Ph.D. Dissertation of Economics

Heuristic Investigations of Direct and Indirect Policy Impacts on Agricultural Income

– Applications of the Comprehensive Rural Village Development Project and Transportation Accessibility –

농촌 및 공간정책의
농업소득 성과에 관한 선험적 고찰
: 농촌마을종합개발사업과 교통SOC를 중심으로

February 2021

Graduate School of Agricultural Economics and Rural Development
Seoul National University
Regional Information Major

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Advised by Professor Seongwoo Lee

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Abstract

The purpose of this research is to propose pragmatic policy evaluation models with scientific rigor and to empirically analyze the effectiveness of large-scale public policies implemented in rural areas of South Korea. The impacts of two policies, the Comprehensive Rural Village Development Project (CRVDP) and the improved transportation accessibility, on agricultural income are analyzed from an ex-post standpoint applying quantitative policy evaluation methods. This dissertation is composed of three empirical essays.

In the first essay, the impact of the CRVDP on agricultural income is analyzed using a quasi-experimental research design. The Heckman selection model was used to overcome selection bias, and the Blinder-Oaxaca decomposition method was employed to estimate the causal impact of the CRVDP. The results revealed that the project had a positive impact on raising farm households' agricultural income. A higher probability of making agricultural income was found in the project implemented areas vis-à-vis project not-implemented areas and in the period after the project implementation vis-à-vis period before the project implementation.

The second essay attempts to analyze the impact of the CRVDP on agricultural income by sub-groups of rural population. The analysis was conducted by applying the propensity score matching and the double cohort model developed from the age-period-cohort framework. The results find that young farmers in their early-career stage experienced a significant increase in the probability to attain a high-level agricultural income with the implementation of the CRVDP. On the other hand, significant effect was not visible for the cohorts of middle-aged and elderly farmers at all experience levels.

The last essay explores the benefits of transportation infrastructural investments to the agricultural sector and rural areas. The paper examines the impact of changes in transportation accessibility over the course of 2005 to 2015 on agricultural income. The impact was analyzed from both micro- and macro-levels of farm households and rural autonomies utilizing the multilevel model and the spatial econometrics model. According to the results, a positive association was found in 2005, but the effect turned negative starting in 2010 which suggest that public investments in transportation accessibility had a meager or negative impact on agricultural income.

There has been a rising call to come up with evidence-based recommendations employing scientifically credible evaluation methods in the public sector. Under this context, this research presents pragmatic approaches to policy evaluation for using credible secondary data. In this research, practical yet rigorous policy impact evaluation methods were applied to Korea's rural sector where evaluation of policies using rigorous scientific methods remains relatively limited.

Keyword : Policy evaluation, Quasi-experimental design, Heckman selection model, Cohort analysis, Multilevel model, Spatial econometrics
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Chapter 1.
Introduction

1.1. Recent Trends in Rural Korea

1.1.1. Urban Bias and the Widening Urban-Rural Income Gap

South Korea (hereafter Korea) has had remarkable success in economic development in a mere half a century, which is globally hailed as an economic miracle. Once a poverty-stricken country with per capita gross national product of USD 80 a year in 1960, Korea is now one of the world's largest economies centered on urban-based, high-tech industrialized sectors. The driver of the rapid economic growth in the 1960s and 1970s was the unbalanced growth strategy for economic and industrial development aimed at modernizing the post-war economy.

Anticipated imbalances became apparent in in many areas, for example, between urban and rural areas, between large-scale and small-scale businesses, and between export and domestic industries. Incorporating the unbalanced strategy along with the successful economic growth resulted in a substantive increase in Koreans' standard of living, by the effect of the benefits has been concentrated in only a few regions. Because the development model focusing on efficiency was supported widely, enduring the so-called growth pole strategy was upheld, and preference was given to a few predetermined industrial projects concentrated within selective locations.

The selected growth poles were concentrated around Seoul, the capital city, and a few other cities with the advantages of agglomeration economies. The inevitable consequence of the unbalanced development strategy was the highly polarized urban development and rising regional economic disparities. Occupying approximately 11% of the country's total area, the capital region that encompasses Seoul Special City and its surrounding areas of Incheon City and Gyunggi Province accounts for 50% of the total population as of 2020. In addition, the capital region is dominant in many data points, for example, compared with all other parts of the country combined, it contributes 51% of gross regional domestic product to the nation's GNP and 77.4% of R&D expenditure and has 90% of the venture capital companies, 74% of the headquarters of major large enterprises, 65% of new jobs, and 41.9% of the universities (*Sisajournal*, 4 Feb. 2020).[1]

Recently, the manufacturing sector has been losing its global competitiveness, and the metropolitan cities along the southeastern coastal area have begun to lose their population. The capital region, Seoul, and its surrounding areas are the heart of Korea and the perception of 'Seoul and elsewhere' prevails in the country. Even with the diverse balanced development policies implemented during the last couple of decades, the

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1 Available at: http://www.sisajournal.com/news/articleView.html?idxno=195218.

disparity between the capital region and the rest of the country has worsened. Jobs are highly concentrated in the capital region, and the apparent income disparity is pulling the young adult population to Seoul. As the capital region becomes increasingly congested, more government resources are being invested in the capital region to alleviate the negative externalities caused by typical urban problems. The distorted pattern of both public and private investments in the capital region further induces the urban bias (Lipton, 1977).[2]

By contrast, rural areas that lag further behind the cities are undergoing a serious economic decline and demographic shrinking. A low level of economic activities in rural areas lead to the urban-rural income gap which, in turn, push rural residents to urban areas in search for better economic prospects. As a result, rural areas suffer from a loss of population and more resources are then allocated to populous urban centers which further undermines economic vitality in rural areas. The process of so-called 'peripheralization' (Wirth et al., 2016) and the phenomenon of 'local extinction' (Masuda, 2014) are seemingly irreversible norms of Korean rural societies.

[2] The theory of urban bias proposed by Lipton (1977) posits that the income gap between city and countryside result from urban-biased policies as urban dwellers increasingly pressure governments to protect their interests at the expense of rural areas.

1.1.2. Diversification of Rural Population

Another noticeable recent trend in rural areas is the changing demographic landscape. The most apparent and worrisome phenomenon in rural demography are young adults migrating to urban areas and the subsequent aging of the remaining population. The depopulation and aging of rural areas is a global phenomenon, but the fast rate of such change distinguishes Korea from other advanced and emerging economies. Today, 46.6% of farm households are aged 65 or older (Statistics Korea, 2019).

An emerging contrary trend, however, is the constant inflow of individuals from urban areas. Although relatively small in number, the reverse urban-to-rural migration has been observed since the late 2000s, coinciding with the retirement of the baby boomer generation and the 2008 financial crisis. In 2009, a notable inflow of urban-to-rural migrants began, and the number of in-migrant householders seeking a career in agriculture increased by 83.4% (from 2,218 to 4,080); by 2011, the number was over 10,000, and this trend has continued (See Appendix A).

Rural in-migration is led by retirees who are in their 50s and 60s of age, but the number of young adults who are in their 20s to 40s is becoming substantial. With the increasing number of internal migrants from urban centers to rural areas, the composition of rural demography of farmers is diversifying. As a result, a new type of population group markedly different from the elderly traditional farmers of the pre-industrialization era is emerging in today's rural societies.

New demographic groups possess distinguished life values and experiences. Before the rapid industrialization period of Korea from 1962 to 1980, rural residents shared a comparatively homogeneous life cycle that affected the formation of rural societies comprised of individuals with similar life experiences, cultures, and values across generations. Unlike previous generations, recent in-migrants with urban backgrounds and successor farmers who chose to remain in rural areas while most of their peers migrated to urban centers for prospective jobs have different life values and career attitudes. They are highly educated and have well-established connections with urban dwellers (Mckillop et al., 2018; Zagata and Suterland, 2015). Such a new demographic trend in rural areas is being considered as an opportunity not only to alleviate the human resource shortage but also to revitalize rural communities (Kim and Kim, 2016, 2017). Young rural in-migrant farmers, in particular, are regarded as important assets of the next generation of agriculture.

1.2. Towards Evidence-based Policymaking in the Rural Sector

In response to the changing rural landscape, the government has been promoting various policies to revitalize rural areas and to strengthen the resilience of rural communities. Massive public funds have been injected into rural areas as a result. Consequently, there is an increasing social demand for improving conditions of rural areas through effective rural policies; at the same time, some critics caution the issue of moral hazard (Hwang et al., 2018).

Despite the consensus on the importance of evidence-based policymaking, the attempts to empirically assess the effectiveness of government policies implemented in rural areas have been limited in Korea. The lack of rigorous evaluation undermines the credibility of existing assessments and lowers the level of public confidence in policy intervention. Therefore, it is imperative to apply rigorous evaluation methods in the assessment of rural policies to resolve the deepening conflict related to resource allocation and to win the public support.

Drawing a causal inference of a policy intervention on the intended targets is an intricate task since various immeasurable factors that are not directly related to a particular policy also affect its outcomes. The assessment of rural policies is even more challenging, given the complex and cross-sectoral nature of rural communities (Castaño et al., 2019).

