HITOTSUBASHI UNIVERSITY TEIKOKU DATABANK

TDB-CAREE Discussion Paper Series

TDB Center for Advanced Empirical Research on Enterprise and Economy

(TDB-CAREE)

Graduate School of Economics

Hitotsubashi University

TDB-CAREE Discussion Paper Series, No. E-2019-02

October 2019

Local R&D support as a driver of network diversification? A comparative evaluation of innovation policies in neighboring prefectures in Japan

Keisuke Takano

(University of Tsukuba, TDB-CAREE)

Hiroyuki Okamuro

(Hitotsubashi University, TDB-CAREE)

Naka 2-1, Kunitachi, Tokyo 186-8601, Japan

Phone: +81-42-580-9129

E-Mail: caree@econ.hit-u.ac.jp

URL: http://www7.econ.hit-u.ac.jp/tdb-caree/index.html

TDB-CAREE Discussion Papers Series aims at widely disseminating research results in the form of scholarly papers, thereby stimulating lively discussions. It should be noted that the opinions in this discussion paper are the sole responsibility of the authors and represent neither those of the organization(s) to which the author(s) belong(s) nor those of TDB-CAREE.

Local R&D support as a driver of network diversification?

A comparative evaluation of innovation policies in neighboring prefectures in Japan

Keisuke Takano

Graduate School of Systems and Information Engineering, University of Tsukuba/

TDB Center for Advanced Empirical Research on Enterprise and Economy, Hitotsubashi University

1-1-1 Tennodai, Tsukuba, Ibaraki, Japan/2-1, Naka, Kunitachi, Tokyo, Japan

s1211270.sk.tsukuba@gmail.com

Hiroyuki Okamuro

Graduate School of Economics, Hitotsubashi University

2-1, Naka, Kunitachi, Tokyo, Japan

okamuro@econ.hit-u.ac.jp

ABSTRACT

This paper compares the effects of local R&D support programs on firm performance between neighboring three prefectures in the same district in Japan. Particularly, we evaluate the policy effect on regional and sectoral diversification of transaction networks. One of these prefectures, A, has a large industrial agglomeration around world-leading manufacturers, which is not the case for the other prefectures, B and C. Empirical evaluation based on firm-level dataset available through TDB-CAREE shows that the programs in Prefectures B and C promoted market development of recipient firms in unexplored sectors or regions, whereas Prefecture A's program did not.

Keywords: place-based policy, R&D support, interregional trade, diversification

JEL code: L25, L52, O38, R11, R12, R58

1. Introduction

Public support to R&D activities of local industries is expected to enhance their performance as a result of both process and product innovation. Based on the concept of evidence-based policy making, quantitative evaluation of innovation policies under the national initiative with firm-level data has been conducted intensively in this decade. However, similar policies by local governments have been rarely evaluated. In this regard, variation in public support formation and its effect across prefectures, as well as the different roles of national and local governments, has yet to be investigated. Additionally, most previous studies evaluate only productivity-related effects of public policies, whereas policy effect can emerge as various aspects of treated firms' business activities.

This paper evaluates the effect of local R&D support programs on firm performance, comparing between neighboring three prefectures located in the same district in Japan by utilizing a large corporate database based on credit investigation. Our investigation has mainly three contributions. Firstly, we do not only examine the effects of support policies on conventional outcomes like productivity, but also on the regional and industrial diversification of transaction networks. The inclusion of these network-based outcomes allows us to provide more in-depth mechanism of contribution of support policies on firms' performance.

Secondly, cross-prefectural comparative analysis can reveal how the effect of R&D support on firms' performance is regionally different depending on support systems and each prefecture's industrial and geographical conditions. One of the three target prefecture, A, has a large industrial agglomeration around world-leading manufacturers. Although the other two prefectures B and C do not have such an agglomeration, they have several manufacturing sectors of comparative advantage and better access to the largest metropolitan areas in Japan.

Thirdly, we utilize large firm-level panel data which includes corporate information about more than 10,000 manufacturing firms in each prefecture. The exploitation of this data enables us to implement empirical evaluation of policy effect with sufficient statistical power and control on firm-level heterogeneity. Additionally, since this dataset has been constructed independently of policy evaluation, unlike the empirical investigations based on survey techniques, we need not be concerned about the overestimation of program impacts due to the tendency that firms receiving money are likely to exaggerate the scheme’s benefits as mentioned in Criscuolo, Martin, Overman, & Reenen (2019).

The rest of this paper is organized as follows. In Section 2, we review the related literature. We briefly describe the recent trend of Japanese innovation policy and local R&D support programs evaluated in this paper in Section 3. In Section 4, we explain detailed methodology for empirical evaluation including conceptual framework, dataset, and econometric methods. We show the estimation results and provide a discussion on them in Section 5. Finally, Section 6 concludes.

2. Literature Review

2.1 Place-based Policies

In the recent two decades, place-based R&D support policies represented by cluster policies have been promoted for the benefit of agglomeration externality such as knowledge spillover between co-located and tied economic agents (Duranton & Puga, 2004). Following this framework, particularly in the literature of regional innovation systems (e.g., Cooke, 2002), the evolution of local industry's capability developed by the interaction between the key agents in a cluster like local firms, research institutes, and local authorities has attracted increasing attention (Nathan & Overman, 2012). Based on this argument, firm-level quantitative evaluations on cluster policies under the national government initiative have been carried out in this decade, targeting, for example, France (Martin, Mayer, & Mayneris, 2011), Japan (Nishimura & Okamuro, 2011a, 2011b), Korea (Doh & Kim, 2014), and Italy (Bronzini & Iachini, 2016). However, empirical investigations on the role and effect of R&D support policies under the local government initiative are scant (Neumark & Simpson, 2015).

The in-depth understanding on the role of local authorities provides an insight to illustrate and examine the changing balance between the central government and local governments towards greater decentralization by contrasting centralized countries with federal countries. It simultaneously serves as a fundamental evidence in showing the path of regional revitalization policies to encourage local authorities to plan and design their own regional growth strategy, taking advantage of better accessibility to the information about local economic conditions and development trends. Beginning with a special issue in *Regional Studies* in 2007 covering seminal studies examining science policy in each country with program-level (Salazar & Holbrook, 2007) or regional case studies (Crespy, Heraud, & Perry, 2007; Sotarauta & Kautonen 2007; Koschatzky & Kroll, 2007) and historical review (Perry, 2007; Kitagawa, 2007), qualitative analyses with case studies of local R&D support have been conducted worldwide including a comparison of local management of biotechnology clusters in Germany, France and Japan (Okamuro & Nishimura, 2015).

As one of a few empirical studies about R&D support policies under the local government initiative, Falck, Heblich, & Kipar (2010) evaluated the effect of R&D support program for high-tech sectors providing, for instance, funds for public-sector research infrastructure and inter-firm networking in the state of Bavaria, Germany, and showed that positive effect of the program on the introduction of a product or process innovation and patent application. Fernandez-Ribas (2009) compared the effects of supranational (EU), national (Spain) and regional (Catalonia) R&D support policies on innovation performance of Catalonian firms to find different advantages of these programs according to different aims. Lanahan (2016) examined positive effects of additional support by US states to the recipients of the federal SBIR program. Finally, Okamuro & Nishimura (2019) examined the effects of public R&D subsidies by national, prefecture and city governments and found that R&D subsidies by prefectures have positive and significant effects on the productivity of recipients, and that these effects become stronger when they simultaneously obtain R&D subsidies from cities and the national government.

We complement these empirical investigations by incorporating a comparative analysis between different R&D support programs conducted by neighboring three prefectures, and by examining in detail how the difference in support systems and surrounding local economic situation are reflected in the difference of treated firms' outcomes. As argued by Tödtling & Trippl (2005), no innovation policy can fit all regions due to a wide variety of regional characteristics. Thus, it is important to consider and compare regional variety in the implementation, design, and consequence of innovation policies by local authorities.

In addition, we also contribute to the literature of place-based R&D policies by introducing outcomes based on inter-firm transaction information. A consensus among empirical investigations about cluster policies is that the inter-firm networking and industrial-university cooperation are crucial outcomes of the support programs (Nishimura and Okamuro 2011b). However, except for a few studies, most of previous studies have only focused on networking activities to create R&D environment. In consideration of the facts that local R&D support policies aim at local economic development and that the exchanges of goods and services also serve as a crucial channel of knowledge spillovers, it can be quite important to examine the policy effect on the inter-firm transaction network as well as the networking directly related to R&D.

As one of the exceptions, Okubo, Okazaki, & Tomiura (2016) examined the effects of the cluster policy by the Ministry of Economy, Trade, and Industry, METI, in Japan on firms' transaction network and showed that firms participated in cluster projects expanded inter-firm transaction networks with firms located in Tokyo at a significantly higher speed. We also complement this empirical investigation by evaluating R&D support programs under the local government initiative from the viewpoint of diversification of transaction networks. We will explain network diversification in more detail in the next section.

2.2 Diversification in Economic Activities

Another objective of this paper is motivated by the discussion regarding the positive relationship between the diversity in local industry or firms and local economic growth which has been shown in the literature of economic geography and international management (e.g. Frenken, Van Oort, & Verburg, 2007; Palich, Cardinal, & Miller, 2000). The literature has emphasized the importance of both inter-industrial or inter-regional diversity and intra-industrial or intra-regional diversity. On one hand, inter-industrial or inter-regional diversity is motivated by the absorption ability of idiosyncratic shock in a specific sector and the adaptability to technological changes (Rugman, 1979; Fujita & Thisse, 2013). On the other hand, intra-industrial or intra-regional diversity is motivated by learning from related (but not the same) others (Jacobs, 1969; Feldman & Audretsch, 1999) and by taking advantage of cognitive proximity, similar institutions and norms shared between industrially or geographically close firms in other words. In the literature, remarkable relationship between the diversity and the performance of firms or regions has been empirically shown.

The literature of economic geography mainly focused on the role of industrial diversity which each region has. As a seminal paper, Boschma & Iammarino (2009) examined the relation between trade diversity and regional growth with Italian NUTS-3 level data and diversity indices defined with entropic measure based on industrial share in export profile. They found positive association between intra-industrial diversity of export profile and local employment and value-added growth. Boschma, Minondo, & Navarro (2012) also confirmed this positive association with the case of Spain.

Meanwhile, the literature of international management mainly focused on the role of both inter-industrial and regional diversity of firms' export destinations or subsidiaries. Nachum (2004) investigated the impact of the industrial and geographical diversification on firms' performance in developing countries and showed positive but nonlinear association between the ratio of profits to sales and both industrial and geographical diversity of export destination measured with indices based on Herfindahl-Hirschman Index. Qian, Li, Li, & Qian (2008) confirmed this curvilinear effect on firm performance with regional diversity measured with entropy based on the geographical distribution of firms' subsidiaries.

Despite the growing body of empirical literature examining the association between diversity and economic performance of firms or regions, little is known about what can form the diversity per se on causality level rather than correlation level[1]. We fill this gap by

---

[1] As reviewed in Cadot, Carrere, & Strauss-Kahn (2013), several papers about international trade have examined the determinants of export diversification like market access and trade

empirically examining whether or not R&D support under the local government initiative may affect the regional and industrial diversity of transaction networks of subsidized firms with rigorous microeconometric approach. In other words, we examine the feasibility of transaction network diversification based on the policy intervention by local government, as Okubo et al. (2016) did for a policy by the national government.

liberalization on causality level. However, most of these investigations are based on country-level data rather than firm-level.

3. Investigated Prefectures and Programs

3.1 General Characteristics of Each Prefecture

Let us explain the characteristics and location of the three target prefectures. Firstly, administrative and geographical characteristics are as follows. Prefecture A covers one of the three major metropolitan areas in Japan and serves as a core region of the district. Prefecture B has mountainous topography, so the usable land for economic activities is relatively small. Prefecture C has two half-million cities and many natural harbors. These three prefectures are directly connected to Greater Tokyo Metropolitan District by Shinkansen super-express, so they all have an advantageous traffic access to the largest economic zone in Japan.

