

Do peers and agglomeration affect farm efficiency?

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Abstract: This study investigates peer effects and agglomeration impacts on the cost efficiency of South Korean rice farms using a five-year panel dataset of production costs. We employed a time-varying stochastic frontier cost function approach to estimate cost efficiency and a linear-in-means model to quantify peer influences. The findings underscore peer effects as central to understanding and enhancing farm productivity, particularly in rice farming regions. Both specialisation and diversity of agglomeration positively influenced efficiency, with specialisation having a larger impact. Peer effects were stronger in highly rice-specialised areas. These findings indicate the necessity of incorporating peer influences and regional specialisation in agricultural policymaking for productivity enhancement. A nuanced, evidence-based approach leveraging peer dynamics and agglomeration economies is advocated to boost the efficiency of farming practices.

Keywords: agglomeration economies; cost efficiency; peer effects; stochastic frontier approach

As in most countries, one of the government's agricultural policy objectives has evolved into enhancing the sustainable development of the agricultural sector. Given that productivity increase is a key element of sustainable development in agriculture, the potential importance of efficiency as a means of increasing productivity has been a focus of many studies. These studies tried to explain the presence of farm efficiency variations across farms. However, heterogeneous farm efficiency could not be fully understood even after controlling for farms' own characteristics, related policies, and agro-climatic factors. Recently, many researchers have focused on social interactions as one of the important determinants of an individual's economic performance or decision-making, which is often referred

to as peer effects (i.e. neighbourhood effects). Peer effects are recognised as an individual's propensity to behave in some way that varies with the prevailing behaviour in some reference group containing the individual (Manski 1993).

Previous studies found strong evidence of peer effects in student achievements (Feng and Li 2016) and firms' decisions on financial strategy or investment (Park et al. 2017). When it comes to the agricultural sector, the findings of several studies also support peer effects. For example, Konar et al. (2014) investigated peer effects on farmers' decisions (tillage choices) and found that when an increasing number of farmers in a county chose not to use tillage, the probability of a representative farmer not using tillage instead of using convention-

al tillage tended to increase. This result indicates that if more people in a neighbourhood do not use tillage, then this leads many others to adopt the same tillage practice, which can be seen as empirical evidence supporting peer effects. Songsermsawas et al. (2016) used a spatial econometric technique to control for endogeneity and found that 60% of farmers' revenue was explained by peer effects. Specifically, they found that peer effects were particularly large in pesticide use and new crop cultivation.

In this study, we focus on peer effects on farm efficiency. Despite increasing interest in peer effects, there has been little consideration with respect to potential peer effects in the context of farm efficiency. As found in previous studies, farm input decisions and technology adoption decisions are affected by peer farms. However, note that these problems are researched separately, i.e. either with a focus on farm input decisions or on technology adoption decisions, respectively. Since total peer effects would result in farm efficiency change as a whole, our paper focuses on farm efficiency to measure total peer effects. Focusing on farm efficiency with respect to peer effects can be a good way of addressing peer effects as far as 'total' peer effects of agricultural production are concerned. This study specifically focused on rice farms' cost efficiency (hereinafter CE), which was estimated using a stochastic cost frontier function approach. In this sense, our paper is similar to the work of Tirkaso and Hailu (2022), who used a stochastic production frontier approach to find evidence of neighbourhood effects on technical efficiency in Ethiopia farms. However, unlike Tirkaso and Hailu (2022), we extend our analysis to further examine dynamic agglomeration effects on farm efficiency and investigate whether peer effects were large in regions with high levels of agglomeration economies or not. In this way, our paper tries to shed some light on the potential linkages between peer effects and a degree of agglomeration economies.

Agglomeration economies capture benefits arising from the spatial concentration of economic activities. Agglomeration economies can be classified as either a static version or a dynamic version. The former is defined as productivity advantages associated with urban size, such as better access to natural resources, transportation advantages, and cost savings in input procurement (Marshall 1890). The latter refers to productivity advantages from interactions between firms or labour. Note that the dynamic agglomeration economies and peer effects are similar in that they both measure social

interactions between economic agents, i.e. these effects take place when producers learn from and communicate with each other. From this point of view, one can anticipate that the peer effects can be larger in regions with high levels of agglomeration economies. In the literature, two channels of agglomeration economies are identified. One is Marshall–Arrow–Romer (MAR) externalities, the other is Jacobs' externalities. While the MAR externalities stress the advantages of knowledge spillovers of intra-industry capturing specialisation benefits, Jacobs' externalities focus on the advantages of knowledge spillovers of inter-industry capturing diversity benefits (Glaeser et al. 2001). Building on this, we examine the impact of MAR (or specialisation) and Jacobs' (or diversity) externalities on farm efficiency in agricultural production and test whether peer effects vary according to the level of these two types of agglomeration economies. We expect that the results can provide useful implications for policymakers seeking to promote farm efficiency, targeting agricultural competitiveness increase by exploiting the role of peer and agglomeration effects.

