
Has New Zealand benefited from its investments in research & development?^a

Robin Johnson, W. A. Razzak* and Steven Stillman

Department of Labour, PO Box 3705, Wellington, New Zealand

We use panel data for nine industries to evaluate research and development (R&D) investments in New Zealand over the past forty years. We estimate the impact of R&D stocks in a particular industry on output per person in that industry and on output per person in the rest of the economy. We examine both public and private R&D investments. Privately provided R&D has a statistically significant positive impact on own-industry output per person, suggesting it increases productivity. However, publicly provided R&D has no impact on own-industry output per person. There is also evidence that private R&D in certain industries positively affects output per person in the rest of the economy, i.e. it generates positive spillovers. There is no evidence of positive spillovers from publicly provided R&D.

I. Introduction

Economists accept that unless there is continuous technical progress, it is unlikely to have sustained economic growth. Solow (1957) introduced the formal neoclassical growth model and implicitly acknowledged that knowledge is a quasi public good, partially nonexcludable and nonrival, thus every one can exploit improvements in technology.¹ Arrow (1962) extended this work to provide an endogenous theory of technical change. These models have been further developed in more recent articles in the endogenous growth literature, e.g., Romer (1986, 1990), Lucas (1988), Benhabib and Jovanovic (1991) and Sala-i-Martin (1990). These models collectively theorize that knowledge spillovers are important determinants of technological progress and eventually productivity and economic growth.

In practice, research and development (R&D) and human capital are used as a common proxy for knowledge. Romer (1990) argues that R&D not only affects the firm that produces it, but also other firms via positive externalities. These spillovers occur through cumulated experiences that enhance the efficiency of production. There is a lot of empirical evidence to support this theoretical work. For example, Griliches (1979) finds that the stock of knowledge, measured by R&D, spills over from one firm to another. Wieser (2004) surveys the international literature on productivity and R&D. He shows that the literature contains reasonable evidence for a positive association between R&D and productivity, especially in manufacturing and that there is evidence that R&D in one firm impacts productivity in the rest of the firms in an industry, i.e. there is evidence of spillovers across firms.

*Corresponding author. E-mail: weshah.razzak@Impg.dol.govt.nz

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¹Nonrival means that the marginal cost for an additional user is negligible.

New Zealand embarked on a widespread economic and institutional reform in 1984. It included among other things: liberalizing interest rates, wages, prices, the exchange rates, international trade, privatising state-owned enterprises and deregulating various markets. Prescott (2002) showed that despite the reform, New Zealand's *relative* productivity performance has been declining substantially since the 1970's.²

Prescott (1997) argues that the frontier of knowledge or R&D need not be in each country as foreign R&D could be adopted domestically. While this is a reasonable general assertion that is consistent with the partial nonexcludability characteristic of R&D, it could still be costly for New Zealand to continuously adopt new foreign technology because small size firms that dominate the economy could not afford it. Also, there are still significant barriers on the transfer and use of new technology. Further, an adequate level of human capital is required for the adoption of foreign new technology, which might be unavailable for small firms. Full evaluation of the effects of R&D on productivity in New Zealand requires examinations of the costs and benefits of both domestic and foreign R&D.

This article examines the relationship between privately and publicly provided (not funded) domestic R&D and output per person over the past 40 years in New Zealand. We created a panel of nine industries over the period 1962 to 2002 to estimate a production function, which allows privately and publicly provided R&D capital stocks in an industry to directly impact output per person in that industry and output per person in the rest of the economy.

We find that privately provided R&D has a statistically significant positive impact on own-industry output per person, suggesting it increases productivity. The effect is larger in the long run. However, publicly provided R&D has a statistically insignificant impact on own-industry output per person.

There is also evidence that private R&D in certain industries positively affects output per person in the rest of the economy, i.e. it generates positive spillovers. We could not find similar evidence of positive spillovers from publicly provided R&D. Our results depend on our specific modelling specifications and methodology, i.e. they are not model, specification and estimation methodology-invariant, but they are consistent with international evidence, e.g. Lichtenberg (1993) and Bönnte (2004).³

The article is organized as follows. In Section II we describe the empirical model. In Section III, we discuss the data and, in Section IV, discuss the estimation approach and present the results. Section V concludes.

II. Empirical Model

Researchers have investigated spillovers using a variety of methods, which are generally divided into econometric and case studies.⁴ However, most recent research consists of econometric studies, which following Griliches (1979), specifies the relationship between R&D and output in terms of a Cobb-Douglas production function and includes R&D as an additional factor input.⁵ This is the approach we take in this article. We start with a general Cobb-Douglas production function, which is given by:

$$Y_{it} = Ae^{\lambda t} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} e^{\varepsilon_{it}} \quad (1)$$

where Y_{it} is the i th industry's real output in year t , A is a constant technical change, λ is the rate of disembodied technical change, K_{it} is the stock of physical capital, L_{it} is labour input, R_{it} is the total stock of R&D and ε_{it} is the error term, which has classical properties.⁶

We extend this model in two dimensions. First, we split R&D into private and public components, which

²It is quite possible that there was an adjustment period that lasted several years after the reform, as growth rates have improved substantially from 1993 onwards.

³We are aware of two papers only that examine R&D spillovers in New Zealand. Eveleens and Scobie (1986a, b) examined R&D spillovers in agriculture using different data and estimation method and found a positive relationship between R&D and agricultural productivity. Johnson (1999) used a data set similar to ours, but a different method to examine economy-wide R&D spillovers and found pretty results similar to ours.

⁴Mansfield *et al.* (1977) is an example of case studies for manufacturing innovations.

⁵Wieser (2004) provides a long list of references using this method. Also see Engelbrecht (1997), Engelbrecht (2002) and Coe and Helpman (1995) for OECD. Another approach is to estimate cost functions as systems of equations that include factor demand equations. For example see Mohnen *et al.* (1986), Bernstein and Ishaq (1991), and Mohnen and Lepine (1991). An additional approach is to regress R&D stocks or expenditures on indirect measures of total factor productivity. For example see, Bönnte (2004), Engelbrecht (2002, 2003), Engelbrecht and McLellan (2001) and Johnson (1999).

⁶Capacity utilization could be a proxy for capital utilisation as an additional regressor. However, the New Zealand Institute for Economic Research (NZIER) survey of capacity utilisation does not match the industry specifications that we have followed in this article, e.g. the industries are very different. For this reason we could not use their data.

allow R&D from different sources to have heterogeneous impacts on output.

$$Y_{it} = Ae^{\lambda t} K_{it}^{\alpha} L_{it}^{\beta} (R_{it}^{\gamma_1})^{\rho v} (R_{it}^{\gamma_2})^{\rho b} e^{\varepsilon_{it}} \quad (2)$$

where output now depends separately on own private R&D stocks, $R_{it}^{\rho v}$ and own public R&D stocks, $R_{it}^{\rho b}$.

Taking logs of Equation 2 (lower case) and subtracting labour l_{it} from both sides gives:

$$\begin{aligned} y_{it} - l_{it} = & a + \lambda t + \alpha(k_{it} - l_{it}) + \delta l_{it} + \gamma_1(r_{it}^{\rho v} - l_{it}) \\ & + \gamma_2(r_{it}^{\rho b} - l_{it}) + \varepsilon_{it} \end{aligned} \quad (3)$$

where $\delta = \alpha + \beta + \gamma_1 + \gamma_2 - 1$ measures the deviation from constant returns to scale.

Second, we allow external R&D from other industries to directly impact output in each industry and for this impact to vary depending on the source industry of the R&D. This is how we allow for spillovers in our empirical model.⁷ Let the external effect be given by $xr^{\rho v}$ and $xr^{\rho b}$ for private and public R&D respectively and let hat denote per person. These variables are different from all other explanatory variables and they are described in the appendix. The final regression model is given by:

$$\begin{aligned} \hat{y}_{it} = & a + \lambda t + \alpha \hat{k}_{it} + \delta l_{it} + \gamma_1 \hat{r}_{it}^{\rho v} + \gamma_2 \hat{r}_{it}^{\rho b} + \theta_1 x \hat{r}_{1t}^{\rho v} \\ & + \theta_2 x \hat{r}_{2t}^{\rho v}, \dots, \theta_9 x \hat{r}_{9t}^{\rho v} + \phi_1 x \hat{r}_{1t}^{\rho b} + \phi_2 x \hat{r}_{2t}^{\rho b}, \dots, \phi_9 x \hat{r}_{9t}^{\rho b} + \varepsilon_{it} \end{aligned} \quad (4)$$

where the hat on top of the variables denote per capita.