We also summarize industrial characteristics of these prefectures based on the latest results of the Census of Manufactures in 2017. Prefecture A's manufacturing sector is highly specialized in transportation machinery, which accounts for approximately 50% of the total value of manufacturing shipments in Prefecture A and nearly 40% in Japan due to a huge industrial agglomeration around world-leading manufacturers. Since Prefecture A's manufacturing shipment accounts for about 15% of that of Japan, the total value of shipments of the manufacturing industries in this prefecture other than transportation machinery is also quite large.

Whereas Prefectures B and C do not have such a huge industrial agglomeration, both prefectures have some specific industrial characteristics. Compared with the national share, Prefecture B is specialized in electronic parts, device, and circuits (13% of its total value of manufacturing shipments) and ICT equipment (9%). While Prefecture C is also specialized in transportation machinery (26% of Prefecture C's manufacturing shipments) and electronic sectors (12%), it also has one of the famous industrial clusters of chemical sectors in Japan. In addition, Prefecture C's manufacturing sector accounts for about 5% of the total value of manufacturing shipments of Japan.

3.2 Overview of R&D Support Program

3.2.1 Decentralization of Japanese Innovation Policy

In this section, we firstly review recent trend of Japanese innovation policy referring to Kitagawa (2007) and Okamuro, Nishimura, & Kitagawa (2019). The key actors of the innovation policies for local SMEs in Japan have been gradually transferred from the central government to local authorities. Aiming at local economic development, a series of programs for supporting local SMEs' innovation activities have been implemented by the Japanese government, including the Consortium R&D Program for Regional Revitalization starting in 1997 in combination with the "Science and Technology Basic Plan", the "Industrial Cluster Project" in 2001 by METI, and the "Knowledge Cluster Initiative" in 2002 by the Ministry of Education, Culture, Sports, Science and Technology (MEXT). The objective of these programs is the promotion of R&D consortia involving university, industry and government at the regional level. R&D subsidies to SMEs was jointly provided and implemented by Small and Medium Enterprise Agency under the METI and local governments, particularly the prefectures.

More recently, under the flag of the regional revitalization ("Chiho Sosei"), local authorities have been required to design and implement their own regional growth strategies. This is also the case for innovation policies: increasing decentralization of the design and implementation of R&D support programs is expected, taking advantage of the accessibility to local demand and conditions.

3.2.2 Local R&D Subsidies in Three Prefectures

The basic information of R&D subsidy programs under the local government initiative is summarized in Table 3.1. Prefecture A's program was founded in 2012 under the direct control of the prefectural government, and continues to the present, 2019. Although Prefectures B's and C's programs were conducted from 2007 to 2017 based on the joint funding by the prefectural government and the Organization for Small & Medium Enterprises and Regional Innovation in Japan, SMRJ, under the jurisdiction of METI, the fund was managed at each prefecture's own discretion.

The objective and design of each prefecture's subsidy are different in terms of up to what stage of R&D procedures it supports. Prefecture A's subsidy program is specialized in the R&D support and the demonstration experiment subject to the cooperation with public research institutes and universities, whereas new market development is beyond the purpose. In contrast, Prefecture B's subsidy supported general matters connected to new businesses and products. In addition, this subsidy was jointly provided with business consulting by a project team organized by specialists of new market development. Prefecture C's subsidy supported R&D activities especially connected to practical use and the new market development is not prescribed as a purpose of the subsidy. Maximum amount of subsidy per project in Prefecture A's program amounts to 100 million yen for SME while that in Prefectures B's and C's program is 7 million and 5 million yen, respectively. Thus, maximum R&D subsidy amount is much larger in Prefecture A than in the other target prefectures.

4. Methodology

4.1 Firm-level Panel Data

We utilize two datasets provided by Teikoku Databank (TDB) available through the TDB Center for Advanced Empirical Research on Enterprise and Economy (TDB-CAREE): the inter-firm transaction database and the financial database. TDB is a major corporate credit research company in Japan that collects various corporate data through door-to-door surveys. Around 1,700 field researchers visit and interview firms to obtain corporate information in every industrial category and location.

The inter-firm transaction database comprises annual transactional relationships among firms. In 2016, the database included 1,136,203 firms out of a total of 1,629,286 incorporated companies in Japan, according to the latest Japanese Economic Census in 2016. Thus, in this period, the database captured inter-firm transactional activities for nearly 70% of all incorporated companies in Japan. In addition, the dataset is connected with a corporate information database, COSMOS, so basic corporate information of each firm, such as sales, number of employees, geographic location of its headquarters, and industrial category, is also available. In the face-to-face interviews, each firm reports up to five of their suppliers and customers. Since this dataset eventually includes transaction information from both partners, the number of customers for each firm often exceeds five. Although it does not capture the transaction amounts and the international transaction information, this transaction database is superior to other similar company databases in other developed countries as it captures the dynamism of the disaggregated supply chain network structure.

With the financial database, we can capture almost all items included in the Financial Statement. In 2015, the database included 213,013 firms, so the coverage is limited compared to the inter-firm transaction data. However, this dataset is very advantageous since it covers financial information of numerous unlisted firms, which is of the focus of our investigation.

In the process of constructing panel data, we firstly collected the lists of subsidized firms from each prefecture's website. After cleansing the firm list, we matched it with the inter-firm transaction database and financial database. Finally, we extract only manufacturing SMEs whose number of employees is less than three hundred.

4.2 Empirical Procedure

4.2.1 Conceptual Framework

In advance of empirical evaluation, we set up following hypotheses about the policy effects on network-based outcomes based on the discussion in Section 2.

H1: R&D support enhances industrial diversity of recipient firm's customer composition.

H2: R&D support enhances regional diversity of recipient firm's customer composition.

We set up these hypotheses assuming that firms that carry out R&D activity may exploit new market opportunities in new regions or industries through product innovation, relying on the incentives of adaptability to technological changes (acquisition of general knowledge, in other words) acquired by inter-regional/industrial diversification or cognitive proximity acquired by intra-regional/industrial diversification.

Additionally, based on the discussion in Section 3, we presume several regional differences in the effects on these outcomes. Firstly, the effect of Prefecture A's program on network diversity may be the weakest among three prefectures since this program is specialized in the support of recipient firms' R&D and demonstration experiment rather than new market development. In contrast, the effect of Prefecture B's program on network diversity may be the strongest since it supports both R&D and new market development. Finally, the effect of Prefecture C's program may be weaker than that of B's program because the former supports solely R&D for practical application.

4.2.2 Definition of Outcomes

We describe the definitions of transaction outcomes which capture industrial or regional diversification of the recipient's customer composition. The outcomes are constructed using entropy measure based on industrial or regional composition of customers for each firm. With regard to entropy index, we define diversification outcomes corresponding to two dimensions as mentioned above: regional or industrial, and inter-class (unrelated) or intra-class (related).

The formal definition of firm i's inter-industrial customer diversification is as follows:

$$INTERIND_i = \sum_g P_{ig} \log_2 \left(\frac{1}{P_{ig}}\right), \quad (1)$$

where P_{ig} is the share of firm i's customers included in 2-digit sector g (Customers' shares are measured by the number, and not by the transaction volume). In a similar way, we define firm i's inter-regional customer diversification as the following index:

$$INTERREG_i = \sum_r p_{ir}\, log_2 \left(\frac{1}{p_{ir}}\right), \quad (2)$$

where p_{ir} represents the share of firm i's customers located in Prefecture r. These outcomes take larger values if the share of customers categorized into each industrial sector or located in each prefecture is nearly uniform, and smaller values if the share of customers is higher in a specific region or sector. In this sense, a firm with a large $INTERIND$ or $INTERREG$ has its customers in various sectors or regions.

Intra-class diversity is derived from the decomposable nature of entropy measure. This decomposition enables us to evaluate whether or not industrial/regional diversity is especially strong between subclasses included in a specific parent class, while inter-class diversity simply evaluate the extent to which the customers are distributed to different classes. Formally, suppose all five-digit sectors k fall exclusively under a two-digit sector S_g, firm i's intra-industrial customer diversification is defined as follows:

$$INTRAIND_i = \sum_g P_{ig} \sum_{k \in S_g} \frac{p_{ik}}{P_{ig}} log_2 \left(\frac{1}{p_{ik}/P_{ig}} \right), \quad (3)$$

where p_{ik} represents the share of firm i's customers included in 5-digit sector k. In a similar way, let all prefectures fall exclusively under a *Koiki* district which includes four or five prefectures on average, S_d, firm i's intra-regional customers diversification is given by the following index:

$$INTRAREG_i = \sum_d P_{id} \sum_{k \in S_d} \frac{p_{ik}}{P_{id}} log_2 \left(\frac{1}{p_{ir}/P_{id}} \right), \quad (4)$$

where P_{id} is the share of firm i's customers in *Koiki* district d. In these indices, since entropy measure calculated based on the composition of subclasses is weighted by the share of their parent class, the diversity within an industrial sector or a region with a large share is empathized. In addition, as a related outcome to $INTRAREG$, we include in our estimation the number of customers in Greater Tokyo District, the largest area of consumption and business in Japan, $TYOCUS$.

Finally, from a comparative perspective, we also employ the total factor productivity (TFP) as a conventional outcome. We estimate TFP based on the method proposed by Levinsohn & Petrin (2003)[2]. Their method (LP) is advantageous in the sense that it can address the endogeneity problem in estimating TFP that emerges due to simultaneity between productivity and capital.

4.2.3 Estimation Methods

In this section, we explain our empirical procedures. To rigorously evaluate the policy effect in each prefecture, it is quite important to be careful about how we evaluate the effect on treated firms' outcomes in comparison with counterfactual situations. Without this

[2] Estimation procedures and results of TFP are shown in Appendix 2.

comparison, we would face serious empirical concerns which prevent us from accurately generating counterfactual situations and eventually implementing the appropriate evaluation. We describe the nature of these concerns in the context of R&D policy evaluation, and then show the countermeasures employed in this paper.

The first empirical concern is the omitted variable bias. That is, without controlling for firms' unobservable characteristics related to R&D activities such as high motivation to develop the business and R&D-friendly corporate culture and surrounding environment can cause upper bias on estimated policy effects because these unobservable variables are positively correlated with both firms' outcomes and the likelihood of receiving R&D subsidies.

The second concern is the selection effect. The likelihood to apply and be adopted to the support program is not exogenously but endogenously decided depending on, for example, firm size, sector, and age. From the perspective of local government, for instance, it often promotes the R&D activities of firms that engage in specific business sectors such as high-tech industries. Thus, there can be differences in firms' characteristics between the treatment (adopted) group and the control (not adopted) group. The ignorance of this difference in empirical evaluation would end up with biased estimation of policy effects.

To tackle the omitted variable bias, we employ the fixed effect model (FE). With FE, unlike OLS, we can eliminate entire estimation bias due to time-invariant unobservable variables such as corporate culture and firm location. Formally, we specify the estimation equation based on FE as follows:

$$\begin{aligned} Y_{it} = \rho_t + \kappa_i + \sum_{k=0}^{2} \beta_k \left(D_{3k+1\_3k+3}\right)_{it} + \gamma ADD_{it} + \delta MULTI_{it} + \zeta INDEC_{it} \\ + \mathbf{x}'_{it}\boldsymbol{\eta} + \varepsilon_{it}, \end{aligned} \quad (5)$$

where i represents the firm, t stands for year. ρ_t is year fixed effect, and κ_i is firm fixed effect. With ρ_t, we can control for entire unobservable factors inherent in year t common to all firms, and all time-invariant unobservable characteristics of firm i are controlled with κ_i. Y is each outcome variable defined in Section 4.2.2. D_{3k+1_3k+3}, the treatment variable of our interest, represents the dummy variable corresponding to the duration after the first adoption for each firm i and period t. For example, $\left(D_{1\_3}\right)_{it}$ equals one if it is within three years since firm i received subsidy in year t. This variable takes zero for all non-adopted firms in year t. ADD is the dummy variable which takes one if the firm received subsidy more than once during the observation period , and zero otherwise. $MULTI$ takes one if a firm receives subsidy for more than one year in the period, and zero otherwise. $INDEC$ captures the change in the number of received subsidies. $\mathbf{x'}_{it}\boldsymbol{\eta}$ is the linear sum of control variables including 2-digit industry dummies and interactions between industry and year dummies. The observation period starts two years before the focal subsidy programs began. Thus, the minimum value of t is 2010 in Prefecture A, and 2005 in Prefectures B and C.

