

An empirical analysis of agglomeration effect in the Japanese Food Industry
-Panel analysis using flexible translog production function-

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**Poster paper prepared for presentation at the International
Association of Agricultural Economists Conference, Gold Coast, Australia,
August 12-18, 2006**

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Abstract

In this paper, we examine the existence of agglomeration effect on production in the Japanese food industry from 1985 to 2000 using plant-level 4-digit subclassification, panel dataset and agglomeration index in Akune and Tokunaga [2], and Tokunaga, Kageyama, and Akune [16], based on Ellison and Glaeser [5]. This is an improvement on the conventional indices such as Location Quotient (LQ) or Location Gini Coefficient (L). When we apply a flexible translog production function and cost share equation as suggested by Kim [10], we find that around 2% of positive agglomeration effect exists in absence of any restriction on homotheticity in the case of employment based agglomeration (γ_{EG}).

Keywords: Agglomeration; Japanese food industry; Panel data analysis; Flexible translog production functions

JEL classification: R12; R3; Q59

1. Introduction

This paper examines the existence of agglomeration effects on production in the Japanese food industry from 1985 to 2000 using plant-level panel data for the 4-digit Japan Standard Industrial Classification (SIC). We use the flexible translog production function based on an inverse input demand function framework of Kim [14].

Recent years have seen a rapid growth in theoretical works within the field of new economic geography spearheaded by Krugman [15], Fujita, Krugman and Venables [8], and Fujita and Thisse [9], which has in turn spurred interest in the empirical implementation of these models. At moment, there are quite a few empirical studies based on 4-digit SIC level data¹. Using plant-level 4-digit SIC data, Akune and Tokunaga [1, 2], Tokunaga and Akune [21], and Tokunaga, Kageyama, Akune [22] analyze the existence of agglomeration in Japanese food industry.

¹ Many studies are based on a 2-digit or 3-digit industrial level data analysis because of data constraint.

The 1985 Plaza Accord with its attendant rapid appreciation of the yen against the dollar, the rapid increase in off shoring of Japanese manufacturing and also, the collapse of the bubble economy have seen a dramatic change in the economic environment in Japan. These influences are fairly observed in the location choice of most Japanese companies. According to Akune and Tokunaga [2] and Tokunaga and Akune [21] when we observe the agglomeration of food industry in detail we notice that many highly agglomerated sub-industries hold their spatial distribution relative to other manufacturing industries. In the present paper, we consider the production side and examine how agglomeration of the food industry affects its production.

The rest of the paper is structured as follows. In the second section, we outline the state of agglomeration in the food industry in Japan. In the third section, we survey the theoretical framework of a flexible translog production function based on Kim [14]. In the fourth section, we show the specification of the estimation model, data sources, and the estimation results of flexible translog production function. Then, we conclude the paper.

2. The relationship between Agglomeration and Production in Japanese food industry
The empirical analysis of agglomeration and co-agglomeration of the Japanese food industry has been conducted by Akune and Tokunaga [1, 2], Tokunaga and Akune [21], and Tokunaga, Kageyama, and Akune [22] using agglomeration index (γ_{EG}) suggested by Ellison and Glaeser [6]. Akune and Tokunaga [1, 2] and Tokunaga and Akune [21] measured the degree of agglomeration with employment based data. Akune and Tokunaga [2] measured the index for 4-digit sub-industries. It shows the dynamics of employment based agglomeration for high-agglomerated 20 food sub-industries. Since the location of the entire food industry is determined by availability of agricultural resources, we observe no agglomeration at this general food industry level. But when considered according to the 4-digit subclassification, we observe that “Agar-agar”, “Wine” and ”Tea” are concentrated in the areas where firms can easily have access to raw materials and natural advantage, and ”Sugar” is located in nearness to the harbor. These industries are strongly agglomerated compared to other manufactures.² The dynamics of agglomeration from 1985 to 2000 shows that “Wine” display monotonously decreasing agglomeration after 1985. But, surprisingly, many highly-agglomerated sub-industries retained their spatial distribution in spite of a somewhat dispersed trend. In other words, agglomeration holds in Japanese food industry.

