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Eri Yamada and Tetsu Kawakami

Abstract In this paper, we first apply the methods of exploratory spatial data analysis (ESDA) and investigate the geographic concentration of interrelated growing industries, or "growth clusters," by using data from the Nagoya metropolitan area in Japan over the period 1986–2006. Second, by applying econometric models, we examine whether and which type of knowledge externalities contribute to region–industry dynamics and to the formulation of the detected growth cluster. As a methodological contribution, spatial dependence caused by the geographical proximity between regions and the technological proximity between industries is incorporated into the empirical models. Combining the information obtained from the ESDA and econometric analysis enables us to assess the role of knowledge externalities for regional growth from a cluster perspective. The empirical results identify the presence of a growth cluster mainly driven by the automobile and associated industries. We find that intra-industry externalities help the substantial growth of the automobile industry and diffuse over a broader area in the cluster. In the core of the cluster, the diversified interrelated structure also contributes to the growth of both the auto-related and non-auto-related manufacturing sectors.

JEL Classifications C31, O18, R11

Keywords Dynamic externality, Knowledge spillover, Exploratory spatial data analysis, Technological proximity, Growth cluster

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1. Introduction

There is a growing body of work confirming that externalities of knowledge spillovers resulting from industrial agglomeration drive economic growth in cities and regions. Following the attention paid to industrial scope by Glaeser et al. (1992), empirical studies have investigated the role of these dynamic externalities for various geographical scales and industrial aggregations.[1] What is still an on-going debate is the exact nature of spillovers that facilitate growth. Marshall–Arrow–Romer (MAR) externalities concern knowledge spillovers enhanced by the agglomeration of local firms within the same industry (Marshall 1920; Arrow 1962; Romer 1986). On the other hand, Jacobs (1969) argues that knowledge spillovers come from outside the industry and stresses agglomeration containing diverse industries for growth. The difference between MAR and Jacobs' externalities are also recognized in the local competition environment. MAR predicts that a local monopoly restricting and internalizing the flow of ideas is better for growth, whereas Jacobs favors local competition to foster the pursuit and adoption of technology. The hypothesis proposed by Porter (1990) is a mix of MAR and Jacobs, and describes knowledge spillovers that are enhanced within the same competitive industries. De Groot et al. (2009) conclude that the evidence as to which type of agglomeration externality is most beneficial for growth is rather mixed and differs across regions, sectors, and time periods.

From a policy perspective, these empirical studies on dynamic externalities provide a significant basis for recent regional development policies. This is particularly true of industrial cluster policies, which have attracted policymakers and been launched in various countries since the 1990s. However, to draw more meaningful policy implications, a closer look at disaggregated spatial levels is required.[2] Note that the spillover effects of knowledge externalities tend to grow stronger as the geographical unit of reference becomes smaller (Jaffe et al. 1993; Baptista 2000). This implies that, when analyzed on smaller spatial scales, an analytical framework that explicitly focuses on geographical proximate dependence would be more informative.[3]

In addition to geographical proximity, recent literature emphasizes the role of

[1] See, for example, Henderson et al. (1995); Feldman and Audretsch (1999); Combes (2000); Drennan et al. (2002); De Lucio et al. (2002); Henderson (2003); Suedekum and Blien (2005); Van Oort (2007); Lim (2007); De Vor and De Groot (2010).

[2] Van Oort (2007) applies a Dutch municipal data set on sectoral employment and specifies the econometric models by hierarchical spatial regimes. De Vol and De Groot (2010) investigate the performance of industrial sites in Amsterdam. Audretsch et al. (2012) apply West German planning regions to test the interrelation between regional characteristics and entrepreneurial activities.

[3] Van Oort (2007) and Lim (2007) introduce spatially lagged explained and explanatory variables into the econometric models. Both studies find significant evidence of spatial dependence in regional growth, but do not confirm clear evidence about geographic knowledge spillover effects.

technological relatedness or proximity for regional growth. Porter (2003) claims that, from a cluster perspective, the hypotheses argued by MAR and Jacobs are too simple, and that the relevant knowledge spillovers should be strongest within clusters and among related industries. Previous studies have proposed several measures to establish relatedness across products. The measures frequently used are based on standard classifications of industries. Here, a subset of larger digit industrial codes within a smaller digit group is regarded as related, whereas industries classified into the other smaller digits are unrelated (Henderson et al. 1995; Lim 2007; Frenken et al. 2007). Boschma et al. (2012) show that the agnostic outcomes-based measures developed by Porter (2003) and Hidalgo et al. (2007) better capture the degree of relatedness to explain regional growth than do the conventional *ex ante* classifications of relatedness.

An expanding body of literature suggests that spatial proximity in both geographical and technological aspects matters to the knowledge transfers that contribute to growth. However, these studies do not give adequate evidence capturing both proximity aspects simultaneously. Yamada and Kawakami (2012) point out that considering geographical proximity alone would fail to detect the significant associations of industries in clusters, and argue for the need to incorporate both proximity aspects in empirical modeling. To establish more reliable statistical inferences, we consider the geographical and technological proximities simultaneously by introducing the extensive spatial weight matrix into the models. As an indicator of technological proximity in particular, we apply the *average propagation length* (APL) proposed by Dietzenbacher et al. (2005). APL is an index that expresses the average number of steps it takes to transmit a demand-pull (or cost-push) from one sector to another. If knowledge transfers are more likely to occur in the nearer rounds of input and output flows, APL is suitable for testing the role played by industry relatedness in growth.

In view of these discussions, the purpose of this paper is twofold. The first is to detect the geographic concentration of interrelated growing industries in a particular location, or “growth clusters,” by using exploratory spatial data analysis (ESDA). Finding growth clusters is becoming more important for policymakers, since, as Porter (1998) put it, government should reinforce and build on existing and emerging clusters rather than attempt to create entirely new ones. Our second purpose is to examine whether and which type of knowledge externalities contribute to the dynamics of a region–industry and, in particular, to the detected growth cluster. We aim to contribute to the debate on dynamic externalities by elaborating on the importance of spillover effects across geographical and technological proximate industries.

We analyze the manufacturing and service sectors in the detailed county-level regions of the Nagoya metropolitan area (hereafter, the Nagoya MA) in Japan, where there is a prominent agglomeration of automobile enterprises, including Toyota Motor Corporation and their related industries. The Nagoya MA has prospered, growing into a global automotive manufacturing center, while at the same time, Metro Detroit has slid into decline. Based on the Industrial Cluster Project, the Ministry of Economy, Trade and Industry (METI) designated the Nagoya MA as a region to promote effective innovations and new technology in manufacturing industries (METI, 2009). Therefore, clarifying the diffuse nature of externalities in this area is of great interest from both an academic and a policy perspective.

The rest of the paper is structured as follows. Section 2 describes the data. Section 3 presents a formal definition of the extensive spatial weight matrix on which the proximity of region–industries relies, and implements ESDA to detect growth clusters in the Nagoya MA. Section 4 specifies the econometric model used to examine the causal relationship between a region–industry's growth and knowledge externalities and presents the results. Section 5 concludes the paper.

2. Study area and data description

The Nagoya MA, with a population of around 10 million as of 2012, is the third largest metropolitan area in Japan after the Tokyo and Osaka MAs (see Figure 1).[4] This area extends into three prefectures, Gifu, Aichi, and Mie, and is subdivided into 13 districts. Each district is broken further into counties, *shi*, *ku*, *cho*, and *mura*, which are the smallest administrative divisions in the Population Census of Japan. Usually, regional economic development initiatives are planned and implemented according to the above three administrative boundaries, in other words, prefectures, districts, and counties. The following empirical studies are based on the data of the 118 counties included in the Nagoya MA.