As we discuss further in the data section, most of our variables exhibit strong serial correlation. Thus, we will estimate a dynamic version of (4) by including lagged output as an explanatory variable.

We directly estimate this model. The coefficient γ_1 measures the average own-effect of privately provided R&D in industry i on output per person in that industry and the coefficient γ_2 measures the average own-effect of publicly provided R&D in industry i on output per person in that industry. The coefficient θ_1 measures the average effect of private R&D in

agriculture on output per person in all other industries. Likewise, the coefficient ϕ_1 measures the average effect of public R&D in agriculture on output in all other industries. The following ‘spillover’ coefficients $\theta_2, \dots, \theta_9$ and ϕ_2, \dots, ϕ_9 can be interpreted in a similar manner. These are our main coefficients of interest.

III. Data

All data used in this article are available from 1962 to 2002, except the data on capital stock which is only available up until 2000 and are measured in 1982/1983 prices. Each data series is collected for nine industries, which is the lowest level of aggregation common to the different data sources used in the article. Table 1 lists the nine industries and shows how they match to the Statistics New Zealand (SNZ) classification.

Industry output, Y_{it} , is measured using industry level real production GDP published by SNZ. The stock of physical capital in each industry, K_{it} , is taken from Philpott (1994, 1995, 1999) and updated to the year 2002.⁸ This measure includes residential buildings, nonresidential buildings, other buildings, land improvements, transport equipment, plant, machinery and other equipments. We also estimate production functions using a measure that excludes all residential buildings and land. We do not report these results because we found no qualitative differences.

Industry full-time equivalent employment, L_{it} , is used to measure labour input. This data is also taken from Philpott (1994, 1995 and 1999) and updated to the year 2002. Data are derived from two different sources. Prior to 1987, the data are from the Quarterly Employment Survey (QES). Since 1987, the Household Labour Force Survey (HLFS) has been used instead. These sources are combined and part-time employment is given a weight equal to 0.35

⁷Romer (1986) used physical capital to test for spillovers, Griliches (1979) used R&D and Lucas (1988) used human capital. Nelson and Phelps (1966) argue that the stock of human capital affects output growth (or per capita output growth) because it affects the adoption and the absorption of new technologies so one can have a product term. Engelbrecht (2002, 2003) tested this hypothesis for many countries and found some evidence for it.

⁸The capital stock measure is subject to common criticisms that arise from guessing the depreciation rate and the initial stock, and the assumption of a constant rate of depreciation. According to Philpott (1994, 1995 and 1996), a base year was established in the past from known statistical collections of asset inventories and then added to each year by new investment, and subtracted from by estimated depreciation. In the gross stock definition, depreciation is based on the expected life of assets and is formally run down in the last eight years of each asset class. By and large, the rate of depreciation on capital allowed by the IRD is higher and hence the size of the net stock (as Philpott called it) is lower. These data are NZSIC-consistent (New Zealand Standard Industrial Classification) and based on existing capital formation data from Statistics New Zealand at that time. For the period since 1989–90, capital formation is taken from NZSIC-consistent capital formation data. Stocks were extrapolated using deflated capital formation series and the average implicit depreciation rate in the Philpott series for 1986–87, 1987–88, 1988–89 and 1989–90.

Table 1. Industry classifications across data sources

Our title	SNZ categories	R&D survey categories
(1) Agriculture	Agriculture	Sheep, Beef, Dairy, Alternative Species, Generic Animal Research, Forage, Horticulture, Arable
(2) Fisheries	Fisheries	Fisheries
(3) Forestry	Forestry	Plantation Forestry
(4) Processing	Food, Wood, Paper, Textiles	Meat, Dairy, Other Food, Fibre, Wood
(5) Manufacturing	Mining, Basic, Chemical, NonMetal and Machine Manufacturing	Material, Engineering, Electronic
(6) Energy	Electricity, Gas and Water	Energy
(7) Building	Building and Construction	Construction
(8) Transport	Transport and Storage	Transport
(9) Other & Services	Wholesale and Retail Trade, Communications, Finance, Personal and Community Services	Commercial and Trade, Information, Planning, History, Relationships, Political, Education, Environmental, Geological, Land Use, Marine, Climate Space, Antarctica, Fundamental Knowledge, Health, Defence

of full-time employment, where part-time is defined as working 20 h or less per week.⁹

R&D expenditure is available from New Zealand Research and Experimental Development Statistics for the years 1989–1990, 1990–1991, 1991–1992, 1992–1993, 1993–1994, 1995–1996, 1997–1998, 1999–2000 and 2001–2002. This survey follows the conventions used by the OECD. R&D is defined as ‘*Creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society and the use of this knowledge to devise new applications.*’ R&D activities exclude consulting and scientific and technological services and market research.

Information is gathered from the *providers* (those who undertake the R&D research) rather than the *funders* of research.¹⁰ Expenditures are reported at the industry level with certain industries also divided into sub-output classes and are split into public (government plus university) and private providers.¹¹ The survey classifies producer board-owned research

organisations (e.g., the Dairy Board) as private business, but state-owned research institutes as public expenditure. Research institutes are classified by the industry they predominantly serve. The industry classifications used for the R&D data differ from the standard classification used by SNZ for our other data series. As shown in Table 1, we try to align the R&D classification as closely as we can to those used by SNZ.

The data are interpolated for the nonsurvey years on the basis of R&D expenditures as a percent of GDP. We also backdated the R&D data to 1962. The data were derived in two parts: government (public) and business (private). Past government expenditures are available in government reports and New Zealand yearbooks (expenditures on scientific research). For many years these figures were collected by the National Research Advisory Council (NRAC). We used 1991–92 survey classification as a guide to allocate these expenditures. The level of business spending was based on the proportion of business

⁹ In international literature, part-time employment is usually defined as working 30 hours or less per week and given a weight of 0.50. Before 1986, the QES did not include agriculture so Philpott used employment from the agriculture Census.

¹⁰ Researchers are asked to tick the type of output class of their research, e.g., if research is about sheep the researcher would classify it as agricultural research and if it is about fish harvest then it is classified as fisheries. They are also asked whether they consider their research as private or government or university research. Although some of privately provided R&D projects are publicly funded the percentages are small. The Ministry of Research, Science and Technology Report (1997, p. 11) publishes the self-funding ratio for private R&D expenditures. We calculate the average over the period 1990 to 1997 to be 86.5%. The remaining money includes not only government funds, but also funds from universities, nonprofit organisations and from abroad.

¹¹ For example, the sub-groups for agriculture are sheep (meat), sheep (wool), sheep (general), beef production, dairy production, alternative animal species and generic animal research; for processing are meat, dairy and other processes; and for manufacturing are material and industrial processing, engineering, electronic and instruments, fibre, textile and skin processing, wood and paper processing. For classifications without subgroups, descriptions of related research are pretty vague. For example, energy research is defined as ‘information bases for prospecting, production and use of all energy sources’.

spending in 1989–90 in relation to GDP for both the total business expenditure and the industry totals.

Following Griliches (1979), the perpetual inventory method is used to compute the stock of R&D in each year. The formula is given by $S_0 = E_0 / (\dot{E} + d)$, where S_0 is initial stock of R&D capital either at the beginning or the end of the period where data on expenditures are available. The term E_0 denotes annual expenditures on R&D at constant prices during the first year, \dot{E} is the average annual growth of R&D expenditures for the nearest relevant year and d is the depreciation or obsolescence rate of knowledge. If it is assumed that the stock had been growing before the first year (0) at a certain rate then the estimate of the total starting stock would be higher than it would have been if the expenditures were capitalised by the rate of depreciation alone. In the calculation, we estimated \dot{E} for the first 10 years after 1962 and d were set at 5% per annum.¹²

As pointed out in Mairesse and Hall (1996), labour and capital includes contributions of physical capital used in R&D laboratories and R&D personnel used in the building of the R&D stock. This type of measurement error will lead to an understatement of the impact of R&D on output (and an overstatement of the impact of labour and capital). Our estimates of the impact of private R&D are also likely to be further biased downwards by the exacerbation of classical measurement caused by our backdating procedure. We are unable to correct for these problems, so our estimates are likely a lower bound on the true impacts of R&D on output.

