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Productivity Growth and R&D Spillovers in Japanese Manufacturing Industry

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Abstract

This paper estimates the contribution of R&D spillovers to productivity growth Japanese manufacturing industry by estimating two alternative measures of productivity growth and two different types of R&D spillovers. The results suggest that TFP growth is affected neither by rent R&D spillovers nor by knowledge R&D spillovers. However, knowledge R&D spillovers were found to have an effect on technical change.

Key words: total factor productivity, technical change, rent R&D spillover, knowledge R&D spillover, Japan

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1. Introduction

A large number of theoretical and empirical studies have demonstrated the importance of R&D spillovers as a source of productivity growth and long-run sustained economic growth.[1] Examining the manufacturing sector in Japan, Odagiri (1985) and Goto and Suzuki (1989) were able to show that rent R&D spillovers through intermediate goods and investment goods had a positive effect on productivity growth. Goto and Suzuki also found that knowledge R&D spillovers through the diffusion of new knowledge from the electronics industry had a significant positive effect on productivity growth. The results of these studies suggest that rent R&D spillovers and knowledge R&D spillovers between industries contributed to productivity growth in Japan. However, despite the considerable number of studies on R&D spillovers – not only in Japan, but also elsewhere –, neither the mechanism nor the effects of R&D spillovers are yet fully understood.

For example, as indicated by Atella and Quintieri (2001), one problem of these studies has been that they used TFP growth derived from standard growth accounting procedures as the dependent variable. This measure requires very restrictive assumptions, such as constant returns

[1] See surveys by Nadiri (1993) and Mohnen (1996)

to scale, competitive factor markets, etc. If scale economies are present, then TFP growth overstates the true rate of technical change even if the assumption of competitive factor markets is imposed. The use of TFP growth as the dependent variable may generate biases that can alter the relationship between productivity growth and its main determinants.

This study attempts to resolve the problems of previous empirical studies and to broaden our understanding of the contribution of R&D spillovers to productivity growth. Long-run level data from the Japanese manufacturing industry are used for the analysis. This chapter has three objectives. The first objective is to construct technical change adjusted scale economies as well as TFP growth, such as are used in previous studies. The second objective is to identify whether the effect on TFP growth or technical change of the diffusion of knowledge differs from that of the flows of intermediate goods. For this purpose, we calculate two different types of R&D spillovers: rent spillovers and knowledge spillovers. That is, our analysis considers the different contributions of two different forms of R&D spillovers to productivity growth. The final objective of this study of to examine whether R&D spillover effects exist or not, can still be shown to exist, even after IT investment, human capital, and capital utilization are controlled for.

The remainder of this paper is organized as follows. In section 2, we explain our measures of TFP growth and technical change. Section 3 presents our measurement of two different types of R&D spillovers, while section 4 introduces our econometric model. Section 5 describes the data, reports the estimation results, and discusses their implications. Finally, section 6 concludes.

2. The measures of productivity growth[2]

In this section, we will derive the two dependent variables that are used in order to estimate the R&D spillover effects. We begin by measuring conventional total factor productivity (TFP) growth. The Tornqvist rate of TFP growth is calculated as:[3]

$$\dot{TFP} = \dot{Q} - \sum_{i=1}^{N} \bar{s}_i \dot{x}_i \qquad (1)$$

where $\bar{s}_{it}$ is the two-period average share of the subscripted input in total cost,

$$\bar{s}_{it} = (s_{it} + s_{it-1})/2 \qquad (2)$$

The calculation of Tornqvist TFP growth requires a number of assumptions: returns to scale are constant, and firms are profit maximizing and operate in competitive input and output markets. Tornqvist TFP is convenient for estimating productivity growth without estimating econometrically the production technology, but the TFP growth obtained using the Tornqvist

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2 This section owes much to the exposition in Michael, Melvyn, and Leonard (1981)

3 The dot over variables represents their rate of growth.

index might be biased by the existence of returns to scale.