To cope with the selection problem, we utilize propensity score matching (PSM). PSM enables a comparison between the treatment firm group and the control firm group controlling for the differences in firms' characteristics by selecting a subset of untreated firms similar to the treated firms based on the likelihood of receiving subsidies. Firstly, the likelihood of firm i to receive R&D subsidy is predicted conditional on observable characteristics. After that, each treated (subsidized) firm is matched with a control (not subsidized) firm based on the proximity of predicted likelihood. This approach enables us to construct a virtual situation as if the treated firms would not have been subsidized, based on the matched control firms' sample. To obtain the likelihood, we estimate a logit model based on the following specification:

$$Prob(Treat_i = 1|\mathbf{z}_i) = \mathbf{z}'_i\boldsymbol{\theta} + u_i, \quad (6)$$

The dependent variable $Treat$ is a dummy variable taking one if D_{3k+1_3k+3} takes one, and zero otherwise. The independent variables $\mathbf{z}_i$ include basic firm characteristics representing their capability of R&D activities such as sales and the number of employees in natural logarithm ($\ln SALES$, $\ln EMP$), and firm age (AGE). We also include industry dummies to roughly distinguish between low-tech and high-tech industries. For improving the fitting of the logit model, we further introduce square terms of each quantitative variable and interaction terms between each variable[3]. In PSM, we use covariates $\mathbf{z}_i$ in three years before the support program started in each prefecture. Thus, covariate $\mathbf{z}_i$ in 2009 is used in PSM for Prefecture A, and in 2004 for Prefectures B and C. In advance of PSM, we extract the sample firms whose transaction information can be observed throughout the period captured in panel data.

After the prediction, we match the treatment firms with the control firms based on 10 nearest-neighbor matching (10NN). This 10NN method matches each treatment firm with approximately ten control firms in the order of closer distance measured with the value of predicted propensity. We discard the firms which do not satisfy the common support assumption. Due to the restriction of sample size, we do not use PSM on panel data for evaluating the effect on TFP.

[3] We exclude covariates which cause serious multicollinearity (appearing as unrealistically large estimated coefficient or standard error) for avoiding imprecise and biased prediction of propensity score (see Weitzen, Lapane, Toledano, & Mor, 2004). In addition, we predict propensity score avoiding complete separation.

5. Results

5.1 Descriptive Analysis

We briefly explain the results of PSM in each prefecture. The summary of PSM is shown in Table 5.1[4]. Since the standardized bias is smaller than 0.1 for most covariates in all prefectures, there is no convincing evidence for remarkable differences between the treatment group and the control group within the limit of observable covariates. Table 5.2 shows the sample size of manufacturing SME panel data with and without PSM, and the number of the observations whose D_{3k+1_3k+3} is equal to one. As shown in Column (7), in the unbalance panel data of Prefecture C for examining the effect on TFP, the number of observations with $D_{7\_9} = 1$ may be too small to obtain reliable and representative estimation results. Thus, for Prefecture C, we substitute D_{4_6} and D_{7_9} with D_{4_9}.

With tree map, we can visualize some benchmarking results regarding the diversification outcomes. Tree map is a visualization tool to display hierarchical data with rectangles representing the nest structure. Nested rectangles represent the branches of a tree diagram, and nesting rectangles represent a parent of the branches. Each rectangle has an area proportional to the amount of data it represents and is tilled with smaller rectangles which represent sub-branches. This tool is particularly advantageous to illustrate the compositional structure captured by intra-class diversity index because, for example, INTRAREG evaluates inter-prefectural diversification nested in *Koiki* districts. We draw tree maps relying on the following procedures. Firstly, we extract each firm's customer information for each period. Secondly, we divide extracted information into the group of observations with $D_{3k+1\_3k+3} = 0\ \forall k$, $D_{1\_3} = 1$, $D_{4\_6} = 1$, $D_{7\_9} = 1$, respectively. Finally, we calculate industrial/regional share of customers within each group.

Figures 5.1, 5.2, and 5.3 show the tree maps based on industrial compositions of firms'

[4] Detailed results of PSM (*e.g.* standardized bias of each covariate) are shown in Appendix 1.

customers in Prefectures A, B, and C, respectively. In Prefecture A's tree map, we can observe neither inter-industrial nor intra-industry diversification of customers because there are no remarkable changes in customer's industry shares throughout the period. In Prefecture B's tree map, inter-industry diversification between 2-digits with small shares can be observed in the group of observations with $D_{1\_3} = 1$ and $D_{4\_6} = 1$, whereas wholesale, electric machinery, and transportation equipment account for large shares consistently. In Prefecture C's tree map, we can observe inter-industry diversification between 2-digits in the group of observations with $D_{1\_3} = 1$ and $D_{4\_6} = 1$, while only transportation equipment accounts for a large share in that with $D_{3k+1\_3k+3} = 0 \ \forall k$.

Figures 5.4, 5.5, and 5.6 show the tree maps based on the firm's regional share of customers in Prefectures A, B, and C, respectively. In Prefecture A's tree map, we can observe neither inter-regional nor intra-regional diversification of customers because there are no remarkable changes in customer's regional shares throughout the period. In Prefecture B's tree map, intra-regional diversification within *Koiki* districts can be clearly observed, especially in Greater Tokyo district and Chubu district. In Greater Tokyo, customer's share in the prefectures surrounding Tokyo (13 in tree map) such as Kanagawa (14) and Saitama (11) increased, while that in Aichi (23) increased in Chubu. In Prefecture C's tree map, we can observe the diversification between the prefectures in the group of observations with $D_{4\_6} = 1$ and $D_{7\_9} = 1$ because customer's share in Aichi (23) increased during this period.

5.2 Regression Results

5.2.1 Policy Effects on TFP

This section describes the estimation results on the effects of R&D subsidy on subsidized firms' TFP, comparing between the three prefectures. We show the results of the fixed effect models in Table 5.3. Column (1) summarizes the results on Prefecture A's program. Whereas the coefficients of the dummy variables for the duration after the first adoption are not statistically significant, we can observe positive effect of $MULTI$ on firms' TFP. This result indicates that TFP of the firms that received a multiple-year subsidy significantly increased, yet without lagged effects. Column (2) shows the results on Prefecture B's program. Contrary to the above results, we cannot find any statistically significant effects on subsidized firms' TFP. Finally, we show the results on Prefecture C's program in Column (3). As is the case of Prefecture B, we find neither statistically significant effects on subsidized firms' TFP. In sum, we find statistically significant and positive effects of local subsidy on subsidized firms' TFP only in Prefecture A.

5.2.2 Policy Effects on Industry Diversification of Customer Composition

We show the estimation results of the policy effects on subsidized firms' industry diversification of customer composition. Table 5.4 shows the results of the fixed effect model whose outcome measure is $INTERIND$. We observe positive and statistically significant lagged effects of the subsidy both in Column (5), summary of estimation results of the unbalanced fixed effect model on Prefecture C's program, and in Column (6), that of the balanced fixed effect model combined with PSM. This result indicates that the magnitude of inter-industry diversification of subsidized firms became robustly larger in Prefecture C. In contrast, we cannot find such a significant change in the magnitude of diversification in the results on Prefectures A and B.

In Table 5.5, in a similar way, we show the estimation results of fixed effect models using $INTRAIND$ as the outcome variable. In each prefecture, we find that estimated parameters and their significance are inconsistent before and after PSM. Due to these inconsistent results, we cannot find robust evidence about whether or not the magnitude of intra-industry diversification became larger about subsidized firms in all prefectures. In sum, it can be concluded that one of our hypotheses, H1 holds only in Prefecture C's results about $INTERIND$.

5.2.3 Policy Effects on Regional Diversification of Customer Composition

We show the estimation results of the policy effects on subsidized firms' regional customer diversification. Table 5.6 shows the results of the fixed effect model whose dependent variable is $INTERREG$. We can observe positive and statistically significant lagged effects of the subsidy in Column (5), the results based on the unbalanced panel data on Prefecture C's program. In the estimation results summarized in Column (6), we can indeed observe positive effect of D_{7_9}, whereas the significance of D_{4_6} vanished after PSM. These results indicate that the magnitude of inter-prefectural diversification of recipient firms in Prefecture C became robustly larger at least seven years after subsidization. In contrast, no significant changes in the magnitude of the diversification can be robustly observed in the results on other prefectures.

In Table 5.7, we show the estimation results of the fixed effect model using $INTRAREG$ as an outcome variable. We can observe positive and statistically significant sustained effects of R&D subsidy both in Column (3), the results with the unbalanced panel model on Prefecture B's program and in Column (4) with the balanced panel model with PSM. From these results, we argue that the magnitude of the intra-*Koiki* diversification in Prefecture B became robustly larger about subsidized firms. On the other hand, we can observe negative and statistically significant effect on $INTRAREG$ in the results on Prefecture A's program within three years after subsidization, while no significant effects can be observed in the results on Prefecture C's program. Finally, we show the results of policy effect on $TYOCUS$. From the results shown in Columns (3) and (4) we can observe positive and statistically significant effects of subsidy within at least three years, which is consistent with Okubo et al. (2016). Thus, we find that the number of customers of subsidized firms in Tokyo Metropolitan Area became significantly larger in Prefecture B, but not in Prefectures A and C. Eventually, it can be concluded that H2 holds in the prefectures except for A. H2 is supported by the estimation results on $INTRAREG$ in Prefecture B and those $on\ INTERREG$ in Prefecture C.

5.3 Discussion

In this section, we summarize and interpret the results presented in the previous section. Firstly, we can observe significant industry or regional diversification for the subsidized firms in Prefectures B and C on average, but not in Prefecture A. This result implies that the treated firms in Prefectures B and C found a way to promote new market development in different sectors or regions whereas those in Prefecture A did not. We may interpret these results as follows.

As described in Section 3.2.2, new market development is beyond the scope of Prefecture A's subsidy. Thus, subsidized firms might have had no motivation to diversify or expand their market relying on the subsidy. In addition, as mentioned in Section 3.1, Prefecture A has a huge industry agglomeration, which forms an integrated industry structure within Prefecture A from the upstream to the downstream sectors. Hence, satisfying the demand of incumbent customers may be enough for them to expand the sales of new products. Interestingly enough, we can observe positive effect of the subsidy on recipients' TFP when the subsidy is for more than one year.

Secondly, we can observe significant and sustained positive effects on subsidized firms' regional diversification of customers in Prefecture B and on industry diversification of customers in Prefecture C. The results for Prefecture B with fixed effect model confirm our benchmarking results demonstrated with the tree maps. Even after controlling for various fixed effects, we can observe regional diversification of customers in specific *Koiki*-districts like Greater Tokyo and Chubu. This may be because Prefecture B's subsidy enabled subsidized firms to promote market development of new products as final goods mainly in Greater Tokyo, the largest consumption area in Japan, and as intermediate goods mainly in Chubu, the largest industrial area, taking advantage of their location. Regarding Prefecture C, we can observe positive effects on subsidized firms' inter-industry customer diversification. This result implies that subsidized firms promoted new market development in various sectors, taking advantage of a wide variety of sectors existing in this prefecture.

6. Conclusion

In this paper, we empirically evaluated the effects of R&D subsidy programs under the local government initiative on firms' performance, comparing between neighboring three prefectures with different regional characteristics, located in the same district in Japan. Through this empirical evaluation, we also examined whether or not local R&D support can be a driver of the regional and industrial diversification of inter-firm transaction networks as a measure of new market development.