Appendix Fig. 1a–1e graph each of our five main data series over time at the industry level. Eyeballing the data indicates that there are significant trends in output, capital, labour and R&D. Because we do not know the nature of the trend in the data, we tested for unit roots in each of the time series using different tests such as the ADF, Phillips-Perron (1987) and Elliott (1999) time series tests. We also ran a number of panel data unit roots to take advantage of additional data points. We used the panel data version of the ADF, Im–Pesaran–Shin (1997) and Levin–Lin–Chu (2002) tests to test for unit root in \hat{y}_{it} , \hat{k}_{it} , \hat{l}_{it} , \hat{r}_{it}^{pv} and \hat{r}_{it}^{pb} . Again, these tests were unable to reject the hypothesis of unit roots, except in a few employment series. We also used the Sarno–Taylor (1998) and Taylor–Sarno (1998) multivariate tests for

unit root. These tests reject the hypothesis of unit root in private and public R&D per capita with one lag. Rejection of the unit root implies that these tests are most powerful.

IV. Estimation and Results

We now turn to estimating the production function presented in Equation 4 using annual data from 1962 to 2002 on nine industries, as described above. Given the unit root tests we presented earlier, we believe that the dependent variable is highly likely to have a unit root and at least one of the independent variables has a unit root, i.e. \hat{k}_{it} , while the rest of the independent variable might be stationary. This equation will be estimated in log-levels.¹³

Heterogeneity is another problem that arises in the estimation of the panel data production functions. It is difficult to argue that the production function is identical in each industry. Not allowing the parameters to vary across industries will introduce a size-related heteroscedasticity into the residuals. We felt that our time series is not long enough to estimate production functions for each industry, but instead allow for heterogeneity across industries by including a fixed effect for each industry in the error term. This allows each industry to have a different scale effect in the production function, but does not allow the impact of inputs to differ across industries.

Inclusion of fixed-effect is meant to capture industry differences. Mairesse and Sassenou (1991) argue that it might be more appropriate to include industry specific variables such as the inter-sector spillover. Wakelin (2001) was first to show that the estimates change significantly by the inclusion of fixed-effect. For these reasons we report regressions with different specifications.

Another important estimation issue is that production function inputs may be endogenously determined with output if there are feedback effects from outputs to inputs or timing issues related to what time period each data series actually measure. The generalized method of moments (GMM) could remedy both endogeneity and measurement error bias if instruments exist such that they are correlated with the

¹² The standard value of depreciation ranges from 0 to 10 (Griliches, 1995). For more details about these calculations see Johnson (1999). He also experimented with different rates of depreciation. He reported that as the rates of depreciation increase the estimated elasticities got smaller, but the rate of returns remained unchanged.

¹³ We tested the OLS regression residuals of Equation 4 ε_{it} for unit root. We used several different tests. Results are not reported, but they are available upon request. There is strong evidence that we can reject the hypothesis of unit root in the residuals ε_{it} . There is only one case out of 20, where the Levin *et al.* (2002) did not reject the hypothesis of a unit root in the residuals. The test seems to be very sensitive to the specification of the lag structure.

production function inputs, but not with the contemporaneous error term. We estimate our regression using GMM with up to eight lags of the regressors as instruments and cross-section weights as the instrument weighting matrix.¹⁴ While lagged regressors are uncorrelated with the contemporaneous error term by design, they are only weakly correlated with the contemporaneous regressors. This ‘weak instruments’ problem typically leads to a downward bias in the estimated share of capital and to, generally, biased results.¹⁵ For this reason, we present results estimated using both OLS and GMM.¹⁶

Table 2 presents the results from estimating the dynamic model using five different estimation approaches. Specification and estimation method seem to affect the results. Results change when the method is changed. We report OLS and GMM estimates with and without industry fixed effects (i.e. cross-sectional dummies) and we report estimates from the Arellano–Bond GMM estimator. All estimated SEs allow for arbitrary correlation in the error term across time within industries (robust Huber–White) and are period-adjusted for degrees of freedom.

The results are sensitive to whether the regression includes fixed effects and to which estimator is used.¹⁷ The J -statistic, which test for the overidentification of the instruments, cannot reject the null hypothesis of overidentification in each GMM specification. This suggests that the GMM estimator with fixed effects may be the correct model, but these estimates are affected by both exacerbated measurement error and weak instrument bias. OLS parameter estimates, on the other hand, are super-consistent under the fully specified model with $I(0)$ residuals, but OLS does not

deal with other problems such as measurements and endogeneity.

Output per person is persistent over time, with ρ , the coefficient on lagged output per person, estimated to be between 0.46 and 0.78 depending on the estimator. The elasticity of capital, α , is statistically significant only in the estimates without fixed effects and is quite small even in these specifications.¹⁸ The fact that this is the case for all regressions including OLS suggests that weak instrument bias is not responsible. Capital stock is highly correlated with R&D stock, which may be contributing to the small estimates.

The coefficient δ measures the deviations from constant returns to scale with the production function exhibiting constant returns to scale if δ is zero. Our estimates are essentially zero with only two of five estimators are -0.22 and -0.32 and borderline significant. A negative estimate implies diminishing returns to scale, which has been found in the international literature. For the UK, Wakelin (2001) found diminishing returns in manufacturing with size estimates similar to ours. She discusses the international findings.¹⁹ Overall, these estimates are most consistent with constant returns to scale.

The coefficients γ_1 and γ_2 are the estimates of the own-effect of private and public R&D on output per person. The elasticity of private R&D, γ_1 , is positive in all regressions and significant in three out of five. The estimates vary between 0.09 and 0.16 suggesting that private R&D has, on average, a positive impact on own industry output. The magnitude of these estimates is close to the mean estimate of R&D elasticity for many international studies, Wieser (2004). Given the range of estimates of γ_1 and aggregate output and private R&D stock, the average

¹⁴ Dropping the subscripts for simplicity, the GMM estimator minimises $S(\beta) = (\sum h'\varepsilon(\beta))'W(\sum h'\varepsilon(\beta)) = g(\beta)'Wg(\beta)$ with respect to β for a chosen $p \times p$ weighting matrix W , where $g(\beta) = \sum g(\beta) = \sum h'\varepsilon(\beta)$ and h is a $T \times p$ matrix of instruments that includes up to 8 lags of the RHS variables.

¹⁵ Mairesse and Hall (1996), Blundell and Bond (1999) and Arellano and Bover (1995) discuss this problem in more detail and introduce small sample adjustments to the weighting matrix to improve inference. As discussed subsequently, we implement one of these adjustments but it has little impact on our results.

¹⁶ We also report the Arellano–Bond (1991) GMM estimator. This is an estimator specifically designed for dynamic panel data with fixed effects and takes advantage of moment conditions beyond the first-order. This approach does not require the assumption of zero covariance across years or homogeneity across industries for efficiency. It involves transformation of instruments in first differences. However, it still suffers from the ‘weak instruments’ problem and, in theory, requires that there are more cross-sectional units than time series observations (i.e. $N > T$), which is not the case in our data. Therefore, the results of this estimator must be interpreted with care.

¹⁷ We also estimated the model in first-difference specifications and found that the results change only slightly.

¹⁸ We also used the Arellano–Bover (1995) orthogonalization method to adjust our Arellano–Bond GMM estimates for weak instrument bias, but this had no impact on the magnitude of α . We also tried using capital stock measured at the beginning of the period instead of the end, but this also had no impact on the results.

¹⁹ Griliches and Mairesse (1990) also found a similar evidence for the United States and even stronger evidence of diminishing returns for Japan. Their explanation was that the exclusion of raw materials and intermediate products from the production function might the reason for these results. Nickell *et al.* (1992) found similar results for the United Kingdom, which they attribute to measurement errors in k_{it} and l_{it} . We don’t have data for intermediate raw material by industry in New Zealand so we could not test the above hypothesis.