We will derive technical change, which is considered as a proportionate shift in the production function over time using the theory of production. Assume that there exists a production function given as:

$$Q = F(X_1 ... X_n, t) \qquad (3)$$

Equation (3) is differentiated by time as follows:

$$\frac{dQ}{dt} = \sum_{i=1}^{N} \frac{\partial Q}{\partial X_i} \frac{dX_i}{dt} + \frac{\partial Q}{\partial t} \qquad (4)$$

We obtain equation (5) by dividing equation (4) by output.

$$\frac{dQ}{dt}\frac{1}{Q} = \sum_{i=1}^{N} \frac{\partial Q}{\partial X_i} \frac{X_i}{Q} \dot{X}_i + \frac{\partial Q}{\partial t}\frac{1}{Q} \qquad (5)$$

The last term on the right hand side of equation (5) denotes the contribution of technical change to output, $\dot{A} = \frac{\partial Q}{\partial t}\frac{1}{Q}$.

Equation (5) can be rewritten as follows:

$$\dot{A} = \dot{Q} - \sum_{i=1}^{N} \eta_{Q,X_i} \dot{X}_i \qquad (6)$$

where η_{Q,X_i} is the elasticity of output with respect to input X.

If we assume the firm minimizes its cost of production, then the first-order condition for minimizing production costs subject to a given level of output yields:

$$\frac{\partial Q}{\partial X_i} = w_i / \frac{\partial C}{\partial Q} \qquad (7)$$

Substituting (7) into (5) and rearranging, we obtain the expression for the proportionate rate of technical change

$$\dot{A} = \dot{Q} - \varepsilon_{C,Q}^{-1} \sum_{i=1}^{N} \frac{w_i X_i}{C} \dot{X}_i \qquad (8)$$

where $\varepsilon_{C,Q}$ is the elasticity of cost with respect to output. Define $\dot{F} = \sum_{i=1}^{N} \frac{w_i X_i}{C} \dot{X}_i$ as the rate of growth of aggregate inputs.

We can then compare the measure of technical change with the total factor productivity measure as follows: $\dot{TFP} = \dot{Q} - \dot{F}$. Using this definition of TFP and rearranging equation (8) yields

$$\dot{TFP} = \dot{A} + (\varepsilon_{C,Q}^{-1} - 1)\dot{F} \qquad (9)$$

or

$$\dot{A} = \dot{TFP} + (1 - \varepsilon_{C,Q}^{-1})\dot{F} \qquad (10)$$

With non-constant returns to scale, the growth in measured TFP can be decomposed into a shift in the production function (technical change) and a movement along the production function (scale economies). Consequently, TFP growth in conventional growth accounting is not identical to technical change as represented by a shift in the production function unless $\varepsilon_{CQ} = 1$ (the production process is characterized by constant returns to scale). If the technology is characterized by increasing (decreasing) returns to scale, then output increases (decreases) may simply be the result of changes in the scale of operations that have nothing to do with technical change.

In order to separate the scale effects from technical change, we need information on the cost elasticity with respect to output. We estimate the translog cost function as follows:

(11)

$$\ln C = a_0 + \sum a_k D_k + a_t t + \sum a_i \ln P_i + a_Q \ln Q + (1/2)[a_{tt} t^2 + \sum \sum a_{ij} \ln P_i \ln P_j + a_{QQ} (\ln Q)^2] + a_{tQ} t \ln Q + \sum a_{it} \ln P_i t + \sum a_{iQ} \ln P_i \ln Q$$

where C is total cost, P_i represents input prices, Q is output, t is a simple time trend, and D_k represents industry-specific dummies.

Using Shephard's lemma, we obtain the share functions as follows:

$$S_i = \frac{\partial \ln C}{\partial \ln P_i} = a_i + a_{it} t + \sum_j a_{ij} \ln P_j + a_{iQ} \ln Q \quad (12)$$

We estimate a system of two cost shares equation and a total cost function by means of seemingly unrelated regression (SUR), using panel data. The materials share equation must be dropped before estimation to avoid singularity. Industry dummies are interacted with output so as to capture inter-industry differences in the cost elasticity parameters. Using the estimation results, we may write the elasticity of cost with respect to output as follows:

$$\varepsilon_{CQ} = \frac{\partial \ln C}{\partial \ln Q} = a_Q + a_{QQ} \ln Q + a_{tQ} t + \sum a_{iQ} \ln P_i \qquad (13)$$

The rate of technical change in equation (8) depends on the parameter estimates in equation (11).