There are two major contributing factors behind the limited application of ex-post rigorous methods in policy evaluation. One is a policy planning culture within the government that places top priority on policymaking, which makes the ex-post policy evaluation the "forgotten phase of planning" (Andersson et al., 2017). Policy makers tend to place a higher priority on policy planning to strategically win the popular support and establish political legitimacy. Another factor is the data availability at the moment of evaluation, which mostly depends on past policy decisions (Colen et al., 2016; Castaño et al. 2019; Andersson et al., 2017). The most commonly adopted quasi-experimental methods require an extensive coverage of databases. Thus, the application barriers of the existing ex-post quantitative evaluation tools highlight the paucity of credible scientific methods. This prompts the need to search for alternative methods that can overcome such hurdles.

The same problems are also evident in ex-post evaluation of agricultural and rural policies (Hwang and Lee, 2015; Castaño et al., 2019; Walker et al., 2010). There has been a rising call to come up with evidence-based recommendations employing scientific evaluation methods in the agricultural and rural sectors (Olfert and Patridge, 2010; Walker et al., 2010; Colen et al., 2016; Clemens and Demombynes, 2011; Espoti and Sotte, 2013). But rural policy evaluators have been embroiled in the problem of the lack of relevant data to apply such methods. Seeking credible combinations using a wide variety of existing quantitative methods can be one valid approach in the search for alternative policy evaluation models.

1.3. Purpose and Scope of the Research

1.3.1. Purpose of the Research

To cope with the widening urban-rural income gap and the aging and related problems in rural areas, the Korean government has been putting much efforts to revitalize rural areas and to reduce rural isolation. A various bottom-up, community-driven rural village development projects were implemented as rural policies, and elaborative efforts to enhance transportation accessibility between rural areas as well as to urban centers took place as part of the national land planning.

Against this backdrop, this research attempts to evaluate the impact of a rural village development project and improved transportation accessibility on farm households' agricultural income. Among various types of rural village development projects, this research examines the Comprehensive Rural Village Development Project (hereafter CRVDP) which is often regarded as Korea's representative rural development policy.[3]

This research has two main objectives: first, to evaluate the effectiveness of selected public policies implemented in rural areas to assist future policy planning, and second, to propose pragmatic evaluation approaches to ultimately support evidence-based policymaking.

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[3] A multiple names exist to refer to the Comprehensive Rural Village Development Project of Korea. In particular, 'integrated' is used interchangeably to refer to 'comprehensive,' but they differ in meaning. In official documents, the CRVDP is defined as a project designed to comprehensively develop participating rural villages by making use of local endowments. In doing so, the project incorporated some components of the integrated rural development strategy such as bottom-up participatory approach, mobilization of local resources, and coordinated approach that bring together diverse sectors and agents. In this study, the above naming is adopted to reflect the explicit definition of the project as put forth by the government.

1.3.2. Scope of the Research

This research is composed of three empirical essays. Two essays in chapter 3 and chapter 4 are concerned with a rural policy and an essay in chapter 5 is related to a national territorial policy. The first two essays examine the question of “Did the representative rural development project in Korea, the CRVDP, achieve its intended effect of raising farm households’ agricultural income?” The question is explored according to project implementation (with and without, before and after) and traits of demographic cohorts. The third essay investigates the question, “Did the investments in transportation infrastructure generate positive benefits for farm households’ agricultural income?”

Farm households’ incomes are comprised of three types of income: (i) agricultural income, (ii) nonfarm income, and (iii) transfer income. This research solely focuses on agricultural income. Formally, agricultural income refers to the gross revenue of farms from the sales of agricultural products (crops and livestock) minus farm operating expenses. However, because of data limitation, this research adopts the annual gross revenue as the indicator of agricultural income.

In the three empirical essays, the Korean Census of Agriculture, Forestry and Fisheries (hereafter Agricultural Census) on different years were used as the main dataset. The analyses were then supplemented with other data that are needed to meet the purpose of each study.

1.4. Structure of the Research

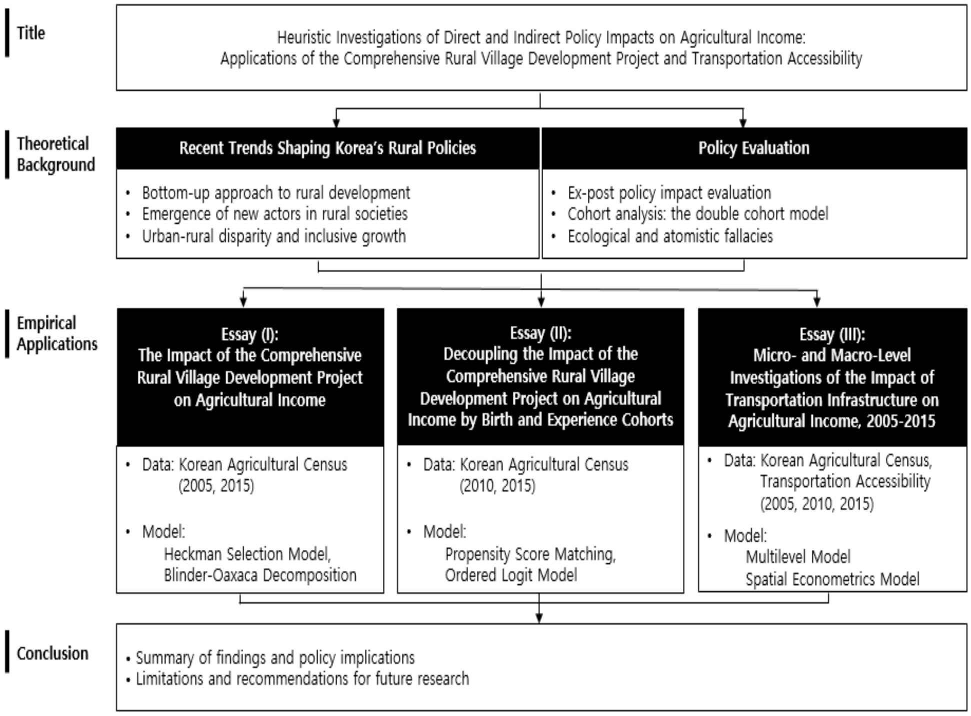
The remaining parts of this research are organized as presented in Figure 1-1. A chronological summary of Korea's rural development policy and a detailed introduction of the CRVDP is presented in chapter 2. The following three chapters are three empirical studies evaluating the impact of the CRVDP on agricultural income, decoupling the impact on agricultural income by sub-groups of rural population engaged in farming, and assessing whether or not the transportation infrastructure investments had been conducive to agricultural activities with respect to farmers' income. The last chapter is the conclusion with policy implications.

A brief introduction of the three empirical studies are as follows. Chapter 3 attempts to conduct an ex-post quantitative evaluation of the effectiveness of the CRVDP in boosting farm households' agricultural income. In doing so, the present study adopts a quasi-experimental research design that is seldom utilized in assessing rural policies. As a pragmatic evaluation tool for using readily available data, the study employs the combined application of the Heckman selection model and the Blinder-Oaxaca decomposition method. The study finds a significant positive impact of the CRVDP on agricultural income of farm households living in the project supported areas from both cross-sectional and longitudinal perspectives.

Chapter 4 investigates certain cohort characteristics that aid or hinder the ability to participate in the CRVDP, and how such differences had affected the outcomes of the project with respect to agricultural income. In doing so, the study pays attention to new types of farmers that are emerging with the changing demographic trends in rural areas. Specific cohorts of farmers are defined according to their age and experience in farming. To jointly incorporate two types of cohorts into one empirical analysis, the double cohort model developed from the traditional age-period-cohort model is employed. A comparison of agricultural income trajectories over the course of the project implementation period reveals an unintended consequence of the CRVDP where the benefits were only accrued to certain groups of farmers who were able to actively participate in the project.

Chapter 5 tries to assess the government efforts to expand the transportation accessibility with regard to agricultural income of farm households. This study particularly concerns methodological aspects of individual and contextual-level sources of bias. Thus, along with a micro-level analysis of farm households' agricultural income, this study adopts a macro-level analysis at the district level to draw broader implications for balanced regional development. In doing so, the study applies the multilevel and spatial econometrics models to evaluate the impact of improved transportation accessibility on agricultural income. The negative empirical findings highlight the necessity to promote an equity-oriented policy for an inclusive rural development.

Figure 1-1. Structure of the Research



Chapter 2.
Korea's Rural Development Policies

2.1. A Chronological Overview

The Korean government's endeavor to strengthen the economic base and improve living conditions in rural areas began with the Community Development (CD) program of the late 1950s. Korea's CD program was modelled after the community development movement adopted by the UN and ICA (International Cooperation Administration) in developing countries in the aftermath of the Second World War (Park, 2019). The CD model was a program in which local residents set up a plan, organize action groups, diagnose local development needs and find appropriate solutions on a voluntary basis. The program was aimed at improving overall living conditions, but back then, such efforts were constrained by limited capacity of local dwellers (Seok, 2007).