Table 2. Regression estimates of industry production function with spillovers

$$\hat{y}_{it} = a + \lambda I + \rho \hat{y}_{i,t-1} + \alpha \hat{k}_{it} + \delta l_{it} + \gamma_1 p_{it}^{pv} + \gamma_2 x_{it}^{pv} + \theta_1 x_{it}^{pv} + \theta_2 x_{it}^{pv} + \theta_3 x_{it}^{pv} + \theta_4 x_{it}^{pv} + \theta_5 x_{it}^{pv} + \theta_6 x_{it}^{pv} + \theta_7 x_{it}^{pv} + \theta_8 x_{it}^{pv} + \theta_9 x_{it}^{pv} + \phi_1 x_{it}^{pb} + \phi_2 x_{it}^{pb} + \phi_3 x_{it}^{pb} + \phi_4 x_{it}^{pb} + \phi_5 x_{it}^{pb} + \phi_6 x_{it}^{pb} + \phi_7 x_{it}^{pb} + \phi_8 x_{it}^{pb} + \phi_9 x_{it}^{pb} + \varepsilon_{it}$$

	OLS fixed effect		OLS no fixed effect		GMM fixed effect ^a		GMM no fixed effect ^b		GMM Arellano-Bond ^c	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
a	3.84	0.0008	1.54	0.0238	3.78	0.0002	1.51	0.0023	-	-
λ	-	-	-0.01	0.0416	-0.02	0.0602	-0.02	0.0080	-	-
ρ	0.62	0.0000	0.71	0.0000	0.75	0.0000	0.78	0.0000	0.46	0.0000
α	-0.05	0.3619	0.07	0.0000	-0.006	0.8927	0.07	0.0048	-0.07	0.4923
δ	-0.22	0.0540	-0.009	0.8357	-0.04	0.7370	-0.03	0.5073	-0.32	0.0430
γ_1	0.12	0.1051	0.09	0.0019	0.16	0.0389	0.09	0.0002	0.15	0.1296
θ_1 (Agriculture)	-0.12	0.1641	-0.005	0.9246	0.17	0.1705	0.01	0.7469	-0.20	0.3699
θ_2 (Fisheries)	0.22	0.2118	-0.027	0.7182	0.26	0.0636	-0.04	0.7109	-0.01	0.9721
θ_3 (Forestry)	0.07	0.0961	0.05	0.0064	0.17	0.0272	0.08	0.0102	0.10	0.2322
θ_4 (Food Processing)	0.20	0.4827	0.11	0.3166	0.05	0.7104	0.08	0.2450	0.11	0.7039
θ_5 (Manufacturing)	-0.04	0.8699	-0.06	0.6371	-0.11	0.5912	-0.03	0.6575	-0.12	0.7914
θ_6 (Energy)	0.04	0.4913	-0.03	0.5023	0.06	0.2209	-0.02	0.6218	-0.02	0.8144
θ_7 (Building)	0.26	0.0000	0.14	0.0007	0.23	0.0000	0.13	0.0000	0.15	0.1977
θ_8 (Transport)	-0.12	0.3292	0.08	0.2462	-0.21	0.0129	0.01	0.8814	-0.14	0.3357
θ_9 (Other & Services)	0.28	0.2186	0.15	0.0920	0.43	0.0003	0.17	0.0209	0.43	0.1875
γ_2	-0.07	0.0192	-0.03	0.1916	-0.07	0.0427	-0.05	0.0954	-0.02	0.7776
ϕ_1 (Agriculture)	0.18	0.0367	0.02	0.4997	-0.16	0.2411	-0.006	0.8817	0.23	0.3378
ϕ_2 (Fisheries)	-0.30	0.0374	-0.01	0.7870	-0.25	0.0237	-0.01	0.8612	-0.09	0.7192
ϕ_3 (Forestry)	-0.10	0.0511	-0.07	0.0062	-0.17	0.0214	-0.06	0.1152	-0.12	0.1080
ϕ_4 (Food Processing)	-0.20	0.4969	-0.09	0.4907	0.01	0.9394	-0.008	0.8870	-0.07	0.8292
ϕ_5 (Manufacturing)	0.10	0.6708	0.16	0.2131	0.17	0.3490	0.12	0.1094	0.21	0.5843
ϕ_6 (Energy)	-0.10	0.0324	-0.02	0.5096	-0.06	0.2020	0.01	0.7329	-0.01	0.8832
ϕ_7 (Building)	-0.14	0.0011	-0.12	0.0194	-0.13	0.0000	-0.13	0.0507	-0.17	0.1305
ϕ_8 (Transport)	0.10	0.2239	-0.03	0.5081	0.20	0.0022	0.03	0.5694	0.17	0.1259
ϕ_9 (Other & Services)	-0.19	0.4083	-0.001	0.9874	-0.33	0.0067	-0.03	0.7778	-0.52	0.1165
Adjusted R^2	0.98		0.98							
σ	0.07		0.07							
J test p-value	-		-		0.22		0.11		0.39	

Notes: The sample is from 1962 to 2002. All variables are in logs. The instruments are lags 2 to 8 of the regressors. All SEs allow for arbitrary correlation in the error term across time within industries (robust Huber-White) and are period-adjusted for degrees of freedom. The J -test is the Sargan test for over-identifying restrictions. Trend and constant terms are dropped out when they are insignificant.

^aCross-section weights instrument weighting matrix.

^bIdentity instrument weighting matrix.

^cDifference specification instrument weighting matrix.

rate of return of investments on private R&D is somewhere between 3 to 6% a year.²⁰

On the other hand, our estimates of γ_2 are negative in all five regressions (significant in only two out of five) ranging from -0.02 to -0.07 . Thus, we find no evidence that publicly provided R&D has a positive impact on own-industry output per person. A negative coefficient could arise from reverse causality if public funds are targeted at industries growing slower than the overall economy. These results are also consistent with international evidence (Bönte, 2004).

There is some evidence that private R&D stocks in certain industries have an external effect on output per person in the overall economy, i.e. that there are spillovers across industries. In particular, there is fairly consistent evidence that private R&D in the building industry has a positive impact on output per person in other industries, with elasticities (θ) ranging from 0.13 to 0.26 and significant in four of five regressions. There is also evidence of spillovers from forestry, with estimates ranging from 0.07 to 0.17 and significant in four of five regressions. For Other Services, we also find evidence of spillovers, where three of five coefficients are significant.

We find no evidence that public R&D stocks have an external effect on output in the overall economy, with only 2 out of 45 relevant coefficients (ϕ 's) positive and significant in the five regressions (Agriculture in the first OLS regression with fixed effect and Transport in the GMM regression with fixed effect).

It is possible that R&D stocks in particular affect output per person with a lag. There is no consensus in the literature on the length of the lag and whether the lag structure is stable or variable. Mairesse and Sassenou (1991) in their survey of the literature report that applying different lag lengths tends to have little impact on results because R&D expenditures are very stable over time. Taking into account our small sample, we re-estimated our regression allowing for an arbitrary lag structure of eight lags in public R&D. This had no qualitative impact on our results. This test should be revisited in the future when more data will be available.

Engelbrecht and McLellan (2001) suggest that New Zealand benefits from international R&D (via trade perhaps) in addition to its own R&D. The production function estimated above does not account for international R&D, except to the extent that the stock of physical capital embodies foreign R&D,

because most of it is imported. We re-estimate our regressions including Australia's R&D stock as an additional explanatory variable to proxy for international R&D. This variable was created using the perpetual inventory equation to convert data on Australian business expenditures from Lattimore (1997) and the Industry Commission (using a depreciation rate of 5%). We find Australian R&D stock to have an insignificant impact on output per person in New Zealand. This might indicate that the Australian R&D stock is a bad proxy for international R&D.

V. Conclusions

This article uses panel data for nine industries to examine the relationship between R&D and productivity in New Zealand over the past 40 years. We find that privately provided R&D has a small positive impact on own-industry output, controlling for capital and labour inputs and that there is some evidence that this R&D spills over from certain industries to the overall economy. However, we could not find evidence that publicly provided R&D has a positive impact on either own-industry output or the overall economy (even allowing for lagged impacts). These results are consistent with international findings both in magnitudes and qualitatively (e.g. Goto and Suzuki, 1989; Wakelin, 2001; Wieser, 2004), but for reasons discussed previously should be considered lower bound estimates. In absence of firm-level data for New Zealand, our result is second-best and should serve as a benchmark for future studies.

