



Economic and social impact assessment of rice research funding in Thailand using the structural equation modeling technique

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Article Info

Article history:

Received 1 February 2018

Revised 28 March 2018

Accepted 14 June 2018

Available online 4 July 2018

Keywords:

economic impact assessment,
research funding,
rice research,
social impact assessment,
structural equation modeling

Abstract

This study quantified the effect sizes of the impact of rice research funding in Thailand, using the structural equation modeling technique. The impact factors were rice crop productivity, farmers' income, rice production cost, and the number of rice farmers. The secondary data were two-dimensional panel data from four regions in Thailand (North, Northeast, Central, and South) for the period 2008–2015. The results showed that the economic impact of rice breeding funding was larger than rice crop processing funding. This may have been due to the fact that Thailand has a large agricultural sector. The main focus of rice R&D studies has been on cultivation rather than processing technology development. Thus, the increases in rice crop productivity and farmers' income were more affected by the breeding research funding than the processing funding. However, production cost and the number of rice farmers were inversely influenced by rice breeding funding, while crop processing funding still provided a positive impact on these two dimensions. This may have been due to the fact that the number of rice farmers has been decreasing substantially while breeding funding has been increasing annually over the past decades.

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Introduction

Thailand research outputs are not as utilized as they should be (Thaipublica, 2012). Assessing the impact from research outputs is challenging, but it is necessary for better funding decisions. The National Research Council of Thailand (NRCT) in collaboration with the Thailand Development Research Institute (TDRI) have attempted to construct an impact assessment system to evaluate research outputs. The assessment of impacts is an approach to study the causality of research implementations from funding that resulted in changes in economic and social status of related stakeholders (Isvilanonda,

2010). Although, there have been many studies on the assessment of research funding in Thailand, to our knowledge, all past studies have focused on the impact of the research funding on agricultural crop total factor productivity (TFP). For example, Chanchareonchai, Virunhaphon, and Vimonsin (2008) estimated the TFP using regression analysis and autoregressive conditional heteroskedastic models. Suwannarat (2011) used regression analysis with a log-linear function to examine the impact of agricultural productivity on poverty incidence. Suphannachart (2013) used the growth accounting method to estimate TFP growth and examined the factors influencing it using regression analysis. Suphannachart and Warr (2012) provided empirical evidence on the TFP measure and the factors influencing it using regression analysis with ordinary least squares (OLS) or linear least squares.

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Peer review under responsibility of Kasetsart University.

The regression methods mentioned above can be used to study the relationship of influencing factors to TFP. However, if the question is to explore the impact on other aspects such as the economic impact, production cost, and the number of rice farmers, then regression analysis may be too limited. In this study, we proposed the structural equation modeling (SEM) model to study both the economic and social impacts of rice research funding, as this model can be used to study multiple independent (exogenous) and dependent (endogenous) variables (Dilalla, 2000).

Literature Review

SEM is a commonly used technique for estimating the relationships between multiple endogenous and multiple exogenous factors. For example, [Yasar, Siwar, and Firdaus \(2015\)](#) employed the structural equation modeling technique to assess paddy farming sustainability in Malaysia as the endogenous latent variable that was assumed to have a direct impact on five latent variables consisting of the economy, society, ecology, institutions, and technology. The independent variables that were used to explain the economic latent variable were incomes, off-farm activities, assets or real estate properties, marketing, market demand, debts, savings, and capital. The social indicators were life status, the social network, passion for work, receptivity to changes, social problems, sizes of family, and the numbers of workers. The ecology indicators were the weather, weeds or diseases or pests, production, soil fertility, planting schedule, pollution, and water availability. Input data for the institutional indicators were government support, NGO support, financial management, drainage or irrigation management, and marketing assistance. In addition, the technology indicator was explained using environmentally friendly technology, infrastructure, fertilizer or pesticide, training, machinery, planning, and technological development. The data were based on the questionnaire responses from 350 farmers.

Their results showed that economic, social, and technology latent variables (excluding the ecology latent variable) provided a positive influence on sustainability. Technology yielded the most positive influence. The economic latent variable was defined by four indicators which were incomes, off-farm activities, marketing, and debts. The four significant indicators determining the social aspect consisted of life status, receptivity to changes, sizes of family, and the numbers of workers. The ecology latent variable was significantly determined by both soil fertility and weather. The technology variable was defined by three significant indicators: environmentally friendly technology, fertilizer or pesticide use, and training. Institution was not a significant variable to explain sustainability, but it was defined by three significant indicators composed of government support, drainage or irrigation management, and marketing assistance.

