Center for Economic Institutions
Working Paper Series

No. 2013-5

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October 2013

Center for Economic Institutions
Working Paper Series

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Keywords*: R&D, spillovers, plant productivity, distance*
JEL codes: D24, O32.

Acknowledgements
This paper is the result of a joint research project of the National Institute of Science and Technology Policy (NISTEP), the Research Institute for Economy, Trade and Industry (RIETI), and Hitotsubashi University, under the "Science for Science, Technology and Innovation Policy" program. The authors are grateful to Masayuki Morikawa, Toshiyuki Matsuura, Chiara Criscuolo, Pierre Mohnen, Jacques Mairesse, and participants at the NISTEP-RIETI Workshop on Intangible Investment, Innovation and Productivity (Tokyo, January 2012), the 2012 CAED conference in Neurenberg (Germany), the 2013 CAED conference in Atlanta, the Workshop on Intangibles, Innovation Policy and Economic Growth at Gakushuin University (December 2012, Tokyo) and the HIT-TDB-RIETI International Workshop on the Economics of Inter-firm Networks (November 2012, Tokyo) for comments on earlier drafts. Rene Belderbos gratefully acknowledges financial support from NISTEP and the Centre for Economic Institutions at the Institute for Economic Research, Hitotsubashi University.

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ABSTRACT

We examine the effects of R&D spillovers on total factor productivity in a large panel of Japanese manufacturing plants matched with R&D survey data (1987-2007). We simultaneously examine the role of public (university and research institutions) and private (firm) R&D spillovers, and examine the differential effects due to technological, geographic and relational (buyer-supplier) proximity. Estimating dynamic long difference models and allowing for gradual convergence in TFP and geographic decay in spillover effects, we find positive effects of technologically proximate private R&D stocks, which decay in distance and become negligible at around 500 kilometres. In addition to knowledge spillovers from technologically proximate R&D stocks, 'relational' spillovers from buyer and supplier R&D stocks exert positive effects on TFP growth that are similar in magnitude. The elasticity of TFP is highest for public R&D (corrected for industrial relevance), in particular for plants operated by R&D conducting firms. We do not find evidence of geographic decay in the impact of public and relational spillovers. Over time, declining R&D spillovers appear to be responsible for a substantial part of the decline in the rate of TFP growth. The exit of proximate plants operated by R&D intensive firms plays a notable role in this process and is an important phenomenon in major industrial agglomerations such as Tokyo, Osaka, and Kanagawa.

1. Introduction

It is well established in the literature that the productivity effects of R&D spillovers are enhanced by technological proximity and geographic proximity (Jaffe et al., 1993; Adams and Jaffe, 1996; Aldieri and Cincera, 2009; Lychagin et al., 2010; Bloom et al., 2013; Orlando, 2004; Griffith et al., 2009; Mairesse and Mulkay, 2008). Despite the increasing number of large-scale firm-level studies on R&D spillovers,[1] existing studies have a number of limitations in scope and methodology. First, they typically relied on data on publicly listed firms, aggregating over the various locations and technologies in which firms are active.[2] Second, the focus has been on inter-firm private spillovers while abstracting from the role of public research. A different research stream focusing on the role of knowledge spillovers from public research conducted at universities and research institutes has however suggested the importance of such spillovers, with an explicit role of proximity (e.g. Jaffe, 1989; Adams, 1990; Anselin et al., 1997; Furman et al., 2005). Third, R&D spillovers at the firm level have in most cases been modelled as knowledge spillovers as a function of proximity between technology portfolios of the firm, while the role of spillovers through supplier and customer linkages has only received limited attention.[3] A separate literature on the role of spillovers in the context of foreign direct investments has strongly suggested that 'vertical' spillovers through buyer-supplier relationships often is the key channel through with spillovers occur (e.g. Haskel et al., 2007; Görg and Strobl, 2001; Javorcik, 2004; Kugler, 2006). While knowledge and technology transfer in these relationships is often purposeful and embedded in intermediates, their value tends not to be fully reflected in the price of such intermediates, leading to ‘pecuniary spillovers (Hall et al., 2012; Crespi et al, 2007). Compared with ‘horizontal’ spillovers in technological proximity within narrowly defined industries, the absence of market rivalry provides greater incentives for productivity and growth enhancing knowledge exchange and spillovers (e.g. Bloom et al., 2013). Since suppliers and clients may be active in a variety of industries, these 'relational' spillovers are yet a different dimension of heterogeneity in spillover pools.

This paper addresses these limitations in prior work. We contribute an analysis of the

[1] Early work examined R&D spillovers at the industry level (e.g. Mohnen and Lepine, 1991; Audretsch and Feldman, 1996; Goto and Suzuki, 1989).

[2] Adams and Jaffe (1996) do analyse plant level productivity but focuses on the effects of internal R&D. The analysis of Griffith et al. (2009) for UK plants focuses on proximity effects but does not incorporate the role of R&D.

[3] An exception is Crespi et al. (2007), who examine data from UK Community Innovation Surveys for direct (self assessed) evidence of incoming knowledge flows at the firm level. They find, among others, that supplier information positively affects TFP growth, but do not examine geographic or technological proximity.

various sources of R&D spillovers, which until now have not been considered simultaneously, and examine these relationships at the plant level. We analyse the effects of technologically, geographically, and relationally proximate private R&D stocks, as well as of technologically and geographically proximate public R&D stocks on TFP in an unbalanced panel of close to 20000 Japanese manufacturing plants, 1987-2007. The plant level data from the Census of Manufacturers are matched with information on R&D expenditures from the comprehensive Survey of R&D Activities in Japan covering virtually all R&D spending firms (and public research institutions). The R&D survey data, which are decomposed by field or industry of application, allow us to construct relevant R&D stocks weighted by technological proximity (e.g. Bloom et al., 2013), while the information on plant locations allows us to explore the role of geographic distance between firms and between firms and public research institutions in much more detail than in previous studies. Relationally proximate R&D stocks are calculated using input-output tables. Public R&D stocks are differentiated by science field, which can be mapped into technologies and industries reflecting their varying relevance for firms. We estimate long (five year) difference models of plant TFP growth to reduce the influence of measurement errors and cyclical effects (e.g. Haskel et al., 2007; Branstetter, 2000). We allow for gradual convergence in TFP by estimating dynamic TFP growth models (e.g. Klette, 1996; Klette and Johanson, 1998; Lokshin et al., 2008), and we identify distance effects by estimating exponential decay parameters (e.g. Lychagin et al., 2010; Duranton and Overman, 2005)). The simultaneous inclusion of multiple sources of spillovers, the detail on location and field of R&D, the long panel, and the uniquely large set of plants should allow more precise estimates of spillover effects and an assessment of their relative importance over time. Our study contributes to the very limited literature on R&D and spillovers at the plant level.

Our research is also motivated by the observation that Japan's total factor productivity growth has been declining since the mid-1980s (e.g. Fukao and Kwon, 2011), while at the same time R&D expenditures as a percentage of GDP have been steadily increasing to reach 3.8% in 2008, from 2.5% in 1980s. The discrepancy between the trends in R&D expenditures and TFP suggests that the aggregate returns to R&D have been falling. One possible explanation for this phenomenon may be a decline in R&D spillovers due to the exit (and potential relocation abroad) of sophisticated manufacturing plants of R&D intensive firms and the accompanied changing patterns of R&D agglomeration, which may have reduced the size and effectiveness of the relevant pool of R&D spillovers across firms. Prior studies suggest that exit rates of relatively productive plants operated by multi-plant (multinational) firms have been typically higher than the exit rates of single establishments (e.g. Fukao and Kwon, 2006; Kneller et al. 2012).

The remainder of the paper is organized as follows. The next section describes the model, the particularities of the data and the empirical strategy followed. Section 3 presents the empirical results and section 4 concludes and discusses avenues for future research.

2. Model Setup and Data

We conduct a plant-level panel analysis of total factor productivity, in which we relate plant-level TFP to firms' own R&D stock, private R&D stocks (the private spillover pool), public R&D stocks, and a set of plant-, firm- and industry-level controls. We assume that firm level R&D stocks are available to all the firms' plants and that R&D spillovers occur between plants due to the R&D stock the plants have access to. This allows us to investigate the geographic dimension of R&D spillover in detail, taking into account the population of R&D conducting firms and the spatial and industry configuration of their plants.

We adopt the standard knowledge stock augmented production function framework (e.g. Hall et al, 2012). We define the production function at the plant-level generally as:

$$Q_{it} = f(L_{it}, K_{it}, M_{it})g(R_{it-1}, S_{it-1}, P_{it-1}, \mathrm{X}_{it})U_{it} \tag{1}$$

Where:

Q_{it}: Gross output of the plant

L_{it}, K_{it}, M_{it}: Inputs of plant i in year t

R_{it-1}: Firm-level R&D stock

S_{it-1}: Private R&D stock

P_{it-1}: Public R&D stock

X_{it}: a vector of other observable factors (control variables) affecting plant productivity

U_{it}: plant-year specific unobserved efficiency.

Total factor productivity (TFP) is defined as:

$$TFP_{it} \equiv \frac{Q_{it}}{f(L_{it}, K_{it}, M_{it})} = g(R_{it-1}, S_{it-1}, P_{it-1}, \mathrm{X}_{it})U_{it} \tag{2}$$

R&D stocks are assumed to influence production with a one-year lag to reflect that the application of new knowledge and insights due to R&D takes time. If we adopt a log-linear specification for $g(R_{it-1}, S_{it-1}, P_{it-1})$ and allow $U_{it} = e^{\eta_i + u_{it}}$, where η_i is a plant specific fixed effect and u_{it} is a plant-year specific efficiency shock, we obtain:

$$\ln TFP_{it} = \alpha_R \ln R_{it-1} + \alpha_S \ln S_{it-1} + \alpha_P \ln P_{it-1} + \gamma' \mathrm{X}_{it} + \eta_i + u_{it} \quad (3)$$

and if we difference the equation between two periods:

$$\Delta \ln TFP_{it} = \alpha_R \Delta \ln R_{it-1} + \alpha_S \Delta \ln S_{it-1} + \alpha_P \ln\Delta P_{it-1} + \gamma' \Delta \mathrm{X}_{it} + \Delta u_{it} \quad (4)$$

where the plant-specific efficiency parameter drops out. We assume that the change in plant-specific efficiency levels (Δu_{it}) is a function of past productivity relative to the industry mean, in order to allow for a gradual convergence in efficiency levels between firms (e.g. Lokshin et al., 2008). Klette (1996) and Griffith et al. (2009) have shown that the empirically observed persistent productivity differences between plants or firms require a model specification that allows for gradual convergence.[4] Specifically, we model:

$$\varDelta u_{it} = u_{it} - u_{it-1} = \rho \ln TFP_{it*} + e_{it} \quad (5)$$

where $\ln TFP_{it*}$ is the level of TFP of plant i relative to the industry mean in the previous period. We expect ρ to fall within the interval [-1,0]. If ρ is zero there is no gradual convergence between leading firms and lagging firms; if ρ is –1 complete convergence materializes in one period. We assume that the error term e_{it} can be decomposed into four components, year-specific effects λ_t, industry-year specific technological opportunity or efficiency shocks μ_{st}(with s denoting industry), regional shocks ρ_r and measurement error ε_{it}:

$$e_{it} = \mu_{st} + \lambda_t + \rho_r + \varepsilon_{it} \quad (6)$$

[4] Kneller et al. (2012) show that productivity catch up is an important phenomenon among Japanese manufacturing plants as well

Data sources and sample

We match plant level data from the Japanese *Census of Manufacturers* with information on R&D expenditures from the yearly (comprehensive) *Survey of R&D Activities* in Japan, 1987-2007. The census has a comprehensive coverage of manufacturing plants with more than 4 employees. From 2001 onwards, information on plant level fixed capital investment has not been surveyed for plants with less than 30 employees, with the exception of the benchmark surveys organized every 5 years. The number of plants for which panel data on TFP can be calculated is roughly 40,000 yearly.

