Public and Private R&D Spillovers and Productivity at the Plant Level: Technological and Geographic Proximity

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ABSTRACT

We examine the effects of public and private 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 differential effects due to technological and geographic proximity. Estimating geographic decay functions based on the location of the universe of manufacturing plants and public research institutions in Japan, we find positive effects of technological proximit-weighted private R&D stocks, which decay in distance and become negligible at around 500 kilometres. The elasticity of TFP with respect to technologically relevant public R&D is higher, in particular for plants of R&D conducting parent firms, but no evidence of geographic decay in public R&D spillovers is observed. Simulations show that declining R&D spillovers are responsible for a substantial part of the decline in the rate of TFP growth Japanese manufacturing. The exit of geographically 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 and Osaka.

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] prior studies have a number of limitations. First, with only some partial exceptions,[2] studies have typically relied on data covering publicly listed firms only. Besides the selective nature of thes samples, the multi-location and multi-technology nature of large publicly listed firms' operations render identification of proximity effects difficult. Second, the focus has been on inter-firm 'private' R&D 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).

This study addresses these limitations in prior work. We contribute a simultaneous analysis of the two sources of R&D spillovers and examine the role of technological and geographic proximity at the plant level. We examine the influence of public and private R&D spillovers on TPF in an unbalanced panel of close to 20000 Japanese manufacturing plants during 1987-2007. A unique feature of our data is that spillovers are asessed by examining proximity to the universe of R&D conducting plants and public R&D institutions in Japan. 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 in the country. R&D expenditures of firms are available by field. Technological proximity between plants is established based on the products manufactured and the similarity in technologies used in industries. Public R&D stocks are differentiated by science fields, which can be mapped into technologies and industries

[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.

reflecting their varying relevance for firms. Geographic distance effects are estabslihed by estimating exponential decay parameters (e.g. Lychagin et al., 2010; Duranton and Overman, 2005) based on all inter-plant distances between plants with access to R&D, and all plant-institution distances in Japan. The simultaneous inclusion of multiple sources of spillovers, the detail and comprehensive nature of locations and technological distance 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.

The properties of our data and model also allow us to conduct simulations analysis to gain more understanding of the declining growth in Japan's total factor productivity. Whereas in the mid-1980s (e.g. Fukao and Kwon, 2011) TFP growth was 2.5 percent a year, this declined to under 1 percent in the late 1990s and the early years of this century. At the same time, though 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 part of the 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. Section 4 presents the simulation analysis. Section 5 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:

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

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:

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

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:

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

We assume that the error term u_{it} can be decomposed into four components, year-specific shocks λ_t, regional effects ρ_r and measurement error ε_{it}:

$$e_{it} = \lambda_t + \rho_r + \varepsilon_{it} \quad (5)$$

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):

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

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[3] 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

[3] 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).

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.

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 and plants, this may be a suitable assumption.[4]

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:

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

where:

$K_{f's't}$: R&D stock of firm f' in field s' at time t;

$d_{if's't}$: 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;

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

[4] 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.

minimum distance to the focal plant, which avoids double counting of R&D. [5] 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.

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.

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

[5] 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.

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:

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

where:

- A_{hmt}: R&D stock of public institute 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 the institute in 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).[6] 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, $\ln\widetilde{tfp}_{st}$, which controls for industry-specific technological opportunity and demand shocks over time affecting TFP growth.

Specification

We estimated plant fixed effects models. We tested whether the strict exogeneity assumptions holds: the test proposed by … suggested no effects of forward lags of the R&D variables. Diagnostics did signal first order autocorrelation. Hence we estimate FGLS models….

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.[7] Error terms are cluster-robust at the plant level.

Table 2 shows descriptive statistics of the variables and Table 3 contains the correlation matrix.

--------Insert Tables 2 and 3-------

3. Empirical results

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

[7] 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).

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.[8] 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 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.

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

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

manufacturing firms based on inventor locations.

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.

4, Simulation 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.

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 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.

We conclude that public as well as private R&D spillovers matter for TFP growth. 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.