The estimation result of the cost function is presented in appendix 2.

The cost elasticity with respect to output derived from the estimation of the translog cost function suggests a very strong presence of scale economies for most Japanese manufacturing sectors. The cost elasticity with respect to output is presented in table 5-2.

3. The measurement of R&D spillovers

As pointed out by Griliches (1979), there are two different concepts of R&D spillovers: rent spillovers and knowledge spillovers.[4] Rent spillovers accrue because producers of knowledge and innovations are unable to charge the full quality price because they cannot perfectly price-discriminate due to competition. Klette et al. (2000) have claimed that this spillover is not true spillover, but measurement errors. Knowledge spillover occurs because of the public goods characteristic of knowledge. This spillover is not embodied in particular products. The extent and level of the diffusion of knowledge depends on the technical relatedness of industries. It is this kind of spillover, they argue, that can produce both endogenous growth and endogenous technical change.

The R&D spillover is constructed as a weighted sum with weights representing industry's ability to internalize pieces of R&D stock from other industries:

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[4] In reality, the distinction between rent spillovers and knowledge spillovers is blurred.

$$T_i = \sum_{j \neq i}^{N} w_{ij} R_j \qquad (14)$$

where T_i is the R&D spillover stock of industry *i*, ω_{ij} represents the weights and R_j is the R&D stock of industry j. *N* denotes the number of industries. In previous studies, the weights have been calculated in a number of ways. According to the survey by Mohnen (1996), candidates for weights are product fields, types of R&D, patent classes, input-output flows, investment flows, and patent flows.

The methodology for computing weights depends on the concept of spillovers. The concept of rent spillovers implies that the lower the price at which an industry can purchase intermediate goods, the more it obtains of the other industries' research efforts. Consequently, rent spillovers occur through market interactions. To compute the stock of rent R&D spillover derived from economic transactions, Terleckyj (1980) used first-order input-output transaction matrices, calculating inputs used directly to produce a given vector of outputs. Since he wrote his paper, rent spillovers have been traced using weight based on intermediate goods flows. Following Terleckyj's methodology, we measure R&D rent spillover using the sum of the flows of R&D embodied in intermediate goods from originating industry *i* to using industry *j*. The amount of R&D obtained through rent spillover is measured by a weighted sum of R&D expenditures by other industries. In this study, the rent spillovers stock, RDSPI, is constructed in the following way:

$$RDSPI_i = \sum_{j \neq i}^{N} b_{ji} R_j \qquad (15)$$

Equation (15) represents the flow of R&D embodied in the intermediate goods from industry *j* to industry *i*. b_{ji} is the proportion of sales to industry *i* relative to the total sales of industry *j*, and R_j is the R&D stock of industry *j*.

In contrast, knowledge R&D spillovers occur through non-market transactions. Therefore, the weights of knowledge R&D spillovers can be calculated by using the technological proximity between industries. One indicator of this technological proximity was introduced by Jaffe (1986). His measure of technological proximity between firm *i* and firm *j* is the uncentered correlation between the two vectors F_i and F_j representing the share of a particular patent class in the total of patents granted to firms *i* and *j* in a certain period. The R&D proximity weight suggested by Jaffe is given as

$$P_{ij} = \frac{F_i F_j^{'}}{[(F_i F_i^{'})(F_j F_j^{'})]^{1/2}} \qquad (16)$$

The value of P_{ij} is bounded between 0 and 1. If the distribution of patents perfectly coincides between firm *i* and firm *j*, P_{ij} takes the value 1; if they do not overlap at all, it is 0. Goto and Suzuki (1989) used the distribution of R&D expenditures across research fields in order to measure the proximity between Japanese manufacturing industries instead of filling the vector with patent data.