The Survey of R&D activities in Japan is a comprehensive and mandatory survey of R&D performing firms and public research institutes and universities in Japan. It contains information on R&D expenditures, differentiated by field, for roughly 9,000 firms yearly and has a response rate greater than 90 percent. Large firms (with more than 1 billion Yen of capital) are always included in the survey; smaller firms are included in higher sampling rates if they are identified as R&D conducting firms in the previous survey. The information on R&D by field (30 fields are distinguished) is easily mapped into industries, and allows us to distinguish R&D expenditures relevant to 20 manufacturing industries. The response rate by research institutes and universities is close to 100 percent.

The matching between the surveys posed a number of challenges. Firm names are only recorded in the R&D survey from 2001 onwards and parent firm names are only provided on the plant records in the census from 1994 onwards. Firm identifiers in the R&D survey are not compatible between the years before and after 2001 because the identifiers for all firms were revised in 2001; only the R&D survey in 2001 includes both the old and new versions of firm identifiers. Because of the absence of common firm identifiers in the surveys, matching had to be done semi-manually (by firm name, address and capitalization). From 2001 onwards, we could match more than 97.5 percent of reported R&D expenditures to firms and plants included in the census (Figure 1). The situation is more complicated for the years 1983-2000, for which we could only match R&D to plants 1) that could be linked to the parent firm in 1994 or one of the later years, and 2) that belong to firms identified in the R&D survey of 2001. This caused the coverage rate to decline from 98 percent in 2001 to 92.5 percent in 2000, declining progressively further to 73 percent in 1983.

Insert Figure 1

The matching issues cause several problems. First, there is a difficulty ascertaining whether a plant belongs to a parent firm conducting R&D or not. Here we excluded all unmatched firms from our sample to avoid measurement error in R&D stocks at the firm level. Second, for some firms R&D series are incomplete. We proceeded to calculate R&D stocks on the basis of the information available only if there was sufficient information to derive an R&D growth rate for a specific period. Firms that are included in the R&D survey multiple times reporting absence of R&D activities are included in the sample with zero R&D stock. Third, we require reliable estimates of private R&D spillover pools. Here we obtained estimates that are as accurate as possible by 1) using the weights provided in the R&D survey to correct for non-response and arrive at an estimate of total R&D expenditures in Japan; 2) allocating the R&D (stocks) to locations and fields/industries for R&D conducting firms that could not be matched to the manufacturing census (and hence for which no geographic information on plants is available) on the basis of the location of the firm, rather than on the basis of the location of plants. The second correction may be a reasonable approximation as most of the unmatched firms are smaller enterprises for which the plant and administrative unit are collocated.

Using the above matching rules, we obtain an unbalanced panel of over 19000 plants, observed for a maximum of 20 years and a minimum of 5 years, during 1987-2007. The five year minimum observation period is due to the fact that we will estimate (five-year) long difference models. About 57 percent of the plant observations, plants are owned by parent firms for which we could confirm the absence of formal R&D. Zero R&D cases are not compatible with the specification in natural logarithms in (4) but provide important variation in the sample. We deal with this in two ways: 1) we include a dummy for continuous engagement in, or absence of, R&D; 2) we add the value 1 to the R&D stock before taking the logarithm, such that we treat the continuous absence of R&D as zero growth.

Table 1 shows the distribution of plants over industries and compares this with the distribution of the population of Japanese manufacturing plants over industries. Plants in technology intensive industries such as drugs & medicine and chemicals are overrepresented in our sample, but the difference with the distribution of all plants over industries is not generally pronounced. The 19389 unique plants are operated by 13188 firms, implying that on average there are 1.5 plant observations per firm in the sample. Parent firm R&D stocks are highest in the home electronics and information and telecommunication sectors, and lowest in pulp & paper and printing.

Insert Table 1

We note that creating a sample of plants for which parent firms' R&D stocks can be calculated leads to various sample selection issues, with a natural oversampling of R&D conducting firms (although the majority of plants in our sample have no access to internal R&D), larger plants (post-2001), surviving plants (1987-1994), and surviving firms (1987-2001). We will conduct several sensitivity analyses to examine potential selection bias.

Variables and Measurement

We utilize plant level TFP data from the Japan Industrial Productivity Database (JIP) 2010 (Fukao et al., 2008). TFP is measured using the index number method, following Good et al (1997):

$$\begin{aligned} \ln TFP_{fsit} = \; & \left(\ln Q_{fsit} - \overline{\ln Q}_{st}\right) - \sum_{X=L,C,M} \frac{1}{2}\left(s_{fsit}^{X} + \bar{s}_{st}^{X}\right)\left(\ln X_{fsit} - \overline{\ln X}_{st}\right) \\ & + \sum_{j=1}^{t}\left(\overline{\ln Q}_{j} - \overline{\ln Q}_{j-1}\right) - \sum_{j=1}^{t}\sum_{X=L,C,M} \frac{1}{2}\left(\bar{s}_{fsij}^{X} + \bar{s}_{sj-1}^{X}\right)\left(\overline{\ln X}_{s} - \overline{\ln X}_{s-1}\right) \end{aligned} \tag{7}$$

where $Q_{fsi,t}$ is the gross output of plant i of firm f in industry s in year t, $s^{X}_{,fsi,t}$ is the cost share of input X, and $X_{fsi,t}$ is the amount inputs of the plant. Three inputs, labour (L), capital (C), and intermediate input (M), are taken into account. Variables with upper bars denote the arithmetic mean of each variable over all plants in that industry s in year t. The JIP database provides index linked TFP estimates distinguishing 58 industries. The TFP indices express the plants' TFP as an index of the TFP level of a hypothetical representative plant in the industry (with an index of 1). One of the main advantages of the index number method is that it allows for heterogeneity in the production technology of individual firms, while other methods controlling for the endogeneity of inputs (e.g. Olley and Pakes, 1996; Levinsohn and Petrin, 2003) assume an identical production technology among firms within an industry (Van Biesebroeck, 2007; Aw et al., 2001).

Drawing on the JIP database, we calculate the five-year growth rate in TPF for the matched sample. We drop the observations with the largest (top 1 percent) and lowest (bottom 1 percent) TFP growth to avoid a potentially strong influence of outliers. Figure 2 shows the 5-year moving average of the gross output weighted average TFP growth rate for the sample. The figure confirms that the rate of TFP growth has been decreasing over time, while there is a modest recovery in growth rates after 1999. The pattern of TFP growth in the sample closely follows the pattern of TFP growth in the population of Japanese plants.

Insert Figure 2

R&D stocks by industry and location

R&D stocks measured at the parent firm level can be separated by industry/field of application to arrive at R&D stocks of the firm per industry. We utilize a question in the R&D survey asking firms to allocate R&D expenditures by field, which easily maps into 20 industries. R&D stock of firm f in industry/field s is defined by:

$$K_{fst} = I_{fst} + (1 - \delta_s)K_{fst-1} \tag{8}$$

where I_{fst} is R&D investment of firm f for activities in industry s in year t and δ is a depreciation rate of the R&D stock. We use industry-specific depreciation rates to reflect differences in the speed of obsolescence and technology life cycles. Industry specific depreciation rates are based on Japanese official surveys of "life-span" of technology conducted in 1986 and 2009 among R&D conducting firms[5] and vary between 8 (food industry) and 25 percent (precision instruments). To calculate initial R&D stocks (Hall and Oriani, 2006), we similarly use industry-specific growth rates, which we calculate from the R&D survey as average R&D growth rates per field in the 1980s**.** R&D investments are deflated using a deflator for private R&D from the JIP database, calculated from the price indices of the input factors for R&D expenditures for each industry; the deflator for public R&D is obtained from the White Paper on Science and Technology.

Matching the field of firms' R&D with the industry of the firms' plants, we can calculate R&D stocks across industries and space, where we assume that the R&D stock in a field/industry is available to each same-industry plant of the firm. We map R&D stocks in geographic space by using the information on the location of the plant, where we distinguish more than 1800 cities, wards, towns, and villages.

Plant R&D stocks

We calculate plant R&D stocks as the R&D stock of the parent and assume that all parent R&D provides relevant productivity improving inputs to the plants. Given that R&D at the firm level is often organized to benefit from scope economies (e.g. Henderson and Cockburn, 1996; Argyres and Silverman, 2004) and involves active knowledge transfer to business units

[5] See "White paper on Science and Technology" (1986, Science and Technology Agency) and "Survey on Research Activities of Private Corporations" (2009, National Institute of Science and Technology Policy).

and plants, this may be a suitable assumption.[6]

Private R&D stocks (spillover pools)

Private R&D stocks (spillover pools) are derived from the calculated parent firms' R&D stocks, while we allow for geographic decay in the effectiveness of spillovers. Technologically proximate R&D stocks are calculated based on the technological proximity between the R&D field/industry of the plant and the industry of other plants. We define the technologically relevant private R&D stock (spillover pool) as the sum total of other firms' R&D assigned to their (nearest) plants in an industry, weighted by the technological relatedness between the industry of the plants and the industry of the focal plant:

$$\boldsymbol{S_{ifst}^{tech}} = \sum_{f' \neq f} \sum_{s'} \boldsymbol{K_{f's't} T_{ss'} e^{\tau d_{if's't}}} \quad (10)$$

where:

$d_{if's't}$: Minimum geographic distance between plant i and the plant of firm f' in the field s' in year t;

$T_{ss'}$: the technological proximity weight;

$e^{\tau d_{if's't}}$: Weight for geographic proximity of plant i to R&D stock firm f' for field s';

τ: a decay parameter, with $\tau < 0$.

If firms operate multiple plants, the R&D stock is only counted once using the plant with the minimum distance to the focal plant, which avoids double counting of R&D.[7] We model an exponential decay function in the effectiveness of spillovers with parameter τ to be estimated, in line with recent studies (e.g. Lychagin et al. 2010). Distance d is the distance between a pair of locations and is measured as the geo-distance between the centre of cities, wards, towns, and villages. In order to correct for differences in the geographic areas covered by the regions, distance is the radius of the region if plants are located in the same region.

[6] We also calculated a technological proximity weighted parent R&D stock, applying the weighting scheme for industries/fields outside the industry of the plant based on the technological proximity matrix used for R&D spillovers, but obtained weaker effects. As the co-occurrence of different technologies in the R&D portfolios of firms is often taken as an indicator of the potential for scope economies (Bloom et al. 2013; Breschi et al. 2003) this is perhaps not surprising.

[7] This would follow from the notion of redundancy in the type of R&D spillovers. On other hand, one may argue that having multiple plants in the vicinity increases the likelihood of knowledge spillovers.