The CD program had become integrated with the rural extension program by the early 1960s. As a result, a community development oriented social program had evolved into a comprehensive rural development program. This had laid a foundation for the famous Samaeul Movement (New Village Movement) in the 1970s. The Samaeul Movement was a nation-wide community development program with objectives to improve the standard of living and agricultural income by modernizing rural villages. The central government provided a fixed amount of sacks of cement and iron bars to each participating village to build physical infrastructure, and villages that demonstrated success were then granted additional raw materials.

This policy achieved a great success in modernizing rural villages and reducing the widening urban-rural income gap. Together with the educational campaigns to change residents' attitude, the participatory approach of the Samaeul Movement is frequently referenced as the model for rural development in developing countries. Nonetheless, the program was a top-down, government-led policy that was strongly backed by the President and government agencies at all levels (Yoon, 2010).

Rural policy was expanded both quantitatively and qualitatively in the 1980s and 1990s (Song, 2006). A new paradigm for regional development that emerged in the 1980s, commonly known as the 'bottom-up' development, had greatly influenced rural development strategy in these periods. Unlike the state-administered, large-scale infrastructure projects of the top-down model, the bottom-up, broad-based approach to rural development led to the promotion of small-scale comprehensive development projects led by rural autonomies and residents.

The Comprehensive Rural Area Development Program in the 1980s was developed as an action plan for the bottom-up model of rural development in Korea. It essence, it was a rural settlement development program that emphasized basic needs are satisfied within rural areas. The unit of rural development was expanded from village to *gun* (county). Also, it was a comprehensive development that advocated development of rural centers and their linkage with hinterlands and introduced diverse social welfare related programs. The program was short-lived, but it had a great influence on subsequent rural development policies emphasizing a territorial approach to rural development (Park, 2019).

Rural policies in the 1990s were promoted in the context of the Uruguay Round negotiations. As a result, the scale of the government investments in the agricultural and rural sector were increased dramatically, and the budget for rural development projects were greatly enlarged. Related laws for the stable implementation of the comprehensive development projects were instituted. Such efforts had laid down the foundation for more stable and full-fledged rural development policy (Song, 2006).

The comprehensive development project of the 1980s had evolved into the Rural Settlement Zone Project in the 1990s. Rural development projects implemented in this period focused on the provision and maintenance of physical infrastructure such as roads. The implementation level of rural development was again changed from *gun* to *myeon* (township), a lower administrative unit.

From the late 1990s, multifunctionality in agriculture and rural areas has emerged as a key policy concept. Multifunctional agriculture emphasizes that in addition to food, various non-commodity outputs and services are produced by agriculture. Such non-market benefits and services include national food security, environmental protection, viability of rural areas, and cultural heritage (OECD, 2001). Rural policies began to seek measures to generate income by expanding rural amenities; rural amenities were expected to attract urban dwellers, and thereby facilitate direct sales, promote sales of local specialties, and develop rural tourism.

It was under this context when the CRVDP was carried out. In addition, with the implementation of the CRVDP, various rural village development projects led by a number of different central government ministries had taken place. These village development projects aimed to improve physical infrastructure, provide basic services, and promote urban and rural interactions. Moreover, these projects commonly emphasized that residents themselves become the active agents, leading diverse activities to enhance viability of their own villages.

Improving the quality of life and developing income sources are the priorities of rural policies today. Among a wide range of rural development projects that are being implemented, an increasing attention has been given to the 6th industrialization of agriculture and rural tourism which are promoted as a strategy to diversify rural economy.[4] Such a strategy is based on the theory of endogenous development that emphasizes the importance and utilization of locally available resources for the creation of value-added in local economies (Margarian, 2011). Various policy efforts are being made

[4] The 6th industrialization of agriculture refers to the strategy to integrate or link the primary, secondary, and tertiary industries to achieve greater value added in products and services.

to promote rural tourism consumption and to foster enterprises that will lead the 6th industrialization.

2.2. The Comprehensive Rural Village Development Project

Among a number of different policy initiatives that were carried out to revitalize rural areas, the CRVDP is noted as Korea's representative rural development project (Lee, 2012; Hwang et al., 2018). The CRVDP was implemented from 2004 to 2013 in selected rural villages throughout Korea based on the underlying principles, including endogenous development, local partnership, and multi-sectoral approach.[5] Specific activities of the project were different for each group of participating villages, but broader measures included improving rural landscape and living environment and expanding the business bases for income generation and stable production.

The CRVDP was co-financed by the Ministry of Agriculture, Food and Rural Affairs (MAFRA), and the local autonomy, and MAFRA took charge of supporting 80 percent of the total fund. The CRVDP was promoted as part of the regional development policy for balanced national development. Initially, the project budget was managed by the central government, but from 2010, the budget was transferred to local autonomies.

It was a brand-new rural initiative for the Korean government and a

[5] There are three different approaches evident in the discourse on the endogenous rural development. The first approach emphasizes the provision of opportunities to rural residents to integrate into external markets, the second approach highlights bottom-up, participatory rural development, and the third approach cherishes values of rural sustainability from both environmental and economic perspectives (Song, 2004). All of the three perspectives were reflected in the CRVDP.

departure from the previous supporting plan, which focused on the expansion of social overhead capital with small-sum, dispersed investments. It concentrated on grouping 3 to 5 small villages (*ri*) that share a common cultural identity and similar developmental needs under one hub village (*myeon*). When selected, each group of villages could receive 4 to 7 billion Korean Won (3.5 to 6.4 million USD) for up to four years.

The CRVDP was aimed at improving the quality of life of rural residents and promoting a balanced growth between urban and rural areas by creating a rural environment in which dwellers enjoy a pleasant living environment and high income. Therefore, specific activities were focused around the maintenance of hardware facilities and rural amenities and construction of facilities for income generation.

A case study on one Korean province reports that in the case of *Chungnam*, 83.5% of investments were allocated to the maintenance and construction of physical facilities. Among such investments, 43.4% were spent on facilities for rural-urban exchanges such as experience centers and village restaurants, 40.6% were spent on income-generating facilities which include agro-processing facilities, markets, lodging and service facilities, and 16% were spent on community centers (Cho et al., cited in Park, 2019). Along with these activities, investments in software such as policy consultation and educational programs were jointly promoted.

Considering the purpose of the research, it might be helpful to list activities of the CRVDP that were intended to promote agricultural income:

- Develop a specialized complex for eco-friendly agriculture;
- Construct agro-processing and storage facilities for organic products and local specialties;
- Hold farmers' markets;
- Facilitate direct sales and diversify marketing channels through rural tourism.

The rural village development projects before the 2000s, which were briefly examined in the previous section, had made great contributions to raising the overall level of standard of living in rural areas. Nonetheless, some common criticisms on rural development projects of the past decades include the excessive concentration on building physical infrastructure, decreased local autonomy due to a top-down nature, and the lack of policy evaluation to measure the effects. More specifically, projects were standardized with identical activities and villagers displayed superficial involvement, and as a result, their capacity and enthusiasm for active participation were undermined. The CRVDP was promoted in response to such criticisms while trying to reflect changes in rural policies in the 2000s. And for this reason, the emphasis was placed on the participation of residents, preservation and management of both tangible and intangible rural resources, and the use of such resources as an income base (Song, 2006).

There have been various attempts to evaluate the effectiveness of Korea's rural village development projects that took bottom-up approach such as the CRVDP. Most of such studies are survey-based analyses measuring project participants' satisfaction. Yet, there are few empirical studies based on objective data and scientific evaluation methods. One empirical study on the CRVDP analyzed the project effects with respect to the standard of living over the years of 2005 to 2010, and found a significant positive impact of the policy (Hwang et al., 2018). Another empirical study attempted to analyze the impact of similar type of project on farm households' nonfarm income. Exploiting a quasi-experimental design, a rigorous assessment of the Rural Traditional Theme Village found that the project was effective in raising nonfarm income of participating areas (Hwang and Lee, 2015).

However, despite the fact that about 30% of activities of the CRVDP were related to supports for raising agricultural income, the effectiveness of this project had not been empirically tested with respect to such an outcome. Quantitative estimation of project impact on agricultural income are investigated in the subsequent chapters. Chapter 3 attempts to evaluate whether the policy efforts to establish income-generating bases achieved the intended effects, and chapter 4 tries to examine whether the benefits of the CRVDP were equally realized among diverse groups of farmers in the project implemented areas.

Chapter 3.
The Impact of the Comprehensive Rural Village Development Project on Agricultural Income[6]

3.1. Introduction

The CRVDP was by far the most expensive and extensive rural development project in Korea. However, the importance of rigorous policy evaluation on this project has been given minor attention. In comparison to government projects in other sectors, such as public health and education, agricultural and rural policies have been relatively free from pressure to apply rigorous evaluation measurements (Hwang et al., 2018). Since agriculture and rural space are considered as public good providers, the increase in government investments was often justified by the multi-functionality of rural areas.

In place of scientifically proven, rigorous analysis of project impact, policy evaluation on rural policies has employed qualitative approaches or quantitative techniques with some limitations at best. Such tendency is not unique to Korea but is also observed in diverse international contexts. Against this backdrop, the key objective of this chapter is to provide a robust causal estimation of a rural policy on a targeted outcome using readily available data from ex-post perspective.