We measure the knowledge R&D spillovers between Japanese industries using technological proximity calculated by the input coefficient vector.[5] The knowledge spillover stock, RDSPK, is constructed in the following way:

$$RDSPK_i = \sum_{j \neq i}^{N} P_{ij} R_j \qquad (17)$$

As is well known, the input coefficient represents the technology of the corresponding industry. The input coefficient, representing the amounts of the various inputs required to produce one value unit of the output of that industry, is termed the technical coefficient. Therefore, similarity measures of production technologies between industries can be derived from input coefficient vectors. Nelson and Winter (1982) also suggest that new technologies which are “close” to the one already in use are assumed to be implemented with a higher probability than technologies which are “distant”, even if the performance of the latter were superior. They define technologically “close” and “distant” industries in terms of whether they have “similar input structures” or “different input structures”. Therefore, an R&D proximity weight between two industries can be calculated using input coefficient vectors. This is a less direct measure of the nature of innovation activity than the patent profile, the distribution of R&D expenditures across research fields or patent information classifications. However, it has the advantage that the necessary data are easily available.

To evaluate the quality of measure used in this chapter, we compute two knowledge

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5 This method was first suggested by Los (2000).

R&D spillovers using the R&D expenditure profiles and input coefficient vectors of 19 industries in 1990. The correlation value between the two computed knowledge R&D spillover measures is 0.4184 (significant at the 10%-level). This means that the linear association between the two variables is relatively weak and positive.

4. The Empirical Model

Following Griliches (1998), we modify the standard, reduced-form R&D productivity growth equation to test whether productivity growth is a function of R&D and R&D spillovers. We also take account of IT investment, capital utilization, and quality of labor. The following productivity growth equation will be estimated:[6]

$$GPs_j = \alpha_0 + \alpha_1 RDOWN_j + \alpha_2 RDSPI_j + \alpha_3 RDSPK_j + \sum_m Z_j^m + \sum_t \lambda_t D_t + u_j \qquad (18)$$

Where GPs_j denotes productivity growth in sector *j*. Productivity growth is measured both as TFP growth (TFPG) using the Tornqvist index and as the more general technical change (TCG) adjusted by returns to scale. $RDOWN_j$, denotes the ratio of the net increase in R&D stock to gross output in sector *j*. $RDSPI_j$, and $RDSPK_j$ denote the ratio of the net increase in rent R&D

[6] In equation (18), we assume that R&D expenditures and IT investments are exogenous. We should note that if there exists a feedback effect from high TFP growth to R&D expenditures and IT investments, our estimates will underestimate the importance of R&D and IT investments. Because of the lack of appropriate instrumental variables, we could not take this problem into account.

spillover and knowledge R&D spillover to gross output in sector *j*.

Z_j^m denotes other factors which might affect productivity growth. We used the ratio of the net increase in IT (information technology) capital stock to gross output in sector *j* to examine the contribution made by IT investment. We also used the change in capital utilization and the growth in the quality of labor. D_t is a year dummy to capture general business cycles.

5. Data Sources and Empirical Results

Table 5–1 lists the variables used in the estimation. The variables can be derived from the JIP database.[7] The JIP database contains annual information on 84 sectors, including 49 non-manufacturing sectors, from 1970 to 1998. It contains detailed information on factor inputs, annual input-output tables, relatively reliable deflators, and some additional statistics, such as IT stock, R&D stock, international trade statistics, etc. at a detailed sector level. The R&D stock is calculated using the perpetual inventory method. We obtained data on sector R&D investment flows using the IO tables and the *Report on the Survey of Research and Development*, Management and Coordination Agency. The R&D deflator is taken from the JIP database. Assuming that R&D investment increased at a constant rate (g) and is depreciated at a constant

[7] See Fukao et al. (2003) for a detailed discussion of the JIP database.

rate (δ), then the R&D stock in the benchmark year (1970) can be computed as $R_t = I_t/(g+\delta)$. The rate of obsolescence is taken from Science and Technology Agency (1985) and g is the actual average growth rate during the sample period.

(Insert Table 5–1)

We estimated the contribution of R&D spillover for 34 manufacturing sectors in Japan. A list of the 34 manufacturing sectors and some summary statistics are presented in table 5–2. Appendix 1 presents summary statistics and the correlation matrix for the variables.

