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The Determinants of Automated Greenhouse Adoption in Korea

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Abstract

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Smart farming is drawing attention of the South Korean government as a solution to tackle the major problems of the South Korean agricultural community by enhancing the productivity and quality of agricultural products. In 2014, the Smart Farm Facility Support Project began to promote rapid dissemination of smart facilities. However, the results have not been satisfactory according to the government reports. Previous studies on the adoption of information and communications technology for farming fall short of the increasing demand to identify the factors affecting the adoption of smart farming. Due to the limited number of samples, these studies could deal only with some of the leading smart farms. This paper contributes to the literature by identifying the factors of technological advancement in the South Korean agricultural community with respect to digital transformation.

This study attempts to deal with the data limitation by using an automated

greenhouse as a proxy for a smart greenhouse. An automated greenhouse is a greenhouse with high-tech equipment and performs the basic functions of a smart greenhouse. The data was drawn from the Census of Agriculture, Forestry and Fisheries, which represents the whole population of South Korean farmers. Two sets of data in 2010 and 2015 were combined, and the proportion of crops supported by the smart farm dissemination policy was included in the model in order to investigate the effect of the policy, which was launched in 2014. The double-hurdle approach was used to distinguish the varying effects of the factors at each decision process.

The results showed a rise in the number and size of automated greenhouses between 2010 and 2015. The crops supported by a smart farm policy had positive effects on the decisions, implying that the government strategies contributed to the promotion of smart greenhouses. In addition, farming as a main source of household income, ability to utilize information technology (IT) devices for farming, farm capital, land tenure, farm specialization, the proportion of automated greenhouses in a village, and organic farming increased both the probability of adoption and the size of the adopted automated greenhouse. The additional policy implication of this study is that the support at the village level, networks to share information on smart farming, education on utilizing agricultural IT devices, and a larger budget for financial support would also be effective.

Key words: Smart Farm, Automated Greenhouse, Agricultural Technology, Technology Adoption, ICT Convergence – Integration Policy, Double-hurdle model

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1. Introduction

1.1. Research Background

The application of information and communications technology (ICT) to the agriculture industry has emerged as a major interest of the South Korean (hereafter, Korean) government as advanced technologies have become available. Examples of advanced ICTs are agricultural drones, cloud computing, remote sensing, and the Internet of thing (IoT). Smart Farming refers to the farming style of using such technologies. The rationale behind this is that ICT is deemed as an effective solution to alleviate the issues of Korean agriculture, including the aging population and labor shortage. [1]

Smart farming allows farmers to be aware of real-time events and on-site crop conditions, which enhances the understanding of farming environment (Wolfert et al., 2014). Smart farming is an extension of precision agriculture (PA) in that PA solely utilizes spatial data for farming (Leonard, 2016). There are many studies proving the effects of ICT-based farming (e.g. Kim et al., 2016; Lee et al., 2017; Choi and Lim, 2018).

The Korean government has been implementing policies for smart farm dissemination since 2013 (Kim et al., 2016). The first policy to facilitate the adoption of the smart farm was “Plan for Promotion of Agro-food and ICT Convergence - Integration”

[1] Ministry of Agriculture, Food and Rural Affairs, “Agriculture in Korea”, 2017. http://www.mafra.go.kr/english/846/subview.do. [accessed June 28, 2019]

in 2013 (Kim et al., 2016), which diagnosed the current condition of ICT applications of farms to establish the guidelines for smart farm promotion (Lee et al., 2018). The practical policy started in 2014, offering subsidies and consulting services to farms installing ICT equipment. In 2018, the Ministry of Agriculture, Food and Rural Affairs (MAFRA) announced a plan to construct Smart Farm Innovation Valley, which is "an agricultural complex based on information and communications technology (ICT)". [2] The purpose of this plan is to foster young farmers and to cultivate upstream and downstream industries of agriculture.[3]

Nevertheless, the adoption rate of the smart farm has been falling short of the policy goals to a great extent. For instance, the policy objectives by 2014 were 330 ha of smart greenhouses and 80 smart livestock farms, but only 60 ha of smart greenhouses and 30 smart livestock farms were installed (Kim et al., 2016). In 2017, the total area of smart greenhouses amounted to 4,010 ha, which comprised only 7.3% of the total greenhouse farmland. The allocated budgets have not been used up as well; only 13%, 6.3%, and 25.8% of the budget was executed in 2015, 2016, and 2017, respectively (Lee et al., 2018).

Therefore, further studies on smart farm adoption are needed for seeking an insight for effective government strategies. While there are many empirical studies on technology adoption, a few are on smart farming due to the small sample size available.

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[2] Lee, Y. and M. Choi, "Korea to Set up Smart Farm Valley in Southern Rural Areas Sangju and Gimje," *Maeil Business News Korea*, August 2, 2018. https://www.mk.co.kr/news/english/view /2018/08/486066/ [accessed June 11, 2019]

[3] Han, S., "Agricultural innovation finds its way through Smart Farming," *Nong-eochon Gyeongje Sinmun*, May 18, 2018. http://www.ekrnews.co.kr/news/article.html?no=6398 [accessed June 28, 2019]

Kim et al. (2015) examined 110 smart farms and revealed the factors that affect the decision of smart farm adoption by using the technology acceptance model (TAM). Kim et al. (2016) surveyed 67 leading smart farms on the motivation for adoption, level of satisfaction and utilization, and the performance of a smart device. Lee et al. (2017) selected two grape farms and investigated the change in productivity of a smart greenhouse.

This paper contributes to the existing literature as follows. First, we used an automated greenhouse as a proxy for a smart greenhouse based on its functional resemblance. Since the data of an automated greenhouse was drawn from the total population of Korean farms, the results of this study represent the Korean rural community. Second, we identified the factors that affect the probability of adopting an automated greenhouse, and the factors that affect the size of an adopted automated greenhouse area by conducting a double-hurdle analysis. Third, we considered the effect of a smart farm dissemination policy by pooling the data of 2010 and 2015, and adding crop variables supported by the policy. These results are expected to be used for the strategic design of a smart greenhouse dissemination policy by specifying the factors that induce the expansion of automated greenhouse adoption.

1.2 Purpose of Study

The Korean rural community is at the beginning stage of practicing smart farming, and the government is struggling with a policy design to support potential farmers who are interested in Smart Farming due to the shortage of sample information. An empirical study on the adoption of smart farming technology would greatly contribute to boosting the speed of smart farm diffusion by specifying the targets or priorities of policy application.

The aim of this study is to analyze the determinants of smart farm adoption in South Korea. The double-hurdle model presented by Cragg (1971) was used for this purpose because an explanatory variable appearing in both hurdles may have different effects on the adoption of smart farming and the level of adoption (Teklewold et al., 2006). The study results show that the separation of the decision process delivers important information on the adoption of ICT-based farming.

An automated greenhouse was used as a proxy for a smart greenhouse in order to replace the small number of smart farms in Korea. An automated greenhouse could be used as a proxy for a smart greenhouse because of its functional resemblance to a smart greenhouse. Furthermore, the components of the automated greenhouse are the preconditions of a smart farm dissemination policy in order to install an advanced ICT device in a greenhouse.[4]

An additional concern of this study is to find out whether a government policy launched in 2014 had a significant effect on smart farm dissemination. Data in 2010 and 2015 were combined, and the crops initially supported by the dissemination policy, were added as an additional variable for investigating the effect of the policy.

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[4] MAFRA, "Guidance on Plan for Promotion of ICT Convergence", [February 2015]

1.3. Literature Review

In general, technology adoption studies in agriculture used various methodologies. Choi et al. (2012) studied the adoption of an automatic switchgear for heat-retaining mulching used on oriental melon farms based on a binomial logit model and a probit model. The result indicated that innovativeness, level of income, and reliability are the strongest influencing factors in technology acceptance.

Jung et al. (2013) analyzed the effect of age of the farmers on the adoption of an elevated hydroponic system for strawberry cultivation. The elevated hydroponic system was suitable for elderly farmers unlike conventional new technology. A binomial logit model was applied to the analysis, which confirmed that the age of the farmers had no significant impact on the adoption when the technology acceptance level was controlled.

Daberkow and McBride (1998) conducted a logit analysis on the adoption of PA technologies of corn-producing farms in the United States. The results indicated that farm size, farm income, expected yield, the use of a computerized farm record system, and age and consulting experiences of the farm operator affected the probability of adoption.

Fernandez-Cornejo et al. (2001) contrasted the effect of farm size on the adoption of two types of innovations by applying a two-limit Tobit analysis. The innovations were genetically-engineered crops and PA technologies, which were classified as scale-neutral and scale-biased. The empirical results showed that farm size had no significant effect on scale-neutral technology unless it was at the early stages of the diffusion, while the acceptance of PA technologies was dependent on farm size. Diseconomies of farm size existed for precision agriculture technologies.

Daberkow and McBride (2003) estimated the effect of technology awareness on

the decision to adopt PA technologies using a two-stage logistic specification. Education, computer literacy, full-time farming, farm size, and age of the farm operator influenced the probability of PA awareness in the first stage logit model. Technology awareness was not significant in the second stage, whilst farm size, full-time farming, and computer literacy affected the likelihood of PA adoption. The study concluded that the efforts to disseminate PA information might not play a major role in diffusion of a technology because farmers who regard the technology profitable, are already aware of it.

Sharma et al. (2010) examined the determinants of technology adoption related to pest management by employing nonparametric and parametric approaches. The number of adopted technologies was used as the dependent variable in order to measure the intensity and diversity of adoption. The results indicated that farm size and age of the farm operator are significant factors on adopting more technologies, while education level and profitability are not. Organic farmers did not utilize more technologies than conventional farmers.

Studies using the double-hurdle model have been mostly conducted in developing countries. Legese et al. (2009) stratified households by wealth and explored the determinants of adopting drought-tolerant maize in Ethiopia by using the double-hurdle approach. The results suggest that the significant factors differ by household endowments.

McFall et al. (2013) examined the production and consumption of hybrid rice of subsistence farmers in Bangladesh. They used the first hurdle as the production model and the second as the consumption model, and concentrated on the consumption decision. The results suggest that poorer households cultivated a larger area of hybrid rice as a cheap calorie source.

