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Author: Jiann-Chyuan Wang, Kuen-Hung Tsai

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8

Productivity Growth and R&D Expenditure in Taiwan's Manufacturing Firms

Jiann-Chyuan Wang and Kuen-Hung Tsai

8.1 Introduction

Ever since the 1960s, research and development (R&D) investment has been regarded as an important factor in the improvement of productivity levels. The rationale is that knowledge, which can be created and accumulated through the R&D efforts of a firm or industry, will subsequently become available to product innovations or to the production process (Mansfield 1965, 1969), and as a result nationwide economic development is promoted; indeed, the advanced countries have invested significant expenditure on R&D activities based upon this rationale.[1]

Two notable issues have been explored, the first of which is the extent to which R&D influences productivity, while the second is concerned with the rates of return provided by R&D. Numerous studies have attempted to estimate the marginal product of R&D capital or the rates of return on R&D investment (see, for example, Griliches 1980, 1994; Scherer 1983, 1993; Griliches and Lichtenberg 1984; Goto and Suzuki 1989). Based upon several different levels of data aggregation, or different types of estimation model, these studies demonstrate that the output elasticity of R&D lies between 0.06 and 0.14, while the rates of return on privately financed R&D investment are between 20 percent and 50 percent. However, these studies have continually failed to produce consistent results, with some even fail-

Jiann-Chyuan Wang is a research fellow at the Chung-Hua Institution for Economic Research. Kuen-Hung Tsai is an assistant professor in the Department of Shipping and Transportation Management at National Taiwan Ocean University.

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1. For example, the average annual rates of R&D expenditure in the United States and Japan, relative to GDP, are around 2.64 percent and 3.04 percent, respectively (NSC 2001).

ing to determine the contribution of R&D to productivity growth (Link 1981; Griliches and Lichtenberg 1984).

A substantial amount of R&D expenditure is invested annually in Taiwan's manufacturing sector. According to data reported by the National Science Council (NSC) (2001), the average share of R&D expenditure within the manufacturing sector accounts for over 95 percent of domestic R&D expenditure; however, the resultant growth in total factor productivity (TFP), the impact of R&D on productivity growth, and the rate of return on R&D expenditure have seldom been seriously examined at firm level. This study sets out, therefore, to estimate firm productivity growth based upon panel data for a sample of 136 firms for the period 1994–2000. The aims of the study are to determine to what degree R&D influences productivity, to further estimate the rates of return on R&D investment within manufacturing firms, and to analyze the differences in productivity growth and the rates of return on R&D investment between industries. Finally, we will test the famous Schumpeterian hypothesis, that the returns on R&D are an increasing function of firm size.

Following this introduction, the remainder of this paper is organized as follows. In the next section we undertake a review of previous studies in this area, followed by an introduction to the methodology adopted in this study, including both the model and the data resources employed in the estimations. Some basic statistics and the results of our estimations and tests are presented and interpreted in the penultimate section. We conclude with some remarks on our findings in the final section, where we also offer some suggestions for further research.

8.2 Literature Review

In any general examination of previous studies, there are two main considerations: The first is the level of data aggregation, and the second is the type of estimation model used. At firm level, Griliches and Mairesse (1984, 1998) and Cuneo and Mairesse (1984) used time series data to estimate the contribution of R&D based on the production function model. They found that the approximate output elasticity of R&D capital lies between 0.06 and 0.10. In a cross-sectional study, Griliches (1995) further demonstrated that the output elasticity of R&D stock was around 0.09–0.14. Adopting the model of R&D intensity, Clark and Griliches (1984), Griliches (1986), and Lichtenberg and Siegel (1991) showed that in U.S. manufacturing firms, the rates of return on R&D were between 10 percent and 39 percent. Goto and Suzuki (1989) further concluded that the rates of return on R&D investment in Japanese manufacturing industries tended to be around 40 percent, and Wakelin (2001) demonstrated that the rates of return on R&D capital were around 27 percent in U.K. manufacturing firms. However, in an earlier study, Link (1983) found that the R&D

coefficient in U.S. manufacturing industries in the 1970s failed to achieve statistical significance.

At industry level, most researchers adopt an R&D intensity model. Terleckyj (1974), Griliches and Lichtenberg (1984), Scherer (1993), and Griliches (1994) each found that the rates of return on privately financed R&D investment were between 20 percent and 50 percent in U.S. manufacturing industries, whereas Goto and Suzuki (1989) showed that the estimated R&D rates of return in Japanese manufacturing industries were around 26 percent. Furthermore, van Meijl (1997), Vuori (1997), and Hanel (2000) found that the rates of return on R&D investment within manufacturing industries in France, Finland, and Canada were around 19 percent, 14 percent, and 34 percent, respectively. It should be noted, however, that Scherer (1983) concluded that the impact of R&D on productivity was insignificant.

There are two points worth noting from any examination of the previous studies. First of all, most of the empirical findings demonstrate that R&D investment does have a significant effect on productivity growth or value added, but we should also keep in mind that such a general summary of prior empirical studies may be overoptimistic because of the "file drawer" problem: that is, the likelihood that studies supporting the null hypothesis (no significant results) will be rejected and therefore buried away in file drawers (Rosenthal 1979; Begg and Berlin 1988).