(Insert Table 5–2)

To take account of possible heteroscedasticity across sectors and the presence of autocorrelation within sectors, we estimated equation (18) using Feasible GLS. The results of estimating equation (18) using the two different dependent variables are summarized in tables 5–3 and 5–4.

(Insert Table 5–3)

(Insert Table 5–4)

The key parameters of our estimation are the coefficients on *RDOWN*, *RDSPI*, and *RDSPK*. The coefficient on *RDOWN* is large and highly significant in TFPG. This result is consistent with previous studies. The effect of *RDOWN* on TCG is smaller and of lower significance than effect on the TFPG.

Contrary to expectations, the rent R&D spillover through intermediate goods is negatively related with TFPG and TCG. The negative effect of rent R&D spillovers is large, but insignificant in most specifications. The contribution of rent R&D spillover to technical change is significant in specifications with knowledge R&D spillover. These estimation results are not consistent with most previous studies, though Yamada *et al.* (1991) obtained a similar result.

Quite interestingly, the estimated coefficients on *RDSPK* are positive and statistically significant in TCG while they are insignificant in TFPG. These results suggest that knowledge R&D spillover through the diffusion of knowledge plays a more important role in true productivity growth. These results are consistent with endogenous growth theory, which emphasizes the role of technology diffusion in sustained economic growth.

The regression results showed that R&D spillover which occur through transactions in intermediate goods and the diffusion of knowledge do not have an effect on TFP growth, whereas knowledge R&D spillovers, that is the diffusion of knowledge, contributed to true productivity growth. This finding indicates that rent spillovers and knowledge spillovers may affect productivity growth through different mechanisms.

Productivity growth is also explained by other factors: IT investment, quality of labor, and capital utilization. Therefore, we first examine the effects of IT investment on TFPG and TCG. As noted by Bernstein (2000), IT investment has led to a significant transformation of production techniques by the existence of network externalities and spillovers through R&D embodied information technology. This transformation has the potential to effectively reduce production costs and significantly increase productivity growth. This implies that the IT investment will affect productivity growth not only directly through its impact on the production process, but should do so also indirectly via its external effects. Unfortunately, the coefficients on ITOWN are large and positive, but statistically insignificant in TFPG. The magnitude of the coefficient is similar to that found in recent work using growth accounting methods to examine the subject. Jorgenson and Motohashi (2003) observed that the contribution of information technology on TFP growth was 24% during 1975–90. The impact of IT investment on TCG is also insignificant and negative. There is no evidence that IT investment is significantly linked to productivity growth in Japanese manufacturing industries.

Instead, the most important contribution to productivity growth was made by improvements in the quality of labor: the relationship between the two is highly significant and stable, regardless of which of the dependent variables we look at. This indicates that productivity growth in Japanese manufacturing industry was achieved primarily by accumulation of the human capital. This result is consistent with the growth accounting analysis at the macro level carried by Ito and Fukao (2003), who found that, compared with the US, Japan's economic growth until 1990 was relatively more dependent on labor quality growth.

We also examined industry-specific business cycles fluctuations, which we proxied by changes in capital utilization. As expected, the estimation results reveal a significant positive relationship between changes in capital utilization and productivity growth. This indicates that to some extent productivity growth is due to an increase in the utilization of existing capital.

6. Conclusion

In this paper, we examined the contributions of R&D spillovers on productivity growth in Japanese manufacturing industry. The main findings of this study can be summarized as follows: first, we found that the effects of the two R&D spillovers types in the R&D-productivity model differ depending on which measure of productivity growth is used as the dependent variable. The technical change in Japanese manufacturing industry is affected not by rent R&D spillovers but knowledge R&D spillovers. Unfortunately, we did not find a statistically significant relationship between rent R&D spillovers and productivity growth. Second, we were able to show that knowledge R&D spillover contributes to technical change even when controlling for IT investment, labor quality, and capital utilization. Third, IT investment has not raised productivity growth in Japanese industry like it seems to have done in the USA. However, productivity growth is positively and significantly related to labor quality and capital utilization.