As a pragmatic evaluation tool for adopting a quasi-experimental design, the present study utilizes the combined applications of the Heckman sample

[6] The original version of this paper was published in *Sustainability* (Choi et al., 2020).

selection model and the Blinder-Oaxaca decomposition method.

3.2. Methodological Challenges in Counterfactual Analysis

Survey-based outcome monitoring and analytical hierarchy process (AHP) approach have been applied extensively to evaluate rural development projects and programs in many contexts (Song and Seong, 2005; Yang and Choi, 2013; Baffoe, 2019). These methods were frequently applied for the assessment of the CRVDP as well (RRI, 2005; Chae and Seo, 2011; Yang and Choi, 2013; Lee, 2012). Despite the usefulness, however, these approaches are based on subjective judgements rather than objective, rigorous measurement of data.

Policy evaluation results based on the opinions of the beneficiaries or expert judgement can be criticized as ‘guesstimates’ (Andersson et al., 2017). A robust evaluation, on the other hand, requires the exploitation of counterfactual situations through which an objective comparison of outcomes between the treatment and control groups can be made (Gertler et al., 2011). Counterfactual methods for policy evaluation accurately investigate the causal impact of a policy on the outcomes of interests. A policy evaluation entailing proper comparisons enables valid estimates of the causal effect fully attributable to the policy intervention (Gertler et al., 2011; Castaño et al., 2019; Leeuw and Vaessen, 2009).

The most valid counterfactual analysis is possible by setting up an experiment through the randomized controlled trial (RCT) or by finding a natural experiment. While the latter may involve a tremendous effort as well as some luck to find dichotomized groups that exist by nature, the experimental-based RCTs, often considered as the golden standard in evaluation, are enormously costly in terms of money and time. The two approaches are limited in practicability in actual application and cannot be employed retrospectively. Ex-post evaluation of an intervention exploiting the counterfactual is possible through quasi-experimental methods using observational data (Athey and Imbens, 2017; Campbell and Stanley, 1963; Rosenbaum, 2017).

The quasi-experimental approach is designed to estimate causal impact of an intervention in a way that resembles the experimental research without the involvement of random assignment. Most commonly applied quasi-experimental identification strategies include difference-in-differences (DID), regression discontinuity (RD), instrumental variable (IV), and matching (Angrist and Pischke, 2009; Khandker et al., 2010). Quantitative estimates attained by converting intangible observations into tangible effects have a particular merit in persuading the public about the effectiveness of a policy.

A number of prominent studies particularly in education, public health, and labor economics used these methods to estimate causal effects of public policies on outcomes. For example, the DID method was utilized to study the impact of a rise in the minimum wage on employment (Card and Krueger, 1994). The IV approach was applied to evaluate the impact of charter schools on student achievement (Angrist et al., 2010). An RD design was used to examine the effect of alcohol consumption on mortality using the minimum drinking age as a group assignment variable (Carpenter and Dobkin, 2009). Among matching methods, a PSM approach is the most developed and popular strategy to create a control comparator population (Rosenbaum and Rubin, 1983) while the synthetic control approach is gaining popularity in recent years (Abadie and Gardeazabal, 2003; Abadie et al., 2010).

The most commonly adopted quasi-experimental methods require an extensive coverage of data. For instance, the parallel trend assumption of DID requires the source of selection bias is time-invariant whereas the omission of any crucial variable will lead to biased results in the case of the propensity score matching (Shin and Kim, 2019; Streiner and Norman, 2012). Also, finding a valid instrumental variable is quite difficult in practice (Bound et al., 1995; Becker, 2016). Thus, the application barriers of the existing quasi-experimental evaluation methods highlight the paucity of credible scientific evaluation techniques.

3.3. Methodology

The present study conducts an ex-post quantitative evaluation of the CRVDP based on the assumptions of counterfactual reasoning. In the case of a policy intervention in which the treated group and the untreated group were not established at the initial stage such as the CRVDP, it is not possible to construct a control group in the ex-post setting. In this case, researchers are tasked to establish a valid comparison group that is theoretically and statistically reasonable. This study attempts to empirically analyze the effect of the CRVDP on agricultural income by setting up a counterfactual comparison group in a way that, one can reasonably assume, is equivalent to the sample who did not benefit from policy implementation.

As a novel way of evaluating the impact of an area-based rural development project on a particular outcome by using secondary data such as a census, this study employs the counterfactual decomposition technique introduced by Blinder (1973) and Oaxaca (1973). The Blinder-Oaxaca (B-O) decomposition method is a convenient way to quantify the separate contributions of group differences using observed characteristics (Fairly, 2005). This method has been most frequently applied in labor economics to explain wage differentials between naturally discrete groups such as males and females, immigrants and natives, and black and white workers.

The B-O decomposition allows quantification of the treatment effect by dividing the outcome differentials between the two groups into an ‘explained’ part (i.e. endowment effect) due to differences in observed characteristics and an ‘unexplained’ part (i.e. residual effect) attributable to the effect that are not clarified by the endowed characteristics or the net effects of group membership (Fortin et al., 2011).

The decomposition technique allows the identification of how much of mean differences on outcomes across two groups can be explained by the differences in observed characteristics. The rest of differences that cannot be explained by observed characteristics can be defined as exogenous effects. When three assumptions explained below are satisfied, counterfactual effects from the decomposition can be interpreted as causal effects (Fortin et al., 2011; Chernozhukov et al., 2013).

The identifying assumptions to draw a causal inference from the B-O decomposition are as follows (Fortin et al., 2011):

1. Counterfactual Assumption: for each particular individual, one can observe only one, but not both, of the two potential outcomes.[7]
2. Common Support Assumption (i.e. overlapping support): there is sufficient overlap in the characteristics of treated and untreated units.
3. Ignorability/Unconfoundedness Assumption (i.e. selection on observables): given a set of covariates, treatment assignment is independent to the potential outcomes.

When the above assumptions are satisfied, the exogenous effects or unexplained component from the B-O decomposition are equivalent to the average treatment effect on the treated (ATT) (Fortin et al., 2011).

The B-O decomposition is comparable to matching techniques that are frequently applied in the policy impact evaluation literature. In this study,

[7] This reasoning is based on the potential outcome framework originally proposed by J. Neyman in the context of randomized experiments (Neyman, 1923).

the B-O decomposition was employed instead because the matching methods require stronger assumptions and involve computational difficulties; such difficulties are avoidable when ATT is estimated by applying the decomposition technique. For instance, the application of a matching method can be limited if size and influence of bias from unobserved variables is unknown. The B-O decomposition, on the other hand, can be applied as long as the dependence structure between unobserved characteristics and the outcome variable is analogous between the treatment and comparison groups (Fortin et al., 2010). Moreover, a systematic distortion or the confounding bias need to be controlled in the policy impact evaluation literature are drawn together under the endowment effect in the case of B-O decomposition.

The selection into the CRVDP was not assigned randomly. As a result, it is likely that the assumption of ignorability may not hold. Since the conventional decomposition technique does not address such sample selection which could result in over or underestimation of true effects, this study applies the Heckman selection model to correct selectivity bias before employing the decomposition analysis.

3.3.1. The Heckman Selection Model

The data constructed for this study assigns Korea's entire farm households into either a project implemented group or not-implemented group, according to whether or not the residential locations of farm households belong to one of the project implemented areas. If the least squares regression was employed on a sample of farm households from the project implemented group, it is highly likely to result in biased estimates due to self-selection.

The assignment to either the project implemented or not-implemented group was not random since whether or not a farm household is located in either area is determined by the decision of the farm household. Similarly, whether or not a farm household remained in a project implemented area over the course of study periods was entirely dependent upon the decision of individual farm household.

The Heckman sample selection model is a statistical method that effectively resolves potential biases caused by the non-random selection process (Heckman, 1979, 1976). The intuition behind this method is that the selection problem is treated as a special case of the omitted variable problem using λ, a bias correction factor.

In this study, the goal is to estimate the impact of the CRVDP on agricultural income (log transformation on total sales of agricultural and livestock products) of farm households in the project implemented areas.

The basic outcome equation can be written as equation (1).

$$\text{Outcome equation: } \ln\ y = \beta' x + \varepsilon \ \cdots(1)$$

Where, *y* is the dependent variable, β' is a vector of coefficients, and ε is an error term.