We do not believe that the differences between private and public R&D are a result of measurement problems because the data come from the same series of surveys. If anything, our backdating of the private R&D data will have led to an increased downward bias in our estimates for private R&D because of measurement problems. These results are consistent with economic theory, in the sense that private R&D investments should be more efficient as private firms will not undertake such investments unless they expect a positive return. On the other hand, publicly provided R&D often has goals beyond profit maximization. That being said, one would expect more spillover at the firm level, but unfortunately the data are unavailable.

²⁰ Given the estimates of ρ , the long-run values of γ_1 are 0.30, 0.32, 0.64 and 0.41 for the four first regressions, which are quite large. Wang and Tsai (2003) reported large elasticities for high-tech firms in Taiwan. In the long run, the estimated returns can be as high as 24%.

One possible explanation for the failure to find significant effect from publicly provided R&D on labour productivity is that New Zealand's publicly provided R&D over the past 40 years lacked commercial value. In other words, the R&D projects never made it to the market, e.g. the lawnmower is designed, but the designer never been able to build it and subsequently the grass never got cut. This is a problem the Americans realized 40 years after they established their national laboratory systems, Mowery and Rosenberg (1998).

This article has taken into account a number of specification and estimation problems, but has also left others unresolved, e.g. measurement problems, short sample and unavailability of firm-level data, which require substantial further research. There are a small number of privately provided R&D projects that are publicly funded, this number has been on the rise and in 2004 account for nearly 30% of all privately provided projects. We do not have sufficient data to examine these effects rigorously, but we think that it is important to take these projects into account in future studies.

Our findings suggest that investments in R&D at the industry level have had, on average, a positive impact on productivity in New Zealand over the past forty years. In general, economic reform did not lead to increased impact of domestically provided R&D on productivity. Our results suggest that private R&D can lead to a small increase in productivity both in the industries making the investment and across the economy. Depending on the availability of data, future research should test whether the adoption of foreign new technologies has positively affected productivity and whether the human capital level in New Zealand played an important role in the process. Hopefully, this article can serve as a benchmark for future studies when more data become available.

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References

- Arellano, M. and Bond, S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *The Review of Economic Studies*, **58**, 277–97.
- Arellano, M. and Bover, O. (1995) Another look at the instrumental variable estimation of error-component models, *Journal of Econometrics*, **68**, 29–52.
- Arrow, K. (1962) The economic implications of learning by doing, *The Review of Economic Studies*, **29**, 155–73.
- Benhabib, J. and Jovanovic, B. (1991) Externalities and growth accounting, *The American Economic Review*, **81**, 82–113.
- Bönte, W. (2004) Spillovers from publicly financed business R&D: some empirical evidence from Germany, *Research Policy*, **33**, 1635–55.
- Blundell, R. and Bond, S. (1999) GMM estimation with persistent panel data: An application to production functions, The Institute of Fiscal Studies Working Paper No. 99/4.
- Coe, D. and Helpman, E. (1995) International R&D spillovers, *European Economic Review*, **39**, 859–87.
- Elliott, G. (1999) Efficient tests for unit root when the initial observation is drawn from its unconditional distribution, *International Economic Review*, **140**, 767–83.
- Engelbrecht, H.-J. (1997) International R&D spillovers, human capital and productivity in OECD economies: An empirical investigation, *European Economic Review*, **41**, 1479–88.
- Engelbrecht, H.-J. (2002) Human capital and international knowledge spillovers in TFP growth of a sample of developing countries: an explanation of alternative approaches, *Applied Economics*, **34**, 831–41.
- Engelbrecht, H.-J. (2003) Human capital and economic growth: cross-section evidence for OECD countries, *Economic Record*, **79**, 40–51.
- Engelbrecht, H.-J. and McLellan, N. (2001) Economic growth revisited: identifying a class of growth models for the New Zealand economy, Massey University, Department of Applied and International Economics Discussion Paper No. 01.10.
- Eveleens, W. M. and Scobie, G. M. (1986a) Agricultural research: What's it worth? Ministry of Agriculture and Fishery Working Paper No. 1/86.
- Eveleens, W. M. and Scobie, G. M. (1986b) Efficiency and equity in agricultural research, Economic Research Section, Ruakura Agricultural Research Centre, Discussion Paper No. 6/86.
- Goto, A. and Suzuki, K. (1989) R&D' capital rate of return on R&D investments and spillover of R&D in Japanese manufacturing industries, *Review of Economics and Statistics*, **71**, 555–64.
- Griliches, Z. (1979) Issues in assessing the contribution of research and development to productivity growth, *Bell Journal of Economics*, **10**, 92–116.
- Griliches, Z. (1991) The search for R&D spillovers, NBER Working Paper No. 3768, Cambridge, MA.
- Griliches, Z. (1995) R&D and productivity: econometric results and measurement issues, in *The Handbook of Economics of Innovation and Technological Change* (Ed.) Paul Stoneman, Blackwell, Oxford, pp. 52–89.
- Griliches, Z. and Mairesse, J. (1990) R&D and Productivity growth: comparing Japanese and US manufacturing firms in C. Hulten (Ed.) *Productivity Growth in Japan and the United States*, Chicago University Press, pp. 317–48.
- Im, K. S., Pesaran, M. H. and Shin, Y. (1997) Dept applied economics cambridge DP Dec 1997 (<http://www.econ.cam.ac.uk/faculty/pesaran/lm.pdf>).

- Johnson, R. (1999) The rate of return to New Zealand R&D, Unpublished Manuscript Presented at the New Zealand Association of Economists Annual Meeting 1999.
- Lattimore, R. (1997) Research and development fiscal incentives in Australia: impacts and policy lessons, Industry Commission, Canberra.
- Levin, A., Lin, C. F. and Chu, C. S. (2002) Unit root tests in panel data: asymptotic and finite sample properties, *Journal of Econometrics*, **108**, 1–24.
- Lichtenberg, F. (1993) R&D investment and international productivity differences, in *Economic Growth in the World Economy, Symposium* (Ed.) Horst Siebert, Tübingen, Mohr.
- Lucas Jr, R. (1988) On the mechanics of development planning, *Journal of Monetary Economics*, **22**, 3–42.
- Mairesse, J. and Hall, B. H. (1996) Estimating the production function of research and development in French and US manufacturing firms: An exploration of simultaneity issues with GMM Methods, in *International Productivity Differences and Their Explanations*, (Eds) K. Wagner and B. Van Ark, Elsevier Science, Amsterdam, pp. 285–315.
- Mairesse, J. and Sassenou, M. (1991) R&D and productivity: a survey of econometric studies at the firm level, *The Science Technology and Industry Review*, **8**, 317–48.
- Mansfield, E., Rapoport, J., Romeo, A., Wagner, S. and Beardsley, G. (1977) Social and private rates of return from industrial innovations, *Quarterly Journal of Economics*, **77**, 221–40.
- Mohnen, P. and Lepine, N. (1991) R&D, R&D spillovers and payments for technology: Canadian evidence, *Structural Change and Economic Dynamics*, **2**, 212–28.
- Mohnen, P., Ishaq, N. and Prucha, I. (1986) R&D, production structure and the rate of return in the US, Japanese and German manufacturing sector: a nonseparable dynamic factor demand model, *European Economic Review*, **30**, 749–71.
- Mowery, D. C. and Rosenberg, N. (1998) *Paths of Innovation: Technological Change in the 20th Century America*, Cambridge University Press, New York.
- Nelson, R. and Phelps, E. (1966) Investments in humans, technological diffusion, and economic growth, *American economic review, Papers and Proceedings*, **51**, 69–75.
- New Zealand Research and Experimental Development Statistics (1990/1991) Ministry of Research, Science and Technology, Wellington, New Zealand, No. 7, p. 45.
- Nickell, S., Wadhvani, S. and Wall, M. (1992) Productivity growth in the UK companies, 1975–1986, *European Economic Review*, **36**, 1055–91.
- Phillips, P. C. B. and Perron, P. (1988) Testing for a unit root in time series regression, *Biometrika*, **75**, 335–46.
- Philpott, B. P. (1994) Data base of nominal and real output, Labour, and Capital Employed by SNA Industry Group 1960–1990, RPEP Paper No. 265, Victoria University.
- Philpott, B. P. (1995) Real net capital stock by SNA production groups New Zealand 1950–1991, RPEP Paper No. 270.
- Philpott, B. P. (1999) Provisional estimates for 1990–1998 of output, Labour and Capital Employed by SNA Industry Group, RPEP Paper No. 293.
- Prescott, E. C. (1997) Needed: a theory of total factor productivity, Federal Reserve Bank of Minneapolis.
- Prescott, E. C. (2002) Prosperity and depression: 2002 Richard T Ely Lecture, the American Economic Annual Meeting, Atlanta, *American Economic Review*, **92**, 1–15.
- Romer, P. (1986) Increasing returns and long run growth, *Journal of Political Economy*, **94**, 1002–37.
- Romer, P. (1990) Endogenous technological change, *Journal of Political Economy*, **89**, S71–102.
- Sala-i-Martin, X. (1990) Lecture notes on economic growth, NBER Working Paper No. 3563.
- Sarno, L. and Taylor, M. (1998) Real exchange rates under the current float: unequivocal evidence of mean reversion, *Economics Letters*, **60**, 131–7.
- Solow, R. (1957) Technical change and the aggregate production function, *Review of Economics and Statistics*, **39**, 312–20.
- Taylor, M. and Sarno, L. (1998) The behaviour of real exchange rates during the post-bretton woods period, *Journal of International Economics*, **46**, 281–312.
- Wakelin, K. (2001) Productivity growth and R&D expenditure in UK manufacturing firms, *Research Policy*, **30**, 1079–90.
- Wang, J.-C. and Kuen-Hung Tsai (2003) Productivity growth and R&D expenditures in Taiwan's manufacturing firms, Working Paper Institute for Economic Research.
- Wieser, R. (2004) R&D productivity and spillovers: Empirical evidence at the firm level, Forthcoming at the journal of economic surveys, Institute of Public Finance and Infrastructure Policy at Vienna University of Technology.
- Wieser, R. (2005) Research and development productivity and spillovers: empirical evidence at the firm level, *Journal of Economic Surveys*, **19**, 587–621.

