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The micro-geographies of industrial diversity and productivity growth: Evidence from the transportation equipment industry in Japan

Tetsu Kawakami[1], Eri Yamada[2] and Jiro Nemoto[3]

1. Introduction

Since the 1990s, promoting industrial clusters has become, in the eyes of many researchers and policy makers, critical for realizing regional innovation and its resultant growth. Following the industrial clusters' iconic success in Silicon Valley and its adoption by European countries, Japan's Ministry of Economy, Trade and Industry (METI) launched 19 cluster projects nationwide as part of the Industry Cluster Project in 2001. Numerous policy reports and related papers offer a comprehensive review of Japan's cluster initiatives and feature a number of its success stories (e.g., Ishikura et al. 2003; METI 2009; Ganne and Lecler 2009). While invaluable, the insights offered by some studies are difficult to generalize due to known limitations of the case study approach. Very few studies make use of sufficiently large samples to offer quantitative evidence in response to open questions (Porter, 2003; Duranton et al., 2010). Where are the well- or poorly-functioning clusters located? What is the geographical boundary of these clusters? What is the industrial composition of these clusters?

This study aims to provide basic quantitative facts on the clusters with demonstrated gains in productivity with a particular focus on the transportation equipment cluster and its related industries in Japan. The Japanese transportation equipment industry (which includes automobile, railway rolling stock, ship, and aircraft manufacturing) uses cutting edge technologies and is expected to play an important role in the development of the regions that have been designated to the cluster projects. Because of the characteristics of vertical and hierarchical organizational structures, consistent clustered productivity growth has been associated with extensive knowledge spillovers among related industries.

There is a growing body of work confirming that externalities from knowledge spillovers associated with industrial agglomeration drive urban and regional economic growth. Following Glaeser et al.'s (1992) focus on industrial scope, subsequent empirical

[1] Faculty of Economics, Kindai University, 3-4-1 Kowakae, Higashiosaka, Osaka 577-8502, Japan

[2] Graduate School of Economics, 1 Kawasumi, Mizuho-cho, Mizuho-ku, Nagoya, 467-8601, Japan

[3] Graduate School of Economics, Furo-cho, Chikusa-ku, Nagoya, 464-8601, Japan

studies have investigated the role that these dynamic externalities play across various geographical scales and industrial aggregations. We aim to contribute to this literature. First, we are able to link the structure of the local clusters to company productivity. The approach that we employ is more consistent with endogenous growth theories than with studies based on the conventional employment approach established through Glaeser et al.'s (1992) seminal work.

Second, we capture each company's productivity growth. To that end, we use the Malmquist total factor productivity (TFP) index. Conventional methods, based on the Törnqvist TFP index or the Solow residual, assume the optimizing behavior of production. In comparison, an advantage of the Malmquist TFP index is that it can be applied without any ad hoc adjustment to the input data even if the varying intensity of input usage conceals true productivity (Nemoto and Goto 2005).

Finally, the physical location of companies is used to visualize the estimated results of the technical change component of the TFP index on maps using geographic information systems (GIS). This approach for detecting clusters allows us to use distance to uncover more realistic geographical areas and decaying patterns compared to research that relies on political borders or predetermined geographical units (Rosenthal and Strange 2005; Catini et al. 2015). The findings may be used to infer the path of knowledge transfer that contributes to productive growth and establish effective regional policies.

2. Calculation of Productivity Change

In this study, the Malmquist TFP index is decomposed into three components: technical change, efficiency change, and scale change. The technical change component measures the degree of the shift in the production frontier which is attributable to technological progress and changes in production circumstances. A focus on the technical change component is suitable when examining the relationship between knowledge spillovers in clusters and productivity growth that is gained through innovation. The large number of observations in our data sets allows us to apply an econometric approach to estimate the required distance functions for deriving the Malmquist TFP index.

To perform the Malmquist TFP index computations, Fuentes et al. (2001) and Orea (2002) specify the translog distance function method. In a single-output production frontier case, the general multi-output distance function is summarized by the following translog stochastic production frontier:

$$\ln y_{it} = \beta_0 + \sum_{n=1}^{3} \beta_n \ln x_{nit} + \frac{1}{2}\sum_{n=1}^{3}\sum_{j=1}^{3} \beta_{nj} \ln x_{nit} \ln x_{jit}$$

$$+ \sum_{n=1}^{3} \beta_{tn} t \ln x_{nit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + v_{it} - u_{it} \qquad (1)$$

where y_{it} is the output of the i-th firm in the t-th year;

x_{nit} is a n-th input variable (n=1, 2, 3);

t is a time trend representing technical change;

the βs are unknown parameters to be estimated;

the v_{it}s are random errors assumed to be iid$\mathrm{N}(0, \sigma_v)$-.