Tarekegn et al. (2018) identified the determinants of improved beehive

technology adoption in Ethiopia based on the double-hurdle model. The results indicate that total income, distance from farmer training center, frequency of extension contact, perception on hive price, and participation in technology demonstration affected the adoption, while education level, total income, frequency of extension contact, credit utilization, participation in technology demonstration, and cooperative membership were significant in the intensity of adoption.

With regard to smart farm adoption, most of the studies in Korea used TAM for analysis. Kim et al. (2015) examined the factors affecting innovation acceptance and resistance by using TAM, and surveyed 110 farms utilizing an ICT hybrid environmental control system. The findings indicate that self-efficacy had no significant effects on innovation acceptance, while suitability of the ICT control system was significant. Technology complexity affected innovation resistance.

Hwang et al. (2016) conducted a survey to study the smart farm scale of horticultural farms. Tomato farms had the largest smart greenhouse cultivation areas, and the proportion of smart paprika farms was the highest. Approximately 89% of existing smart greenhouses were funded by the ICT dissemination project, and 9.7% were supported by local government projects.

Kim and Ahn (2018) conducted an analysis on the factors affecting the acceptance of ICT based on TAM. They investigated 124 smart farms, and found that innovative propensity positively affected perceived usefulness, self-efficacy, social influence, network effect, and the perceived ease of use exerted a positive influence on perceived usefulness. Perceived usefulness had a positive impact on the perceived value, which increased the intention to accept technology.

Kim et al. (2019) investigated the structural relationship by using an innovation

resistance model and partial least squares structural equation modeling (PLS-SEM). The survey respondents were 180 farmers who did not participate in technology dissemination projects. The results showed that complexity and risk of the technology affected innovation resistance. Innovative propensity had no effect on innovation resistance, but it directly affected acceptance intention of new technology.

In smart farm performance, Kim et al. (2016) revealed that production, gross profit, and wage increased after the adoption of an ICT device in farming. The data was drawn from 67 early-adopting farmers. Horticultural smart farms experienced the greatest improvement in production, and the overall effect on production and gross income was largest in floricultural smart farms. Changes in labor were significant and working hours decreased while wages increased. The number of employees was either augmented or reduced depending on the types of farming.

Lee et al. (2017) selectively studied two smart grape farms and showed that a remote control system contributed to more production and less working hours. However, the quality of grapes did not improve substantially. Kim et al. (2017) examined two strawberry farms to see the effect of the first generation smart farm technology. The yield and quality of strawberries increased, while the amount of labor decreased. Choi and Lim (2018) analyzed production efficiency of 29 strawberry farms using a data development analysis (DEA) method. The comparison between before and after smart farming suggested that yield and crop quality increased, which led to a higher level of total income.

1.4. Contents and Structure

There are a few studies on the adoption of smart farm technology, and they either present descriptive statistics or use a limited number of samples drawn from a survey of leading farms in Korea. Therefore, a general conclusion from the study results are difficult to reach. This study alleviates the limitation by conducting an empirical analysis based on the Census of Agriculture, Forestry and Fisheries.

This study is organized as follows: the first chapter presents the research background, purpose of study, and literature review. The second chapter provides a comparison of a smart farm and an automated greenhouse, a summary of related policies, and underlying factors on the low adoption rate of a smart farm. Chapter Three describes the data and double-hurdle model. Chapter Four presents and interprets the estimation results. Chapter Five provides policy implications and limitations of the study.

2. Smart Farm and Government Policies

2.1 Smart Farm and Automated Greenhouse

The concept of smart farming originated from software engineering and computer science (Beecham Research. 2014) that allowed ubiquitous management of the overall environment (Wolfert et al., 2017). The concrete conception and technical terms associated with smart farming have not reached an agreement since they were developed recently (Pivoto et al., 2017).

A smart farm is defined as "a farm that can remotely and automatically maintain and manage the growing environment of crops and livestock by utilizing ICT in vinyl houses, stables, orchards and other facilities" (Kim et al., 2016). Although smart farming includes the collective processes of an agricultural value chain such as production, distribution, and consumption (Seo, 2016), policies that support smart farming in Korea are mainly focusing on production, especially indoor horticultural farms utilizing ICT device and sensors, because smart farm technologies are at the early stage of development and utilization (Lee et al., 2018; Nam, 2018).

Therefore, the focus of this study is chiefly on a smart greenhouse among a smart livestock farm, a smart orchard, and a smart greenhouse. We used an automated greenhouse as a proxy for a smart greenhouse. An automated greenhouse (AG) is "a greenhouse equipped with high-tech machinery for the purpose of producing high-quality crops than conventional greenhouse".[5] The main components of an automated greenhouse

[5] Statistics Korea, "Survey guidebook of 2015 Census of Agriculture", 2015.

are an automatic multi-variable control system, an automatic covering system, and a heating device. An automatic multi-variable control system operates other gadgets in the automated greenhouse and optimize the growing condition of crops. [6] It is one of the ICT devices that a smart farm dispersion policy provides subsidies for installation.[7] An automatic covering system controls the windows and drapes in the automated greenhouse. A heating device controls the temperature. In short, an automated greenhouse performs similar functions to a smart greenhouse, and the sensors and gadgets of an automated greenhouse are required to be installed before applying for the government subsidy because advanced ICT devices could function based on them.[8]

Automated greenhouses have been increasing in the number and size significantly. <Table 1> presents the increasing number of automated greenhouses from 2005 to 2015. The proportion of automated greenhouses to the all types of facilities was 5.6 % in 2005, but it increased to 14.5 % in 2015, which is a three-fold increase.

<Table 1> Statistics of Automated Greenhouses

(Unit: N, %)

Year	Number of AG	Number of Greenhouses	Proportion (%)
2005	10,375	185,515	5.6
2010	15,293	121,781	12.6
2015	18,185	125,079	14.5

Source: □Census of Agriculture, Forestry, and Fisheries□
Note: Greenhouses refer to all the facilities including AG, conventional greenhouses, mushroom farms, and glass greenhouses.

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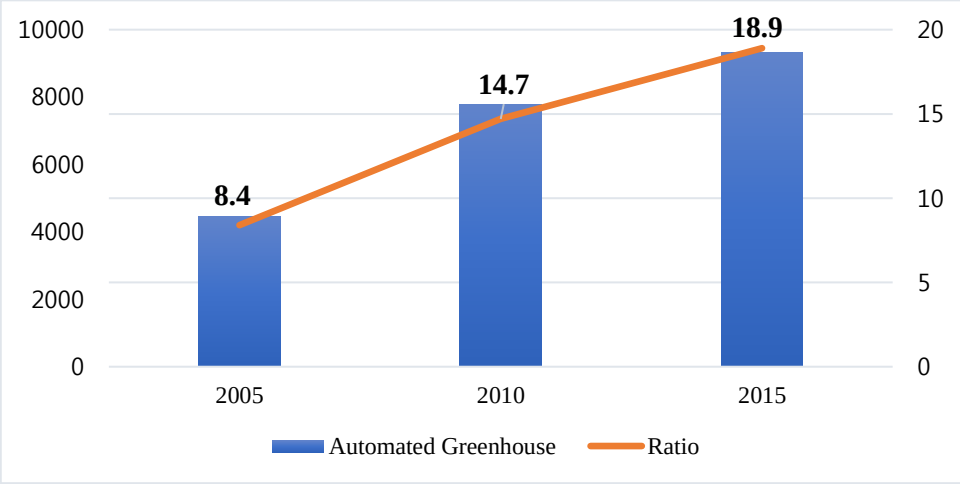
[6] Nongsaro, "Information on Farming Technology", http://www.nongsaro.go.kr/portal/ps/psb/psbk/kidofcomdtyDtl.ps;jsessionid=jPnMaLZQtkisMWEniBCH1ZXaCvUkxk42Md0ukCTJdbvu8gisMC65ioRzbFAj1osV.nongsaro-web_servlet_engine1?menuId=PS00067&kidofcomdtyNo=28927 [accessed June 11, 2019]
[7] MAFRA, "Guidance on Plan for Promotion of ICT Convergence – Integration in Facility Horticulture", [February 2015], http://www.smartfarmkorea.net/board/list.do [accessed June 11, 2019]
[8] MAFRA, "Guidance on Plan for Promotion of ICT Convergence", [February 2015]

<Figure 1> shows the increasing area of automated greenhouses during the same period. In 2005, the total area of automated greenhouses was approximately 4,465 ha, which forms 8.4 % of the total facility area. The total area of AG increased to 7790 ha (14.7 %) in 2010, and 9322 ha (18.9 %).

<Figure 1> Increasing Trend of Automated Greenhouse

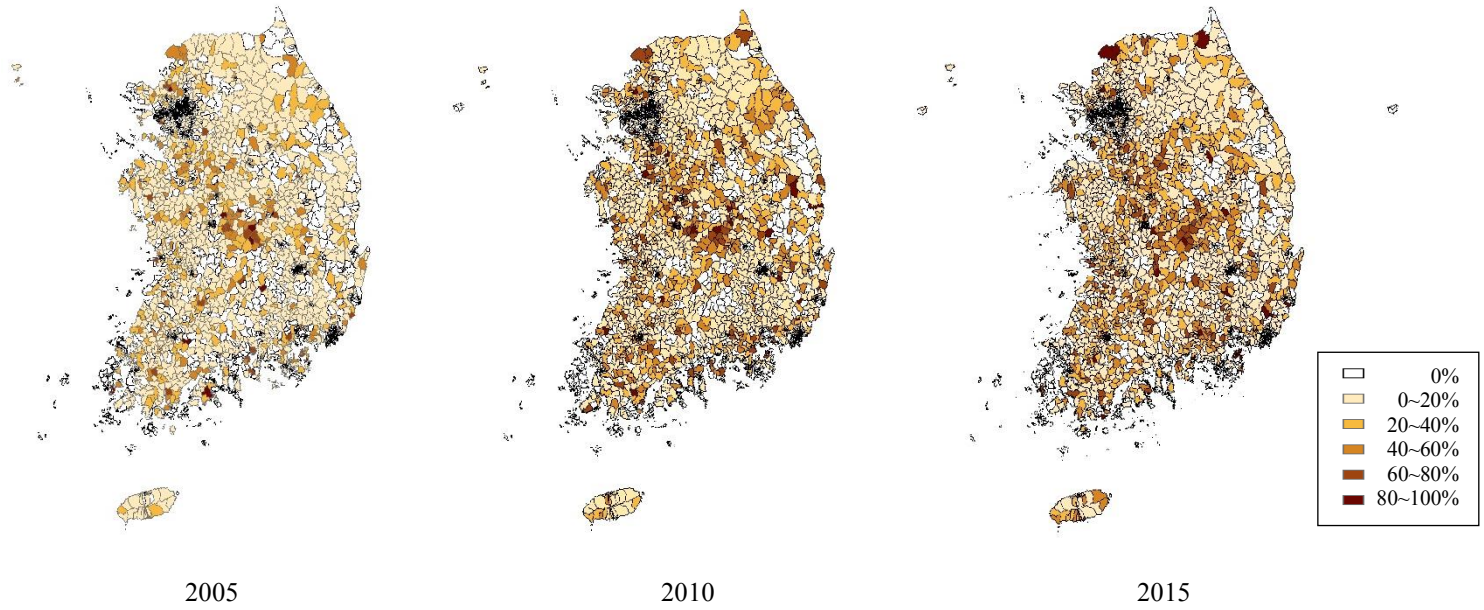
(Unit: ha, %)



Source: □Census of Agriculture, Forestry, and Fisheries□

<Figure 2> shows the increasing adoption rates of automated greenhouses in Korea at the village level. The ratio presents the total area of automated greenhouses to the total area of facilities at a village. It reveals a tendency of specialization in the central district of Korea, and the northern part is rapidly adopting automated greenhouses. However, the northeast shows decline in the adoption rates.