Our technological relatedness measure is derived from patent data and based on Leten et al. (2007). The relatedness between technologies will be reflected in the intensity with which technologies in a field build on prior art in a different field. Patent citation data are available at the 4-digit IPC level. The IPC codes can subsequently be mapped onto industries using the industry-technology concordance table developed by Schmoch et al. (2003) in which each technology field is uniquely linked to its corresponding NACE two-digit industry. Appendix A shows the resulting technological relatedness coefficients (weights) between industries used in our analyses, with weights for the own industry normalized at 1.

We measure relationally proximate R&D stocks by the R&D stocks of supplier and customer industries, identifying the importance of supplier and customer transactions from Input-Output tables (yearly between 1987 and 2007) for 52 JIP industries. The calculation of R&D stocks follows (10) but with $T_{ss'}$ substituted by supplier industry proximity weights $SUP_{ss'}$ and customer proximity weights $CUS_{ss'}$, with:

$$SUP_{ss't} = \frac{Q^*{}_{s'st}}{\sum_j Q^*{}_{jst}} \tag{12}$$

$$CUS_{ss't} = \frac{Q_{ss't}}{EX_{st}+Q_{st}} \tag{13}$$

where $Q^*{}_{s'st}$ denotes domestic sales of industry s' to industry s and EX_{st} denotes exports of industry s. In equation (12), $Q^*{}_{s'st}$ is the estimated output of industry s' sold to industry s. Since domestic sales in the input-output tables include domestic sales of imported goods, we estimate $Q *_{s'st}$ by applying the following correction to the domestic sales data: $Q^*{}_{s'st} = Q_{s'st} * (\sum_s Q_{s'st})/(\sum_s Q_{s'st} + I_{s't})$, with I_{st} imports of industry s. Hence we assume that the imported goods of the industry are sold to other industries in proportion to total sales to these industries. We note that industries s include services and other industries' sales to industry s', such that the sum of input shares for industry s' does not add up to 1. Weights for customer R&D stocks for industry s are the shares of sales by industry s to industry s' in total sales, with the latter including sales to non-manufacturing industries and exports. We use-yearly input output tables provided by the JIP database, such that weights are varying by year. Appendix B and C show the average the input and output share weights for the industries in the analysis for the year 1990.

Public R&D stocks

Public R&D spillover pools derived from the R&D surveys have few measurement issues, as response rates are virtually 100 percent. We differentiate public R&D by location based on the region (city, ward, town, village) of the research institute or university, and by industry/R&D field utilizing information on science fields with varying relevance for specific industries. We define the R&D stock of public research institution h in science field m as:

$$A_{hmt} = E_{hmt} + (1 - \delta_A) A_{hmt-1} \tag{14}$$

where E_{hmt} is research expenditure of public research institution h in science field m in year t and δ_A is a depreciation rate of public R&D stock, which we set at 15 percent per year. Although the surveys do not include research expenditures by science field, they do contain information on the number of researchers by science field for each institution for each year. We estimate the public R&D expenditure E_{hmt} by mutliplying total R&D expenditures with the share of the number of scientists in the field in the total number of scientists for each institution and year.

Second, we estimate a 'relevant' public R&D stock per industry/R&D field using weights derived from a concordance matrix between science fields and industries. The weights are based on a study by Van Looy et al. (2004) examining citation frequencies on patent documents classified in different technology fields to Web of Science publications in each of the science fields. The concordance attaches to each scientific discipline probabilities that it is of relevance to each technology field (4-digit IPC fields). Applying this concordance to the public R&D expenditures per science field, we subsequently apply the concordance matrix between IPC classes and industries due to Schmoch et al. (2003) to arrive at public R&D stocks per industry. Appendix D shows the compound weights used to relate R&D stocks per science field to industries.

Using the above procedure, the technologically and geographically proximate public R&D stock is defined as:

$$P_{its} = \sum_h \sum_m A_{hmt} \tilde{T}_{sm} e^{\theta \tilde{d}_{ih}} \tag{15}$$

where:

A_{hmt}: R&D stock of public institutes in location h for academic field m in year t;

$\tilde{T}_{sm}$: The compound proximity weights between industry/R&D field s and science field m;

$\tilde{d}_{ih}$: geographic distance between plant i and location h;

θ: the geographic decay parameter, $\theta < 0$.

Figure 3 shows the 5-year moving average growth rates in the levels of public and private R&D stocks. The growth in both public and private R&D shows a declining trend, as the increase in overall R&D investments (Figure 1) has slowed over time and had just exceeded deprecation rates in the most recent years.

Insert Figure 3

Control variables

The vector of time varying plant-specific characteristics X_{it} includes plant size (number of employees) and a dummy variable indicating whether the plant is active in multiple industries (at the 4 digit level).[8] In addition, we control for parent firm size (number of employees) and the number of plants of the parent firm. On the one hand, increases in the number of a firm's plants may correlate with unmeasured firm-specific advantages. On the other hand a larger numbers of plants drawing on the same R&D pool may lead to reduced effective knowledge transfer (Adams and Jaffe, 1996). We include a set of year dummies λ_t and region (prefecture) dummies ρ_r. We model μ_{st} as a set of industry dummies μ_s in addition to the average TFP growth rate for all plants in the industry, $\widetilde{\ln tfp}_{st}$, which controls for industry-specific technological opportunity and demand shocks over time affecting TFP growth.

Specification

We estimate equation (4) in its long difference form. The long difference models, while sacrificing degrees of freedom, is a conservative estimation method to reduce the influence of measurement error and cyclical effects (e.g. Haskel et al, 2007; Branstetter, 2000). To strike a balance between degrees of freedom and reduction in measurement error, we take 5-year differences starting from 1987, which leaves a maximum of exactly 4 non-overlapping long differenced observations (for plants observed over the entire period): 1987-1992, 1993-1997, 1998-2002 and 2003-2007. To facilitate interpretation of the descriptives, we divide the long

[8] Note that age effects are of no interest in differenced models, since the difference in age would be identical for all plants.

difference by 5 to arrive at annual average growth rates of TFP and R&D stocks during the 5-year periods. Since the geographic decay specification introduces nonlinearity in the TFP equation, we estimate equation (4) with nonlinear least squares. The distance decay parameters are estimated using a Taylor approximation.[9] Error terms are cluster-robust at the plant level.

Table 2 shows descriptive statistics of the variables and Table 3 contains the correlation matrix. The correlations between the (growth in) relationally proximate R&D stocks (buyers and suppliers) and the technologically proximate R&D stock are rather high at 0.66-0.78. This is mainly stemming from the correlation in same-industry R&D stocks, while correlations between stocks in other industries range between -0.04 and 0.12. Hence, the different measures of proximity do suggest rather different weightings for R&D stocks and the resulting spillovers potential.

Insert Tables 2 and 3

3. Empirical results

Table 4 reports the estimation results. Model 1 only includes the technologically proximate R&D stock and the parent firm R&D stock. The coefficient on parent R&D suggests an elasticity of TFP with respect to R&D of 0.033 percent, which is within, but at the lower end, of the range estimated in Adams and Jaffe (1996) for plant level R&D effects.[10] The elasticity of the private R&D stock is higher – a common finding in R&D spillover studies- at 0.058, while spillover effects decay in distance, as the significant distance parameter suggests. The estimates on the past TFP level suggest that plants that are 1 percent more productive than the average TFP level in the industry have a 0.08 percent point

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[9] Without approximation we would need to sum up over all R&D conducting firm-pairs and industries for each plant to arrive at an update of the distance parameter τ, which is computationally infeasible. We therefore approximate the distance function by taking a H-order Taylor's expansion: $e^{\tau d_{if's't}} \cong \sum_{n=0}^{H} e^{\tau \bar{d}} (\tau)^n \frac{\left(d_{if's't}-\bar{d}\right)^n}{n!}$, such that the expression for the plant level technologically proximate R&D stock becomes:

$$S_{ifst}^{tech} =\cong \sum_{n=0}^{H}\left[e^{\tau\bar{d}}(\tau)^n \sum_{f'\neq f}\sum_{s'}\left(K_{f's't}T_{ss'}\frac{\left(d_{if's't}-\bar{d}\right)^n}{n!}\right)\right]$$

The summation over f' and s' no longer depends on the distance decay parameter τ, and summation over H suffices. We set H conservatively at 50 and $\bar{d}$ at 1500 km (the midpoint of the smallest and largest possible distance).

[10] We note that their specification was cross sectional, and one may expect smaller effects in a differenced model.

smaller TFP growth rate, indicating that there is a modest gradual convergence in productivity. TFP growth of the plants is strongly influenced by opportunities and shocks captured by the average TFP growth in the industry, with an estimated elasticity of 0.89. Of the plant and firm control variables, only (growth in) the number of plants operated by the parent firm has a marginally significant positive effect on TFP.

Insert Table 4

In model 2 we add the dummy variable indicating continuous positive R&D. Both the dummy variable indicating positive R&D and the R&D stock are significant. The dummy variable suggests that R&D performing firms generate on average 0.5 percent points higher TFP growth (independent of variation in their R&D stocks). At the same time, the coefficient of the parent R&D stock declines to about 0.01. Model 3 adds the technologically proximate public R&D stock. The coefficient on public R&D, at 0.077 is larger than the coefficient on technologically proximate private R&D, demonstrating the importance of knowledge spillovers from public R&D. The estimates however do not suggest a significant geographic decay effect of public R&D spillovers. The addition of public R&D in model 3 does not materially affect the estimated coefficient on private R&D, which may indicate little overlap in the type of knowledge from technologically proximate private and public R&D.

In model 4 the relationally proximate R&D stocks of customers and suppliers are added. The relationally proximate R&D stock due to supplier linkages has a significant effect on TFP growth with an elasticity of 0.031. The significant elasticity of customer R&D stocks is slightly smaller at 0.026. Meanwhile, the coefficient on the technologically proximate R&D stock reduces with the inclusion of the supplier and customer R&D stock variables, and at 0.035 is similar in magnitude as the elasticity of the supplier R&D stock. The estimated distance decay for private R&D spillovers becomes smaller overall, suggesting weaker proximity influences for relationally proximate R&D. Model 5 confirms this pattern: when we allow separate decay parameters for the three private R&D stocks, the decay parameter for technologically proximate R&D increases in strength whereas the model does not identify a distance decay effects for R&D spillovers from buyers and suppliers. For technologically proximate R&D spillovers, the decay function on the basis of model 5 is depicted in Figure 4. Spillover effects decline and become negligible at about 500 kilometers. This pattern is similar to the estimates reported in Lychagin et al. (2010) for US listed manufacturing firms based on inventor locations.

Model 6 presents the results of an alternative model with one parameter estimated for the (unweighted) sum of the three types of private R&D. The estimated coefficient for this combined private R&D stock is close to 0.08 and larger than the estimated coefficient for technologically proximate R&D in models 1-3. This underscores that failure to take into account relational proximity may lead to an underestimation of R&D spillover effects. The estimate of the distance parameter for the combined private R&D stock is close to the parameter estimated in model 4.

Prior studies have suggested that firms need to invest in internal R&D in order to benefit from academic research (e.g. Cassiman and Veugelers, 2006; Anselin et al., 1997; Belderbos et al., 2009), as firms need the absorptive capacity to screen, understand, and utilize the fruits of relevant scientific research (Cohen and Levinthal, 1990). In model 7, we separate the effect of public R&D into an effect for firms without formal R&D expenditures and an effect for firms with positive R&D. The results confirm that the presence of internal R&D increases the magnitude of public R&D spillovers: the elasticity increases to 0.12, while the coefficient for firms without internal R&D is only marginally significant (at 0.068). The difference between the two coefficients is statistically significant.

