEMG) estimator, the cross-sectionally augmented distributed lag pooled (CSDLP) estimator recently proposed by Chudik et al. (2016), and Chudik et al.'s (2016) cross-sectionally augmented distributed lag mean group (CSDLMG) estimator. The PDOLS, GMDOLS, and PMG estimators, which are first-generation estimators, are based on the assumption of error cross-sectional independence and are

Footnote 15 (continued)
units. However, if this assumption does not hold, the demeaning procedure may be ineffective in eliminating error cross-sectional dependence.

Table 2 Panel cointegration tests

Tests for cointegration between $\log A_{Tit}$, $\log PRS_{it}$, and $\log PUS_{it}$			
	Pedroni (1999)	Westerlund (2005)	Gengenbach et al. (2016)
Panel PP *t*-statistic	−3.134***		
Panel ADF *t*-statistic	−1.099		
Group mean PP *t*-statistic	−3.250***		
Group mean ADF *t*-statistic	−0.996		
Panel variance ratio statistic		−2.302**	
Group mean variance ratio statistic		−3.362***	
ECM *t*-statistic			−4.260***
ECM Wald statistic			23.377***
Tests for cointegration between $\log A_{Tit}$, $\log PRR_{it}$, and $\log PUR_{it}$			
	Pedroni (1999)	Westerlund (2005)	Gengenbach et al. (2016)
Panel PP *t*-statistic	−2.872***		
Panel ADF *t*-statistic	−2.087**		
Group mean PP *t*-statistic	−4.402***		
Group mean ADF *t*-statistic	−3.473***		
Panel variance ratio statistic		−1.407*	
Group mean variance ratio statistic		−2.368***	
ECM *t*-statistic			−4.163***
ECM Wald statistic			26.7134***

The dependent variable in the Pedroni (1999) and Westerlund (2005) tests is $\log A_{Tit}$; the dependent variable in the tests of Gengenbach et al. (2016) is $\Delta \log A_{Tit}$. For the Pedroni (1999) tests, the lag length was chosen using the modified Schwarz criterion, with a maximum of four lags allowed. For the Gengenbach et al. (2016) test, we used the general-to-specific procedure; we started with a lag length of one (longer lags were not feasible given the limited number of time-series observations available (for some countries) here), and then, all insignificant first differences according to individual *t*-tests were eliminated to obtain more efficient estimates of the coefficients of the level variables. The critical values for the Gengenbach et al. (2016) *t*-test/Wald test (for $N=20$) are as follows: −3.396/16.077 (1% level), −3.003/15.137 (5% level), −2.948/14.587 (10% level). To account for error cross-sectional dependence (due to possible non-stationary common factors), the results of the Pedroni (1999) and Westerlund (2005) tests are based on demeaned data. The Gengenbach et al. (2016) test accounts for error cross-sectional dependence via the use of cross-sectional averages

***Significance at the 1% level

**Significance at the 5% level

*Significance at the 10% level

therefore applied to the demeaned data. The PCCE, CCEMG, CSDLP, and CSDLMG estimators, which are second-generation estimators and explicitly account for potential error cross-sectional dependence (via the use of weighted cross-sectional averages), are applied to the raw data. The PDOLS, PMG, PCCE, and CSDLP estimators assume homogeneous long-run coefficients, whereas the other estimators allow the slope coefficients to vary across countries. The DOLS estimators allow for endogenous regressors; the PMG estimator allows the regressors to be weakly exogenous; and the CCE and CSDL estimators assume strictly exogenous regressors.

Table 3 Estimates of the long-run relationship between TFP, private R&D, and public R&D

	Results based on R&D capital stocks							Results based on the number of researchers						
	PDOLS	GMDOLS	PMG	PCCE	CCEMG	CSDLP	CSDLMG	PDOLS	GMDOLS	PMG	PCCE	CCEMG	CSDLP	CSDLMG
$\log PRS_{it}$	0.091*** (0.030)	0.040 [−2.302]	0.240*** (0.023)	0.130** (0.064)	0.0511 (0.069)	0.120 (0.220)	0.237 (0.145)							
$\log PUS_{it}$	0.039 (0.040)	0.146*** [11.75]	−0.175*** (0.033)	−0.029 (0.111)	0.158** (0.074)	−0.022 (0.258)	0.088 (0.148)							
$\log PRR_{it}$								0.058*** (0.020)	0.043*** [9.243]	0.054*** (0.007)	0.045* (0.026)	0.067*** (0.024)	0.040** (0.020)	0.072** (0.029)
$\log PUR_{it}$								0.061* (0.034)	0.098*** [13.44]	0.206*** (0.011)	0.113* (0.060)	0.087* (0.050)	0.092** (0.045)	0.142*** (0.054)
Number of obs	517	517	497	577	577	517	517	517	517	497	577	577	517	517

