Can Creative Industries and Occupations Drive Regional Growth? Evidence from Local Employment Spillovers in Japan*

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1. Introduction

In Japan, since the early 2010s, policies promoting regional revitalization advance, and regional economies increasingly require not only the development of the *earning power* of regional industries but also the creation of employment. The term *earning power* refers to basic industries (export industries) that provide goods and services to areas outside the region and thereby acquire money from outside. The logic that income earned in this way induces consumption by workers, which in turn generates multiplier effects for non-basic industries serving the regional market, is theoretically grounded in the economic base model as a regional growth model.

In studies of the economic base model, recent empirical analyses since Moretti (2010) revisit the role of basic industries that earn income from outside the region. Traditionally, agriculture, forestry and fisheries, and manufacturing constitute the core of regional basic industries. However, as industrial structures evolve over time, service industries utilizing IT also appear to have potential as basic industries. Moretti (2014) indicates that, along with structural shifts, basic industries transform from conventional manufacturing to industries associated with knowledge, ideas, and innovation. This raises the question of whether creative industries can also function as basic industries driving regional economies.

Moretti (2010) and Moretti and Thulin (2013) conduct empirical analyses of the multiplier effect in the economic base model using employment data. Specifically, from the perspectives of *human capital*, represented by differences in worker educational attainment, and technological levels of industries, they demonstrate that highly skilled workers possess larger multiplier effects. Florida (2004), on the other hand, proposes two conceptual perspectives for understanding the relationship between knowledge, ideas, innovation, and regional growth: the *human capital* perspective emphasized by Moretti and colleagues, and the *creative capital* perspective. The former is known as the "human capital theory," and the latter as the "creative capital theory." Based on Florida's dual perspectives, analyses of multiplier effects can incorporate not only the human capital–based approach used by Moretti but also an approach grounded in the creative capital theory, thereby enabling empirical evaluation of whether creative industries and occupations function as basic industries that earn income for regions.

Motivated by recent contributions in the local-multiplier literature, this paper asks whether creative activities generate measurable local employment spillovers in Japan. We focus on creative (orange-economy and related) activities and creative/knowledge-intensive occupations and examine whether growth in these base-like categories is associated with indirect employment responses in the wider local economy. The analysis is implemented at two spatial scales—municipalities and Urban Employment Areas (UEAs)—to assess how spatial aggregation shapes measured spillovers.

Contributions. (1) Using fine-grained occupational sub-classes, we adopt an occupation-based definition to locate

* This work was supported by JSPS KAKENHI Grant Number JP25K16631 and by the Research Grant from the Chugoku–Shikoku Branch of the Japan Association for Planning and Public Management.
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creative functions at the worker level and mitigate misclassification due to within-industry heterogeneity. (2) A two-scale design (municipalities vs UEAs) clarifies why local-multiplier estimates may vary with spatial aggregation. (3) In explicit parallel to Moretti (2010) inside manufacturing, we implement an occupation-based counterpart by isolating knowledge-intensive workers within manufacturing and comparing their spillovers with manufacturing-wide spillovers. (4) Using official census tabulations for Japan provides non-Anglophone evidence; to our knowledge, this is the first Japan-based empirical analysis that explicitly defines creative activity and identifies the associated local employment spillovers.

Thus, this study, grounded in the economic base model, empirically examines whether creative industries generate multiplier effects for regions in the same way as manufacturing and other traditional basic industries. Chapter 2 defines creative industries and occupations in the context of this study. Chapter 3 then conducts empirical analyses of multiplier effects using employment data at the municipal level and urban employment area level in Japan. Here, the multiplier effect represents the extent to which an increase in workers engaged in creative activities expands total regional employment. Chapter 4 provides an analysis corresponding to the works of Moretti and others. Specifically, whereas Moretti classifies highly skilled workers within manufacturing as creative and innovative from a human capital perspective, this study classifies workers engaged in *creative activities* and estimates multiplier effects to examine whether creative workers deliver larger multiplier effects. Chapters 5 and 6 correspond to the Discussion and Conclusion sections.

If the approach of this study demonstrates that workers engaged in creative activities generate significant multiplier effects for regions, it may suggest the possibility that creative industries and occupations assume roles as basic industries that lead regional economies in place of manufacturing and other traditional sectors.

