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R&D spending in the high-tech sector and economic growth☆

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Abstract

The present paper provides new estimates of the impact of investment in R&D on long-term economic growth. In particular, we estimate a dynamic empirical growth model using panel data for OECD countries from 1970 to 2004. This study is the first to investigate whether the specialization of R&D activities (i.e. share of R&D investment in the high-tech sector) has an additional effect on GDP per working age population. Using a system GMM estimator in order to control for endogeneity, we find that both the ratio of business enterprises' R&D expenditures to GDP and the share of R&D investment in the high-tech sector have strong positive effects on GDP per capita and GDP per hour worked in the long term.

Keywords: Economic growth; R&D; Dynamic panel data models

1. Introduction

OECD countries in the 1990s were characterized by widening disparities of the growth rates of GDP per capita and multifactor productivity (OECD, 2003). In the empirical literature, there is widespread agreement on the importance of innovation activities, human capital, product market and labour market reforms for long-term economic growth (see Bassanini et al. (2001), Bassanini and Scarpetta (2002), OECD (2003)). In particular, industrial R&D expenditures are generally considered as one of the most important factors in explaining the growth of output or total factor productivity (see Bassanini et al. (2001), Coe and Helpman (1995); Guellec and Van Pottelsberghe De La Potterie (2004), Khan and Lunitel (2006) and Nadiri (1993)). This is consistent with the economic theory that investment in R&D generates spillovers to the rest of the economy (Aghion and Howitt, 1998). It is clear, however, that not only the level but also the composition of R&D spending matters for economic growth and productivity change. For instance, Griliches and Mairesse (1984) and Nadiri (1993) suggest that R&D expenditures in the high-tech sectors generate a higher return to the economy compared with R&D in other sectors. Furthermore, the composition of R&D has shifted from low- to high-tech areas (see also Acemoglu (2002)). When we look at the correlation between multifactor productivity growth and the change in industrial R&D performed in the high-technology sector for the OECD countries, we see that both

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variables are significantly positively related (with a correlation coefficient of 0.44 and a p-value of 0.07, see graph (Fig. 1) in the Appendix). In other words, a change in the composition of R&D from low- to high-tech areas leads to a higher growth of multifactor productivity.

The aim of the present paper is to provide new insights into the impact of investment in R&D and its composition on economic growth. In particular, we estimate cross-country growth models based on a panel of OECD countries for the period 1970–2004, in which the data are measured as five-year averages. The growth equation is estimated using a generalized method of moments (GMM) panel estimator in order to control for endogeneity. We address the key question of whether R&D spending in the high-tech sector has an additional effect on the long-term growth of GDP per capita after controlling for investment ratio, industrial R&D intensity, and average years of education. It is noteworthy that the structure of R&D, as a factor of economic growth, has been widely neglected in the literature. We also perform a number of robustness checks including alternative dependent variables (e.g. growth of GDP per hour worked) and specifications employing ten year averages of all variables.

The structure of the present paper is as follows: Section 2 introduces the empirical model and the hypotheses. Section 3 presents the data that were used, followed by a discussion of the empirical results in Section 4. Some concluding remarks are provided in Section 5.

2. The empirical growth model

There are two strands in the empirical literature on the impact of R&D on the output and productivity growth at the aggregate level. One estimates the impact of R&D on total factor productivity. The second type uses an augmented Solow growth model that was introduced by Mankiw et al. (1992). Nonneman and Vanhoudt (1996) extended the MRW model by adding the ratio of R&D to GDP. Based on panel data, the steady state level of GDP per capita based on the panel data can be described as:

$$\begin{aligned}\ln(y_{it}) &= \alpha \ln(y_{it-1}) + \beta_1 \ln(\mathrm{INV}_{it}) + \beta_2 \ln(\mathrm{EDU}_{it}) + \beta_3 \ln(\mathrm{BERDXGDP}_{it}) \\ &\quad + \beta_4 \ln(\mathrm{BERDHT}_{it}) + \eta_i + \lambda_t + \varepsilon_{it},\end{aligned}$$