PDOLS = panel DOLS estimator of Kao and Chiang (2000), GMDOLS = group mean panel DOLS estimator of Pedroni (2001), PMG = pooled mean-group estimator of Pesaran et al. (1999), PCCE (CCEMG) = pooled common correlated effects estimator (common correlated effects mean-group estimator) of Pesaran (2006), CSDLP (CSDLMG) = cross-sectionally augmented distributed lag pooled (mean-group) estimator of Chudik et al. (2016). The dependent variable in the PMG regressions is $\Delta \log A_{Tit}$; in all other regressions, the dependent variable is $\log A_{Tit}$. All regressions include country-fixed effects. The DOLS regressions were estimated with one lead and one lag. The lag order in the PMG regressions was chosen using the Akaike criterion, with a maximum of four lags allowed. The DOLS and PMG regressions were performed using demeaned data to account for potential error cross-sectional dependence; the PCCE CCEMG, PCSDL, and CSDLMG estimators control for error cross-sectional dependence via the use of (weighted) cross-sectional averages; the CSDL results are based on a specification with three lags of the cross-sectional averages of the explanatory variables (and one lag of the first differences). Heteroskedasticity and autocorrelation consistent standard errors are in parentheses; the CSDLMG standard errors are also robust to general forms of spatial and temporal dependence. The group mean DOLS procedure does not yield standard errors of the parameters. For this estimator, we therefore report the associated group mean *t*-statistics (in brackets)

***Significance at the 1% level

**Significance at the 5% level

*Significance at the 10% level

Table 3 depicts the results of these estimation procedures. We first turn to the results based on R&D stocks. The coefficient on $\log PRS_{it}$ is positive and significant in three of the seven regressions and not significantly different from zero in the other four regressions.[16] The coefficient on $\log PUS_{it}$ is significant and negative in one regression, significant and positive in two regressions, and insignificant in four regressions. Thus, the results based on R&D stocks are contradictory. In addition, none of the regressions based on R&D stocks yields significant and positive coefficients on both $\log PRS_{it}$ and $\log PUS_{it}$, implying that each estimation of Eq. (10), based on stocks, contradicts at least two of our three hypotheses (that the long-run elasticity of TFP with respect to private R&D is positive, the long-run elasticity of TFP with respect to public R&D is (also) positive, and the long-run elasticity of TFP with respect to public R&D is greater than the long-run elasticity of TFP with respect to private R&D)—regardless of whether first- or second-generation estimators are used to estimate the long-run elasticities of TFP with respect to public and private R&D.

This failure to support our hypotheses may, in large part, be due to the use of stocks of public and private R&D capital, which are constructed under the implicit (and incorrect) assumption that the prices of GDP, public R&D, and private R&D move identically. In fact, the results based on numbers of researchers are not contradictory and support each of our three hypotheses. The coefficient on $\log PRR_{it}$ is positive and significant across all seven regressions; the coefficient on $\log PUR_{it}$ is also positive and significant across all estimators; and the coefficient on $\log PUR_{it}$ is always greater than the coefficient on $\log PRR_{it}$. Thus, using numbers of public and private sector researchers, we find—contrary to previous work, but consistent with our theoretical expectations—very strong evidence that that both public and private R&D contribute to TFP and that the long-run elasticity of TFP with respect to public R&D is greater than the long-run elasticity of TFP with respect to private R&D.

Conclusions

In this note, we examined the long-run effects of public and private R&D on TFP in an unbalanced panel of 20 OECD countries from 1981 to 2017. Our objectives were (i) to develop a simple theoretical model which formalizes the intuition of how public and private R&D affect TFP, and from which testable hypotheses can be derived, (ii) to estimate the long-run elasticities of TFP with respect to public and private R&D using the number of researchers in the public/private sector as a measure of public/private R&D activity, (iii) to show that the number of researchers in the public/private sector yields more intuitively plausible results than the perpetual inventory stock of public/private R&D capital, which has been used as a measure of public/private R&D activity in previous studies of the effects of public and private R&D on TFP, and (iv) to contribute to the literature by using

[16] It should perhaps be noted that the GMDOLS elasticity for PRS_{it} is positive, but its t-statistic is negative.

not only traditional (or first generation) panel methods, but also more recent (or second generation) panel methods.

We argued that perpetual inventory stocks of public and private R&D capital are constructed under the implicit assumption of identical price movements for GDP as a whole and for public and private R&D, and that, because this assumption is unlikely to hold over many years, changes in public and private R&D stocks might not accurately reflect the true changes in public and private R&D activity. In contrast, the number of public/private sector researchers does not depend on assumptions about the real price of public/private R&D and, therefore, might more accurately reflect the true public/private R&D activity.

Consistent with these arguments, we found mixed results using public and private R&D stocks (in line with the pattern of results in previous studies) and qualitatively identical results across all estimations using numbers of public and private sector researchers. Specifically, and consistent with our theoretical expectations, we found, using numbers of public and private sector researchers, that both the long-run TFP elasticity with respect to private R&D and the long-run TFP elasticity with respect to public R&D is positive and that the long-run elasticity of TFP with respect to public R&D is greater than that with respect to private R&D.

There are two implications of these results. First, the use of stocks of public/private R&D capital can lead to highly misleading estimates of the effects of public/private R&D on TFP (and other variables). Second, the number of researchers in the public/private sector is a better measure of public/private R&D activity, or input, than the stock of public/private R&D capital. The overall conclusion from these results is that researchers in both the public and private sector contribute to the stock of technical knowledge relevant to the development of new and better products and production processes—indirectly, by conducting basic scientific research, and/or directly, by conducting practical applied research. Finally, we recognize that our study is limited in that it does not examine how much governments should spend on science nor in what areas they should invest their finite resources for R&D. We leave these questions for future research.

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