Second, estimations with the R&D intensity model often neglect the obsolescence of R&D. Most of the previous studies have substituted R&D expenditure for increments in R&D capital in order to avoid the difficult task of measuring R&D capital; however, such a substitution not only neglects the reduction in the effective appropriation of knowledge but also overestimates the net rates of return on R&D (see, for example, Wakelin 2001; Hanel 2000; Lichtenberg and Siegel 1991; Griliches and Lichtenberg 1984).

8.3 Methodology

8.3.1 The Model

In common with most analyses of the contribution to productivity growth from R&D (see, for example, Griliches 1986; Goto and Suzuki 1989; Lichtenberg and Siegel 1991; Hanel 2000; Wakelin 2001), the model adopted for this study is the extended Cobb-Douglas production function model:[2]

2. One could of course consider more complicated functional forms, such as the translog or constant elasticity of substitution (CES) functions, but we use the Cobb-Douglas function based on most empirical studies and on some exploratory computations.

$$Q_{it} = Ae^{\lambda t} L_{it}^{\alpha} K_{it}^{1-\alpha} R_{it}^{\gamma} e^{\varepsilon_{it}}, \tag{1}$$

where Q, L, K, and R respectively represent value added (or sales), labor, physical capital, and R&D capital. The R&D capital is a measurement of the stock of knowledge possessed by a firm at a given point in time; λ is the rate of disembodied technical change; A is a constant; and constant returns to scale have been assumed with respect to the conventional factors (L and K). The parameters, α and γ, are the output elasticity of labor and R&D capital.

By taking logarithms of the variables, equation (1) can be expressed in log form:[3]

$$(q - k)_{it} = a + \lambda t + \alpha(\ell - k)_{it} + \gamma r_{it} + \nu_{it}, \tag{2}$$

where the variables in lower case (q, l, k, and r) are the respective logarithms of value added, labor, and physical and R&D capital, and ν_{it} is the error term in the equation. Equation (2) is the model employed to estimate the impact of R&D on productivity growth. Based upon the estimate of γ in equation (2) and the definition of R&D output elasticity, the rates of return on R&D investment can be easily estimated across firms and over periods. Furthermore, to test the Schumpeterian hypothesis, another equation, as follows, is considered:

$$(q - k)_{it} = a + \lambda t + a(l - k)_{it} + \gamma r_{it} + \gamma_s s_{it} + e_{it}, \tag{3}$$

where the variable s is the logarithm of the product of R&D capital by assets, γ_s is the coefficient linking the relationship between the firm size and the impact of R&D on productivity, and e_{it} is the error term in equation (3).

Two points are worth noting relating to the disturbance terms, ν_{it} and e_{it}. First, in addition to the inputs listed in the model, some unobservable factors, such as managerial capabilities, also have considerable impacts on the creation of a firm's value added (Wernerfelt 1984; Barney 1991; Peteraf, 1993). These factors will vary across firms; thus, the variances of ν_{it} and e_{it} are heteroskedastic. In other words, the variance derived from some unobservable factors is viewed as an error component of ν_{it} and e_{it}.

Second, within our data set, each firm is observed at several points during each year, and some factors omitted from equations (2) and (3) may be correlated across periods. After accounting for this possibility, it seems reasonable to model the data as having serial correlation. Since the empir-

3. By taking logs differentiated with respect to time and imposing the equality of rates of return on R&D across firms, or over periods, we can rewrite equation (1) as a linear function of R&D intensity: $(dQ/Q - dK/K)_{it} = \lambda + \alpha(dL/L - dK/K)_{it} + \rho(dR/Q)_{it} + e_{it}$, where $\rho = dQ/dR$, representing the increment in value added generated by a unit increase in R&D resource θ years earlier. With the newly expressed model, we would obviously estimate ρ directly; however, we have not pursued such an alternative model here since this model presupposes that the rate of obsolescence of R&D capital is zero and assumes that the rates of return on R&D investment are equal across firms and over periods.

Table 8.1 **Growth Rate of Major Variables and R&D-Sales Ratio**

Industry	N	Labor	Capital	Value Added	GRS	RS
Food	11	0.03	6.31	5.35	–0.007	0.85 (0.29)
Chemicals	30	0.19	7.68	2.73	0.035	1.61 (2.00)
Textiles	31	–0.52	8.06	5.20	–0.004	0.49 (0.51)
Machinery	12	–1.25	6.58	9.70	0.003	1.59 (0.98)
Metals	9	0.41	1.93	1.02	–0.027	0.66 (0.29)
Electronic equipment	43	5.72	18.85	22.53	0.052	3.79 (2.35)
Total	136	1.65	10.71	10.67	0.021	1.68 (2.44)

Notes: N = the number of firms; GRS = the growth rates of R&D to sales ratio; RS = the R&D to sales ratio in year 2000. Figures in parentheses are standard deviations.

ical literature is overwhelmingly dominated by the autoregression with first-order serial correlation (AR [1]) model (Greene 1993), the disturbance process with an AR (1) form is assumed in our model. To summarize, these two problems will be considered in the estimations since they could result in biased or inefficient estimates.

