Farm size and Distance-to-Field in Scattered Rice Field Areas
with Integration of Plot and Farm Data

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Abstract

An empirical bid-rent model is applied with a multinomial logit (MNL) for analyses of rice production in Japan, which is characterized by cultivation by producers working with various farm sizes. By combining plot and farm databases, the distances to respective field plots from potential holders in different farm size classes are examined using the model. The impact of land resource scarcity on farm size is explained by interpreting the distance effect. Results clarify that field plots at a greater distance from a farm command less rent. Especially in steeper areas with scarce land resources, large farms have no advantage in bid-rent competition with smaller farms.

***JEL** classification*: Q15, R14, Q12
Key words: land use; farm size; bid rent; land resource scarcity; rice production; multinomial logit

1. Introduction

Asian rice production has typical features related to its land use: small farm size and scattered field plots. The average rice farm size is less than 0.5 ha in China, Indonesian Java, and the Red River Delta in Vietnam. It is less than 1 ha in Bangladesh, eastern India, and the Mekong River Delta in Vietnam. It is about 1 ha in Japan and 1–2 ha in most other Asian countries. Only in Thailand, Myanmar, Cambodia, and Punjab, India is the average farm size larger than 2 ha (Hossain and Narciso, 2004). Increased wages, land, and other input prices under circumstances of globalization, along with pressure from World Trade Organization (WTO) negotiations and the Free Trade Agreement (FTA) have raised the issue of competitiveness and inefficient farm size compared to rice exporters such as United States, where the average farm size is about 180 ha. Rice production in Japan faces gradual price decreases even given its prohibitively high tariff rate. It is of great concern whether Asian rice farms can overcome farm size and land resource limitations, and eventually survive with global competition.

The relation between farm size and the return on land area has puzzled economists for some time (Assuncao and Braido, 2007). The issue is particularly important for agriculture, which requires wide areas of land. Therefore, farm size leads to physical and management limitations. An often used approach to analysis is to investigate the input–output relation considering land resource characteristics. Kawasaki (2010) clarified the impact of scattered farm plots in Japan on rice production costs. Since many reports of the econometric literature emphasize observation of a firm as a minimum unit based on the hypothesis of profit maximization behavior, the literature has been unable to address the effect of distance to a farm varying on a plot level rather than on a farm level. Tittonel et al. (2007) investigated the relation between a variable input and crop yield by plot level observation, although the farm size effect has not been elucidated adequately. Practical obstacles include not only the difficulty of observing plot-specific input use such as those of seed, fertilizer, and labor, but also the impossibility of dividing overhead costs among the field plots used by a farm.

Another line of research has used empirical land use models explaining observed land use patterns.

Multinomial logit (MNL) models have been widely applied to investigate the determinants of observed land use as a reflection of bid rent by the land holders. In the context of forest development or conservation, many studies of the literature have applied either an MNL or binomial logit model (Chosmitz and Grey, 1996, Lewis and Plantinga, 2007, Wyman and Stein, 2010, Mann et al., 2010). The model also has been implemented in a study of land use change resulting from urbanization (Zhou and Kockelman, 2010). Lewis and Plantinga (2007) applied the MNL incorporating net return on land by uses of different types. Rashford et al. (2011) also used the MNL model with variables of net return on land and examined land use conversion from grassland to cropland. Moreno and Sunding (2005) applied a nested logit model to the simultaneous decision making of technology and crops. Along with the recent use of geographical information systems (GIS), others have used satellite and remote sensing land use information as datasets (Nelson and Hellerstein 1997, Muller and Zeller 2002). Spatial autocorrelation has been considered in logit models described in recent reports of the spatial econometric literature (Anselin 2010, Zhou and Kockelman, 2010, Fox et al., 1994).

Nevertheless, no empirical bid-rent model has been used to examine the farm size problem given equivalent land use. Such research would be valuable if plot level observations can convey the prospect of farm size in the future. Analyses require a combination of plot and farm data to express the plot attributes: not only distance to the cultivating farmer but also to potential farmers who can bid on the land. We apply an empirical bid-rent model with MNL to rice production in Japan, with cultivation by producers operating at various farm sizes. By combining the plot and farm level databases, the distance to field plots from potential farmers are considered in the model. The impact of land resource scarcity on farm size is examined by interpreting the distance effect.