Insert Figure 4

Sensitivity analysis

We further explored the role of distance for public spillovers and the assumption that (private) R&D spillovers as a function of distance play out at the plant level. In an alternative specification, we examine distance between the firms' R&D laboratories and between R&D laboratories and the location of public R&D institutions. In particular for public spillovers, linkages may occur at the laboratory level and not necessarily at the plant level, while the R&D laboratories may not necessarily be located close to the firms' plants. We derived the location of R&D laboratories from published directories of R&D establishments in Japan. For R&D performing firms lacking laboratory location information, we assigned R&D to the location of headquarters – the safest option for these -mostly smaller- firms (e.g. Adams and Jaffe, 1996; Orlando, 2004). Our results, however, did not show geographic decay effects in this specification either.

We conducted a number of additional sensitivity analyses, estimating model 6 on different samples. First, we estimated productivity models for the entire population of Japanese manufacturing plants (plants with TFP information; more than 230000 observations) to examine the robustness of our estimates. Here we treated the unmatched plants as zero R&D plants while including a separate dummy variable indicating that the plants lack R&D information. Second we estimated the model without smaller plants (leaving about 36000 observations) and on a balanced sample (limited to about 16000 observations), to explore the implications of potential sample selection bias. All these models produced broadly similar results, with some exceptions. The distance effect for technologically proximate R&D proved difficult to identify in some of the models, while in two specifications only two of the individual effects of supplier, customer, and technologically proximate R&D were simultaneously estimated as significant. We aim to further explore the robustness of our empirical model in future work.

Decomposition analysis

Given the time dimension in our data and the changes over time in R&D investments and agglomeration, we can decompose long term TFP growth effects into several factors: firms' internal R&D effects, private R&D spillover effects, and public R&D spillover effects. The results of the decomposition analysis based on model 7 are presented in Figures 5-8. The decomposition analysis is conducted for a balanced sample of close to 4200 plants. Keeping the sample of spillover receiving plants stable ensures that the decomposition is not influenced by period-on-period changes in the sample but highlights effects of the changing 'supply' of spillovers. The decomposition uses plants' gross output as weights. Figure 5 shows that declining R&D spillovers, in particular private R&D spillovers, play an important role in the decline in TFP growth over the years. The contribution of private R&D spillovers to TFP growth for the plants in the balanced sample reduced from 0.896 percent points in 1987-1992 to 0.182 percent points in 2002-2007. The contribution of public R&D spillovers also declined, but less so in relative and absolute terms. This is related to the more modest decline in the growth in public R&D and a changing composition of public R&D expenditures in the direction of life sciences with greater relevance for the private sector. The role of internal R&D remained relatively stable, although this is to an important extent due to the fact that R&D active firms record generally higher TFP growth than firms that are not engaged in R&D.

We can further decompose the changing role of private R&D spillovers into the three types of spillovers: spillovers due to technological proximity, buyer effects, and supplier effects. Figure 6 shows that the technological proximity based spillovers and customer spillovers have declined most, while the decline in supplier spillovers has been more modest.

These divergent effects arise because the share of procurement from (R&D intensive) local manufacturing industries has not decreased that much over time, while an increasing role of exports has reduced relational proximity to Japanese customer industries.

Figure 7 decomposes private spillovers into effects due to the exit of R&D active plants, the entry of such plants, and the changing R&D stocks of surviving plants. The exit of R&D active plants reduces the R&D stock available to other plants and has a negative effect on TPF growth. However, if the parent firm operates multiple plants, the exit of one of its plants implies that another plant of the firm takes its place as 'minimum distance' plant providing R&D spillovers, such that there is a compensating 'plant substitution effect'. In such cases, net spillovers decline only to the extent that the exit increases average distance between plants. Similarly, if a firm opens up a new plant, this may increase the R&D stock available to plants in its proximity, but at the same time it displaces the R&D stock of the firm's plant that was previously located at minimum distance to these receiving plants. Hence, in case of entry there is a partially compensating negative substitution effect. This decomposition exercise shows that while the largest part of the decline in spillovers is due to a slowing down of R&D stock growth in surviving plants, increasing exit effects and reduced entry effects over time also play an important role. Figure 8 shows that most of the exits have taken place in the major industrial agglomerations in Japan around Tokyo and Kanagawa, Osaka, and Aichi (home of a large automobile cluster) during 1997-2007

4. Conclusions

This paper examined the effects of R&D spillovers on total factor productivity in a large panel of Japanese manufacturing plants matched with R&D survey data. We simultaneously analyse the role of public (universities and research institutes) and private R&D spillovers, while examining effects due to 'relational' (supplier-customer) proximity as well as technological and geographic proximity. Our analysis confirms the importance of positive spillover effects from R&D by firms with plants in technologically related industries. The latter spillover effects are attenuated by distance and our estimates suggest that most spillover effects disappear beyond 500 kilometres. We also observe positive effects of public R&D spillovers, with the effects substantially larger for plants with access to internal R&D. We do not find evidence that public R&D spillover effects are attenuated by distance. In addition to knowledge spillovers from technologically proximate plants, we find evidence that 'relational proximity' due to buyer and supplier linkages generates additional 'pecuniary' R&D spillovers of similar magnitude as the knowledge spillovers due to technological proximity.

We could not identify the role of geographic distance in these buyer and supplier spillovers.

We conclude that public as well as private R&D spillovers matter for TFP growth, while relational proximity as well as technological proximity needs to be taken into account to arrive at representative estimates of the social effects of private R&D. Decomposition analysis shows that the contribution of private R&D spillovers to TFP growth has declined since the late 1990s. This is due to a declining growth in R&D stocks while another important factor is the exit of proximate plants operated by R&D intensive firms. A mildly declining contribution of public R&D spillovers is primarily due to a reduction in the growth of R&D by public research organization since the late 1990s. If we explore effects at the regional level, we observe that strong adverse exit effects occurred in particular in Japan’s major industrial agglomerations such as Tokyo and Osaka.

Our results help to explain the twin stylized facts of Japanese productivity growth: the exit of relatively productive plants and the declining TFP growth or surviving plants (Fukao and Kwon, 2006; Kneller et al., 2012). They suggest that these two trends may be causally related. The exit of plants by R&D intensive firms reduces the available R&D spillovers and hampers TPF growth of the surviving plants.

In future work, we aim to get a better understanding of the (absence of) distance effects in R&D spillovers. One reason for the lack of estimated distance effects for public R&D may be that public R&D spillovers occur most often through active collaboration across larger distances (Okamuro and Nishimura, 2013; Gittelman, 2007). We can explore these explanations by incorporating information available on research relationships between firms and universities. Second, we aim to investigate the role of proximity effects in buyer-supplier relationships in more detail by utilizing data on the most important buyers and suppliers of individual Japanese firms. Third, we are planning to match the data with the Basic Surveys on Business Activities in Japan, which contain information on corporate relationships and foreign activities. Matching with the Basic Surveys allows bringing in controls on overseas R&D conducted/outsourced by the firms and the potentially resulting international transfers and knowledge spillovers (e.g. Branstetter, 2001; Griffith et al., 2008). It also allows analysis of potentially greater R&D spillovers for firms operating within business groups (Suzuki, 1993; Branstetter, 2000). Collectively, the remaining challenges for exploration of R&D spillover effects present a rich research agenda.

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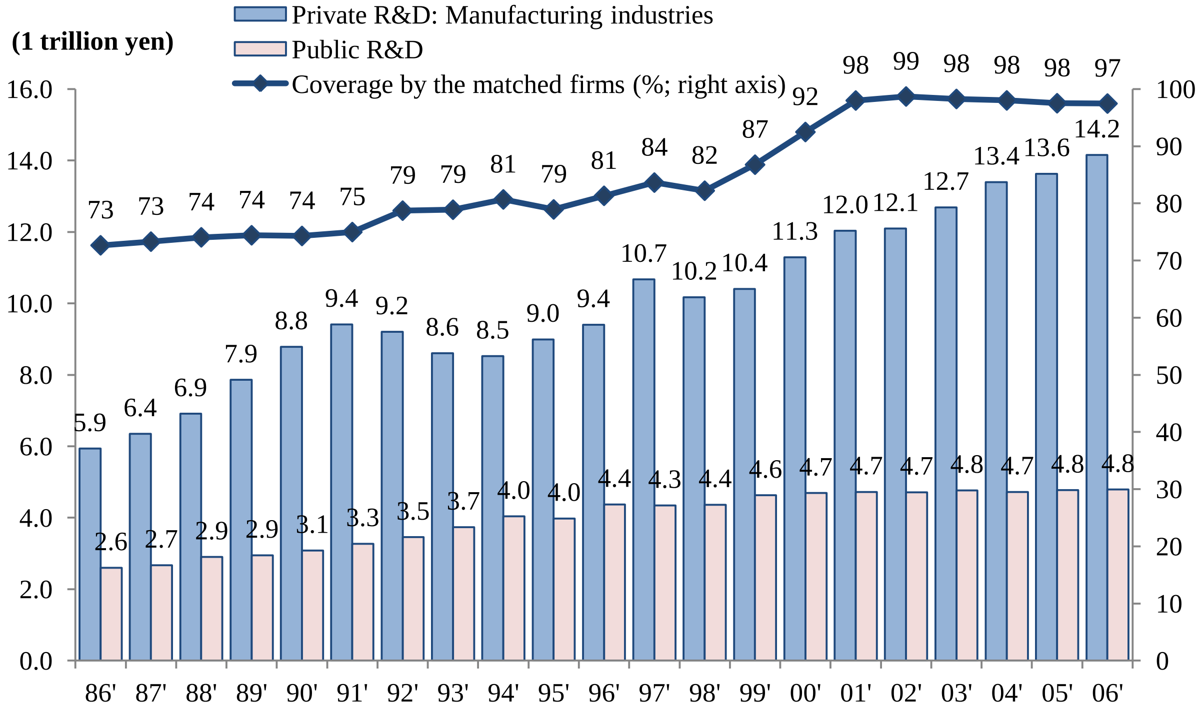
Figure 1: R&D expenditures and matching rate with census of manufacturers



Note: Nominal values are reported as R&D expenditures.

