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Technical Change and Scale Effects in Relation to Profit Efficiency—Case of Family-Based Eggplant Production in Japan

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Abstract

Little is known about how data-driven greenhouse horticulture impacts profit efficiency. Furthermore, the interaction between technical change (*e.g.*, adoption of ECDs) and scale effects (*e.g.*, farmland size) remains underexplored, particularly during periods of high fuel costs. Thus, by investigating the adoption of environmental control devices and farmland size, this study aims to determine whether technical changes (TC) and scale effects (SEs) contribute positively to profit effciency. Therefore, we hypothesize that both factors, TC and SEs, synergistically enhance profit efficiency. For our study, we observed both technical change affecting profit efficiency between 2017 and 2019. However, the technical change effect diminished in recent years, especially since 2020, due to increased input costs. Further, scale effects were rather limited as we observed an inverted U-shaped relationship between profit efficiency and farm size, the optimal farm size being equal and more than 41 and less than 46 *are.* The input costs negatively impacting the profit efficiency, namely repair and labor hiring costs, should be the foremost urgent issues to be resolved for TC and SEs to take place in the family-based facilitated greenhouse eggplant production in Japan.

Keywords: stochastic frontier profit analysis, profit inefficiency, eggplant, Japan

1. Introduction

1.1 Introduce the Problem

In recent years, data-driven efforts have been made to improve the efficiency of horticultural production in Japan. Greenhouse horticultural farms in Japan have adopted the environmental control system since the 1980s to control on-farm information such as temperature, humidity, and CO_2 at the individual farm level. The environmental control system was developed to increase agricultural productivity by controlling the environment inside plastic greenhouses. Specifically, environmental factors such as temperature, humidity, and solar radiation are monitored, and it optimizes the growing environment in the greenhouse through the activation of other environmental control devices (ECDs) such as carbon dioxide gas generators (gas machine), ventilation windows, irrigation equipment (water machine), etc. However, adoption of ECDs has been relatively slow in Japan. The total area of greenhouses with ECE is 39,452 ha (2.9%) out of the total facility-based horticulture, an increase of 0.7% compared to 2015 (MAFF, 2022).

However, fuel oil prices fluctuate widely due to exchange rates and international commodity market conditions, making it difficult to forecast future prices for production materials and the profit of horticultural production. Fuel costs account for a high proportion of management costs in horticulture, which is easily affected by fuel price hikes. In particular, the income of horticulture facility farmers who grow winter/spring vegetables is strongly affected by fuel oil prices because heavy oil is used for heating equipment to maintain a constant indoor temperature, and kerosene or liquefied petroleum gas is used for carbon dioxide gas generation equipment. Thus, the need to stabilize profit margins amidst rising input costs underscores the importance of identifying and addressing key variables affecting profit efficiency.

Despite the challenges, facility-based horticulture remains a viable business model for small-scale family farms in Japan. The average production land area of facility-based horticultural vegetables in Japan is 24.9 *are* (2490

m^2), which is not large. However, the specific impact of data-driven agriculture on profit efficiency and optimal land size in facility-based horticultural crop production at the time of the current high fuel costs remains to be not yet discussed. To address the impact of data-driven production and the land size at the time of the high input costs, the theory of efficiency through technical change or scale change could be useful. Previous research in the U.S. (Schimmelpfennig, 2016) and Brazil (Griffin & Lowenberg-Deboer, 2005) has examined the effect of precision agriculture on profits, with varying results depending on the technology adopted. In facility-based horticulture, farmers utilize several technologies. For facility-based horticulture, the technologies can range from electronic automation to ECS that regulates the environment inside a greenhouse (Achour et al., 2021). Improving resource use efficiency in agriculture can enhance profit efficiency through technical changes (TC) and scale effects (SEs). This increases productivity as farmers optimize inputs based on the specific environment. Parikoglou et al. (2022) conducted a study on precision dairy agriculture, finding that milk recording improved resource utilization and productivity in Ireland. The researchers observed rapid productivity growth through TC and efficiency improvements rather than scale effects. To comprehend profitability efficiency, it is crucial to determine whether profit efficiency improvement is driven by TC, SEs, or both.

In the case of Japan, little is known about how data-driven greenhouse horticulture impacts profit efficiency. Furthermore, the interplay between technical change (*e.g.*, adoption of ECDs) and scale effects (*e.g.*, land size) remains underexplored, particularly during periods of high fuel costs. Thus, by investigating the degree of ECD adoption, this study aims to shed light on the relationship between technology adoption and land size on profit efficiency at a time of high fuel costs. Specifically, it seeks to determine whether technical changes (adoption of ECDs) and scale changes (land size) contribute positively to profitability, especially under high input cost conditions. Therefore, we hypothesize that both factors, technical advancements and optimal scale, synergistically enhance profit efficiency. By addressing this research gap, the study will provide valuable insights into the economic benefits of adopting data-driven technologies in greenhouse horticulture. It will also offer practical recommendations for policymakers and farmers on improving resource use efficiency and profitability during periods of volatile fuel prices. Additionally, the findings may inform strategies for scaling up the adoption of ECS and optimizing land use to achieve sustainable agricultural practices in Japan. For the remaining paper, the next section discusses methodology, followed by a description of the study area in the third section. The fourth section explains our analytical results, followed by a discussion and conclusion.

2. Method

2.1 Study Area and Data Collection

Kochi enjoys a mild climate with long hours of sunlight, making it ideal for growing a wide variety of crops, namely eggplant, green pepper, sweet chili green pepper, Japanese ginger, cucumber, and Chive. The region’s hilly terrain and coastal plains are well-suited for agriculture, providing diverse microclimates that enable the cultivation of both seasonal and off-season crops. These conditions have made Kochi a hub for the production of high-quality greenhouse vegetables, fruits, and flowers. Kochi produces the largest amount of eggplant, shishito, and myoga for the market in Japan (MAFF, 2022). These crops are produced with high productivity and profitability due to their climatic conditions and the introduction of advanced technology. In particular, facility horticultural crops shipped in the winter/spring season often fetch high prices in markets throughout Japan.