<Figure 2> Ratio of Automated Greenhouse in 2005, 2010, 2015



Source: □Census of Agriculture, Forestry, and Fisheries□
Note: Ratio=the area of automated greenhouses/the area of the total facilities. Presented at the village level.

2.2. Smart Farm Dissemination and the Related Policies in Korea

The governmental efforts to disseminate smart farms in Korea has begun since 2008, with a project named “Plan to Modernize Facility Horticulture Farming” (Lee et al., 2018). It was an act to protect domestic agricultural economy after the Korea-U.S. FTA in 2007. It provided farmers with extension services and subsidies for remodeling facilities, such as automatic machinery installation and repairment. (Kim et al., 2016; Lee et al., 2018). In addition, Ministry of Knowledge Economy developed smart farm models which were suitable for Korean orchards, greenhouses, and livestock farms under the project “U-Farm Leading Business” from 2004 to 2009. Ministry of Agriculture, Food and Rural Affairs took charge of the project later with a new name of “u-IT Business in Agriculture, Fisheries, and Livestock” in 2010 (Kim et al., 2016). Most of the developed models were smart greenhouse models, which were designed for specific crops such as tomatoes and paprikas (Kim et al., 2016).

The basic guidance for disseminating smart farm models was established in 2013 as a project named “Plan for Promotion of Agro-food and ICT Convergence – Integration” (Kim et al., 2016). “Plan for Promotion of ICT Convergence – Integration: Smart Farm Facility Support Project” was launched in 2014 to disseminate the models, but it did not reach the policy objective to a huge extent (Kim et al., 2016). The project planned to distribute 330 ha of smart greenhouses and 80 smart livestock farms, but it ended up with only 60 ha of smart greenhouses, and 30 smart livestock farms (Kim et al., 2016).

A unified authority system was established for smart farm promotion by “Plan for High-tech Farming·Happy Rural Community based on ICT” in 2015, and it fostered

the environment conducive to the smart farm industry (Kim et al., 2016; Lee et al., 2018).

The second "Plan for Promotion of Agro-food and ICT Convergence – Integration" was implemented in 2015, which reset the primary goal of the smart farm policy. <Table 2-1> presents the revised goal of dissemination 4,000 ha of smart greenhouses by 2017 and 7,000 ha by 2022. It is approximately 40 % of the total area of modern greenhouses. The proportion (B/A) presents the proportion of smart greenhouse area to the total facility area. It increased from 0.7 % in 2014 and 7.3 % in 2017 (Kim et al., 2016).

<Table 2-1> Area of Smart Greenhouses

(Unit: ha, %)

Area \ Year	2013	2014	2015	2016	2017	2022
Greenhouse (A)	51,058[a]	54,371	55,015	54,218	54,632	
Modern greenhouse			10,500			
Automated greenhouse			7,728[c]			
Smart greenhouse(B)	345[b]	405	769	1,912	4,010	
Proportion (B/A)		0.7	1.4	3.5	7.3	
Policy goal for Smart greenhouse					4,000	7,000

Sources: Kim et al. (2016), p.114; Lee et al. (2018), pp.75-76; Han, S. "Agricultural Innovation Finds its Way through Smart Farming,"

[a]Data from MAFRA. (2013). "Yield of Facility Vegetables and Area of Greenhouses"
[b]Smart greenhouses before 2014 were funded by individuals.
[c]*Source*: □Census of Agriculture, Forestry, and Fisheries□

The upcoming project named "Dissemination of Smart Farming" designated four cities in Korea (Gimje, Sangju, Gohung, and Miryang) as smart farm innovation valleys. Agricultural ICT complexes are planned to be established in the four cities. It aimed to

promote the mutual growth of the agriculture industry and other related fields, and cultivate young farmers.[9] <Table 2-2> summarizes the policies related to smart farm dissemination.

<Table 2-2> Smart Farm Policies in Korea

Year	Policy	Objective
2008	Plan to Modernize Facility Horticulture Farming	Replace aged greenhouse facilities with new ones
2004-2013	U-Farm Leading Business u-IT Business in Agriculture, Fisheries, and Livestock	Develop Smart Farm models for greenhouse, livestock, distribution and others
2013	Plan for Promotion of Agro-food and ICT Convergence – Integration (1st)	- Promotion of ICT Convergence – Integration - ICT industry ecosystem development - Basic Infrastructure Expansion
2014	Plan for Promotion of ICT Convergence – Integration: Smart Farm Facility Support Project	Support the supply of ICT equipment
2015	Plan for High-tech Farming・Happy Rural Community based on ICT	Unification of the Smart Farm authorities Linked with Facility Modernization Project
	Plan for Promotion of Agro-food and ICT Convergence – Integration (2nd)	Set the primary goals and authority systems
2018	Smart Farm Dissemination	Cultivate young farmers, infrastructure, and base complex in Smart Farm Innovation Valley[10]

Sources: Kim et al. (2016), pp.13-15; Lee et al. (2018), pp.63-64.

Nevertheless, the growth of Smart Farm has fell short of the expectations set by government policies. For instance, the budgets reserved for the smart farm dissemination

[9] Yu-sup, Lee, and Mira, Choi. 2018. Korea to Set up Smart Farm Valley in Southern Rural Areas Sangju and Gimje. *Maeil Business News Korea*, August 2. https://www.mk.co.kr/news/english/view /2018/08/486066/ [accessed June 11, 2019]

[10] Han, S. "Agricultural Innovation Finds its Way through Smart Farming," [accessed June 28, 2019]

policy have not been used up over 50 % although the amount of budget has increased as shown in <Table 2-3> and <Table 2-4>. <Table 2-3> shows that only 13% of the allocated budget was executed in 2015, 6.3% in 2016, and 25.8% in 2017 (Lee et al., 2018).

<Table 2-3> Settlement of Accounts: ICT Convergence – Integration Facility Dissemination

(Unit: One Million Won, %)

Year	2014	2015	2016	2017
Budget	12,600	12,700	20,600	27,145
Expenditure	1,590	1,657	1,288	6,996
Execution rate	12.6	13.0	6.3	25.8

Sources: Lee et al. (2018), pp.71-72.

<Table 2-4> Budget Plans for Horticultural Smart Farms

(Unit: One Million Won)

	2014	2015	2016	2017	2018	2019
Total	20,000	20,000	20,000	21,000	21,000	21,000
Government	4,000	4,000	4,000	4,200	4,200	4,200
Loan	6,000	6,000	6,000	6,300	6,300	6,300
Local Subsidy	6,000	6,000	6,000	6,300	6,300	6,300
Self-Payment	4,000	4,000	4,000	4,200	4,200	4,200

Sources: Kim et al. (2016), p.17; MAFRA (2019), p.1.

2.3. Causes of Low Adoption Rates and Underlying Factors

There are several explanations on the low adoption rates of smart greenhouses. The government explained that administrative inefficiency, lack of promotion, and delay in procuring local subsidies are the primary causes of low adoption rates (Lee et al., 2018). In contrast, farmers who did not install ICT devices for farming replied that the uncertainty of profits kept them from applying for the smart farm policy (Lee et al., 2018). Small size of farmlands and high operating costs were cited as other reasons. Researchers analyzed that it was due to the shortage of modern greenhouses (Kim, 2014). Most of the facilities in Korea are outdated and in need of maintenance prior to the smart device installation. For instance, single-span vinyl houses account for approximately 90 % of vinyl houses in Korea in 2014, which represents the poor condition of Korean facilities. (Kim, 2014). Lack of greenhouses available to install ICT equipment has been pointed out as a critical obstacle to hinder smart greenhouse dissemination (Kim et al., 2016; Kim and Huh, 2015, Kim, 2014). <Table 2-5> presents the summary of different opinions.

<Table 2-5> Underlying Factors on the Low Adoption Rates of Smart Farms

Causes of Low Adoption Rates	
Government	• Administrational inefficiency (dual departments) • Lack of promotion • Difficulty in procuring local subsidies
Farmers	• Uncertainty of profits • Small size farmland • High operating costs
Researchers	• Shortage of modern greenhouses

Sources: Kim (2014), p.24; Lee et al. (2018), p.72

3. Data and Model

3.1. Data

The data used for the study is the Census of Agriculture, Forestry and Fisheries in Korea. It is a survey on the total population of Korean farms, and conducted every five years. There are other public data regarding the Korean rural community such as Survey of Agriculture, Forestry and Fisheries, but automated greenhouses are only surveyed by the Census of Agriculture, Forestry and Fisheries since 2005. However, the analysis in this study is based on the data of 2010 and 2015, because some variables included in the model were not available in the data of 2005.

The population being studied was restricted to the farms which harvested crops in the facilities, and had positive sales figures during the year of the survey. We excluded the farms of which the primary sales were livestock sales, which had glass greenhouses, [11] or which had zero farmland.[12] The number of observations was 107,003 in 2010, and 99,982 in 2015.

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[11] Glasshouses were excluded because the total area of them formed approximately 1% of the area of the total facilities, but 81% of the glasshouses were reported as smart greenhouses in 2016 (MAFRA, 2017). Therefore, the inclusion of them could disturb the estimation results.