(Fig. 1 around here)

We briefly describe the data to provide an impression of the industrial structure in the Nagoya MA. We use data extracted from the Establishment and Enterprise Census of 1986, 1991, 1996, 1999, 2001, 2004, and 2006, produced by the Ministry of

[4] The geographical coverage of this study is based on the *Metropolitan Employment Area* proposed by Kanemoto and Tokuoka (2002), which is defined in terms of population density and commuting flows. The residential population is taken from the Basic Resident Register.

International Affairs and Communications.[5] Each contains information on the number of employees and establishments on both a geographical and industrial level.

Table 1 presents the number of employees by industry in 1986 and 2006, together with the compound annual growth rates (CAGR) over this period. The data sample comprises 20 manufacturing (including construction) and 11 service sectors. It appears that, in 1986, the manufacturing sectors (sectors 1–20) accounted for 43% of total employment, while services (sectors 21–31) represented around 56%. The most represented sector is wholesale and retail (sector 23), followed by personal services (sector 30). Over the period 1986–2006, most service employment grew, accumulating to 66% of total employment, whereas manufacturing decreased to a share of 33%.[6] However, among the manufacturing sectors, transportation (sector 19) showed a CAGR of 1.2%, which subsequently stimulated growth in those sectors strongly related to transportation, such as plastic, rubber, and electrical (sectors 10, 11, and 18).

Two additional indicators are presented in Table 1 that reveals more detailed characteristics of the Nagoya MA industries. According to the employment CAGR by industry in the three major MAs (Tokyo, Osaka, and Nagoya), the trend of employment growth in Nagoya appears similar to Tokyo and Osaka (i.e., growth in service sectors, and shrinking of manufacturing sectors). However, the positive growth rates for transportation, plastic, rubber and electronics are only reported in Nagoya. Another indicator that shows the degree of industrial concentration is the county–industry's share of county employment relative to the industry's share of the three major MAs employment in 1986. On the whole, the manufacturing sectors in Nagoya are more concentrated than those in Tokyo and Osaka. In particular, the degree of concentration is remarkable for the textile and apparel, lumber, ceramic, and transportation sectors (sectors 3, 4, 13, and 19), while the service sectors other than utilities and public services (sectors 21 and 31) are less concentrated in the Nagoya MAs.

(Table 1 around here)

Table 2 lists the top three industries that are highly concentrated in each district. As shown, the manufacturing sectors dominate services in all districts other than Gifu, Nagoya, and Chusei (districts 1, 5, and 12), which contain the prefectural capitals. Of the concentrated manufacturing sectors, the textile and apparel sector is distributed

[5] Since the past census surveys were not regularly conducted, our data set is based on a panel with irregular periods.

[6] Of the service sectors, the only sector with a decrease in employment is finance and insurance (sector 24), presumably due to the burst of the Japanese bubble economy in the early 1990s.

among the north western districts (districts 1, 2, and 6), while ceramics is concentrated in the northern area (districts 2, 3, 4, and 7) and Chita (district 8). There is a substantial concentration of transportation in West Mikawa (district 9), including a prominent agglomeration of transportation machinery and related industries. A number of plants that process imported resources are located in Chita and Hokusei (districts 8 and 11), as this is where the international hub ports designated by Japanese government are located.

(Table 2 around here)

Table 3 shows the county–industries with the ten highest and lowest CAGR of employment. Seven of the ten highest CAGR sectors are business services and two are medical, health care, and welfare. Rapidly declining sectors include textile and apparel, and some manufacturing sectors. To plan efficient regional development policies, policymakers need to know if these county–industries are being affected by some exogenous (inter)national trends or by endogenous region-specific conditions.

(Table 3 around here)

In the following empirical studies, we manipulate the data from 777 region industries, each of which employed over 1,000 people as of 1986, since we aim to highlight long-term industrial growth due to the considerable scale of initial agglomeration.

3. Detecting growth clusters

Applying the ESDA method, we explore the spatial pattern of industry dynamics in the Nagoya MA counties. ESDA is a collection of techniques used to describe and visualize spatial distributions; identify atypical locations or spatial outliers; discover patterns of spatial association, clusters, or hot spots; and suggest spatial regimes or other forms of spatial heterogeneity (Anselin 1994).

3.1. Spatial weight matrix

For ESDA purposes, we summarize the proximity of units under observations by defining a spatial weight matrix. In this study, the growth of industry i $(i = 1, \cdots, N_i)$ in region r $(r = 1, \cdots, N_r)$ is employed as the observation so that the scale of the spatial weight matrix is extended to $N_r N_i \times N_r N_i$. That is, an extensive spatial weight matrix that reflects both the geographical and technological proximities is put forward. The construction of the extensive spatial weight matrix builds on the work of Yamada and Kawakami (2012).

The geographical proximity between industry i in region r and industry j in region s is denoted by $w_{ri,sj}^{geo}$, and defined as follows:

$$\begin{cases} w_{ri,sj}^{geo} = 1/d_{rs} \quad if \ \ r \neq s \\ w_{ri,sj}^{geo} = 1/0.5 d_{rs}^{min} \quad if \ \ r = s \end{cases} \tag{1}$$

where d_{rs} is the transportation time by road between the municipal offices of counties r and s. Using the National Integrated Transportation Analysis System developed by the Ministry of Land, Infrastructure, Transport and Tourism, the values of d_{rs} of the road networks in 1991 are measured so that the generalized cost of each connection is at a minimum. The geographical linkages between industries i and j (with $i \neq j$) within the same county are given as half the time distance to the nearest neighbor, $0.5 d_{rs}^{min}$, as defined by the second equation of Eq. 1.

Technological proximity is measured using the average propagation length (APL) developed by Dietzenbacher et al. (2005). The APL is an index that measures how closely the round flows of intermediate goods between industries arise, and can be used to represent an "economic distance."[7] In the conventional input–output model, we can extend the Leontief inverse matrix with endogenized imports, say $\mathbf{L}$, to a power series after neglecting the initial exogenous injection:

$$\mathbf{L} - \mathbf{I} = (\mathbf{I} - \widehat{\mathbf{M}})\mathbf{A} + \{(\mathbf{I} - \widehat{\mathbf{M}})\mathbf{A}\}^2 + \{(\mathbf{I} - \widehat{\mathbf{M}})\mathbf{A}\}^3 + \cdots \tag{2}$$

where $\mathbf{I}$ denotes the identity matrix and $\mathbf{A}$ is the input coefficient matrix. The import coefficient matrix, $\widehat{\mathbf{M}}$, has a diagonal element, which gives the import share of the domestic products in each sector. The APL is defined as the weighted average of production rounds in industry i required for a demand-pull in industry j. Using the share of the total effect required in each round as a weight, the APL between industries i and j, apl_{ij}, is the element of the following matrix:

$$\mathbf{APL} = [1 \cdot (\mathbf{I} - \widehat{\mathbf{M}})\mathbf{A} + 2 \cdot \{(\mathbf{I} - \widehat{\mathbf{M}})\mathbf{A}\}^2 + 3 \cdot \{(\mathbf{I} - \widehat{\mathbf{M}})\mathbf{A}\}^3 + \cdots]./(\mathbf{L} - \mathbf{I}) \tag{3}$$

where "./" represents element-by-element division. After some matrix algebra, Eq. 3 can be rewritten as:

$$\mathbf{APL} = \mathbf{L}(\mathbf{L} - \mathbf{I})./(\mathbf{L} - \mathbf{I}) \tag{4}$$

The APL can also be interpreted from the cost-push direction. In this case, apl_{ij} measures the weighted average number of steps it takes an exogenous cost-push in

[7] Antras et al. (2012) introduce a measure analogous to the APLs to describe industry "upstreamness," or average distance from final use.

industry i to affect industry j (Dietzenbacher et al. 2005).