[Evenson \(2003\)](#) summarized the evaluators' perspectives on crop variety adoption of farmers in three countries (China, India, and Brazil). He studied whether economic equilibrium and crop yield changed after farmers' adoption. In China, [Rozelle, Jin, Huang, and Hu \(2003\)](#) focused on assessing the TFP impact of national and international crop

research funding by using simultaneous equations and two-stage least square techniques to estimate the effect of the various indicators on TFP. The nine indicators that they used to assess TFP consisted of crop varietal turnover, crop system extension, irrigation, weather event index, provincial dummies, crop research stock, China's germplasm contribution, yield frontier, and period-varying factors. Both primary provincial survey data and secondary data were used. The major finding of their results revealed that investment in crop research led to an increase in TFP.

In India, crop breeding research had a major impact on enhancing farmers' welfare. [McKinsey and Evenson \(2003\)](#) evaluated the relationship between crop modern variety (MV) adoption, and irrigation investment and yield for five crops (rice, wheat, maize, sorghum, and pearl millet) using SEM with three-stage least square estimation. The data in each factor were secondary data from researchers at an international crops research institute for the semi-arid tropics and Yale University during 1980–1990. The four endogenous variables consisted of crop area share, MV adoption, ratio of gross irrigated area to gross cropped area in the district, and crop yield while the six sets of exogenous variables consisted of government policy, price, weather, climate, edaphic, and International Agricultural Research Center (IARC) content. The index of extension services supplied to the state farmers, public research funding, the number of regulated markets in the state, and private R&D studies in the chemical and seed industries were used to indicate government policy contributions, while the price of chemical fertilizers and the quantity of fertilizer used in the cropped area were used for the price variables. The rainfall in millimeters in June, July, and August defined the weather variables and climatic variables were represented by five indicators: drought-prone areas, winter and summer temperature, and winter and summer rainfalls. The edaphic variable was defined by five indicators: index of organic matter content, soil type, topsoil depth, agro-biological region, and soil temperature in July, and the four indicators which were the average area of land for variety adoption and the IARC content variables were: percentage of variety adoption from the International Rice Research Institute (IRRI) cross, IRRI-crossed parent average and IRRI-crossed non-parent ancestor. The results confirmed that crop productivity had been increased because of MV adoption.

In Brazil, [Avila, Evenson, De Silva, and Almeida \(2003\)](#) also used SEM with three-stage least square estimation to evaluate the impact of crop breeding on production. The SEM model consisted of three endogenous variables and eight exogenous variables. The endogenous variables in their model associated with economic impact consisted of the crop yield index, varietal turnover, and the rate of seed utilization. The exogenous variables were agro-ecological zones, schooling levels of farmers, public extension services to farmers, the price ratio of crop producer to nitrogen fertilizer, crop breeding research, varietal characteristics supplied, area share, and IARC content. Secondary data for each variable were utilized at the Brazilian state level during 1978–1998. Their results showed that crop breeding was a major factor that enhanced crop productivity.

Shadfar and Malekmohammadi (2013) utilized SEM to analyze the policies of the state in the rice sector with one endogenous variable (rice production development) and five latent variables consisting of: infrastructure development (ID), science-technology research and extension investment and finance (STREF), farming technologies (FT), trade and marketing (TM), and market regulations (MR). Seven indicators were used to indicate ID: rice saving and packaging facilities, health care and welfare service, rural road and transportation network, local infrastructure development plans, anti-poverty plans and women empowerment, IT facility (IRRID8), and rural and local institutions (IRRID6). Thirteen variables determined the STREF, consisting of: direct cash payment to rice farmers (FC3), rice export promotion plans (IEP4), extension services provisions, farm management support, production waste reduction plans, irrigation efficiency increased projects (STER4), rice pest control studies, local rice research and study center (STER6), complementary products and local agro-businesses, rice clearing and milling facilities (IRRID2), co-cultivation plans, rural financial institution (FC4), and fertilizer and pesticide subsidies. The adoption of modern seed varieties, cultivation technologies (RP14), mechanization of rice farming (IRRID4), and pesticides were the indicators that determined FT. Three indicators defined MR: public distribution system, different pricing mechanism, and controlled price at milling. In addition, the collection and distribution system (RP15), minimum purchasing prices (MRP1), rice export, guaranteed purchasing price (MRP2), rice import restrictions, and cheap loans were used to identify TM. The data were based on the questionnaire responses of 385 farmers in 147 different statements. The results indicated that only four significant latent variables (STREF, TM, FT, and ID) explained rice production development.