[12] A farm reporting positive facility area in the data could own no farmland including the facilities at the time of the survey since the question on the facilities is, "Did you grow crops in facilities during the past year?" In contrast, the questions on the size of paddy field and dry field are as follow: "As of Dec. 1, 2015, do you have any paddy fields?"

The Data contain five types of facilities: a conventional greenhouse, an automated greenhouse, a mushroom farm, a glass greenhouse, and the other. A conventional greenhouse refers to a greenhouse of which the covering materials are made of vinyl. The other facilities have their covering materials other than vinyl, such as fiber reinforced polyester and fiberglass reinforced acryl. <Table 3-1> presents the distribution of farms of which their main source of incomes are crops cultivated in facilities in the data. 81.28 % of the farms cultivated vegetables and wild greens. The second largest group is cash crops and mushrooms, accounting for 5.94 %.

<Table 3-1> Distribution of Main Crops among Greenhouse Farms

Main crops	Frequencies	Percentage
Food crops	1,260	1.04
Vegetables and wild greens	98,118	81.28
Cash crops and mushrooms	7,168	5.94
Fruits	1,645	1.36
Medicinal crops	381	0.32
Flowering and ornamental crops	7,966	6.60
Others	4,178	3.46
Total	120,716	100

3.2. Methodology

The double-hurdle model presented by Cragg (1971) was used in this study. It contains two equations: the selection equation and the outcome equation. The selection equation refers to the first hurdle, and the maximum likelihood estimator is obtained using a probit estimator (Ricker-Gilbert et al., 2011). The outcome equation refers to the second hurdle, and the maximum likelihood estimator is obtained using a tobit estimator (Engel and Moffatt, 2014). The order of the two hurdles could be switched by interpretation, but the functional form remains equivalent. The second equation could be a linear model or an exponential model. We set the second hurdle as a linear model using zero-truncated data.

There are several econometric models suitable for analyzing zero-censored data: a logistic model, a probit model, and a tobit model. A logit and a probit model take dichotomous dependent variables, transforming the data over 0 to 1. Therefore, there exists a loss of information unless the raw data is binary. In contrast, a tobit model adopts a latent variable and fully utilizes the given data. However, a tobit model has an implicit assumption that zero observation is a result of the economic constraint, which is called as a corner solution (Martinez-Espineira, 2004). It can be an over-restrictive assumption because some technologies or commodities are never used by some individuals.

The double-hurdle model is a parametric generalization of the tobit model, and two separate stochastic processes in the tobit model determine the decision to adopt and the amount of adoption (Greene, 2000). The observed dependent variable could be zero

either due to the non-adoption in the first hurdle, or due to the zero amount of adoption in the second hurdle. The explanatory variables in the two hurdles could be different. The equations are presented in (1):

$$
\begin{gathered}
d_i = 1 \quad \text{if} \quad d_i^* > 0 \quad and \quad 0 \quad if \quad d_i^* \leq 0 \\
d_i^* = z_i'\alpha + \epsilon_{1,i} \\
y_i = y_i^* \quad if\ y_i^* > 0 \quad and \quad d_i^* > 0 \\
y_i^* = x_i'\beta + \epsilon_{2,i} \\
\epsilon_{1,i} \sim N(0,1) \\
\epsilon_{2,i} \sim N(0, \sigma^2)
\end{gathered}
\tag{1}
$$

d_i^* represents the latent variable in the first hurdle, and d_i represents the observed decision whether a farm adopts an automated greenhouse. y_i^* represents the latent variable in the second hurdle, and y_i refers to the observed size of an automated greenhouse. z_i and x_i are the vectors of the explanatory variables in each decision process. The error terms are assumed to be normally distributed. When the two decisions are assumed to be jointly made, the error terms are assumed to follow bivariate normal distribution as shown in (2):

$$
(\epsilon_{1,i}, \epsilon_{2,i}) \sim \mathrm{N}(0, \Sigma) \quad where \tag{2}
$$

$$
\Sigma = \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{bmatrix}
$$

The double-hurdle model by Cragg (1971) assumes that the two error terms are independent, which implies $\rho = 0$. This indicates that the model could be decomposed into a probit model and a truncated model. Smith (2003) provides a theoretical explanation on why the independency could be a valid assumption even when dependency truly exists. The log-likelihood function of the double hurdle model is presented in (3) below:

$$LogL = \sum_{y_i = 0} \ln(1 - \Phi(z'_i\alpha)\Phi(\frac{x_i'\beta}{\sigma})) + \sum_{y_i \geq 0} \ln(\Phi(z_i'\alpha)\frac{1}{\sigma}\phi(\frac{y_i - x_i'\beta}{\sigma})) \quad (3)$$

3.3. Model Specification

The empirical model in this study was specified to identify the factors that affect the decision to adopt and the intensity of adoption conditional on the adoption, which is called the double-hurdle model. The model at the decision level is specified as (4):

$$\mathrm{d}_{\mathrm{i}}^{*} = SocioEcon_i\mathrm{A} + Operation_i\mathrm{B} + Institution_i\Gamma + Policy_i\Delta + Region_i\mathrm{E} + \epsilon_{1,i}$$

$$d_i = \begin{cases} 1 & (adopt\ AG)\quad if\ d_{\mathrm{i}}^{*} > 0 \\ 0 & (does\ not\ adopt\ AG)\quad otherwise \end{cases} \tag{4}$$

Farmers' characteristics and circumstances were grouped into five categories: *SocioEcon* refers to the socio-economic factors, including the age, formal education level, and farming experiences of the farm operator, main source of income of the farm household, and the use of IT device for farming. *Operation* refers to the on-farm operational factors, including the proportion of the size of own land to the size of the total farmland, farm size, farm employment, the number of adults in the farm household, the number of cultivated crops, direct marketing, and organic marketing. *Institution* refers to the institutional factors, including the proportion of the farms having automated greenhouses to the total farms in the village, the membership of an agricultural corporation or an agricultural cooperative, and the rural location. *Policy* presents the policy factors, including the proportion of

farmlands cultivating the crops supported by a smart farm dissemination policy and a year dummy variable. There are crops which were the prior targets of the smart farm dissemination policy when the policy started (Kim et al., 2016). *Region* presents the regional factors, including Gyeonggi, Gangwon, Chungcheong, Jeolla, Gyeongsang, and Jeju. $\epsilon_{1,i}$ indicates the error term. $\mathrm{A}, \mathrm{B}, \Gamma, \Delta,$ and E are the coefficient vectors, indicating the effects of the explanatory variables. The decision d_i is observed as 1 if the latent variable d_i^* is positive. It takes zero otherwise. The second hurdle can be written as (5):

$$\mathrm{y}_\mathrm{i}^* = SocioEcon_i\mathrm{A} + Operation_i\mathrm{B} + Institution_i\Gamma + Policy_i\Delta + Region_i\mathrm{E} + \epsilon_{2,i}$$

$$y_i = \begin{cases} \mathrm{y}_\mathrm{i}^* & (positive\ area\ of\ AG) \quad if\ \mathrm{y}_\mathrm{i}^* > 0 \\ 0 & (zero\ area\ of\ AG) \quad otherwise \end{cases} \tag{5}$$

The second hurdle contains the same explanatory variables. y_i refers to the observed size of the automated greenhouse. y_i is equivalent to the latent variable y_i^* if $\mathrm{y}_\mathrm{i}^* > 0$. It takes zero otherwise.

3.4. Variables and Descriptive Statistics

The explanatory variables are classified into four categories: socio-economic factors, on-farm operational factors, institutional factors, and policy factors. [13] Regional influence was controlled by the dummy variables for five provinces.

Socio-economic factors

Adopting Information-intensive technologies requires a high level of knowledge, capacities and abilities (Daberkow and McBride, 1998), and socio-economic factors represent the human capital of the farm's main decision maker (Tey and Brindal, 2012). In this study, the age, formal education level, and years of the farming experiences of the farm operator, main source of the farm income, and the use of IT device for farming are included.

The age of the farm operator was recorded as a categorical variable: the age under fifty, age between fifty and sixty-four, and age over sixty-four. The age sixty-five was decided based on the legal age of the elderly in Korea. The reference age is the age below fifty. The formal education level was categorized into two groups: those who did not

[13] The name of socio-economic factors, on-farm operational factors, and institutional factors were derived from the study of Tey and Brindal (2012).

complete high school, and those who were high school graduates. The former group was the reference group.

The years of farming experiences was included in the model with its quadratic term in order to investigate the changing effect of it. Farming experiences may work in the opposite directions regarding technology adoption (Tey and Brindal, 2012), because more experienced farmers can feel either confident or less motivated to adopt new technologies (Isgin et al., 2008; Daberkow and McBride, 2003). Major source of the farm income is categorized into three groups: the full-time farmers, the part-time farmers with more income from farming (Part_time1), and the part-time farmers with more income from off-farm work (Part_time2). The reference group is the part-time farmers earning more income from non-agricultural jobs (Part_time2).

The use of IT device (IT_device) refers to the case where the farm operator uses any IT devices for farming during the past year. IT devices include computers, smart phones, and the others. The purpose of using the IT device can be for the sales of agricultural products, for the tourism business such as weekend farms, for the farm management such as facility automation, and for the collection of agricultural information. The ability to simply utilize a IT device had no significant impact on the adoption of a smart farm in the study of Kim et al. (2015).

On-farm operational factors

The on-farm operational factors embody the characteristics of the farm in terms of operation: the proportion of own farmland, the farm size, the on-farm employment, the number of adults in the farm household, the number of crops, and marketing channels.

The proportion of own farmland refers to the proportion of the own farmland to the total farmland of the farm household. Land ownership affects the decision to adopt innovation when the innovation requires investments related to the farmland (Fernandez-Cornejo et al., 2001). The empirical studies have consistently proved that the higher percentage of land ownership increases the incentive of the farm operator to adopt a precision agriculture technology (PAT) because the farm operator can manage the farmland in his or her preferred way and enjoy the merits of adoption from the innovation (Roberts et al. 2004; Isgin et al. 2008).

The farm size is the size of total farmland of the farm after natural logarithmic transformation. It represents the farm capital. It is a proxy for economies of scale as well (Tey and Brindal, 2012). The farm size below a critical limit can prohibit the adoption of technology because of the fixed transaction and information costs when adopting innovation (Just et al., 1980). A quadratic term was added in the model because the effect of farm size may differ as the farm size changes. The on-farm employment and the number of family members over 19 years old are the proxies for the farm capital along with the farm size. The employment was recorded as a dummy variable.