An auxiliary probit model or the selection equation expressed in equation (2) describes the process of generating latent *z** that estimates the probability of individual farm households to belong to the project implemented areas. The observed counterpart of *z** expressed as *z* is determined by equation (3) where *z* is a binary variable that indicates a farm household is observed in the sample (*z* = 1) or not (*z* = 0). Values of *y* and *x* are observed only when *z* equals 1.

$$\text{Selection equation: } z^* = \alpha' w + u \ \cdots(2)$$

$$z = 1 \text{ if } z^* > 0 \ \text{ and } \ z = 0 \text{ if } z^* \leq 0 \ \cdots(3)$$

Given the non-randomness of project participation, there is a high likelihood that ε and u are correlated. Heckman (1979) proposes the likelihood estimation method by way of a two-step method. For the subsample with a positive *y*, the conditional expectation of *y* is given by equation (4).

$$\begin{aligned} E[y_i|x_i, in\ sample] &= E[y_i|x_i, Z=1] \\ &= E[y_i|x_i, \alpha' w_i + u_i > 0] \\ &= \beta' x_i + E[\epsilon'|u_i > -\alpha' w_i] \ \cdots(4) \\ &= \beta' x_i + (\rho\sigma_\epsilon\sigma_u)\left\{\frac{\phi(-\alpha' w_i)}{1-\Phi(-\alpha' w_i)}\right\} \ \cdots(5) \\ &= \beta' x_i + (\rho\sigma_\epsilon\sigma_u)\left\{\frac{\phi(-\alpha' w_i)}{\Phi(\alpha' w_i)}\right\} \ \cdots(6) \end{aligned}$$

Assuming a bivariate normal distribution of ε and u, the conditional expectation of the error term can be expressed as equations (5) and (6) where ϕ is the standard normal probability density function and Φ is the cumulative standard normal distribution function. Heckman (1979) computes the inverse Mill's ratio (IMR) $\lambda_i = \frac{\phi(W_i \alpha_i)}{\Phi(W_i \alpha_i)}$ by a way of a probit model. Then, the IMR is included as an additional control variable in the outcome as in equation (7).

$$\mathrm{E}[y_i|x_i, in\ sample] = \beta' x_i + (\rho\sigma_\varepsilon)\lambda_i = \beta' x_i + \theta\lambda_i \quad \cdots(7)$$

Where, y_i denotes the outcome variables, x_i denotes the observable features of the independent variables, β denotes the parameters to be estimated, ρ is the correction coefficient, and σ is the variance of the error terms.

In this study, a multiple regression is a carried out using the estimated coefficients of the maximum likelihood estimation (MLE) model. The MLE model is more widely used than the simple ordinary linear (OLS) model since more efficient estimates can be attained (Puhani, 2000; Nawata, 1994). In the Heckman selection model using the MLE, the correction factor (λ) is expressed as the product of rho (ρ) and sigma (σ).

3.3.2. The Blinder-Oaxaca Decomposition Technique

Once potential selection bias is addressed, the net impact of a policy can be estimated under the B-O decomposition framework. Using the decomposition technique, policy impact can be identified either from cross-sectional or longitudinal perspectives.[8] A cross-sectional analysis compares the outcomes of a policy intervention between a treatment group and a comparison group, while a longitudinal analysis measures a change in outcomes of pre- and post-intervention. In this study, the outcomes are compared from both cross-sectional and longitudinal perspectives to ensure the validity of the analysis.

To identify the net policy impact using the B-O decomposition, the linear regression defined by equation (7) is divided into the treatment group (E(Y_A)), and comparison group (E(Y_B)), as shown below:

$$\text{Group (A):}\quad E(Y_A) = \sum_{j=1}^{k} \beta_j^A \bar{X}_j^A \quad \cdots(8)$$

$$\text{Group (B):}\quad E(Y_B) = \sum_{j=1}^{k} \beta_j^B \bar{X}_j^B \quad \cdots(9)$$

Where, β is the vector of coefficients and is $\bar{X}$ the mean of independent variables.

---

8 Using repeated cross-section data such as a census, the comparison of outcomes between the implemented and not-implemented areas could be estimated by employing a conventional policy evaluation method of the difference-in-differences (DID). The application of the DID method requires that the composition of groups in pre- and post-intervention periods are stable and the assignment to a treatment is not determined by a baseline outcome. In this study, however, such preconditions were not met due to a new trend of urban-to-rural migration since 2009 as well as the growing rate of rural exodus. Moreover, as it is revealed in the empirical findings, relatively less favorable rural villages were selected as project beneficiaries. This renders it necessary to seek for alternative evaluation methods.

In a cross-sectional analysis, equation (8) applies to the area (A) where the project had been implemented (i.e. treatment group), and equation (9) applies to the area (B) where the project had not been implemented (i.e. comparison group). In this case, a comparison of outcomes is made between farm households in the project implemented areas and farm households in the project not-implemented areas.

On the other hand, in a longitudinal analysis, changes in outcomes before and after implementation of the project in the project implemented areas are compared. Therefore, equation (8) is for the group in (A) period after the project had been implemented, whereas equation (9) is for the identical group in (B) period before the project introduction. Since the equations (8) and (9) are defined as forms of the expected value, the expected differences between the two groups can be directly compared in both cases. The mathematical expression of this theoretical concept is as follows:

$$\mathrm{E}(Y_A)\text{-}\mathrm{E}(Y_B) = \sum_{j=1}^{k} \beta_j^A \bar{X}_j^A - \sum_{j=1}^{k} \beta_j^B \bar{X}_j^B$$

$$= \sum_{j=1}^{k} \beta_j^A \left(\bar{X}_j^A - \bar{X}_j^B\right) + \sum_{j=1}^{k} \beta_j^A \bar{X}_j^B - \sum_{j=1}^{k} \beta_j^B \bar{X}_j^B \quad \cdots(10)$$

$$= \sum_{j=1}^{k} \beta_j^A \left(\bar{X}_j^A - \bar{X}_j^B\right) + \sum_{j=1}^{k} \bar{X}_j^B \left(\beta_j^A - \beta_j^B\right) \quad \cdots(11)$$

The left-hand side of equation (10) denotes the difference in the project impact between the treatment group (Y_A) and comparison group (Y_B). Equation (11) is obtained by the mathematical decomposition of equation (10) which distinguishes the differences in policy evaluation estimates between the two groups. The first part of the equation (11) shows the total effect expressed in terms of the endowment effect and the residual effect.

In a cross-sectional analysis, the endowment effect is the effect produced by the initial differences in observed characteristics across two groups in the same time period. In contrast, in a longitudinal analysis, the endowment effect is the differences in observed characteristics across the pre- and post-implementation samples in the beneficiary areas that are unrelated to the project implementation. Therefore, the endowment effect is the effect not directly related to the CRVDP and is denoted in the first term on the right-hand side of equation (11).

On the other hand, the second part of this equation is the residual effect that indicates the difference in the outcomes between the two groups generated by the project implementation. The residual effect is the effect reflected by factors other than the differences in the independent variables between the two groups in comparison, and thus, the residual effect captures the ATT.

3.4. Data and Variables

The data for the analysis were collected from the Korea Agricultural Census from two different years: 2005, before the implementation of the CRVDP, and 2015, after the completion of the project. This data provided by Statistics Korea contain a set of micro-level individual and household characteristics of all Korean farm households.

An internal data of the MAFRA with a full list of villages (*ri*) where the CRVDP had been carried out during the period of 2004 to 2013 was acquired through the Rural Development Corporation, a major project implementation agency. Using this data, a total of 301 rural towns and townships (*eup* and *myeon*) that encompass villages that received the support were identified as project implemented areas. This data was matched with the 2005 and 2015 agricultural censuses, through which farm households were dichotomized into the treatment group (i.e. project implemented areas) and the comparison group (i.e. project not-implemented areas).

The original census data had 1,272,882 farm households in 2005 and 1,087,843 farm households in 2015. In order to obtain balanced sample sizes between two study areas, a 10% random sampling for the project implemented areas and a 5% random sampling for the project not-implemented areas were applied. As a result, the final sample drawn from the 2005 census contains 21,951 farm households in the policy implemented areas and 47,062 farm households in the policy not-implemented areas. The final sample obtained from the 2015 census includes 17,686 farm households in the project implemented areas and 39,344 farm households in the project not-implemented areas. Moreover, in this study, the target of the analysis was limited to farm households whose householders were 19 years old or older at respective time periods. The descriptive statistics of the final samples are presented in Appendix B.

Table 3-1 displays a description of dependent and independent variables of this study. The independent variables were classified into demographic, socioeconomic, and agricultural management characteristics of farm households. The probable determinants that affect the likelihood of earning agricultural income were selected based on the previous literature and information available in the census.

Reflecting the structure of the Heckman selection model, the first dependent variable in the binomial probit model is the probability of selection into the treated sample. In the cross-sectional analysis, it is the probability of an individual household to belong to the project implemented group. On the other hand, in the longitudinal analysis, it can be expressed as the probability of being in the sample of post-project period.

In the second stage of the Heckman selection model, the dependent variable is agricultural income described by the gross revenue from the sales of agricultural products.[9] Since the total sales amount of agricultural and livestock products were coded in categorical format, the data were linearized by the median value of the sales taking a natural logarithm.