2. Definition of Creative Industries and Occupations

This section defines creative industries and occupations. Research on creative industries and occupations appears to follow three main approaches. The first defines the content of creative industries and identifies them based on industrial classifications. The second focuses on knowledge-intensive business services (KIBS), which constitute service-sector industries within creative industries. The third, following Florida (2002), defines creative occupations and identifies them using occupational classifications.

This study reviews these three approaches and adopts the method based on occupational classifications to define "knowledge-intensive occupations." The reason follows Asada (2015), who argues that creativity, including the creation of knowledge, fundamentally resides in individuals. Additionally, as noted by Nomura Research Institute (2012), definitions based on industrial classifications cannot accurately capture creative elements. Within a single industry classification, individuals engaged in creative activities coexist with those who are not, thus occupational classifications, which focus on individual activities, allow clearer identification of creative workers. Therefore, this study adopts occupational classifications based on individual activities.

Some previous studies define creative industries based on the share of creative occupations within industries. However, this method includes non-creative workers within creative industries, leading this study not to define "knowledge-intensive industries" using industrial classifications. Instead, as an alternative approach, this study cross-tabulates occupational and industrial classification data to separate workers engaged in creative occupations from other workers within each industry. Reviewing Moretti (2010) confirms that his study classifies workers in manufacturing based on educational attainment as a proxy for human capital and demonstrates that highly educated workers possess larger employment multiplier effects. This study incorporates the same logic using the separation of creative occupations. Specifically, among workers in manufacturing, this study separates those engaged in creative occupations and estimates employment spillover effects, enabling analysis of whether workers engaged in creative activities deliver larger multiplier effects.

Accordingly, this study first (i) assumes that “knowledge-intensive occupations,” defined by occupational classifications, correspond to the “basic sector workers” in the economic base model, and empirically examines whether workers in knowledge-intensive occupations generate multiplier effects for regions. Next, for comparison with Moretti (2010), this study (ii) focuses on manufacturing, which traditionally functions as the core basic industry, and cross-tabulates occupational and industrial classifications to separate workers engaged in “knowledge-intensive occupations” within manufacturing, then analyzes their employment spillover effects.

Table 1 presents the definition of “knowledge-intensive occupations” used in this study. The data derive from the National Census (Statistics Bureau of Japan), using workplace-based units and detailed minor occupational classifications, which constitute a notable feature by allowing highly detailed identification of creative activities. The definition draws on Florida (2002), Okada (2010, 2011), and Asada (2015), all of which define creative occupations using occupational classifications, and all categories fall under the major occupational group “Professional and Technical Workers.”

The extraction of workers engaged in knowledge-intensive occupations within manufacturing, corresponding to step (ii) above, uses the 2010 and 2015 Census and the medium classifications of industries and occupations (Statistics Bureau of Japan). However, within the category “(10) Teachers,” the proportion of workers classified into “51 University Teachers” and “52 Other Teachers” is relatively small within the overall “(10) Teachers” group. Including “(10) Teachers” within “knowledge-intensive occupations” would therefore incorporate a large number of non-creative workers. Consequently, “(10) Teachers” is excluded from the definition of knowledge-intensive occupations.

Table 1. Definition of “Knowledge-Intensive Occupations”

Occupational group

- B Professional and engineering workers
  - (4)Researchers
    - 6 Natural science researchers
    - 7 Humanities, social science, and other researchers
  - (5)Engineers
    - 8 Agriculture, forestry, fishery, and food engineers
    - 9 Electrical, electronics and telecommunication engineers (except communication network engineers)
    - 10 Machinery engineers
    - 11Transport equipment engineers
    - 12 Metal engineers
    - 13 Chemical engineers
    - 14 Architectural engineers
    - 15 Civil engineering and surveying engineers
    - 16 System consultants and designers
    - 17 Software creators
    - 18 Other data processing and communication engineers
    - 19 Other engineers
  - (8)Legal workers
    - 38 Judges, public prosecutors, and attorneys-at-law
    - 39 Patent attorneys and judicial scriveners
    - 40 Other legal workers
  - (9)Management, finance and insurance professionals
    - 41 Certified public accountants
    - 42 Tax accountants
    - 43 Labor and social security attorneys
    - 44 Other management, finance, and insurance professionals
  - (10)Teachers
    - 50 University teachers
    - 51 Other teachers
  - (12)Authors, journalists, editors
    - 53 Authors
    - 54 Journalists and editors
  - (13)Artists, designers, photographers, film operators
    - 55 Sculptors, painters and craft artists
    - 56 Designers
    - 57 Photographers and film operators
  - (14)Musicians, stage designers
    - 58 Musicians
    - 59 Dancers, actors, directors, and entertainers
  - (15)Other specialist professionals
    - 61 Private tutors (music)
    - 62 Private tutors (dance, acting, directing, entertainment)
    - 63 Private tutors (sports)
    - 64 Private tutors (academic instruction)
    - 65 Private tutors, n.e.c.
    - 66 Professional athletes