Utilizing large firm-level panel data of local manufacturing SMEs based on credit investigation, we showed that the effects of subsidy programs were quite heterogeneous between these three prefectures. Firstly, we observed positive effect of R&D subsidy on TFP of the treated firms in Prefecture A, but not in the other prefectures. Secondly, we observed significant and sustained positive effects on the subsidized firms' regional or industrial customer diversification in Prefectures B and C, but not in Prefecture A. These results suggest that the subsidized firms in Prefecture A improved their performance (TFP) utilizing R&D subsidy without developing new markets, while those in Prefectures B and C attempted to develop new markets in various sectors and regions based on R&D subsidies.

Our evaluation analysis has the following two main implications for the literature and policymakers. Firstly, we should pay more attention to the role of local R&D support as a driver of the regional and industrial diversification of local firms' business activities. Secondly, we should evaluate the policy effects from a long-term perspective. Particularly regarding Prefectures B and C, we could not observe any positive effects on the treated firms' productivity at least within a decade after subsidization, while positive effects on network diversification could be observed in a longer term. Thus, in the future, empirical evaluations with longitudinal data are required.

Despite these contributions, our study has some limitations. Firstly, we do not explicitly consider the differences in program design between the prefectures such as the amount of subsidy. To overcome this disadvantage, we need more detailed information about each public support program. Secondly, the identification strategy of policy effects employed in this paper is still insufficient due to the following two issues.

One empirical concern is insufficient control for time-variant firm characteristics. A potential and powerful approach to overcome this problem would be the difference-in-differences approach, which we could not employ because the timing (year) of receiving R&D support differs across firms. Another empirical concern is that we could not consider the selection problem sufficiently because our PSM was based on a limited number of observable independent variables. We would alleviate this problem with detailed information about selection procedures and criteria. Such information could enable us to conduct more rigorous evaluation with, for example, the regression discontinuity design.

In spite of these limitations, however, our investigation has remarkable contributions to the literature in that we provided an in-depth examination and comparison of the effects of R&D support programs under the local government initiative, considering inter- and intra-regional/industrial diversification of transaction networks.

Acknowledgments

An early version of this paper was presented at the Regional Studies Association (RSA) Annual Conference in Santiago de Compostela, Spain, in June 2019. We thank the participants of this conference for helpful comments and suggestions. This study is a part of the research projects conducted at the TDB Center for Advanced Empirical Research on Enterprise and Economy, TDB-CAREE, at Hitotsubashi University, and we also thank members of the TDB-CAREE, Takeo Goto, Yoshiki Hiramine, Shinya Kitamura and Yosuke Okada. This research was financially supported by JSPS KAKENHI Grant Number 18J20392.

References

- Boschma, R., & Iammarino, S. (2009). Related variety, trade linkages, and regional growth in Italy. Economic Geography, 85(3), 289-311.
- Boschma, R., Minondo, A., & Navarro, M. (2012). Related variety and regional growth in Spain. Papers in Regional Science, 91(2), 241-256.
- Bronzini, R., & Piselli, P. (2016). The impact of R&D subsidies on firm innovation. Research Policy, 45(2), 442-457.
- Cadot, O., Carrere, C., & Strauss-Kahn, V. (2013). Trade diversification, income, and growth: what do we know?. Journal of Economic Surveys, 27(4), 790-812.
- Crespy, C., Heraud, J. A., & Perry, B. (2007). Multi-level governance, regions and science in France: between competition and equality. Regional Studies, 41(8), 1069-1084.
- Criscuolo, C., Martin, R., Overman, H. G., & Van Reenen, J. (2019). Some causal effects of an industrial policy. American Economic Review, 109(1), 48-85.
- Doh, S., & Kim, B. (2014). Government support for SME innovations in the regional industries: The case of government financial support program in South Korea. Research Policy, 43(9), 1557-1569.
- Duranton, G., & Puga, D. (eds.) (2004). Micro-foundations of urban agglomeration economies. In Handbook of regional and urban economics (Vol. 4, pp. 2063-2117). Elsevier.
- Falck, O., Heblich, S., & Kipar, S. (2010). Industrial innovation: Direct evidence from a cluster-oriented policy. Regional Science and Urban Economics, 40(6), 574-582.
- Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. European Economic Review, 43(2), 409-429.
- Fernandez-Ribas, A. (2009). Public support to private innovation in multi-level governance systems: an empirical investigation. Science and Public Policy 36 (6), 457-467.
- Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. Regional Studies, 41(5), 685-697.
- Fujita, M., & Thisse, J. F. (2013). Economics of agglomeration: cities, industrial location, and globalization. Cambridge University Press, Cambridge.
- Jacobs, J. (1969). The economy of cities. Vintage.
- Kitagawa, F. (2007). The regionalization of science and innovation governance in Japan?. Regional Studies, 41(8), 1099-1114.
- Koschatzky, K., & Kroll, H. (2007). Which side of the coin? The regional governance of science and innovation. Regional Studies, 41(8), 1115-1127.
- Lanahan, L. (2016). Multilevel public funding for small business innovation: a review of US state SBIR match programs. Journal of Technology Transfer 41, 220-249.
- Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. Review of Economic Studies, 70(2), 317-341.
- Martin, P., Mayer, T., & Mayneris, F. (2011). Public support to clusters: A firm level study of French "Local Productive Systems". Regional Science and Urban Economics, 41(2), 108-123.
- Nachum, L. (2004). Geographic and industrial diversification of developing country firms. Journal of Management Studies, 41(2), 273-294.
- Nathan, M., & Overman, H. (2013). Agglomeration, clusters, and industrial policy. Oxford Review of Economic Policy, 29(2), 383-404.

- Neumark, D., & Simpson, H. (eds.) (2015). Place-based policies. In Handbook of regional and urban economics (Vol. 5, pp. 1197-1287). Elsevier.
- Nishimura, J., & Okamuro, H. (2011a). R&D productivity and the organization of cluster policy: An empirical evaluation of the Industrial Cluster Project in Japan. Journal of Technology Transfer, 36(2), 117-144.
- Nishimura, J., & Okamuro, H. (2011b). Subsidy and networking: The effects of direct and indirect support programs of the cluster program. Research Policy, 40 (5), 714-727.
- Okamuro, H., & Nishimura, J. (2015). Local management of national cluster policies: Comparative case studies of Japanese, German, and French biotechnology clusters. Administrative Sciences, 5(4), 213-239.
- Okamuro, H., & Nishimura, J. (2019). Effects of multilevel policy mix of public R&D subsidies: Empirical evidence from Japanese local SMEs. CCES Discussion Paper Series, No. 70, Hitotsubashi University Graduate School of Economics.
- Okamuro, H., Nishimura, J., & Kitagawa, F. (2019). Multilevel policy governance and territorial adaptability: evidence from Japanese SME innovation programmes. Regional Studies, 53 (6), 803-814.
- Okubo, T., Okazaki, T., & Tomiura, E. (2016). Industrial Cluster Policy and Transaction Networks: Evidence from firm-level data in Japan. RIETI Discussion Paper Series, 16-E-071.
- Palich, L. E., Cardinal, L. B., & Miller, C. C. (2000). Curvilinearity in the diversification–performance linkage: an examination of over three decades of research. Strategic Management Journal, 21(2), 155-174.
- Perry, B. (2007). The multi-level governance of science policy in England. Regional Studies, 41(8), 1051-1067.
- Qian, G., Li, L., Li, J., & Qian, Z. (2008). Regional diversification and firm performance. Journal of International Business Studies, 39(2), 197-214.
- Rugman, A. M. (1979). International diversification and the multinational enterprise. Lexington Books, Lanham.
- Salazar, M., & Holbrook, A. (2007). Canadian science, technology and innovation policy: the product of regional networking?. Regional Studies, 41(8), 1129-1141.
- Sotarauta, M., & Kautonen, M. (2007). Co-evolution of the Finnish national and local innovation and science arenas: towards a dynamic understanding of multi-level governance. Regional Studies, 41(8), 1085-1098.
- Tödtling, F., & Trippl, M. (2005). One size fits all?: Towards a differentiated regional innovation policy approach. Research Policy, 34(8), 1203-1219.
- Weitzen, S., Lapane, K. L., Toledano, A. Y., Hume, A. L., & Mor, V. (2004). Principles for modeling propensity scores in medical research: a systematic literature review. Pharmacoepidemiology and drug safety, 13(12), 841-853.

Table 3.1 Support programs provided by each prefecture

	A	B	C
Established by prefecture alone	Yes	No (supported by SMRJ)	No (supported by SMRJ)
Supports	R&D, experiment	New businesses and products	R&D for practical use
Requirements on collaboration pattern	Collaboration with public research institutes	None	None
Constraint on firm size	None	Only SMEs	Only SMEs
Start-end	2012-present	2007-2017	2007-2017
Maximum budget per project [Yen]	100 million for SME	7 million	5 million
Support after acceptance	None	Business consultation	None
Additional adoptions per firm	Available up to 3 years	Available up to 3 times	Unavailable within 3 years after previous receipt
Cumulative number of subsidized projects	521 (including non-SME firms)	96	90

Source: each prefecture's program WEB page.

Table 5.1 Summary of PSM results

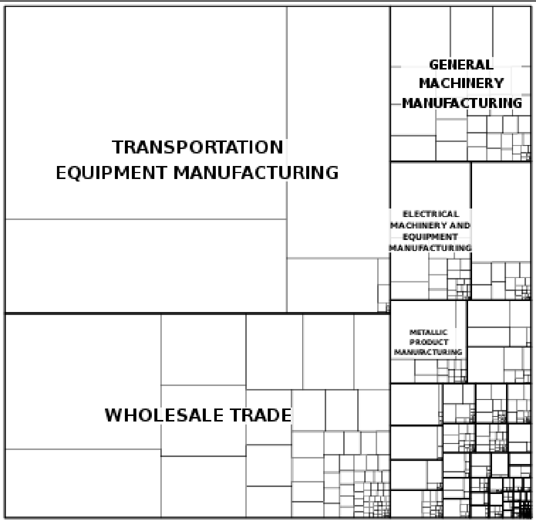
Prefecture	A	B	C
Matched with covariates in	2009	2004	2004
Predicted prob. with logit	Adoption in 2012-2016	Adoption in 2007-2016	Adoption in 2007-2016
Pseudo-R2	0.195	0.151	0.169
# of covariates with standardized bias larger than 0.1 (# of all covariate)	0 (22)	2 (9) but no covariate with standardized bias > 0.15	0 (17)

Notes: Balanced covariates are selected based on forward-backward stepwise method in logistic regression.