² The degree of agglomeration in total manufacturing industry is measured by Tokunaga and Akune [21].

The agglomeration index (γ_{EG}) and shipment (Y), on the whole, flatten from 1985 to 2000 regardless of high and low contours. When we observe these relationships by sub-industries, “Agar-agar (1)”³ has an increasing trend in both γ_{EG} and Y from 1985 to 1995, but a decreasing trend in 2000. In “Sugar (2)”, “Canned seafood and seaweed (7)”, and “Glucose, starch syrup and high-fructose corn syrup (17)”, γ_{EG} and Y have a downward trend. “Miso (13)”, “Soy sauce "shoyu" and edible amino acids (14)”, and “Manufactured ice” seem to be flat for 20 years. “Wine”, the plants concentrated in Yamanashi Prefecture depicts decreased agglomeration from 1985 to 2000, but shipment increases. In Japan, demand for wine has been increasing rapidly on the background of wine boom and hence, the development of some new sources of wine such as Hokkaido and Nagano Prefecture. With this background, γ_{EG} and Y show an inverse movement.⁴

3. Theoretical model of a flexible translog production function

The translog function has become an essential tool for analyzing the production structure of many firms and industries (Christensen, Jorgenson, and Lau [4]). The translog function does not impose a priori restriction on elasticities of substitution and return to scale, hence many economists employ such functions for various empirical analysis. In the case of estimation, cost share equations are often used under the condition of constant returns to scale. But assumption of constant returns to scale is not appropriate when we examine firms’ location behavior. Kim [14] extends Chan and Mountain [3] suggests more flexible production functions based on the inverse input demand function. Kim’s production function enables estimation without introducing restrictions such as homotheticity, homogeneity, and constant return to scale. In this study, we examine how the agglomeration of food industry affects production based on Kim’s production function. The following production function and its cost share equation are estimated jointly.

Translog production function

$$\begin{aligned}
 \ln Y = & \alpha_0 + \alpha_k \ln K + \alpha_l \ln L + \alpha_m \ln M \\
 & + \frac{1}{2} \beta_{kk} (\ln K)^2 + \frac{1}{2} \beta_{ll} (\ln L)^2 + \frac{1}{2} \beta_{mm} (\ln M)^2 \\
 & + \beta_{kl} \ln K \ln L + \beta_{km} \ln K \ln M + \beta_{lm} \ln L \ln M \\
 & + \delta_a \ln A + \frac{1}{2} \delta_{aa} (\ln A)^2 \\
 & + \gamma_{ka} \ln K \ln A + \gamma_{la} \ln L \ln A + \gamma_{ma} \ln M \ln A
 \end{aligned} \tag{1}$$

³ Rank of agglomeration index for Japanese food industry in 2000 is in parentheses.

⁴ See Kageyama, Tokunaga, and Akune [13] for detail explanation about the actual condition of wine industry’s agglomeration.

Cost share equation

$$S_i = \frac{\alpha_i + \sum_j \beta_{ij} \ln X_j + \gamma_{iA} A}{\sum_i \alpha_i + \sum_i \sum_j \beta_{ij} \ln X_j + \sum_i \gamma_{iA} A} \quad (2)$$

where Y , K , L , E , M , A are output, capital, labor, materials, agglomeration respectively. In (2), subscript i means input, and S_i means cost share of the i th input.

X is input vector, that is, capital, labor, and materials. α_i , β_{ij} , δ_a , δ_{aa} , γ_{ij} are parameters to be estimated. For estimation, we try to test the following cases: (1) impose no restriction, (2) homotheticity is imposed ($\sum_j \beta_{ij} = 0$), (3) homogeneity is imposed ($\sum_i \alpha_i = \theta$, $\sum_j \beta_{ij} = 0$, $\sum_i \gamma_{iT} = 0$), (4) constant return to scale (linear homogeneity) is imposed ($\sum_i \alpha_i = 1$, $\sum_j \beta_{ij} = 0$, $\sum_i \gamma_{iT} = 0$). We carry out the estimation using the iterative nonlinear seemingly unrelated regression method (SUR).