Figure 1. Kochi Prefecture (created by the authors using GoogleMaps)

Among them, eggplant is an essential vegetable in Japan. The prices of 13 important crops, including eggplant, are monitored because of their impact on price indexes and the consumer price index (CPI) in Japan. Kochi has 279 ha of eggplant (Figure 2) and 1.5 tons per ha in 2022, which is the highest productivity in Japan (Figure 3). Although the proportion of family-based eggplant production is decreasing in Kochi prefecture, they are still the core of domestic eggplant production as their production accounts for 34% of the total yield of facility-based eggplant production in Japan.

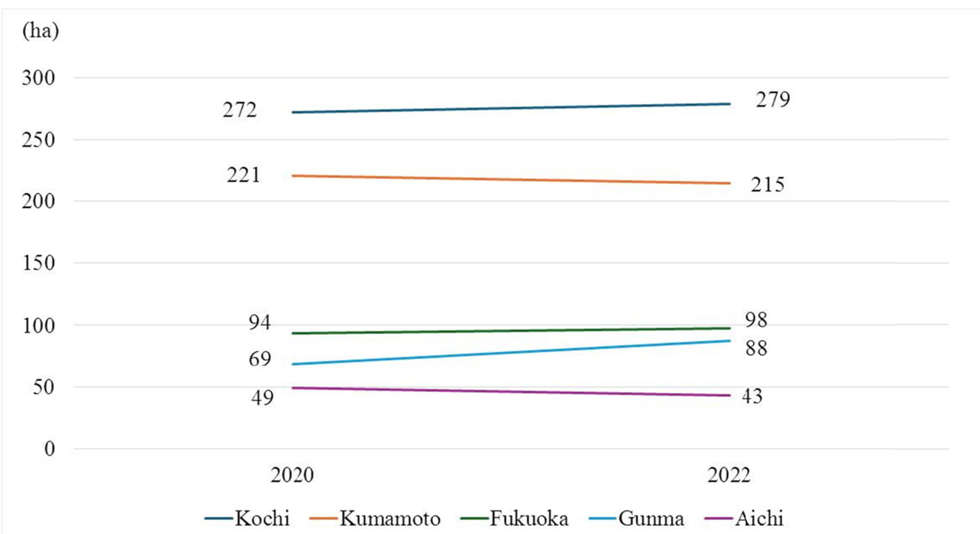

Figure 2. Top five eggplant cultivation by prefecture

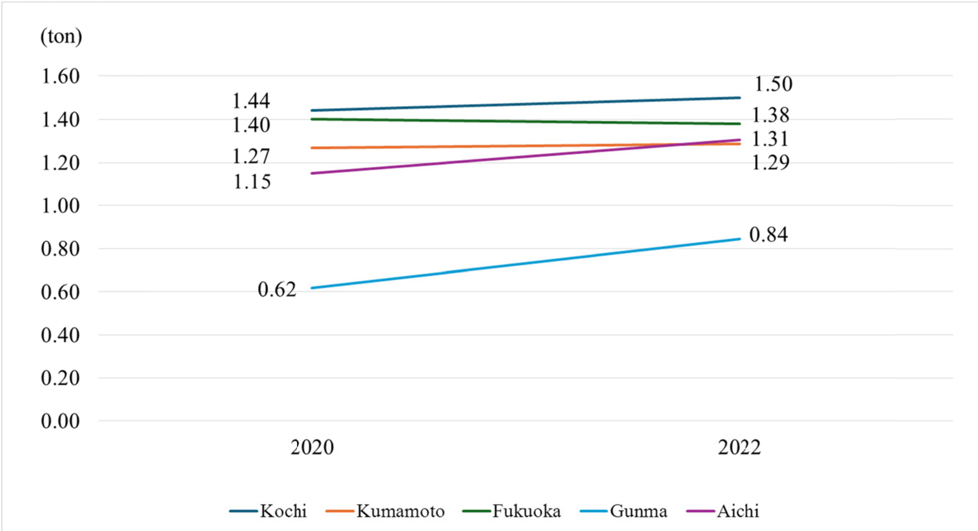

Figure 3. Top five eggplant productivity

2.2 Sampling Procedures and Sample Size

Data is provided by the Kochi prefecture, and farmers' tax return data was used, with their personal identities being anonymous. Data between 2017 and 2021 had 90 samples, while 2022 had only 77. Also, as we wanted to capture the impact of the high fuel costs, we separately analyzed data from 2017-2019 and 2020-2022. Thus, the sample size for the 2017-2019 data was 270, whereas the sample size for the 2020-2022 data was 257. The farmers mainly produced eggplant for commercial purposes and had a small plot of rice fields for house consumption.

2.3 Analytical Framework

2.3.1 Profit Function (Profit Frontier Equation)

A stochastic frontier profit function model is applied in this study. The stochastic frontier analysis (SFA) was introduced initially by Meeusen and van Den Broeck (1977) and Aigner, Lovell, and Schmidt (1977) as follows:

$$Y_i = \mathrm{f}(X_i,\beta)\exp(v_i - u_i) \qquad i = 1, \cdots, N \tag{1}$$

where, Y_i represents the output variable, and X_i represents a sector of input variables. β is the elasticity of the input factors, reflecting the influence of input factors on the output. v_i accounts for measurement errors, usually assumed to follow a normal distribution. u_i is a non-negative random variable that represents the lack of technical efficiency, which is assumed to follow various distributions, such as a half-normal distribution (Aigner et al., 1977), gamma distribution (Greene, 1990), and truncated distribution (Stevenson, 1980).