We also reflect the size of the linkage between industries in terms of the technological proximity. In line with the fact that the APLs can be interpreted from demand-pull and cost-push directions, the size of the linkages is given by the matrix $\mathbf{F}$, with elements f_{ij}, which are defined as the average of the backward effect of a demand-pull and the forward effect of a cost-push:

$$\mathbf{F} = 0.5 \times \{(\mathbf{L} - \mathbf{I}) + (\mathbf{G} - \mathbf{I})\} \tag{5}$$

where $\mathbf{G}$ denotes the Ghosh inverse.

Since we do not establish the direction of the technological proximity *a priori*, we take the average of the size of the linkage between industries i and j. The economic distance between industries i and j is also given by the weighted average, each of which is weighted by the respective size of the linkage:

$$\begin{aligned} \bar{f}_{ij} &= \bar{f}_{ji} = 0.5 \times (f_{ij} + f_{ji}) \\ \overline{apl}_{ij} &= \overline{apl}_{ji} = (f_{ij} \cdot apl_{ij} + f_{ji} \cdot apl_{ji})/(f_{ij} + f_{ji}) \end{aligned} \tag{6}$$

The technological proximity between industry i in region r and industry j in region s is denoted by $w_{ri,sj}^{tech}$, and defined as follows:[8]

$$\begin{cases} w_{ri,sj}^{tech} = \bar{f}_{ij}/\overline{apl}_{ij} \quad if \;\; \bar{f}_{ij}/\overline{apl}_{ij} \geq 0.01 \\ w_{ri,sj}^{tech} = 0 \quad if \;\; \bar{f}_{ij}/\overline{apl}_{ij} < 0.01 \end{cases} \tag{7}$$

As with the relatedness measures introduced by Hidalgo et al. (2007) and Boschma et al. (2012), we place the critical cutoff threshold on the technological proximity. We consider that industries have an intra- or inter-sectoral linkage if their proximity is greater than 0.01. For our empirical analysis, the technological proximity between 31 industries is measured using the input–output table of the Chubu region for 1990, as developed by the Chubu Bureau of Economy, Trade, and Industry. While the Chubu region is geographically bigger than the Nagoya MA, the Nagoya MA has 74% of the number of employees in the Chubu region, as of 1986. Figure 2 presents the distribution of the proximity values calculated from our sample, and shows that 27.6% of all industry combinations meet the criterion.

(Fig. 2 around here)

Finally, each element of the extensive spatial weight matrix, $w_{ri,sj}$, is defined as the product of the geographical weight and the technological weight, as follows:

$$w_{ri,sj} = w_{ri,sj}^{geo} \times w_{ri,sj}^{tech} \tag{8}$$

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[8] Franco et al. (2010) analyze the impact on total factor productivity of trade-related R&D spillovers by introducing a similar measure using the economic distance between countries.

3.2. Exploratory spatial data analysis

We conduct a detailed statistical analysis of local spatial association focusing on the region–industry's growth. One of the local spatial statistics that allows for testing a hypothesis about the spatial dependence of the variable is the local Moran, which is a kind of local indicator of spatial association (LISA), as defined by Anselin (1995). In this study, we extend the local Moran statistics of industry i in region r to a geographical and technological space context, as follows:

$$I_{ri} = \frac{y_{ri} - \bar{y}}{m} \sum_{s} \sum_{j} w_{ri,sj} \left(y_{ri} - \bar{y} \right) \tag{9}$$

where:

$$m = \sum_{r} \sum_{i} \frac{(y_{ri} - \bar{y})^2}{N_r N_i}$$

We focus here on the adjusted long-term employment growth of industry i in region r, y_{ri}, which is not affected by the industry-mix or time-specific effects.[9] Further, to reflect the respective importance of region–industry to aggregate employment, we apply the observations weighted by the region–industry's share of the aggregate employment across all industries.

Note that a positive (negative) local Moran value indicates positive (negative) spatial autocorrelation or spatial similarities (dissimilarities). Combining the information obtained from the local Moran values and the Moran scatterplot, we can assess whether each industry in any of the four quadrants is significantly associated with geographical and technological proximate industries.[10] For the Nagoya MA as a whole, 297 industries (38.2% of the total sample) are significant at the 5% pseudo-significance level.[11] Of these, 105 industries (13.5%) fall within quadrant I in the scatterplot, and 116 industries (14.9%) within quadrant III; 28.4% of the regional industries exhibit significant positive spatial associations. Meanwhile, 76 industries (9.8%) exhibit significant atypical patterns; 30 industries (3.9%) fall within quadrant IV and 46 industries (5.9%) within quadrant II.

We undertake a detailed analysis of whether the growing industries form a cluster

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[9] An error-component model that decomposes the growth rates into the contributions specific to regional, industrial, temporal, and their combination effects is specified. We then employ the decomposed region and region–industry specific components as the ESDA observations. Refer to Yamada and Kawakami (2012) for details of the estimation.

[10] The Moran scatterplot splits the sample into the four quadrants: quadrant I (III) shows growing (declining) regional industries accompanied by their growing (declining) neighbors. Quadrant II (IV) shows growing regional industries accompanied by declining (growing) neighbors.

[11] To implement statistical inferences, the empirical distribution function is derived using 9,999 conditional permutations (Anselin 1995) for each of the local Moran statistics.

with geographical and technological neighbors. To detect growth clusters, we focus in particular on the geographical distribution of the significant region–industries classified into quadrant I. Figure 3 visualizes the result of the local spatial statistics on maps, where each county is categorized using a color code according to the number of local spatial statistics judged to be significant.

(Fig. 3 around here)

Figure 3 reveals that a growth cluster is formed as a core in West Mikawa, and extends, leaping over the center of the MA, to the peripheral counties in the Gifu and Mie prefectures.[12] Regardless of the core or periphery of the cluster, all 45 shaded counties in Figure 3 contain transportation equipment and/or transportation-related industries as highly significant industries. In particular, transportation equipment, with significant local spatial statistics, is observed in the 29 counties. This result confirms, with statistical significance, that the growth cluster is driven mainly by the automobile and associated industries. The dark-shaded counties on the map are Toyota-shi and Okazaki-shi, which contain 12 and 10 of the constituent industries, respectively. It is worth noting that the core of the cluster contains not only manufacturing (plastic, rubber, electrical machinery, transportation equipment, fabricated metal, general machinery, and construction), but also several service sectors (transport, wholesale and retail, finance and insurance, education and research, and business services). However, the periphery of the cluster has less variety, mostly containing transportation equipment and/or a few manufacturing sectors that are technologically proximate to transportation, such as electrical machinery. In the next section, we examine whether and which type of knowledge externalities contribute to the formulation of this detected growth cluster by estimating econometric models.