The model specification by Battese and Coelli (1995) assumes the u_{it}s, which accounts for technical inefficiency in production, is independently distributed as truncated at zero of the $\mathrm{N}(\boldsymbol{z_{it}\delta}, \sigma_u)$. $\boldsymbol{z_{it}}$ is a vector of variables that may influence the efficiency of a firm, and $\boldsymbol{\delta}$ is the corresponding vector of parameters to be estimated.

In this parametric case, the technical change index for the i-th firm between periods s and t is calculated as the geometric mean of the partial derivative of $\ln y_{it}$ with respect to time;

$$TC_{i,st} = \exp\left[\frac{1}{2}\left(\frac{\partial \ln y_{is}}{\partial s} + \frac{\partial \ln y_{it}}{\partial t}\right)\right]. \qquad (2)$$

The technical efficiency change can be measured

$$TE_{it} = E[\exp(-u_{it})\,|e_{it}] \qquad (3)$$

where $e_{it} = v_{it} - u_{it}$. Then, the technical efficiency chance index is calculated as

$$TEC_{i,st} = \frac{TE_{it}}{TE_{is}}. \qquad (4)$$

The scale efficiency change can be measured based on the scale elasticity value ε_{nis} with respect to the n-th input (Orea, 2002);

$$SEC_{i,st} = exp\left[\frac{1}{2}\sum_{n=1}^{N}[\varepsilon_{nis}SF_{is} + \varepsilon_{nit}SF_{it}]ln\left(\frac{x_{nit}}{x_{nis}}\right)\right] \qquad (5)$$

where $SF_{is} = (\varepsilon_{is} - 1)/\varepsilon_{is}$, $\varepsilon_{is} = \sum_{n=1}^{N}\varepsilon_{nis}$ and $\varepsilon_{nis} = \partial \ln y_{is}/\partial \ln x_{nis}$. Once we have satisfactorily measured these productivity change components, we can measure the overall TFP change for the i-th firm over periods s to period t:

$$TFP_{i,st} = TC_{i,st} \times TEC_{i,st} \times SEC_{i,st}. \qquad (6)$$

3. Empirical application

3.1. Data

We use data extracted from the Census of Manufactures provided by the METI. Our data covers the time period 2004–2012. It includes information on firms with no less than 30 employees. The Malmquist TFP index and its decomposition are calculated for firms classified into the industries that manufacture motor vehicles and bodies (coachwork) for motor vehicles (4-digit industrial classification 3011 and 3012: 1,967 observations); and parts and accessories for motor vehicles (industrial classification 3013: 27,826 observations). The data also include information on each firm's location.

We consider three types of inputs and one output. The inputs include intermediate inputs (constant value in 2000), including raw material, electricity, and consignment costs; firms' tangible fixed assets (constant in 2000); and firms' total number of workers measured as a count of self-employed, family workers, and full-time employees multiplied by sectoral working hours. The output is a firm's total sales (constant in 2000) as measured by the value of manufactured shipments, processing charge, and other sources of income.

3.2. Estimation results

Maximum-likelihood estimates of the translog stochastic frontier model for downstream factories (manufacturers of motor vehicles and vehicle's body) are presented in Table 1. Note that the estimations were performed with variables expressed in deviations with respect to average values. Hence, the first-order parameters are to be interpreted as the elasticities at the sample means. All elasticities of outputs with respect to each input are significant and positive. In addition, many of the other cross terms are also significant.

(Table 1 around here)

The estimated parameters can be used to calculate annual percent change measures of technical change (TC), technical efficiency change (TEC), scale efficiency change (SEC), and overall TFP change for each firm over the period under study. These indices are averaged across firms and then converted into cumulative percent change reported in Figure 1.

(Figure 1 around here)

The results shown in Figure 1 reveal several interesting findings. Overall, TFP decreases from 2004 to 2009, a trend that is driven primarily by the rapid decline of TEC. The business environment for export oriented manufacturing sectors such as motor vehicle companies was extremely harsh during this period. It is likely that TEC declined as a consequence of the yen's rapid appreciation and the Lehman shock. Furthermore, the industry was negatively affected by a massive recall on defective braking systems issued by Toyota Motor Corporation at the end of 2009. This accelerated the contraction of Toyota's sales and prompted a decline in TEC in all auto-related industries. The shock of the great earthquake that hit the Pacific coastal regions in 2011 contributed to a decline in TEC, but it recovered soon. However, TC experienced a steadily expanding trend over the same period, playing a leading role in the improvement of overall TFP especially in 2010 and later. The size of a firm's average SEC is smaller than the other productivity components.