3. Estimating the Employment Multiplier Effects of Knowledge-Intensive Occupations

This section empirically examines whether workers engaged in “knowledge-intensive occupations,” defined based on occupational classifications, generate multiplier effects for regions when these occupations are assumed to correspond to the "basic sector workers" in the economic base model. The multiplier effect examined here does not perfectly correspond to the spillover effects generated by export industries in the economic base model. However, if the multiplier effects of knowledge-intensive occupations are observed in employment data, these occupations can be understood as contributing to the evolution of cities and regions. In other words, this section investigates whether knowledge-intensive occupations can function as driving factors of regional growth from the perspective of employment spillover effects.

The analysis covers both municipalities in Japan and Urban Employment Areas. The reason for including Urban Employment Areas is that workers engaged in creative occupations may not exist as observable data in some rural municipalities, necessitating analysis at a broader regional scale. Municipal-level analysis adopts the municipal boundaries as of 2015; however, government ordinance cities are treated as single entities without dividing into wards. The 23 special wards of Tokyo are treated collectively as a single municipality ("Tokyo-ku-area"). Municipalities designated as evacuation zones following the Fukushima Daiichi Nuclear Power Plant accident in 2011 are excluded from the analysis. Urban Employment Areas follow the definition provided by Kanemoto and Tokuoka (2002).

The estimation method uses regression analysis to estimate employment multiplier effects between two points in time. First, workers in knowledge-intensive occupations are identified according to the definition in the previous chapter. Following the logic of Moretti (2010), the multiplier effect from workers in knowledge-intensive occupations to total regional employment is estimated. Employment data follow prior studies and consist of two types: (i) changes in the number of workers between two time points and (ii) growth rates between the two time points. Regression analyses are conducted using both measures.

The estimation equation using changes in the number of workers between two time points is expressed as follows:

$$L_{j,t} - L_{j,t-s} = \alpha_1 + \beta_1 \left(L_{Cj,t} - L_{Cj,t-s} \right) + \gamma_1 X_{j,t-s} + \varepsilon_{j,t} \tag{1}$$

Here, $L_{j,t}$ and $L_{Cj,t}$ denote the total number of workers and the number of workers in knowledge-intensive occupations (C), respectively, in region j at time t. Because the data cover two time points, 2010 and 2015, $t = 2015$ and $t–s = 2010$. $X_{j,t–s}$ represents regional attributes in region j at the base year $t–s$, and these variables function as controls to remove influences other than changes in the number of workers in knowledge-intensive occupations (Table 2). All data are taken from the Population Census. The selected variables follow the specifications used in Van Dijk (2015) and Moretti (2010). The variables "commuting-out rate" and "commuting-in rate" were excluded due to concerns about multicollinearity.

Table 2. Regional control variables

Indicators Showing Whether a Region Functions as a Work Center or a Residential (Bedroom) Community	
	Commuting-out rate (%)
	Commuting-in rate (%)
	Daytime-to-nighttime population ratio (%)
Indicators Reflecting Regional Vitality	
	Elderly population ratio (%)
	Population growth rate (%)
	Unemployment rate (%)
Indicators of Human Capital in the Region	
	College-educated population ratio (%)

The coefficient β_1 captures the employment multiplier. That is, an increase of one worker in knowledge-intensive occupations is associated with an increase of β_1 workers in total employment.

Similarly, the estimation using growth rates is expressed as follows:

$$\frac{L_{j,t} - L_{j,t-s}}{L_{j,t-s}} - = \alpha_2 + \beta_2 \frac{L_{Cj,t} - L_{Cj,t-s}}{L_{Cj,t-s}} + \gamma_2 X_{j,t-s} + \varepsilon_{j,t} \tag{2}$$

β_2 represents the elasticity between the number of workers in knowledge-intensive occupations and total employment. For the major cities Tokyo-ku-area, Osaka City, Nagoya City, Yokohama City, and Sapporo City, the changes in total employment recorded in the 2009 and 2014 Economic Census–Basic Survey differ substantially from those in the National Census during the same period.[1] Therefore, regions containing these cities are treated as outliers, and either removed from the dataset or controlled using dummy variables. Because the estimation results are almost identical under both treatments, this study reports only the results obtained after removing these regions. This treatment aligns with the purpose of the paper, which focuses on the contribution of creative industries and occupations to regional growth, especially outside large metropolitan regions. The descriptive statistics are presented in Table 3.