4. Econometric analysis of dynamic externalities

4.1. Empirical specification

The presence of dynamic externalities associated with the location-specific industrial agglomeration is investigated by estimating econometric models. Following the framework developed by Glaeser et al. (1992) and Henderson et al. (1995), the model

[12] In Nagoya-shi (district 5 in Figure 1), located in the center of the MA, the significant geographic concentration composed of shrinking manufacturing and service sectors is detected. For more details, refer to Yamada and Kawakami (2012).

specification is based on a reduced form equation. Here, the long-term employment industry growth rates in regions are determined by, among others, the growth of location-specific technology. Specifically, the model under study hypothesizes that the growth of county-specific technology is an exponential function of the initial industrial structure expressed by concentration ($CONC$), diversity (DIV), and competition ($COMP$), as follows:

$$A_{r,i,t} = A_{r,i,t-1} exp\left[g\left(CONC_{r,i,0}, DIV_{r,i,0}, COMP_{r,i,0}\right)t\right] \tag{10}$$

where $A_{r,i,t}$ represents the level of technology specific to region r and industry i at year t.

We reflect the technological proximity in the usually used measures for testing dynamic externalities in each region. Our measure of the extent of concentration is given by:

$$CONC_{r,i,0} = w_{ri,ri} \times \frac{Emp_{r,i,0}/\sum_r Emp_{r,i,0}}{\sum_i Emp_{r,i,0}/\sum_r \sum_i Emp_{r,i,0}} \tag{11}$$

where Emp denotes employment. The second term of Eq. 11 is the fraction of region r's employment share of industry i, relative to region r's share of the overall industry. Since we consider a relatively small area as a sample, local concentration is better expressed by referring to the three major MAs (Tokyo, Osaka, and Nagoya), rather than only to Nagoya. Multiplying this ratio by the extensive spatial weight ($w_{ri,ri}$), the region–industries with strong intra-industrial proximities are evaluated as highly concentrated.

The diversity index represents a variety of industries. It is measured by the inverse of the Hirschman–Herfindahl index (HHI), which is a slight modification of the index proposed by Adelman (1969) and Henderson et al. (1995). Formally, let S_r denote the set of industries technologically proximate to the industry in question.[13] With the employment share of industry i of the technologically proximate industries (including industry i itself), the diversity index is given by:

$$DIV_{r,i,0} = 1/HHI_{r,i,0} \text{ with } HHI_{r,i,0} = \sum_{j\in S_r}\left(\frac{Emp_{r,i,0}}{\sum_{j\in S_r} Emp_{r,j,0}}\right)^2 \tag{12}$$

For industry i, the larger this value, the more diverse the region.

To more closely inspect the competition hypothesis, we introduce the two measures of intra- and inter-industry competition. Intra-industry competition is captured by the number of establishments per employee in the region–industry relative to the establishments per employee in this industry for all three major MAs:

[13] As described in section 3, how technologically proximate industries j is to industry i is judged on the threshold value of proximity being at least equal to 0.01.

$$COMP_{r,i,0}^{intra} = w_{ri,ri} \times \frac{Est_{r,i,0}/Emp_{r,i,0}}{\sum_r Est_{r,i,0}/\sum_r Emp_{r,i,0}} \tag{13}$$

where Est denotes the number of establishments. As with the concentration index, after multiplying the ratio by $w_{ri,ri}$, the region–industries with strong intra-industrial proximities are evaluated to be highly competitive.

The measure of inter-industry competition for industry i captures the extent to which industry j, which is closely related to, but not involving industry i, is competitive in region r. We consider the number of establishments per employee in industry j, which is technologically proximate to industry i, in terms of the overall number in the three major MAs. Since the number of proximate industries, j, varies by industry, the inter-industry competition is given by the window weighted average of the relative competition:

$$COMP_{r,i,0}^{inter} = \sum_{j \in S_r, j \neq i} \left[w_{ri,rj} \times \frac{Est_{r,j,0}/Emp_{r,j,0}}{\sum_r Est_{r,j,0}/\sum_r Emp_{r,j,0}} \right] \Big/ \sum_{j \in S_r, j \neq i} w_{ri,rj} \tag{14}$$

where using the extensive spatial weights within a region replaces the value for an industry with an average based on the values of the proximate industries.

Except for the measures of intra- and inter-industry externalities, the following control variables are included in the regression models: the log of initial employment of industry i in region r ($LNEMP_{r,i,0}$); the log of initial wage in industry i at the prefectural level ($LNWAGE_{i,0}$); and the log of initial industry-wide wage in region r ($LNWAGE_{r,0}$). To correct for the industry-mix and temporal demand shifts, we also incorporate the following national employment change: the employment CAGR in industry i in Japan during the period from $t-1$ to t ($GRNATION_{i,t}$); the industry-wide CAGR of employment in Japan during the period from $t-1$ to t ($GRNATION_t$); and the employment CAGR in industry i in Japan over the entire period ($GRNATION_i$).

To explain employment growth across region–industries using the abovementioned explanatory variables, we can specify the empirical model as follows:

$$\begin{aligned} GROWTH_{r,i,t} = {} & \beta_0 + \beta_1 CONC_{r,i,0} + \beta_2 DIV_{r,i,0} + \beta_3\, COMP_{r,i,0}^{intra} + \beta_4 COMP_{r,i,0}^{inter} \\ & + \beta_5 LNEMP_{r,i,0} + \beta_6 LNWAGE_{i,0} + \beta_7 LNWAGE_{r,0} \\ & + \beta_8 GRNATION_{i,t} + \beta_9 GRNATION_t + \beta_{10} GRNATION_i + \varepsilon_{r,i,t} \end{aligned} \tag{15}$$

where $GROWTH_{r,i,t}$ denotes the employment CAGR across region–industries in each period, and $\varepsilon_{r,i,t}$ is an idiosyncratic disturbance assumed to be orthogonal to the explanatory variables. All independent variables other than the national employment changes were measured in 1986.

As suggested by Henderson et al. (1995), the regression parameters for the externality indices could take on distinct values in subsets of industries. Given that the growth cluster appears to be driven by transportation equipment and its related industries, the model considers the structural instability of the coefficients among auto-related manufacturing $(Auto\_MANU)$, auto-related services $(Auto\_SERV)$, and other manufacturing $(Other\_MANU)$ and services $(Other\_SERV)$.[14] To address an inherent heteroskedasticity problem, the entire estimation model is then weighted by the region–industry's employment share of the aggregate employment across all industries during the period. This weight also reflects each region–industry's relative importance to aggregate employment.

4.2. Estimation results

We pool the all the observations and start with an ordinary least squares (OLS) estimate. As shown in column (1) of Table 4, the Lagrange multiplier tests indicate both spatial-lag and spatial-error dependence in the OLS estimation. Following the outline in Florax et al. (2003), we carry out the robust versions of the Lagrange multiplier tests for spatial-lag and spatial-error dependence (Anselin et al, 1996), with the result that the spatial error model (SEM) seems to be the appropriate specification. The result based on the SEM in column (2) differs very little from that estimated by the OLS.[15]

(Table 4 around here)

The effect of knowledge externalities does not necessarily diffuse only within a county, and may transcend geographical boundaries. To conduct a detailed investigation on geographical spillover effects, we also estimate the models that replace the domestic externality measures in Eq. 15 with the locally weighted average of these measures.[16] Note that, in contrast to standard practice in spatial autocorrelation analysis, the location itself is included by setting the weights $w_{ri,ri}$ when taking an average (Anselin et al. 2006). Each locally weighted measure of externalities is denoted by the prefix "LW". The result estimated by OLS is shown in

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[14] For the definition of the sectoral subsets, see Appendix.