MATERIAL AND METHODS

Empirical model. Our empirical research was organised into two distinct stages. In the first stage, we assessed the cost efficiency (CE) of farms using a time-varying stochastic cost function. In the second stage, we explored the peer effects on CE by employing a linear-in-means model, which is grounded in Manski's (1993) general linear model. Essentially, this approach involves estimating efficiency in the first step and identifying the factors influencing it in the second step. As Wang and Schmidt (2002) have pointed out, this method can lead to endogeneity issues due to the correlation between an inefficiency variable and the input variables in the cost function. Typically, this problem can be resolved using a simultaneous (one-step) estimation method, but we were unable to use this approach as the average of the efficiency estimated in the first step was used to estimate peer effects in the second step. Instead, as an alternative method, we addressed the endogeneity problem using the correlated random effects (CRE) approach (Mundlak 1978). While this method helped to resolve some aspects of endogeneity issues related to time-invariant unobserved heterogeneity, we acknowledge that it did not address all potential sources of endogeneity problems. Other methods, such as an instrumental variable approach or a system generalized method of moments

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(GMM) estimation method, are difficult to apply to our research due to the challenge of finding suitable instruments and the structure of our data. Furthermore, a simultaneous equation estimation method is precluded by the nature of our peer effects measure, which used the average efficiency of peers and was thus endogenously determined within the system. Despite these limitations, we expect our approach, combined with the use of lagged variables and fixed effects, to provide meaningful analytical results on the relationship between peer effects, agglomeration economies, and farm efficiency. A detailed discussion of the efficiency estimation method is provided below.

Estimation of cost efficiency. This study estimated the *CE* using stochastic frontier panel data. As is well known, the stochastic frontier analysis incorporates two error terms, one accounting for cost inefficiency and the other accounting for random errors caused by weather conditions, disease and pest infestation, and measurement errors. We applied a trans-log functional form for the cost function as in Equation (1). This approach needs two assumptions. First, the farm's objective is to produce a given level of output at the lowest cost possible. Second, in the context of cost minimisation, the farm is inefficient in general, meaning that it uses more inputs than necessary to produce a given output level (Kumbhakar et al. 2015).

$$\begin{aligned} \ln C_{it} = & \beta_0 + \beta_q \ln q_{it} + \sum_j \beta_j \ln w_{ijt} + \beta_t t + \\ & + 0.5 \beta_{qq} (\ln q_{it})^2 + 0.5 \sum_j \sum_k \beta_{jk} \ln w_{ijt} \ln w_{ikt} + \\ & + 0.5 \beta_{tt} t^2 + \sum_j \beta_{qj} \ln q_{it} \ln w_{ijt} + \beta_{qt} \ln q_{it} t + \\ & + \sum_j \beta_{jt} \ln w_{ijt} t + v_{it} + u_{it} \end{aligned} \quad (1)$$

where: $\beta_{jk} = \beta_{kj}$ for all j and k ; $j, k = \text{labour, land, intermediates}$; $i = 1, 2, \dots, N$; $t = 1, 2, \dots, T_i$; $v_{it} \stackrel{iid}{\sim} N^+(0, \sigma_v^2)$; $u_{it} \stackrel{iid}{\sim} N^+(\mu, \sigma_u^2)$; $\sum_j \beta_j = 1$ and $\sum_j \beta_{jk} = 0$ for all k ; C_{it} – rice production cost of farm i at time t ; w_{it} – input price (e.g., labour, land, intermediate input costs) of farm i at time t ; q – quantity of output (rice); v_{it} – error of measurement; u_{it} – cost inefficiency.

The potential correlation between explanatory variables of the cost function and characteristics of farms that were not directly observed (like soil quality, managerial ability, and agroecological metrics) might lead to inaccuracies. The endogeneity problem arises due to the omission of these crucial factors. For example, soil quality or managerial ability can have a signifi-

cant impact on production costs. Fertile soils or farms with high management capacity can use fewer inputs (e.g. fertilisers and pesticides) to increase yields; therefore, production costs will be low.

As noted, the sequential or two-step estimation of these equations may produce biased and inconsistent estimates of the cost function (and hence the estimate of cost efficiency) if the variables in the inefficiency functions are correlated with the inputs in the cost function (Wang and Schmidt 2002). To effectively address potential endogeneity concerns, which might stem from omitted variables or the simultaneous determination of inputs, outputs, and cost, we adopted the correlated random-effects (CRE) approach, as proposed by Mundlak (1978). This methodology has gained support from recent research, including studies by Do et al. (2023) and Nguyen et al. (2021). Central to this approach is the integration of time-averaged explanatory variables suspected of endogeneity problems, such as quantity of output, and input costs (labour, land, and intermediate) into the estimation model. This addition aims to mitigate the impact of time-invariant unobserved heterogeneity that might correlate with the explanatory variables.

This study assumes that farm inefficiency can change over time, and thus the inefficiency u_{it} can be defined as in Equation (2).

$$u_{it} = \exp [-\eta (t - T_i) u_i] \quad (2)$$

where: T_i – last period in the i -th panel; η – decay parameter.

Identification of peer effects. Manski (1993) identified three effects causing similar behavioural patterns within a group: endogenous effects (individual behaviour aligns with group behaviour), exogenous effects (individual behaviour influenced by group characteristics), and correlated effects (similar behaviours due to shared environment). Endogenous and exogenous effects result from social interactions, with endogenous effects interpreted as peer effects.