where y_{it} is the GDP of the respective working-age population, expressed in 1995 purchasing power parity in country i in period t; η_i is a country-specific effect; λ_t is a period-specific effect; and ε_{it} is an error term. Two alternative dependent variables are also used in the analysis: GDP per hour worked and the labour productivity index defined as GDP per employed person in the business sector. The set of variables describing GDP per capita includes the ratio of business enterprise R&D expenditures to GDP (BERDXGDP), average years of education in the working-age population (from 25 to 64 years of age) (EDU) as a proxy for human capital, and the investment ratio (INV). The key variable of interest is the share of BERD performed in the high-tech sector (BERDHT). The regression equation also includes six period dummy variables, η_t, which enables us to control for the common business-cycle effects. We can derive the regression equation by taking first differences in order to remove the unobserved time-invariant, and the country-specific effects (for the sake of convenience, x comprises the explanatory variables):

$$\ln(y_{it}) - \ln(y_{it-1}) = \tilde{\alpha}(\ln(y_{it-1}) - \ln(y_{it-2})) + \tilde{\beta}'(\ln(x_{it}) - \ln(x_{it-1})) + \lambda_t + (\varepsilon_{it} - \varepsilon_{it-1}).$$

Assuming that the residuals of the level equation are serially uncorrelated, the values of y that are lagged two periods or more can be used as instruments in the first-differenced equation. This implies the following moment condition:

$$E(y_{it-s}, \Delta\varepsilon_{it}) = 0 \quad t = 3, \ldots, T \text{ and } s \geqslant 2.$$

In order to deal with the potential endogeneity problem, we assume that the explanatory variables in x are predetermined rather than strictly exogenous, which implies the following moment conditions:

$$E(\Delta x_{it-s}, \Delta\varepsilon_{it}) = 0 \quad t = 3, \ldots, T \text{ and } s \geqslant 2.$$

The estimation equation and moment conditions can be estimated by first-differenced GMM, which was developed by Arellano and Bond (1991). However, conventional GMM estimation, also developed by Arellano and Bond (1991), exhibits a major drawback if the explanatory variables display persistence over time — as is the case for variables such as R&D intensity. In this case, their lagged levels may be very poor instruments for their differences. Blundell and Bond (1998) show that the first-differenced GMM panel estimator performs poorly when the time series are persistent and small in number, which is typically the case in empirical growth models. To reduce the potential bias and imprecision associated with the difference estimator, an alternative system GMM estimator is suggested by Arellano and Bover (1995) and implemented by Blundell and Bond (1998). The system GMM estimator combines the regression equation in first differences – instrumented with lagged levels of the regressors – with the regression equation in levels, instrumented with lagged differences of the regressors. Following Blundell and Bond (1998), we supplement the moment conditions based on the first-differenced equation with the following level moment conditions:

$$E(\varepsilon_{it}, \Delta y_{it-1},) = 0 \quad t = 3, \ldots, T, \qquad E(\varepsilon_{it}, \Delta X_{it-1},) = 0 \quad t = 3, \ldots, T\ s \geqslant 1.$$

The system GMM is obtained by level and first-differenced moment conditions. Blundell and Bond (1998) show that the system GMM estimator produces large increases in both consistency and efficiency. In order to check whether the right-hand variables are characterized by a near unit root process, we run simple $AR(1)$ regressions using the system GMM estimator. Unreported results show that R&D intensity is characterized by a very high $AR(1)$ coefficient of about 0.92.

The sign of the coefficient for Business sector R&D expenditures as a percentage of GDP is expected to be positive. The share of BERD devoted to high-tech industries may have an additional growth effect. This can be explained by the fact that R&D investment in the high-tech sector generates spillovers to other industries.

3. Data and stylized facts

We use ANBERD and OECD Science and Technology indicators to calculate the share of R&D spending in the high-tech sector. According to the OECD, manufacturing industries can be classified in four categories according to their R&D intensity: (i) high, (ii) medium–high, (iii) medium–low, and (iv) low technology. The two ANBERD databases cover 19 OECD countries and 58 sectors based on ISIC rev. 3 from the period 1987 to 2004 and 1973 and the ANBERD R-2 data series, consisting of industrial R&D expenditure data for 15 OECD countries. Both data sources can be easily merged into one database. In addition, we use the OECD's Science and Technology indicators and Economic Outlook database for the period 1960–2004, available for download at www.sourceoecd.org. Aggregate R&D intensity is defined as the ratio of total or business enterprise expenditures in research and development (BERD) to GDP, and is drawn from the OECD's MSTI database. The data on average years of education are drawn from the educational attainment database developed by Barro and Lee (2000). In order to assemble data for the year 2000, we update the series using data from the OECD's *Education at a Glance*. GDP per capita, investment ratio and the labour productivity index in the business sector are drawn from the OECD Economic Outlook database. GDP per hour worked is drawn from the OECD productivity database.