8.3.2 The Data and Variables

The examination of related issues is based on a longitudinal data set that includes a sample of 156 large firms stratified from the Taiwan Stock Exchange (TSE). As a result of a number of missing observations on R&D expenditure and questionable data on other variables, we have limited the sample to 136 firms. These samples are fully balanced over the seven-year period, 1994–2000.

The sample covers most R&D-performing manufacturing industries, including food (11 firms), textiles (31 firms), chemicals (30 firms), metals (9 firms), machinery (12 firms), and electronic equipment (43 firms).[4] Since the number of firms within each of these industries is too small to work with separately, we classify the sample into two groups: high-tech firms within the electronic equipment industry (32 percent), and other industrial firms (68 percent).[5] Through this method of classification, in addition to alleviating the problem of heterogeneity, we can also explore the difference in R&D effect on productivity growth between the high-tech sector and other manufacturing firms.

Table 8.1 provides some general information on the samples and variables, in the form of descriptive statistics, with columns (3) to (6) respectively representing labor growth rates, physical capital, value added, and R&D-sales ratio (R&D intensity) across each sector for the period 1994–

4. Electronic equipment includes computers and peripherals, integrated circuits (IC), telecommunications, and other electronics.

5. Here we divide the sample into two because R&D expenditure is the indicator most widely used in identifying high-tech organizations or industries (Baruch 1997).

2000. The figures in the last column of table 8.1 represent R&D intensity for each industry in 2000.

Based on the figures provided in table 8.1, there are a number of interesting observations to be made. First of all, the growth rates of labor and physical capital in the electronic equipment industry are, to a great extent, higher than in other industries. Second, the average growth rate of the R&D-sales ratio is much more rapid in high-tech firms than in other firms. Moreover, the R&D intensity in high-tech firms is much higher than in other firms; for example, in 2000, the average ratio of R&D to sales in electronic equipment was around two to five times that of other firms. Third, there is much more rapid growth in both R&D intensity and value added in high-tech firms. In summary, the statistics provided in table 8.1 suggest substantially noticeable development of the electronic equipment industry in Taiwan.

While noting the descriptive statistics provided in table 8.1, it is worth keeping in mind that although our sample firms are so-called large manufacturing firms, firm size differs significantly. During the observed periods, for all industries, all of the variation coefficients of the variables are large; for example, in 2000, the respective variation coefficients of labor and fixed assets in the electronic equipment industry were around 137 percent and 60 percent. These figures show that to a large degree, the dispersion of firm size is high.

In addition to output (value added), labor, and physical capital, another major variable in the estimation model is R&D capital, which has been viewed as a measurement of the current state of technical knowledge, determined, in part, by current and past R&D expenditure (Griliches 1979). In other words, an increase in R&D capital in period t reflects not only the R&D expenditure of period t but also previous R&D expenditure that bears fruit during the period. There is some sort of distributed lag structure that connects past R&D expenditure to a current increase in technical knowledge, and ideally one would like to estimate the lag structure from the data. Unfortunately, it is difficult to obtain the information required to determine the lag structure; thus, we simply use the average lag.

With the simplification of R&D impact lag structure (average lag), the measurement of firm R&D capital is often expressed as $R_t = E_{t-\theta} + (1 - \delta)R_{t-1}$ (following Griliches 1980; Goto and Suzuki 1989; and Odagiri and Kinukawa 1997), where E is a deflated measure of R&D, θ is the average lag, and δ is the rate of obsolescence of R&D capital.[6] The equation leads to R&D expenditure in period $t - \theta$ becoming R&D capital in period t. Assuming that the growth rate of R&D capital is equal to the growth rate of

6. Other forms of lag structure, such as geometrically declining weights, could be assumed; however, various constructed lag measures and different initial conditions make little difference to the results (Griliches and Mairesse 1984).

E, the R&D capital of the original period is obtained as $R_0 = E_{1-\theta}/(g + \delta)$, where g is the growth rate of E.

Following the approach of Goto and Suzuki (1989), we use the average lag θ, based on simplifying evidence. Patents are a good indicator of benefit creation (Bound, Griliches, and Jaffe 1984; Pakes and Griliches 1984; Griliches 1998), and according to Lin and Lee (1996) and Tsai (1997), R&D investment has a significant impact on patents two years later. Moreover, a simulation study indicated that the lag length of the effect of R&D expenditure on productivity growth lies between one and three years (Xu, Wang, and Tsai 1998). These findings suggest that the average lag in Taiwan is around two years. Pakes and Schankerman (1984) also demonstrated that the R&D lag for the chemicals, machinery, and electronics industries is around two years; therefore, we set the average lag length as 2 ($\theta = 2$) to measure R&D capital.[7]