To estimate farm *CE* peer effects, this study used Blume et al.'s (2011) linear-in-means model based on Manski's (1993) general linear model. It assumes individual performance is affected by the individual's characteristics and the average performance and characteristics of peers in the same group (Equation 3). Administrative divisions in South Korea are divided into three levels: Special cities and Provincial level, Municipal level, and Sub-municipal level. We considered the

Municipal level (Si, Gun, and Gu), which is the second level, as the relevant reference groups for this study

$$CE_{igt} = \alpha_0 + \alpha_1 \overline{CE}_{(-i)gt} + \alpha_2 Z_{igt} + \alpha_3 \bar{Z}_{(-i)gt} + \tau_i + e_{igt} \quad (3)$$

where: i, g such that $i \in g$ and satisfying $E(e_{igt}|Z_i, Z_g, i \in g) = 0$, $\tau_i \sim (0, \alpha_u^2)$; subscript i – farm; g – group to which the farm belongs; t – time; CE_{igt} – CE estimated in the previous step; $\overline{CE}_{(-i)gt}$ – average CE of peer farms in the same group as farm i (excluding farm i 's CE); Z_{igt} – farm characteristics that may affect CE ; $\bar{Z}_{(-i)gt}$ – mean characteristics of peer farms (excluding farm i); α_1, α_3 – coefficients measuring endogenous and exogenous effects (thus, there exists peer effects if $\alpha_1 \neq 0$); τ_i – time-invariant farm characteristics; e_{igt} – error term.

Manski (1993) argued that identification issues caused by simultaneity and omitted variable bias must be noted when empirically estimating the peer effects. Simultaneity problem arises out of linear dependence caused by the simultaneity of $\overline{CE}_{(-i)gt}$ and $\bar{Z}_{(-i)gt}$, which Manski (1993) referred to as the reflection problem. In this case, $\overline{CE}_{(-i)gt}$ and $\bar{Z}_{(-i)gt}$ tend to move together, making it difficult to distinguish between exogenous effects and endogenous effects, thereby complicating the identification of peer effects (i.e. endogenous effects). To solve these problems, this study introduced a lagged variable of peer farms' average CE and a variable capturing regional fixed effects in our model. Following Blume et al. (2011), we introduced a lagged CE variable as a proxy variable for CE to cope with the simultaneity problem. Then, a dynamic model for our study can be expressed as Equation (4). Note that in Equation (4), it is assumed that the CE of a farm at time t is affected by the average CE of peers at time $t - 1$ ($\overline{CE}_{(-i)gt-1}$). This lagged effect is implied by the fact that interactions between a farm and its peers have been present both time t and time $t - 1$, which in turn affects the CE of a farm at time t .

$$\begin{aligned} CE_{igt} &= \alpha_0 + \alpha_1 \overline{CE}_{(-i)gt-1} + \alpha_2 Z_{igt} + \alpha_3 \bar{Z}_{(-i)gt} + \tau_i + e_{igt} \\ &= \alpha_0 + \alpha_1 L\overline{CE}_{(-i)gt} + \alpha_2 Z_{igt} + \alpha_3 \bar{Z}_{(-i)gt} + \tau_i + e_{igt} \end{aligned} \quad (4)$$

where: $\overline{CE}_{(-i)gt-1} = L\overline{CE}_{(-i)gt}$; L – lag operator

Taking the expectation of Equation (4), due to the lag operator (L), a linear independence relationship between $\overline{CE}_{(-i)gt}$ and $\bar{Z}_{(-i)gt}$ is formed, as shown in Equation (5).

$$\overline{CE}_{(-i)gt} = \frac{\alpha_0 + (\alpha_2 + \alpha_3) \bar{Z}_{(-i)gt}}{1 - L\alpha_1} \quad (5)$$

Note that in Equation (4), serial correlation may be an important issue. That is, $\overline{CE}_{(-i)gt}$ and $\overline{CE}_{(-i)gt-1}$ can be correlated due to the correlation between e_{igt} and e_{igt-1} . To address the autocorrelation problem found in the empirical model, the Cochrane-Orcutt procedure was applied. Endogeneity issues may occur in the average CE variable due to time-varying unobservable shocks affecting the reference group. Although an instrumental variable approach is a common solution, finding suitable instrumental variables is challenging. In this study, an interaction term between a regional dummy variable (R_r) and a time dummy variable ($time$) was used to control for unobservable shocks in the region (R_r) each year. To minimise the loss of degrees of freedom, first-level administrative divisions were reclassified into regional dummy variables based on geographical proximity, such as metropolitan areas, Gangwon, Choongchung, Jeolla, and Gyeongsang regions. The result is Equation (6).

$$\begin{aligned} CE_{igt} &= \alpha_0 + \alpha_1 \overline{CE}_{(-i)gt-1} + \alpha_2 Z_{igt} + \alpha_3 \bar{Z}_{(-i)gt} + \\ &+ \sum_{r=1}^4 \alpha_{4r} time \times R_r + \tau_i + e_{igt} \end{aligned} \quad (6)$$

To capture farm owners' characteristics, we introduced the owners' age, degree of specialisation, the existence of a farming successor, and rice direct payments from the government.