Table 1 contains the means of the variables, averaged over each of the seven five-year periods: 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999 and 2000–2004. The mean investment ratio increased until the first half of the 1970s, after which it decreased. The average ratio of business enterprise R&D (BERD) to GDP reached 1.4% during the period 2000–2004, compared to 0.8% in the first half of the 1980s. Furthermore, the composition of R&D has shifted from low- to high-tech areas. Between 1980 and 2004, the share of BERD performed in the high-tech sector increased from 39% to 52%, on average.

Unreported results show that the change in the share of industrial R&D in the high-tech sector was uneven among the countries observed: Canada, Ireland, Sweden, Finland and the Netherlands show strong growth in R&D expenditures in the high-tech sector, while the same figure stagnated in France, Germany and the USA (OECD, 2005). Table 2 reports means, standard deviations, and minima and maxima for the sample periods.

4. Estimation results

Table 3 shows the estimation results for the growth equation for three different specifications. The specification (i) includes lagged GDP per capita, the investment ratio and the share of R&D in the high-tech sector and six period

Table 1
Summary statistics over time

	1970–1974	1975–1979	1980–1984	1985–1989	1990–1994	1995–1999	2000–2004
GDP per capita, working-age population, in PPP (thousands).	24.0	26.3	28.1	30.0	33.1	36.0	41.4
Investment ratio (%)	22.9	21.8	20.2	20.4	19.6	19.5	20.5
Average years of education	7.5	7.8	8.3	8.7	9.0	9.2	9.7
Business sector R&D expenditures (BERD) % GDP	0.80	0.84	0.92	1.02	1.05	1.18	1.33
Share of BERD in the high-tech sector in total manufacturing BERD (%)	36.2	36.6	39.2	42.1	47.8	50.6	51.6
Alternative dependent variables:[a]							
GDP per hour worked (index 1995–1999 = 100)	62	66	68	90	100	104	
Labour productivity index in the business sector (1995–1999 = 100)	71	77	85	91	100	109	
Number of countries	14	15	17	19	16	14	15

Source: OECD ANBERD, OECD Economic Outlook database, OECD Science and Technology indicators, Barro and Lee (2000). Germany is excluded from the period 1990 to 1994 onwards. The number of observations is 110.
[a] The sample based on two alternative dependent variables only includes 86 observations due to data availability of total hours worked.

Table 2
Summary statistics (total sample)

	Mean	s.d.	Min	Max
GDP per capita, working-age population, in constant PPP (thousands)	31.2	7.2	15.3	57.1
Investment ratio (%)	20.7	3.7	13.1	30.7
Average years of education	8.6	1.7	4.7	12.0
Business sector R&D expenditures (BERD) % GDP	1.02	0.61	0.08	3.13
Share of BERD in the high-tech sector in total manufacturing BERD (%)	43.4	12.8	17.8	72.8

Source: see Table 1.

dummy variables. In specification (ii), we also include average years of education and BERD as a percentage of GDP. Specification (iii) includes all of the regressors. In order to reduce the influence of potential outliers, we exclude data points whose standardized residual falls outside the interval from −2 to 2. This reduces the sample by seven observations and leaves us with 110 observations.[1] In all cases, the Sargan test of overidentifying restrictions cannot reject the null hypothesis that the instruments are uncorrelated with the error term at the 5% level. Similarly, the tests of serial correlation reject the hypothesis that the error term exhibits second-order serial correlation.

As expected, we find that both business enterprise expenditures as a percentage of GDP (BERD % GDP) and the investment ratio have a positive and highly significant effect on GDP per capita. The short- and long-term elasticity of GDP per capita with regard to the investment ratio are 0.15 and 1.4, respectively. Furthermore, lagged GDP per capita has a positive and large coefficient of about 0.89.

The elasticities of GDP per capita with respect to BERD % GDP are 0.024 in the short term and 0.22 in the long term. Average years of education is positive, but the coefficient is not significantly different from zero. However, the Wald-test indicates that the variables average years of education, BERD % GDP, and the share of R&D in the high-tech sector are jointly significant at the 1% level. The long-term coefficient for average years of education (about 0.12) indicates that a one-year increase in the average length of education raises the GDP per capita by 1.3%. The main result is that the impact of the share of R&D in the high-tech sector is significantly positive, even when

[1] Because of the exclusion of outliers, the coefficient on the share of R&D in the high-tech exports is decreasing while the coefficient for business R&D intensity is slightly increasing. Empirical results based on the estimation sample including outliers are available from the author upon request.