Battese and Coelli (1995) extend the SFA of cross-sectional to panel data. They define a stochastic frontier production function for panel data, in which the non-negative technical inefficiency is assumed to be a function of individual-specific variables and time variables. The time-varying stochastic frontier function model is presented in the form.

$$Y_{it} = \mathrm{f}(X_{it},\beta)\exp(v_{it} - u_{it}) \qquad i = 1, \cdots N; t = 1, \cdots T \tag{2}$$

where, Y_{it} denotes the output index of the farmer "i" at time "t". X_{it} is a $(1 \times k)$ vector of values of known functions of production inputs and those of other explanatory variables associated with the farmer "i" at time "t". β is a $(k \times 1)$ vector of unknown parameters to be estimated. v_{it} is assumed to be $N(0, \sigma_v^2)$ random errors that are independently distributed of u_{it}. u_{it} is a non-negative random variable associated with the technical inefficiency of production, which is assumed to be independently distributed.

Production profits are used as the output variable in the stochastic frontier profit function, thus rewriting Equation (2) as follows:

$$\pi_{it} = \mathrm{f}(X_{it},\beta)\exp(v_{it} - u_{it}) \qquad i = 1, \cdots N; t = 1, \cdots T \tag{3}$$

where, π_{it} denotes the production profit of farmer "*i*" in the year "*t*". u_{it} represents the technical inefficiency of production profits for the farmer "*i*" at time "*t*". It is worth noting that the profits and input indicators used are expressed in terms of amount, not quantity. Therefore, input and output prices are not included in the model. In addition, all the indicators are standardized.

Regarding $f(X_{it},\beta)$ settings, two choices usually exist the Cobb-Douglas production function (CD function) and the transcendental logarithm function (Translog function). The CD function adds only the first-order terms of input variables. In contrast, the Translog function overcomes the defect of the CD function, in which the elasticity of substitution is fixed to 1, by adding the cross-multiplication terms and square terms of all input variables in addition to the first-order terms. According to the results of the likelihood ratio test, the Translog production model is adopted to conduct this study's empirical research. Equation (3) is rewritten as,

$$\ln\pi_{it} = \beta_0 + \sum_{k=1}^{m}\beta_k \ln X_{it,k} + \frac{1}{2}\sum_{k=1}^{m}\sum_{l=1}^{m}\beta_{kl}\ln X_{it,k}\ln X_{it,l} - u_{it} \quad (4)$$

where, $\ln\pi_{it}$ is the logarithmic form of the production profits (*Profits*). $\ln X_{it,k}$ represents the logarithmic form of the *k-th* input variable, X_{it} comprises *Seedling*, *Fertilizer*, *Equip*, *Pesticide*, *Material*, *Fix*, *Power utility, Depreciation*, *Transportation*, and *Hiring fee*. The regression coefficients and error terms are clustered at the farmer level to control for potential heteroskedasticity and serial correlation.

2.3.2 Profit Inefficiency Equation

According to Battese and Coelli (1995), the profit efficiency PE_{it} for the farmer "*i*" at time "*t*" is defined by the following equation:

$$PE_{it} = \mathrm{EXP}(-u_{it}) \quad i = 1, \cdots N; t = 1, \cdots T \quad (5)$$

If $PE_{it} = 1$, the farm is fully profit-efficient, meaning operating on the profit frontier. If $PE_{it} < 1$, inefficiency reduces the farm's profit. Further, profit inefficiency accounts for both technical inefficiency and allocative inefficiency, meaning it considers how well the farmer chooses input combinations to maximize profit. The profit inefficiency model is presented as,

$$u_{it} = \theta_0 + \theta_1 Landsize_{it} + \theta_2 \ln Labor_{it} + \sum_{c=1}^{3}\eta_d ECDs_{it,d} + \epsilon_{it} \quad (6)$$

where, u_{it} represents the inefficiency term of production profits for the farmer "*i*" at time "*t*". A larger u_{it} replies greater deviation from the profit frontier. The following variables are used to explain the extent of any inefficiency. $Labor_{it}$ is the number of laborers of farmer household "*i*" at time "*t*".

To improve profit efficiency, eggplant farmers are encouraged to use gas machines, automated roof windows, environmental-measuring machines, and water machines in the greenhouse production process. Thus, $ECDs_{it,c}$ it represents the dummy four types of devices adopted. They are namely carbon dioxide gas generators (*Gas*), ventilation windows (*Ventilation*), and irrigation equipment (*Water*), which the local government extension collects annual change of such data over time. *Landsize* is divided into eight categories: 0-24, 25, 26-30, 31-35, 36-40, 41-45, 46-50, and 51-70 *are*. The 26-30 *are* group is set as the control group and assigned a value of "0" to indicate the farm-size group to which farmers belong. The remaining farm-size groups are assigned a value of "1". Finally, ϵ_{it} is the error term of the model.

There are two methods for estimating Equation (4) in academia: the "one-step" method and the "two-step" method. The "two-step" method does not consider factors affecting technical and allocative inefficiency in the first step; it first estimates Equation (4) to obtain the profit inefficiency term u_{it}, and then, the second step is to estimate the impact of influence factors as the dependent variables on the profit inefficiency. Wang and Schmidt (2002) state that a defect of this method is that the technical inefficiency distribution is different in the two stages, leading to inconsistent estimation results. Thus, we use the "One-step" method proposed by Coelli and Battese (1996), that is, substituting Equation (6) into Equation (4) to directly perform one-step estimation to obtain more accurate results than the "Two-step" method.