The degree of specialisation is a share of rice revenue out of the total farm revenue (= sum of crop revenue and livestock revenue). This variable was included to consider a degree of farm specialisation in rice production. The percentage of rice revenue captures all benefits related to farm specialisation, such as the ability to obtain in-depth knowledge about rice production or economies of scale that can be obtained by increasing the size of the rice production operation (Zhu and Lansink 2010). Direct payments, which during the data span of 2008–2012 consisted of coupled payments paid when the rice price fell below a certain target price and decoupled payments paid according to the area of paddy fields, are the sum of coupled and decoupled payments. These direct payments alleviate the financial constraints of a farm by increasing its financial resources. Additionally, they may improve ac-

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cess to credit, further easing financial constraints. The relaxation of financial constraints may serve as an incentive for investment in rice production technology, which may ultimately lead to an increase in farm efficiency (Zhu and Lansink 2010).

Effects of agglomeration economies. Agglomeration economies can be classified into two types: the MAR model capturing specialisation effects and the Jacobs model capturing diversification effects. The MAR model highlights knowledge externalities from specialisation, which arises when multiple firms in the same industry cluster together in a region, engaging in related activities and exchanges. These externalities can emerge in areas where firms utilising similar production technologies are concentrated. On the other hand, Jacobs (1970) posited that firms located in regions characterised by a diverse industrial base, where businesses and employees span various sectors, are apt to benefit from a broader array of knowledge sources, foster greater technological innovation, and facilitate more effective knowledge exchange through interactions within the regional economic network.

Following this line of literature, we defined the effect caused by agglomeration of farms cultivating the same crop (e.g. rice) as the MAR externalities (or crop specialisation effects). We also defined effects caused by the cultivation of various crops as the Jacobs' externalities (or crop diversification effects). In this study, location quotient (hereinafter *LQ*) was used as a measurement index for the MAR externalities (or crop specialisation effects), and inverse Hirschman-Herfindahl index was used as a measurement index for the Jacobs' externalities (or crop diversification effects). The *LQ*, defined as in Equation (7), represented a degree of specialisation of rice in a region (*g*) relative to that of rice in the whole country. This means that the regional rice specialisation index was defined as the share of rice farms (*rice farm_{g,t}*) relative to the total number of farms (*farm_{g,t}*) in a specific region *g*, compared to the share of the total rice farms (*rice farm_t*) relative to the total number of farms (*farm_t*) at the national level.

$$LQ_{g,t} = \frac{\frac{\text{rice farm}_{g,t}}{\text{farm}_{g,t}}}{\frac{\text{rice farm}_t}{\text{farm}_t}} \quad (7)$$

The Hirschman-Herfindahl index (hereinafter *HHI*) is an index measuring industrial concentration in general. Applying this index to measure the specialisation degree in farming, we have Equation (8), where *s_{type,g,t}* is the share of farm type relative to the total number of farms at time *t*. Note that farm type is defined by the farming activity which has the largest proportion of farm household gross revenues in our dataset: *i*) paddy rice farming; *ii*) fruit farming; *iii*) vegetable farming; *iv*) speciality crops farming; *v*) floriculture farming; *vi*) upland farming; *vii*) livestock farming; and *viii*) others. The inverse of *HHI* (hereinafter *DIV_{g,t}*) in Equation (9) indicates the regional Jacobs' externalities (crop diversity effects) (Beaudry and Schiffrava 2009). The boundary of *HHI* is between $1/r$ and 1, where *r* ranges over farm types in a dataset (Lhabitant 2017), and the boundary of the *DIV* is $1 \leq DIV \leq r$ (Baltagi et al. 2016). Thus, if a region *g* has only one farm type, *HHI* and *DIV* are equal to 1. On the other hand, the *HHI* of a region that has eight farm types with equal shares is $1/8$ (or *DIV* = 8), reflecting a scenario with a high level of diversity.

$$HHI_{g,t} = \sum_{type=1}^8 s_{type,g,t}^2 = \sum_{type=1}^8 \left(\frac{\text{farm}_{type,g,t}}{\text{farm}_{g,t}} \right)^2 \quad (8)$$

$$DIV_{g,t} = \frac{1}{HHI_{g,t}} \quad (9)$$

Following Peiró-Signes et al. (2015), we introduced a dummy variable to examine the impact of peer effects in regions with high agglomeration economies. The dummy variable indicates whether a region has high-level agglomeration effects, with cut-off values of 1.25 for MAR externalities and 4 for Jacobs' externalities. Recent research defines industrial clustering using an *LQ* cut-off value of 1.25 (Morrissey 2016), while an *HHI* above 0.25 indicates a high concentration (Silberglitt et al. 2013). Thus, regions with Jacobs' externality values of 4 or above are considered to have high crop diversity. An interaction variable between the agglomeration economies dummy and average peer *CE* was included to explore differences in peer effects between regions with and without high agglomeration effects.