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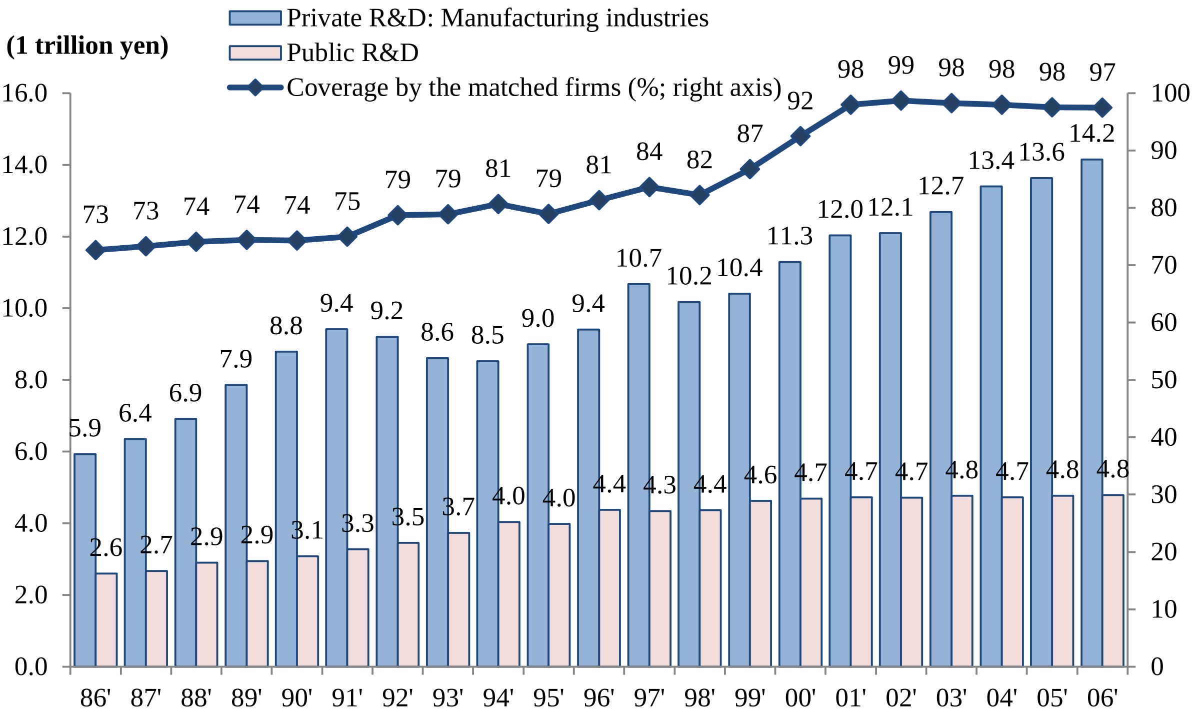
Figure 1: R&D expenditures and matching rate with census of manufacturers



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

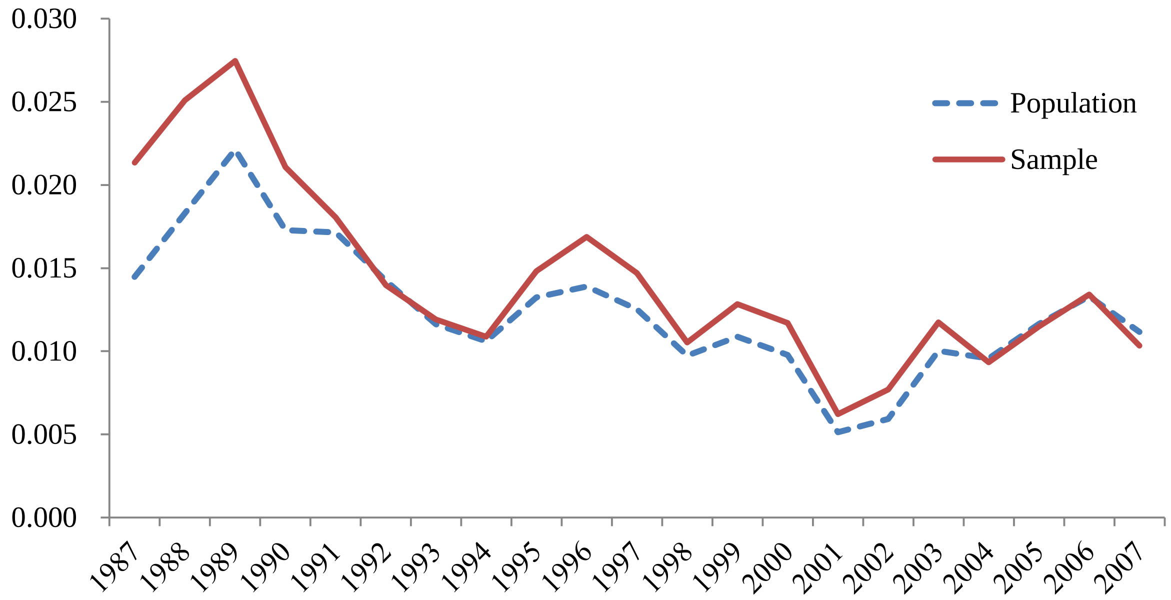


Figure 3: Growth rate in R&D stocks (5 year moving average)