Methods

The SEM method was used to study the relationships between exogenous and endogenous factors of rice research funding in Thailand. The exogenous factor was rice research funding categorized into two types: 1) funding on breeding and 2) funding on crop processing, since it was of interest to study the impact of each type of funding on each endogenous variable. The endogenous factors consisted of rice crop productivity, farmers' income, rice production cost, and the number of rice farmers.

Data and Sources

The secondary data used in this study were obtained from the Office of Agricultural Economics (2016). Funding data (both for breeding and crop processing) were obtained from the National Research Management Systems (NRMS) database for 2008–2015. Hence, the impact data were also limited to the same period as the readily available funding data. To increase the degrees of freedom in our study, we expanded the dimensions of the data to consider different regions (North, Northeast, Central, and South). The available impact datasets were rice crop productivity, farmers' income, rice production cost, and the number of rice farmers.

The data on breeding funding and processing funding were the research funding (in THB millions) from Thai government in each year. The information on rice crop productivity was the average value of rice yield (in kilograms) per hectare per year. The farmers' income data consisted of the agricultural cash income per household from rice cultivation. The definition of rice production cost was the total amount of fixed and variable costs to produce one kilogram of rice. The cost data consisted of the average value of rice production cost per kilogram. The data used for the numbers of rice farmers were the total number of cultivated rice farmers per year. Table 1 shows the descriptive statistics of the variables used in this study. Since the data on rice production cost were not differentiated among the four regions, we assumed that all regions incurred similar costs.

Hypothesis Model and Methodological Approach

We constructed the hypotheses based on our researchers' interviews. These hypotheses were drawn mainly from our previous study (Jaijit, Paoprasert, & Pichitlamken, 2017). For example, when exploring the impact of several breeding research studies, interviews results showed that the selected research studies could increase farmers' income and productivity. Thus, we studied the relationship between breeding funding and their impacts—crop productivity and farmers' income. This study also explored how crop processing funding affected both crop productivity and rice production cost. The hypotheses were whether “the crop productivity and farmers' income impacts were positively influenced by funding on breeding and crop processing,” and whether “the cost of rice production and the number of rice farmers were positively influenced by crop processing funding but were negatively influenced by breeding funding.” These relationships in the form of a structural model are shown in Figure 1.

Table 1
Descriptive statistics of variables used in this study

Variable	Region in Thailand			
	North	Northeast	Central	South
Breeding funding (THB million)				
Average	13.8	4.4	151.1	0.8
Standard deviation	15.3	3.4	63.7	0.8
Processing funding (THB million)				
Average	18.6	11.9	35.7	1.6
Standard deviation	17.1	14.6	18.5	1.1
Crop productivity (kg/ha)				
Average	97.0	71.0	104.0	76.0
Standard deviation	4.2	1.3	3.9	3.9
Farmers' income (THB/yr)				
Average	68,670.0	26,946.0	95,185.0	4,630.0
Standard deviation	5,187.2	2,008.1	13,476.1	1,170.4
Production cost (THB/t)				
Average	8,999.0	8,999.0	8,999.0	8,999.0
Standard deviation	832.3	832.3	832.3	832.3
The number of rice farmers (millions of farmers)				
Average	4.5	9.9	2.4	0.6
Standard deviation	0.2	0.5	0.2	0.2