Our final empirical model for estimating agglomeration economies and their interactions with peer effects is given in Equation (10). Cost efficiency variables (*CE_{igt}*, *CE_{(-i)gt-1}*) are log-transformed in order to interpret the coefficient as elasticity.

$$\begin{aligned}
\ln CE_{igt} = & \alpha_0 + \alpha_1 \ln \overline{CE}_{(-i)gt-1} + \alpha_2 Z_{igt} + \alpha_3 \overline{Z}_{(-i)gt} + \\
& + \sum_{r=1}^4 \alpha_{4r} time \times R_r + \alpha_5 LQ_{gt} + \alpha_6 DIV_{gt} + \\
& + \alpha_7 LQ_DUM_{gt} \times \ln \overline{CE}_{(-i)gt-1} + \\
& + \alpha_8 DIV_DUM_{gt} \times \ln \overline{CE}_{(-i)gt-1} + \tau_i + e_{igt}
\end{aligned} \quad (10)$$

where: α_1 – peer effects; α_3 – exogenous social effects; α_5 (α_6) – agglomeration economic effects of specialisation (diversification) of crop production.

To compare agglomeration variables (LQ_{gt} and DIV_{gt}) which have different scales, these variables were converted to z-scores. α_7 (α_8) measures differences in peer effects between regions one with high crop specialisation (diversification) effects and the others without these effects.

Data. The data used in this study are from the Rice Production Cost Survey (2008–2012), the Farm Household Economy Survey (2008–2012), and the Census of Agriculture (2005, 2010, and 2015) prepared by Statistics Korea (Statistics Korea 2012a,b, 2015). The farm-house ID numbers of the Rice Production Cost Survey and Farm Household Economy Survey were used to combine the two sets of data for the analysis. For more recent years, the data was only available at the first-level administrative divisions. However, for the 2008–2013 period, the Statistics Korea provided information at the more detailed city (Si), county (Gun), and district (Gu) level upon request. This level of geographical detail was crucial for our analysis of peer effects and cost efficiency. Therefore, we utilised the 2008–2013 dataset as it offered the necessary granularity for our research objectives, despite of not being the most recent available data.

The Rice Production Cost Survey and the Farm Household Economy Survey are panel data. Since their samples overlap, these two datasets can be merged into one panel dataset. Rice production cost data and input price data in the Rice Production Cost Survey were used for the estimation of CE , and the Farm Household Economy Survey dataset was used to set up a set of independent variables, including age, successor, degree of specialisation, and rice direct payments, which are supposed to affect the CE of a farm. Finally, the Census of Agriculture dataset was used to set up MAR externality (crop specialisation effects) and Jacobs externality (crop diversification effects) variables that represent the level of dynamic agglomeration economies within a reference group [i.e. city (Si), county (Gun), and district (Gu)].

The descriptive statistics of variables used in establishing the cost function are presented in Table 1. The prices of inputs (i.e. capital, labour, land, and intermediates) were recovered in the following way. The price of capital was measured as the sum of per-unit costs for various capital components, including farm operation (machinery, equipment, and tools), farm facilities, irrigation, and fixed capital (Kim et al. 2012). This approach provided a measure of capital cost that can be used to calculate the price of capital, which is standardised to the farm's production scale. Labour price was obtained by a weighted sum of self-labour costs and hired labour costs, with weight being input labour hours. The land price was obtained by the weighted sum of the rental cost of the owned land, for which the rent of nearby similar land was applied, and the rental cost per unit of the rented land. The price of intermediates was measured as the sum of per-unit costs for various input components, including seeds, pesticides, fertilisers, and farming electricity.

Given the constraints of our dataset, which lacks specific price and quantity information, we employed per-

Table 1. Descriptive statistics for cost function variables (3 940 observations; 913 farms)

Variable	Description	Unit	Mean	SD	Min.	Max.
<i>C</i>	total production cost	USD	5 566.63	6 729.18	626.33	97 211.19
<i>Land</i>	rice acreage	m ²	11 887.87	15 135.91	1 556.00	193 360.00
<i>Q</i>	output	kg	14 416.08	19 297.15	855.00	259 770.00
<i>K</i>	capital price	USD / kg	0.03	0.04	0.00	0.86
<i>L</i>	labour price	USD / h	5.71	2.13	2.43	10.14
<i>A</i>	land rent	USD / m ²	0.16	0.04	0.02	0.35
<i>M</i>	intermediate price	USD / kg	0.16	0.06	0.02	0.77

The average exchange rate (1 365.1 won / USD) in April 2024 was applied

Source: Author's calculations

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Table 2. Descriptive statistics for *CE* model variables (3 027 observations; 913 farms)

Variable name		Description	Unit	Mean	SD	Min.	Max.
Farm specific variables	age	age of farmer	year	66.48	9.55	33.00	90.00
	degree of specialization	share of rice revenue in total farming revenue	%	48.40	27.68	0.68	100.00
	rice direct payments	rice income direct payments	USD	952.31	1 289.28	0.00	18 357.63
	successor	children engaged in agriculture	dummy	0.02	0.14	0.00	1.00
	peer	No. of peers	farm	14.04	4.89	8.00	27.00
Agglomeration economies variables	<i>LQ</i>	crop specialization	index	0.01	1.01	−2.94	2.01
	<i>DIV</i>	crop diversity	index	0.04	1.00	−2.31	2.31

The average exchange rate (1 365.1 won / USD) in April 2024 is applied; *CE* – cost efficiency; *LQ* – location quotient; *DIV* – diversity index (inverse of the Hirschman-Herfindahl Index)

Source: Author's calculations

unit costs as proxies for input prices. While this methodology enabled our analysis to proceed, it is important to note its limitations. These proxy measures may inadvertently incorporate farm-specific efficiency differentials, potentially introducing bias into our estimates. However, we believe that our large sample size and panel data techniques help mitigate this potential bias.