[15] For the spatial weight matrix reflecting the geographical and technological dependence in the disturbance term, say $\mathbf{W}$, we replace the diagonal elements of the extensive spatial weight matrix by zero and convert it to have row sums of unity. Further, since we use the sample for six periods, the spatial weight matrix is extended by $\mathbf{W} \otimes \mathbf{I_6}$.

[16] As an example, the locally weighted measure of concentration is given by:

$$LW\_CONC_{r,i,0} = \sum_s \left[w_{ri,si} \times \frac{Emp_{s,i,0}/\sum_r Emp_{r,i,0}}{\sum_i Emp_{s,i,0}/\sum_r \sum_i Emp_{r,i,0}} \right] / \sum_s w_{ri,si}$$

Strictly speaking, since we take an average by using the extensive spatial weights, the locally weighted measures also consider the technological proximity to geographical neighbors.

column (1) of Table 5. The result based on the SEM is shown in column (2).

(Table 5 around here)

In terms of the control variables, there is not much difference between the results shown in Tables 4 and 5. The coefficients on the initial level of employment are significantly negative, with the exception of non-auto-related manufacturing. In the auto-related industries, high wages lead to faster growth in employment. The substantial positive coefficients on $GRNATION_{i,t}$ indicate that employment growth in the region–industries is associated with the national trends specific to the industries. The coefficients of $GRNATION_t$ and $GRNATION_i$ are significantly positive in the service sectors, whereas those of $GRNATION_t$ are negative in the manufacturing sectors. This suggests that national employment growth promotes a shift of regional employment from manufacturing to services.

The estimated results on externalities unveil several interesting findings. Table 4 shows that, for auto-related manufacturing, the effects of within-county concentration ($CONC_{r,i,0}$) and intra-competition ($COMP_{r,i,0}^{intra}$) are not significant in terms of growth. However, as shown in Table 5, the coefficients of the locally weighted measures of concentration ($LW\_CONC_{r,i,0}$) and intra-competition ($LW\_COMP_{r,i,0}^{intra}$) are significantly positive and negative, respectively. These results are consistent with the hypothesis stressed by MAR when we consider the effects of externalities in a broader area than the county. The MAR-type externalities diffuse beyond the county boundaries and help the substantial growth of transportation equipment in particular, which accounts for the largest share of employment in the auto-related industries. Furthermore, the diversity of related industries ($DIV_{r,i,0}$) matters to the growth of the auto-related industries. The effect of diversity becomes stronger when we use the locally weighted measure ($LW\_DIV_{r,i,0}$), suggesting that the externalities from outside the industry also transcend county boundaries. For non-auto-related manufacturing, the coefficient of $LW\_DIV_{r,i,0}$ is significantly positive, although that of $DIV_{r,i,0}$ is not significant. The diversified industrial structure in a broader area than the county is important for growth of, in particular, fabricated metal and general machinery, for which the values of $LW\_DIV_{r,i,0}$ are substantial.

It is observed that the MAR hypothesis is significantly supported by the coefficients of $CONC_{r,i,0}$ and $COMP_{r,i,0}^{intra}$ for the auto-related services, but not by those of $LW\_CONC_{r,i,0}$ and $LW\_COMP_{r,i,0}^{intra}$. In contrast to auto-related manufacturing, this outcome confirms the MAR externality that diffuses only within the county. The significant positive estimates of $COMP_{r,i,0}^{inter}$ and $LW\_COMP_{r,i,0}^{inter}$ suggest that more competition among firms in related industries promotes growth in auto-related services. For non-auto-related services, concentration within their own industries retards their growth. The negative effect of concentration becomes much stronger when we use $COMP_{r,i,0}^{intra}$ rather than $LW\_COMP_{r,i,0}^{intra}$ as the competition measure.

Based on these econometric analysis results, we elaborate on how knowledge externalities contribute to the formulation of the growth cluster shown in Figure 3. Transportation equipment that is regionally concentrated over a broader area in the detected cluster benefits from within-industry knowledge transfers, and realizes steady growth. Transportation equipment located around the core (West Mikawa) grows faster than that in the periphery, because of its higher concentration and larger-scale establishments around the core. A certain amount of both auto-related and non-auto-related manufacturing sectors in the core enables them to share in the benefits of the diversified productive structure and contributes to their growth. For the development of the periphery of the cluster, the formation of inter-related concentrations, if not a diversified structure, should be reinforced.

According to the results of the ESDA, we also find some growing auto-related services accompanied by geographical and technological neighbors in the core. The econometric analysis proves that the auto-related services benefit from the MAR-type externalities, but this is not the case for the growing services in the core. The extent of the concentration and establishment size is far smaller in the core of the cluster than in the center of the Nagoya MA. Hence, the growth of some services observed in the core would not be attributed to knowledge spillovers within an industry, but would rather depend on the demand induced by expanding manufacturing outputs and the associated income growth. For further development in the core regions, our findings reveal the need to enhance the productivity of services through the channels of intra- and inter-sectoral knowledge spillovers.

5. Conclusions

This study applies the methods of ESDA and investigates the geographic concentration of interrelated growing industries, or "growth clusters," by using data from the Nagoya MA over the period 1986–2006. Further, it examines the causal relationship between region–industry dynamics and knowledge externalities by applying an econometric analysis. As a methodological contribution, spatial dependence caused by the geographical proximity among regions and the technological proximity of industrial linkages is incorporated into the empirical models applied in this study. Combining the information obtained from the ESDA and econometric analysis enables us to assess the role played by knowledge externalities in regional growth from a cluster perspective.

The result of the ESDA identifies the presence of a growth cluster that is mainly driven by the automobile and associated industries. What is noteworthy is that the constituent industries of the core of the cluster (West Mikawa) are not only manufacturing, but also include several service sectors. Meanwhile, the periphery of the cluster is composed only of transportation equipment and/or a few auto-related manufacturing.

The econometric analysis reveals evidence of MAR-type externalities in transportation equipment, which diffuse over a broader area in the detected cluster. In the core regions, the diversified interrelated structure contributes significantly to the growth of the auto-related and non-auto-related manufacturing sectors. The result also confirms that auto-related services benefit from the MAR-type externalities diffusing within the county. However, the growth of the services in the core cannot be explained by the positive endogenous effects of knowledge externalities. Instead, this growth relies mainly on the exogenous demand induced by expanding manufacturing outputs. These findings give useful information to policymakers for recent regional development policies, such as the direct R&D and indirect networking/coordination supports.

The issue that remains is how the size of establishments is related to the externalities of knowledge spillovers. The Japanese automobile and related industries are notably characterized by a vertical and hierarchical organizational structure. It might be interesting to investigate, for example, whether the different nature of the knowledge externalities is confirmed in large-sized firms at the top of the hierarchy and small- and medium-sized firms at the bottom, and what type of externalities spill over between different sizes of firms. This will be elaborated on in future research.