Appendix

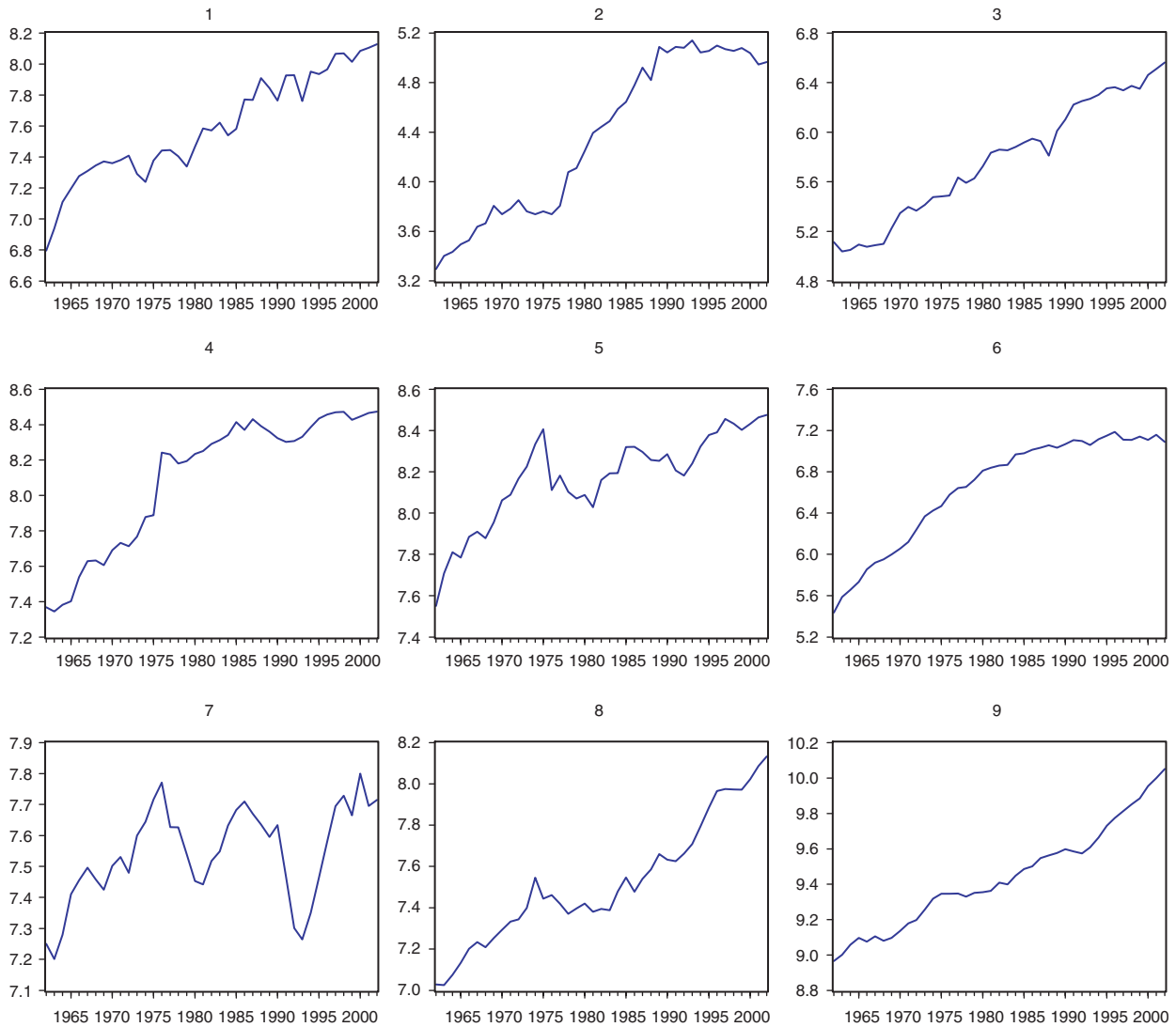


Fig. 1a. Log output from 1962 to 2002

Notes: (1) Agriculture, (2) Fisheries, (3) Forestry, (4) Food, (5) Manufacturing, (6) Energy, (7) Building, (8) Transport and (9) Services.