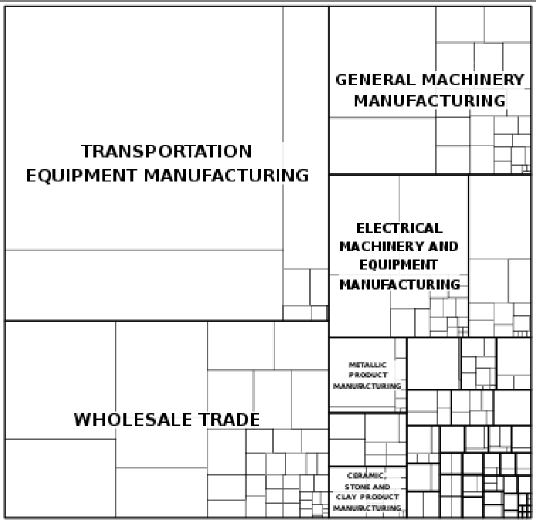
Table 5.2 Sample size of manufacturing SME panel data with/without PSM

Prefecture	A			B			C		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Unbalance w/ TFP	Unbalance wo/ TFP	Balance wo/ TFP	Unbalance w/ TFP	Unbalance wo/ TFP	Balance wo/ TFP	Unbalance w/ TFP	Unbalance wo/ TFP	Balance wo/ TFP
$D_{1\_3} = 1$	69	190	162	39	85	75	31	84	66
$D_{4\_6} = 1$		20	18	25	56	42	13	40	28
$D_{7\_9} = 1$				7	22	18	2	10	5
n	11010	57614	6041	3716	32875	3744	8883	52049	3120

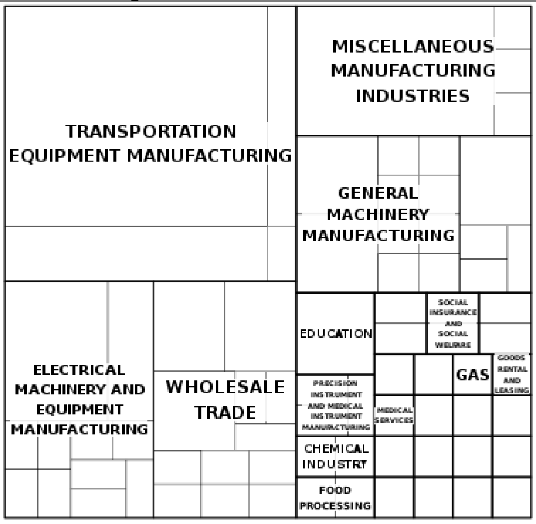
Notes: “Unbalance” stands for panel data without PSM, “Balance” stands for that with PSM. “w/TFP” means panel data used for evaluating the effect on TFP, “wo/TFP” means that used for evaluating the effect on outcomes other than TFP. $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k + 1,\ 3k + 2,\ 3k + 3$ years have passed since a firm was firstly adopted. The rows whose name is D_{3k+1_3k+3} show the number of records corresponding to each duration.



Industrial share of customers of firms in A satisfying $D_{3k+1\_3k+3} = 0, \forall k$ (# of firms: 863)



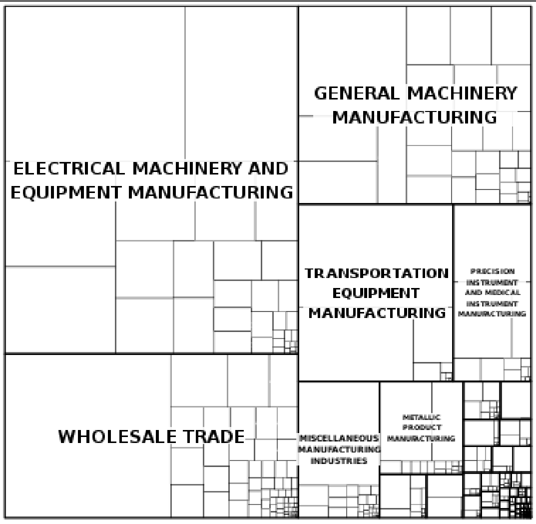
Industrial share of customers of firms in A satisfying $D_{1\_3} = 0$ (# of firms: 65)



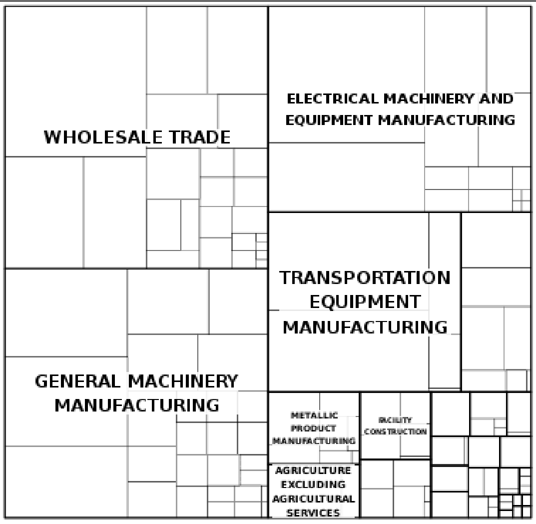
Industrial share of customers of firms in A satisfying $D_{4\_6} = 0$ (# of firms: 18)

Figure 5.1 Tree maps based on industrial share of customers of firms in A

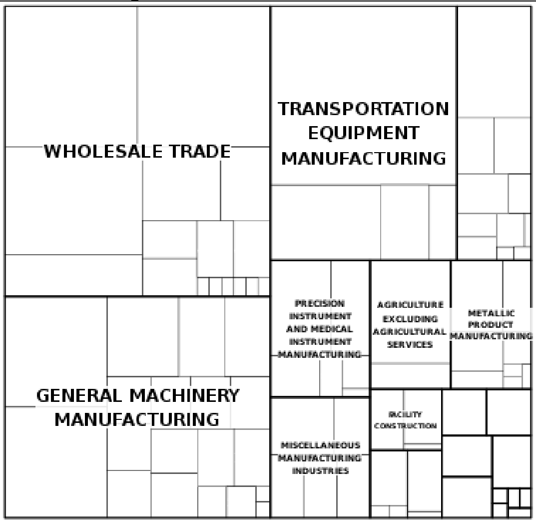
Notes: $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k+1$, $3k+2$, $3k+3$ years have passed since a firm was firstly adopted. These maps are drawn with matched panel data obtained in PSM. First layer is represented with 2-digit level industrial share of customers and second layer is represented with 5-digit level industrial share of customers Area of a rectangle corresponding to second layer is proportional to square of industrial share of customers.



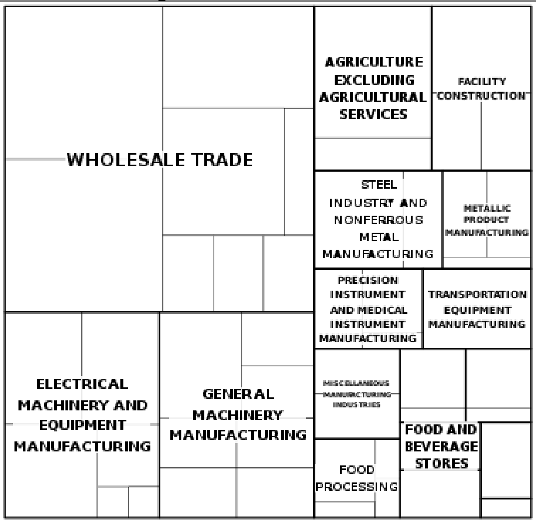
Industrial share of customers of firms in B satisfying $D_{3k+1\_3k+3} = 0, \forall k$ (# of firms: 312)



Industrial share of customers of firms in B satisfying $D_{1\_3} = 0$ (# of firms: 29)



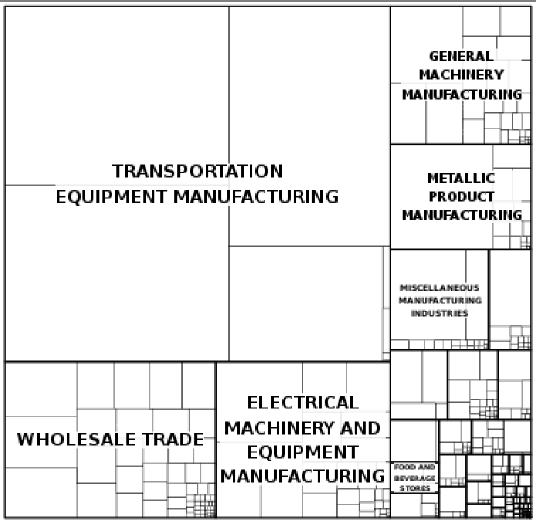
Industrial share of customers of firms in B satisfying $D_{4\_6} = 0$ (# of firms: 18)



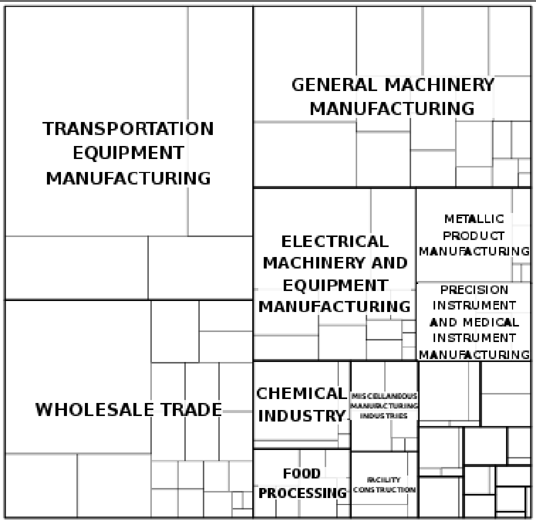
Industrial share of customers of firms in B satisfying $D_{7\_9} = 0$ (# of firms: 8)

Figure 5.2 Tree maps based on industrial share of customers of firms in B

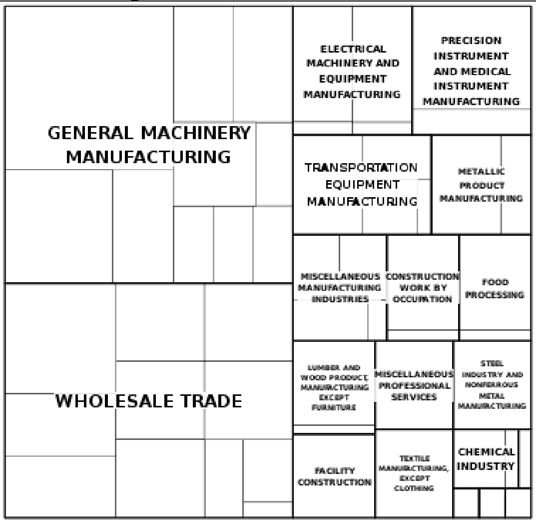
Notes: $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k+1$, $3k+2$, $3k+3$ years have passed since a firm was firstly adopted. These maps are drawn with matched panel data obtained in PSM. First layer is represented with 2-digit level industrial share of customers and second layer is represented with 5-digit level industrial share of customers Area of a rectangle corresponding to second layer is proportional to square of industrial share of customers.



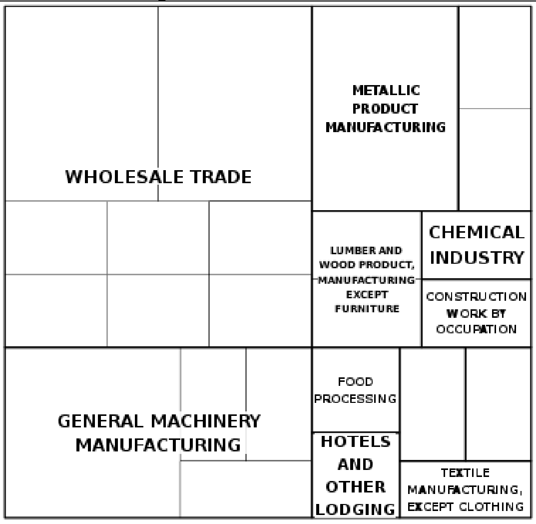
Industrial share of customers of firms in C satisfying $D_{3k+1\_3k+3} = 0, \forall k$ (# of firms: 260)



Industrial share of customers of firms in C satisfying $D_{1\_3} = 0$ (# of firms: 26)



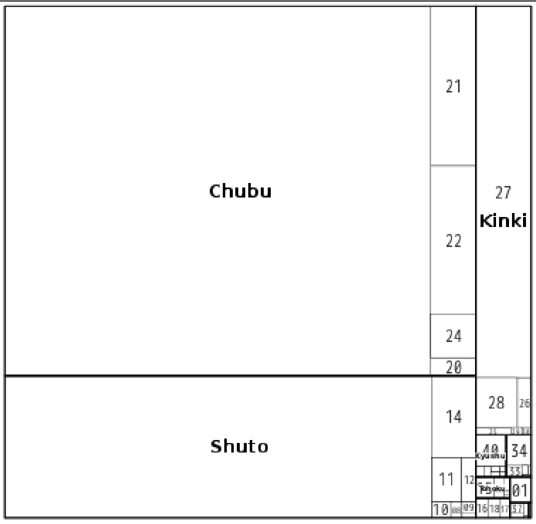
Industrial share of customers of firms in C satisfying $D_{4\_6} = 0$ (# of firms: 11)