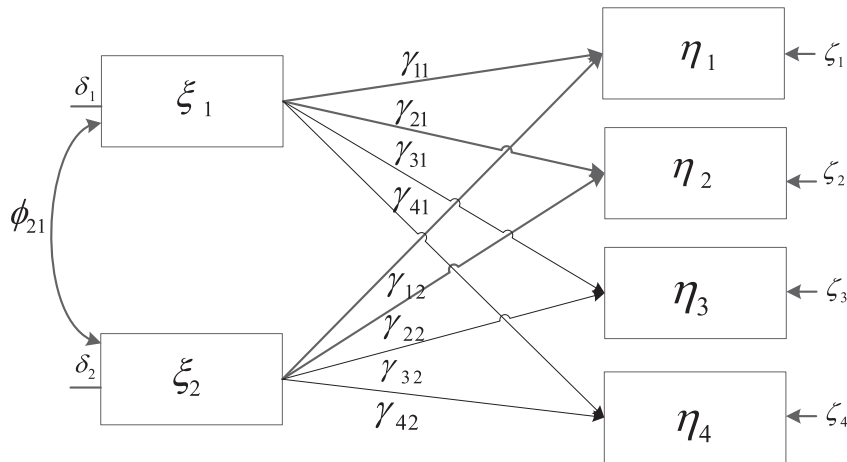


Figure 1 Conceptual structure of the rice research impact study

In each path, the coefficients γ_{11} , γ_{12} , γ_{21} , γ_{22} , γ_{31} , γ_{32} , γ_{41} , and γ_{42} indicate the effects of both exogenous variables (ξ_1 and ξ_2) and endogenous variables (η_1 , η_2 , η_3 , and η_4). Within the exogenous variables, there may also be a non-directional relationship ϕ_{21} representing a correlation between exogenous variables. The errors of both exogenous and endogenous variables are defined as δ_1 and δ_2 (measurement errors), and ζ_1 , ζ_2 , ζ_3 , and ζ_4 , respectively.

The equation forms of this structure (Figure 1) are expressed in Equations (1)–(4).

$$\eta_1 = \gamma_{11}\xi_1 + \gamma_{12}\xi_2 + \zeta_1 \quad (1)$$

$$\eta_2 = \gamma_{21}\xi_1 + \gamma_{22}\xi_2 + \zeta_2 \quad (2)$$

$$\eta_3 = \gamma_{31}\xi_1 + \gamma_{32}\xi_2 + \zeta_3 \quad (3)$$

$$\eta_4 = \gamma_{41}\xi_1 + \gamma_{42}\xi_2 + \zeta_4 \quad (4)$$

where ξ_i , $i = 1, 2$ are exogenous variables, η_j , $j = 1, 2, 3, 4$ are endogenous variables, γ_{ji} , $i = 1, 2$ and $j = 1, 2, 3, 4$ are coefficient relating ξ_i to η_j , and ζ_j , $j = 1, 2, 3, 4$ are residual terms in equations (1)–(4).

After the hypotheses had been formulated, model identification was conducted to test whether the model was sufficient to further analyze the relationship between all variables. The first test was to check whether the number of estimated parameters was fewer than or equal to the non-redundant number of observations of sample covariance matrix represented as $n(n+1)/2$, where n was the number of factors ($n = 6$).

LISREL 9.3 was used to test our hypothesis. The estimation method was the maximum-likelihood with the robust standard error estimator to effectively deal with the non-normally distributed data (Kline, 2011). Hooper, Coughlan, and Mullen (2008) suggested the widely used fit indices for model adequacy checking: the χ^2 test, the

goodness-of-fit index (GFI), the comparative fit index (CFI), the standardized root mean square residual (SRMR) and the root mean square error of approximation (RMSEA). The χ^2 test, GFI, SRMR, and RMSEA indices are absolute fit indices. These indices define how well a baseline model fits with the hypothesis model. The CFI index, on the other hand, defines how well the hypothesis model fits with the non-nested model (Hooper et al., 2008).

The χ^2 test can identify the sum of differences between the observed and the expected outcome frequencies. A non-significant χ^2 test ($p > .05$) signifies that the data provided a good fit to the model. This means that the observed covariance matrix is similar to the expected covariance matrix. The GFI is a measurement of fit by estimation on the proportion between the squared covariance residuals and the total sum of squares in the data matrix. The CFI is used to analyze the model fit by examining the chi-square non-centrality parameter in both the hypothesized model and the baseline model. Both GFI and CFI indices are normally accepted at a value of at least 0.9 to indicate the model fit (Hooper et al., 2008). The SRMR describes the differences between the observed and predicted covariance (that is, residuals). If these residuals are approximately zero, the model fit will be acceptable (Kline, 2011). However, Hooper et al. (2008) accepted a model fit in a threshold of $\text{SRMR} < 0.05$. The RMSEA measures the amount of discrepancy between the observed covariance matrix per degree of freedom and the hypothesized covariance matrix. The threshold of $\text{RMSEA} < 0.05$ is an acceptable for a model fit (Hooper et al., 2008). The criterion of each fit index are summarized in Table 2.