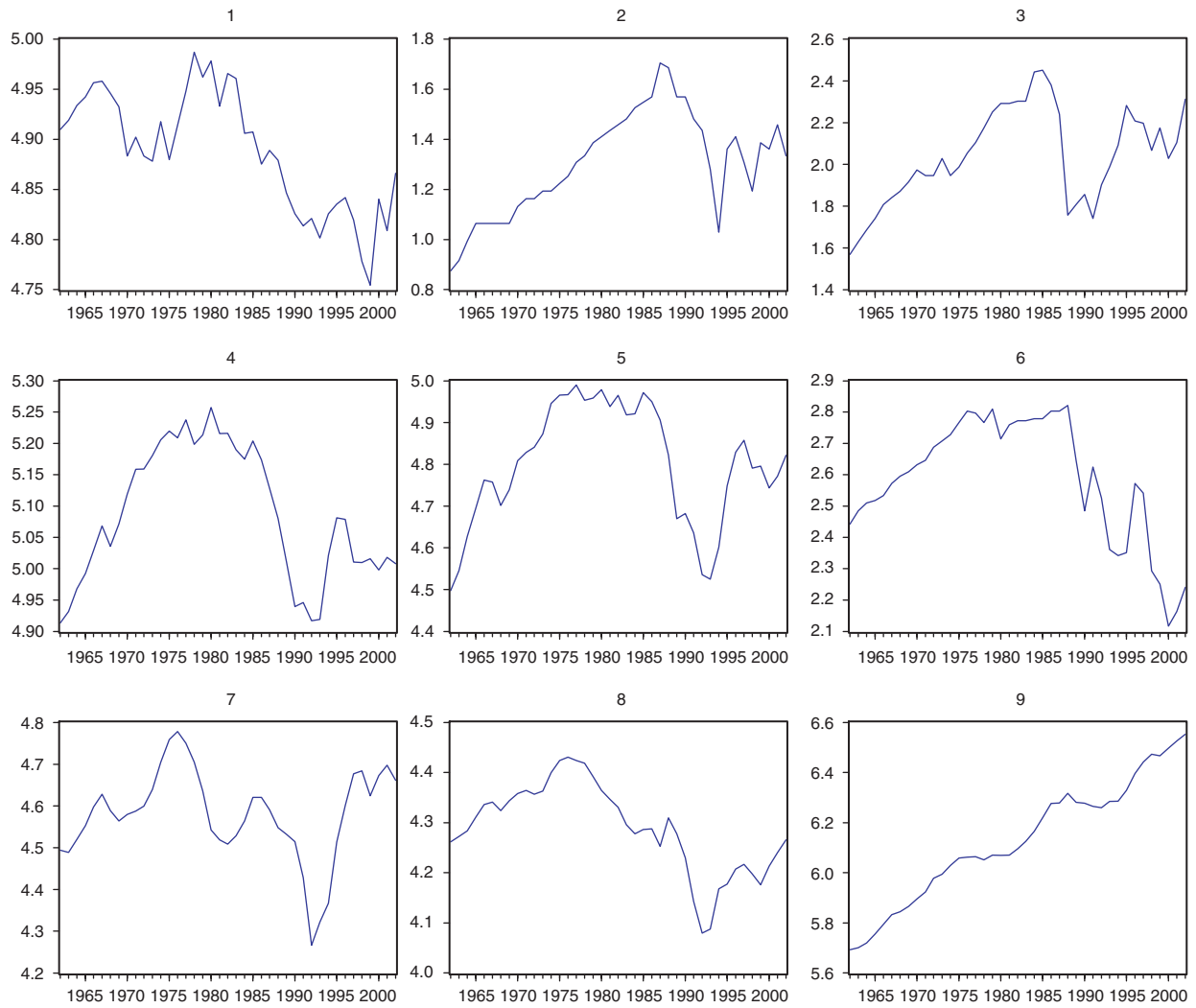


Fig. 1b. Log employment from 1962 to 2002

Notes: (1) Agriculture, (2) Fisheries, (3) Forestry, (4) Food, (5) Manufacturing, (6) Energy, (7) Building, (8) Transport and (9) Services.

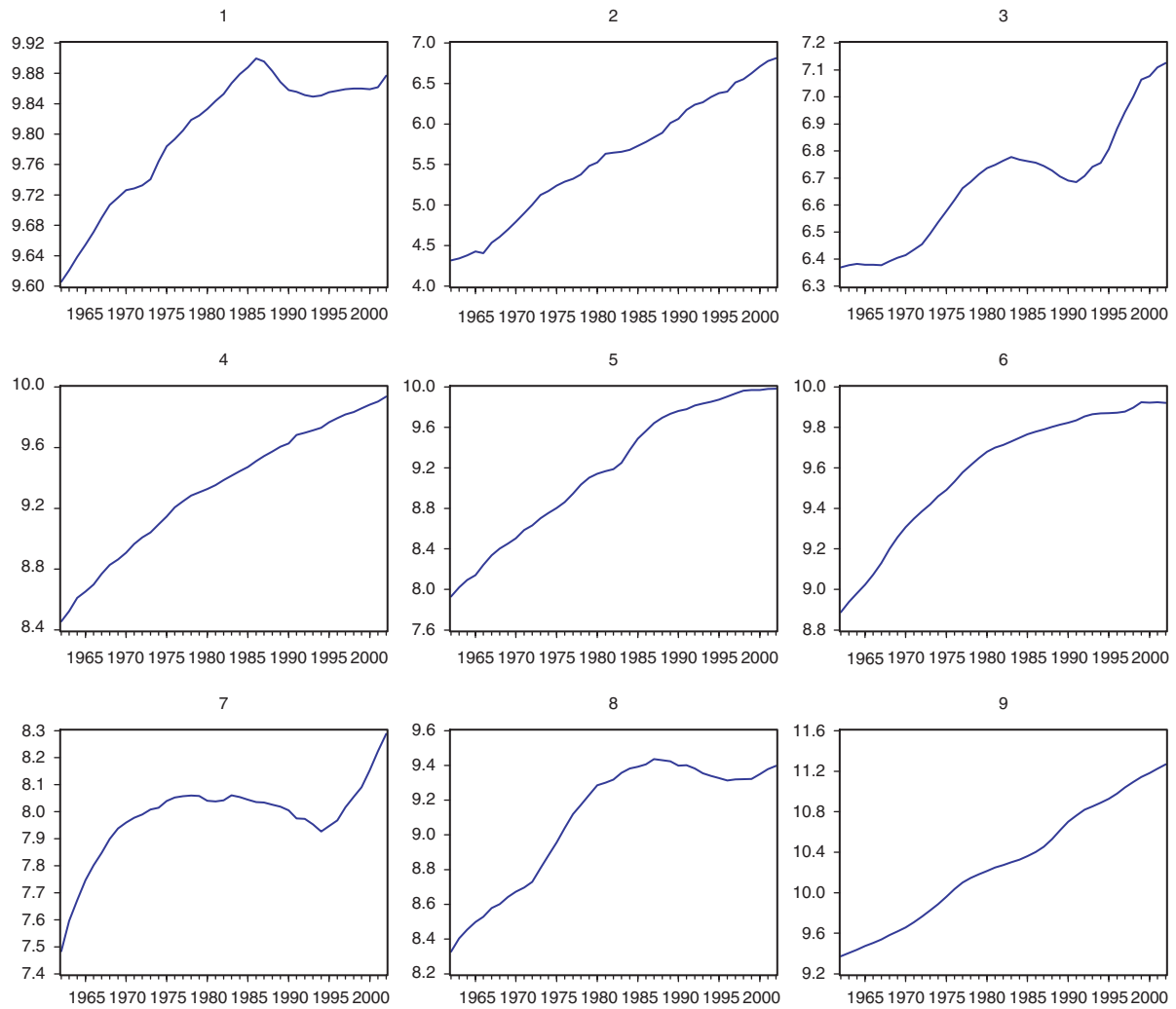


Fig. 1c. Log capital from 1962 to 2000

Notes: (1) Agriculture, (2) Fisheries, (3) Forestry, (4) Food, (5) Manufacturing, (6) Energy, (7) Building, (8) Transport and (9) Services.