The number of crops harvested and marketing channel are the factors that reveal the risk attitude of the farm. The mix of commodities is one of the diversification strategies of a farm to be less at risk, and it reveals that the farm is prone to be risk averse (Harwood et al., 1999). The number of crops also indicates the specialization of the farm.

The marketing channel reflects the risk management strategy of the farm in order to secure the consistent price of agricultural products (Hwang et al., 2016). Many surveys showed that the uncertainty in commodity price and the crop yield variability ranked as the top risk sources among all the risk factors (USDA, 1999).[14] In other words, the choice of marketing channel reveals the risk attitude of the farm.

Selling to individual consumers, which is called direct marketing, was rated as a riskier marketing strategy than selling wholesale in a case-study of four small-scale horticultural farms because of high marketing costs and low sales volume (LeRoux et al., 2009). Large farms with production contracts are less likely to adopt a direct marketing strategy (Detre et al., 2010). Small farms specializing in vegetables, fruits, and nursery are more likely to sell their products directly to consumers (Monson et al., 2008). This variable represents the risk-seeking attitude of a small farm specialized in horticulture. Direct marketing sales in this paper refers to the case that the farm is selling the agricultural products directly to the consumers via the Internet, phone call, or mail.

[14] The risk factors included the ability to adopt new technology, lawsuit, changes in consumer preferences, changes in government laws and regulations, injury, illness, or death of the operator, and natural disasters.

Whether the farm earns the highest sales income from the deal with environment-friendly farm product distributors was added in the model as a dummy variable. The rationale behind this was Heo (2005) showed that more than half of the environment-friendly farmers were participating in agricultural technology organizations such as a research association on grapes and an organic farming association. Furthermore, organic farmers have been included in the priority group of the smart greenhouse dissemination policy since 2016. Therefore, the positive estimates of the variable can support the efficiency of the policy standard by testing the hypothesis whether organic farmers are more likely to adopt advanced technologies for farming. The environment-friendly farm product distributors were one of the ten main marketing channels[15] in the survey.

Institutional factors

The institutional factors include the factors that can provoke the farmer's behavioral change (Tey and Brindal, 2012). To be specific, they refer to the variables putting pressure on the farmer to change for more productive farming practices (Tey and Brindal, 2012). The proportion of automated greenhouses in the village, the membership of an agricultural corporation or an agricultural cooperative, and whether a farm is located in the rural village were used in this study. Agricultural corporations include agricultural

[15] wholesale market, producer's market, agricultural cooperative federation or agricultural corporation, government purchase (i.e. public reserve), intermediary merchant, environment-friendly farm product distributors including life cooperatives, individual consumers, agricultural and livestock product processors, agricultural and livestock product retailers, and the others.

companies and other associations for farming. The agricultural cooperatives are classified by the types of crops, and the types were vegetables and wild greens, cash and medicinal crops, flowering and ornamental crops.

Policy factors

The policy factors reflect the specific features of the smart farm dissemination policy in Korea. Since the policy launched in 2014, with the data of 2010 and 2015 being combined, the year dummy of 2015 can capture whether there were significant improvements in the number and size of automated houses in 2015. The estimated coefficients of the policy factors are expected to be positive. Furthermore, the proportion of the farmlands cultivating the crops supported by the policy to the total farmland was included in the policy factors. The crops were tomatoes, strawberries, western vegetables including paprikas, flowers, and the other crops including melon. The smart farm models were developed for these crops in advance to the launch of the dissemination policy, and the farms which cultivated those crops were the prior targets of the government support since the policy started (Kim et al., 2016). This variable was expected to show positive influence on the adoption of automated greenhouse (AG).

<Table 3-2> Definition of Variables

Variables			Definition	Unit
Dependent variables		Adoption of AG	Adoption=1	Dummy
		Adopted AG area	ln AG	Natural logarithm
Explanatory variables	Socio-economic factors	Age_50-	Under 50=1	Dummy
		Age_50_64	50-64 years old=1	
		Age_65+	65 and over=1	
		Highschool_graduate	Highschool graduate=1	Dummy
		Exp	Farming experience	Years
		Exp^2	$Exp^2/100$	
		Full_time	Full-time farmer=1	Dummy
		Part_time1	Part-time farmer1=1	
		Part_time2	Part-time farmer2=1	
		IT_device	IT device for farming=1	Dummy
	On-farm operational factors	Ownland	Ratio of own farmland	%
		Farmsize	ln total farmland	Natural logarithm
		$Farmsize^2$	$(\ln \text{total farmland})^2$	
		Employment	Farm employment=1	Dummy
		Adultnumber	Adults in a household	Integer
		Cropnumber	Number of crops	Integer
		Direct_marketing	Selling to individual consumers	Dummy
		Organic_marketing	Main marketing channel	Dummy
	Institutional factors	AG_in_village	Ratio of AG farms in a village	%
		Corporation	Participation in	Dummy
		Cooperative	Producer organization	Dummy
		Rural	Located in a small village	Dummy
	Policy factors	Policy_crop	Percentage of farmland under policy	%
		Year2015	Year	Dummy
	Region	Gyeonggi Gangwon Chungcheong Jeolla Gyeongsang Jeju	Farm location	Dummy

<Table 3-3> Descriptive Statistics

Variables	2010		2015		Total	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Adoption of AG	0.12	(0.32)	0.14	(0.35)	0.13	(0.33)
Adopted AG area	0.95	(2.64)	1.15	(2.86)	1.04	(2.75)
Age_50-	0.19	(0.39)	0.12	(0.32)	0.16	(0.36)
Age_50_64	0.51	(0.50)	0.50	(0.50)	0.50	(0.50)
Age_65+	0.30	(0.46)	0.38	(0.49)	0.34	(0.47)
Under_highschool	0.62	(0.48)	0.57	(0.50)	0.60	(0.49)
Highschool_graduate	0.38	(0.48)	0.32	(0.47)	0.40	(0.49)
Exp	31.10	(14.82)	31.33	(15.89)	31.18	(15.34)
Exp^2	24.07	(3.84)	12.34	(10.07)	18.41	(9.53)
Full_time	0.61	(0.49)	0.61	(0.49)	0.61	(0.49)
Part_time1	0.27	(0.44)	0.25	(0.43)	0.26	(0.44)
Part_time2	0.12	(0.33)	0.14	(0.35)	0.13	(0.34)
IT_device	0.35	(0.48)	0.33	(0.47)	0.34	(0.47)
Ownland	0.63	(0.38)	0.67	(0.38)	0.65	(0.38)
Farmsize	9.28	(0.99)	9.22	(1.04)	9.25	(1.01)
Farmsize2	87.00	(18.34)	86.06	(19.25)	86.56	(18.79)
Employment	0.49	(0.50)	0.41	(0.49)	0.45	(0.50)
adultnumber	2.97	(1.35)	2.66	(1.22)	2.82	(1.30)
Cropnumber	4.84	(3.40)	4.66	(3.48)	4.75	(3.44)
Direct_marketing	0.10	(0.30)	0.20	(0.40)	0.15	(0.36)
Organic_marketing	0.01	(0.12)	0.02	(0.15)	0.02	(0.13)
AG_in_village	0.02	(0.05)	0.03	(0.06)	0.03	(0.05)
Corporation	0.12	(0.33)	0.14	(0.35)	0.13	(0.34)
Cooperative	0.44	(0.50)	0.36	(0.48)	0.40	(0.49)
Rural	0.82	(0.38)	0.83	(0.37)	0.82	(0.38)
Policy_crop	0.25	(0.33)	0.15	(0.28)	0.20	(0.31)
Year2015	0.48	(0.50)	0.48	(0.50)	0.48	(0.50)
Gyeonggi	0.15	(0.36)	0.16	(0.37)	0.16	(0.37)
Gangwon	0.08	(0.27)	0.10	(0.30)	0.09	(0.28)
Chungcheong	0.21	(0.41)	0.22	(0.41)	0.22	(0.41)
Jeolla	0.19	(0.39)	0.18	(0.39)	0.19	(0.39)
Gyeongsang	0.36	(0.48)	0.32	(0.47)	0.14	(0.35)
Jeju	0.01	(0.08)	0.01	(0.08)	0.03	(0.05)
Number of observations	106,488		99,176		205,664	

4. Results

4.1. Cross-tabulations Analysis

<Table 4-1> indicates that the age of the farm operator and the adoption of automated greenhouse were highly correlated. Most of the farm operators were aged from fifty to sixty-four (Age_50_64), whether they adopted an automated greenhouse or not. However, it shows a stark difference that the second biggest age group among adopters were under fifty years old (Age_50-), whereas the next largest group among non-adopters were over sixty-four years old (Age_65+). The elder group (Age_65+) was 2.46 times bigger than the youngest group (Age_50-) among the non-adopters. In short, the young age of the farm operator had a positive correlation with the adoption of an automated greenhouse.[16]

<Table 4-1> Cross-tabulation of Age by AG Adoption

Age	Non-adoption	Adoption	χ^2-statistics	p-value
Age under 50	26,124	5,727		
Age from 50 to 64	88,889	14,876	2,400	(0.00)
Age over 64	64,348	5,700		
Number of observations	26,303	179,361	205,664	

[16] The average age of farm operator was 60.5 in the case of non-adopters, while it was 57.0 for the adopters. The result of t-test rejected the null hypothesis of at 1% significance level.

The adoption of an automated greenhouse and the formal education level were significantly related (<Table 4-2>). Approximately 61 % of the non-adopters did not graduate from high school (Under_highschool). In contrast, more than half of the adopters were high school graduate. High level of formal education was correlated with the adoption of automated greenhouse. <Table 4-3> shows that the average farming years of adopters were shorter than those of the non-adopters.

<Table 4-2> Cross-tabulation of Education by AG Adoption

Education	Non-adoption	Adoption	χ^2-statistics	p-value
Under high school	109,868	12,859	1,500	(0.00)
High school graduate	69,493	13,444		
Number of observations	26,303	179,361	205,664	

<Table 4-3> Cross-tabulation of Farming Experiences by AG Adoption

Farming experiences	Non-adoption	Adoption	t-statistics	p-value
Farming experiences	31.67	27.97	39.54	(0.00)
Number of observations	26,303	179,361	205,664	

The decision to adopt an automated greenhouse and the main source of income of the farm were highly correlated (<Table 4-4>). Less than 10 % of the adopters were earning most of their income from other jobs, and over 90 % of the adopters were either earning most of their income from farming or farming was the only source of their income. In contrast, 14 % of the non-adopters were the part-time farmers. It implies that the farmers

adopting automated greenhouses were more likely to be committed to farming than those who did not utilize automated greenhouses.