Table 1: Sample characteristics

Industries (R&D fields)	# of obs. #	# of obs. (%)	# of (unique) plants in sample #	# of (unique) plants in sample (%)	# of (unique) plants in Japan (%)	# of (unique) parent firms	Avg. # of plants per firm	Avg. parent R&D stock per plant (billion yen)	% of plants with positive parent R&D
Food products	5,048	(10.8)	1,961	(10.1)	(12.7)	1,032	1.9	7.3	42.8
Textile mill products	1,741	(3.7)	641	(3.3)	(10.5)	432	1.5	7.3	37.4
Pulp and paper products	1,838	(3.9)	660	(3.4)	(3.2)	365	1.8	2.6	32.6
Printing	1,270	(2.7)	489	(2.5)	(5.6)	332	1.5	4.1	15.7
Chemical fertilizers and industrial chemicals	2,049	(4.4)	786	(4.1)	(0.8)	519	1.5	17.6	61.0
Drugs and medicine	1,154	(2.5)	490	(2.5)	(0.5)	398	1.2	22.2	47.6
Miscellaneous chemicals	2,135	(4.6)	913	(4.7)	(1.1)	655	1.4	11.9	53.3
Petroleum and coal products	511	(1.1)	225	(1.2)	(0.3)	113	2.0	7.6	58.5
Rubber products	1,072	(2.3)	426	(2.2)	(1.4)	295	1.4	13.4	37.2
Ceramic, stone and clay products	2,969	(6.3)	1,187	(6.1)	(5.5)	669	1.8	5.7	41.4
Iron and steel	1,744	(3.7)	642	(3.3)	(2.6)	425	1.5	16.6	37.7
Non-ferrous metals and products	1,331	(2.8)	513	(2.6)	(1.7)	371	1.4	11.2	39.5
Fabricated metal products	4,196	(8.9)	1,818	(9.4)	(14.0)	1,271	1.4	3.8	31.3
General-purpose machinery	6,925	(14.8)	2,951	(15.2)	(14.1)	2,284	1.3	15.8	33.1
Home electronics	444	(0.9)	225	(1.2)	(1.9)	185	1.2	83.1	32.9
Electrical machinery	3,455	(7.4)	1,508	(7.8)	(6.8)	1,101	1.4	26.3	36.6
Info.&com. electronics	3,585	(7.6)	1,714	(8.8)	(7.7)	1,247	1.4	56.9	31.5
Motor vehicles, parts and accessories	3,285	(7.0)	1,304	(6.7)	(5.1)	756	1.7	58.4	43.1
Other transportation equipment	724	(1.5)	289	(1.5)	(1.7)	235	1.2	36.5	39.5
Precision instruments and machinery	1,447	(3.1)	647	(3.3)	(2.7)	503	1.3	6.0	28.3
Total	46,923	(100.0)	19,389	(100.0)	(100.0)	13,188	1.5	19.4	38.2

Figure 2: Trends in TFP growth: sample plants and population of Japanese plants

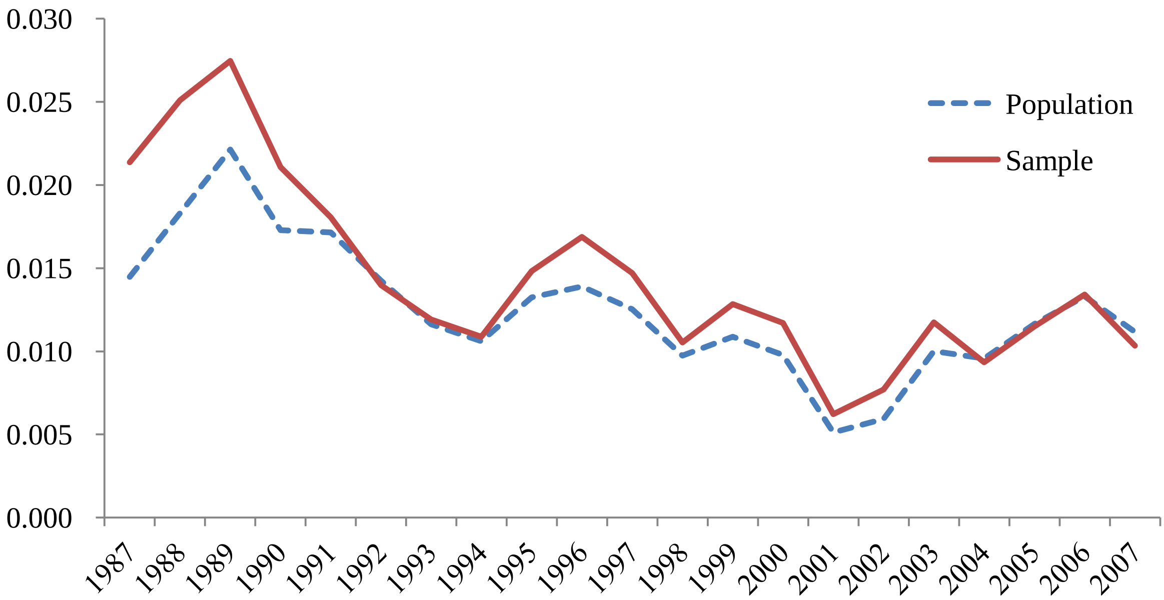


Figure 3: Growth rate in R&D stocks (5 year moving average)

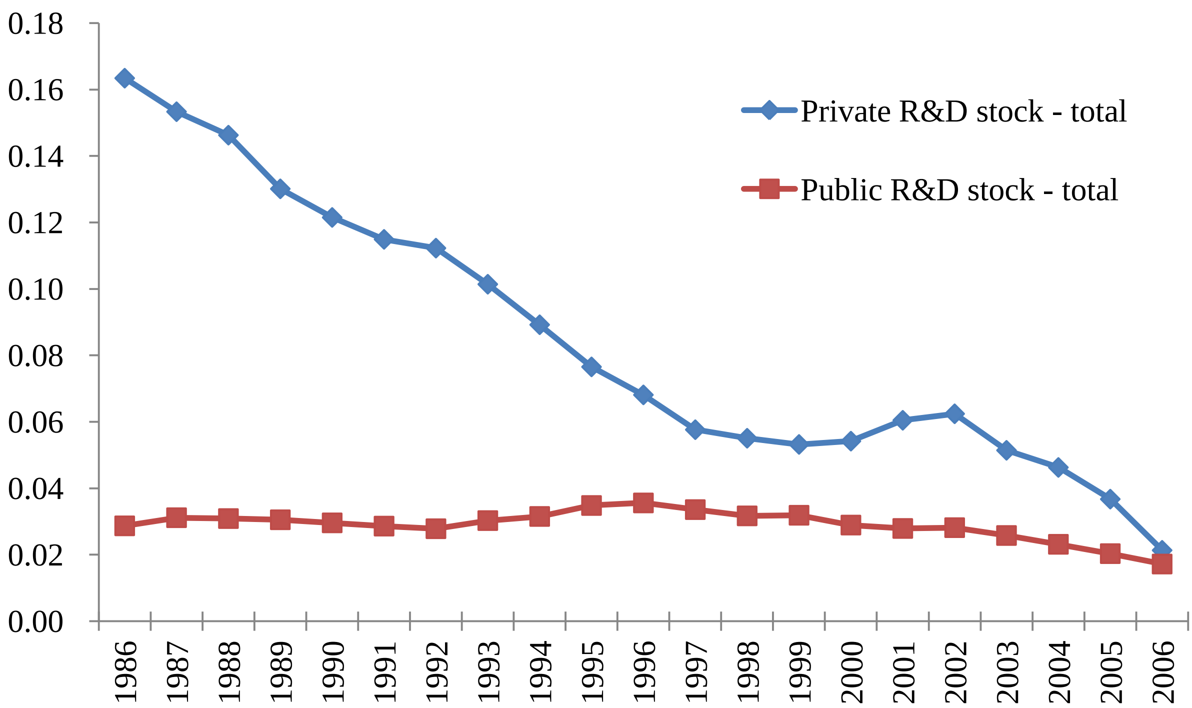


Table 2: Descriptive statistics

	Mean	SD	Min	Median	Max
TFP	0.007	0.079	-1.409	0.006	1.025
PARENT R&D	0.023	0.055	-0.563	0.000	1.604
Tech-proximate PRIVATE R&D	0.040	0.038	-0.155	0.035	0.421
Supplier PRIVATE R&D	0.043	0.043	-0.168	0.036	0.237
Customer PRIVATE R&D	0.040	0.041	-0.751	0.033	0.420
PUBLIC R&D	0.030	0.008	0.002	0.030	0.072
Number of other plants of the parent firm	0.004	0.058	-1.099	0.000	1.099
Number of firm employees	-0.003	0.095	-2.290	-0.002	3.306
Number of plant employees)	-0.005	0.082	-2.297	-0.004	1.285
Multi-products (4 digit) plant dummy	-0.001	0.093	-1.000	0.000	1.000
Parent R&D stock > 0 (dummy)	0.435	0.485	0.000	0.000	1.000
Industry average TFP growth rate	0.006	0.019	-0.124	0.003	0.184
Prior TFP level relative to industry average	0.054	0.269	-1.529	0.036	1.383

Note: all variables are expressed as average 5-year differences, except for prior TFP

Table 3: Correlation coefficients

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
[1]	TFP	1.000												
[2]	PARENT R&D	0.020	1.000											
[3]	Tech-proximate PRIVATE R&D	0.071	0.086	1.000										
[4]	Supplier PRIVATE R&D	0.076	0.103	0.612	1.000									
[5]	Customer PRIVATE R&D	0.091	0.108	0.656	0.746	1.000								
[6]	PUBLIC R&D	0.026	-0.021	0.065	0.213	0.100	1.000							
[7]	Number of other plants of the parent firm	0.012	0.041	0.059	0.082	0.075	0.021	1.000						
[8]	Number of firm employees	0.018	0.046	0.061	0.086	0.082	-0.057	0.297	1.000					
[9]	Number of plant employees)	0.014	0.030	0.051	0.073	0.072	-0.070	-0.012	0.562	1.000				
[10]	Multi-products (4 digit) plant dummy	-0.004	0.004	-0.001	0.001	0.005	0.000	-0.013	0.001	0.025	1.000			
[11]	Parent R&D stock > 0 (dummy)	-0.017	0.451	-0.101	-0.099	-0.095	-0.077	-0.038	-0.059	-0.039	0.001	1.000		
[12]	Industry average TFP growth rate	0.212	0.074	0.345	0.380	0.432	0.006	0.011	0.052	0.057	0.001	-0.045	1.000	
[13]	Prior TFP level relative to industry average	-0.271	0.064	0.049	0.038	0.021	-0.004	0.000	-0.005	0.009	-0.010	0.128	-0.018	1.000