The depreciation rate (δ) reflects the replacement of old knowledge with new knowledge, or the reduction in the effective appropriation of knowledge. As suggested by Goto and Suzuki (1989), we examine the length of time taken by firms' patents to generate revenue in order to estimate the rate of obsolescence of R&D capital. We use the inverse of the length of time to measure the rate of obsolescence of R&D capital, with the firms investigated being the sample used in our analysis. Among these firms, the average rates of obsolescence were around 14.5 percent in general machinery, 6.2 percent in food, 12.4 percent in chemicals, 7.2 percent in textiles, 6.5 percent in metals, and 20.4 percent in electronic equipment.[8]

As suggested in Griliches and Mairesse (1984) and undertaken by Goto and Suzuki (1989), we measure output (Q) by value added, deflated by the wholesale price index rather than by sales. Another consideration is that one element of the observations on non–energy intermediate materials or energy input is unavailable. Labor (L) is measured simply by the total number of employees because there is no available information on the labor working hours of firms. Note that R&D manpower is deducted from labor since R&D manpower is evaluated as R&D expenditure. Our measure of physical capital (K) is total fixed gross assets; however, fixed gross assets in firms' financial statements are measured by nominal value (book value).

7. Lagged R&D expenditure is used in many studies, but there is no general agreement on the correct lag length. Hall and Mairesse (1995) pointed to the stability of firm R&D expenditure in the United States and Germany and to the insensitivity of the results to the choice of lag.

8. Odagiri and Kinukawa (1997) estimated the rate of obsolescence of R&D capital in four Japanese industries: electrical machinery, transportation machinery, general machinery, and chemicals. The respective rates of obsolescence were 13.9 percent, 11.3 percent, 7.2 percent, and 9.2 percent. Goto and Suzuki (1989) also demonstrated that the respective rates of obsolescence of R&D capital in seven Japanese industries were 24.6 percent (precision machinery), 14.5 percent (communications equipment), 14.2 percent (transportation equipment), 6 percent (food), 7.2 percent (general machinery), 7.2 percent (stone, clay, and glass) and 7.5 percent (nonferrous metals).

We use the gross fixed capital price index from *The Trends in Multi-Factor Productivity,* published by the Directorate-General of Budget, Accounting, and Statistics (DGBAS; 2001) to deflate total fixed gross assets.

Not only is the composition of R&D expenditure little known, but the available data concerning real R&D expenditure are also bedeviled by the lack of a suitable price index for R&D inputs. In view of the inherent difficulties, most of the previous studies have adopted the same means used by U.S. government officials: that is, the use of the gross domestic product (GDP) index to deflate R&D expenditure. However, based on the GDP deflator, the rate of increase of R&D expenditure is usually overestimated. Here we construct the deflator index to deflate R&D expenditure as in Mansfield, Romeo, and Switzer (1983).[9]

8.4 The Results

Since the analyzed sample is a panel data set, a random effects model is assumed in our analysis.[10] A number of different models based upon equation (2) are estimated using the feasible generalized least squared (FGLS) method.[11] The estimates of the production function with and without year dummy variables (with year dummies as opposed to a time trend) are listed separately in tables 8.2 and 8.3. Note that tables 8.2 and 8.3 also provide the estimates of the product term of R&D capital by assets for all firms as well as separately for high-tech and other firms. The estimates, denoted by γ_s, of the product of R&D stock by assets are used to test the Schumpeterian hypothesis.

The comparisons of table 8.2 and table 8.3 clearly show that using year dummy variables instead of a linear trend makes little difference to the estimates of the whole sample. The estimate of R&D capital elasticity (γ), lying between 0.18 and 0.20, is significant at the 1 percent level, with the results showing that R&D has a significant impact on productivity growth.

Since the sample comprised firms engaging in R&D in rather diverse industries, it was also of interest to investigate the differences between sectors. When the sample is split into two categories, the estimates for the two

9. Although we used the GDP deflator of each industry to deflate R&D expenditure and then constructed R&D capital, such an alternative construction makes little difference to the estimates.

10. Equation (2) can be treated as a fixed or random effects panel model. Since the chi-square tests, suggested by Hausman (1978), coming from different models based upon equation (2) show that the exploratory variables are most likely uncorrelated with the individual effects, a random effects panel model is assumed in this study.

11. Before estimating the model, in order to test the assumption of constant returns to scale with respect to the conventional factors, we rewrite equation (2) as $(q - k)_I = a + \lambda_t + \alpha(l - k)_{it} + \omega k_{it} + \gamma r_{it} + v_{it}$, where $\omega = \alpha + \beta - 1$. If ω is significantly different from zero, the constant returns to scale for labor and physical capital can then be rejected. Here the estimate of ω is approximately 0.021 ($t = 0.96$, $P > 0.05$), which indicates that the assumption is not rejected at the 5 percent significance level.