Table 2
Key indicators to evaluate the model fit

Fit index	Criterion	Implication
$\chi^2 = 4.77$, $p = 0.31$	Non-significant ($p > .05$)	Acceptable
GFI = 0.95	>0.90	Acceptable
CFI = 0.99	>0.90	Acceptable
SRMR = 0.05	<0.05	Acceptable
RMSEA = 0.08	<0.05	Unacceptable

Results and Discussion

Figure 2 shows the sizes of the effects of both breeding and crop processing funding on crop productivity, farmers' income, rice production cost, and the number of rice farmers. All absolute t -values in the paths were greater than 1.96 except for the absolute t -value of the effect from processing funding to productivity (1.82). This indicates that the breeding funding is statistically significant (at the 95% confidence level) in explaining the overall endogenous variables (productivity, farmers' income, rice production cost, and the number of rice farmers), while the processing funding is statistically significant in explaining farmers' income, rice production cost, and the number of rice farmers. However, the processing funding is statistically significant at the 91.8 percent confidence level in explaining productivity.

Table 1 provides a summary of the results from the five model verification tests. The results of model verification confirmed the adequacy of the structural model to explain the relationship of all variables. In Figure 2, the signs of the effect sizes show the directions of the relationships between rice research funding and the impacts. For example, the direct effect of breeding funding on productivity impact is 0.46. This means that a 1-point increase in the breeding funding variable results in a 0.46-point increase in the productivity variable by controlling the processing funding.

The results show that the economic impact of rice breeding funding is larger than the rice crop processing funding. This may potentially be due to the fact that Thailand has a large agricultural sector. The main focus of rice R&D studies has been on cultivation rather than processing technology development. Thus, the increase in rice crop productivity and farmers' income are more affected by the breeding funding than the processing funding. This result may come from the fact that processing funding could affect some other aspects such as the rice product export value or the country's overall GDP. Hence, considering only the impact on farmers, processing funding seemed to be less effective than breeding funding. If the government aims to diminish farmers' poverty, processing funding spending should be improved. However, this is one of the biggest challenges for government funding agencies.

While increasing the processing funding also increases all aspects of impact considered in this study, the breeding funding is inversely proportional to the rice production cost and the number of rice farmers. This result makes sense, especially the inverse impact between the breeding funding and the rice production cost. For example, rice breeding research for pest resistance could help to reduce the cost of insecticides used for rice production. Considering the data on the number of rice farmers, breeding funding, and crop processing funding, the inverse effect between breeding funding and the number of rice farmers may be because the number of rice farmers has been decreasing substantially while breeding funding has been increasing gradually every year over the past decades. The plots between rice breeding and processing funding and the number of farmers are shown in Figure 3. Both breeding and processing funding declined in 2011 due to the great flood crisis in that year.

Since Thailand had been aiming to develop the country from being agricultural-based to a more industrial and service country, processing funding began to receive large amounts of funding since 2012 when the country's policy was to stimulate R&D studies in adding "value" to agricultural products. Furthermore, in terms of production cost, it is possible that due to a high inflation rate and the cost of high technology for rice farming production, the overall production cost may also increase over the years.

Our results were consistent with those from Suphannachart (2013) who in particular reported a positive impact from rice research investment in Thailand on the economic impact represented by total factor productivity (TFP). The difference between the model of Suphannachart (2013) and our model is the relationship between the cause and effect factors. While the cause factor in Suphannachart (2013) was the total rice research funding and the effect factor was the TFP, our study added social aspects as effect factors. We also classified funding (the causal factor) into two categories—breeding technology and processing technology—to capture interesting findings about the differences in the effect sizes influenced by these two types of funding.