3. Results

3.1 Descriptive Summary of Variables

Table 1 summarizes all the definitions of dependent and independent variables, measurement units, and summary statistics. The *profitspa* was calculated by subtracting the total input cost from the total revenue per 10 *are* (1000 m^2), which is a standard unit used for horticultural production analysis in Japan. On average, the profit was 2,167,691.0 JPY (13,735.04 USD) per 10 *are*, ranging from 169,041.5 JPY (1071.09 USD) to 5,096,416.0 JPY (32,292.18 USD) per 10 *are*. 37 farmers fall under 1,000,000 JPY (6336.25 USD) per 10 *are*. The mean Land size is 29.677 *are*.

Table 1. Descriptive summary of variables used in the study (n = 527) unit = per 10 *are* (1000 m^2)

Variables	Definition	Mean	Standard Deviation	Minimum	Maximum
Profit Function					
profitspa	Net income (yen)	2,167,691.0	859,925.7	169,041.5	5,096,416.0
seedlingspa	Seedlings	174,632.6	51,737.0	0.0	424,705.9
fertilizerpa	Fertilizer	419,464.2	169,807.8	82,985.3	1,030,556.0
pesticidepa	Pesticide	175,143.7	78,402.1	27,692.3	736,428.6
materialpa	Material	419,647.4	208,832.5	3,030.3	1,211,116.0
repairpa	Repair	146,488.9	126,437.9	0.0	1,009,053.0
clothespa	Clothes	31,552.3	28,866.3	0.0	173,333.3
power_fuelspa	Fuels	595,466.9	283,397.7	86,091.2	1,756,044.0
farm_equippa	Equipment	80,790.4	111,294.4	0.0	752,800.0
depreciationpa	Depreciation	451,592.5	284,521.1	0.0	1,602,941.0
transportationpa	Transportation	872,514.6	793,418.8	0.0	2,855,390.0
hiring_feepa	Labor hire	75,518.4	179,522.2	0.0	2,492,770.0
Profit Inefficiency Function					
dventilation	1 = Have automated ventilation, 0 = Do not have	0.069	0.253	0	1
dirrigation	1 = Have automated irrigation, 0 = Do not have	0.248	0.432	0	1
dgas	1 = Have automated CO_2 gas, 0 = Do not have	0.359	0.480	0	1
land_size	Land size	29.677	10.753	10	70
landsize < 20	dummy of Land size < 20	0.239	0.427	0	1
landsize ≥ 20 and < 26	dummy of Land size ≥ 20 and < 26	0.130	0.336	0	1
landsize ≥ 26 and < 31	dummy of Land size ≥ 26 and < 31	0.180	0.384	0	1
landsize ≥ 31 and < 36	dummy of Land size ≥ 31 and < 36	0.159	0.366	0	1
landsize ≥ 36 and < 41	dummy of Land size ≥ 36 and < 41	0.176	0.381	0	1
landsize ≥ 41 and < 46	dummy of Land size ≥ 41 and < 46	0.035	0.184	0	1
landsize ≥ 46	dummy of Land size ≥ 46	0.081	0.274	0	1
labor	Labor number	2.751	0.932	1	5

In terms of inputs, *seedlingspa* cost 174,632.6 JPY (1106.52 USD) per 10 *are*, with a range from 0 to 424,705.9 JPY (2691.04 USD) per 10 *are*. The fertilizer, *fertilizerpa*, costs 419,464.2 JPY (2657.83 USD) per 10 *are*, with a range from 82,985.3 (525.82 USD) to 1,030,556.0 JPY (6529.86 USD) per 10 *are*. The pesticide, *pesticidepa* costs 175,143.7 JPY (1109.75 USD) per 10 *are*, with a range from 27,692.3 (175.47 USD) to 736,428.6 JPY (4666.20 USD) per 10 *are*. The cost of various materials for greenhouse horticulture is one of the most expensive inputs and refers to the cost of vinyl for plastic greenhouses and consumables such as insect nets, cold gauze, mulch, rope, wire, etc. The mean *materialpa* costs 419,647.4 JPY (2658.99 USD) ranging from 3,030.3 JPY (19.20 USD) to 1,211,116.0 JPY (7673.94 USD). The repair expenses, *repairpa*, refer to the cost of repairing previously purchased items. The mean repair costs 146,488.9 JPY (928.29 USD), with a range of 0 and 1,009,053.0 JPY (6394.27 USD) per 10 *are*. The clothes, *clothespa*, are expenses for work clothing such as work clothes, boots, hats, gloves, and tabi socks can be charged to expenses as "work clothing expenses". The mean clothes costs is 31,552.3 JPY (199.94 USD), ranging from 0 to 173,333.3 JPY (1098.40 USD) per 10 *are*. The power_fuelspa is the fuel costs used for greenhouses. The mean fuels cost 595,466.9 JPY (3773.41 USD) per 10 *are*, ranging from 86,091.2 JPY (545.55 USD) to 1,756,044.0 JPY (11,127.88) and standard deviation is large.

Agricultural equipment expenses for facility horticulture refer to the cost of purchasing agricultural equipment such as farm machinery and agricultural warehouses. Expenses that can be recorded as farming equipment expenses are the purchase of farming equipment with a useful life of less than one year or an acquisition cost of less than 100,000 yen (633.69 USD). The mean *farm_equippa*, costs 80,790.4 JPY (511.96) per 10 *are*, ranging from 0 to 752,800.0 JPY (4770.42 USD) per 10 *are*. Depreciation of greenhouse horticulture is an account used to record the cost of purchasing assets used in facility horticulture by dividing the cost of such assets over future periods. Tractors, mowers, haulers, etc., are uniformly depreciated over a period of 7 years. Vinyl greenhouses: Depreciation depends on the material of the skeleton part and is calculated over 14 years for steel frame greenhouses, 5 years for wooden greenhouses, and 8 years for other materials. The mean depreciation, *depreciationpa*, costs 451,592.5 JPY (2861.70 USD), ranging between 0 to 1,602,941.0 JPY (10157.68 USD) per 10 *are*. Also, the standard deviation of depreciation is large.