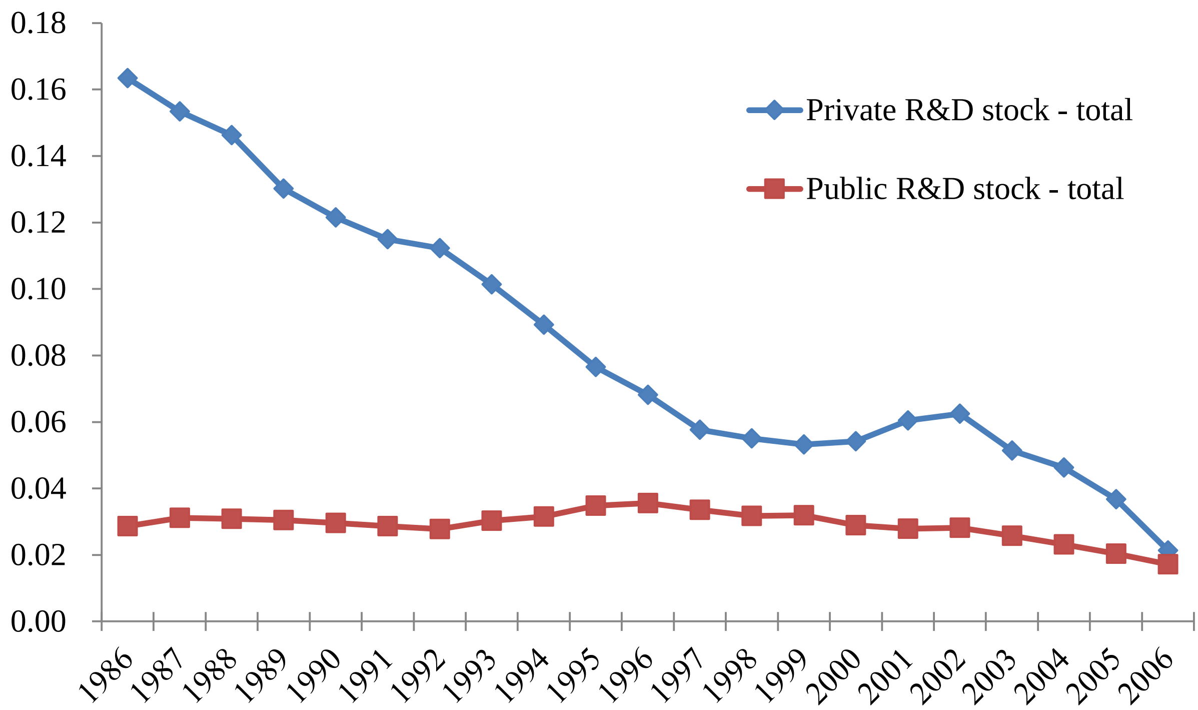


Table 2: Descriptive statistics

	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