4. Estimation Results.

Target for estimation is 54 sub-industries (4-digit industrial subclassification) excluding “tobacco” which belongs to SIC 12 and 13 in the Census of Manufactures (hereafter CM) reported by Ministry of Economy.⁵ The data required are output, capital, labor, materials, agglomeration, and costs. Output is manufactured goods shipments. The data source is CM. The value is realized by output deflator by kind of economic activities (Base year is 1995) which is available from Annual Report on National Account (NA) reported by Economic and Social Research Institute (ESRI). We can get capital stock data by 2-digit SIC level which is obtainable from Central Research Institute of Electric Power Industry (CRIEPI). We divide this data proportionally by the sub-industry share (4-digit SIC level) of tangible fixed assets of establishment (end of the year) reported by CM and use it as capital data. About labor, we consider both employees and total hours worked. Employee data is available from CM, total hours worked by industry is obtained from Ministry of Health, Labor and Welfare. We multiply employees and total hours worked to create make labor data. Materials are also from CM. The value is realized by deflators on inputs by kind of economic activity (Base year is 1995) reported from NA. Capital cost is calculated using the following equation.

⁵ Refer to Otsuka [19] for details on construction of the dataset.

$$\text{Capital Cost} = p_K (r + d) / (1 - \tau)$$

where p_K is capital price, r is interest rate, d is depreciation rate, and τ is corporation tax rate. Capital price is from gross domestic capital formation deflator of plant and equipment reported by NA. Interest rate is from Average contracted interest rate on loans and discounts reported by Bank of Japan. For the depreciation rate, we divide depreciation by capital stock in the previous year. Corporation tax rate is from National Tax Agency Report. Total labor costs are the total cash wages and salaries which are available from CM. We use deflator on inputs by kind of economic activity reported from NA as materials cost.⁶ Agglomeration data is from Akune and Tokunaga [2], that is, employment based agglomeration index (γ_{EG}). The descriptive statistics is shown in Table.1.

Table.3 shows the four different model specification estimation results. This is the case of employment based agglomeration (γ_{EG}). Monotonicity and convexity are satisfied for each estimated function.⁷ Results of the Wald tests for six hypotheses are shown in Table.2. In the case of γ_{EG} , the restriction of homotheticity is rejected at 10 % significance level, and the restrictions of homogeneity and linear homogeneity are rejected at 1% significance level. According to the results of Wald test, nonhomotheticity model for γ_{EG} seem to be the most favorable. On the basis of Wald test, we check the Table.2 and Table.3. From the result of Nonhomotheticity for γ_{EG} , almost estimated parameter are significant at 1% or 5% level except for β_{KL} and sign conditions of parameters are theoretically appropriate. Since the individual parameters are not readily interpretable, we have calculated the output elasticities of input, return to scale, and the agglomeration effect on production. These results are shown Table.4.⁸

The rate of agglomeration effect is calculated by $\frac{\partial \ln Y}{\partial \ln A} = \delta_A + \delta_{AA} \ln A + \sum_i \gamma_{iA} \ln X_i$.

Firstly, we observe that output elasticity of materials is much larger than other two inputs and the elasticity of capital is low in γ_{EG} case. This result corresponds with Kim [14] and other empirical results. Feser [7] targets on SIC 382 (measuring and controlling device industry), he found that the elasticity of material (0.411) is less than that of labor (0.506). In the machinery industry, material is not a crucial factor for productivity, but contrastively it is especially important for food industry to secure raw materials and we could confirm that material is the most elastic factor from our estimation results. Scale economics is over 1 in all the models except in the linear homogeneity model and

⁶ Deflator data is not published by 4-digit level, therefore we substitute 2-digit for sub-industry data.

⁷ Monotonicity was checked at each data point. Convexity, which is ensured if the bordered Hessian matrix of first and second derivatives is negative definite, was checked at the means of the sample.