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(Appendix around here)

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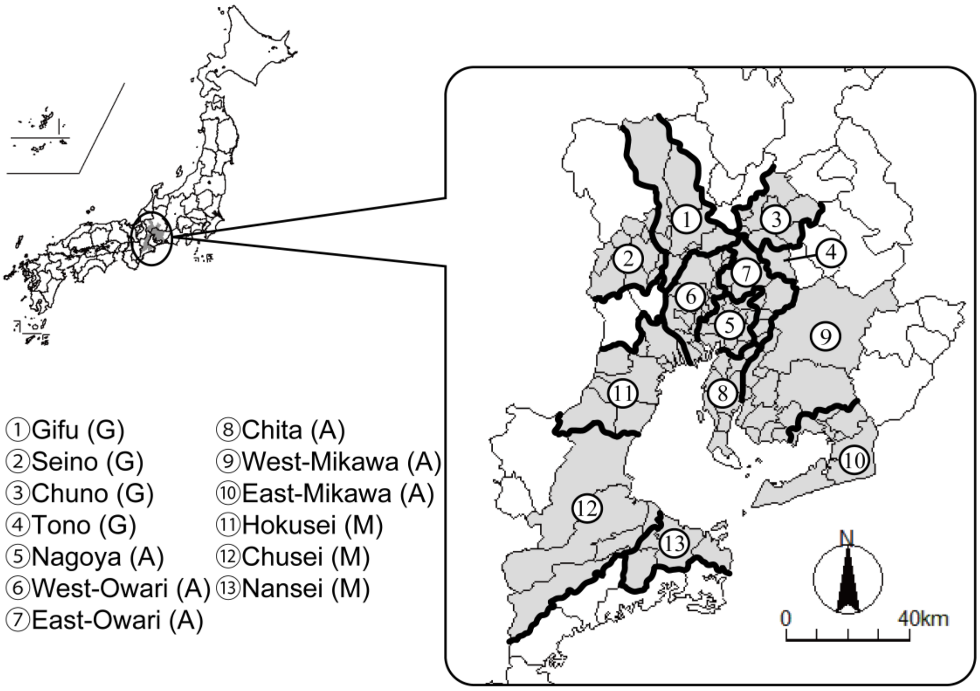

Fig. 1 The Nagoya metropolitan area

Note (G), (A), and (M) denote the districts belonging to Gifu, Aichi, and Mie prefectures, respectively.

Table 1 Industrial structure in terms of the number of employees in the Nagoya metropolitan area

No.	Industry	1986 Number of employees		2006 Number of employees		1986-2006 Employment CAGR (Nagoya MA)	1986-2006 Employment CAGR (3 major MAs)	1986 Concentration relative to the 3 majour MAs
1	Construction	324,879	7.96%	323,212	6.83%	-0.03%	-0.54%	1.03
2	Food and beverages	106,325	2.61%	105,906	2.24%	-0.02%	0.05%	1.26
3	Textile and apparel	213,758	5.24%	63,799	1.35%	-5.87%	-5.19%	2.12
4	Lumber	29,406	0.72%	14,892	0.31%	-3.34%	-3.52%	2.14
5	Furniture	38,249	0.94%	23,682	0.50%	-2.37%	-2.62%	1.83
6	Pulp and paper	27,378	0.67%	23,175	0.49%	-0.83%	-1.71%	1.02
7	Printing	46,578	1.14%	43,163	0.91%	-0.38%	-0.86%	0.56
8	Chemical	39,818	0.98%	34,348	0.73%	-0.74%	-0.46%	0.77
9	Petroleum and coal	3,548	0.09%	2,702	0.06%	-1.35%	-1.90%	0.80
10	Plastic	57,825	1.42%	65,378	1.38%	0.62%	-0.82%	1.38
11	Rubber	22,486	0.55%	24,327	0.51%	0.39%	-2.03%	1.12
12	Leather	3,647	0.09%	1,433	0.03%	-4.56%	-3.90%	0.29
13	Ceramic	96,202	2.36%	59,593	1.26%	-2.37%	-2.54%	2.70
14	Iron and steel	49,165	1.21%	37,026	0.78%	-1.41%	-2.74%	1.24
15	Non-ferrous metals	15,476	0.38%	14,833	0.31%	-0.21%	-1.78%	0.84
16	Fabricated metal	113,478	2.78%	98,672	2.08%	-0.70%	-1.78%	1.15
17	General machinery	171,935	4.21%	154,845	3.27%	-0.52%	-1.33%	1.34
18	Electrical	135,554	3.32%	139,669	2.95%	0.15%	-2.08%	0.80
19	Transportation	248,049	6.08%	315,176	6.66%	1.20%	-0.42%	2.37
20	Precision	21,238	0.52%	15,339	0.32%	-1.61%	-1.97%	0.70
21	Utilities	25,101	0.62%	32,276	0.68%	1.27%	0.94%	1.10
22	Transport	196,205	4.81%	266,185	5.62%	1.54%	0.86%	0.86
23	Wholesale and retail	953,026	23.36%	1,015,518	21.46%	0.32%	0.05%	0.93
24	Finance and insurance	121,748	2.98%	104,576	2.21%	-0.76%	-1.06%	0.74
25	Real estate	43,351	1.06%	60,387	1.28%	1.67%	1.45%	0.57
26	Information and communications	23,916	0.59%	49,407	1.04%	3.69%	4.07%	0.89
27	Education and research	49,030	1.20%	78,951	1.67%	2.41%	2.03%	0.63
28	Medical, health care and welfare	137,800	3.38%	324,113	6.85%	4.37%	4.47%	0.90
29	Business services	181,481	4.45%	481,166	10.17%	5.00%	4.18%	0.67
30	Personal sevices	487,028	11.94%	661,200	13.97%	1.54%	1.19%	0.89
31	Public services	55,000	1.35%	55,605	1.17%	0.05%	0.40%	1.16
	Total Nagoya MA	4,079,438		4,732,882		0.75%	0.58%	

Source Author's calculations based on the Establishment and Enterprise Census.

Table 2 Highly concentrated industries in each district in the Nagoya metropolitan area

No.	District	Concentraion relative to the 3 major MAs in 1986.					
		Industry	Concentration	Industry	Concentration	Industry	Concentration
1	Gifu	Textile	2.44	Public Service	1.29	Finance	1.22
2	Seino	Textile	2.19	Plastic	1.99	Ceramic	1.75
3	Chuno	Electorical machinery	2.67	Pulp	2.30	Ceramic	2.07
4	Tono	Ceramic	12.46	Pulp	2.93	Information	1.27
5	Nagoya-shi	Printing	1.73	Business service	1.60	Information	1.57
6	West Owari	Textile	3.25	Leather	1.69	Plastic	1.64
7	East Owari	Pulp	3.55	Ceramic	3.18	Rubber	2.85
8	Chita	Iron	9.12	Petroleum	5.56	Ceramic	2.78
9	West Mikawa	Transportation	3.58	Precision	2.38	General machinery	1.49
10	East Mikawa	Precision	4.07	Food	1.67	Lumber	1.55
11	Hokusei	Petroleum	6.06	Chemical	4.45	Non-ferrous Metals	2.53
12	Chusei	Public Service	2.56	Lumber	2.46	Electorical machinery	2.31
13	Nansei	Rubber	3.00	Electorical machinery	2.37	Public Service	2.00

Source Author's calculations based on the Establishment and Enterprise Census.
Note The cord number identifying the location of the districts corresponds to that in Figure 1.

Table 3 Fastest and slowest growing county–industries in the Nagoya metropolitan area

10 fastest growing region-industries			
No.	District	County	Industry
9	West Mikawa	Kariya	Business services
7	East Owari	Komaki	Business services
9	West Mikawa	Toyota	Business services
5	Nagoya	Midoriku	Medical, health care and welfare
9	West Mikawa	Anjo	Business services
1	Gifu	Kakamigahara	Business services
5	Nagoya	Nakamuraku	Business services
9	West Mikawa	Okazaki	Business services
8	Chita	Handa	Transportation
6	West Owari	Inazawa	Medical, health care and welfare

10 slowest growing region-industries			
No.	District	County	Industry
8	Chita	Higashiura	Textile and apparel
8	Chita	Handa	Textile and apparel
8	Chita	Chita	General machinery
5	Nagoya	Mizuhoku	Precision
8	Chita	Chita	Textile and apparel
8	Chita	Agui	Textile and apparel
9	West Mikawa	Kota	Textile and apparel
13	Nansei	Ise	Textile and apparel
6	West Owari	Kiyosu	Electrical
2	Seino	Tarui	Textile and apparel

Source Author's calculations based on the Establishment and Enterprise Census.