Table 3. Descriptive Statistics

			Municipalities				Urban Employment Areas			
Variable	Year	Unit	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Total Employment	2010	persons	34,863	184,090	137	6,644,955	256,857	1,173,432	8,860	16,191,076
Knowledge-Intensive Occupation Employn	2010	persons	2,191	21,489	1	836,073	16,666	107,960	165	1,544,433
Total Employment	2015	persons	34,454	180,265	143	6,494,216	253,965	1,108,829	8,768	16,010,001
Knowledge-Intensive Occupation Employn	2015	persons	2,344	23,411	0	914,180	17,828	115,569	165	1,653,704
Sample Size			1,707				219			

		Municipalities				Urban Employment Areas			
Variable	Unit	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Commuting-out rate	%	38.43	20.53	0	82.12	25.67	12.49	1.95	62.94
Commuting-in rate	%	33.83	17.27	0.31	88.32	24.95	11.88	1.75	67.52
Daytime-to-nighttime population ratio	%	95.49	10.83	65.04	290.85	99.31	2.54	85.35	109.01
Elderly population ratio	%	27.93	6.09	9.19	57.24	26.19	4.15	16.14	38.62
Population growth rate	%	−3.54	5.25	−29.48	35.31	−2.74	8.85	−10.48	7.19
Unemployment rate	%	2.31	2.18	0	22.72	6.63	6.65	1.53	15.67
College-educated population ratio	%	11.56	5.73	2.27	40.95	11.48	3.56	5.25	23.58
Sample size		1,707				219			

The estimation results in Table 4 show that the employment multiplier effect in equation (1) is not statistically significant at the Urban Employment Area level but is positive and statistically significant at the 1% level at the municipal level, consistent with spillovers materialising within daily urban systems where commuting and local consumption links are dense.

In addition, as indicated in Table 5, although the coefficient of determination is not high—meaning that changes in knowledge-intensive occupations do not fully explain changes in total employment—the elasticity estimates for both municipalities and Urban Employment Areas are statistically significant at the 1% level. Therefore, knowledge-intensive occupations, when measured using employment data, can be regarded as having positive impacts on regional growth.

[1] A plausible source of these numerical discrepancies is statistical error resulting from low response rates to surveys conducted in large urban areas. Osaka City, Nagoya City, Yokohama City, and Sapporo City are also among the largest cities following the Tokyo ward area, and similar causes are likely to generate comparable discrepancies.

Table 4. Estimation Results of the Multipliers of Knowledge-Intensive Occupations

	Municipality level			Urban Employment Area level		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in the number of workers in knowledge-intensive occupations	0.953 ***	1.016 ***	0.983 ***	0.548	0.807	0.900
(%)	[0.28]	[0.28]	[0.29]	[0.61]	[0.63]	[0.62]
Daytime-to-nighttime population ratio		-15.254 ***			18.353	
(%)		[5.29]			[61.56]	
Elderly population ratio		2.331			-54.885	
(%)		[6.28]			[83.47]	
Population growth rate		28.136 ***			343.240 **	
(%)		[9.20]			[153.65]	
Unemployment rate		3.212	16.534		113.049	202.340
(%)		[12.32]	[11.85]		[117.13]	[126.82]
share of university graduates		-28.588 ***	-9.044		-456.879 ***	-218.750 **
(%)		[9.88]	[7.89]		[122.81]	[88.44]
Constant	-336.931 ***	1457.413 **	-339.689 ***	-1732.845 ***	3159.726	-762.502
	[36.40]	[576.53]	[96.35]	[251.46]	[6330.58]	[1264.90]
R-squared	0.074	0.088	0.075	0.032	0.124	0.076
Sample size	1,702	1,702	1,702	215	215	215

Note 1: Values in parentheses indicate robust standard errors.