Packing and freight charges in facility horticulture refer to transportation costs, *transportationpa*, freight, and fees incurred when shipping and selling agricultural products. Specifically, it refers to the cost of purchasing packing materials (cardboard, duct tape, etc.), shipping costs for courier services etc., fees paid to shipping (receiving) agencies, country fixed costs, and costs associated with sales measures. The mean transportation costs is 872,514.6 JPY (5529.04 USD) ranging from 0 to 2,855,390.0 JPY (18,094.32 USD) per 10 *are*. Among the input costs, the standard deviation of the transportation is the largest, 793,418.8 JPY (5027.82 USD). On October 1, 2019, with the transition of the consumption tax rate from 8% to 10%, a reduced tax rate was introduced to the sector for certain parts of the transaction. As a result, a reduced tax rate of 8% will be applied to a portion of taxable sales, while the consumption tax rate will be 10% for items not subject to the reduced rate. Until September 30, 2019, the flat 8% rate allowed agricultural products shipped to agricultural cooperatives to be considered taxable sales minus consignment sales fees. After October 1 of the same year, the tax rate was different, and the consignment sales commission was also recorded. Therefore, packing and freight charges before and after FY2020 are different, and sales are likewise different. Thus, for the analysis, we separately analyze the dataset between 2017 and 2019 and another dataset between 2020 and 2022. Finally, labor hire is 75,518.4 JPY (478.55 USD) ranging from 0 to 2,492,770.0 JPY (15,796.43 USD) per 10 *are*.

For the profit inefficiency function, the *dventilation* is a dummy variable that, if farmers have automated ventilation, indicates 1 and, if not, 0. The *dirriagation* is a dummy variable that, if farmers have automated irrigation, indicates 1 and, if not, 0. The *dgas* is a dummy variable that, if farmers have automated CO_2 gas emitter, indicates 1 and, if not, 0. The mean *land_size* is 29.677 *are*, ranging from 10 *are* to 70 *are*. The *landsize* < 20 is land size segment dummy if land size is less than 20. The *landsize* ≥ 20 and < 26 is land size segment dummy if land size ≥ 20 and < 26. The *landsize* ≥ 26 and < 31 is land size segment dummy if Land size ≥ 26 and < 31. The *landsize* ≥ 31 and < 36 is land size segment dummy if land size ≥ 31 and < 36. The *landsize* ≥ 36 and < 41 is land size segment dummy if land size ≥ 36 and < 41. The *landsize* ≥ 41 and < 46 is land size segment dummy if land size ≥ 41 and < 46. The *landsize* ≥ 46 is land size segment dummy if land size ≥ 46. The proportion is 23.9%, 13.0%, 18.0%, 15.9%, 17.6%, 3.5%, and 8.1%, respectively. Finally, the *labor* is the number of family members contributing to eggplant farming.

3.2 Statistic Frontier Profit Function Model Estimation

Table 2 presents the estimated parameters for the stochastic frontier profit efficiency translog model. The coefficients and standard errors for different variables are reported, along with their significance levels. We prepare two models to estimate the influence of pre-2020, *i.e.*, the 2017-2019 dataset as model 1 and the 2017-2020 dataset as model 2. In particular, we estimated the technical changes to profit inefficiency function of the technical variable, namely "*dventilation*", "*dirrigation*", and "*dgas*", as well as the scale variable, "land" segment dummies "landsize".

Table 2. The estimated parameters for the eggplant profit per 10 *are* stochastic frontier translog model (n = 141)

Variables	**Model 1** (n = 270) **Year 2017-2019**			**Model 2** (n = 462) **Year 2017-2022**		
	Coef.		Std. Err.	Coef.		Std. Err.
Frontier						
lnseedlingspa	-0.13		(0.11)	0.18		(0.14)
lnfertilizerpa	-0.04		(0.11)	0.13		(0.11)
lnpesticidepa	0.21	*	(0.02)	-0.04		(0.12)
lnmaterialpa	0.00		(0.12)	-0.08		(0.08)
lnrepairpa	-0.14	***	(0.08)	-0.23	***	(0.05)
lnclothespa	0.01		(0.05)	0.08	***	(0.02)
lnpower_fuelspa	-0.20	**	(0.03)	-0.06		(0.09)
lnfarm_equippa	0.00		(0.09)	0.01		(0.02)
lndepreciationpa	-0.08		(0.07)	0.04		(0.05)
lntransportationpa	0.04	*	(0.02)	0.10	***	(0.03)
lnhiring_feepa	-0.09	***	(0.03)	-0.10	**	(0.04)
Cons.	14.80	***	(0.21)	14.72	***	(0.304)
2017	base			base		
2018	-0.10	**	(0.05)	-0.05		(0.06)
2019	-0.08		(0.07)	-0.12		(0.08)
2020				-0.24	**	(0.10)
2021				-0.19	*	(0.10)
2022				-0.31	***	(0.10)
Profit Inefficiency						
dventilation	-0.15		(0.12)	0.16	*	(0.08)
dirrigation	0.01		(0.07)	-0.06		(0.06)
dgas	-0.10	*	(0.06)	-0.01		(0.06)
landsize ≥ 20 and < 26	0.06		(0.08)	-0.13	*	(0.07)
landsize ≥ 26 and < 31	-0.37	***	(0.07)	-0.37	***	(0.06)
landsize ≥ 31 and < 36	-0.40	***	(0.08)	-0.61	***	(0.07)
landsize ≥ 36 and < 41	-0.27	***	(0.09)	-0.60	***	(0.09)
landsize ≥ 41 and < 46	-1.04		(0.70)	-0.82	***	(0.12)
landsize ≥ 46	-0.54	***	(0.13)	-0.75	***	(0.11)
labor	-0.25	***	(0.04)	-0.17	***	(0.03)
Cons.	1.71	***	(0.19)	1.95		(19.16)
Usigma cons.	-3.68	***	(0.95)	-5.28		(16.15)
Vsigma cons.	-3.20	***	(0.54)	-2.26	***	(0.79)
Sigma_u	0.16	**	(0.08)	0.07		(0.58)
Sigma_v	0.20	***	(0.05)	0.32	**	(0.13)
Lamda	0.78	***	(0.13)	0.22		(0.70)
Log-likelihood	298.4			313.95		

Note. *ln* is the natural logarithm; standard errors are in parentheses; significant at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, respectively.