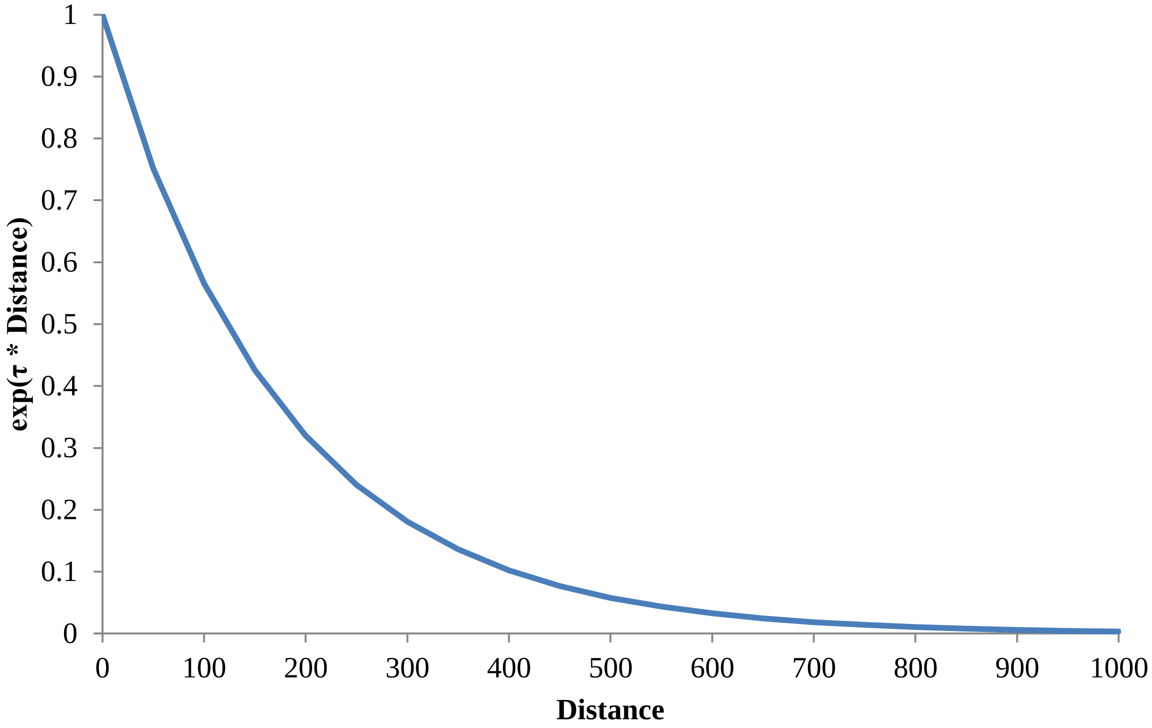
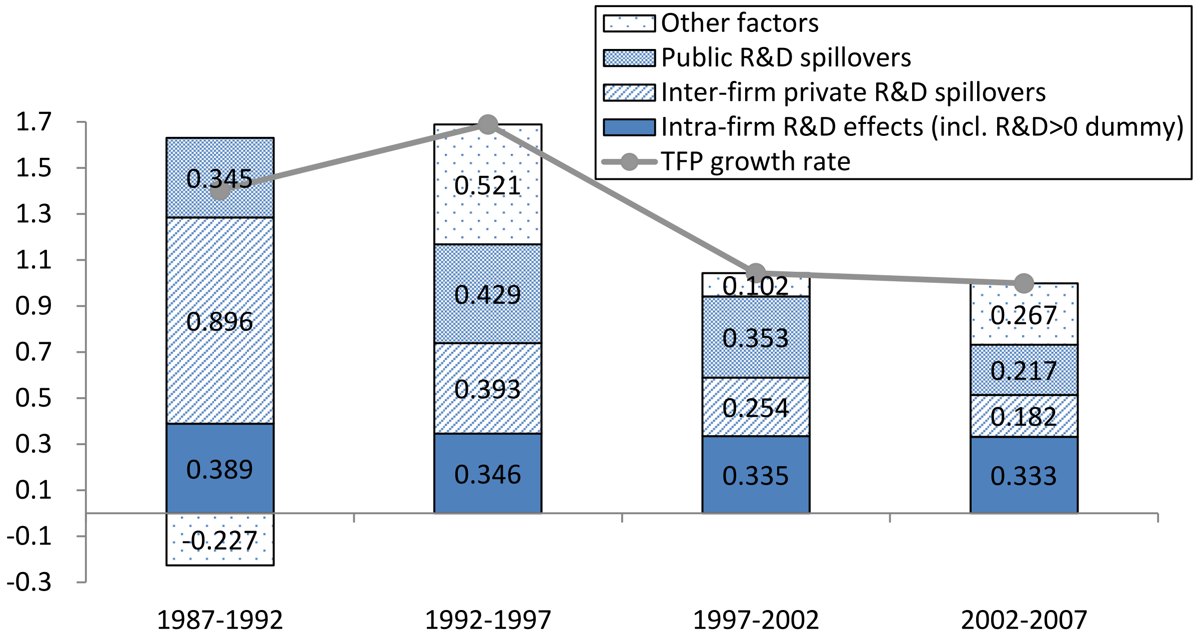
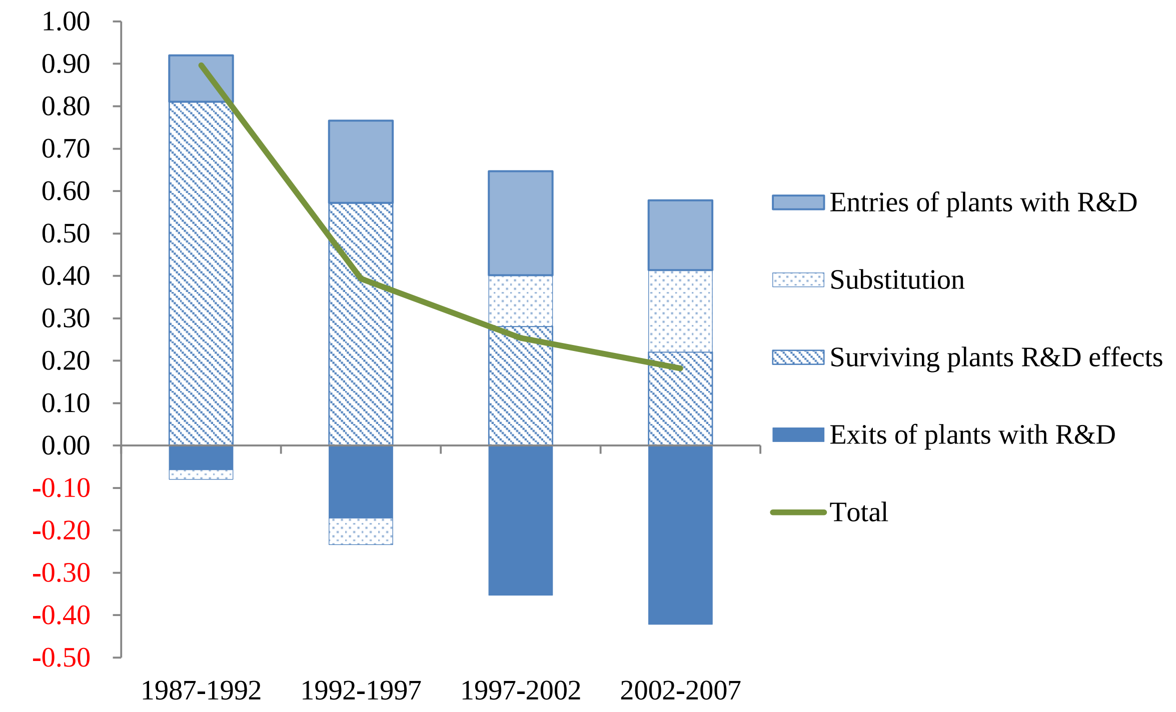