Table 8.2 **Production Function Estimates, Excluding Year Dummies**

Regressions	α	γ	λ	γ_s	R^2	MSE
All firms (N = 136)						
(1)	0.485***	0.187***	0.037**		0.352	0.167
	(0.071)	(0.031)	(0.015)			
(2)	0.467***	0.184***	0.037**	0.004	0.354	0.168
	(0.079)	(0.032)	(0.015)	(0.007)		
High-tech firms (N = 43)						
(3)	0.305***	0.297***	0.125***		0.468	0.190
	(0.115)	(0.073)	(0.032)			
(4)	0.325***	0.299***	0.125***	–0.003	0.468	0.191
	(0.130)	(0.074)	(0.033)	(0.017)		
Other firms (N = 93)						
(5)	0.674***	0.055	0.021		0.326	0.133
	(0.087)	(0.037)	(0.016)			
(6)	0.613***	0.049	0.021	0.017*	0.333	0.133
	(0.094)	(0.037)	(0.016)	(0.010)		

Note: Figures in parentheses are estimated standard errors.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 8.3 **Production Function Estimates, Including Year Dummies**

Regressions	α	γ	γ_s	R^2	MSE
All firms (N = 136)					
(1′)	0.472***	0.199***		0.360	0.165
	(0.071)	(0.031)			
(2′)	0.459***	0.197***	0.003	0.362	0.160
	(0.079)	(0.032)	(0.007)		
High-tech firms (N = 43)					
(3′)	0.292***	0.308***		0.473	0.191
	(0.117)	(0.074)			
(4′)	0.308**	0.309***	–0.003	0.473	0.192
	(0.132)	(0.075)	(0.011)		
Other firms (N = 93)					
(5′)	0.668***	0.070*		0.346	0.129
	(0.087)	(0.037)			
(6′)	0.613***	0.064*	0.016	0.351	0.129
	(0.093)	(0.037)	(0.010)		

Note: Figures in parentheses are estimated standard errors.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

groups are indeed rather distinct.[12] The estimate of R&D capital elasticity, at around 0.30 for high-tech firms, is much larger than for other firms. Note that the estimate of R&D output elasticity for other firms is around only 0.06, which is even insignificant in the model without year dummies. In addition, although the difference in the estimated time trend coefficients (the rate of technical progress λ) between high-tech firms and other firms is rather significant, the estimates of λ are significant in the high-tech firms ($\lambda = 0.125$, $p < 0.01$) but insignificant for other firms.

Given estimates of γ, the estimates of dQ/dR are calculated by multiplying the estimates of γ by the ratio of value added to the stock of R&D. The estimated average rates of return on R&D investment for the whole sample during the periods 1996–2000 were around 23 to 25 percent. Compared to the findings of previous studies—that the analytical unit is at firm level—our results are consistent with the similar estimates of 21 percent for the United States (Lichtenberg and Siegel 1991) and 27 percent for the United Kingdom (Wakelin 2001) but considerably lower than the 40 percent found in Japan (Goto and Suzuki 1989). Furthermore, the estimated rates of return on investment in R&D for each industry, for the years 1996 to 2000, are listed in table 8.4. The estimates in table 8.4 suggest that the average rates of return on R&D capital for the high-tech industry, at around 35 percent, are much larger than in other industries, at around 8 to 10 percent.

The Schumpeterian hypothesis (Schumpeter 1950) supported the belief of a greater likelihood of large firms' both undertaking research activities and achieving a measure of success. However, although Link (1981) found evidence of a systematic relationship between firm size and the impact of R&D on productivity, the empirical results of Lichtenberg and Siegel (1991) did not provide support for the Schumpeterian hypothesis. In our investigation, using total assets as a proxy for firm size, the estimates are positive for all firms, irrespective of whether the model contains year dummy variables, but insignificant at the 5 percent level.

When the sample is divided into two categories (high-tech firms and other firms), the γ_s estimates (the parameter of the product term of R&D capital by total assets) are still insignificant. Obviously, with respect to R&D impact on productivity, we are unable to determine from these findings whether different size "regimes" exist. Aside from total fixed assets, we also use sales as a proxy variable for firm size. At the 5 percent significance level, the tests of the estimates of γ_t still do not demonstrate that the impact of R&D on productivity growth is an increasing function of firm size.[13]

12. Dividing the sample into two allows for much of the heterogeneity, bringing down the sum of the square of errors (SSE) by around 12 percent (corresponding to a high F ratio of 16.05, $p < 0.01$).

13. One attribution of the statistical insignificance is that all of our sample firms are "large" firms. However, firm size among these so-called large firms differs significantly. For example, in 2000, the average amount of total fixed assets in high-tech firms was NT$15,187,200, and the standard deviation was NT$8,760,197. The coefficient of variation (the ratio of standard deviation to mean) exceeds 50 percent.

Table 8.4 **Average Rates of Return on R&D Investment (%)**

Industry	1996	1997	1998	1999	2000
Food	9.79	9.24	8.97	8.75	8.96
	(2.50)	(1.87)	(1.75)	(0.79)	(0.95)
Chemicals	8.54	8.17	7.96	7.59	7.84
	(1.36)	(1.38)	(1.93)	(1.02)	(0.89)
Textiles	9.60	9.30	8.94	8.28	8.75
	(2.37)	(2.28)	(1.11)	(1.03)	(0.95)
Machinery	8.32	8.12	8.08	7.93	8.03
	(2.12)	(1.98)	(1.16)	(1.06)	(1.14)
Metals	10.73	10.04	9.88	9.66	9.90
	(2.67)	(2.41)	(2.44)	(2.11)	(2.01)
Electronic equipment	36.84	35.97	35.31	34.99	35.12
	(4.97)	(4.47)	(4.23)	(4.11)	(3.91)

Note: Figures in parentheses are standard deviations.