Table 3-1. Definition of Variables

Variable		Definition	M1	M2
Dependent Variable				
(First stage)				
Cross-sectional	Project implemented areas (=1), Otherwise (=0)		✓	
Longitudinal	After project implementation (=1), Before (=0)		✓	
(Second stage)				
	Agricultural income (log(total amount of sales))			✓
Independent Variables				
Demographic				
Age of householder	AGE1	19~34 (=1), otherwise (=0) (Ref.)	✓	
	AGE2	35~44 (=1), otherwise (=0)	✓	
	AGE3	45~54 (=1), otherwise (=0)	✓	
	AGE4	55~64 (=1), otherwise (=0)	✓	
	AGE5	Over 65 (=1), otherwise (=0)	✓	
	AGE	Householder's age (linear)		✓
	AGE_SQ	AGE*AGE		✓
Gender	MALE	Male (=1), Female (=0.)	✓	✓
Marital status	MARRY	Married (=1), Otherwise (=0)		✓
Number of household members	HHNUM1	1~2 (=1), Otherwise (=0)	✓	
	HHNUM2	3~4 (=1), Otherwise (=0)	✓	
	HHNUM3	Over 5 (=1), Otherwise (=0) (Ref.)	✓	
	HHNUM	Household size (linear)		✓
Socioeconomic				
Education	EDU1	Below high school (=1), Otherwise (=0)	✓	
	EDU2	High school diploma or some college (=1), Otherwise (=0)	✓	
	EDU3	BA or higher degree (=1), Otherwise (=0) (Ref.)	✓	
	EDUY	Years of education (linear)		✓
	EDUY_SQ	EDUY*EDUY		✓
Experience in farming	EXP1	Under 10 years (=1), Otherwise (=0) (Ref.)	✓	
	EXP2	10~20 years (=1), Otherwise (=0)	✓	
	EXP3	Over 20 years (=1), Otherwise (=0)	✓	
	NEW	Less than 6 years (=1), Otherwise (=0)		✓

[9] The Consumer Price Index was used to adjust agricultural income for inflation (2015=100.0, 2005=78.444).

Agricultural				
Farm household characteristics	MACHINE	Possession of agricultural machinery (=1), Otherwise (=0)	✓	
	INFO	Utilize computer (=1), Otherwise (=0)		✓
	OTHER	Participation in other agriculture-related businesses (=1), Otherwise (=0)		✓
Crop	CROP1	Rice (=1), Otherwise (=0)		✓
	CROP2	Fruit (=1), Otherwise (=0)		✓
	CROP3	Other types of crop (=1), Otherwise (=0)		✓
	CROP4	Upland crop (=1), Otherwise (=0) (Ref.)		✓
	CROP5	Livestock (=1), Otherwise (=0)		✓
Sales Place	S_PLACE1	Wholesale market, production market (=1), Otherwise (=0)		✓
	S_PLACE2	Agricultural cooperative(NH), agricultural corporation (=1), Otherwise (=0)		✓
	S_PLACE3	Government, collector, mediator (=1), Otherwise (=0)		✓
	S_PLACE4	Direct sales (=1), Otherwise (=0) (Ref.)		✓
	S_PLACE5	Retailer, agricultural processing company (=1), Otherwise (=0)		✓

Note: Different variables were used for each stage of the Heckman selection model
M1 indicates variables used for the first stage binary probit model, and
M2 indicates variables used for the second stage MLE model.

3.5. Empirical Results

3.5.1. Average Agricultural Income by Policy Implementation

Prior to analyzing the effect of the CRVDP on agricultural income using the sample population drawn randomly from the census, the simple difference in the average agricultural earnings between the project implemented areas and not-implemented areas were compared using the original censuses. Table 3-2 presents the comparison of average nominal agricultural income between the two groups of areas.

In 2005, just after the launch of the CRVDP, the average agricultural income per household in the project implemented areas and not-implemented areas was similar. On the other hand, in 2015, after the termination of the project, farm households in the project implemented areas became relatively richer than the those living in the project not-implemented areas.

In terms of a change in agricultural income before and after the project intervention, the income growth rate of the implemented areas was much higher than that of not-implemented areas. In the period between 2005 and 2015, the project implemented areas experienced an increase in average nominal income by 51.27%, while that of project not-implemented areas was 35.57% during the same period.

Table 3-2. Comparison of Average Agricultural Income by Policy Implementation

	2005	**2015**	**Change**
Implemented	14,648 (USD 13,000)	22,158 (USD 20,000)	51.27%
Not Implemented	14,521 (USD 13,000)	19,686 (USD 18,000)	35.57%

Unit: KRW, Thousand.
Source: Author’s calculations based on data from Statistics Korea (2005, 2015)

3.5.2. Cross-sectional Evaluation on Making Agricultural Income

3.5.2.1. Comparison of agricultural income between the project implemented areas and not-implemented areas

Table 3-3 reports the results obtained by employing the Heckman selection model to compare outcome estimates of the project implemented areas and not-implemented areas. The first stage binomial probit analysis as presented in columns (1) and (5) in Table 3-3 reveals that the effect of the independent variables on the probability of project participation between the two areas was similar in 2005 and 2015 in terms of coefficient signs and statistical significance. The probability of living in the project implemented areas is lower when the householder is older (AGE2→AGE5) as compared to householders who are younger than 34 (AGE1). Generally, the younger the age, the easier it is to acquire and utilize new skills and knowledge. Therefore, this observation is reasonable since younger farmers are more likely to be cognizant of the importance of the project and are more receptive to try new initiatives.

In terms of gender (GENDER), farm households with female householders were more likely to live in project implementation areas than male householders. The number of family members is found to be negatively associated with the probability of living in project implemented areas as shown by the decreasing trend of coefficients as the number of family members increases (HHNUM1 → HHNUM2). Also, a negative association was found between the educational level of the farm householder and the probability of living in the project implemented areas. Farm households whose householder has an educational level of below high school (EDU1) or a high school diploma or 2-year college degree (EDU2) were more likely to live in the project implemented areas than those with a 4-year university or higher degree (EDU3). Such observation may be associated with the fact that sarcastic criticisms on the effectiveness of the CRVDP are more prevalent among people with a higher educational background.

Concerning experience in farming as career, householders with more than 21 years of experience (EXP3) were more likely to be found in the project implemented areas compared to those with 10 years or less experience (EXP1). But such evidence was not found for the group with more than 11 years and less than 20 years of experience (EXP2). Lastly, a positive correlation between the possession of farm machinery and residency in the project implemented areas was found.

The estimated results of the second stage of the Heckman selection model using the MLE are presented in columns (2) and (3) for the pre-project period and columns (6) and (7) for the post-project period. The results present the effect of the independent variables on the probability of making higher agricultural income, which shows the determinants of agricultural income in each group. In overall, direction and magnitude of the effects of socioeconomic and demographic characteristics such as age, gender, marital status, family size, and career experience on the probability of earning agricultural income were found to be similar for both groups in the periods before and after the project implementation.

In regard to age of householders (AGE), the probability of agricultural income increases as the householder’s age increases, regardless of the residential areas. The older the householder, the higher the householder’s chance of making agricultural income; but since the squared term of age is negative, the marginal effect is expected to be a decreasing trend. Concerning gender (GENDER), households headed by males were found to have a higher probability to earn agricultural income than female-headed households.

The number of family members (HHNUM) has a strong, positive effect on agricultural income. Households of bigger family size are more likely to make higher agricultural income than households with fewer members. A positive association between years of education (EDUY) and agricultural income was apparent only in the project implemented areas. The squared term of education presents a negative sign through which it can be assumed that the effect of educational background is non-linear.

Farming experience (NEW) had a positive effect on agricultural income. The likelihood of making agricultural income was found to be lower for householders with less than 6 years of agricultural experience than that of skilled agriculturalists. On the other hand, the utilization of computer (INFO) and participation in other agriculture-related businesses (OTHER) were found to be positively associated with the chance of agricultural income earning.

In terms of major crops, the probability of obtaining agricultural income was higher for farmers who cultivate rice (CROP1), fruits (CROP2), other crops (CROP3), and livestock (CROP5) in comparison to those who are primarily engaged in the cultivation of upland crops (CROP4). For sales place, farm households that trade in agricultural products through wholesale markets (S_PLACE1), agricultural cooperatives and corporations (S_PLACE2), government agencies and other mediators (S_PLACE3), and retailers and processing companies (S_PLACE5) have a higher earning potential than households selling directly to consumers (S_PLACE4). Such propensity is particularly prominent where the project was not carried out.

The results of the asymptotic t-test that compare the significant differences between the implemented areas and not-implemented areas show whether or not the two groups were profoundly different with respect to each independent variable.[10] Looking at the comparison between the project implemented areas and not-implemented areas in the pre-project period as presented in column (4) in Table 3-3, it can be extrapolated whether or not there was an initial difference between the two areas. A statistical difference between the two areas is evident in regard to age, number of household members, years of education, participation in other agriculture-related businesses, all crop types and sales place - except for those who sell to retailers and processing companies.

The result of t-statistics in column (9) in Table 3-3 highlights the differences between the project implemented areas and not-implemented areas in the post-project period. It shows that age, age_sq, number of family members, years of education, participation in other agricultural-related businesses, cultivation of fruits and other crops, and sales place (excluding those who trade through retailers and processing companies) affected the chance of earning agricultural income differently for the project

[10] $t = \frac{\beta_1 - \beta_2}{\sqrt{se(\beta_2)^2 + se(\beta_2)^2 - 2COV(\beta_1, \beta_2)}}$

implemented areas and not-implemented areas.

In the bottom of Table 3-3, sigma (σ) and rho (ρ) are obtained for each time period. In both time periods, estimates of sigma and rho are statistically significant at 1% level. This implies that a selection bias would have caused a problem if a simple ordinary linear regression (OLS) model was applied instead of the Heckman selection model. Moreover, the negative sign of rho (ρ) with a strong statistical significance in both periods highlights a differential gap between the two areas with respect to earning agricultural income. This implies that the expected agricultural income of the project not-implemented areas would have been higher if their initial conditions were the same as the project implemented areas.[11] It suggests that rural villages with relatively low potentials to generate agricultural income were selected as the project beneficiaries.