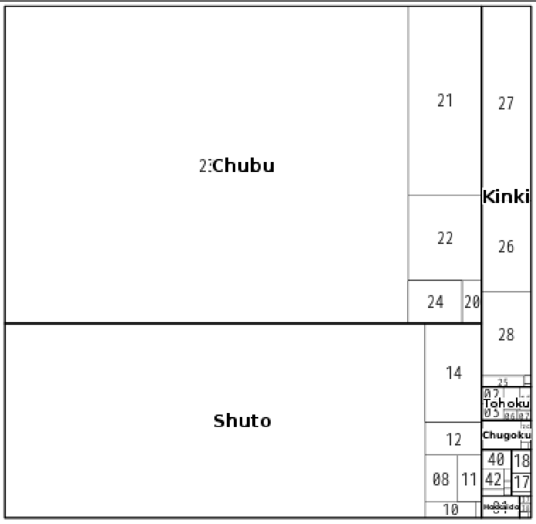
Industrial share of customers of firms in C satisfying $D_{7\_9} = 0$ (# of firms: 4)

Figure 5.3 Tree maps based on industrial share of customers of firms in C

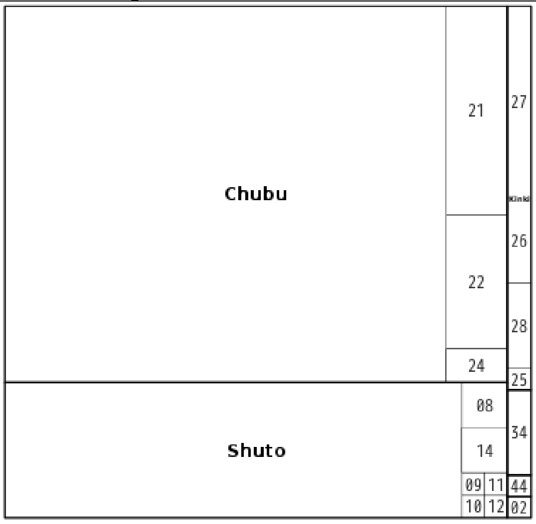
Notes: $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k+1$, $3k+2$, $3k+3$ years have passed since a firm was firstly adopted. These maps are drawn with matched panel data obtained in PSM. First layer is represented with 2-digit level industrial share of customers and second layer is represented with 5-digit level industrial share of customers Area of a rectangle corresponding to second layer is proportional to square of industrial share of customers.



Regional share of customers of firms in A satisfying $D_{3k+1\_3k+3} = 0, \forall k$ (# of firms: 863)



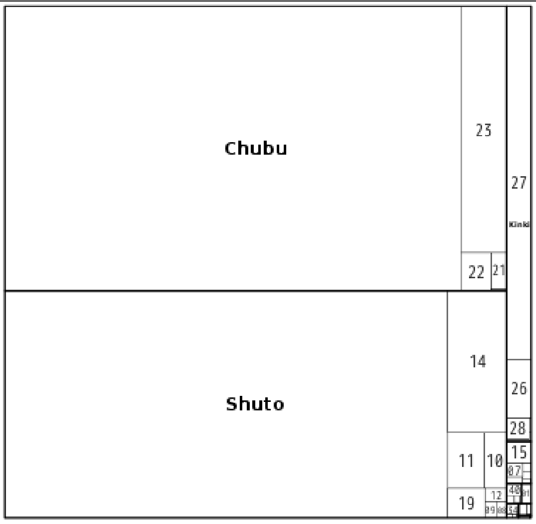
Regional share of customers of firms in A satisfying $D_{1\_3} = 0$ (# of firms: 65)



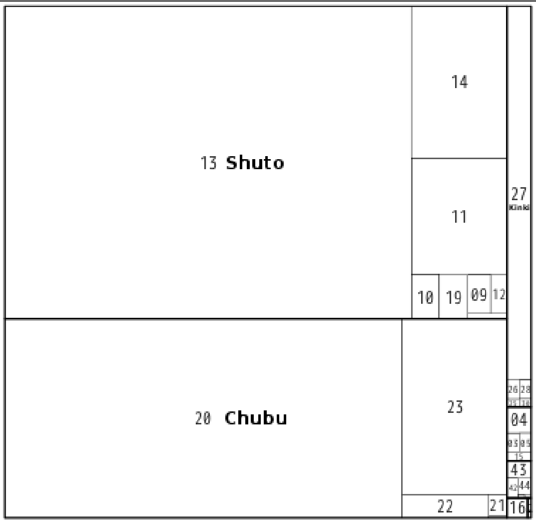
Regional share of customers of firms in A satisfying $D_{4\_6} = 0$ (# of firms: 18)

Figure 5.4 Tree maps based on regional share of customers of firms in A

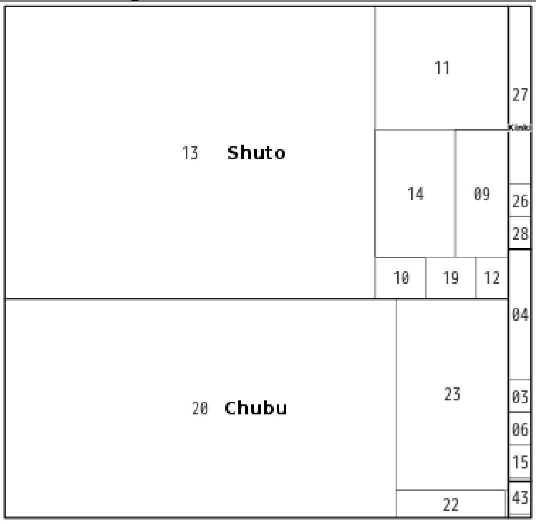
Notes: $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k + 1$, $3k + 2$, $3k + 3$ years have passed since a firm was firstly adopted. These maps are drawn with matched panel data obtained in PSM. First layer is represented with *Koiki* district level regional share of customers and second layer is represented with prefectural level regional share of customers Area of a rectangle corresponding to second layer is proportional to square of regional share of customers. *Shuto* represents Greater Tokyo District.



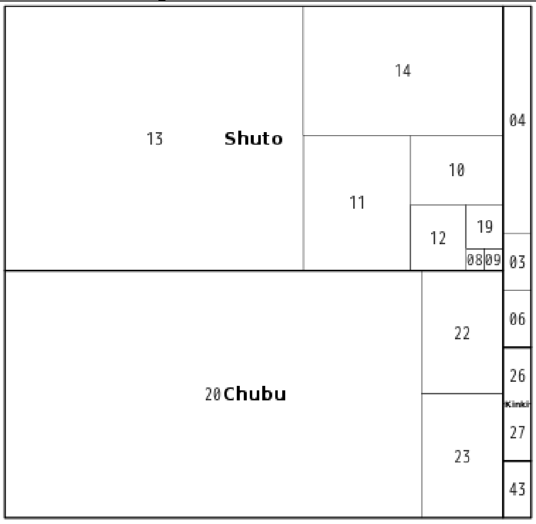
Regional share of customers of firms in B satisfying $D_{3k+1\_3k+3} = 0, \forall k$ (# of firms: 312)



Regional share of customers of firms in B satisfying $D_{1\_3} = 0$ (# of firms: 29)



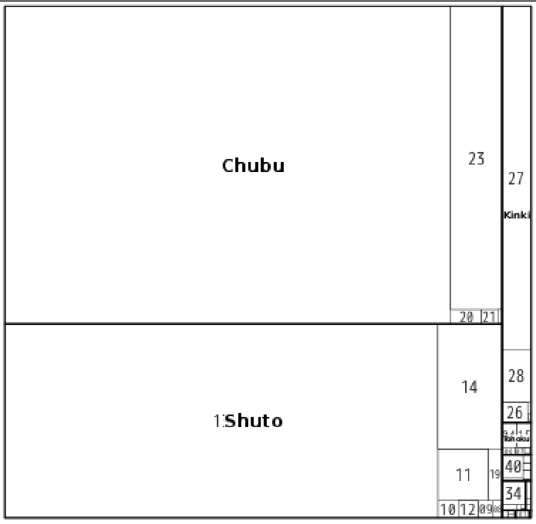
Regional share of customers of firms in B satisfying $D_{4\_6} = 0$ (# of firms: 18)



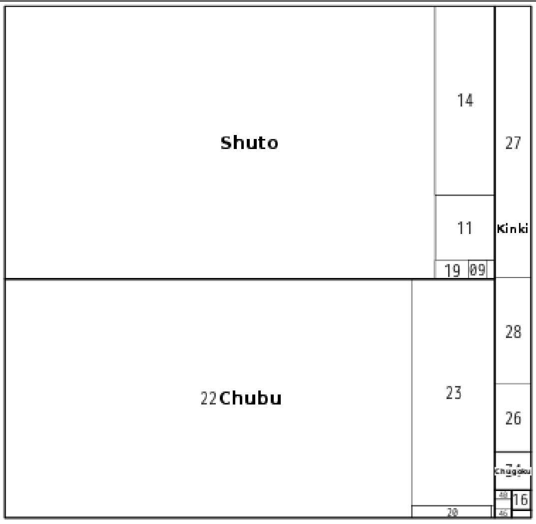
Regional share of customers of firms in B satisfying $D_{7\_9} = 0$ (# of firms: 8)

Figure 5.5 Tree maps based on regional share of customers of firms in B

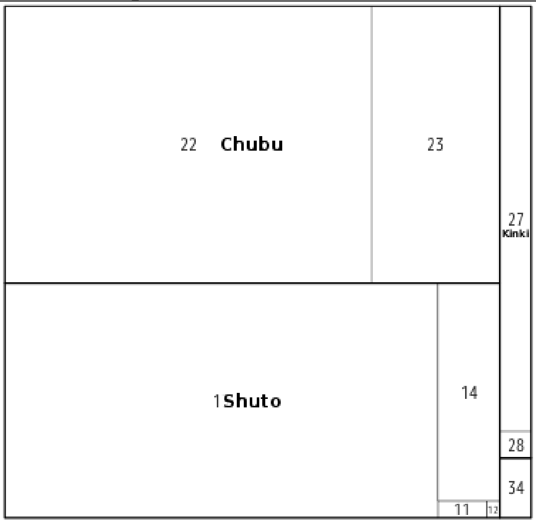
Notes: $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k+1$, $3k+2$, $3k+3$ years have passed since a firm was firstly adopted. These maps are drawn with matched panel data obtained in PSM. First layer is represented with *Koiki* district level regional share of customers and second layer is represented with prefectural level regional share of customers Area of a rectangle corresponding to second layer is proportional to square of regional share of customers. *Shuto* represents Greater Tokyo District.



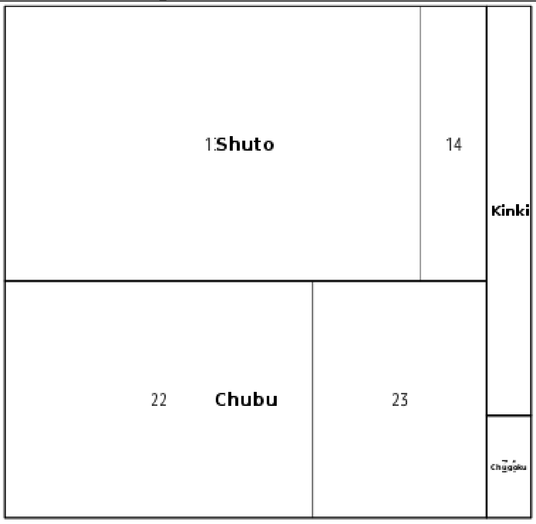
Regional share of customers of firms in C satisfying $D_{3k+1\_3k+3} = 0, \forall k$ (# of firms: 260)



Regional share of customers of firms in C satisfying $D_{1\_3} = 0$ (# of firms: 26)



Regional share of customers of firms in C satisfying $D_{4\_6} = 0$ (# of firms: 11)



Regional share of customers of firms in C satisfying $D_{7\_9} = 0$ (# of firms: 4)

Figure 5.6 Tree maps based on regional share of customers of firms in C

Notes: $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k+1$, $3k+2$, $3k+3$ years have passed since a firm was firstly adopted. These maps are drawn with matched panel data obtained in PSM. First layer is represented with *Koiki* district level regional share of customers and second layer is represented with prefectural level regional share of customers Area of a rectangle corresponding to second layer is proportional to square of regional share of customers. *Shuto* represents Greater Tokyo District.