Total production cost was obtained by adding an entrusted management service fee, which indicates a form of agricultural management in which the owner of farmland entrusts all or part of the farming works to another person by agreeing with them to pay certain remuneration for such works, to the cost of the items above.

Table 2 reports descriptive statistics for variables which affect *CE* and agglomeration economies variables. The degree of specialisation indicates the share of rice revenue in the revenues from farming. Successor is a dummy variable that indicates that there was at least one child engaging in agriculture. Rice income direct payments were measured using the size of the paddy, rice acreage, and direct payments unit price. The agglomeration economies variables consist of *LQ* and *DIV* (inverse *HHI*). Both indices were established using the Census of Agriculture and calculated based on the number of farms.

While the Census of Agriculture is conducted every five years (2005, 2010, and 2015), the Production Cost Survey and the Farm Household Economy Survey (2008–2012) were conducted every year, thus the cycles of these datasets were different. Due to this discrepancy, there is no regional data for the years 2008, 2009, 2011, and 2012. To cope with this problem, this study used a linear interpolation technique to recover miss-

ing data points such as the number of farms by regional level (i.e., municipal level, Si / Gun / Gu in South Korea). These interpolated data were used to build indices for measuring the agglomeration economies.

RESULTS AND DISCUSSION

Cost function estimation. Table 3 shows the estimation results of our time-varying stochastic frontier cost function. Coefficient estimates for output ($P < 0.01$) and most of the input variables, such as labour ($P < 0.05$) and intermediates ($P < 0.01$), were statistically significant. A negative sign of the coefficient estimate of the time dummy indicates that rice production costs decreased over time.

The average cost efficiency (*CE*) of rice farms estimated from Equation (6) was 0.881, implying that there existed cost inefficiency in South Korean rice farms, and the magnitude of the inefficiency was about 11%. The mean and standard deviation of the scale elasticity were 0.882 and 0.0061, respectively. The statistical significance of this result was further supported by a robust z-score (144.33) and *P*-value (0.000).

This elasticity measure indicates that cost increased by 0.882% when the quantity of output increased by 1% while holding other factors constant, which indicates the presence of economies of scale in rice production in South Korea.

Peer effects on cost efficiency. Table 4 shows the results of peer effects analysis based on the predicted *CE* score from the first step. Model 1 was the baseline model used to estimate peer effects, estimating the impacts of the average *CE* of peers at time $t - 1$,

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Table 3. Estimation results for the time varying SFA cost function

Variable	Coefficient	SE
$\ln(\text{Output})$	0.846***	0.058
$\ln(\text{Labour})$	0.223**	0.106
$\ln(\text{Land})$	−0.002	0.091
$\ln(\text{Intermediates})$	0.741***	0.069
$0.5 \times \ln(\text{Output})^2$	0.016***	0.006
$0.5 \times \ln(\text{Labour})^2$	0.078***	0.027
$0.5 \times \ln(\text{Land})^2$	0.126***	0.016
$0.5 \times \ln(\text{Intermediates})^2$	0.273***	0.014
$\ln(\text{Output}) \times \ln(\text{Labour})$	−0.036***	0.008
$\ln(\text{Output}) \times \ln(\text{Land})$	0.025***	0.007
$\ln(\text{Output}) \times \ln(\text{Intermediates})$	0.014**	0.007
$\ln(\text{Output}) \times \text{time}$	0.003	0.002
$\ln(\text{Labour}) \times \ln(\text{Land})$	0.010	0.017
$\ln(\text{Labour}) \times \ln(\text{Intermediates})$	−0.131***	0.016
$\ln(\text{Labour}) \times \text{time}$	0.017***	0.006
$\ln(\text{Land}) \times \ln(\text{Intermediates})$	−0.108***	0.012
$\ln(\text{Land}) \times \text{time}$	−0.009*	0.005
$\ln(\text{Intermediates}) \times \text{time}$	0.002	0.004
time	−0.101***	0.026
time^2	−0.007**	0.003
Mean variables for CRE		
$\ln(\text{Output})$	0.065***	0.007
$\ln(\text{Labour})$	0.046***	0.014
$\ln(\text{Land})$	0.016	0.011
$\ln(\text{Intermediates})$	−0.067***	0.011
constant	0.991***	0.354
σ_u^2	0.0102	
σ_v^2	0.0064	
Log likelihood	3 684.998	
Observations	3 940	

***, **, * Statistical significance at 1%, 5%, and 10% levels, respectively; SFA – stochastic frontier analysis; CRE – correlated random effects; σ – standard deviation; u – inefficiency term; v – random error term

Source: Author's calculations

the farm's characteristics, and the average factors of peer farms on the *CE* of the farm. Model 2 added agglomeration economies variables (*LQ* for capturing specialisation effects and *DIV* for capturing diversity effects) to Model 1. In order to test whether peer effects differ by the degree of agglomeration economies, Model 3 added an interaction term comprised of the average *CE* of peers at time $t - 1$ and the dummy vari-