Note The cord number identifying the location of the districts corresponds to that in Figure 1.

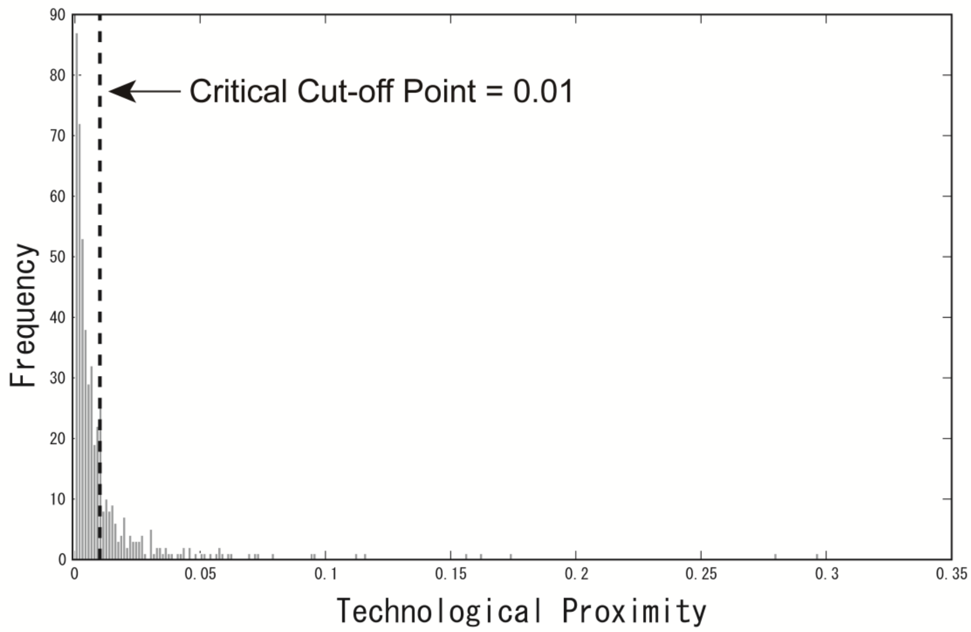

Fig. 2 Distribution of the technological proximity values
Source Author's calculations based on the input–output table of the Chubu region for 1990.

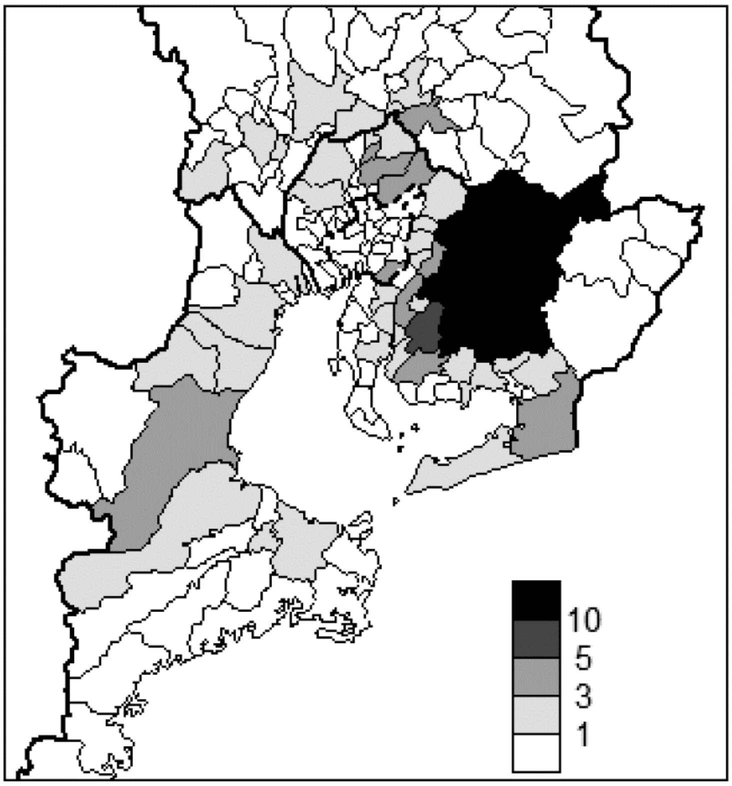

Fig. 3 Number of significant growing region–industries accompanied by the growing neighbors.

Table 4 Region–industry's employment growth between 1986 and 2006, explained by domestic externality measures

Independent variables	Dependent variable: $GROWTH_{r,i,t}$							
	(1) OLS				(2) SEM			
	Auto_MANU	Other_MANU	Auto_SERV	Other_SERV	Auto_MANU	Other_MANU	Auto_SERV	Other_SERV
Constant	-0.590 ***	0.018	-0.142 *	-0.169	-0.583 ***	0.026	-0.140 ***	-0.133
	(-3.354)	(0.082)	(-1.819)	(-1.202)	(-26.417)	(0.129)	(-3.664)	(-0.963)
$CONC_{r,i,0}$	-0.007	-0.026	0.106 ***	-0.327 ***	-0.008	-0.027	0.100 ***	-0.320 ***
	(-0.983)	(-0.705)	(3.541)	(-3.025)	(-1.266)	(-0.734)	(3.410)	(-3.068)
$DIV_{r,i,0}$	0.007 ***	0.003	-0.001	0.003 *	0.007 ***	0.002	-0.001	0.003
	(2.760)	(1.113)	(-1.331)	(1.727)	(2.815)	(0.981)	(-1.413)	(1.602)
$COMP_{r,i,0}^{intra}$	-0.135	-0.242	-0.238 ***	0.545	-0.115	-0.208	-0.223 ***	0.536
	(-1.309)	(-1.197)	(-2.803)	(1.335)	(-1.114)	(-1.011)	(-2.641)	(1.354)
$COMP_{r,i,0}^{inter}$	0.000	0.005	0.004 ***	0.003	-0.000	0.005	0.004 ***	0.002
	(0.097)	(1.190)	(3.004)	(1.122)	(-0.088)	(1.278)	(3.003)	(1.082)
$LNEMP_{r,i,0}$	-0.006 **	-0.000	-0.006 ***	-0.003	-0.006 **	-0.001	-0.006 ***	-0.004 *
	(-2.533)	(-0.072)	(-6.933)	(-1.518)	(-2.440)	(-0.552)	(-7.156)	(-1.935)
$LNWAGE_{i,0}$	0.022 **	0.011	0.025 ***	0.008	0.023 ***	0.010	0.024 ***	0.007
	(2.227)	(1.064)	(4.885)	(1.178)	(2.651)	(1.059)	(27.927)	(1.094)
$LNWAGE_{r,0}$	0.018 *	-0.013	-0.013 ***	0.003	0.016 **	-0.012	-0.012 ***	0.002
	(1.902)	(-1.304)	(-5.053)	(0.661)	(2.420)	(-1.240)	(-5.068)	(0.465)
$GRNATION_{it}$	1.035 ***	0.921 ***	0.477 ***	0.352 ***	0.955 ***	0.941 ***	0.514 ***	0.283 ***
	(9.522)	(10.101)	(7.714)	(5.516)	(8.378)	(10.235)	(8.699)	(4.576)
$GRNATION_{t}$	-0.588 ***	-0.125	0.817 ***	0.284 ***	-0.621 ***	-0.120	0.788 ***	0.356 ***
	(-4.514)	(-0.924)	(11.879)	(3.459)	(-4.526)	(-0.862)	(11.932)	(4.342)
$GRNATION_{i}$	-0.173	0.082	1.081 ***	0.770 ***	-0.162	0.093	1.031 ***	0.866 ***
	(-0.560)	(0.359)	(11.074)	(3.629)	(-0.579)	(0.392)	(10.780)	(4.143)
Spatial error					0.544***			
					(29.548)			
Number of observations	4662				4662			
Adjusted R^2/ML	0.480				39654			
Moran's I	33.893							
LMerror	986.641							
Robust LMerror	894.655							
LMlag	92.244							
Robust LMerror	0.259							