Note 2: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Estimation Results of the Elasticities of Knowledge-Intensive Occupations

	Municipality level			Urban Employment Area level		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth rate of workers in knowledge-intensive occupations	0.023 ***	0.023 ***	0.023 ***	0.060 ***	0.055 ***	0.062 ***
(%)	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]
Daytime-to-nighttime population ratio		-0.003			0.022	
(%)		[0.02]			[0.09]	
Elderly population ratio		-0.239 ***			-0.176 *	
(%)		[0.05]			[0.09]	
Population growth rate		0.064			0.418 **	
(%)		[0.07]			[0.17]	
Unemployment rate		0.305 ***	0.411 ***		0.132	0.296 **
(%)		[0.08]	[0.08]		[0.09]	[0.12]
share of university graduates		0.090 **	0.313 ***		-0.067	0.330 ***
(%)		[0.04]	[0.03]		[0.07]	[0.05]
Constant	-1.889 ***	2.355	-8.096 ***	-2.443 ***	1.095	-8.158 ***
	[0.18]	[2.51]	[0.60]	[0.22]	[8.76]	[1.17]
R-squared	0.043	0.173	0.125	0.117	0.398	0.24
Sample size	1,702	1,702	1,702	215	215	215

Note 1: Values in parentheses indicate robust standard errors.

Note 2: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4. Estimating the Employment Multiplier Effects of Knowledge-Intensive Occupations within Manufacturing

This section extends the analysis to manufacturing in correspondence with Moretti (2010). In Moretti's framework, manufacturing is assumed to be a basic industry, and workers in manufacturing are divided into those with a college degree or higher (skilled) and others, after which the basic multiplier is estimated. Because workers classified as skilled exhibit larger employment multipliers, Moretti demonstrates the substantial spillover effects generated by creative and highly educated workers. Following this approach, this study separates workers engaged in knowledge-intensive occupations within manufacturing and estimates the employment spillover effects generated by creative workers.

First, following Moretti (2010), this study assumes manufacturing as a basic industry and estimates the employment spillover effects generated by manufacturing workers. Subsequently, workers in knowledge-intensive occupations within manufacturing are separated, and their multiplier effects are estimated and compared with those for all manufacturing workers. This enables examination of whether creative workers exhibit larger multiplier effects. As in the previous section, the estimation uses two approaches: (i) changes in the number of workers between two time points and (ii) growth rates between the two time points. Workers engaged in knowledge-intensive occupations within manufacturing are identified by cross-tabulating industrial and occupational classifications from the National Census, using the definition of knowledge-intensive occupations established in the previous section. The regions included in the analysis follow the same criteria as in the previous chapter.

First, the estimation equation for manufacturing can be expressed as follows.

$$L_{j,t} - L_{j,t-s} = \alpha_1 + \beta_1 \left(L_{Mj,t} - L_{Mj,t-s} \right) + \gamma_1 X_{j,t-s} + \varepsilon_{j,t} \tag{3}$$

$$\frac{L_{j,t} - L_{j,t-s}}{L_{j,t-s}} - = \alpha_2 + \beta_2 \frac{L_{Mj,t} - L_{Mj,t-s}}{L_{Mj,t-s}} + \gamma_2 X_{j,t-s} + \varepsilon_{j,t} \tag{4}$$

L : total employment,

L_M : employment in manufacturing

Next, the estimation equation for Knowledge-Intensive Occupations within manufacturing can be expressed as follows.

$$L_{j,t} - L_{j,t-s} = \alpha_3 + \beta_3 \left(L_{MCj,t} - L_{MCj,t-s} \right) + \gamma_3 X_{j,t-s} + \varepsilon_{j,t} \tag{5}$$

$$\frac{L_{j,t} - L_{j,t-s}}{L_{j,t-s}} - = \alpha_4 + \beta_4 \frac{L_{MCj,t} - L_{MCj,t-s}}{L_{MCj,t-s}} + \gamma_4 X_{j,t-s} + \varepsilon_{j,t} \tag{6}$$

L : total employment,

L_{MC}: employment in knowledge-intensive occupations within manufacturing

The descriptive statistics are presented in Table 6.