Table 4. Peer effects on cost efficiency estimates

Variable	Model 1	Model 2	Model 3	Model 4
Peer effect	0.9185*** (0.028)	0.8911*** (0.029)	0.8710*** (0.031)	0.8009*** (0.034)
Age	−0.0002 (0.000)	−0.0002 (0.000)	−0.0002 (0.000)	−0.0001 (0.000)
Degree of specialization	3.0×10^{-6} (0.000)	2.0×10^{-6} (0.000)	2.2×10^{-6} (0.000)	2.3×10^{-6} (0.000)
Rice direct payments	0.0004*** (0.000)	0.0004*** (0.000)	0.0005*** (0.000)	0.0005*** (0.000)
Successor	0.0024** (0.001)	0.0025** (0.001)	0.0025** (0.001)	0.0023** (0.001)
Peer_Age	−0.0006** (0.000)	−0.0007*** (0.000)	−0.0007*** (0.000)	−0.0004* (0.000)
Peer_Degree of specialization	7.0×10^{-6} (0.000)	9.5×10^{-6} (0.000)	1.2×10^{-5} (0.000)	1.6×10^{-5} (0.000)
Peer_Rice direct payments	0.0013*** (0.000)	0.0019*** (0.000)	0.0019*** (0.000)	0.0020*** (0.000)
Peer_Successor	0.0042 (0.004)	0.0046 (0.004)	0.0060* (0.004)	0.0043 (0.004)
<i>LQ</i> (specialization)	–	0.0152*** (0.004)	0.0138*** (0.004)	0.0230*** (0.005)
<i>DIV</i> (diversity)	–	0.0124*** (0.005)	0.0108** (0.005)	0.0177*** (0.005)
<i>LQ_DUM</i> × peer effect	–	–	0.0144** (0.006)	0.0114* (0.006)
<i>DIV_DUM</i> × peer effect	–	–	0.1065** (0.006)	0.0264 (0.006)
Constant	0.0138* (0.008)	0.0126* (0.008)	0.0110 (0.008)	0.0065 (0.008)
Year × region fixed effect	no	no	no	yes
<i>N</i>	2 114	2 114	2 114	2 114
Adjusted <i>R</i> ²	0.66034	0.66404	0.66617	0.67120
Modified <i>B-D-W</i>	0.8593	0.8599	0.8624	0.8624
<i>F</i>	558.7783	463.5850	395.5070	308.3818

***, **, * statistical significance at 1%, 5%, and 10% levels, respectively; the peer effect is captured by the estimated coefficient of $\ln \overline{CE}_{(-i)gt-1}$. *LQ* – location quotient; *DIV* – diversity index; *DUM* – dummy variable; *B-D-W* – Bhargava-Franzini-Narendranathan Durbin-Watson statistic

Source: Author's calculations

able of agglomeration economies to Model 2. Finally, to account for possible regional fixed effects, Model 4 added an interaction term of year and regional dummy variables to Model 3. The estimation results revealed that in all models, the average *CE* of peer farms at time

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$t - 1$ was statistically significant, supporting the existence of peer effects on the *CE* of rice farms in our dataset. Note that the estimated coefficient of the peer effect was 0.80 in Model 4, where possible regional fixed effects were taken into consideration. This result indicates that the *CE* of a farm tends to increase by 0.8% when the average *CE* of peer farms increases by 1%. In addition, we found the following statistically significant farm-specific factors: rice direct payments ($P < 0.01$) and the presence of successors ($P < 0.05$).

These variables tended to have positive effects on *CE*. Direct payments may induce investment in farms by relaxing their budget constraints. When subsidies alter financial factors such as debt or overall wealth, investment decisions are also affected. Thus, direct payments can influence farm efficiency (Cillero et al. 2018). If a farm owner has a child engaging in agriculture, they have a motivation to stay in the farming business and are more likely to invest in agriculture (Kazukauskas et al. 2010). This leads to positive effects on farm efficiency.

Among the average characteristics of peers, age and rice direct payments were found to affect the *CE*. This implies the presence of exogenous social effects on the farm *CE*. In general, the exogenous social effects based on exogenous characteristics of peers can motivate and / or affect individual performances. A typical example of exogenous social effects is that individual learning outcomes decrease when a classmate's parents are poor. If a classmate's parents are poor, an individual perceives that the reward from education is low, which leads to lower learning motivation, ultimately resulting in low learning outcomes (Manski 1993). We found a negative and significant relationship between the average age of peers and the *CE* levels. This suggests that, as younger farmers have more flexibility in coping with technological change and innovation (Jaime and Salazar 2011), the lower average age of surrounding farmers positively affected the *CE* of a farm.

On the other hand, peers' average rice direct payment variables had positive effects on the *CE* of a farm. This result reflected that an increase in received direct payments can serve as an investment-facilitating factor for production technology (Zhu and Lansink 2010). Thus, if surrounding farmers increase investment using direct payments to increase rice productivity, it may motivate an increase in *CE* for an individual farm.

The estimation results in Model 4 also showed that both specialisation (*LQ*) and diversity (*DIV*) of crop production had positive effects on the *CE* of rice farms. This indicates that regions with higher crop specialisa-

tion and higher diversity tended to enjoy higher farm efficiency. Moreover, the coefficient of the specialisation (0.023) was found to be greater than that of diversity (0.018), suggesting that knowledge spillover effects among farms cultivating the same crop tended to be bigger than that among farms cultivating different and diverse crops (Widodo et al. 2015). Moreover, note that the endogeneity problem that may occur from the omitted variable bias was solved by using a fixed effects model with the inclusion of an interaction term between year and regional dummy variables.