As with the estimation for downstream industries, we estimated the translog stochastic frontier model for upstream industries (manufacturers of parts and accessories). Since the size of companies in these industries varies significantly, we estimate the model in cohorts. The model is estimated for firms with less than 100 employees, firms with 100 to 300 employees, and firms with more than 300 employees as of 2004. Table 2 shows the estimation results for the sample of firms with 100 to 300 employees.[4] Based on the estimated parameters, annual percent change measures of TC, TEC, SEC, and overall TFP are calculated for each firm. Aggregate cumulative percent change measures of productivity components are shown in Figure 2.

(Table 2 around here)

(Figure 2 around here)

Figure 2 shows that the productivity change of parts and accessories manufacturers is similar to that of downstream assembling factories. From 2004 to 2008, overall TFP increase is led by significant upward TC. In 2009, TFP plunges due to the effect of TEC.

3.3. Spatial patterns of technological change

[4] The signs and the significance of the estimated coefficients in the model using the other samples are similar to the result shown in Table 2.

Section 3.2 discusses sample average patterns of productivity change, which are based upon aggregate results. TC, TEC, SEC, and overall TFP change can be calculated for each firm over the period under study. In particular, we focus on the TC component of TFP, which is the movement of firm's production frontier and comes from technological advances. Then, using the address information of observations, we investigate the relationship between the size of TC and its geography.

Figure 3 shows the location of manufacturers of motor vehicles and vehicle's body (red), and manufacturers of parts and accessories with 100 or more employees (green). The firms that achieve higher degree of TC are shown in a darker shade of green.[5] Figure 3 shows that relatively large-scale parts and accessories manufacturers that experienced significant improvement in their frontiers tended to be located near downstream assembling factories.

Figure 4 shows the location of manufacturers of motor vehicles and vehicle body (red), and manufacturers of parts and accessories with less than 100 employees (purple). The firms that achieve higher degree of TC are shown in darker purple. The small-scale parts and accessories manufacturers, which are located near downstream assembling factories, also realized high production frontier improvements. These findings suggest that the upstream parts and accessories firms with high TC improvements are closely related to downstream assembling firms. Therefore, geography may determine firms' capacities to achieve technological progress.

(Figure 3 around here)

(Figure 4 around here)

4. Conclusion

This study offers basic quantitative facts about the clusters that demonstrate growth, focusing on transportation equipment industries in Japan. To specify the location and extent of the well-functioning auto-related clusters, we first calculate the Malmquist TFP index to evaluate the change in firm productivity. In the TFP index, the TC component that is not affected by exogenous demand shocks can be measured through parametric estimation. A focus on the TC component of the index is suitable to examine the relationship between knowledge spillovers in clusters and productivity growth

[5] The top 25% firms of the sample in terms of the size of TC are shown in darker green.

through innovation. The estimated results of the TC component are visualized on maps using a GIS. This approach for detecting clusters allows us to use spatial features to uncover more realistic geographical areas and decaying patterns compared to research that relies on political borders or predetermined geographical units. The results show that the final assembly or the large-scale downstream factories have achieved steady frontier improvements. Manufacturers of parts and accessories that are located near large-scale assembling factories also realized relatively large improvements in technological progresses. These findings suggest that geography is important for firms to realize technological progress.

In future research, statistical methods will be employed to evaluate the productivity of growth clusters (some preliminary results will be reported at the conference). The role of other industries that are closely related to automobile manufacturers also needs to be considered. Further, a comparative analysis on industrial clusters between Japan, EU, and the US may be useful to study effective cluster policies and to promote regional economic growth.