Note: all variables are expressed as 5-year differences, except for prior TFP

Table 4: Long Difference Analysis of Plant-level TFP (1987-2007)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Distance parameters:							
Tech-proximate PRIVATE R&D	-0.0040	-0.0038	-0.0040		-0.0057		-0.0058
	[0.0012]***	[0.0011]***	[0.0012]***		[0.0027]**		[0.0027]**
all PRIVATE R&D				-0.0018		-0.0017	
				[0.0008]**		[0.0010]*	
Supplier PRIVATE R&D					0.0000		0.0000
					[0.0027]		[0.0027]
Customer PRIVATE R&D					0.0000		0.0000
					[0.0037]		[0.0037]
PUBLIC R&D			0.0000	0.0000	0.0000	0.0000	
			[0.0024]	[0.0025]	[0.0024]	[0.0025]	
PUBLIC R&D (parent R&D>0)							0.0000
							[0.0020]
PUBLIC R&D (parent R&D=0)							-0.0060
							[0.0059]
R&D parameters:							
Parent R&D	0.0331	0.0097	0.0097	0.0096	0.0096	0.0096	0.0096
	[0.0036]***	[0.0043]**	[0.0043]**	[0.0043]**	[0.0043]**	[0.0043]**	[0.0043]**
Parent R&D stock > 0 (dummy)		0.0050	0.0050	0.0050	0.0050	0.0050	0.0034
		[0.0004]***	[0.0004]***	[0.0004]***	[0.0004]***	[0.0004]***	[0.0012]***
Tech-proximate PRIVATE R&D	0.0583	0.0600	0.0582	0.0392	0.0346		0.0347
	[0.0167]***	[0.0168]***	[0.0167]***	[0.0194]**	[0.0167]**		[0.0167]**
Supplier PRIVATE R&D				0.0311	0.0360		0.0364
				[0.0141]**	[0.0140]**		[0.0140]***
Customer PRIVATE R&D				0.0260	0.0260		0.0259
				[0.0131]**	[0.0131]**		[0.0130]**
all PRIVATE R&D						0.0775	
						[0.0180]***	
PUBLIC R&D			0.0766	0.0766	0.0832	0.0746	
			[0.0364]**	[0.0373]**	[0.0378]**	[0.0363]**	
PUBLIC R&D (parent R&D>0)							0.1211
							[0.0416]***
PUBLIC R&D (parent R&D=0)							0.0678
							[0.0356]*
Other parameters:							
Plant's relative prior TFP	-0.0792	-0.0802	-0.0802	-0.0803	-0.0803	-0.0802	-0.0803
	[0.0007]***	[0.0007]***	[0.0007]***	[0.0007]***	[0.0007]***	[0.0007]***	[0.0007]***
Industry average TFP growth	0.8917	0.8919	0.8971	0.8962	0.8966	0.8977	0.8970
	[0.0193]***	[0.0193]***	[0.0197]***	[0.0197]***	[0.0198]***	[0.0196]***	[0.0196]***
Number of other plants	0.0077	0.0087	0.0087	0.0087	0.0087	0.0087	0.0086
	[0.0053]	[0.0053]*	[0.0053]	[0.0053]	[0.0053]	[0.0053]	[0.0053]
Number of firm employees	-0.0008	0.0011	0.0012	0.0010	0.0010	0.0011	0.0010
	[0.0047]	[0.0047]	[0.0047]	[0.0047]	[0.0047]	[0.0047]	[0.0047]
Number of plant employees	-0.0040	-0.0032	-0.0031	-0.0033	-0.0033	-0.0032	-0.0032
	[0.0051]	[0.0051]	[0.0051]	[0.0051]	[0.0051]	[0.0051]	[0.0051]
Multi-products (4digit) plant (dummy)	-0.0033	-0.0033	-0.0034	-0.0033	-0.0033	-0.0033	-0.0033
	[0.0029]	[0.0029]	[0.0029]	[0.0029]	[0.0029]	[0.0029]	[0.0029]
Constant	-0.0040	-0.0035	-0.0057	-0.0092	-0.0086	-0.0072	-0.0084
	[0.0073]	[0.0073]	[0.0073]	[0.0074]	[0.0074]	[0.0073]	[0.0073]
Industry dummies (JIP industry level)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	46,923	46,923	46,923	46,923	46,923	46,923	46,923
R-squared	0.1685	0.1696	0.1696	0.1697	0.1697	0.1696	0.1698
F statistic	9486.43***	9555.59***	9556.97***	9563.57***	9566.77***	9556.55***	9568.20***

* p < 0.1, ** p < 0.05, *** p < 0.01.

Figure 4: Decay in the effect of technologically proximate R&D spillovers as a function of distance

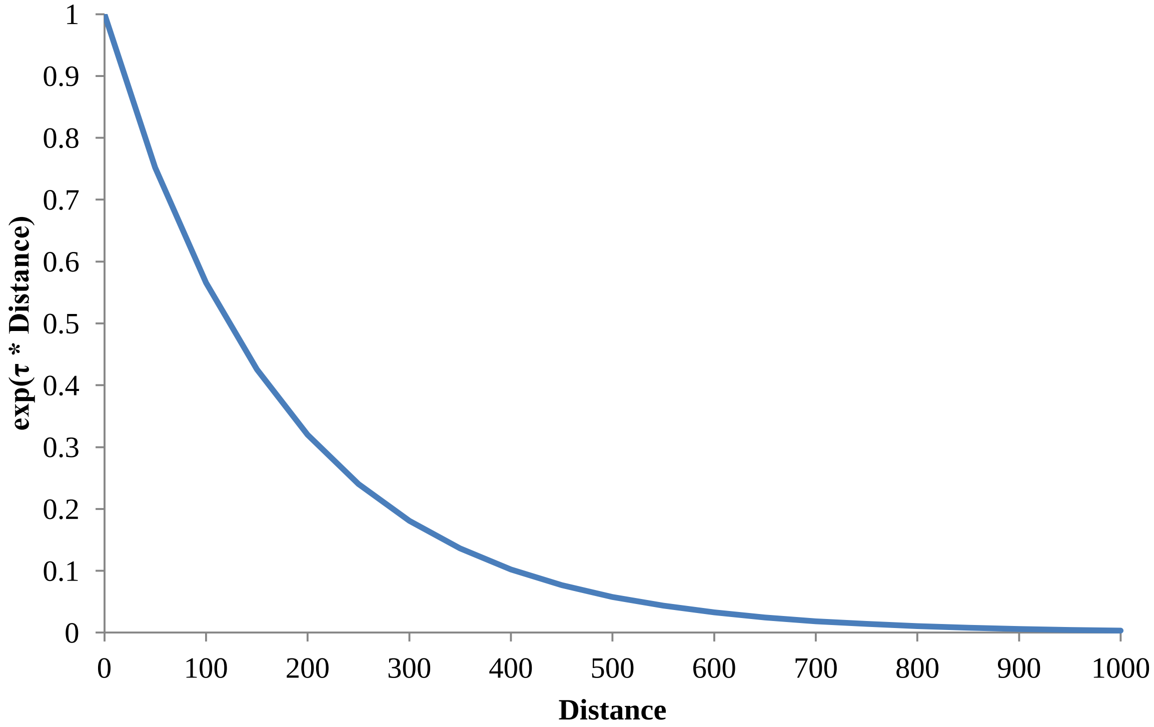
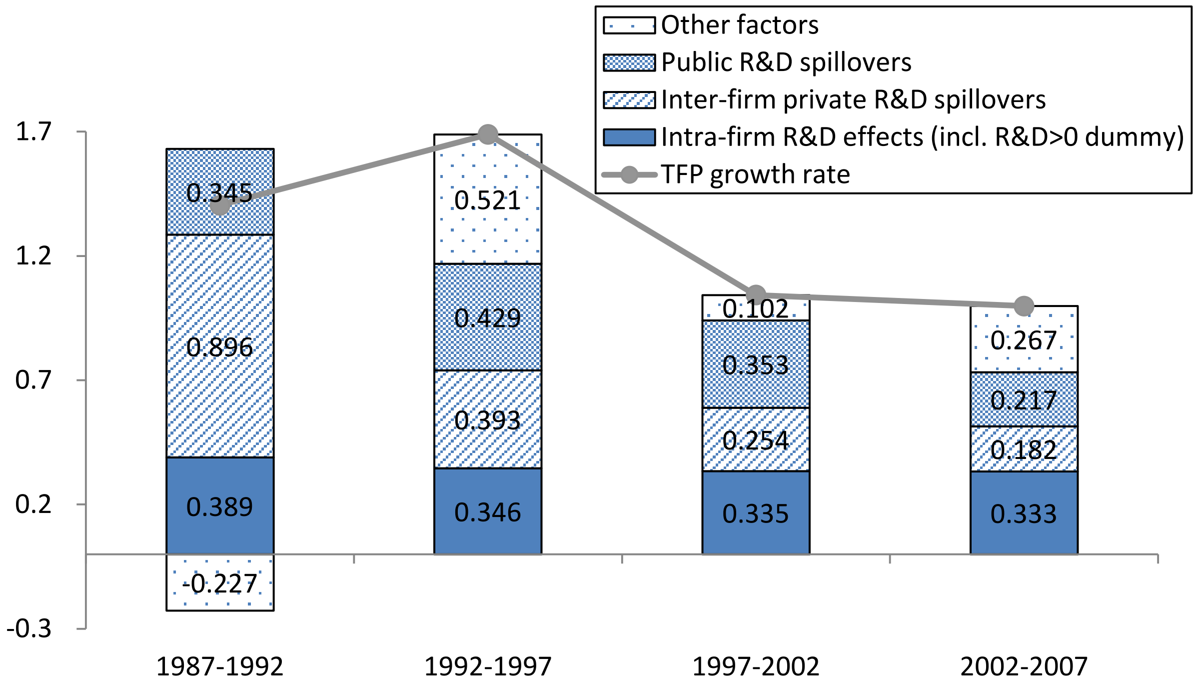
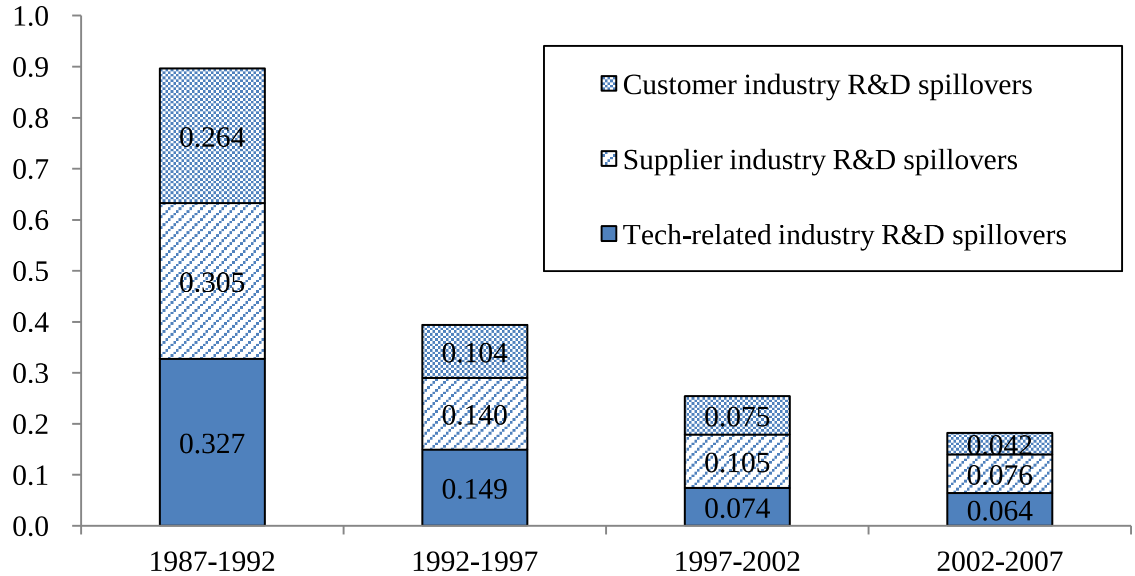


Figure 5: TFP Growth Composition: Intra-firm R&D vs. Private and Public Spillovers