In the frontier function of the determinants of profit efficiency, we see the effects of various input costs and years on profit efficiency. The coefficient of seedlings (*seedlingspa*) is insignificant in both models, indicating that changes in seedling costs have no statistically significant impact on profit efficiency. For fertilizer (*fertilizerpa*): In Model 1, the effect is insignificant. In Model 2, it is positive but also insignificant. For pesticides (*pesticidepa*), in Model 1, a significant positive coefficient ($p < 0.10$) suggests higher pesticide use improves profit efficiency. In Model 2, the effect becomes negative and insignificant, showing that the impact may vary over different years. For, materials (*materialpa*), the variable is insignificant in both models, indicating that material costs do not strongly affect profit efficiency. For repair costs (*repairpa*), it is negative and significant in both models ($p < 0.01$), suggesting that higher repair expenses reduce profit efficiency. This may imply inefficiencies associated with frequent or high repair costs. For, clothing costs (*clothespa*), in Model 2, the positive and significant coefficient ($p < 0.01$) implies that spending on clothing improves efficiency, perhaps by improving working conditions. For fuel costs (*power_fuelspa*), it indicates negative and significant in Model 1 ($p < 0.05$), suggesting that higher fuel expenses reduce profit efficiency. However, the effect is insignificant in Model 2, indicating that the impact may vary over different years. On the other hand, for transportation costs (*transportationpa*), are positive and significant in both models at the 10% level and the 1% level, respectively, indicating that efficient transportation and related logistics improve profit efficiency. Finally, labor hiring costs (*hiring_feepa*) show negative and significant in both models, at the 1% significant level and the 5% significant level, respectively, indicating that higher labor hiring costs reduce profit efficiency. This could reflect inefficiencies in hired labor use.

Also, based on the ML random-effects time-varying inefficiency effects model (Battese & Coelli, 1995), we also observed year effects. In Model 1, 2018 shows a slight decline in profit efficiency ($p < 0.05$) compared to 2017, while 2019 is insignificant. In Model 2, the entire study years (2017-2022) show significant declines in profit efficiency, with the most substantial decline observed in 2022 ($p < 0.01$). This reflects declined prices due to weather factors and oversupply.

Now, we look at the profit inefficiency function to estimate the determinants of inefficiency in profit generation. First, we check the technical changes of greenhouse production. For automated ventilation (*dventilation*), in Model 2, having automated ventilation increases inefficiency ($p < 0.10$). This counterintuitive result may suggest improper or inefficient use of the technology. The automated irrigation (*dirrigation*) shows insignificant in both models, indicating no clear impact on efficiency in profit generation. The automated CO_2 Gas (*dgas*) indicates, having automated gas emitter increases efficiency ($p < 0.10$) in Model 1. However its effect diminishes in Model 2. For *landsize* as a scale variable, larger land sizes generally reduce inefficiency. For example, segments *landsize* ≥ 26 and < 31, *landsize* ≥ 31 and < 36, and *landsize* ≥ 36 and < 41 have consistently negative and significant coefficients, suggesting larger farms are more efficient. The most significant efficiency gains occur in the largest land sizes (*landsize* ≥ 41 and < 46 and *landsize* ≥ 46), but the coefficient of *landsize* ≥ 41 and < 46 is larger than that of *landsize* ≥ 46. Finally, for labor (*labor*), it shows negative and highly significant in both models ($p < 0.01$). This indicates that having more labor (family or otherwise) reduces inefficiency, possibly due to better resource allocation and management.

Sigma_u and Sigma_v represent variance components of inefficiency (u) and noise (v). Both are significant in Model 1, indicating meaningful variation due to inefficiency and random noise. Lambda suggests the ratio of inefficiency variance to noise variance, which is significant in Model 1, indicating inefficiency contributes significantly to overall variance in profit. On the other hand, Lambda is insignificant in Model 2; when we include 2020-2022 data in the dataset, profit inefficiency determinants no longer contribute significantly to the overall variance in profit.

3.3 Profit Efficiency Score

Table 3 summarizes the mean, minimum, and maximum levels of profit efficiency, revealing an average efficiency score of 0.562, with values ranging from 0.210 to 0.964 for 2017-2019. This indicates that producers could reduce their input usage by approximately 43.8% while maintaining current output levels if they achieved full efficiency, thereby increasing their gross margins.

Additionally, this average score suggests that profitability could improve by 93.05% [(0.562 − 1)/0.562 × 100] if full efficiency were attained. On average, profit efficient producers could lower their costs by 41.70% [(1 − 0.518/0.964) × 100], assuming they optimized costs to match the highest efficiency level. Furthermore, the least efficient producers, with a profit efficiency of 0.210, could achieve cost savings of 78.22% [(1 − 0.210/0.964) × 100] if they matched the maximum efficiency level of their peers, improving from 0.210 to 0.964.

Table 3 summarizes the profit efficiency score for the year 2017-2022. It is clear from the mean minimum and maximum that the profit efficiency has declined when 2020-2022 is included. Based on the Table 3, profitability could improve by 179.89% [(0.357 − 1)/0.357 × 100] if full efficiency were attained. On average, profit efficient producers could lower their costs by 50.1% [(1 − 0.357/0.715) × 100], assuming they optimized costs to match the highest efficiency level. Furthermore, the least efficient producers, with a profit efficiency of 0.147, could achieve cost savings of 79.67% [(1 − 0.147/0.715) × 100] if they matched the maximum efficiency level of their peers, improving from 0.147 to 0.715.