Table 8.5 **Average Annual Rates of TFP Growth (%)**

Industry	1996	1997	1998	1999	2000
Food	5.14	0.54	–16.01	7.67	5.73
	(2.23)	(2.83)	(5.82)	(2.35)	(2.78)
Chemicals	2.31	–0.15	–19.63	12.50	5.46
	(2.72)	(2.39)	(3.76)	(2.80)	(1.72)
Textiles	1.24	0.04	–15.28	–6.30	7.39
	(2.11)	(2.41)	(2.71)	(2.88)	(2.39)
Machinery	4.12	0.95	–15.82	5.40	8.33
	(2.97)	(3.18)	(5.92)	(2.25)	(2.97)
Metals	2.78	0.59	–1.19	–0.60	–1.49
	(1.98)	(1.74)	(1.45)	(1.52)	(1.72)
Electronic equipment	6.39	9.08	–7.26	4.41	13.21
	(2.44)	(2.58)	(2.85)	(2.72)	(1.99)

Note: Figures in parentheses are standard deviations.

In addition, the estimates listed in tables 8.2 and 8.3 also show that the labor share (α) in high-tech firms is small. One possible explanation is that the value added in high-tech firms is created mainly through their R&D efforts, such as new product development, represented by the amount of R&D expenditure, and the input of R&D manpower is deducted from the total numbers of employees. Since the contribution from ordinary labor (the remaining employees of totality) to value added is always lower, the estimates here seem to be reasonable. The results are also consistent with the finding of 0.27 by Griliches and Mairesse (1984) in scientific firms ($N = 77$).

Based on the estimates of α for each of the two categories, and the conventional definition of TFP (TFP $= Q/L^{\alpha}K^{1-\alpha}$), we can further calculate the annual TFP growth rates for each industry. The estimates are listed in table 8.5, which shows that there was a dramatic decline in TFP growth rates in 1998, which nevertheless started to rise again after 1999.[14] The results show that the TFP growth in these industries seems to depend upon short-term fluctuations, and one obvious and possible explanation for this is the severe impact on the Taiwanese economy of the Asian financial crises between the fourth quarter of 1997 and the first quarter of 1999.

8.5 Conclusions

In this study, we have analyzed the relationship existing between output (value added), employment, physical capital, and R&D capital, based upon a complete sample of 136 large firms listed in the TSE over the period 1994–2000. Our findings suggest that R&D investment was a significant determinant of firm productivity growth during the second half of the 1990s. For the whole sample, R&D output elasticity was around 0.18; however, when the sample is divided into two categories, high-tech and other firms, we observe a statistically significant difference in R&D elasticity between the two samples. The R&D elasticity for high-tech firms is around 0.3, but only 0.07 for other firms. In addition, we find that the average rate of return on investment in high-tech firms, at around 35 percent, is larger than that estimated in other firms, at around 9 percent. Our study also demonstrates that TFP growth declined across all the selected industries in 1998 but then started to pick up again after 1999. We speculate that the slump in TFP growth rates in 1998 can be attributed, to a large extent, to the Asian financial crisis. Moreover, our empirical results do not support the Schumpeterian hypothesis, which states that the impact of R&D on productivity is an increasing function of firm size.

Nevertheless, a couple of related points need to be discussed further. First, the impact on productivity from these different types of R&D may differ markedly. In general terms, R&D work can be classified into three types: basic research, applied research, and technical development. A number of studies have found that the contribution from basic research is greater than that of either applied research or technical development (see, for example, Lichtenberg and Siegel 1991; Martin 1998; Salter and Martin 2001). However, since the proportion of R&D expenditure spent on basic research in Taiwanese manufacturing firms has been rather small, our estimations should still be valid, even though we do not take into consideration the distinction between these different types of R&D.

Second, the double-counting of capital and R&D capital may bias the estimated effects of R&D. The estimate of R&D intensity or R&D capital is not particularly accurate when certain types of expenditure are ac-

14. This trend is consistent with the calculation reported in DGBAS (2001). However, the figures listed in table 8.5 cannot be compared with overall estimates of TFP since the estimates in Taiwan are always calculated at industry level.

counted for in both R&D capital and ordinary capital (Schankerman 1981). Expenditure on R&D in Taiwan has been clearly defined as all spending attributed to R&D activities, such as labor costs, administration, maintenance, and the acquisition of equipment for R&D purposes (NSC 2001). In accordance with the Statute for Industrial Upgrading, the R&D expenditure of any firms in Taiwan applying for R&D tax credits is closely scrutinized by the tax authorities; therefore, the purchase of equipment for R&D projects has to be recorded in R&D expenses but not necessarily in fixed assets. Thus, potential double-counting of capital should have little impact on the estimated effects of R&D.