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Table 1. Estimates of the stochastic frontier model for the downstream industries

Coefficients in determinstic compornents				Coefficients in efficiency componenet (u_{it})	
Constant	1.6306 ***			Constant	1.7424 ***
ln X	0.2830 ***	ln X×D_{Large}	0.2830 ***	ln X	-2.5113 ***
ln K	0.2523 ***	ln K×D_{Large}	0.2523 ***	ln K	0.1461 ***
ln L	0.7542 ***			ln L	0.2650 ***
t	0.0687 ***	t×D_{Large}	0.0537 ***	t	0.0416 ***
$(\ln X)^2$	0.0479 ***	$(\ln X)^2$×D_{Large}	0.0479 ***	$(\ln X)^2$	-0.9631 ***
ln X×ln K	-0.0431 ***	(ln X×ln K)×D_{Large}	-0.0431 ***	ln X×ln K	-0.0135
ln X×ln L	-0.0644 **			ln X×ln L	0.1177 ***
ln X×t	-0.0005	(ln X×t)×D_{Large}	-0.0005	ln X×t	0.0063 *
$(\ln K)^2$	0.0025			$(\ln K)^2$	-0.0193
ln K×ln L	0.1292 ***	(ln K×ln L)×D_{Large}	0.1292 ***	ln K×ln L	0.0796 ***
ln K×t	0.0053	(ln K×t)×D_{Large}	0.0053	ln K×t	0.0009
$(\ln L)^2$	-0.1858 **	$(\ln L)^2$×D_{Large}	-0.1858 **	$(\ln L)^2$	-0.3688 ***
ln L×t	0.0134	(ln L×t)×D_{Large}	0.0134	ln L×t	-0.0010
t^2	-0.0078	t^2×D_{Large}	-0.0078	t^2	-0.0064 *
D_{2009}	-0.0559 ***				
D_{2010}	-0.0362 *				
D_{2011}	0.0036				
σ_v^2	0.2938			σ_u^2	0.0920
$\lambda=\sigma_u/\sigma_v$	1.7695				
Log-likelihood	299.69				
# of observations	1967				

* Significant at the 10 % level; ** at the 5 % level; *** at the 1 % level

Table 2. Estimates of the stochastic frontier model for parts and accessories manufacturers

Coefficients in determinstic compornents			Coefficients in efficiency componenet (u_{it})		
Constant	0.8539	***	Constant	1.2401	***
ln X	0.1111	***	ln X	-0.4007	***
ln K	0.1680	***	ln K	0.1327	***
ln L	0.6247	***	ln L	0.1908	***
t	0.0532	***	t	0.0078	***
$(\ln X)^2$	0.3759	***	$(\ln X)^2$	-0.0326	***
ln X×ln K	-0.0644	***	ln X×ln K	0.0103	***
ln X×ln L	-0.2910	***	ln X×ln L	-0.0068	
ln X×t	-0.0229	***	ln X×t	-0.0003	
$(\ln K)^2$	0.0272	***	$(\ln K)^2$	0.0011	
ln K×ln L	0.0107		ln K×ln L	-0.0034	
ln K×t	0.0052	***	ln K×t	0.0012	**
$(\ln L)^2$	0.2527	***	$(\ln L)^2$	0.1466	***
ln L×t	-0.0071		ln L×t	0.0080	***
t^2	-0.0040	***	t^2	-0.0016	**
D_{2009}	-0.0674	***			
D_{2011}	-0.0165	**			
σ_v^2	0.1841		σ_u^2	0.1830	
$\lambda=\sigma_u/\sigma_v$	0.9941				
Log-likelihood	573.78				
# of observations	7868				