<Table 4-4> Cross-tabulation of Main Occupation by AG Adoption

Main Occupation	Non-adoption	Adoption	χ^2-statistics	p-value
Full time	108,484	16,694		
Part time1	45,670	7,684	946.74	(0.00)
Part time2	25,207	1,925		
Number of observations	26,303	179,361	205,664	

The use of IT device and the adoption of automated greenhouse were significantly related (<Table 4-5>). Approximately 50 % of the adopters were utilizing IT device for farming, while about 70 % of non-adopters were not using IT device for farming. It indicates that the ability to apply IT to farming has a positive correlation with the utilization of an automated greenhouse.

<Table 4-5> Cross-tabulation of IT Device by AG Adoption

IT Device	Non-adoption	Adoption	χ^2-statistics	p-value
Not using IT device	122,039	13,575	2,800	(0.00)
Using IT device	57,322	12,728		
Number of observations	26,303	179,361	205,664	

However, the difference between the average proportion of own farmland was not significant (<Table 4-6>). The farm size and the adoption of automated greenhouse were highly correlated (<Table 4-7>). The average farm size of adopters was larger than that of the non-adopters.

<Table 4-6> Cross-tabulation of Own Land by AG Adoption

Own land	Non-adoption	Adoption	t-statistics	p-value
Own Land	0.652	0.6522	-0.18	(0.86)
Number of observations	26,303	179,361	205,664	

<Table 4-7> Cross-tabulation of Farm Size by AG Adoption

Farm Size	Non-adoption	Adoption	t-statistics	p-value
Farm size	0.652	0.6522	-0.18	(0.86)
Number of observations	26,303	179,361	205,664	

Whether the farmer hired a worker for farming and whether the farmer adopted an automated greenhouse were highly correlated (<Table 4-8>). Approximately 58 % of the adopters were employing workers for farming, while 57 % of the non-adopters were not employing any workers. There were differences in the average number of the adults in the farm household between the adopters and the non-adopters. The adopters had approximately three adult family members on average, while the non-adopters had fewer adults than that (<Table 4-9>). These results reveal that the farmers who adopted automated greenhouse tend to have larger farm capital than the others such as farm size, employment, and the number of adults in the farm household.

<Table 4-8> Cross-tabulation of Employment by AG Adoption

Employment	Non-adoption	Adoption	χ^2-statistics	p-value
No Farm Employment	101,703	11,088	2,000	(0.00)
Farm Employment	77,658	15,215		
Number of observations	26,303	179,361	205,664	

<Table 4-9> Cross-tabulation of Adult Number by AG Adoption

Adult Number	Non-adoption	Adoption	t-statistics	p-value
Adult Number	2.79	3.02	-26.34	(0.86)
Number of observations	26,303	179,361	205,664	

<Table 4-10> shows that the number of crops and the adoption of an automated greenhouse were significantly related. The adopters tend to cultivate fewer crops than the non-adopters. The average number of crops was 3.9 for the adopters, while it was 4.9 for the non-adopters. Considering that the adopters had a larger farm size and fewer crops than the non-adopters, it implies that the farmers with automated greenhouse tend to prefer specialized farming.

<Table 4-10> Cross-tabulation of Crop Number by AG Adoption

Crop Number	Non-adoption	Adoption	t-statistics	p-value
Crop Number	4.87	3.92	46.62	(0.00)
Number of observations	26,303	179,361	205,664	

The marketing strategies of the adopters and the non-adopters were different. The direct marketing and the adoption of an automated greenhouse were highly correlated (<Table 4-11>). Approximately 16.5 % of the farms with automated greenhouses were selling their agricultural products directly to the individual consumers via the Internet, phone call, or mail. The non-adopters were less likely to practice the direct marketing than the adopters. About 14.7 % of the non-adopters were selling directly.

<Table 4-11> Cross-tabulation of Direct Marketing by AG Adoption

Direct Marketing	Non-adoption	Adoption	χ^2-statistics	p-value
No direct marketing	153,014	21,975	56.31	(0.00)
Direct marketing	26,347	4,328		
Number of observations	26,303	179,361	205,664	

As for organic farming, about 2.9 % of adopters were earning most of their agricultural sales income from environment-friendly farm product distributors, while 1.6 % of non-adopters were dealing with them as the main source of income (<Table 4-12>). It shows that the farmers who used automated greenhouse were more likely to practice organic farming than the non-adopters.

<Table 4-12> Cross-tabulation of Organic Marketing by AG Adoption

Organic Marketing	Non-adoption	Adoption	χ^2-statistics	p-value
No organic marketing	176,504	25,540	226.94	(0.00)
Organic marketing	2,857	763		
Number of observations	26,303	179,361	205,664	

The ratio of farms having automated greenhouse in the village was highly correlated with the decision to adopt an automated greenhouse (<Table 4-13>). The non-adopters were living in the villages with the average ratio of 0.2, indicating that approximately 2 % of the farms had automated greenhouses in their villages. The average ratio in the adopters' villages was 0.7, indicating that about 7 % of the farms were using automated greenhouses. It implies that being surrounded by more automated greenhouses affects the adoption of an automated greenhouse.

<Table 4-13> Cross-tabulation of AG in Village by AG Adoption

AG in Village	Non-adoption	Adoption	t-statistics	p-value
AG in village	0.02	0.07	-82.90	(0.00)
Number of observations	26,303	179,361	205,664	

The membership of a producer's organization and the adoption of automated greenhouse were significantly related. About 21 % of the adopters were the members of agricultural corporations, while only 12 % of the non-adopters joined any of them (<Table 4-14>). Approximately 54 % of the adopters were participating in agricultural cooperatives, while only 38 % of the non-adopters were the members of them (<Table 4-15>). The results show that the adopters were more likely to participate in the producer's organizations. As for the agricultural cooperative federation and agricultural corporation, both group of the farms showed similar ratio, but the adopters had a higher percentage of marketing rate: 32 % among adopters, and 31 % among the non-adopters. The direct marketing strategy was adopted by 15 percent of the non-adopters of an automated greenhouse, and 8 percent of the adopters.

<Table 4-14> Cross-tabulation of Corporation by AG Adoption

Corporation	Non-adoption	Adoption	χ^2-statistics	p-value
Non-member of corporation	157,282	20,771	1,500	(0.00)
Member of corporation	22,079	5,532		
Number of observations	26,303	179,361	205,664	

<Table 4-15> Cross-tabulation of Cooperative by AG Adoption

Corporation	Non-adoption	Adoption	χ^2-statistics	p-value
Non-member of cooperative	110,489	12,217	2,200	(0.00)
Member of cooperative	68,872	14,086		
Number of observations	26,303	179,361	205,664	

Whether the farm was located in the rural village and whether it adopted an automated greenhouse were highly correlated (<Table 4-16>). Approximately 17 % of the adopters' farms were located in the urban villages, while about 18 % of the non-adopted farms were in the urban villages. Both groups had the majority of their farms in the rural villages. This indicates that the adopters were more likely to cultivate crops in the rural villages when compared to the non-adopters. However, the estimation results indicate that this factor was not significant in the adoption of an automated greenhouse, and it had a negative impact on the size of the adopted automated greenhouse (<Table 4-20>).

<Table 4-16> Cross-tabulation of Rural Village by AG Adoption

Rural Village	Non-adoption	Adoption	χ^2-statistics	p-value
Urban village	31,609	4,394	18.38	(0.00)
Rural village	147,752	21,909		
Number of observations	26,303	179,361	205,664	

The proportion of policy crops was significantly related to the adoption of automated greenhouse (<Table 4-17>). The adopters had the average ratio of 0.29, while the non-adopters had the ratio of 0.19 on average. It indicates that the adopters allocated approximately 29 % of their farmlands for the crops supported by the smart farm

dissemination policy, while the non-adopters allocated only 19 % of their farmlands. The year and AG adoption were correlated (<Table 4-18>). Approximately 53 % of the adopters were nested in the 2015 data, while 48 % of the non-adopters were from the 2015 dataset. This indicates that the number of automated greenhouses has been on the rise.

<Table 4-17> Cross-tabulation of Policy Crop by AG Adoption

Policy Crop	Non-adoption	Adoption	t-statistics	p-value
Policy Crop	0.19	0.29	-45.01	(0.00)
Number of observations	26,303	179,361	205,664	

<Table 4-18> Cross-tabulation of Year by AG Adoption

Rural Village	Non-adoption	Adoption	χ^2-statistics	p-value
Year 2010	94,130	12,358	227.66	(0.00)
Year 2015	85,231	13,945		
Number of observations	26,303	179,361	205,664	

The location of the farm and the adoption of an automated greenhouse were highly correlated (<Table 4-19>). Most of the adopters and the non-adopters were in Gyeongsang, which were 34.05 % and 34.02%. However, the proportion of farms in Chungcheong among the adopters was 24.4 %, which was bigger than 21.3% among the non-adopters. The proportion of the farms adopting automated greenhouses in Jeolla province was 20.2 %, which was higher than 18.4 % among the non-adopters. Most of the adopters were located in the Gyeongsang, Chungcheong, and Jeolla provinces.

<Table 4-19> Cross-tabulation of Region by AG Adoption

Main Occupation	Non-adoption	Adoption	χ^2-statistics	p-value
Gyeonggi	29,381	3,402	426.24	(0.00)
Gangwon	16,510	1,946		
Chungcheong	38,153	6,423		
Jeolla	33,049	5,312		
Gyeongsang	61,011	8,956		
Jeju	1,257	264		
Number of observations	26,303	179,361	205,664	

4.2. Estimation Results

The results of the double hurdle analysis are presented in <Table 4-20>. It includes the estimated coefficients and robust standard errors. In the socio-economic factors, most of the variables were significant except the age and formal education level of the farm operator. The effect of the age between fifty and sixty-four (Age_50_64) was insignificant in the adoption of an automated greenhouse and the size of the automated greenhouse. However, when the age of farm operator was over 64 (Age_65+), it had a negative effect on both the adoption and the adopted area. Considering that the average age of farm operator was 60 years old, it indicates that the young age of farm operator was significant in the adoption of an automated greenhouse.