Table 5.3 Estimation results of FE (Dependent variable: TFP)

	Prefecture A			Prefecture B		Prefecture C	
	(1)			(2)		(3)	
	beta	t val		beta	t val	beta	t val
D_1_3	0.055	0.843		0.057	0.676	−0.029	−0.341
D_4_9						−0.047	−0.255
D_4_6				−0.140	−1.285		
D_7_9				−0.082	−0.442		
MULTI	0.113	2.421	**	−0.004	−0.042		
INDEC	−0.009	−0.351		−0.032	−0.564		
ADD	−0.103	−1.280		−0.168	−1.606		
Firm FE	YES			YES		YES	
Year FE	YES			YES		YES	
2-digit FE	YES			YES		YES	
2-digit×Year FE	YES			YES		YES	
n	11010			6041		8883	

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level. Main treatment variable $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k + 1$, $3k + 2$, $3k + 3$ years have passed since a firm was firstly adopted.

Table 5.4 Estimation results of FE (Dependent variable: INTERIND)

	Prefecture A				Prefecture B				Prefecture C					
	(1)		(2)		(3)		(4)		(5)			(6)		
	beta	t val	beta	t val	beta	t val	beta	t val	beta	t val		beta	t val	
D_1_3	0.041	0.698	0.083	1.348	−0.058	−0.427	−0.035	−0.241	0.013	0.189		0.041	0.532	
D_4_6	0.160	1.551	0.151	1.457	0.112	1.026	0.059	0.523	0.360	2.413	**	0.290	1.712	*
D_7_9					0.022	0.167	0.007	0.047	0.290	3.125	***	0.442	3.907	***
MULTI	−0.075	−0.493	0.038	0.339	−0.060	−0.548	−0.084	−0.700						
INDEC	0.018	0.796	0.041	1.608	0.019	0.26	0.010	0.124						
ADD	−0.071	−1.012	−0.092	−1.16	0.004	0.031	0.116	0.722						
Firm FE	YES		YES		YES		YES		YES			YES		
Year FE	YES		YES		YES		YES		YES			YES		
2-digit FE	YES		YES		YES		YES		YES			YES		
2-digit×Year FE	YES		YES		YES		YES		YES			YES		
PSM	NO		YES		NO		YES		NO			YES		
n	57614		6041		32875		3744		52049			3120		

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level. Main treatment variable $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k + 1,\ 3k + 2,\ 3k + 3$ years have passed since a firm was firstly adopted. The method of PSM is 10 nearest neighbor matching.

Table 5.5 Estimation results of FE (Dependent variable: INTRAIND)

	Prefecture A						Prefecture B						Prefecture C					
	(1)			(2)			(3)			(4)			(5)			(6)		
	beta	t val		beta	t val		beta	t val		beta	t val		beta	t val		beta	t val	
D_1_3	−0.006	−0.133		0.005	0.112		0.108	1.224		0.139	1.695	*	0.040	0.862		0.063	1.078	
D_4_6	−0.118	−1.658	*	−0.048	−0.708		−0.112	−1.331		−0.028	−0.384		−0.145	−2.003	**	−0.011	−0.135	
D_7_9							−0.131	−1.256		−0.139	−1.344		−0.177	−1.592		−0.278	−2.074	**
MULTI	0.080	2.905	***	0.037	0.625		−0.127	−0.99		−0.149	−1.144							
INDEC	−0.031	−1.706	*	−0.025	−1.212		0.000	−0.002		0.051	1.330							
ADD	0.025	0.516		0.060	1.095		−0.126	−1.082		−0.226	−2.211	**						
Firm FE	YES			YES			YES			YES			YES			YES		
Year FE	YES			YES			YES			YES			YES			YES		
2-digit FE	YES			YES			YES			YES			YES			YES		
2-digit×Year FE	YES			YES			YES			YES			YES			YES		
PSM	NO			YES			NO			YES			NO			YES		
n	57614			6041			32875			3744			52049			3120		

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level. Main treatment variable $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k + 1$, $3k + 2$, $3k + 3$ years have passed since a firm was firstly adopted. The method of PSM is 10 nearest neighbor matching.

Table 5.6 Estimation results of FE (Dependent variable: INTERREG)

	Prefecture A						Prefecture B						Prefecture C					
	(1)			(2)			(3)			(4)			(5)			(6)		
	beta	t val		beta	t val		beta	t val		beta	t val		beta	t val		beta	t val	
D_1_3	−0.060	−0.970		−0.062	−0.936		0.041	0.318		0.014	0.113		0.006	0.096		−0.012	−0.138	
D_4_6	−0.057	−0.437		−0.084	−0.672		−0.048	−0.299		−0.085	−0.501		0.221	1.711	*	0.043	0.466	
D_7_9							−0.078	−0.374		−0.087	−0.381		0.346	2.976	***	0.311	2.235	**
MULTI	−0.101	−2.175	**	−0.072	−1.154		−0.047	−0.605		0.033	0.358							
INDEC	−0.025	−0.823		−0.030	−0.934		0.062	1.046		0.032	0.532							
ADD	0.108	1.379		0.195	2.511	**	−0.160	−1.035		−0.227	−1.521							
Firm FE	YES			YES			YES			YES			YES			YES		
Year FE	YES			YES			YES			YES			YES			YES		
2-digit FE	YES			YES			YES			YES			YES			YES		
2-digit×Year FE	YES			YES			YES			YES			YES			YES		
PSM	NO			YES			NO			YES			NO			YES		
n	57614			6041			32875			3744			52049			3120		

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level. Main treatment variable $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k + 1$, $3k + 2$, $3k + 3$ years have passed since a firm was firstly adopted. The method of PSM is 10 nearest neighbor matching.

Table 5.7 Estimation results of FE (Dependent variable: INTRAREG)

	Prefecture A						Prefecture B						Prefecture C			
	(1)			(2)			(3)			(4)			(5)		(6)	
	beta	t val		beta	t val		beta	t val		beta	t val		beta	t val	beta	t val
D_1_3	−0.064	−1.866	*	−0.073	−1.846	*	0.229	3.322	***	0.192	2.945	***	−0.016	−0.384	−0.038	−0.917
D_4_6	−0.102	−1.848	*	−0.077	−1.143		0.189	2.017	**	0.196	2.119	**	−0.021	−0.243	−0.075	−1.096
D_7_9							0.203	1.693	*	0.222	1.726	*	0.034	0.223	0.172	0.986
MULTI	−0.160	−0.671		−0.107	−0.484		−0.031	−0.625		−0.065	−1.193					
INDEC	−0.038	−2.358	**	−0.049	−2.517	**	0.069	1.911	*	0.063	1.700	*				
ADD	0.081	1.714	*	0.113	1.859	*	−0.185	−2.251	**	−0.115	−1.263					
Firm FE	YES			YES			YES			YES			YES		YES	
Year FE	YES			YES			YES			YES			YES		YES	
2-digit FE	YES			YES			YES			YES			YES		YES	
2-digit×Year FE	YES			YES			YES			YES			YES		YES	
PSM	NO			YES			NO			YES			NO		YES	
n	57614			6041			32875			3744			52049		3120	

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level. Main treatment variable $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k+1$, $3k+2$, $3k+3$ years have passed since a firm was firstly adopted. The method of PSM is 10 nearest neighbor matching.

Table 5.7 Estimation results of FE (Dependent variable: TYOCUS)

	Prefecture A						Prefecture B						Prefecture C			
	(1)			(2)			(3)			(4)			(5)		(6)	
	beta	t val		beta	t val		beta	t val		beta	t val		beta	t val	beta	t val
D_1_3	0.006	0.045		0.104	0.594		0.671	2.781	***	0.517	1.834	*	0.140	0.905	0.173	0.977
D_4_6	−0.157	−0.835		0.074	0.261		0.392	1.478		0.535	2.052	**	0.388	1.384	0.512	1.427
D_7_9							0.233	1.118		0.336	1.563		0.198	0.863	0.409	1.541
MULTI	−0.835	−4.406	***	−0.603	−2.496	**	−0.164	−0.622		−0.329	−1.344					
INDEC	−0.013	−0.226		0.027	0.402		0.217	1.076		0.274	1.348					
ADD	0.186	1.322		0.093	0.470		−0.598	−1.557		0.027	0.075					
Firm FE	YES			YES			YES			YES			YES		YES	
Year FE	YES			YES			YES			YES			YES		YES	
2-digit FE	YES			YES			YES			YES			YES		YES	
2-digit×Year FE	YES			YES			YES			YES			YES		YES	
PSM	NO			YES			NO			YES			NO		YES	
n	57614			6041			32875			3744			52049		3120	

Notes: Significant in ***1%, **5%, *10%. Standard errors are clustered at the firm level. Main treatment variable $D_{3k+1\_3k+3}, k = 0,1,2$ is a dummy variable which takes 1 if $3k+1$, $3k+2$, $3k+3$ years have passed since a firm was firstly adopted. The method of PSM is 10 nearest neighbor matching.

Appendix 1. Covariate balance in PSM

Appendix 1.1 Estimation results of logistic regression to predict propensity scores

Table A1.1 Estimation result about Prefecture A

	beta	z val	
AGE	−0.045	−1.721	*
lnEMP	3.400	2.747	***
lnSALES	1.865	1.556	
(lnEMP)^2	−0.234	−1.579	
(lnSALES)^2	−0.154	−1.833	*
D_GENERAL_MACH	3.137	2.224	**
D_TEXTILE	6.119	2.892	***
D_FOOD	−1.798	−0.462	
D_CERAMIC	6.674	2.909	***
D_CHEMICAL	1.378	2.811	***
D_PAPER	11.790	1.840	*
D_METALLIC	7.419	3.134	***
AGE×lnSALES	0.005	1.500	
AGE×D_FOOD	0.018	2.383	**
AGE×D_CERAMIC	0.027	1.663	*
lnEMP×D_FOOD	−1.785	−1.969	**
lnEMP×D_TEXTILE	−1.133	−2.024	**
lnEMP×D_CERAMIC	−2.147	−2.885	***
lnEMP×D_METALLIC	−2.268	−3.146	***
lnEMP×D_GENERAL_MACH	−0.534	−1.604	
lnSALES×D_FOOD	1.041	1.429	
lnSALES×D_PAPER	−1.827	−1.707	*
(Intercept)	−18.667	−4.622	***
PseudoR-sq		0.195	
N		6066	

Notes: Significant in ***1%, **5%, *10%. Dependent variable is $Prob(Treat_i = 1)$. $Treat_i$ takes 1 if $D_{3k+1\_3k+3}, k = 0,1,2$, dummy variable indicating the duration after first adoption, takes one at some point. Covariates are selected based on forward-backward stepwise method with AIC.

Table A1.2 Estimation result about Prefecture B

	beta	z val	
lnSALES	6.980	1.590	
AGE	−0.025	−1.668	*
lnEMP	−6.002	−1.320	
(lnSALES)^2	−1.321	−1.733	*
(lnEMP)^2	−1.489	−1.475	
D_ELECTRICAL_MACH	0.832	1.684	*
D_GENERAL_MACH	0.135	0.152	
lnSALES×lnEMP	2.743	1.616	
AGE×D_GENERAL_MACH	0.032	1.751	*
(Intercept)	−15.836	−2.149	**
PseudoR-sq	0.151		
N	1644		

Notes: Significant in ***1%, **5%, *10%. Dependent variable is $Prob(Treat_i = 1)$. $Treat_i$ takes 1 if $D_{3k+1\_3k+3}, k = 0,1,2$, dummy variable indicating the duration after first adoption, takes one at some point. Covariates are selected based on forward-backward stepwise method with AIC.