⁸ Elasticities are evaluated at the sample means.

significant at 1% level. The elasticity of agglomeration effect on production is estimated at 0.023, and significant at 1% level. Nakamura and Ejima [18] estimate Cobb-Douglas production function by 2-digit SIC level using city-level data in 2000 and found that the agglomeration effect for SIC 12 (Food) is 0.022 and equal to our result, but not significant. In this study, we use prefecture-level data, therefore both results are not comparable in this sense, but we found that agglomeration in Japanese food industry has positive effect on production with 4-digit subclassification data. Compared to Feser [7], the localization effect for SIC 382 (measuring and controlling devices) is 0.02 and the effect is substantially equivalent to that of Japanese food industry.

5. Conclusion

In this paper, we estimated flexible translog production function based on Kim [14] using 4-digit subclassification food industry panel data and found the existence of positive agglomeration effect in Japanese food industry. In the previous research about agglomeration economies, the degree of agglomeration is simply measured by the indices such as Location Quotient (LQ) or Location Gini Coefficient (L) suggested by Krugman [15]. In terms of these indices, an industry is regarded as localized as soon as its employment is concentrated in a small number of plants' location decisions are independent. In order to overcome this problem, Ellison and Glaeser [6] have proposed agglomeration indices. We used the Ellison and Glaeser [6]'s agglomeration index as agglomeration data measured by Akune and Tokunaga [2], Tokunaga, Kageyama, and Akune [22]. In the case of employment based agglomeration (γ_{EG}), we got theoretically appropriate and significant result without technical restriction. In summary, estimation results for the Japanese food industry reveal that return to scale is not proper description of the underlying production technology. Our influential findings are as follows. In the Japanese food industry, with existence of scale economies, productivity increases around 2% by plants' agglomeration. In other words, positive circulation linkage that increasing returns to scale arises by plants included in same sub-industry choosing their location close to another in one particular area, and holding plants' agglomeration spins off more production generates. Previous researches about productivity in Japanese food industry tend to be focused on technical structure and changes, but we suggest there is need to include the concept of firms' location behavior into productivity analysis.

Table.1 Descriptive statistics

Variables	Description	4-digit sub-industries in Food Industry	
		Mean	S.D.
Y	Output (millions of 1995 Yen)	572,970	604,366
K	Capital (millions of 1995 Yen)	447,923	525,698
L	Labor (manhours)	3,994,735	5,116,612
M	Materials (millions of 1995 Yen)	317,988	353,702
S _K	Capital cost share	0.123	0.059
S _L	Labor cost share	0.255	0.111
S _M	Material cost share	0.615	0.135
EG	Agglomeration (Employment based)	0.041	0.097

Source: Census of Manufacture, dataset offered by CRIEPI, Akune and Tokunaga (2005), Tokunaga, Kageyama, and Akune (2005) etc.

Table.2 Wald test on technology assumptions

Technology assumptions	The case of γ_{EG}	
	χ^2	p-value
Homotheticity	3.22	0.073
Homogeneity	12.75	0.000
Linear homogeneity	8.67	0.003

Source: Authors' calculation

Table.3 Estimation of flexible translog production function (The case of γ_{EG})