The formal education level was significant in the first hurdle, but not in the second one. When the farm operator was a high school graduate (Highschool_graduate), it increased the probability of adopting an automated greenhouse. However, it had no significant influence on the expansion of the automated greenhouse. Whether utilizing a IT device for farming (IT_device) was significant in both the adoption and the adopted size of the automated greenhouse. It implies that a high level of formal education lowers the barrier to the adoption of advanced technology for farming, but it is not a relevant factor when it comes to the extended application. Rather, the knowledge on agricultural technology facilitates the expansion of an automated greenhouse.

The farming experiences showed a negative impact on both of the hurdles. The quadratic terms for farming experience (Exp2) were less significant than the linear terms (Exp), which were significant at 1 % significance level. In addition, they turned insignificant when the sample was limited to the greenhouse farms (<Table 4-21>, <Table 4-22>). The effects of the farming experiences were negative when the quadratic term was omitted. These results reveal that as the farming experiences accumulate, farmers become more likely to stick to the conventional farming technique. The major source of the farm income was significant in both of the hurdles. When the farm's main source of income was farming (Part_time1) or farming was the only source of the income (Full_time), it contributed to the decision to adopt an automated greenhouse and the decision to install a larger size of it. It shows that dedicated farmers are more likely to adopt automated greenhouses.

The estimates of the on-farm operational factors reveal that the farm capital is critical in the adoption of an automated greenhouse and the size of it. The higher land tenure (Ownland), the larger farm size (Farmsize), [17] employing farm workers (Employment), and more adults in the farm household (Adultnumber) contributed to the adoption of an automated greenhouse and its expansion. The number of crops (Cropnumber) had a negative impact on the two hurdles. It implies that the farms specialized in several crops are more likely to utilize automated greenhouses and have

[17] The critical value of the variable *Farmsize* was 11.24, which is bigger than the 95% of the farms in the sample. It indicates that the adoption of AG and its size increase with the total farm size at a decreasing rate.

larger sizes of them. The farms adopting the direct marketing strategy (Direct_marketing) were more likely to adopt automated greenhouses, but they were less likely to install larger sizes of automated greenhouses. These results support the previous studies that small-size horticultural farms were more likely to sell their products directly to the consumers (Monson et al., 2008). It implies that the less risk-averse farmer is willing to install an automated greenhouse despite the small farm capital.

The estimates of the institutional factors reveal that the effects of farm environment were significant in both the adoption of an automated greenhouse and the size of it. A higher ratio of the automated greenhouses in the village (AG_in_village) affected the probability of adopting an automated greenhouse and the size of the adopted area. It implies that the exposure to automated greenhouses induces the farmer to adopt an automated greenhouse and expand the size. Joining producer's organizations such as agricultural cooperatives (Cooperative) or agricultural corporations (Corporation) affected the two hurdles as well. However, it became less significant or insignificant in the estimation results where the sample was restricted to the greenhouse farms (<Table 4-21>, <Table 4-22>). Whether the farm was located in the rural village (Rural) showed no significant effects on the adoption of an automated greenhouse, but it hindered the expansion of the adopted automated greenhouse. It implies that a large customer base near the farm location could induce the expansion of the automated greenhouse, while most of the farms adopting automated greenhouses were located in the rural villages.

The proportion of policy crops (Policy_crop) was crucial in both the adoption of an automated greenhouse and its size. Between five years (Year2015), the number of automated greenhouses increased and the area of them extended. It indicates that the policy contributed to the dissemination of smart greenhouses. Considering that the ratio of policy crops was significant in the regression using the 2010 data and 2005 data, the crops initially supported by the government policy were cultivated in the modern facilities. It implies that the attention of the farmers on the advanced agricultural technologies is on the rise.

The estimates based on the greenhouse farms are presented in <Table 4-21>. Greenhouse farms refer to the farms with their highest sales income from facility crops. The regression results in <Table 4-21> showed that the factors affecting the adoption of an automated greenhouse were identical by the samples except the membership of an agricultural cooperative and the location of the farm. The estimates of the quadratic term for the farming experiences (Exp^2) turned insignificant, but they consistently showed the decreasing trend. It indicates that the negative impact of the farming experiences on the adoption of an agricultural technology exists although an automated greenhouse is closely related to their main source of income. The impact of participating in agricultural cooperatives (Cooperative) turned insignificant in the decision of expanding the size of the adopted automated greenhouse. It indicates that if a greenhouse farm participates in an agricultural cooperative on vegetables, wild greens, cash and medicinal crops, flowers or ornamental crops, it increased the probability of adopting an automated greenhouse, but it had no significant effects on the size of the adopted automated greenhouse area. It implies

that sharing information through the agricultural cooperatives promotes the adoption of an automated greenhouse, but the adopted size is not dependent on the exposure to the information when horticultural farming is the main source of the farm's income. This result is partly consistent with the study of Daberkow and McBride (2003). They showed that the farmer's awareness on the technology did not simply promote the adoption of it because profitable agricultural technologies were already known to the farmer if they were profitable.

<Table 4-22> presents the results including the effects of the organic marketing channel (Organic_marketing).[18] The estimates indicate that the farmers mainly dealing with eco-friendly farm product distributors were more likely to adopt and expand the automated greenhouses. It supports the study results of Heo (2005). He showed that environment-friendly farmers actively participated in agricultural associations or institutes on the advanced farming techniques and shared information. It implies that the participation in the associations or the institutes on agricultural technologies consistently contribute to the adoption and the adopted area of the automated greenhouse. Considering the positive effect of the use of IT device (IT_device), the interests and knowledge on the

[18] This variable was additionally examined due to the low participation rates. Whether a farm is practicing organic farming could be identified in the data of 2005 and 2010, but the 2015 data lacks such information. Organic marketing channel is the only option in 2015 data to identify whether a farm is practicing eco-friendly farming. However, it is a highly restricted variable because it indicates that the farmers are earning most of their income from the sales to eco-friendly farm product distributors. Further information on organic farming would support the results of this study that organic farmers are more interested in utilizing automated greenhouse.

advanced agricultural technologies are critical in adopting an automated greenhouse and augment the size of it.

<Table 4-20> The Regression Results of AG Adoption Decision

Sub-category		Adoption		Adopted Area	
Socio-economic factors	Age_50_64	-0.001		0.003	
		(0.012)		(0.013)	
	Age_65+	-0.177	***	-0.096	***
		(0.016)		(0.018)	
	Highschool_graduate	0.110	***	0.001	
		(0.009)		(0.010)	
	Exp	-0.003	***	-0.003	***
		(0.0004)		(0.001)	
	Exp^2	0.001	*	-0.002	**
		(0.001)		(0.001)	
	Full_time	0.219	***	0.329	***
		(0.015)		(0.021)	
	Part_time1	0.233	***	0.219	***
		(0.015)		(0.021)	
	IT_device	0.206	***	0.042	***
		(0.009)		(0.009)	
On-farm operational factors	Ownland	0.200	***	0.059	***
		(0.011)		(0.012)	
	Farmsize	0.380	***	2.599	***
		(0.051)		(0.086)	
	$Farmsize^2$	-0.015	***	-0.116	***
		(0.003)		(0.005)	
	Employment	0.089	***	0.236	***
		(0.008)		(0.009)	
	Adultnumber	0.031	***	0.037	***
		(0.003)		(0.004)	
	Cropnumber	-0.016	***	-0.086	***
		(0.001)		(0.002)	
	Direct_marketing	0.058	**	-0.044	***
		(0.011)		(0.013)	
Institutional factors	AG_in_village	7.382	***	0.625	***
		(0.082)		(0.036)	
	Corporation	0.293	***	0.071	***
		(0.011)		(0.012)	
	Cooperative	0.218	***	0.139	***
		(0.008)		(0.009)	
	Rural	-0.001		-0.087	***
		(0.011)		(0.012)	
Policy factors	Policy_crop	0.429	***	0.618	***
		(0.013)		(0.012)	

	Year2015	0.187	***	0.070	***
		(0.013)		(0.017)	
Region	Gangwon	-0.080	***	-0.056	
		(0.017)		(0.024)	
	Chungcheong	0.081	***	0.220	***
		(0.013)		(0.017)	
	Jeolla	0.156	***	0.137	***
		(0.013)		(0.018)	
	Gyeongsang	-0.138	***	0.183	***
		(0.013)		(0.016)	
	Jeju	0.008		0.036	
		(0.042)		(0.045)	
Constant		-4.351	***	-6.416	***
		(0.236)		(0.386)	
Number of observations		205,664			
Log pseudolikelihood		-93672.814			
Pseudo R^2		0.1726			

Note: Numbers in parentheses are robust standard errors. ***,**,* designate significance at 1%, 5%, and 10%, respectively.

<Table 4-21> The Regression Results of AG Adoption Decision: Greenhouse Farms (1)

Sub-category		Adoption		Area of Adoption	
Socio-economic factors	Age_50_64	0.003		-0.005	
		(0.014)		(0.011)	
	Age_65+	-0.175	***	-0.051	***
		(0.019)		(0.016)	
	Highschool_graduate	0.126	***	0.001	
		(0.011)		(0.010)	
	Exp	-0.004	***	-0.003	***
		(0.001)		(0.0005)	
	Exp^2	0.003	***	-0.0005	
		(0.001)		(0.001)	
	Full_time	0.215	***	0.185	***
		(0.019)		(0.020)	
	Part_time1	0.237	***	0.125	***
		(0.020)		(0.020)	
	IT_device	0.225	***	0.036	***
		(0.011)		(0.009)	
On-farm operational factors	Ownland	0.228	***	0.023	**
		(0.013)		(0.010)	
	Farmsize	0.439	***	2.124	***
		(0.073)		(0.106)	
	Farmsize2	-0.018	***	-0.085	***
		(0.004)		(0.006)	
	Employment	0.073	***	0.172	***
		(0.010)		(0.008)	
	Adultnumber	0.028	***	0.015	***
		(0.004)		(0.003)	
	Cropnumber	-0.009	***	-0.076	***
		(0.002)		(0.002)	
	Direct_marketing	0.106	***	-0.032	**
		(0.015)		(0.013)	
Institutional factors	AG_in_village	7.319	***	0.360	***
		(0.090)		(0.032)	
	Corporation	0.299	***	0.025	**
		(0.013)		(0.011)	
	Cooperative	0.185	***	-0.008	
		(0.010)		(0.009)	
	Rural	-0.019		-0.070	***
		(0.013)		(0.010)	
Policy factors	Policy_crop	0.349	***	0.382	***
		(0.014)		(0.011)	

	Year2015	0.219	***	0.102	***
		(0.017)		(0.016)	
Region	Gangwon	-0.019		-0.060	***
		(0.025)		(0.023)	
	Chungcheong	0.049	***	0.135	***
		(0.017)		(0.015)	
	Jeolla	0.125	***	-0.012	
		(0.017)		(0.016)	
	Gyeongsang	-0.229	***	0.047	***
		(0.016)		(0.014)	
	Jeju	-0.062		0.027	
		(0.055)		(0.040)	
Constant		-4.557	***	-4.072	***
		(0.329)		(0.466)	
Number of observations		120,716			
Log pseudolikelihood		-59717.512			
Pseudo R^2		0.2039			

Note: Numbers in parentheses are robust standard errors. ***,**,* designate significance at 1%, 5%, and 10%, respectively. Greenhouse farms refer to the farms with their highest sales income from facility crops.