Table 3. Profit efficiency scores summary (n = 270) year 2017-2019

	Mean	Std.	Min.	Max.
PE(1)	0.518	0.193	0.210	0.964

Note. (1) Profit Efficiency.

Table 4. Profit efficiency scores summary (n = 462) year 2017-2022

	Mean	Std.	Min.	Max.
PE(1)	0.357	0.141	0.147	0.715

Note. (1) Profit Efficiency.

Table 5 presents the profit efficiency scores categorized by whether farmers have ECDs or not. Prior to 2020, in Model 1, having an automated irrigation system and a CO_2 gas emitter resulted in higher profit efficiency scores than those who did not. However, Model 2 shows that while having an automated irrigation system and a CO_2 gas emitter resulted in similar results as Model 1, farmers who have automated ventilation have lower profit efficiency than those who do not.

Table 5. Profit efficiency scores by having ECDs or not

Variables	**Model 1** (n = 270) **Year 2017-2019**					**Model 2** (n = 462) **Year 2017-2022**				
	Not have		**Have**		**t-test**	**Not have**		**Have**		**t-test**
	Mean	Std. Err.	Mean	Std. Err.		Mean	Std. Err.	Mean	Std. Err.	
dventilation	0.52	0.01	0.56	0.01		0.36	0.01	0.27	0.01	***
dirrigation	0.5	0.01	0.58	0.02	***	0.34	0.01	0.40	0.02	***
dgas	0.48	0.01	0.59	0.02	***	0.33	0.01	0.40	0.02	***

Note. based on the two-tailed test.

Next, the two tables (Tables 6 and 7) present the profit efficiency (PE) scores categorized by land size for two different periods, 2017-2019 and 2017-2022. We conducted a sensitivity analysis for other peak points of land size, namely *landsize* < 20, *landsize* ≥ 21 and < 26, *landsize* ≥ 26 and < 31, *landsize* ≥ 31 and < 36, *landsize* ≥ 36 and < 41, *landsize* ≥ 41 and < 46, and *landsize* ≥ 46. Table 6 of the years 2017-2019, profit efficiency scores increase as the land size increases, indicating that producers with larger land sizes tend to operate more efficiently. The lowest PE mean score (0.30) is observed for the smallest land size group, *landsize* < 21, while the highest PE mean score (0.92) is observed for *landsize* ≥ 41 and < 46. Producers with medium to large land sizes (*landsize* ≥ 26 and < 31, *landsize* ≥ 31 and < 36, *landsize* ≥ 36 and < 41, *landsize* ≥ 41 and < 46) are more profit efficient than those with smaller land sizes. A slight decline in efficiency is observed for the largest land size group (*landsize* ≥ 46), which might indicate diminishing returns to scale or management challenges associated with larger operations.

Now, we look at Table 7 of the year 2017-2022. Similar to Table 4, profit efficiency increases with land size, but the efficiency levels are generally lower compared to the shorter period (2017-2019). The lowest PE mean score (0.20) is observed for Landsize (< 21), while the highest PE mean scores (0.56) are observed for both *landsize* ≥ 41 and < 46 and *landsize* ≥ 46. Although overall efficiency declined when we include recent years' data, to gain profitability, increased land size seems to capture higher profit efficiency.

Table 6. Profit efficiency scores by land size (n = 270) for year 2017-2019

Density	Obs	Mean	Std. Err.	Min.	Max.
landsize< 20	59	0.30	0.07	0.21	0.49
landsize ≥ 20 and < 26	38	0.34	0.08	0.23	0.57
landsize ≥ 26 and < 31	46	0.54	0.07	0.31	0.66
landsize ≥ 31 and < 36	42	0.59	0.12	0.38	0.81
landsize ≥ 36 and < 41	57	0.63	0.11	0.38	0.81
landsize ≥ 41 and < 46	11	0.92	0.03	0.86	0.96
landsize ≥ 46	17	0.78	0.13	0.52	0.93

Table 7. Profit efficiency scores by land size (n = 462) for years 2017-2022

Density	Obs	Mean	Std. Err.	Min.	Max.
landsize< 20	116	0.20	0.03	0.15	0.29
landsize ≥ 20 and < 26	65	0.26	0.03	0.21	0.34
landsize ≥ 26 and < 31	90	0.32	0.04	0.24	0.38
landsize ≥ 31 and < 36	72	0.45	0.07	0.30	0.63
landsize ≥ 36 and < 41	70	0.51	0.05	0.41	0.62
landsize ≥ 41 and < 46	19	0.56	0.08	0.46	0.72
landsize ≥ 46	30	0.56	0.10	0.36	0.65

4. Discussion and Policy Implication

In this section, we discuss the results relating to our hypothesis that both factors, technical change (TC) and scale effects (SEs), synergistically enhance profit efficiency. First, we examine whether TC enhance profit efficiency. Among ECDs, namely the automated ventilation and the automated irrigation system, and the CO_2 gas emitter, at least until 2019, the CO_2 gas emitter was contributing to the profit efficiency according to Model 1 of Table 2. However, in Model 2, for the data of the year 2017-2022, the CO_2 gas emitter is no longer contributing to the profit efficiency. Also, the automated ventilation was causing profit inefficiency.

One of the main reasons is that market prices have not risen as much as the cost of agricultural production materials has risen in recent years. Looking at the price trends in the Tokyo Metropolitan Central Wholesale Market, the average annual price per kilogram of eggplant was 435 JPY (2.77 USD) in 2020, except in 2020, when eggplant consumption increased due to the stay-at-home demand in the first year of COVID-19 (Figure 4). The eggplant price was 375 yen per kilogram in 2022, a difference of 60 JPY (0.38 USD) per kilogram. That means the total sales were 19,575,000 JPY (124,550.64 USD) in 2020 and then 16,875,000 JPY (107,371.24 USD), which caused a loss of 2,700,000 (17,179.40 USD) in sales. As a result, the profit margin also diminished since 2017, from 0.43 to 0.29 in 2022.