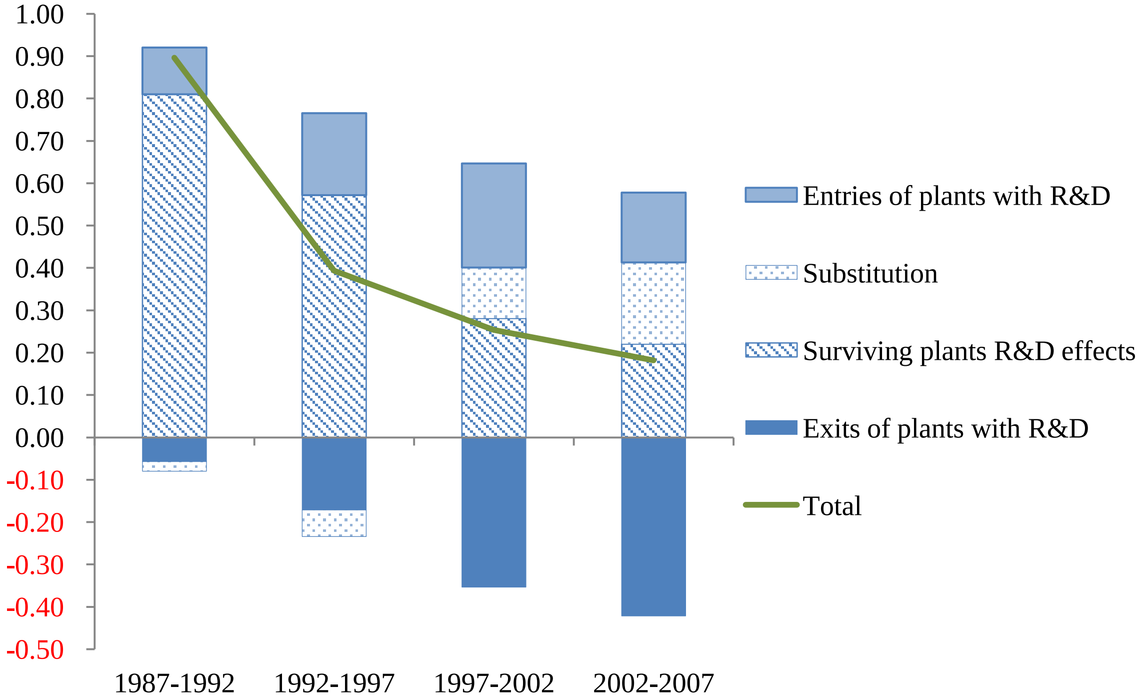
Note: based on a balanced sample, 1987-2007

Figure 6: TFP Growth Composition: Effects of types of Private R&D spillovers



Note: based on a balanced sample, 1987-2007

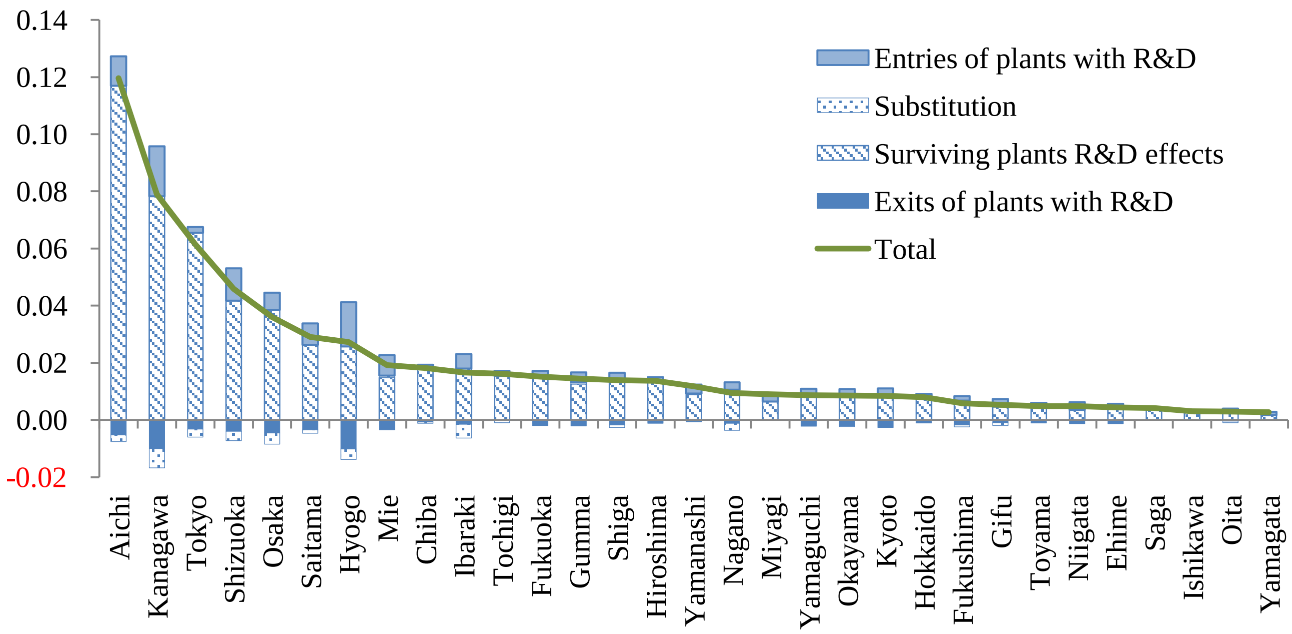
Figure 7: TFP Growth Composition: Effects of R&D Active Firms' Plant Entry and Exit



Note: based on a balanced sample, 1987-2007

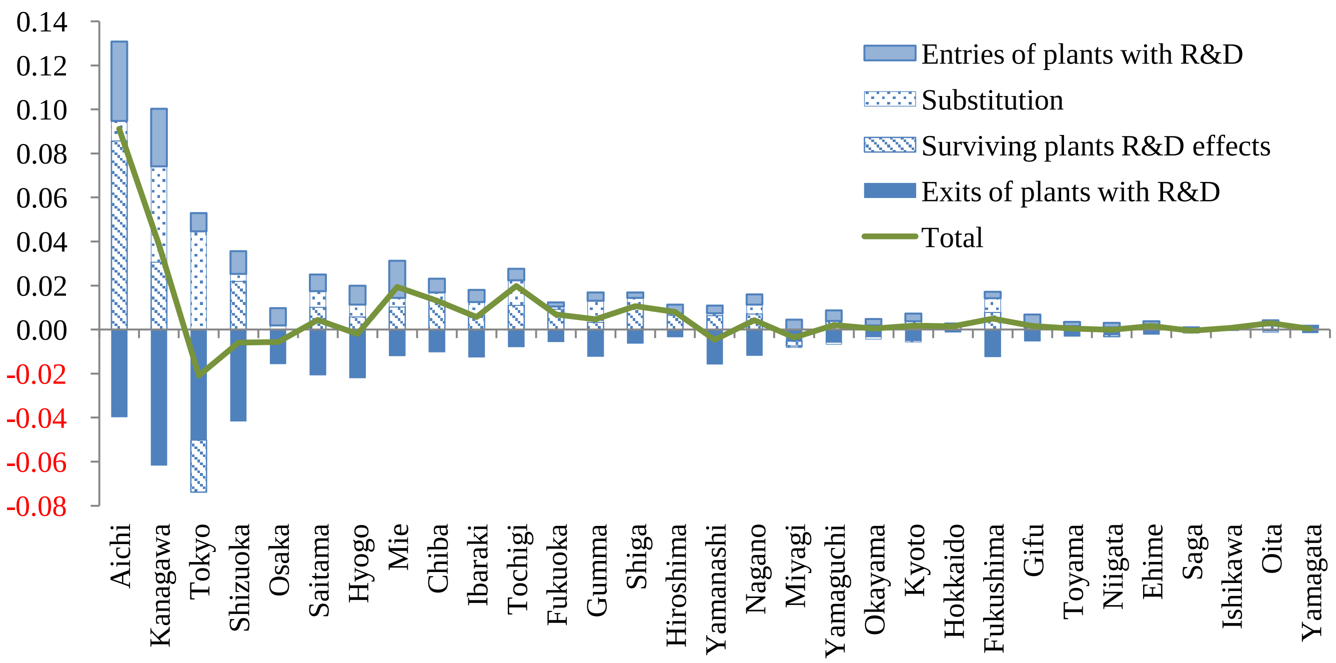
Figure 8: TFP Growth Composition: Effects Plant Entry and Exit by Prefecture

a. 1987-1997



Note: based on a balanced sample, 1987-1997

b. 1997-2007



Note: based on a balanced sample, 1997-2007

Appendix A. Technological proximity between industries

Focal industries (citing) \ Spillovers sources (cited)	[04]	[05]	[06]	[07]	[08]	[09]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]
[04] Food products	1.00	.003	.006	.000	.125	.359	.041	.001	.000	.004	.001	.001	.001	.094	.021	.001	.003	.002	.000	.026	.026
[05] Textile mill products	.007	1.00	.045	.024	.631	.065	.104	.001	.002	.172	.007	.006	.023	.243	.026	.013	.033	.019	.005	.148	.114
[06] Pulp and paper products	.022	.073	1.00	.126	.415	.049	.089	.002	.000	.100	.003	.003	.043	.301	.009	.008	.190	.004	.001	.123	.083
[07] Printing	.000	.011	.042	1.00	.270	.021	.095	.000	.000	.028	.008	.011	.020	.085	.003	.003	.181	.002	.000	.087	.017
[08] Chemical fertilizers and industrial chemicals	.009	.020	.008	.015	1.00	.147	.050	.012	.004	.039	.007	.007	.005	.070	.005	.010	.032	.006	.001	.041	.027
[09] Drugs and medicine	.026	.002	.001	.001	.147	1.00	.013	.000	.000	.002	.000	.000	.000	.010	.001	.000	.005	.000	.000	.076	.001
[10] Miscellaneous chemicals	.031	.032	.012	.035	.488	.128	1.00	.020	.000	.038	.008	.007	.010	.093	.010	.006	.057	.014	.003	.055	.036
[11] Petroleum and coal products	.004	.004	.002	.001	.763	.031	.143	1.00	.000	.008	.006	.005	.014	.209	.003	.036	.074	.030	.004	.130	.014
[12] Rubber products	.000	.008	.001	.001	.400	.002	.006	.000	1.00	.008	.014	.011	.004	.030	.001	.005	.028	.064	.002	.050	.116
[13] Ceramic, stone and clay products	.003	.064	.026	.021	.439	.015	.047	.001	.001	1.00	.030	.027	.073	.225	.020	.022	.108	.032	.008	.112	.197
[14] Iron and steel	.001	.006	.002	.013	.248	.011	.028	.004	.007	.120	1.00	.580	.069	.410	.030	.059	.152	.036	.008	.065	.048
[15] Non-ferrous metals and products	.001	.009	.003	.030	.392	.020	.042	.004	.010	.187	1.00	1.00	.108	.486	.034	.111	.233	.052	.009	.097	.075
[16] Fabricated metal products	.001	.009	.012	.015	.066	.006	.016	.004	.000	.104	.025	.024	1.00	.259	.027	.050	.082	.081	.025	.070	.102
[17] General-purpose machinery	.010	.012	.008	.007	.114	.019	.018	.005	.001	.040	.019	.013	.033	1.00	.018	.020	.059	.078	.014	.082	.058
[18] Household appliances	.022	.015	.003	.004	.091	.012	.022	.001	.000	.039	.014	.010	.039	.188	1.00	.057	.121	.056	.004	.079	.106
[19] Electrical machinery	.000	.003	.001	.001	.080	.003	.004	.003	.000	.019	.013	.015	.026	.084	.022	1.00	.244	.082	.009	.127	.031
[20] Info.&com. electronics	.000	.001	.003	.008	.024	.003	.005	.001	.000	.008	.003	.003	.005	.027	.005	.026	1.00	.010	.001	.068	.009
[21] Motor vehicles, parts and accessories	.000	.003	.001	.001	.028	.001	.008	.002	.003	.017	.004	.004	.029	.183	.012	.046	.055	1.00	.022	.076	.041
[22] Other transportation equipment	.000	.004	.001	.001	.032	.002	.012	.003	.000	.031	.006	.005	.064	.260	.008	.043	.041	.197	1.00	.060	.064
[23] Precision instruments and machinery	.003	.009	.004	.007	.070	.129	.011	.003	.001	.019	.003	.003	.009	.078	.007	.030	.151	.030	.003	1.00	.035
[24] Miscellaneous manufacturing	.011	.019	.009	.007	.180	.007	.024	.001	.008	.106	.007	.006	.042	.184	.034	.023	.076	.048	.009	.117	1.00