Table 6. Descriptive Statistics

			Municipalities				Urban Employment Areas			
Variable	Year	Unit	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Total employment	2010	persons	34,863	184,090	137	6,644,958	256,857	1,173,442	8,867	16,191,201
Manufacturing employment	2010	persons	5,534	18,834	0	610,674	40,771	153,206	458	1,966,554
Knowledge-intensive occupation employment (within manufacturing)	2010	persons	379	1,789	0	55,468	2,887	14,901	0	203,008
Share of knowledge-intensive occupations	2010	%	3.60	4.27	0.00	32.83	3.91	2.74	0.00	13.65
Total employment	2015	persons	34,454	180,265	145	6,494,215	253,964	1,160,288	8,772	16,009,962
Manufacturing employment	2015	persons	5,310	16,885	1	527,367	39,107	141,559	434	1,786,815
Knowledge-intensive occupation employment (within manufacturing)	2015	persons	425	1,857	0	55,565	3,228	15,552	0	209,022
Share of knowledge-intensive occupations	2015	%	3.79	4.72	0.00	45.85	4.06	2.86	0.00	14.14
Sample size			1,707				219			

The estimation results are reported in Tables 7–10, which show that both the multiplier and elasticity for all manufacturing workers are positive and statistically significant, indicating that manufacturing continues to generate employment spillover effects for regions. However, when estimating the multiplier and elasticity for workers engaged in knowledge-intensive occupations within manufacturing, only the elasticity at the municipal level becomes positive and statistically significant. The other estimation patterns do not yield statistically significant results. Therefore, this study does not find evidence that workers engaged in knowledge-intensive activities within manufacturing exhibit larger multiplier effects than manufacturing workers as a whole.

Table 7 Estimation Results of the Multipliers of Workers in Manufacturing

	Municipality level			Urban Employment Area level		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in the number of manufacturing workers	0.863 ***	0.887 ***	0.900 ***	1.201 ***	1.157 ***	1.227 ***
	[0.25]	[0.25]	[0.25]	[0.27]	[0.27]	[0.27]
Daytime-to-nighttime population ratio		-8.325 *			20.306	
(%)		[4.39]			[57.59]	
Elderly population ratio		-7.996			-64.256	
(%)		[8.83]			[72.14]	
Population growth rate		43.114 ***			222.868 *	
(%)		[14.26]			[127.44]	
Unemployment rate		41.022 *	49.143 **		199.299	284.948 **
(%)		[21.41]	[21.63]		[124.65]	[130.15]
share of university graduates		3.255	34.546 ***		-127.335	68.882
(%)		[10.91]	[9.12]		[114.25]	[96.13]
Constant	-126.424 ***	682.244	-867.191 ***	-758.639 ***	-387.438	-3426.049 **
	[44.65]	[513.69]	[135.57]	[239.52]	[6625.21]	[1584.54]
R-squared	0.168	0.193	0.181	0.273	0.314	0.29
Sample size	1,310	1,310	1,310	208	208	208

Note 1: Values in parentheses indicate robust standard errors.

Note 2: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Estimation Results of the Multipliers of Workers in Knowledge-Intensive Occupations within Manufacturing

	Municipality level			Urban Employment Area level		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in the number of knowledge-intensive occupation workers within manufacturing	0.613	0.621	0.594	-0.272	-0.280	-0.017
	[0.45]	[0.47]	[0.46]	[0.83]	[0.78]	[0.84]
Daytime-to-nighttime population ratio		-12.583 **			77.974	
(%)		[5.89]			[68.08]	
Elderly population ratio		-5.193			-129.182	
(%)		[9.94]			[81.88]	
Population growth rate		54.410 ***			321.381 **	
(%)		[14.94]			[152.09]	
Unemployment rate		20.321	29.457		93.017	232.228
(%)		[22.62]	[22.87]		[133.48]	[150.24]
share of university graduates		-25.084 *	11.564		-327.619 **	-43.119
(%)		[13.57]	[11.69]		[152.46]	[128.54]
Constant	-321.485 ***	1329.431 *	-653.733 ***	-1414.783 ***	-1777.661	-2536.158
	[52.87]	[680.28]	[163.64]	[229.91]	[7745.90]	[1955.58]
R-squared	0.006	0.026	0.008	0.002	0.08	0.015
Sample size	1,310	1,310	1,310	208	208	208

Note 1: Values in parentheses indicate robust standard errors.