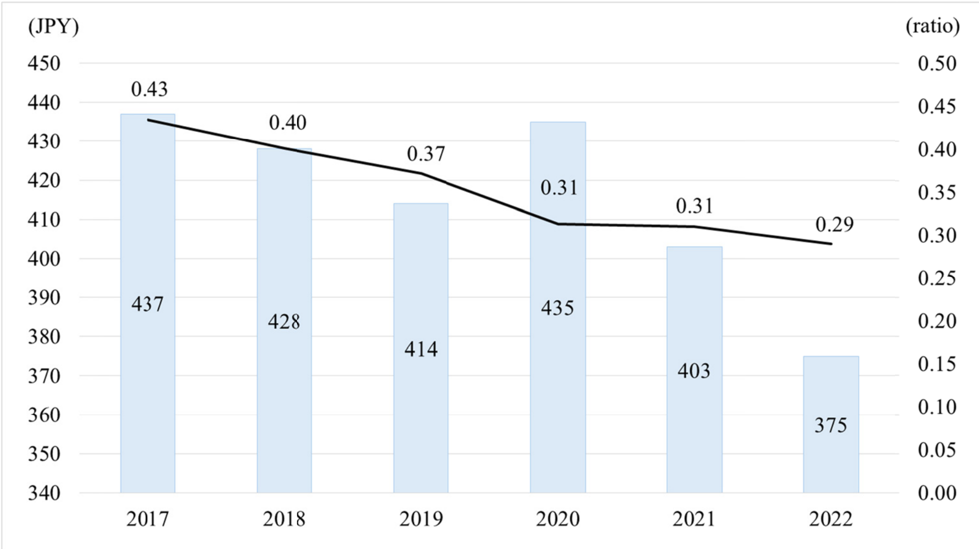

Figure 4. The annual average wholesale price of eggplant and the ratio of mean profit margin

Second, we examine the scale effect to enhance the profit efficiency. Table 2 shows the optimal farm size is equal to more than 41 and less than 46, which shows the negative, largest coefficient, which indicates profit efficiency. The optimal farm size is equal and more than 41 and less than 46 *are* was not significant in Model 1, but significant and largest coefficient in Model 2. The farm size larger than 46 is not able to capture the largest profit efficiency indicating that the scale effect seems prevented by high input prices and low wholesale market of the eggplant. Further, Tables 6 and 7 of profit efficiency scores by land size also confirm an inverted U-shaped relationship between profit efficiency and farm size. Initially, profit efficiency gradually increases with the expansion of the scale, but it starts to decline after reaching the optimal farm size.

In sum, our result confirms a synergistic effect of both technical change and scale on profit efficiency up to 2019. However, due to the recent lower wholesale market of the commodity and increased input prices, both factors have a limited effect on profit efficiency. To overcome this, market prices should rise as much as the cost of agricultural production materials. Exogenous factors such as weather and temperature influence commodity prices, and that is a challenge that is always faced by the agricultural sector. We cannot control for oversupply. However, decreasing the input costs, which significantly negatively affects profit efficiency, is possible—namely, repair cost, the cost of repairing previously purchased items, and the hiring fee. Farmers need to repair horticultural facilities occasionally, especially if typhoons or unexpected torrential rains damage them. To mitigate the unexpected repair, they should have insurance. Regarding the hiring fee, this is consistent with earlier studies, which reported that the extensive use of and increased wages for labor could reduce the net profit of rice production (Rahman, 2003; Okoruwa et al., 2009). On the other hand, as food prices increase, the hiring fee should be increased with influation. Also, hiring labor fees is also essential to reducing the burden of household labor. Therefore, optimizing the hiring fee while maximizing profit should be a necessary investigation in our future study.

Finally, our study is limited as we do not have socio-economic factors such as age and farming experience of the farmers. For further study, we can collect socio-economic factors influencing profit effciency in detail. Also, it may require monitoring for a long time to evaluate the TC and SEs effects. To see TC in terms of adopting ECDs, further training in machine use may be required to fully capture profit by using the machine to capture the learning-by-doing or training effect for human resource development (Nanseki, 2019) in the long term.

5. Conclusion

The study result indicates a decreased profit efficiency in recent years in family-based eggplant production in Japan. Improving resource use efficiency in agriculture can enhance profit efficiency through technical changes (TC) and scale effects (SEs). For our study, we observed both technical change affecting profit efficiency between 2017 and 2019. However, the technical change effect has diminished in recent years, especially since 2020. Further, scale effects were rather limited as we observed an inverted U-shaped relationship between profit efficiency and farm size, the optimal farm size being equal and more than 41 and less than 46. We argue that the inputs, namely repair cost and hiring cost, which are negatively affecting profit efficiency, should be reduced. Although the proportion of family-based eggplant production is decreasing in Kochi prefecture, they are still the core of domestic eggplant production as their production accounts for 34% of the total yield of facility-based eggplant production in Japan. The decrease in profit efficiency and profit margin directly impacts the family-based eggplant farmers. The input cost factors negatively impacting the profit efficiency, namely repair and labor hiring costs, should be the foremost urgent issues to be resolved for TC and SEs to take place in the facilitated greenhouse eggplant production in Japan.

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Authors Contributions

Dr. Nomura and Dr. Osaki were responsible for study design and revising. Dr. Nomura was responsible for data collection. Dr. Lin and Dr. Nomura drafted the manuscript and Dr. Osaki revised it. All authors read and approved the final manuscript.

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Competing Interests

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Data Sharing Statement

No additional data are available.