Third, capital utilization rates should be considered in this analysis.[15] In this study we have assumed that the short-term fluctuations in TFP came as a result of the Asian financial crisis. According to the findings of Wang, Hsin, and Tsai (1999), the Asian financial crisis damaged the exports of Taiwan's manufacturing industries and further reduced the utilization rates of manufacturing equipment. Thus, in order to exclude the demand shock from the Asian financial crisis, one should regard capital utilization rates as an exploratory variable in the empirical model. Unfortunately, the capital utilization rates of the sample firms cannot be determined, and the variable cannot be constructed from other variables in the current dataset.

Fourth, we have tried to separate the effects arising from interindustry differences. Our analysis covers several industries, and in order to reduce the estimated bias of R&D effects on the characteristic differences across these industries, we include industry dummies in the estimated model. However, the use of industry dummy variables brings down the sum of the square of errors (SSE) by only around 0.62 percent, corresponding to a low F ratio of 0.69 ($p > 0.05$), and since the omnibus test (F-test) is not significant at the 5 percent significant level, we ignore the impact of the industry dummy variable on the estimation.

Fifth, one may doubt that the larger R&D estimate in the high-tech firms is coming spuriously at the expense of the labor coefficient. To address this concern, alpha is fixed to labor's share in the model. This restriction does not make the estimates significantly different compared to the findings in tables 8.2 and 8.3. This robustness check confirms our finding that the R&D output elasticity in high-tech firms is significantly greater than that of other firms.

Finally, the sample period that we have observed, from 1994 to 2000, coincides with the information technology (IT) boom; therefore, the potential exists for the IT bubble to have caused a disturbance to TFP growth trends during our study period. Throughout the IT bubble period, tele-

15. We appreciate the insightful suggestions provided by Tsutomu Miyagawa and Jungho Yoo, and we have tried to use industrial utilization rates of manufacturing equipment as a proxy for firms' capacity utilization rates. Although the estimates are not significant at the 5 percent level, we consider that this insignificance is most likely the result of the use of a proxy.

communications and the Internet formed the backbone of IT investment, and although Taiwanese firms were involved in the IT boom, their Internet business was still at a rather embryonic stage and the telecommunications industry remained small, thus limiting the impact of the IT bubble.

Our study does of course have its limitations. First of all, as in the standard approach, we aggregate R&D expenditure linearly into R&D stock, ignoring the possibility that knowledge production depends nonlinearly, not only on current efforts, but also on previously accumulated outcomes. Second, the results cannot explain the time-dimensional differences of R&D performance across firms, since the time period is not yet long enough; our estimation also fails to reveal how the impacts of R&D on productivity growth are actually realized. Third, it may be worth trying to include in the estimation model a skills variable, such as the number of engineers and technicians; however, we cannot separate the effects of a skills variable because most of the firms in the sample omit many of the observations on these related variables. Fourth, we do not discuss the more general topic of simultaneous R&D decisions (simultaneity), which has recently entered into the discussion. If R&D is chosen on the basis of economic incentives, it is unlikely to be completely independent of the errors that affect the production relations that we attempt to estimate in this study. Finally, although our sample does cover 136 large manufacturing firms belonging to six industries, it clearly cannot represent all manufacturing firms; therefore, the interpretation of the findings in our study should remain conservative.

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Comment Tsutomu Miyagawa

An Overview of the Paper

The paper examined effects of R&D on productivity at the firm level, for firms listed on the Taiwan Stock Exchange. It adopted a standard methodology for estimation in output elasticity of R&D capital. Following Griliches (1986), the authors assumed a Cobb-Douglas production function with total factor productivity (TFP) that depends on R&D capital and disembodied technical change. Using firm-level microdata (136 large manufacturing firms listed on the Taiwan Stock Exchange), they estimated output elasticity of R&D capital.

The main results are as follows. In all industries, the estimated elasticity was between 0.18 and 0.2, which was larger than that of previous studies. The estimated elasticity was higher in high-tech firms than in other firms. The rate of return on R&D capital was also higher in high-tech firms than in other firms.

Schumpeter asserted that large firms tend to carry out R&D expenditure actively. Tsai and Wang tried to test the Schumpeterian hypothesis. They added the product term of R&D capital by firm assets to the standard estimation and examined the parameters of the new term. However, the estimated parameters were not significant, and the Schumpeterian hypothesis was not supported. Finally, using the estimated parameters, they calculated late 1990s TFP. A rapid slowdown in TFP growth was found in the period of the Asian currency crisis.

The estimation methodology in the paper is standard, and the estimated results are reasonable. In particular, the high output elasticity and high rate of return on R&D capital in high-tech industries are very impressive. This conclusion is not found in the previous Japanese analyses about R&D expenditure. The results in the paper will stimulate Japanese research in this field.

Why Is the Rate of Return on Research and Development Capital in High-Tech Firms So High?

One of the main results Tsai and Wang included in the paper is that output elasticity and rate of return on R&D capital were higher in high-tech firms than in other firms. They noted that estimated values of output elasticity and rate of return were reasonable from the viewpoint of international comparison. However, they did not explain the reason for high-tech firms' higher rates of return on R&D capital.