* Significant at the 10 % level; ** at the 5 % level; *** at the 1 % level

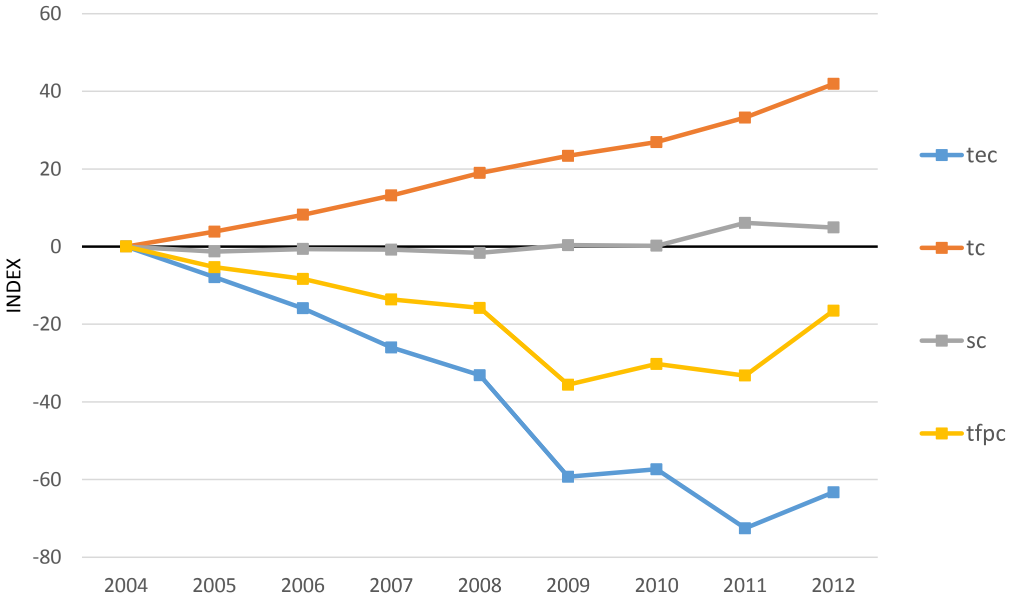

Figure 1. Change in productivity for the downstream industries

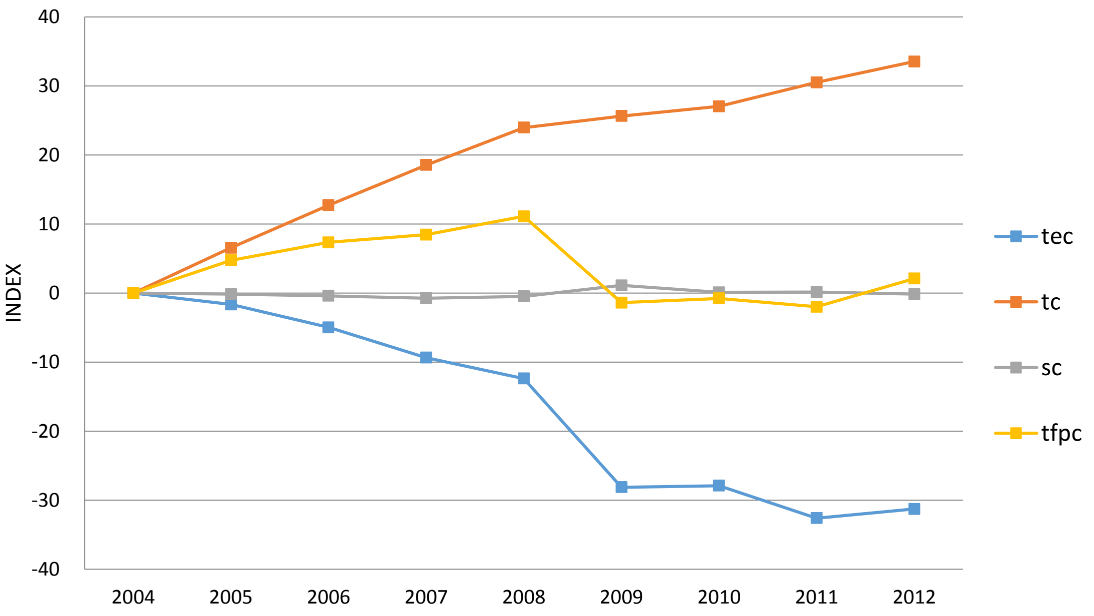

Figure 2. Change in productivity for parts and accessories manufacturers