Figure 5: TFP Growth Composition: Intra-firm R&D vs. Private and Public Spillovers



Note: based on a balanced sample, 1987-2007

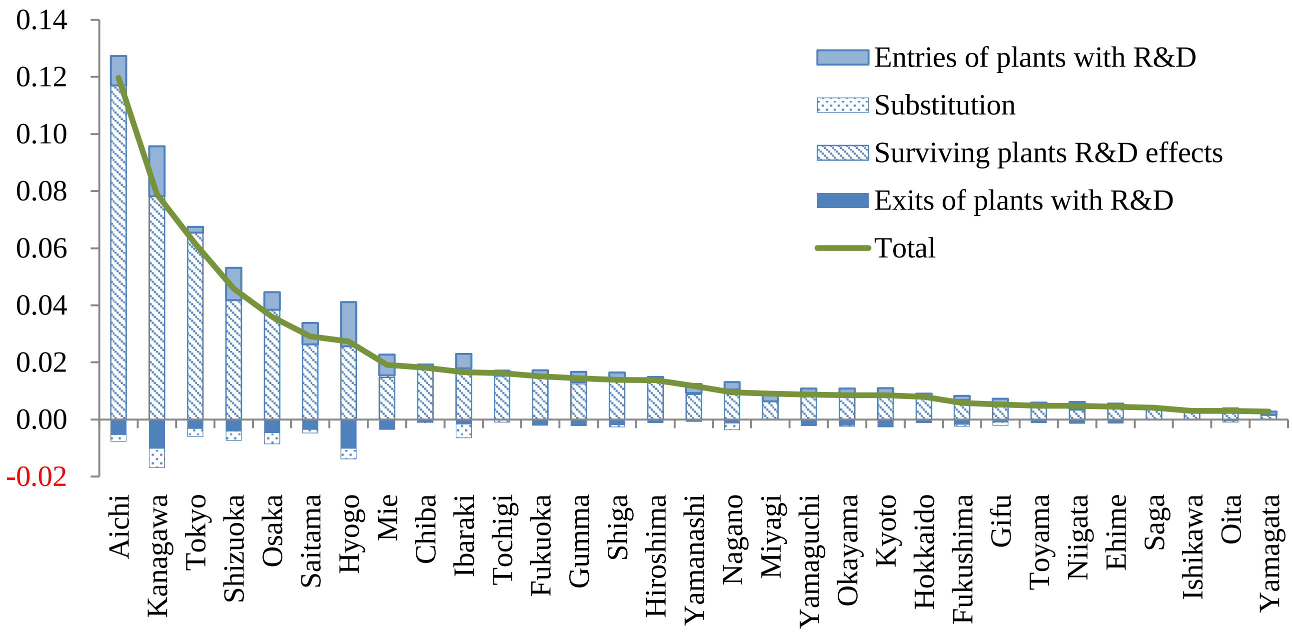
Figure 7: TFP Growth Composition: Effects of R&D Active Firms' Plant Entry and Exit