To try to do this, I think the authors can examine three hypotheses. The first hypothesis is that TFP was higher in high-tech firms than in other

Tsutomu Miyagawa is professor of economics at Gakushuin University.

firms. To prove the first hypothesis, they need to show TFP growth data in high-tech firms and in other firms.

The second hypothesis is that the difference in rate of return reflects a difference in the depreciation rate of R&D capital. The rate of return they measured is gross rate of return, including depreciation rate. High-tech firms tend to hold assets that depreciate faster than assets held in other firms, due to rapid technological progress. If they compare the net rate of return of the two types of firms, they may find smaller differences.

The last hypothesis is that spillover effects are stronger in high-tech firms than in other firms. Griliches (2000) pointed out that the positive contribution of knowledge externalities has increased due to the declining cost of communication. If spillover effects dominated in high-tech industries, then γ and rate of return in high-tech firms may be overestimated. To check the significance of spillover effects, they should estimate the following production function (based on their equation [2]) including externalities.

$$(2') \qquad (q-k)_{it} = a + \lambda t + \alpha(l-k)_{it} + \gamma r_{it} + \mu R_t + \nu_{it},$$

where R_t is R&D expenditures at the industry level.

If all three hypotheses are rejected, other candidate explanations would be market imperfection or government intervention. The authors should check whether either market imperfection in Taiwan's financial market or government subsidization of high-tech firms has generated the difference in rate of return of R&D capital. I think that these tasks will become further research topics for the authors.

Other Comments

Besides the problem of rate of return, I will make two more comments on the paper. First, the authors assumed a Cobb-Douglas type production function described in equation (1). They assumed that the total of the labor share and real capital share is equal to 1 and that all value added is distributed to ordinary labor and real capital. However, R&D capital also includes labor costs for researchers, as they noted later in the paper. Although the labor cost in R&D capital should be distributed from value added, the assumption of the production function does not consider this. Thus, I propose that they also estimate a production function without the restriction that the total of the labor share and real capital share is equal to 1. In addition, it would be better that they revise footnote 10.

My second additional comment concerns the assumption that the rapid fall in the TFP growth rate was an effect of the Asian currency crisis (table 8.5). The result showed that TFP growth depended on short-term fluctuations. In my opinion, TFP should be interpreted from the supply side, although several interpretations of TFP were proposed in this conference. From this point, I recommend that the authors consider capital utilization rate in estimating parameters, in order to exclude demand shock from the short-term fluctuations of TFP.

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Comment

Jungho Yoo

This paper estimates the elasticity of output at firm level with respect to R&D capital, utilizing data on 136 manufacturing firms in Taiwan for the 1994–2000 period. It finds that the output elasticity was around 0.18, which seems somewhat high but falls within the range of estimates in earlier, similar empirical studies conducted by others for other countries.

The authors divide the sample into high-tech and conventional firms and find the R&D elasticity of output to be around 0.3 for the high-tech firms and 0.07 for the others. This also tends to confirm the findings of earlier studies that differentiate "scientific" sectors from other sectors and obtain much higher elasticity estimates for the former and lower estimates for the latter, except that the scientific sectors referred to chemicals, drug, electrical and electronic equipment, and scientific instruments.

The paper also computes the growth rates of TFP, utilizing the estimated labor share in the Cobb-Douglas function, and finds very high growth rates. For example, in year 2000, in five industries—except for the metal industry, for which the growth rate turned out to be negative—the growth rates of TFP were all greater than 5 percent, electronic equipment registering 13.2 percent.

The paper is very much focused on what it sets out to do and achieves its purpose; that is, it confirms significant contribution made by R&D capital to productivity growth for Taiwanese manufacturing firms. It reports only what is directly related to the estimation. Some description of the Taiwanese manufacturing industries would give the readers, especially foreign readers, a better understanding of the context within which this study is conducted.

First, I would like to see some more discussion of the data themselves. For example, some discussion would help of changes in output and of cap-

Jungho Yoo is a senior fellow at the Korea Development Institute.

ital inputs over the period under study, at the aggregate and industry levels, and also of relative magnitude of R&D stock in comparison with physical capital.

Second, it seems worthwhile in a future study to try including skill variables such as share of engineers, technicians, skilled workers, and so on. Doing so produced lower estimates of the R&D elasticity in earlier, similar studies, although interpretation of this result requires caution, as it is related to the substitutability and complementarity between labor skill and R&D stock.

The third comment is not directed just to this paper but is relevant more generally to other studies as well where actual output is used in the estimation of R&D elasticity of output and indeed in the estimation of a production function. Firms do not always produce at their maximum capacity, but the capacity utilization is almost always less than 100 percent and tends to rise during a period of expansion. If a capacity utilization variable is missing in a regression that covers a period of business expansion, it will produce an upwardly biased estimate of R&D elasticity. This may indeed be a matter of some importance to this paper, since the 1994–2000 period under study coincides with the global IT boom.