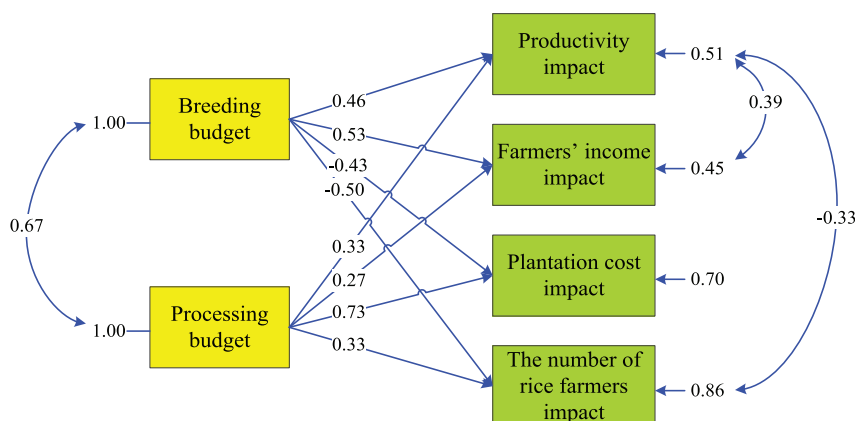


Figure 2 Effect sizes for the structural model of rice R&D studies

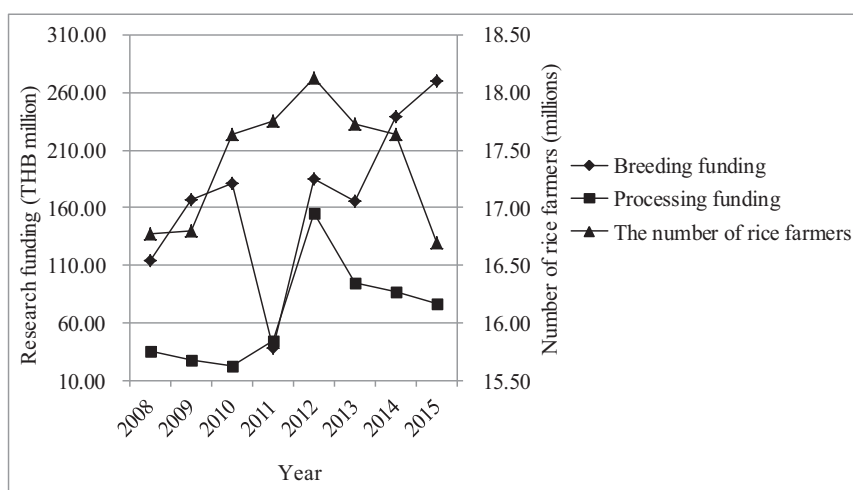


Figure 3 Rice research funding relative to number of rice farmers in Thailand, 2008–2015

Conclusions and Recommendations

This study applied the structural equation modeling (SEM) technique to examine the impact of rice research funding in Thailand and its influence on rice crop productivity, farmers' income, rice production cost, and the number of rice farmers. The causal factor categorized rice funding into two categories—breeding funding and processing funding. The model fit indicators suggested that SEM was able to be applied to further investigate the impacts.

The results indicated that breeding funding provided a positive impact on both crop productivity and farmers' income. However, breeding funding provided a negative impact on rice production cost and the number of rice farmers. The inverse impact between breeding funding and the number of rice farmers may have been due to the overall reduction in the number of farmers in Thailand and not from research funding.

Processing funding, on the other hand, provided a positive impact on all the effect factors. For policy implication, since this current study showed a promising positive impact of breeding funding, this type of funding could still be continuously funded; however, for processing funding, the criteria or strategies to successfully select the “high-potential” R&D studies in terms of raising farmers' overall economic status could be reconsidered. However, if the aim for the government is to increase other aspects besides the farmers' economic status, other parameters could be added to future studies to investigate the impacts of processing funding to those aspects.

Since the data available were only for the period 2008–2015, the number of data points might be too small. However, this study showed promising results. Further study should be done using data for more recent years once available. Funding allocation data should also be collected properly by dividing the rice funding into broader categories to observe the impact from broader funding objectives.

Unfortunately, other aspects of social impact could not be included in this current study since the necessary data were not readily available at the time we conducted the current study. For example, it would be interesting to gather data on the number of low-income rice farmers to study the question of whether rice R&D studies can reduce farmers' poverty. Moreover, it might be interesting to analyze the relationship between rice R&D studies and food sustainability.

Conflict of Interest

There is no conflict of interest.

Acknowledgments

This study was funded by the National Research Council of Thailand (NRCT) and the Faculty of Engineering, Kasetsart University, Bangkok, Thailand.

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