Table 3
Estimation results for the system GMM estimator (dependent variable: Δ ln GDP per capita in PPP)

	(i)			(ii)			(iii)		
	Coeff		t	Coeff		t	Coeff		t
Lagged Δ ln GDP, working-age pop., in const. PPP	0.960	[b]	19.55	0.890	[b]	17.64	0.889	[b]	16.47
Δ ln investment ratio (INV)	0.177	[b]	4.06	0.124	[b]	3.89	0.151	[b]	4.74
Δ ln average years education (EDU)				0.006		0.41	0.013		1.00
Δ ln BERD % GDP (BERDXGDP)				0.027	[b]	3.42	0.024	[b]	2.66
Δ ln share BERD in high-tech sector (BERDHT)	0.042	[b]	2.33		[b]		0.026	[a]	1.87
Period dummy 1975–1979	−0.055	[b]	−4.78	−0.047	[b]	−5.55	−0.044	[b]	−4.28
Period dummy 1980–1984	−0.082	[b]	−5.50	−0.072	[b]	−6.43	−0.069	[b]	−5.39
Period dummy 1985–1989	−0.058	[b]	−2.82	−0.043	[b]	−2.84	−0.043	[b]	−2.47
Period dummy 1990–1994	−0.064	[b]	−2.76	−0.041	[b]	−2.17	−0.043	[b]	−2.21
Period dummy 1995–2000	−0.041		−1.58	−0.012		−0.68	−0.016		−0.79
Period dummy 2000–2004	−0.036		−1.32	0.000		0.00	−0.005		−0.22
Constant	0.328		1.37	−0.069		−0.31	−0.019		−0.08
Sargan test of overidentifying restrictions (p-value)	0.032			0.062			0.064		
AB test for $AR(1)$ (p-value)	0.043			0.012			0.026		
AB test for $AR(2)$ (p-value)	0.760			0.735			0.719		
No. of observations (no. of countries)	110 (19)			110 (19)			110 (19)		
Wald-test: EDU = BERDXGDP = 0				$F(2, 18) = 7.29$ (p-value 0.005)					
Wald-test: BERDHT = EDU = BERDXGDP = 0							$F(3, 18) = 5.23$ (p-value 0.009)		
Wald-test: BERDHT == BERDXGDP = 0							$F(2, 18) = 4.75$ (p-value 0.022)		

The table provides the results of the one-step system GMM estimator. t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005) and are robust to heteroscedasticity. The model uses data averaged over periods 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999, and 2000–2004. Germany is excluded starting from the period 1990 to 1994. For each period, we treat right-hand variables as endogenous in all regressions, instrumenting them using lags from $t-2/t-3$ in the first-differenced equation and lags from $t-1$ in the level equation. In order to reduce the influence of potential outliers, we exclude data points whose standardized residual falls outside the interval from −2 to two. This reduces the sample by seven observations and leaves us with 110 observations. Source: OECD, own calculations.

[a] Statistically significant at the 10% level.

[b] Statistically significant at the 5% level.

BERD % GDP is included. The magnitude of the effect indicates that an increase of 10% in the share of R&D performed in the high-tech sector amounts to a 0.26% increase in GDP per capita in the short term and a 2.3% increase in the long term.

In order to shed additional light on the magnitude of the estimates we also calculate the change in GDP per working age population from a one standard deviation increase from the sample mean for each variable. A one standard deviation increase in the share of R&D performed in the high-tech sector (from 43% to 56%) increases GDP per working age population by 7%. An increase of one standard deviation in business sector R&D intensity (from 1% to 1.6%) is associated with an increase in GDP per working age population by 13%. This indicates that the growth effect of total business sector R&D is larger than that of the share of high-tech R&D expenditures.