Note 2: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Estimation Results of the Elasticities of Workers in Manufacturing

	Municipality level			Urban Employment Area level		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth rate of manufacturing workers	0.232 ***	0.218 ***	0.228 ***	0.191 ***	0.123 ***	0.167 ***
(%)	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	[0.03]
Daytime-to-nighttime population ratio		-0.01			0.008	
(%)		[0.02]			[0.07]	
Elderly population ratio		-0.183 ***			-0.116	
(%)		[0.05]			[0.10]	
Population growth rate		0.120			0.381 ***	
(%)		[0.07]			[0.14]	
Unemployment rate		0.397 ***	0.467 ***		0.128	0.253 **
(%)		[0.09]	[0.08]		[0.10]	[0.11]
share of university graduates		0.018	0.205 ***		-0.081	0.219 ***
(%)		[0.04]	[0.03]		[0.06]	[0.06]
Constant	-0.626 ***	2.652	-6.190 ***	-1.350 ***	1.756	-5.623 ***
	[0.16]	[2.42]	[0.65]	[0.21]	[7.97]	[1.15]
R-squared	0.297	0.384	0.347	0.234	0.378	0.288
Sample size	1,310	1,310	1,310	208	208	208

Note 1: Values in parentheses indicate robust standard errors.

Note 2: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Estimation Results of the Elasticities of Workers in Knowledge-Intensive Occupations within Manufacturing

	Municipality level			Urban Employment Area level		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth rate of workers in knowledge-intensive occupations within manufacturing	0.005 ***	0.004 **	0.005 ***	0.001	0.003	0.002
(%)	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Daytime-to-nighttime population ratio		-0.005			0.021	
(%)		[0.02]			[0.09]	
Elderly population ratio		-0.257 ***			-0.198 *	
(%)		[0.06]			[0.12]	
Population growth rate		0.128			0.441 **	
(%)		[0.09]			[0.18]	
Unemployment rate		0.305 ***	0.392 ***		0.139	0.347 ***
(%)		[0.10]	[0.10]		[0.10]	[0.13]
share of university graduates		0.004	0.244 ***		-0.107	0.323 ***
(%)		[0.04]	[0.03]		[0.07]	[0.06]
Constant	-1.383 ***	4.239	-6.944 ***	-2.037 ***	2.474	-8.049 ***
	[0.18]	[2.82]	[0.75]	[0.24]	[9.44]	[1.32]
R-squared	0.014	0.136	0.073	0.001	0.302	0.122
Sample size	1,310	1,310	1,310	208	208	208

Note 1: Values in parentheses indicate robust standard errors.

Note 2: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5. Conclusion

This study corresponds to the analysis of Moretti (2010) and estimates the employment spillover effects generated by workers in manufacturing as a whole and by workers engaged in knowledge-intensive occupations within manufacturing. For all manufacturing workers, both the multiplier effect and elasticity estimated using changes in employment levels and employment growth rates produce positive and statistically significant values. In contrast, for workers engaged in knowledge-intensive occupations within manufacturing, only the elasticity estimated using employment growth rates at the municipal level yields a statistically significant value, while other results do not become significant. These findings differ from those of Moretti (2010). This suggests that in Moretti's analysis, workers with a college degree or higher do not merely represent creative or innovative workers; rather, when creative workers are identified based on occupational classifications within manufacturing—as in this study—their employment growth does not strongly influence overall employment growth in manufacturing.

From another perspective, many workers classified into knowledge-intensive occupations within manufacturing are likely researchers and engineers, occupational groups that can be considered upstream within the industrial linkages of manufacturing. Instead of assuming that creative workers in manufacturing generate broader spillover effects across industries, an alternative interpretation is that employment growth among upstream creative workers induces spillover effects on other occupations within manufacturing through backward linkage effects. Such a perspective may reveal a different dimension of the employment spillover mechanisms.

Nevertheless, when knowledge-intensive occupations are identified among all workers—regardless of industry—and assumed to correspond to basic sector workers, both estimation approaches using employment level changes and growth rates produce positive and statistically significant results at both the municipal and Urban Employment Area levels.

In the context of the economic base model in Japan, this study is likely the first to clearly define innovative and creative industries and occupations and confirm that these industries and occupations generate multiplier effects for regions. This contributes policy-relevant evidence for Japan and complements findings from U.S./European contexts. Although, as discussed earlier, employment growth in knowledge-intensive occupations does not perfectly correspond to growth in export-oriented basic industries within the economic base model, the results indicate that these occupations nevertheless contribute to the evolution of cities.

Moretti (2012) explains that the employment spillover effects of innovative and creative industries are large because these industries are labor-intensive and rely heavily on human labor—for example, research institutes and software firms—making automation difficult. However, the actual pathways through which these industries generate employment spillovers are not yet theoretically established in the same way as the distinction between basic and non-basic industries in the economic base model. Clarifying these mechanisms remains an important issue for future research.

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