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[11] 1. If ρ is greater than zero ($\rho > 0$) and statistically significant, then $E(Y \mid Z = 1) > E(Y \text{ if } Z = 1 \mid Z = 0)$, and
2. If ρ is less than zero ($\rho < 0$) and statistically significant, then E $E(Y \mid Z = 1) < E(Y \text{ if } Z = 1 \mid Z = 0)$.

Table 3-3. Estimation Results of the Heckman Selection Model

	Before implementation (2005)							
Variables	(1) 1st Stage		(2) 2nd Stage Implemented		(3) 2nd Stage Not-implemented		(4) T-test	
INTERCEPT	-0.8456	***	13.2356	***	11.2578	***	6.7481	***
AGE2	-0.0907	**						
AGE3	-0.1844	***						
AGE4	-0.2445	***						
AGE5	-0.2423	***						
AGE			0.0888	***	0.0679	***	2.2120	**
AGE_SQ			-0.0009	***	-0.0007	***	-2.4212	**
GENDER	-0.0930	***	0.3653	***	0.3826	***	-0.3904	
MARRY	-0.0930		0.2806	***	0.2909	***	-0.2757	
HHNUM1	0.2224	***						
HHNUM2	0.0884	***						
HHNUM			0.1091	***	0.0556	***	5.3679	***
EDU1	0.2976	***						
EDU2	0.1825	***						
EDUY			-0.0017		0.0465	***	-6.7113	***
EDUY_SQ			0.0029	***	-0.0021	***	9.5423	***
EXP2	-0.0042							
EXP3	0.0534	***						
NEW			-0.6321	***	-0.6339	***	0.0358	
MECH	0.2958	***						
INFO			0.5306	***	0.5696	***	-1.2029	
OTHER			0.1009	***	0.1941	***	-2.7115	***
CROP1			0.2821	***	0.4278	***	-4.2341	***
CROP2			0.8897	***	0.9685	***	-1.8327	*
CROP3			0.6886	***	0.7760	***	-2.3379	**
CROP5			1.2110	***	1.5066	***	-6.0624	***
S_PLACE1			1.1357	***	1.4943	***	-8.9165	***
S_PLACE2			0.9768	***	1.2178	***	-7.8822	***
S_PLACE3			0.9457	***	1.1145	***	-5.6843	***
S_PLACE5			1.1185	***	1.1099	***	0.2180	
SIGMA			1.8546	***	1.3316	***		
RHO			-0.9083	***	-0.6018	***		
-2LL			153,810		235,722			
AIC			153,878		235,790			
N	69,013		21,951		47,062			

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 3-3. Estimation Results of the Heckman Selection Model (Cont'd)

	After implementation (2015)							
Variables	(1) 1st Stage		(2) 2nd Stage Implemented		(3) 2nd Stage Not-implemented		(4) T-test	
INTERCEPT	-0.9253	***	13.6643	***	12.4904	***	3.1718	***
AGE2	-0.0073							
AGE3	-0.1220							
AGE4	-0.1875	**						
AGE5	-0.2236	***						
AGE			0.0720	***	0.0366	***	3.1701	***
AGE_SQ			-0.0007	***	-0.0004	***	-3.5679	***
GENDER	-0.0508	***	0.3304	***	0.3125	***	0.4079	
MARRY			0.1562	***	0.1635	***	-0.1945	
HHNUM1	0.1920	***						
HHNUM2	0.0609	**						
HHNUM			0.1228	***	0.0489	***	5.7839	***
EDU1	0.2213	***						
EDU2	0.1150	***						
EDUY			0.0062		0.0445	***	-4.4015	***
EDUY_SQ			0.0010	**	-0.0028	***	6.8621	***
EXP2	0.0300							
EXP3	0.1619	***						
NEW			-0.4565	***	-0.4913	***	0.7074	
MECH	0.3086	***						
INFO			0.3733	***	0.3391	***	1.1436	
OTHER			0.5241	***	0.6066	***	-2.7609	***
CROP1			0.1992	***	0.2312	***	-0.7997	
CROP2			0.7904	***	0.6823	***	2.4538	**
CROP3			0.4378	***	0.5075	***	-1.7303	*
CROP5			1.6291	***	1.7152	***	-1.4403	
S_PLACE1			1.3646	***	1.4971	***	-3.2972	***
S_PLACE2			1.1725	***	1.2903	***	-3.8108	***
S_PLACE3			1.1435	***	1.2361	***	-2.6468	***
S_PLACE5			0.4369	***	0.4352	***	0.0372	
SIGMA			1.6411	***	1.4430	***	3.1718	
RHO			-0.8244	***	-0.7693	***		
-2LL			124,908		195,886			
AIC			124,976		195,954			
N	57,030		17,686		39,344			

Note: ***p<0.01, **p<0.05, *p<0.1.

3.5.2.2. Decomposition for cross-sectional project effectiveness

The apparent differential gap in agricultural income across two groups of areas in 2015 (after the project completion) is estimated from the decomposition. The estimates elicited from the Heckman selection model show that even when farm households in the project implemented areas and not-implemented areas were analogous on average, the expected earnings of the supported areas were higher than the unsupported areas. Using such results, the B-O decomposition model provides the explanations for what had determined the average differences on outcomes between the two groups.

The results of the B-O decomposition for the cross-sectional analysis employed on the selectivity corrected outcomes are reported in Table 3-4. In the decomposition model, the difference between the treatment group and the comparison group is explained by the total effect. And the total effect is composed of the endowment effect and the residual effect. The ATT of the CRVDP on agricultural income is represented by the residual effect.

Table 3-4. Cross-sectional Decomposition on Probability of Making Agricultural Income

	Implemented		**Not-Implemented**
Estimated	17.3437		15.0675
Hypothetical Estimates		17.3328	
Difference		2.2762	
Endowment Effect		0.0108	
Residual Effect		2.2653	
Gap(%) explained by			
Endowment Effect		0.48%	
Residual Effect		99.52%	

The difference in the income estimates between the two groups converted into a natural logarithm was 2.2762. The endowment effect that arises from the differences in observed characteristics between the two groups was 0.0108 (0.48%), and the residual effect, which is the treatment effect, was 2.2653 (99.52%). This implies that 99.52% of the difference in agricultural income between the two groups is likely to be caused by the project implementation. From Table 3-1, it was observed that the difference in agricultural income on average between the project implemented areas and not-implemented areas was about 247.2 million Won. Based on the results of the decomposition, it can be concluded that 99.52% of the difference in average farm household income from sales of agricultural products was caused by the CRVDP.

3.5.3. Longitudinal Evaluation on Making Agricultural Income

3.5.3.1. Comparison of agricultural income before and after project implementation

Table 3-5 provides the estimation results of the Heckman selection model applied solely on the project implemented areas to compare outcomes between the pre- and post-project periods.

The first stage binomial probit analysis shown in column (1) in Table 3-5 presents the effect of each independent variable on the probability of being in the sample of the post-project period. The positive signs of age variables show that householders in the post-project period are more likely to belong to the older group as seen by the incrementing coefficients for older age groups (AGE2 → AGE5). This implies that over time, from 2005 to 2015, the age of householders in the project supported areas had increased, which seems to be reasonable in light of the acceleration of aging in rural areas.

The negative coefficient of the gender variable (GENDER) indicates that farm households headed by male householders are more likely to be households of the post-project period. This means that the number of households with male householders had increased over the course of the project within the project implemented areas. With respect to householder's level of education, the households in the post-project period are less likely to have lower levels of education since the lower the educational level, the bigger the negative coefficients of the estimation. From this result, in can be inferred that more educated farmers participated in the CRVDP over time.

Concerning experience in farming, there were more experienced farmers after the project in the areas that received the government support. A positive coefficient for those with more than 20 years of experience (EXP3) proves this observation, whereas statistical significance was not obtained for those with more than 10 or less than 20 years of experience (EXP2). Lastly, households in the post-project period in the implemented areas were more prone to possess agricultural machinery (MECH) than households in the pre-project period in the same areas.

The second stage estimation of the sample selection regression results are reported in columns (2) and (3) in Table 3-5, which highlights the effect of determinants of agricultural income in the pre- and post-project periods. After adjusting for selection, coefficients of all variables except for age (AGE) show that the statistical significance as well as the direction of impact on agricultural income are consistent before and after the project.

In the period before the project implementation, the age variable (AGE) shows a positive sign, while the coefficient of its squared term (AGE_SQ) presents a negative sign. It indicates that before the project was implemented, the probability of making agricultural income was higher for households with older householders, although the effect lessoned as people get older. But in the period after the project implementation, statistical significance was not found for the age variable (AGE) as age squared (AGE_SQ) had a significantly negative effect on agricultural income. This suggests that unlike the households in the pre-project period, the age of farming householders did not have a non-linear effect on agricultural income in the post-project period.