According to these results we can conclude that technical change in Japanese manufacturing industry is affected not by rent R&D spillovers but by knowledge R&D spillovers. We also see that the quality of labor and capital utilization play a significant role in technical change and TFP growth in Japanese manufacturing industry.

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Table 5-1. Definition of variables

Dependent variables	
TFPGj	Growth rate of TFP in industry j
TCGj	Growth rate of technical change in industry j

Independent variables		**[Expected sign of coefficients]**
RDOWNj	R&D intensity: Ratio of net increase in R&D stock to gross output in industry j	[+]
RDSPIj	rent R&D spillovers intensity: Ratio of the net increase rent R&D spillover to gross output in industry j.	[+]
RDSPKj	knowledge R&D spillovers intensity: Ratio of the net increase knowledge R&D spillover to gross output in industry j.	[+]
ITOWNj	IT intensity: Ratio of net increase in IT stock to gross output in industry j.	[+]
CUj	Growth rate of capital utilization in industry j	[+]
Humanj	Growth rate of labor quality in industry j	[+]

Table 5-2. Mean values of variables for Japanese manufacturing industries, 197(–1998

JIP classification	TFPG(%)	TCG(%)	RDOWN(%)	RDSPI(%)	RDSPK(%)	ITOWN(%)	CU(%)	Human(%)	Cost elasticities w.r.t Output
Livestock products	0.514	0.427	0.173	0.027	2.171	0.054	-0.437	0.416	0.963
Processed marine products	0.957	0.774	0.051	0.021	2.830	0.026	0.480	0.781	0.718
Rice polishing, flour milling	0.228	1.559	-0.045	0.005	5.548	0.012	-0.779	0.271	0.454
Other foods	0.251	0.389	0.235	0.045	0.988	0.077	-0.940	0.519	1.085
Beverages	0.230	0.569	0.367	0.093	5.718	0.054	-1.764	1.074	1.146
Silk	0.607	1.826	-3.540	0.058	9.340	0.116	-0.530	0.805	0.782
Spinning	0.054	1.597	-1.185	0.240	5.687	0.156	-0.555	0.342	0.709
Fabrics and other textile products	0.471	1.277	0.121	-0.337	1.861	0.113	-0.555	0.847	0.740
Apparel and accessories	0.886	0.809	0.116	0.021	0.555	0.078	-0.530	1.448	0.916
Lumber and woods products	0.414	0.525	-0.639	0.067	2.077	0.040	-0.500	0.433	0.936
Furniture	0.701	0.662	0.150	-0.002	4.937	0.068	-1.220	0.744	0.969
Pulp, paper, paper products	0.601	0.377	0.118	0.019	1.633	0.132	0.382	0.769	0.872
Publishing and printing	-0.443	-0.041	0.069	0.083	1.636	0.346	-1.122	0.857	1.204
Leather and leather products	0.373	0.342	0.066	0.066	10.012	0.057	-0.935	0.956	0.942
Rubber products	0.371	0.436	0.888	0.184	16.023	0.108	-0.561	1.198	1.032
Basic chemicals	0.839	0.865	0.595	0.055	2.895	0.267	-0.571	0.773	1.024
Chemical fiber	1.678	2.356	0.792	0.283	48.951	0.304	-0.373	1.218	0.538
Other chemicals	2.111	0.773	2.555	0.144	2.627	0.172	-0.527	1.260	0.737
Petroleum products	0.267	-0.123	0.221	0.018	2.378	0.083	-0.625	1.129	0.592
Coal products	-0.385	-0.370	0.185	0.045	5.518	0.013	-0.475	0.895	1.059
Stone, clay & glass products	0.711	0.620	0.667	0.053	2.717	0.114	-0.688	0.731	0.857
Steel manufacturing	0.410	0.388	0.309	0.061	0.900	-0.051	-1.191	0.899	0.897
Other steel	0.426	0.212	0.247	0.104	0.949	0.214	-1.267	0.899	0.778
Non-ferrous metals	0.737	0.495	0.601	0.030	3.277	0.089	-0.001	0.819	0.906
Metal products	0.599	0.516	0.183	0.127	2.400	0.093	0.040	0.713	0.967
General machinery equipment	0.603	0.073	0.581	0.190	1.222	0.343	-1.276	0.812	0.851
Electrical machinery	0.884	0.688	0.858	0.286	12.944	0.874	-0.533	0.968	0.946
Equipment and supplies for household use	1.348	0.810	0.679	0.427	5.221	0.615	-1.070	1.409	0.865
Other electrical machinery	3.338	1.468	3.608	0.121	1.863	0.671	-0.950	1.400	0.827
Motor vehicles	0.247	0.235	1.144	0.227	0.731	0.135	-0.720	0.962	0.988
Ships	-1.497	-1.011	0.103	0.348	33.551	0.806	-0.563	0.601	0.666
Other transportation equipment	0.000	-0.067	1.006	0.235	10.761	0.183	-1.060	0.665	0.985
Precision machinery & equipment	2.037	1.520	1.328	0.196	11.101	0.803	0.339	1.080	0.835
Other manufacturing	0.606	0.470	0.334	0.155	3.530	0.225	-1.272	1.030	0.955