Table A1.3 Estimation result about Prefecture C

	beta	z val	
AGE	0.015	1.238	
lnEMP	2.019	1.751	*
lnSALES	0.968	1.337	
D_GENERAL_MACH	4.260	3.097	***
D_FOOD	−16.157	−2.442	**
D_TRANSPORTATION	−6.298	−1.609	
D_ELECTRICAL_MACH	−0.758	−0.301	
D_METALLIC	−5.253	−1.381	
D_MISCELLANEOUS	−12.931	−1.806	*
AGE×D_GENERAL_MACH	−0.133	−2.510	**
AGE×D_ELECTRICAL_MACH	−0.053	−1.602	
lnEMP×lnSALES	−0.332	−1.845	*
lnEMP×D_METALLIC	1.580	1.602	
lnEMP×D_ELECTRICAL_MACH	1.335	1.909	*
lnEMP×D_TRANSPORTATION	2.018	2.128	**
lnSALES×D_FOOD	2.172	2.642	***
lnSALES×D_MISCELLANEOUS	1.943	2.047	**
(Intercept)	−11.506	−2.745	***
PseudoR-sq	0.169		
n	2624		

Notes: Significant in ***1%, **5%, *10%. Dependent variable is $Prob(Treat_i = 1)$. $Treat_i$ takes 1 if $D_{3k+1\_3k+3}, k = 0,1,2$, dummy variable indicating the duration after first adoption, takes one at some point. Covariates are selected based on forward-backward stepwise method with AIC.

Appendix 1.2 Covariate valance before/after PSM

Table A1.4 Mean value of each covariate before/after PSM about Prefecture A

	Before PSM			After PSM		
	Treated	Control	Std. Bias	Treated	Control	Std. Bias
AGE	58.966	47.244	0.266	52.036	52.252	−0.005
lnEMP	4.029	2.7	1.39	3.983	3.978	0.006
lnSALES	7.137	5.818	1.129	7.056	7.06	−0.004
(lnEMP)^2	17.137	8.724	1.176	16.759	16.834	−0.011
(lnSALES)^2	52.287	35.7	1.03	51.034	51.208	−0.011
D_GENERAL_MACH	0.341	0.23	0.232	0.357	0.35	0.014
D_TEXTILE	0.08	0.028	0.188	0.083	0.075	0.031
D_FOOD	0.08	0.072	0.027	0.048	0.052	−0.016
D_CERAMIC	0.045	0.048	−0.011	0.048	0.051	−0.017
D_CHEMICAL	0.068	0.019	0.192	0.06	0.058	0.005
D_PAPER	0.011	0.031	−0.182	0.012	0.013	−0.011
D_METALLIC	0.045	0.136	−0.431	0.048	0.043	0.023
AGE×lnSALES	434.479	280.317	0.398	369.825	375.334	−0.014
AGE×D_FOOD	11.83	4.465	0.147	3.512	3.888	−0.008
AGE×D_CERAMIC	3.159	2.614	0.034	3.31	2.788	0.033
lnEMP×D_FOOD	0.335	0.205	0.112	0.178	0.203	−0.021
lnEMP×D_TEXTILE	0.279	0.073	0.211	0.292	0.266	0.026
lnEMP×D_CERAMIC	0.138	0.13	0.012	0.144	0.144	0.001
lnEMP×D_METALLIC	0.128	0.373	−0.353	0.134	0.129	0.008
lnEMP×D_GENERAL_MACH	1.34	0.594	0.388	1.404	1.371	0.017
lnSALES×D_FOOD	0.635	0.454	0.082	0.352	0.39	−0.017
lnSALES×D_PAPER	0.066	0.181	−0.186	0.069	0.076	−0.012

Notes: The method of PSM is 10 nearest neighbor matching.

Table A1.5 Mean value of each covariate before/after PSM about Prefecture B

	Before PSM			After PSM		
	Treated	Control	Std. Bias	Treated	Control	Std. Bias
lnSALES	6.81	5.869	0.792	6.752	6.73	0.018
AGE	41.25	41.322	−0.004	40.806	38.278	0.123
lnEMP	3.881	2.883	0.972	3.831	3.788	0.042
(lnSALES) ^2	47.751	36.099	0.711	46.886	46.375	0.031
(lnEMP) ^2	16.085	9.666	0.812	15.65	15.177	0.06
D_ELECTRICAL_MACH	0.25	0.15	0.228	0.258	0.201	0.13
D_GENERAL_MACH	0.406	0.179	0.456	0.387	0.428	−0.082
lnSALES×lnEMP	27.548	18.222	0.81	26.921	26.371	0.048
AGE×D_GENERAL_MACH	20.062	6.244	0.481	18.935	17.927	0.035

Notes: The method of PSM is 10 nearest neighbor matching.

Table A1.6 Mean value of each covariate before/after PSM about Prefecture C

	Before PSM			After PSM		
	Treated	Control	Std. Bias	Treated	Control	Std. Bias
AGE	40.308	41.962	−0.089	40.308	41.909	−0.086
lnEMP	3.687	2.965	0.715	3.687	3.66	0.027
lnSALES	6.894	6.117	0.595	6.894	6.892	0.002
D_GENERAL_MACH	0.154	0.196	−0.113	0.154	0.161	−0.018
D_FOOD	0.077	0.133	−0.207	0.077	0.064	0.046
D_TRANSPORTATION	0.154	0.07	0.229	0.154	0.17	−0.045
D_ELECTRICAL_MACH	0.269	0.07	0.44	0.269	0.245	0.053
D_METALLIC	0.115	0.156	−0.124	0.115	0.127	−0.035
D_MISCELLANEOUS	0.077	0.094	−0.061	0.077	0.055	0.079
lnEMP×lnSALES	26.572	19.317	0.635	26.572	26.199	0.033
AGE×D_GENERAL_MACH	2.885	7.96	−0.669	2.885	3.022	−0.018
AGE×D_ELECTRICAL_MACH	7.692	2.216	0.351	7.692	7.796	−0.007
lnEMP×D_METALLIC	0.461	0.465	−0.004	0.461	0.524	−0.048
lnEMP×D_ELECTRICAL_MACH	1.037	0.214	0.45	1.037	0.945	0.05
lnEMP×D_TRANSPORTATION	0.705	0.229	0.279	0.705	0.784	−0.046
lnSALES×D_FOOD	0.654	0.856	−0.087	0.654	0.528	0.054
lnSALES×D_MISCELLANEOUS	0.598	0.56	0.018	0.598	0.435	0.077

Notes: The method of PSM is 10 nearest neighbor matching.

Appendix 2 Descriptive statistics of panel data

Table A2.1 Descriptive statistics of unbalance panel data for examining effect on TFP

Pref	Variables	n	Mean	SD	Min	Max
A	TFP	11010	11.996	1.077	5.872	16.226
	D_1_3	11010	0.006	0.079	0	1
	CUM	11010	0.013	0.139	0	3
	MULTI	11010	0	0.01	0	1
	INDEC	11010	0.002	0.081	−1	1
	ADD	11010	0.002	0.049	0	1
B	TFP	3716	11.728	1.072	8.045	15.328
	D_1_3	3716	0.01	0.102	0	1
	D_4_6	3716	0.007	0.082	0	1
	D_7_9	3716	0.002	0.043	0	1
	CUM	3716	0.03	0.209	0	3
	MULTI	3716	0.005	0.067	0	1
	INDEC	3716	0.001	0.085	−1	1
	ADD	3716	0.006	0.078	0	1
C	TFP	8883	12.002	1.058	6.812	15.293
	D_1_3	8883	0.003	0.059	0	1
	D_4_9	8883	0.002	0.041	0	1

Table A2.2 Descriptive statistics of unbalance panel data for examining effect on outcomes except for TFP

Pref	Variables	n	Mean	SD	Min	Max
A	INTERIND	57614	1.032	0.764	0	3.865
	INTERREG	57614	0.836	0.83	0	4.871
	INTRAIND	57614	0.37	0.471	0	3.122
	INTRAREG	57614	0.232	0.381	0	2.322
	TYOCUS	57614	0.939	2.707	0	190
	D_1_3	57614	0.003	0.057	0	1
	D_4_6	57614	0	0.019	0	1
	MULTI	57614	0	0.007	0	1
	INDEC	57614	0	0.054	−1	1
	ADD	57614	0.001	0.038	0	1
B	INTERIND	32875	0.966	0.755	0	3.775
	INTERREG	32875	0.878	0.81	0	4.139
	INTRAIND	32875	0.413	0.505	0	2.948
	INTRAREG	32875	0.229	0.38	0	2.156
	TYOCUS	32875	1.409	1.994	0	47
	D_1_3	32875	0.003	0.051	0	1
	D_4_6	32875	0.002	0.041	0	1
	D_7_9	32875	0.001	0.026	0	1
	MULTI	32875	0.001	0.034	0	1
	INDEC	32875	0	0.043	−1	1
	ADD	32875	0.002	0.044	0	1
C	INTERIND	52049	0.93	0.752	0	3.24
	INTERREG	52049	0.87	0.817	0	5.365
	INTRAIND	52049	0.356	0.474	0	2.948
	INTRAREG	52049	0.229	0.38	0	2.45
	TYOCUS	52049	1.506	2.466	0	85
	D_1_3	52049	0.002	0.04	0	1
	D_4_6	52049	0.001	0.028	0	1
	D_7_9	52049	0	0.014	0	1

Table A2.3 Descriptive statistics of balance panel data for examining effect on outcomes except for TFP

Pref	Variables	n	Mean	SD	Min	Max
A	INTERIND	6041	1.334	0.718	0	3.865
	INTERREG	6041	1.304	0.947	0	4.615
	INTRAIND	6041	0.548	0.491	0	2.608
	INTRAREG	6041	0.373	0.425	0	2
	TYOCUS	6041	1.752	2.378	0	27
	D_1_3	6041	0.027	0.162	0	1
	D_4_6	6041	0.003	0.055	0	1
	MULTI	6041	0.001	0.026	0	1
	INDEC	6041	0.003	0.151	−1	1
	ADD	6041	0.011	0.105	0	1
B	INTERIND	3744	1.347	0.724	0	3.328
	INTERREG	3744	1.323	0.782	0	3.889
	INTRAIND	3744	0.597	0.527	0	2.948
	INTRAREG	3744	0.361	0.404	0	1.961
	TYOCUS	3744	2.233	2.062	0	18
	D_1_3	3744	0.02	0.14	0	1
	D_4_6	3744	0.011	0.105	0	1
	D_7_9	3744	0.005	0.069	0	1
	MULTI	3744	0.009	0.092	0	1
	INDEC	3744	0.001	0.121	−1	1
	ADD	3744	0.012	0.108	0	1
C	INTERIND	3120	1.263	0.728	0	3.181
	INTERREG	3120	1.223	0.848	0	4.844
	INTRAIND	3120	0.578	0.541	0	2.322
	INTRAREG	3120	0.357	0.425	0	2.176
	TYOCUS	3120	2.227	3.597	0	53
	D_1_3	3120	0.021	0.144	0	1
	D_4_6	3120	0.009	0.094	0	1
	D_7_9	3120	0.002	0.04	0	1

Appendix 3. Estimation of TFP based on Levinsohn & Petrin (2003) method

Table A3.1 Estimation result of TFP

	beta	SE
ln(EMP)	0.1803	0.00084
ln(CAPITAL)	0.0727	0.00073
n	3305734	

Notes: Dependent variable is sales due to limited availability of value-added data. As independent variables, we use the number of employees (labor input as a free variable), and the amount of tangible fixed asset (capital input as a state variable). As a proxy variable, we use the cost of sales. Dataset utilized to estimate TFP is unbalanced panel data from 2000 to 2015 including firms throughout Japan and industrial sectors based on the financial database.