2. Relation of Bid rent and farm size

Bid-rent theory is based on the different rent provision capabilities of land occupants. Net return on land π_s, viz. payable rent, is $\pi_s = (pq - C)/A$ where *p* and *q* respectively denote the unit price and quantity of output, *C* is the total cost except for land rent, and *A* is the land area. Figure 1 shows the net return on land for rice cropping in Japan (MAFF, 2004, 2009). Because of the price condition, the value of net return on land for rice cultivation has decreased recently in every farm size class. In 2009, the figure became positive for farm size classes of 3 ha and larger. The return is almost equivalent for classes for 5–15 ha planted area of rice.

Figure 2 presents a conceptual image of the bid-rent theory for farms requiring farmland resources for two farms (Farm *t* and Farm *u*) with different size. Depending on the larger farm size, farm *t* can pay more for land than farm *u* can. The bid rent for a plot, however, decreases as the distance from the main home or building increases. Farm *t* cannot bid a higher rent for plot 2, although it can bid much higher for plot 1 than farm *u* can.

Farmland resources in the area are scarcer according to their distance from the cultivator. Simple geometric calculations can illustrate how far a farmer should travel in a scarce land condition. Let d_{max} represent the maximum distance for the farm with a certain farm size. Thus we have the following expression

$$d_{max} = \sqrt{\frac{A}{pi \cdot f}} \qquad (1)$$

where *pi* represents the circular constant, *f* signifies the ratio of available farm for the farm on total land area, and where *A* stands for farm size. Figure 3 portrays the calculated result of d_{max} by different farm sizes and scarcities of farmland resources. Reflecting the mountainous and highly populated condition of the country, the average *f* is 2.6% in Japan. If a farm expands its size to 20 ha in a typical situation, for example, a farmer would most likely have to travel at most 1.5 km to a field plot.

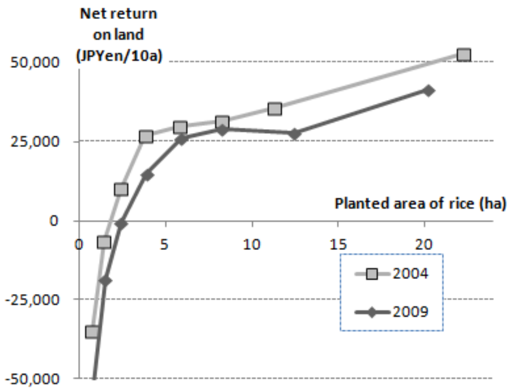

Fig. 1. Net return on land for rice

Note: Source MAFF 2004 and 2009.

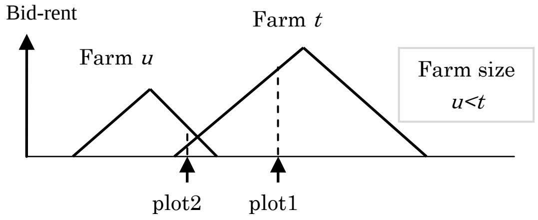

Fig. 2. Farm size and bid rent for land-based farmers.

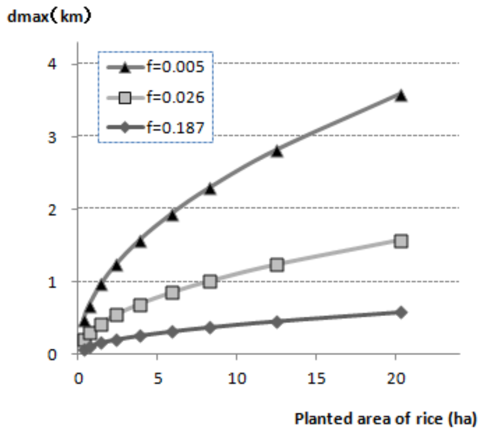

Fig. 3. Maximum distance from the farm to a plot (d_{max}) by different farm size and land resource characteristics.

Note: Based on calculation where f is the ratio of farmland on total land area. f=0.026, 0.005, and 0.187 are, respectively, national average, average of flat regions and average of mountainous region in Japan.