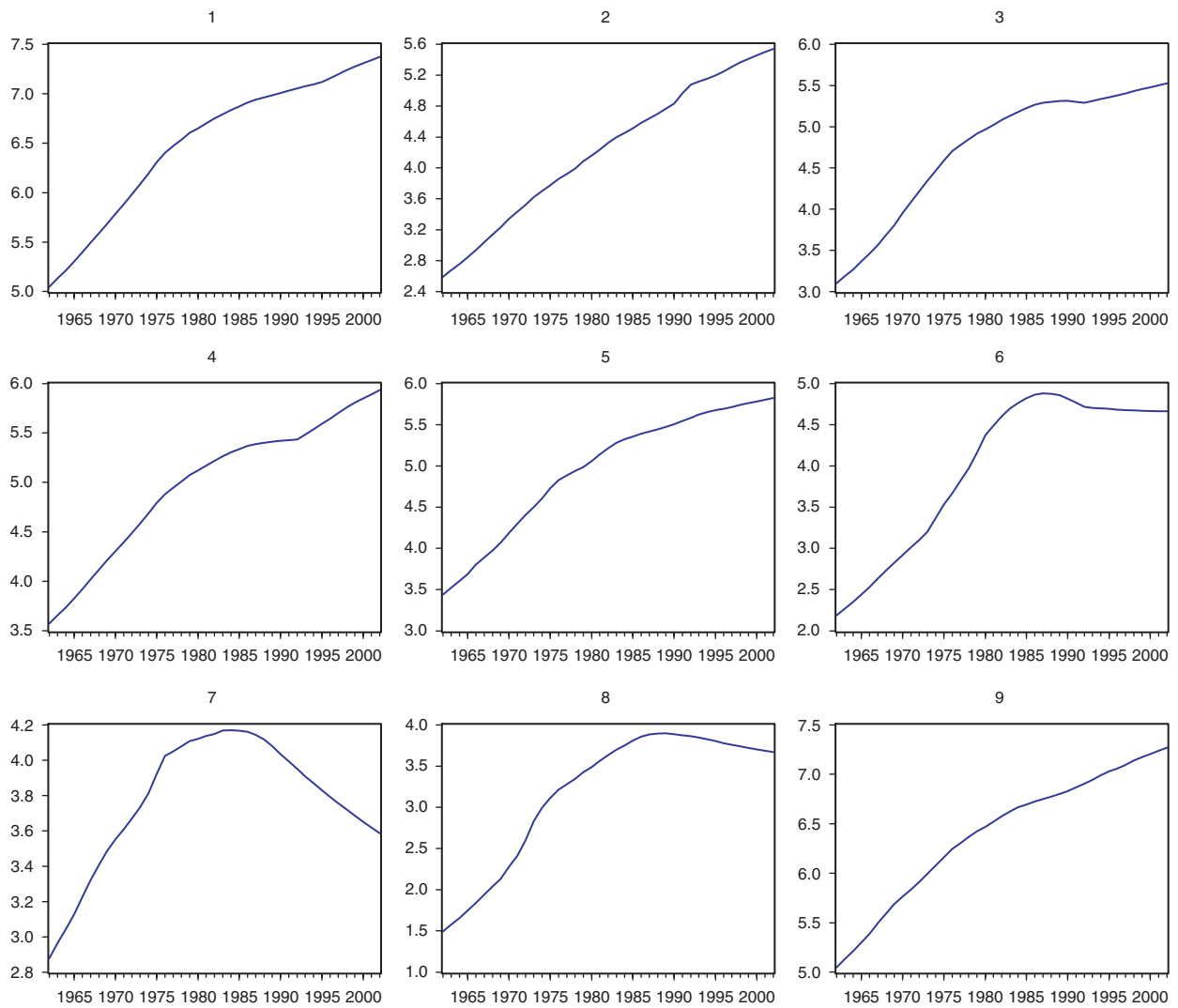


Fig. 1d. Log public R&D Stock from 1962 to 2002

Notes: (1) Agriculture, (2) Fisheries, (3) Forestry, (4) Food, (5) Manufacturing, (6) Energy, (7) Building, (8) Transport and (9) Services.

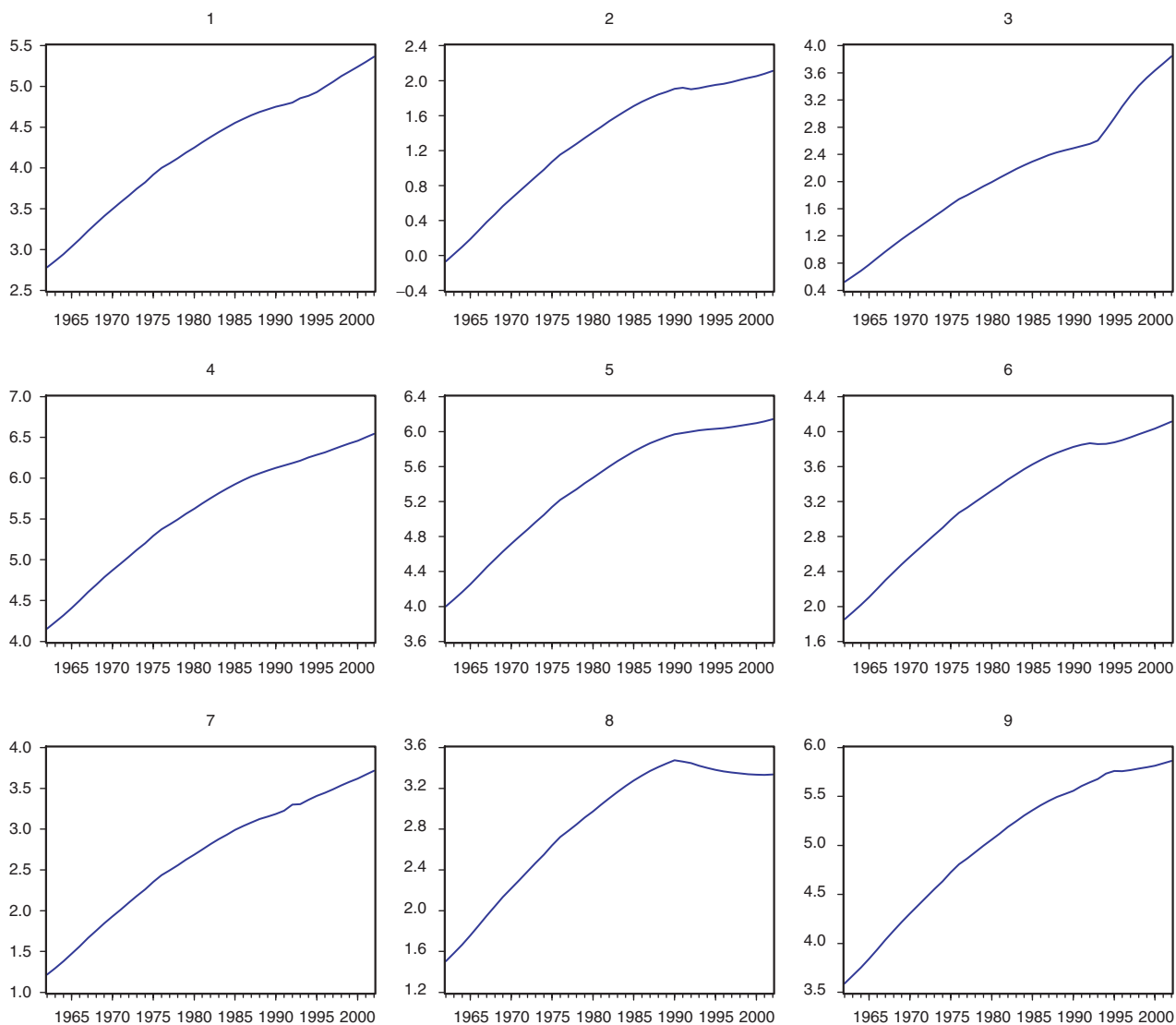


Fig. 1e. Log Private R&D Stock from 1962 to 2002

Notes: (1) Agriculture, (2) Fisheries, (3) Forestry, (4) Food, (5) Manufacturing, (6) Energy, (7) Building, (8) Transport and (9) Services.

Appendix: The description of $(x\hat{r})_t^{pa}$ and $(x\hat{r})_t^{pb}$

The data consist of $N=9$, $T \times 1$ vectors stacked (T : 1962–2002), where 1 is agriculture, 2 is Fisheries, 3 is Forestry, 4 is Food, 5 is Manufacturing, 6 is Energy, 7 is Building, 8 is Transport and 9 is Services. Zeros mean the own-effect is suppressed. 1, 2 . . . 9 denote per capita private R&D stock. A similar matrix is designed for public R&D stock per capita.

$$\begin{bmatrix}
 \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix} & \begin{bmatrix} 2 \\ 2 \\ \cdot \\ \cdot \\ 2 \end{bmatrix} & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \begin{bmatrix} 9 \\ 9 \\ \cdot \\ \cdot \\ 9 \end{bmatrix} \\
 \begin{bmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ 1 \end{bmatrix} & \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix} & & & & & & & & & \begin{bmatrix} 9 \\ 9 \\ \cdot \\ \cdot \\ 9 \end{bmatrix} \\
 \begin{bmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ 1 \end{bmatrix} & \begin{bmatrix} 2 \\ 2 \\ \cdot \\ \cdot \\ 2 \end{bmatrix} & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \begin{bmatrix} 9 \\ 9 \\ \cdot \\ \cdot \\ 9 \end{bmatrix} \\
 \begin{bmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ 1 \end{bmatrix} & \begin{bmatrix} 2 \\ 2 \\ \cdot \\ \cdot \\ 2 \end{bmatrix} & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \begin{bmatrix} 9 \\ 9 \\ \cdot \\ \cdot \\ 9 \end{bmatrix} \\
 \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
 \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
 \begin{bmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ 1 \end{bmatrix} & \begin{bmatrix} 2 \\ 2 \\ \cdot \\ \cdot \\ 2 \end{bmatrix} & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \begin{bmatrix} 9 \\ 9 \\ \cdot \\ \cdot \\ 9 \end{bmatrix} \\
 \begin{bmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ 1 \end{bmatrix} & \begin{bmatrix} 2 \\ 2 \\ \cdot \\ \cdot \\ 2 \end{bmatrix} & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \\
 \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
 \begin{bmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ 1 \end{bmatrix} & \begin{bmatrix} 2 \\ 2 \\ \cdot \\ \cdot \\ 2 \end{bmatrix} & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}
 \end{bmatrix}$$