< Table 4-22> The Regression Results of AG Adoption Decision: Greenhouse Farms (2)

Sub-category		Adoption		Area of Adoption	
Socio-economic factors	Age_50_64	0.003		-0.005	
		(0.014)		(0.011)	
	Age_65+	-0.173	***	-0.050	***
		(0.019)		(0.016)	
	Highschool_graduate	0.125	***	0.0002	
		(0.011)		(0.009)	
	Exp^2	-0.004	***	-0.003	***
		(0.001)		(0.0005)	
	Exp2	0.003	***	-0.0005	
		(0.001)		(0.001)	
	Full_time	0.213	***	0.183	***
		(0.019)		(0.020)	
	Part_time1	0.235	***	0.123	***
		(0.020)		(0.020)	
	IT_device	0.223	***	0.035	***
		(0.011)		(0.009)	
On-farm operational factors	Ownland	0.228	***	0.022	**
		(0.013)		(0.010)	
	Farmsize	0.440	***	2.122	***
		(0.073)		(0.106)	
	Farmsize2	-0.018	***	-0.085	***
		(0.004)		(0.006)	
	Employment	0.071	***	0.170	***
		(0.010)		(0.008)	
	Adultnumber	0.028	***	0.016	***
		(0.004)		(0.003)	
	Cropnumber	-0.010	***	-0.077	***
		(0.002)		(0.002)	
	Direct_marketing	0.105	***	-0.033	**
		(0.015)		(0.013)	
	Organic_marketing	0.282	***	0.182	***
		(0.032)		(0.026)	
Institutional factors	AG_in_village	7.340	***	0.375	***
		(0.091)		(0.032)	
	Corporation	0.288	***	0.018	*
		(0.014)		(0.011)	
	Cooperative	0.184	***	-0.008	
		(0.010)		(0.009)	
	Rural	-0.023	*	-0.072	***

		(0.013)		(0.010)	
Policy factors	Policy_crop	0.349	***	0.383	***
		(0.014)		(0.011)	
	Year2015	0.215	***	0.101	***
		(0.017)		(0.016)	
Region	Gangwon	-0.018		-0.060	***
		(0.025)		(0.023)	
	Chungcheong	0.049	***	0.134	***
		(0.017)		(0.015)	
	Jeolla	0.125	***	-0.011	
		(0.017)		(0.016)	
	Gyeongsang	-0.227	***	0.047	***
		(0.016)		(0.014)	
	Jeju	-0.062		0.028	
		(0.055)		(0.040)	
Constant		-4.555	***	-4.063	***
		(0.329)		(0.463)	
Number of observations		120,716			
Log pseudolikelihood		-59644.34			
Pseudo R^2		0.2049			

Note: Number in parentheses are robust standard errors. ***,**,* designate significance at 1%, 5%, and 10%, respectively.

5. Conclusions

The purpose of this study was to investigate the determinants of smart farm adoption of horticultural farms in Korea, so the government strategies could become more efficient in supporting potential farmers who are interested in smart farming. Previous studies on smart farms in Korea are based on a limited number of sample data because smart technologies are relatively new and costly for farmers.

This study used the data of an automated greenhouse as a proxy for a smart greenhouse and examined the involved properties. An automated greenhouse shares many features with a smart greenhouse in its components and functions. The data of an automated greenhouse practically includes a smart greenhouse because the census of agriculture lacks smart greenhouse variables. Thus, an automated greenhouse is a suitable proxy variable to investigate the characteristics of smart farms. The method adopted in this research is the double hurdle model, which separates two types of decisions in technology adoption.

The results suggest that the main source of farm income, ability to utilize an IT device for farming, farm capital, ratio of own land, farm specialization, the number of adjacent farms an having automated greenhouse, organic farming, and the crops supported by smart farm policies have positive influences on both the adoption and expansion of an automated greenhouse. In contrast, accumulated farming experiences consistently

decreased the probability of adoption and the size of an automated greenhouse, indicating that accustomed farmers are less likely to change their farming methods and adopt new technologies. The age of farm operator, formal education level, direct marketing, participation in producer's organizations, and urban location of a farm had limited or inconsistent influences on technology adoption.

The positive estimates of crops supported by a smart farm policy and a year dummy variable revealed that a smart greenhouse dissemination policy contributed to the increased adoption rates and expansion of a smart greenhouse. The interpretations of these variables are restricted because the data on whether a farm has received the government subsidies to install a smart greenhouse, was unavailable. However, the results suggest that the crops supported by a smart farm dissemination policy, are suitable for disseminating a smart greenhouse, and an increasing number of horticultural farms are adopting advanced facilities. Organic farms showed the tendency to adopt and increase the size of an automated greenhouse, indicating that the government standard of providing prior support to eco-friendly farms is effective.

Therefore, the government can increase the adoption rates of a smart greenhouse by providing prior support to the farmers whose main source of income is farming, farmers utilizing an IT device for farming, and villages where the proportion of automated greenhouses is high. The estimates of the high proportion of automated greenhouse, agricultural cooperatives, and agricultural corporations reveal that there exists a spill-over effect on the adoption and the expansion of an automated greenhouse by social networks.

Therefore, establishing agricultural associations to share information on smart farming would also be effective. On the other hand, the government can offer education on utilizing an agricultural IT device in order to increase the accessibility of smart greenhouses. In addition, raising the budget of a smart farm dissemination policy would alleviate the financial burden of technology adoption as farm capital proved to be critical in installing an automated greenhouse.

There are several limitations in this study. First, the direct effects of a smart farm dissemination policy at the farm level were not taken into account because of data limitations. Second, we could not distinguish the difference in the technology level of an automated greenhouse due to the lack of such data. Third, we are uncertain whether a crop was cultivated in an automated greenhouse or in the other facilities when a farm owned multiple facilities such as a conventional greenhouse and a mushroom farm. Nonetheless, the results of this study can contribute to the existing literature and government policy design by identifying the determinants of technological advancement in the South Korean agricultural community.

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국문초록

자동화 비닐하우스 도입 결정요인 분석

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강새솔

스마트팜(smart farm)은 농가 생산성과 농산물의 질을 높임으로써 개방화, 고령화 등 한국 농업이 겪고 있는 주요 문제들을 극복할 대안으로 주목받고 있다. 정부는 2014년 시설원예, 과수 및 양돈 ICT 융복합 확산사업을 시작하여 국내 농가에 ICT 시설을 보급하고자 하였다. 그러나 스마트팜 확산을 위한 예산 투자는 확대되고 있는데 반해, 예산 실집행률은 절반에도 미치지 못하고 있어 스마트팜 도입에 대한 연구가 필요하다. 스마트팜 도입을 다룬 국내 연구들은 스마트팜을 도입한 일부 선도 농가의 자료를 사용하여 대표성에 한계를 갖는다.

이에 따라 본 연구는 자동화 비닐하우스를 스마트팜의 대리 변수(proxy variable)로 사용하여 농가가 스마트팜을 도입하는 데 영향을 미치는 요인들을 더블 허들 모형(double hurdle model)으로 분석하고자 하였다. 자동화 비닐하우스는 일반 비닐하우스보다 고품질의 생산을 위해 첨단시설을 설치한

것으로, 스마트 온실 도입에 직접적인 영향을 미친다. 분석 자료로는 농림어업총조사를 사용하였으며 자동화 비닐하우스를 설치할 유인이 있는 국내 모든 농가를 모집단으로 설정하였다. 2014년에 시작한 ICT 융복합 확산 사업의 영향력을 파악하기 위해 2010년과 2015년의 데이터를 결합하고 정책에서 우선적으로 지원한 작물의 경지 비중을 설명변수로 포함하였다.

분석 결과, 2010년과 2015년 동안 자동화 비닐하우스의 수와 면적 모두 유의하게 증가하였으며, 정책 작물의 경작 비중이 높을 수록 자동화 비닐하우스 사용 확률이 높은 것으로 나타났다. 이는 ICT 융복합 확산 사업이 스마트 온실 확산에 기여하였음을 시사한다. 전업농, 정보화 기기 활용 여부, 농가 자산, 자가 경지 비율, 지역 내 자동화 비닐하우스 농가 비중, 친환경 농업 등은 자동화 비닐하우스 도입 결정과 도입 면적 확대 결정에 모두 긍정적인 영향을 미쳤다.

본 연구의 분석결과는 향후 스마트팜 확산 정책의 우선 지원 기준을 고려할 때 기초자료로 활용할 수 있을 것으로 기대된다. 구체적으로 전업농, 정책 작물 경작 농가, 정보화 기기 활용 농가, 자동화 비닐하우스 농가 비중이 높은 읍·면·동에 위치한 농가에게 우선적으로 사업 참여 기회를 부여할 때 스마트 온실 확산은 더욱 빠르게 이루어질 수 있을 것이다. 추가적으로 지역권별 집중 지원과 스마트 농업 기술 정보를 공유할 수 있는 네트워크 조성, 정보화 기기 활용에 대한 영농 교육 실시, 지원 금액 확대도 효과적인 방안이 될 수 있을 것이다.

주요어: 스마트팜(smart farm), 자동화 비닐하우스, 농업 기술, 기술 수용, ICT 융복합 확산 사업, 더블 허들 모형(double-hurdle model)