3. Empirical model

3.1 Bid-rent model with multinomial logit (MNL) estimation

Multinomial logit (MNL) models have been applied for empirical bid-rent estimation. Presuming that x is a variable matrix with vectors of variables x_k (k=1…K), consisting of plot i (i =1…n) characteristics, land market situation for the plot, and distance from the farm with different farm size, then the net return on land□$_s$ for different farm size class s (s=1…S) can be expressed as

$$\pi_s = x\, b_s + e_s\ , \qquad (2)$$

where b_s is a vector of coefficients with factor b_{ks} , and e_s is an error term.

The probability of occupancy of plot i by a class t farm ($t=1..S$, $t\neq s$) is

$$P(\mathrm{t}) = P(\pi_t \geq \pi_s) = P(x\, b_t – x\, b_s \geq e_t – e_s). \qquad (3)$$

The MNL for the estimation is written as shown below

$$P(t)= \frac{\exp\,(\mathrm{x}\beta_t)}{\sum_{s=1}^{S} \exp\,(\mathrm{x}\beta_s)}\ , \qquad (4)$$

where β_t and β_s are the parameters for estimation.

3.2. Equiprobability distance lines

We next regard the relation among distance, size, and the land resource scarcity. The MNL result derives the occupancy probability for each size class associated with the distance from each class farm.

When probability for class t equals that of class u ($t\neq u$), $P(t) = P(u)$ that is $x^{*}\cdot \hat{\beta}_t = x^{*}\cdot \hat{\beta}_u$ for given x^{*}. Assigning regional characteristics to x^{*}, but with distance variables, produces equiprobability lines in the dimension of variant distance from each class farm. These equiprobability distance lines are equivalent to isorent lines by different distance and farm size.

Finally, subsistence of the large scale farm is examined using the combination of maximum distance d_{max} and equiprobability lines. If a farm in a particular class should travel to the extent of less probable distance, that is, to a less affordable field plot, then compared to the smaller class farm, it struggles at gathering farmland and is unlikely to exist as a large-scale farm operation.

4. Data and hypothesis

Our study area is the Tokamachi city in Niigata prefecture in Japan, where the most famous rice brand, Uonuma Koshihikari, is produced under a severe climate with a huge amount of snowfall. Although the average farm size is 1.25 ha, the number of large scale rice farms larger than 10 ha, or than 30 ha, has increased during the last decade.

With the assistance of the local city authority and agricultural cooperative, planting plans for 2010 and farm identification numbers (Farm ID) for every rice field plot were collected as a plot database. Location features obtained through the Agricultural Census of 2005are added as plot attributes, such as the degree of the steepness in the neighborhood area, distance from a Densely Inhabited District (DID), and so on. The farm database consists of a Farm ID and farm characteristics such as farm size and government scheme enrollment.

The integrated database of both plot and farm database is generated with Geographic Information System (GIS). It enables calculate the distance to field plots from different size class farms.

Among total 33,170 plots in the integrated database, 12,381 plots were excluded because of the lack of statistical information or their current land use if different from rice cropping. We therefore apply 20,789 field plot data to the MNL estimation.

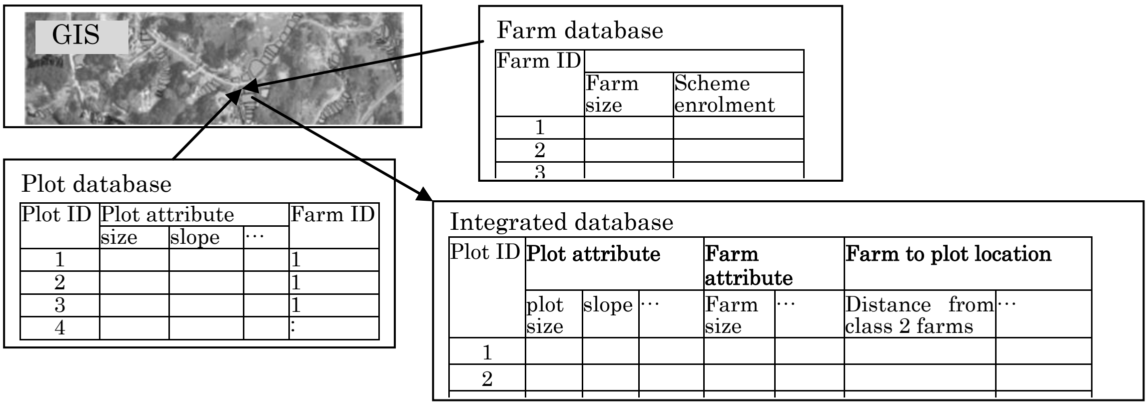

Fig. 4. Integrated database used for estimation.