Note *t*-values (asymptotic *t*-values) are in parentheses for OLS (SEM). * Significant at the 10 % level; ** at the 5% level; ***at the 1% level. LMerror (LMlag) denotes the Lagrange multiplier statistics for spatial-error (spatial-lag) dependence.

Table 5 Region–industry's employment growth between 1986 and 2006, explained by the locally weighted externality measures

Independent variables	Dependent variable: $GROWTH_{r,i,t}$							
	(1) OLS				(2) SEM			
	Auto_MANU	Other_MANU	Auto_SERV	Other_SERV	Auto_MANU	Other_MANU	Auto_SERV	Other_SERV
Constant	-0.345 **	0.074	-0.406 ***	-0.014	-0.357 ***	0.087	-0.397 ***	0.053
	(-2.124)	(0.347)	(-4.620)	(-0.086)	(-2.772)	(0.466)	(-4.632)	(0.351)
$LW\_CONC_{r,i,0}$	0.006 **	-0.000	-0.010	-0.024	0.005 **	-0.002	-0.008	-0.029 *
	(2.501)	(-0.080)	(-0.993)	(-1.408)	(2.070)	(-0.413)	(-0.859)	(-1.731)
$LW\_DIV_{r,i,0}$	0.033 ***	0.014 ***	0.000	-0.002	0.030 ***	0.014 ***	0.000	-0.003
	(3.344)	(2.730)	(0.097)	(-0.344)	(3.486)	(2.687)	(0.021)	(-0.462)
$LW\_COMP_{r,i,0}^{intra}$	-0.023 ***	-0.000	-0.004	-0.008	-0.021 ***	0.000	-0.004	-0.005
	(-2.899)	(-0.054)	(-0.556)	(-1.193)	(-2.650)	(0.012)	(-0.581)	(-0.851)
$LW\_COMP_{r,i,0}^{inter}$	-0.013	-0.010	0.009 **	0.001	-0.010	-0.011	0.009 ***	-0.000
	(-1.062)	(-1.085)	(2.500)	(0.209)	(-1.060)	(-1.085)	(3.658)	(-0.045)
$LNEMP_{r,i,0}$	-0.008 ***	-0.001	-0.004 ***	-0.004 **	-0.008 ***	-0.002	-0.004 ***	-0.005 ***
	(-4.222)	(-0.554)	(-3.465)	(-2.432)	(-3.844)	(-0.943)	(-3.993)	(-2.627)
$LNWAGE_{i,0}$	0.023 **	0.012	0.028 ***	0.007	0.022 ***	0.011	0.028 ***	0.007
	(2.467)	(1.132)	(5.267)	(0.976)	(2.732)	(1.100)	(5.957)	(0.989)
$LNWAGE_{r,0}$	0.001	-0.018	-0.001	-0.001	0.003	-0.017 *	-0.001	-0.005
	(0.137)	(-1.489)	(-0.410)	(-0.240)	(0.842)	(-1.667)	(-0.983)	(-0.846)
$GRNATION_{it}$	1.027 ***	0.936 ***	0.469 ***	0.361 ***	0.953 ***	0.957 ***	0.508 ***	0.289 ***
	(9.437)	(10.225)	(7.566)	(5.622)	(8.341)	(10.379)	(8.566)	(4.636)
$GRNATION_{t}$	-0.582 ***	-0.137	0.824 ***	0.277 ***	-0.621 ***	-0.134	0.793 ***	0.351 ***
	(-4.468)	(-1.013)	(11.960)	(3.356)	(-4.515)	(-0.960)	(11.990)	(4.268)
$GRNATION_{i}$	0.942 ***	-0.146	1.022 ***	0.480	0.896 ***	-0.286	0.987 ***	0.605 *
	(2.596)	(-0.443)	(10.040)	(1.478)	(2.661)	(-0.822)	(10.082)	(1.908)
Spatial error					0.540***			
					(20.566)			
Number of observations	4662				4662			
Adjusted R^2/ML	0.479				39650			
Moran's I	33.644							
LMerror	962.371							
Robust LMerror	867.134							
LMlag	0.000							
Robust LMlag	0.056							

Note t-values (asymptotic t-values) are in parentheses for OLS (SEM). * Significant at the 10 % level; ** at the 5% level; ***at the 1% level. LMerror (LMlag) denotes the Lagrange multiplier statistics for spatial-error (spatial-lag) dependence.

Appendix

Table 6 Sector classification

No.	Industy name	Description	Sectoral subset
1	Construction	Construction	Other_MANU
2	Food and beverages	Manufacture of food, bevarages, tobbaco and feed	Other_MANU
3	Textile and apparel	Manufacture of textile mill, apparel and other finished products	Other_MANU
4	Lumber	Manufacture of lumber and wood prodcts	Other_MANU
5	Furniture	Manufacture of furniture and fixtures	Other_MANU
6	Pulp and paper	Manufacture of pulp, paper and paper products	Other_MANU
7	Printing	Printing and allied industries	Auto_MANU
8	Chemical	Manufacture of chemical and allied products	Other_MANU
9	Petroleum and coal	Manufacture of petroleum and coal products	Other_MANU
10	Plastic	Manufacture of plastic products	Auto_MANU
11	Rubber	Manufacture of rubber products	Auto_MANU
12	Leather	Manufacture of leather tanning, leather products and fur skins	Other_MANU
13	Ceramic	Manufacture of ceramic, stone and clay products	Auto_MANU
14	Iron and steel	Manufacture of iron and steel	Auto_MANU
15	Non-ferrous metals	Manufacture of non-ferrous metals and products	Auto_MANU
16	Fabricated metal	Manufacture of fabricated metal	Other_MANU
17	General machinery	Manufacture of general machinery	Other_MANU
18	Electrical	Manufacture of electrical machinery	Auto_MANU
19	Transportation	Manufacture of transportation equipment	Auto_MANU
20	Precision	Manufacture of precision instruments and machinery	Other_MANU
21	Utilities	Electricity, gas, heat supply and water	Auto_SERV
22	Transport	Transport	Auto_SERV
23	Wholesale and retail	Wholesale and retail trade	Auto_SERV
24	Finance and insurance	Finance and insurance	Auto_SERV
25	Real estate	Real estate	Other_SERV
26	Information and communications	Information and communications	Other_SERV
27	Education and research	Education and research	Auto_SERV
28	Medical, health care and welfare	Medical, health care and welfare	Other_SERV
29	Business services	Business services	Auto_SERV
30	Personal sevices	Personal sevices	Other_SERV
31	Public services	Public services	Other_SERV