To check the robustness of the results we provide results based on two alternative dependent variables as well as a regression results based on ten-year averages. Table 4 in the Appendix examines the robustness of our results to alternative dependent variables: the upper panel includes the results for the determinants of the change in log GDP in constant prices per hour worked and the lower panel contains the results for the determinants of the growth of labour productivity in the business sector. Column (ii) of the upper panel in Table 4 shows that the coefficient on the high-tech R&D share is again significant at the five per cent level and its size is similar to that reported in Table 3. Column (iii) shows that BERD % GDP and the share of R&D in the high-tech sector are jointly significant at the 5% level. The results using the labour productivity index in the business sector do also not lead to any qualitative or quantitative difference in the results (see lower panel of Table 4 in the Appendix). Additionally, we test the robustness of our results by re-estimating all three specifications employing ten-year averages (i.e. 1975–1984, 1985–1994 and 1995–2004) of the all variables instead of the five year averages. Since the number of observations decreases considerably if only three periods are considered we provide results for the static model estimated by fixed effects as well as OLS applied to first differences (see Tables 5 and 6, respectively). The fixed effects results show that both R&D in the business sector and the share of high-tech R&D are positive and significant at the five per cent level in all cases (see Table 5). Using specifications based on OLS applied to first-differences, we find that both BERD % GDP and the share of R&D in the high-tech sector are jointly significant at the 5% level for the specifications employing GDP per hours worked and labour productivity as dependent variables (see Table 6).

5. Summary and outlook

In OECD countries, the composition of R&D has shifted from low- to high-tech areas. This paper provides new empirical evidence of the relationship between R&D intensity and economic growth. It is also the first to control for the composition of R&D, a subject that has been neglected in previous work. The set of dependent variables includes the investment ratio, business enterprise expenditures on R&D as a percentage of GDP, and average years of education. These variables are complemented by the share of R&D expenditures in the high-tech sector in total manufacturing R&D expenditures. Using the GMM instrumental variable estimator to control for endogeneity, we find a significantly positive impact of increases in the share of R&D in the high-tech sector on the growth of GDP in working-age populations, even when controlling for business R&D intensity. Finally, we have also explored whether the results are robust if we use alternative dependent variables, namely GDP per hour worked and the labour productivity index in the business sector. In addition, we also consider 10-year averages instead of five-year averages to proxy for long-term economic growth. We find that the results are robust to the alternative measures of economic growth and to specifications based on 10-year averages.

Appendix

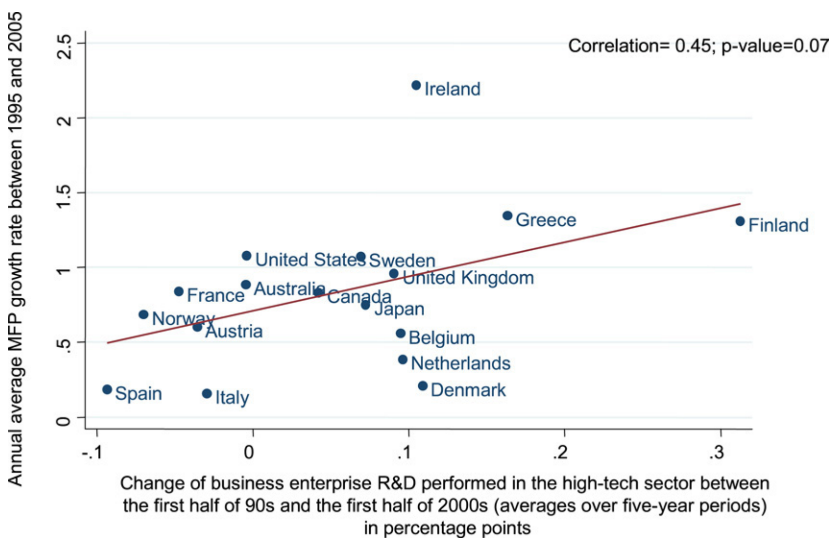

Fig. 1. Correlation between multifactor productivity growth and change in the share of R&D performed in the high-tech sector. Source: OECD MFP growth based on 'harmonized' price indices for ICT capital goods, in per cent and OECD MSTI.

Table 4
Robustness to the use of alternative dependent variables: Estimation results for the system GMM estimator