Table 1 presents denominations, descriptions, data sources, and expected signs of variables used for estimation. Dependent variable *P*(s: s=1..4) represents the probability of plot i occupancy by corresponding farm size class s. Farms are classified into four size classes (Cl) considering of net return on land and actual shares in the region: farms operating with less than 3 ha (Cl1), 3–5 ha (Cl2), 5–15 ha (Cl3), and 15 ha and larger (Cl4).

A set of independent variables consists of six attributes of the plot, farm, and areal characteristics and three distance-to-farm variables. Coefficients estimated by MNL denote relative probabilities compared with a norm category. We set Cl1, the smallest class, as the norm. Positive signs are therefore expected when the attribute has a positive relation with farm size and vice versa. The plot size variable is based on the plot database and is expected to be positive. The larger a farm becomes, the larger machinery it can afford to hold, which is efficient for operating in large plot fields.

Both elderly farm labor and distance to DID are proxies of the land market situation around the plot. Because of aging of farmers, more productive field plots are released to the market, which is expected to be a positive sign. In contrast, adjacency to DID compels land owners to anticipate capital gains of development. Therefore, a negative sign is expected.

We use two dummy variables, steepest area and steep area, to denote the classes of steepness of the area surrounding the plot[1]. If both dummies are zero, then the plot belongs to a flat area. It can be assumed that

[1] A steepest area is that of 1/20 and steeper. A steep area is steeper than 1/100 and but less steep than 1/20.

expected signs of steepness condition are negative. Scarcer farmland resources in steeper areas cause difficulties for large farms to subsist, as described in the earlier section, although direct payment in less favored areas might ease the condition[2].

Governments promote enlarging farm size and the increase of professional farming through farmer certification programs. Enrollment for this scheme is therefore regarded as having a positive relation with farm size.

The d_s (s=2..4) [3]are distances from any farm in the class s to plot i. The expected sign is negative for the probability equation of corresponding class, i.e. d_s for P(s) because the more distant the plot is from the farm, the lower the rent that can be paid, as the theory would dictate.

Table 1
Variables and expected sign

Variables	Description (source)	Expected sign
Dependent variables *P*(s: s=1..4) Farm size class	*s*=1: 0–3 ha, 2:3–5 ha, 3:5–15 ha and 4:15 ha and more (integrated database)	
Independent variables		
Plot size	Field plot size (a) (Plot database)	+
Elderly farm labor	Share of aged farm labor in the community (MAFF2005)	+
DID	Travel time (min) from DID (*ditto*)	-
Steepest area	1: in the steepest area, 0: no (*ditto*)	-
Steep area	1: in the steep area, 0: no (*ditto*)	-
Scheme enrollment	1: enrolled, 0: not enrolled (Farm database)	+
d_4 d_3 d_2	Distance (km) from class *s* farm to the plot (Integrated database)	- for the categorized class, +/- otherwise

Descriptive statistics of the variables are presented in Table 2. The plot size is smallest in Cl1 and largest in Cl4. Regarding the 30 a standard consolidation rice field plot, average plot size of less than 10 a in the steepest area is considerably small. Situations of aged farm labor are almost identical among classes. Furthermore, Cl4 farms are located close to DID and flat areas, whereas Cl2 farms are observed in steeper areas. Fewer Cl1 farmers enrolled as certified farmers. However, all Cl4 farmers are certified by the scheme. Regarding distance-to-farm variables, d_4 is larger than d_2 and d_3 in three classes, except for Cl4.

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[2] Most farmers in steeper areas receive a direct payment according to the criteria coinciding with our classification of steep conditions. The payment rates are 21,000 yen/10 a for rice field in steepest area and 8,000 yen/10 a for steeper areas.
[3] d_1 (*s*=1) is excluded because it is the smallest class and it exists everywhere in the region.