Source: calculations based on Leten et al. (2008)

Appendix B. Applied weights for relationally proximate (Supplier) R&D stocks

Focal industries (buyer) \ Spillover sources (supplier)	[04]	[05]	[06]	[07]	[08]	[09]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	Total
[04] Food products	.120	.001	.015	.007	.006	.000	.002	.004	.000	.005	.000	.001	.018	.000	.000	.000	.000	.000	.000	.000	.181
[05] Textile mill products	.003	.223	.009	.008	.034	.000	.009	.006	.003	.000	.000	.000	.002	.000	.000	.000	.001	.000	.000	.000	.298
[06] Pulp and paper products	.003	.006	.275	.014	.018	.000	.012	.012	.001	.001	.000	.000	.001	.000	.000	.000	.001	.000	.000	.000	.344
[07] Printing	.002	.001	.111	.081	.001	.000	.029	.002	.001	.000	.000	.002	.000	.000	.000	.000	.002	.000	.000	.000	.233
[08] Chemical fertilizers and industrial chemicals	.003	.001	.005	.002	.339	.000	.007	.084	.001	.003	.000	.003	.005	.000	.000	.000	.001	.000	.000	.000	.454
[09] Drugs and medicine	.012	.002	.033	.008	.071	.048	.013	.003	.002	.013	.000	.001	.013	.001	.000	.000	.002	.000	.000	.000	.222
[10] Miscellaneous chemicals	.005	.001	.034	.012	.177	.001	.083	.005	.001	.006	.000	.004	.016	.001	.000	.000	.001	.000	.000	.000	.346
[11] Petroleum and coal products	.001	.001	.000	.000	.002	.000	.003	.050	.000	.001	.000	.000	.002	.000	.000	.000	.000	.000	.000	.000	.060
[12] Rubber products	.001	.017	.008	.002	.185	.000	.007	.005	.041	.001	.003	.001	.025	.000	.000	.000	.001	.000	.000	.000	.296
[13] Ceramic, stone and clay products	.002	.003	.017	.003	.016	.000	.007	.022	.002	.090	.010	.003	.009	.003	.000	.000	.001	.000	.000	.000	.187
[14] Iron and steel	.001	.001	.001	.001	.005	.000	.001	.029	.001	.007	.453	.006	.001	.001	.000	.000	.000	.000	.000	.000	.508
[15] Non-ferrous metals and products	.001	.002	.004	.002	.013	.000	.003	.007	.000	.007	.002	.245	.002	.001	.000	.000	.001	.000	.000	.000	.289
[16] Fabricated metal products	.002	.002	.004	.004	.002	.000	.008	.005	.002	.004	.192	.046	.062	.002	.000	.001	.004	.000	.000	.000	.342
[17] General-purpose machinery	.001	.001	.003	.004	.001	.000	.005	.002	.011	.005	.073	.014	.034	.189	.000	.020	.022	.000	.000	.004	.391
[18] Home electronics	.002	.003	.012	.014	.012	.000	.004	.002	.006	.003	.023	.022	.027	.021	.099	.033	.132	.000	.000	.002	.417
[19] Electrical machinery	.002	.002	.011	.004	.007	.000	.005	.003	.006	.009	.039	.052	.025	.016	.000	.123	.028	.000	.000	.001	.334
[20] Info.&com. electronics	.003	.003	.012	.009	.008	.000	.005	.003	.004	.015	.004	.018	.016	.005	.001	.034	.256	.000	.000	.000	.396
[21] Motor vehicles, parts and accessories	.001	.002	.003	.002	.002	.000	.007	.002	.015	.006	.030	.012	.007	.009	.005	.031	.005	.445	.000	.000	.583
[22] Other transportation equipment	.001	.003	.002	.004	.002	.000	.013	.003	.014	.006	.092	.013	.028	.036	.003	.020	.008	.030	.189	.001	.470
[23] Precision instruments and machinery	.001	.002	.010	.005	.004	.000	.003	.003	.005	.018	.011	.017	.016	.011	.000	.014	.066	.000	.000	.095	.284

Source: JIP database. Data are for 1990.

Appendix C. Applied weights for relationally proximate Buyer R&D stocks

Spillover sources (buyer) / Focal industries (supplier)	[04]	[05]	[06]	[07]	[08]	[09]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	Total
[04] Food products	.120	.001	.001	.000	.001	.002	.001	.000	.000	.000	.000	.000	.001	.001	.000	.000	.001	.001	.000	.000	.132
[05] Textile mill products	.006	.223	.005	.001	.001	.001	.001	.001	.005	.003	.001	.001	.002	.004	.002	.003	.007	.006	.001	.001	.275
[06] Pulp and paper products	.067	.011	.275	.088	.007	.022	.026	.001	.003	.017	.002	.003	.006	.010	.009	.014	.029	.011	.001	.005	.607
[07] Printing	.039	.012	.018	.081	.003	.007	.011	.001	.001	.004	.002	.002	.008	.017	.014	.005	.027	.010	.003	.003	.269
[08] Chemical fertilizers and industrial chemicals	.020	.030	.014	.001	.339	.034	.100	.002	.049	.012	.008	.006	.003	.003	.006	.007	.015	.005	.001	.001	.655
[09] Drugs and medicine	.002	.000	.000	.000	.000	.048	.002	.000	.000	.000	.000	.000	.000	.001	.000	.000	.001	.000	.000	.000	.056
[10] Miscellaneous chemicals	.009	.013	.015	.030	.013	.011	.083	.006	.003	.009	.004	.002	.016	.020	.004	.007	.018	.038	.010	.002	.313
[11] Petroleum and coal products	.011	.004	.008	.001	.073	.001	.002	.050	.001	.015	.041	.003	.005	.005	.001	.003	.004	.004	.001	.001	.236
[12] Rubber products	.002	.008	.002	.002	.003	.003	.001	.000	.041	.004	.008	.000	.009	.098	.013	.021	.029	.179	.023	.006	.453
[13] Ceramic, stone and clay products	.023	.001	.001	.000	.004	.009	.005	.001	.000	.090	.016	.004	.006	.017	.003	.011	.043	.027	.004	.008	.273
[14] Iron and steel	.000	.000	.000	.000	.000	.000	.000	.000	.001	.004	.453	.001	.139	.107	.008	.022	.005	.059	.025	.002	.827
[15] Non-ferrous metals and products	.005	.000	.000	.002	.006	.001	.004	.000	.001	.004	.018	.245	.107	.069	.026	.096	.067	.078	.011	.012	.751
[16] Fabricated metal products	.051	.002	.001	.000	.004	.006	.008	.002	.006	.006	.001	.001	.062	.070	.014	.020	.025	.019	.011	.005	.312
[17] General-purpose machinery	.000	.000	.000	.000	.000	.000	.000	.000	.000	.001	.000	.000	.001	.189	.005	.006	.004	.012	.007	.002	.227
[18] Home electronics	.001	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.001	.001	.099	.000	.002	.026	.002	.000	.134
[19] Electrical machinery	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.002	.053	.021	.123	.067	.102	.009	.005	.381
[20] Info.&com. electronics	.001	.000	.000	.001	.000	.000	.000	.000	.000	.000	.000	.000	.002	.023	.039	.012	.256	.007	.002	.008	.352
[21] Motor vehicles, parts and accessories	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.445	.004	.000	.449
[22] Other transportation equipment	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.189	.000	.189
[23] Precision instruments and machinery	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.029	.004	.004	.002	.004	.002	.095	.140

Source: JIP database. Data are for 1990.

Appendix D: Applied weights in the science field - industry concordance

Focal industries (citing industries) \ Spillover sources (cited science fields)		Agriculture	Biology	Medicine	Nursing	Dentistry	Chemistry	Applied-Chemistry	Physics	Geology	Engineering	Electronics	Energy	Material Science	Mathematics	Education	Art-Literature-Society	Economics-Business-Management	History-Politics-Law	Philosophy
[04]	Food products	1.5	0.5	0.1	0.2	0.0	0.1	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
[05]	Textile mill products	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
[06]	Pulp and paper products	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0
[07]	Printing	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
[08]	Chemical fertilizers and industrial chemicals	1.8	3.9	1.2	0.4	0.7	4.5	3.2	0.3	0.1	0.2	0.1	0.5	1.3	0.0	0.0	0.0	0.0	0.0	0.0
[09]	Drugs and medicine	3.4	15.6	5.8	2.3	2.1	7.0	3.2	0.3	0.1	0.2	0.3	0.4	0.3	0.0	0.1	0.2	0.0	0.0	0.0
[10]	Miscellaneous chemicals	0.2	0.1	0.0	0.0	0.0	0.2	0.5	0.1	0.0	0.0	0.1	0.1	0.2	0.0	0.0	0.0	0.0	0.0	0.0
[11]	Petroleum and coal products	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
[12]	Rubber products	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.0	0.0	0.1	0.1	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
[13]	Ceramic, stone and clay products	0.1	0.1	0.0	0.0	0.0	0.3	0.4	0.2	0.0	0.1	0.1	0.1	1.0	0.0	0.0	0.0	0.0	0.0	0.0
[14]	Iron and steel	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.0	0.1	0.2	0.1	0.9	0.0	0.0	0.0	0.0	0.0	0.0
[15]	Non-ferrous metals and products	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.2	0.0	0.1	0.2	0.1	0.9	0.0	0.0	0.0	0.0	0.0	0.0
[16]	Fabricated metal products	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.2	0.0	0.0	0.0	0.0	0.0	0.0
[17]	General-purpose machinery	1.5	1.4	0.4	0.2	0.1	1.1	1.8	0.5	0.1	0.5	0.4	0.5	1.7	0.0	0.0	0.0	0.0	0.0	0.0
[18]	Home electronics	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0
[19]	Electrical machinery	0.0	0.0	0.0	0.0	0.0	0.3	0.1	0.6	0.0	0.3	1.0	0.4	0.7	0.0	0.1	0.0	0.0	0.0	0.0
[20]	Info.&com. electronics	0.1	0.4	0.2	0.1	0.1	0.9	0.4	2.5	0.2	1.2	12.5	0.8	2.0	0.3	2.2	0.1	0.3	0.0	0.0
[21]	Motor vehicles, parts and accessories	0.0	0.1	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.1	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
[22]	Other transportation equipment	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
[23]	Precision instruments and machinery	0.7	3.7	2.4	0.9	1.7	2.9	1.2	1.5	0.3	0.6	1.9	0.7	0.7	0.0	0.1	0.1	0.0	0.0	0.0
[24]	Miscellaneous manufacturing	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
[25]	Electricity and gas	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Source: Calculations based on Van Looy et al. (2004) and Schmoch et al. (2004)