	Nonhomotheticity			Homotheticity			Homogeneity			Linear homogeneity					
	Estimate	S.E.	t-stat.	Estimate	S.E.	t-stat.	Estimate	S.E.	t-stat.	Estimate	S.E.	t-stat.			
α_0	-0.673	0.980	-0.686	α_0	-1.911	0.647	-2.956***	α_0	-1.902	0.636	-2.989***	α_0	0.134	0.057	2.360***
α_K	0.077	0.048	1.591*	α_K	0.072	0.046	1.568*	α_K	0.105	0.045	2.332***	α_K	0.017	0.021	0.812
α_L	0.170	0.064	2.658***	α_L	0.246	0.049	4.990***	α_L	0.265	0.051	5.216***	α_L	0.157	0.037	4.287***
α_M	0.791	0.097	8.159***	α_M	0.933	0.043	21.805***	α_M	0.935	0.043	21.810***	α_M	0.827	0.019	42.460***
β_{KK}	0.069	0.007	10.544***	β_{KK}	0.075	0.006	12.889***	β_{KK}	0.076	0.006	13.409***	β_{KK}	0.079	0.006	13.990***
β_{LL}	0.103	0.005	19.296***	β_{LL}	0.100	0.005	18.702***	β_{LL}	0.099	0.006	17.424***	β_{LL}	0.100	0.005	19.437***
β_{MM}	0.210	0.007	29.485***	β_{MM}	0.201	0.006	35.100***	β_{MM}	0.199	0.006	34.809***	β_{MM}	0.201	0.005	43.598***
β_{KL}	0.004	0.005	0.939	β_{KL}	0.003	0.004	0.634	β_{KL}	0.001	0.004	0.155	β_{KL}	0.004	0.004	0.864
β_{KM}	-0.068	0.005	-14.035***	β_{KM}	-0.072	0.004	-16.217***	β_{KM}	-0.074	0.004	-16.927***	β_{KM}	-0.073	0.004	-17.434***
β_{LM}	-0.123	0.004	-28.869***	β_{LM}	-0.123	0.004	-33.653***	β_{LM}	-0.123	0.004	-33.052***	β_{LM}	-0.118	0.003	-35.092***
δ_A	-0.190	0.064	-2.953***	δ_A	-0.121	0.058	-2.074**	δ_A	0.076	0.021	3.546***	δ_A	0.051	0.021	2.409***
δ_{AA}	0.020	0.007	2.953***	δ_{AA}	0.020	0.007	2.819***	δ_{AA}	0.011	0.007	1.604*	δ_{AA}	0.005	0.007	0.752
γ_{KA}	0.010	0.003	4.021***	γ_{KA}	0.012	0.002	4.983***	γ_{KA}	0.009	0.002	3.928***	γ_{KA}	0.009	0.002	4.184***
γ_{LA}	-0.002	0.003	-0.937	γ_{LA}	-0.003	0.003	-1.191	γ_{LA}	-0.008	0.002	-3.205***	γ_{LA}	-0.007	0.002	-2.944***
γ_{MA}	0.016	0.004	4.111***	γ_{MA}	0.009	0.004	2.671***	γ_{MA}	-0.001	0.002	-0.566	γ_{MA}	-0.002	0.002	-1.385*
Sample	216			Sample	216			Sample	216			Sample	216		
Adj.R ²	0.973			Adj.R ²	0.974			Adj.R ²	0.973			Adj.R ²	0.972		

Source: Authors' calculation

Note: * significant at 1% level, ** significant at 5% level, and *** significant at 1% level.

Table.4 Output elasticities, scale economies, and agglomeration effect (The case of γ_{EG})

	Estimate	S.E.	t-stat.
Nonhomotheticity			
Output elasticities			
Capital	0.136	0.003	40.2***
Labor	0.255	0.007	36.9***
Materials	0.634	0.010	61.7***
Returns to scale	1.025	0.003	7.8***
Agglomeration effects	0.023	0.003	8.4***
Homotheticity			
Output elasticities			
Capital	0.134	0.004	36.2***
Labor	0.255	0.007	36.8***
Materials	0.637	0.010	66.2***
Returns to scale	1.026	0.003	8.4***
Agglomeration effects	0.027	0.003	10.7***
Homogeneity			
Output elasticities			
Capital	0.133	0.004	36.3***
Labor	0.254	0.007	35.7***
Materials	0.635	0.009	68.4***
Returns to scale	1.022	0.002	11.7***
Agglomeration effects	0.024	0.002	16.2***
Linear homogeneity			
Output elasticities			
Capital	0.133	0.004	36.6***
Labor	0.248	0.007	36.6***
Materials	0.623	0.009	67.1***
Returns to scale	1.000	n.a.	n.a.
Agglomeration effects	0.022	0.001	25.4***

Source: Authors' calculation

Note 1: * significant at 1% level, ** significant at 5% level, and *** significant at 1% level.

Note 2: Elasticities are evaluated at the sample means.

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