Table 5-3. The impact of R&D spillovers on TFP growth (I)

Independent Variables	Dependent Variables											
	TFPG						TCG					
	(1)		(2)		(3)		(4)		(5)		(6)	
RDOWN	0.615		0.597		0.619		0.249		0.213		0.265	
	(5.56)	***	(5.50)	***	(5.59)	***	(2.21)	**	(1.94)	*	(2.36)	**
RDSPI	-0.753				-0.807		-1.256				-1.797	
	(-0.97)				(-1.00)		(-1.47)				(-2.04)	**
RDSPK			0.000		0.004				0.025		0.033	
			(0.01)		(0.28)				(1.70)	*	(2.22)	**
Constant	0.019		0.019		0.019		0.017		0.016		0.016	
	(3.58)	***	(3.56)	***	(3.57)	***	(3.20)	***	(3.04)	***	(3.10)	***
No. of obs	952		952		952		952		952		952	
No. of groups	34		34		34		34		34		34	

Note: 1) The numbers in parentheses are z-statistics.
2) All regressions include year dummies.
3) *P=.10, **P=.05, ***P=.01 (two-tailed test)
4) In each estimation, we assumed a model with heteroscedasticity across groups and first-order autocorrelation, where the correlation is the same for all groups.

Table 5-4. The impact of R&D spillovers on TFP growth (II)

Independent Variables	Dependent Variables											
	TFPG						TCG					
	(1)		(2)		(3)		(4)		(5)		(6)	
RDOWN	0.554		0.537		0.557		0.217		0.210		0.243	
	(4.98)	***	(4.88)	***	(5.00)	***	(1.84)	*	(1.80)	*	(2.06)	**
RDSPI	-0.974				-0.985		-1.242				-1.742	
	(-1.26)				(-1.23)		(-1.41)				(-1.93)	*
RDSPK			-0.003		0.001				0.025		0.033	
			(-0.22)		(0.09)				(1.69)	*	(2.14)	**
ITOWN	0.320		0.245		0.312		-0.132		-0.335		-0.227	
	(0.96)		(0.74)		(0.93)		(-0.39)		(-0.99)		(-0.66)	
CU	0.112		0.113		0.112		0.064		0.063		0.063	
	(4.72)	***	(4.73)	***	(4.71)	***	(2.59)	***	(2.56)	**	(2.56)	**
Human	0.291		0.278		0.288		0.300		0.277		0.298	
	(2.50)	**	(2.40)	**	(2.48)	**	(2.32)	**	(2.13)	**	(2.30)	**
Constant	0.015		0.015		0.015		0.013		0.012		0.012	
	(2.77)	***	(2.80)	***	(2.78)	***	(2.27)	**	(2.20)	**	(2.19)	**
No. of obs	952		952		952		952		952		952	
No. of groups	34		34		34		34		34		34	

Note: 1) The numbers in parentheses are z-statistics.
2) All regressions include year dummies.
3) *P=.10, **P=.05, ***P=.01 (two-tailed test)
4) In each estimation, we assumed a model with heteroscedasticity across groups and first-order autocorrelation where the correlation is the same for all groups