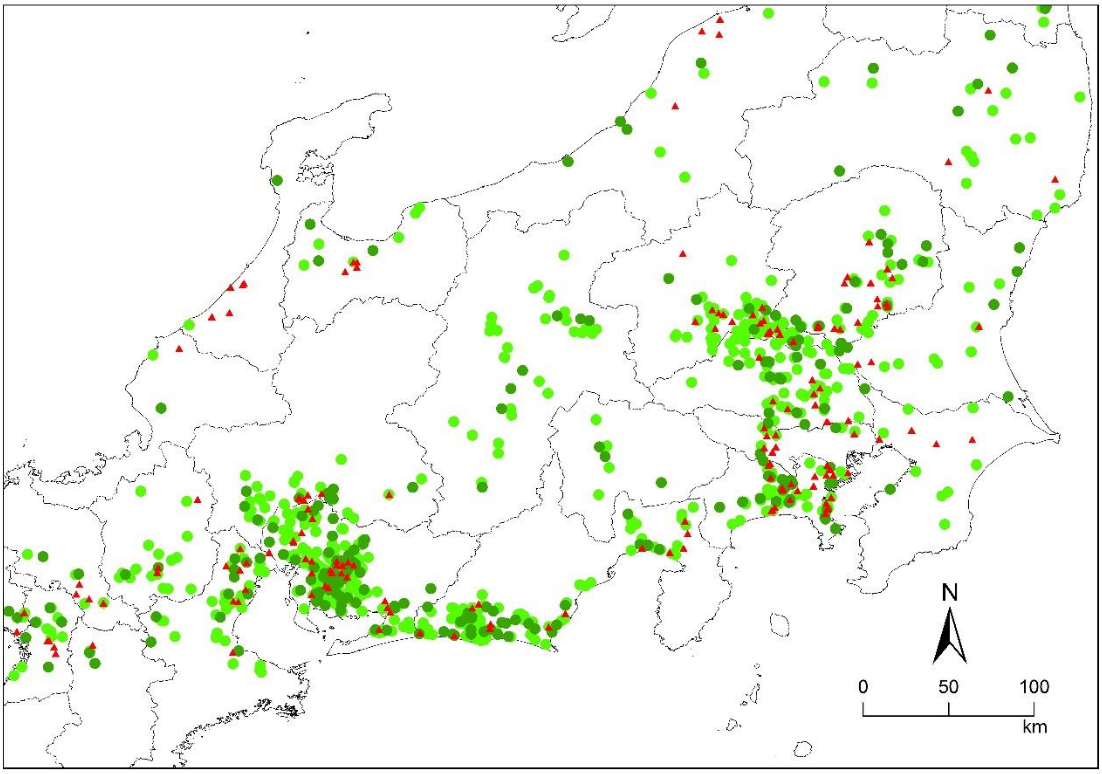

Figure 3. Spatial pattern of technological change for parts and accessories manufacturers with 100 or more employees

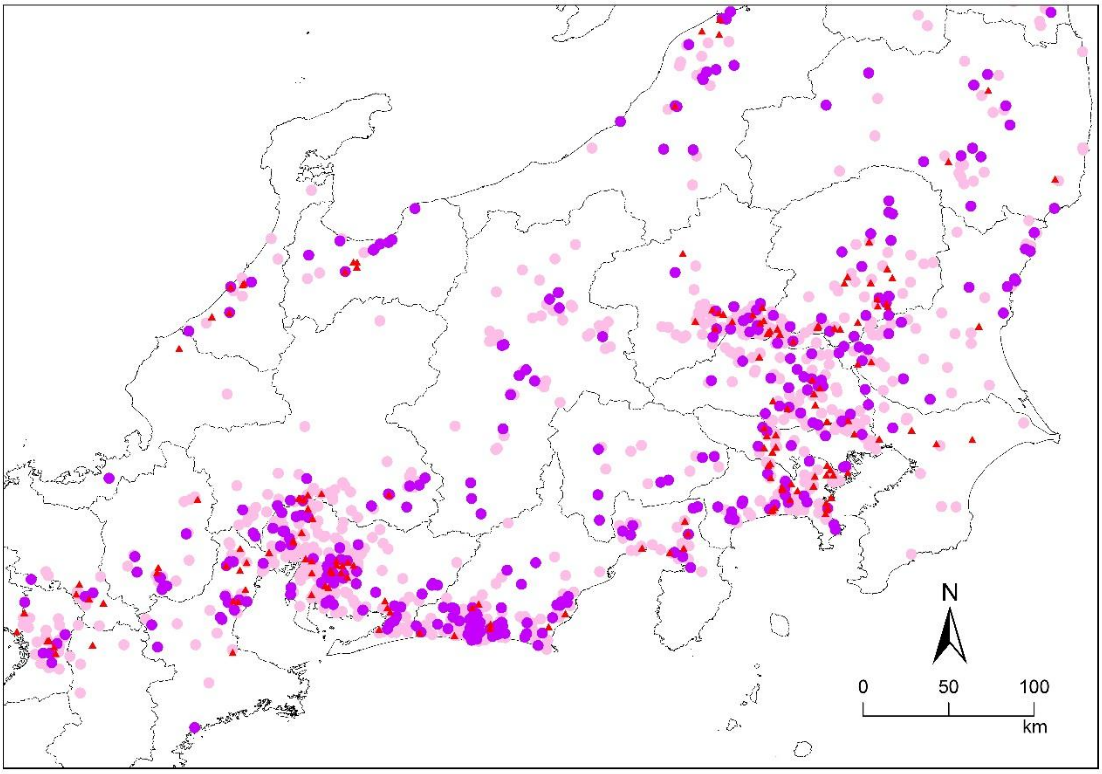

Figure 4. Spatial pattern of technological change for parts and accessories manufacturers with less than 100 employees