For interaction terms comprised of dummy variables of agglomeration economies and the average *CE* of peers at time $t - 1$, only the interaction term of rice specialisation was found to have a statistically significant and positive relationship with farm efficiency. The result shows the peer effect of a region where *LQ* is greater than 1.25 was 0.01 greater than that of others. If the *LQ* of a region exceeds 1.25, it can be classified as an industry cluster (Morrissey 2016). Thus, this indicates that peer effects on rice farms are greater in a rice industrial cluster. The results also suggest that the farm efficiency can be further increased by being a member of the industrial cluster since this farm can enjoy enhanced positive interactions with peers.

CONCLUSION

This study contributes to the literature on farm efficiency by considering peer effects. We also investigated whether peer effects differ across agglomeration degrees. *CE* was estimated by applying a time-varying stochastic frontier model, and peer effects were estimated by using a linear-in-means model. The reflection problem associated with the identification of peer effects was solved by applying a dynamic model (Blume et al. 2011). Moreover, the endogeneity problem that may occur from the omitted variable bias was solved by using a fixed effects model including an interaction term between year and regional dummy variables.

Both the average *CE* and the average scale elasticity of rice farms in South Korea were estimated to be 0.881 and 0.882, respectively, which is consistent with the presence of economies of scale. Additionally, empirical results demonstrated that the average *CE* of peer farms residing in the same region had a statistically significant positive impact on the *CE* of individual farms. This indicates that a farm's *CE* was influenced not only by its own characteristics but also by interactions with peer farms, emphasising the peer effects on efficiency enhancement. We suggest that considerations of social

capital should be integrated into policy recommendations for improving productivity. Moreover, estimation results for the effects of crop (rice) specialisation (MAR externalities) and crop diversity (Jacob's externalities) on farms' *CE* showed that both agglomeration economies had positive effects on a farm's *CE*. These findings confirm that agriculture, like the manufacturing sector, is also positively affected by Marshall's and Jacob's externality (Widodo et al. 2015). In particular, the effect of rice specialisation on *CE* was greater than that of crop diversity. This implies that knowledge spillovers occur more cost-efficiently among farms cultivating the same crop than among those cultivating different crops. We also found that peer effects were greater in a region specialised in rice than in other regions. This finding is consistent with previous studies arguing that productivity may increase through information exchange when agglomeration economies exist (Haliu and Deaton 2016; Tirkaso and Haliu 2022).

In agricultural policy, our study presents the pivotal finding that regions with a pronounced concentration of a specific crop exhibit significantly enhanced production efficiency owing to pronounced agglomeration and peer effects. This insight underscores the necessity of incorporating these dynamics into the regional selection criteria for crop productivity enhancement projects to optimise policy outcomes. Furthermore, policymakers and agricultural strategists should pursue a tailored approach that carefully examines regional characteristics and relies on empirical evidence to leverage these peer dynamics and agglomeration economies, thereby enhancing the competitiveness of crop productivity.

Our findings have significant implications for achieving multiple Sustainable Development Goals, particularly SDG 2 (Zero Hunger) and SDG 8 (Decent Work and Economic Growth). By leveraging peer effects and agglomeration economies, policymakers can promote knowledge sharing among farmers, foster high levels of specialisation and diversification in specific agricultural sectors (e.g. rice farming), and increase productivity within the agricultural sector, which are key components of SDG 2. Additionally, these strategies can support regional economic development by enhancing agricultural productivity and efficiency, contributing to SDG 8 goal of promoting sustained and inclusive economic growth.

While our study provides valuable insights into peer effects and agglomeration economies in agricultural efficiency, it is important to acknowledge a certain methodological consideration. As noted by Sauer et al. (2006), the deviation of the estimated cost function

from full concavity at the sample mean warrants some attention. This aspect introduces nuances in the interpretation of our efficiency measurements. Specifically, the partial violation of theoretical consistency may lead to some imprecision in estimating relative inefficiencies, potentially affecting our understanding of individual production units. It also complicates the economic interpretation of efficiency scores, as it suggests that cost minimisation conditions may not always hold uniformly across the sample.

Despite these considerations, the strength of our research lies in its comprehensive analysis of peer effects and agglomeration economies, providing crucial insights for policy formulation. Our results robustly demonstrate the positive impact of both specialisation and diversity on farm efficiency, with important implications for regional agricultural development strategies. Future research could build upon this foundation by exploring alternative functional forms or estimation methods that allow theoretical consistency while maintaining flexibility.

Additionally, examining farmers' risk preferences under production uncertainty could provide complementary insights, further enriching our understanding of farmers' behaviour and peer influences. Future research efforts, in line with our current findings, may have the potential to build adequate agricultural policy formulation in this area and to contribute to the realisation of SDGs 2 and 8. However, one needs to be cautious in interpreting our results due to the methodological nuances in the estimation process of the cost function. Yet, we argue that they do not undermine the substantial contributions of this study to the field of agricultural economics.

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