Note: based on a balanced sample, 1987-2007

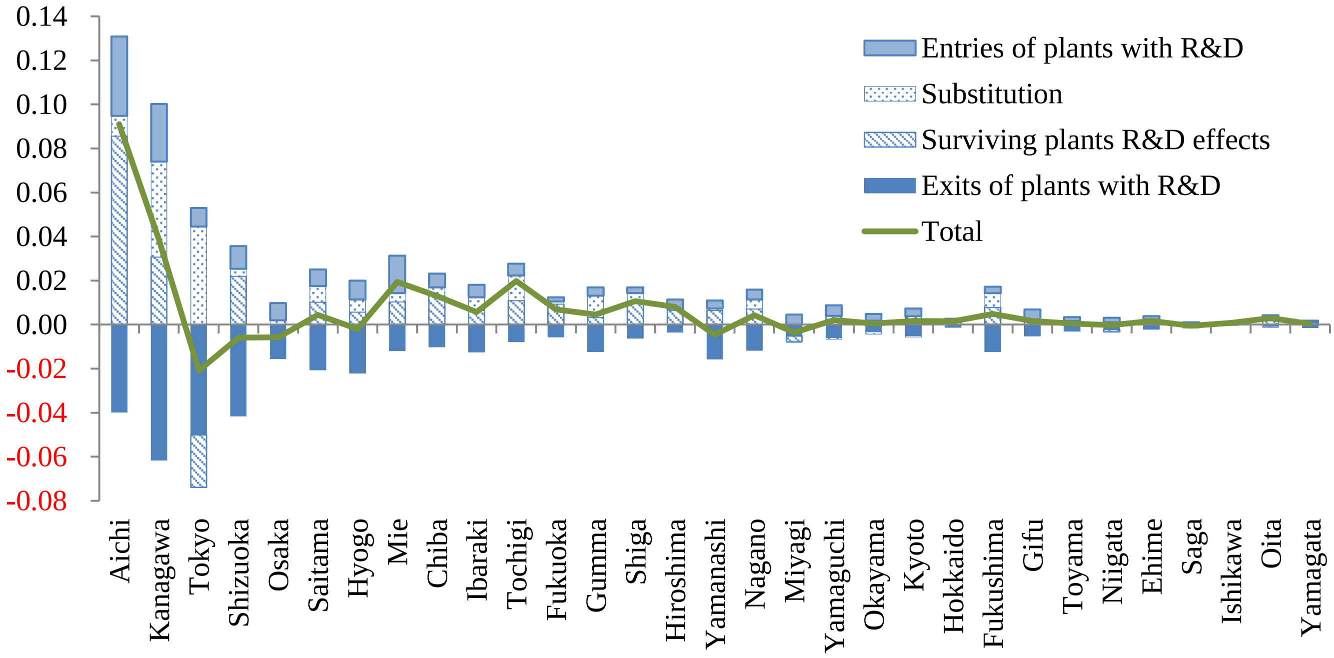
Figure 8: TFP Growth Composition: Effects Plant Entry and Exit by Prefecture

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

Spillovers sources (cited) / Focal industries (citing)	[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 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)