Table 2
Descriptive statistics of variables used in the logit model

variables	Class 1 (0-3ha)				Class2 (3-5ha)				Class 3 (5-15ha)				Class 4 (15ha-)			
	mean	s.d.	min	max	mean	s.d.	min	max	mean	s.d.	min	max	mean	s.d.	min	max
Plot size	9.88	8.88	0.10	113.8	12.48	10.88	0.20	128.5	10.57	9.60	0.10	96.1	14.46	11.39	0.30	94.0
Aged farm labor	0.42	0.15	0.06	0.82	0.40	0.14	0.06	0.82	0.38	0.12	0.06	0.82	0.43	0.17	0.06	0.82
DID	10.70	6.15	7.50	22.5	11.36	6.56	7.50	22.50	10.30	5.85	7.50	22.50	7.94	2.52	7.50	22.50
Steepest area	0.24	0.42	0.00	1.00	0.35	0.48	0.00	1.00	0.13	0.34	0.00	1.00	0.02	0.15	0.00	1.00
Steep area	0.28	0.45	0.00	1.00	0.24	0.43	0.00	1.00	0.41	0.49	0.00	1.00	0.09	0.28	0.00	1.00
Scheme enrollment	0.03	0.17	0.00	1.00	0.41	0.49	0.00	1.00	0.49	0.50	0.00	1.00	1.00	0.00	1.00	1.00
d_4	3.17	1.88	0.00	7.14	3.59	1.97	0.00	7.14	3.38	1.73	0.00	7.14	1.23	1.25	0.00	6.36
d_3	1.17	1.05	0.00	4.62	1.15	1.06	0.00	3.77	0.30	0.57	0.00	3.13	1.45	1.03	0.00	3.86
d_2	0.65	0.72	0.00	2.57	0.15	0.39	0.00	2.11	0.50	0.69	0.00	2.21	0.86	0.76	0.00	2.35

5. Results of MNL estimation

Table 3 presents the results of MNL estimation[4]. Expected signs are met in most of the variables. Cl2 and Cl4 farms hold larger plots, although Cl3 does not. The coefficient of the plot size is largest for Cl2 rather than Cl4, which has a larger mean value of plot size. This result demonstrates that the largest class is not necessarily advantageous for holding large size plots with high operational efficiency.

As elderly farmers become increasingly numerous, the average farm size is likely to expand. In contrast, adjacency to a city center negatively impacts farm size. Both the steepness condition variables are negative for Cl4 farms indicating that largest class farms are located in flat areas. Enrollment in farmer certification programs has a positive impact for Cl2 and Cl3 farmers.

Distance-to-farm variable d_s also shows expected signs: it is negative for probabilities of the own category. The distance from farm to plot therefore has a negative impact on farmland occupancy by the farm.

[4] We also estimated the spatial autocorrelation model as $e=\lambda We+u$; λ was not significant.

Table 3
Estimated result of MNL

	Class 2		Class3		Class 4	
	β	p.	β	p.	β	p.
constant	-2.462	.000	-2.658	.000	1.671	.000
Plot size	.021	.000	-.010	.003	.009	.078
Aged farm labor	-.739	.001	1.317	.000	1.991	.000
DID	-.003	.592	-.035	.000	-.078	.000
Steepest area	.678	.000	-.393	.000	-.469	.085
Steep area	.512	.000	.897	.000	-.159	.382
Scheme enrollment	3.037	.000	3.594	.000	—	
d_4	-.055	.011	.120	.000	-.711	.000
d_3	.221	.000	-1.440	.000	.276	.000
d_2	-1.578	.000	.095	.071	.306	.002

Note: McFadden r^2=0.40. χ^2=1.29 × 10^{-4} (level of significance: 0.00).

6. Competition among farms with different size

Equiprobability distance lines can be calculated through the MNL estimated result. By substituting the average value to x^*, except for distance and steepness conditions, line $P(t)=P(u)$ is derived. Steepness conditions are presumed to be 1 or 0 to clarify the impact of different conditions. Each of the three distance variables is set as 10 (km) to examine the relation between the remaining two.