	Dependent variable: Δln GDP per hour worked								
	(i)			(ii)			(iii)		
	Coeff.		*t*	Coeff.		*t*	Coeff.		*t*
Lagged Δ ln GDP in const. prices, per hour worked	0.993	b	273.5	0.997	b	309.81	0.993	b	275.42
Δ ln investment ratio (INV)	0.152	b	5.19	0.162	b	4.98	0.176	b	5.41
Δ ln BERD % GDP (BERDXGDP)	0.017	b	2.42				0.014	b	2.03
Δ ln share BERD in high-tech sector (BERDHT)				0.040	b	2.08	0.031	a	1.62
Period dummy variables	Yes			Yes			Yes		
Constant	0.499	b	7.32	0.432	b	7.86	0.468	b	6.90
Sargan test of overidentifying restrictions (p-value)	0.441			0.406			0.446		
AB test for $AR(1)$ (p-value)	0.517			0.572			0.483		
AB test for $AR(2)$ (p-value)	0.672			0.685			0.637		
No. of observations	86			86			86		
Wald-test: BERDHT == BERDXGDP = 0							$F(2, 76) = 4.31$; p-value:0.017		
	Dependent variable: Δ ln labour productivity index measured as GDP in constant prices								
	Coeff.		*t*	Coeff.		*t*	Coeff.		*t*
Lagged Δ ln labour productivity index	0.739	b	24.74	0.753	b	24.40	0.745	b	24.31
Δ ln investment ratio (INV)	0.045	b	2.20	0.063	b	2.63	0.064	b	2.73
Δ ln BERD % GDP (BERDXGDP)	0.012	b	2.75				0.009	a	1.88
Δ ln share BERD in high-tech sector (BERDHT)				0.030	b	2.16	0.024	a	1.74
Period dummy variables	Yes			Yes			Yes		
Constant	1.249	b	10.62	1.248	b	10.25	1.279	b	10.57
Sargan test of overidentifying restrictions (p-value)	0.561			0.470			0.481		
AB test for $AR(1)$ (p-value)	0.200			0.348			0.283		
AB test for $AR(2)$ (p-value)	0.308			0.356			0.400		
No. of observations	86			86			86		
Wald-test: BERDHT == BERDXGDP = 0							$F(2, 76) = 4.17$, p-value: 0.019		

The table provides the results of the one-step system GMM estimator. t-values are based on the small sample correction of the variance estimates proposed by Windmeijer (2005). The model uses data averaged over periods 1970–1974, 1975–1979, 1980–1984, 1985–1989, 1990–1994, 1995–1999, and 2000–2004. Germany is excluded starting from the period 1990 to 1994. In order to reduce the influence of potential outliers, we exclude data points whose standardized residual falls outside the interval from −2 to 2. This reduces the sample by four observations. Source: OECD, own calculations.

[a] Statistically significant at the 10% level.

[b] Statistically significant at the 5% level.

Table 5
Fixed effects results based on ten year averages

Dependent variables:	GDP, working-age pop., in const. PPP			ln GDP per hour worked			ln labour productivity index		
	(i)			(ii)			(iii)		
	Coeff.		*t*	Coeff.		*t*	Coeff.		*t*
ln investment ratio (INV)	0.25		0.94	0.07		0.24	0.03		0.13
ln BERD % GDP (BERDXGDP)	0.24	b	2.46	0.29	a,b	2.78	0.27	a,b	3.55
ln share BERD in high-tech sector (BERDHT)	0.37	b	2.19	0.40	b	2.23	0.28	b	2.06
Constant	−2.69	a,b	−5.47	4.47	a,b	8.62	4.74	a,b	12.14
R^2 (within)	0.61			0.66			0.70		
# of obs	50			50			50		

The model uses data averaged over periods 1975–1984, 1985–1994, 1995–2004. Germany is excluded.

[a] Statistically significant at the 10% level.

[b] Statistically significant at the 5% level.

Table 6
OLS first differences estimates based on ten-year averages

Dependent variables:	Δ GDP, working-age pop., in const. PPP (i)			Δln GDP per hour worked (ii)			Δln labour productivity index (iii)		
	Coeff.		t	Coeff.		t	Coeff.		t
Δ ln BERD % GDP (BERDXGDP)	0.023		0.53	0.052		1.30	0.097	[a]	1.96
Δ ln share BERD in high-tech sector (BERDHT)	−0.007		−0.14	0.083		1.26	0.040		0.57
Constant	0.192	[a,b]	14.88	0.193	[a,b]	13.80	0.145	[a,b]	10.55
Adj $-$ R^2	0.030			0.084			0.220		
# of obs	31			31			31		
Wald-test: BERDHT == BERDXGDP = 0	$F(2, 28) = 0.18$; p-value: 0.84			$F(2, 28) = 3.68$; p-value: 0.038			$F(2, 28) = 5.99$, p-value: 0.007		

The model uses data averaged over periods 1975–1984, 1985–1994, 1995–2004. Germany is excluded.
[a] Statistically significant at the 10% level.
[b] Statistically significant at the 5% level.

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