Appendix 1a. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min.	Max.
TFPG	952	0.006	0.056	-0.426	0.391
TCG	952	0.006	0.069	-0.554	0.394
RDOWN	952	0.004	0.012	-0.082	0.050
RDSPI	952	0.001	0.002	-0.010	0.006
RDSPK	952	0.066	0.114	-0.070	0.862
ITOWN	952	0.002	0.005	-0.008	0.045
CU	952	-0.007	0.054	-0.292	0.226
Human	952	0.009	0.009	-0.031	0.043

Appendix 1b. Correlation matrix

	TFPG	TCG	RDOWN	RDSPI	RDSPK	ITOWN	CU	Human
TFPG	1							
TCG	0.9047*	1						
RDOWN	0.0851*	0.0075	1					
RDSPI	-0.0148	-0.0278	0.1846*	1				
RDSPK	-0.0477	0.0007	-0.003	0.4134*	1			
ITOWN	-0.013	-0.044	0.2082*	0.3617*	0.3464*	1		
CU	0.1539*	0.0688*	0.0148	0.0077	0.0076	-0.0094	1	
Human	0.0578*	0.0352	0.1360*	-0.0466	-0.1287*	-0.1555*	-0.0960*	1

Note) *significant at the 10% level.

Appendix 2. SUR results for translog cost function

Parameter	Estimate	z-statistic	Parameter	Estimate	z-statistic
a_l	0.6453	9.52	a_{Q12}	-0.0301	-0.39
a_k	-0.0049	-0.15	a_{Q13}	0.3487	5.17
a_t	-0.0530	-5.62	a_{Q14}	-0.1815	-1.75
a_{ll}	0.1375	10.02	a_{Q15}	-0.0746	-1.16
a_{kk}	0.0511	8.5	a_{Q16}	-0.1876	-2.42
a_{QQ}	-0.1293	-4.31	a_{Q17}	-0.6372	-6.05
a_{tt}	0.0002	2.03	a_{Q18}	-0.1398	-2.81
a_{lQ}	-0.0083	-3.29	a_{Q19}	-0.2901	-2.07
a_{lk}	-0.0500	-7.71	a_{Q20}	0.0897	0.51
a_{lt}	-0.0045	-7.67	a_{Q21}	-0.0632	-0.48
a_{kQ}	-0.0180	-14.81	a_{Q22}	0.2876	1.63
a_{tQ}	0.0022	4.68	a_{Q23}	0.0100	0.08
a_{kt}	0.0040	14.63	a_{Q24}	0.0095	0.14
a_Q	2.7310	6.13	a_{Q25}	0.1590	2.04
a_{Q2}	-0.2169	-2.17	a_{Q26}	0.1359	1.77
a_{Q3}	-0.4742	-4.8	a_{Q27}	0.0836	1.48
a_{Q4}	0.2662	3.34	a_{Q28}	-0.0749	-1.47
a_{Q5}	0.2021	3.3	a_{Q29}	-0.0064	-0.12
a_{Q6}	-0.4117	-4.79	a_{Q30}	0.2588	3.68
a_{Q7}	-0.5409	-5.3	a_{Q31}	-0.3956	-5.99
a_{Q8}	-0.1647	-1.84	a_{Q32}	0.1139	1.09
a_{Q9}	-0.0157	-0.19	a_{Q33}	-0.1619	-3.2
a_{Q10}	-0.0998	-0.86	a_{Q34}	0.1219	2.01
a_{Q11}	-0.0543	-0.52	a_0	-10.3327	-3.15

Note: Regression includes industry dummies.

Factor share equations

Labor share			Capital share		
a_{ll}	0.1375	10.02	a_{kk}	0.0511	8.5
a_{lQ}	-0.0083	-3.29	a_{kQ}	-0.0180	-14.81
a_{lk}	-0.0500	-7.71	a_{lk}	-0.0500	-7.71
a_{lt}	-0.0045	-7.67	a_{kt}	0.0040	14.63
a_{0l}	0.7188	11.37	a_{0k}	0.0078	0.26