Equiprobability lines for P(Cl2)=P(Cl3) and P(Cl2)=P(Cl4) for different steepness conditions are depicted in Figures 5 and 6. Each represents the equiprobability distance from the farm and either size class of farm more probably holds the plot in either side of the line. In flat areas, large-scale farms are widely subsistent compared to those in the steepest areas. For example, a Cl4 farm has an advantage over Cl2 in an area when the plot is less than about 3 km distant from Cl4, even though it is as close as 0 km from Cl2. In the steepest area, Cl4 farms are not dominant unless the plot is a few hundred meters away from Cl2 farms.

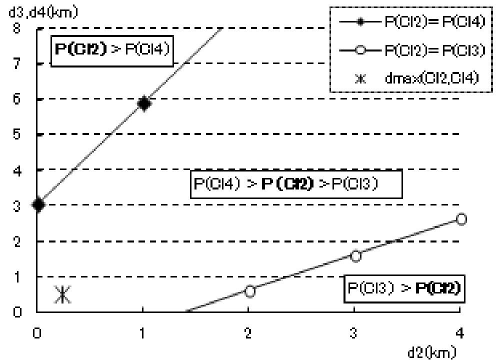

Fig. 5. Equiprobability lines in flat areas.

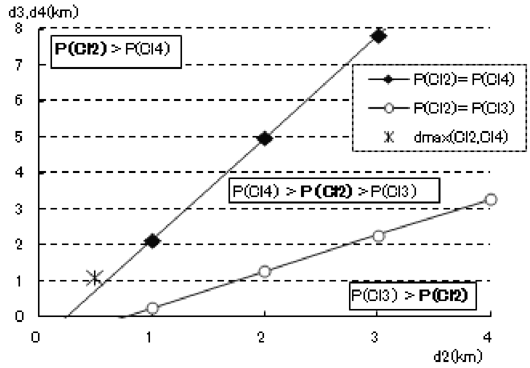

Fig. 6. Equiprobability lines in steepest areas.

Points representing d_{max} in Figures 5 and 6 are maximum distances from farms to field plots based on the calculation explained in Table 4. In flat areas, about one-fourth of land is devoted to rice fields. The calculated d_{max} are, respectively, 0.23 and 0.51 for Cl2 and Cl4. As shown by d_{max} in Figure 5, Cl4 farms therefore can be quite subsistent even in competition over the most distant land. In contrast, in steepest areas, the ratio of rice fields to total land area is only 5%, which respectively engenders d_{max} of 0.49 and 1.09 for Cl2 and Cl4. Bid-rent competition over the most distant land between Cl2 and Cl4 probably results in occupancy by Cl2.

Table 4
Calculation of maximum distance of a farm using the steepness condition

		Flat area	Steepest area
f: ratio of rice field to total land area		0.24	0.05
d_{max}(km)	Cl2 (*A*=4 ha)	0.23	0.49
	Cl4 (*A*=20 ha)	0.51	1.09

Note: $d_{max}=\sqrt{\frac{A}{pi \cdot f}}$

7. Conclusion

The inverse relation of farm size and productivity, and bid rent, has long been discussed and examined. The phenomenon is particularly pronounced with agriculture, where vast areas of land are necessary for efficient production and where farm size expansion is expected to reach the physical and management limitations of a farm. The problem is particularly important with regard to Asian rice production, which must confront global competition with small scattered plots in steep conditions. However, no report in the relevant literature has described a study clarifying the relation of land resource scarcity, distance to a farm, and farm size. By applying a bid-rent model incorporating distance-to-farm plot attributes with a combined farm and plot database, these situations are explained empirically in this paper.

Our MNL estimation result supports the bid-rent theory considering resource scarcity and farm size. The more distant a plot is from a farm, the less rent it can earn. In steeper areas, large farms have no sufficient advantage in bid-rent competition with smaller farms. Direct payment in steep areas is apparently insufficient to compensate for the disadvantage to larger scale farms. Moreover, efficient plots are not easily held by large farms.

The model does not employ rent variables directly. Consequently, it is difficult to simulate a case of economical situation change. If the local average net return on land by size class were incorporated, then the estimated probability might be comparable with the rent level at certain points. Another limitation of this study is its restricted use of a special autocorrelation model. Examining countless specifications of special econometric models is far beyond the scope of this paper, but we were able to clarify interesting special relations through the use of a GIS device and distance-to-farm information, which had not been fully applied in any earlier study.

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