In both before- and after-project implementation, households whose householder is male (GENDER) and married (MARRY) and with a bigger family size (HHNUM) had a higher chance to earn agricultural income in the project implemented areas. The impact of marital status on agricultural income was stronger in the pre-project period, while that of family size was greater in the post-project period. In respect to years of education (EDUY) and its squared term (EDUY_SQ), the result indicates that the probability of making agricultural income increased as the years of education increased, but this effect lessened with the lapse of time.

Households who are new to farming (NEW) had a lower chance of making agricultural income, and such negative effect is found to be slightly weaker after the implementation of CRVDP. On the contrary, households with a higher frequency of using computer (INFO) had a greater chance to make agricultural income, the effect of which became relatively weaker after the project implementation. It can be reasonably assumed that such trend is observed with the penetration of computer into general households over time since obtaining information became easier even for novice farmers and the comparative advantage of utilizing computer weakened. Also, households who are involved in other agriculture-related businesses (OTHER) were found to be more likely to make agricultural income, the effect of which was shown to be stronger after the implementation of the project.

In regard to major crop type, households that grow rice (CROP1), fruits (CROP2), other crops (CROP3), and livestock (CROP5) show a higher probability to make more agricultural income than those that grow upland crops (CROP4). Moreover, farm households that trade agricultural products through wholesale markets (S_PLACE1), agricultural cooperatives and corporations (S_PLACE2), government agencies and other mediators (S_PLACE3), and retailers and processing companies (S_PLACE5) were found to have a higher probability to earn income than households selling directly to consumers (S_PLACE4). The difference in the influence of these variables on agricultural income before and after the project implementation was particularly stronger in the case of direct sales (S_PLACE5).

The result of the asymptotic t-test in column (4) in Table 3-5 presents the significance of differences in outcomes between pre- and post-project periods. The two years were different with respect to age, age squared, marital status, number of family members, squared term of education years, utilization of computer, participation in other agriculture-related businesses, crop types and sales places.

The estimates of sigma (σ) and rho (ρ) presented in the bottom of Table3-5 are found to be statistically significant at 1% level. This implies that sample selection bias could have been problematic in the before-and-after comparison if the correction was not addressed by the Heckman selection model. As in the case of the cross-sectional analysis, estimates of the correction factor calculated by the product of sigma (σ) and rho (ρ) is negative. This indicates that in the project implemented areas, the expected agricultural income of farm households prior to the project participation would have been higher if the same households were exposed to the same contextual setting presented in the post-project period.

Table 3-5. Estimation Results of the Heckman Selection Model on Policy Implemented Areas

Variables	(1) 1st Stage		(2) 2nd Stage Before implementation		(3) 2nd Stage After implementation		(4) T-test	
INTERCEPT	-0.7014	***	12.5738	***	16.1035	***	-8.9054	***
AGE2	0.0923							
AGE3	0.5116	***						
AGE4	0.8579	***						
AGE5	1.0547	***						
AGE			0.0511	***	-0.0070		4.7898	***
AGE_SQ			-0.0007	***	-0.0002	***	-4.9902	***
GENDER	-0.1441	***	0.3532	***	0.3381	***	0.3053	
MARRY			0.3648	***	0.2380	***	2.8728	***
HHNUM1	0.4380	***						
HHNUM2	0.2256	***						
HHNUM			0.0764	***	0.1337	***	-4.3269	***
EDU1	-1.1129	***						
EDU2	-0.4342	***						
EDUY			0.0581	***	0.0538	***	0.4544	
EDUY_SQ			-0.0049	***	-0.0061	***	1.7677	*
EXP2	0.2160							
EXP3	0.1327	***						
NEW			-0.6973	***	-0.4704	***	-3.7039	*
MECH	0.3416	***						
INFO			0.5598	***	0.3629	***	5.1936	***
OTHER			0.0581	**	0.4841	***	-10.9759	***
CROP1			0.3526	***	0.1575	***	4.5198	***
CROP2			1.0523	***	0.7192	***	6.5673	***
CROP3			0.7495	***	0.3905	***	8.0011	***
CROP5			1.3135	***	1.4506	***	-2.1904	**
S_PLACE1			1.2105	***	1.3476	***	-2.8228	**
S_PLACE2			1.0813	***	1.1741	***	-2.5230	**
S_PLACE3			1.0537	***	1.1328	***	-2.0319	**
S_PLACE5			1.1643	***	0.3813	***	15.3646	***
SIGMA			1.2845	***	1.4427	***		
RHO			-0.5347	***	-0.7213	***		
-2LL			120,566		105,740			
AIC			120,634		105,809			
N	39.679		22,114		17,376			

Note: ***p<0.01, **p<0.05, *p<0.1.

3.5.3.2. Decomposition for longitudinal project effectiveness

Table 3-6 shows the estimation of outcome gap in pre- and post-project periods using the B-O decomposition approach after adjusting for selection. The result finds that the project supported areas have benefited from the CRVDP when their chance of earning agricultural income before and after the project implementation is compared.

Table 3-6. Longitudinal Decomposition on Probability of Making Agricultural Income

	After implementation		Before implementation
Estimated	16.7145		15.3670
Hypothetical Estimates		16.9207	
Difference		1.3475	
Endowment Effect		-0.2110	
Residual Effect		1.5585	
Gap(%) explained by			
Endowment Effect		-15.66%	
Residual Effect		115.66%	

The total difference in the estimated values between before- and after-project implementation is 1.3475, of which 115.66% is explained by the residual effect. The negative endowment effect (-15.66%) implies that the probability of making agricultural income has become less favorable over time. This can be explained by the current rural issues such as aging and out-migration of the youth population. This signifies that if the project was not carried out in the project implemented areas, the chance to make agricultural income for households in these areas would have reduced due to the changes in characteristics of farm households over the course of the project period. But fortunately, farm households were able to sustain the level of agricultural income thanks to the implementation of the CRVDP.

The negative endowment effect has been offset by the residual effect, and, therefore, the project had positive influence on farm households' agricultural income even under deteriorated conditions.

3.6. Conclusion

Despite the consensus on the necessity of rural revitalization, value for money has been called into question both at home and abroad. A skeptical view has been heightened for the case of the Comprehensive Rural Village Development Project in Korea. The results of this empirical analysis from both the cross-sectional and longitudinal perspectives support that the CRVDP had a positive impact on raising agricultural income of farm households.[12] Unlike other quasi-experimental evaluation tools that are often unsuitable due to the coverage of available data, the study attained robust results using secondary data by employing the combined use of the Heckman selection model and the Blinder-Oaxaca decomposition. The findings can be summarized as follows:

First, the study found that in both with-and-without and before-and-after analyses of project impact, drawing a valid causal inference would have been difficult in the absence of the attempt to address potential selection bias. The negative sign of the correction factor was found in both

[12] A cost benefit analysis (CBA) conducted by Choi et al. (2019) found positive net benefits of the CRVDP. Assuming that operating costs occurred from 2004 to 2010, negative net benefits were estimated until 2010 but in 2011, positive benefits began to appear. Net benefits were turned positive in 2015, and as of 2019, it was estimated that the project generated a net present value exceeding twice the total project costs.

cross-sectional and longitudinal comparisons. In this study, such possible errors were addressed by employing the Heckman selection model.

Second, in a cross-sectional analysis that compared the project implemented areas with the not-implemented areas, the probability of making agricultural income was found to be much higher for the project implemented group than for the project not-implemented group. By decomposing the total difference in the probability of making higher agricultural income between the two groups, it was found that only 0.48% is attributable to endowment effect, while 99.52% is explained by residual difference across the two groups. This finding implies that endowed resources or observed characteristics controlled in the model do not explain the existing differences between the two groups. On the other hand, the residual effect that captures the average treatment effect of the project on the implemented samples proves a strong positive net effect on earning agricultural income.

Third, in a longitudinal analysis exploring outcome differences between pre- and post-project periods, a higher probability of making agricultural income was found after the termination of the project. Decomposing the total difference in the probability of making higher agricultural income, it was found that -15.66% is attributable to endowment effect and 115.66% is explained by the residual difference between the post- and the pre-project samples. A negative endowment effect implies that the probability of earning agricultural income became less favorable after the project implementation. Nevertheless, the negative endowment effect is offset by a strong residual effect (115.6%). Such results signify that the project was carried out in relatively poor areas with low potential and had a positive effect on making agricultural income in those areas.

Finally, based on the findings above, this study concludes that the CRVDP generated a significant positive impact on enhancing households' chance to make agricultural income. The study also finds that the selection of beneficiaries was appropriate. If there had been no government support, the project implemented areas could have been exposed to a difficult situation in terms of income earning.

Chapter 4.
Decoupling the Impact of the Comprehensive Rural Village Development Project on Agricultural Income by Birth and Experience Cohorts

4.1. Introduction

This chapter attempts to examine the impact of the changing rural demography on the outcomes of a rural policy. Rural demographic change yields important shifts in the economic structure, local culture and policy, and environmental context (Hunter et al., 2005). In a rural setting where new groups of farmers with distinguished life values and experiences are emerging, certain traits of these individuals may either facilitate or hinder local policy participation. Thus, it can be anticipated that certain traits represented by the generation and farming experience may lead to differentiated outcomes of a rural policy implemented at a community level.

The economic and demographic dimensions of the emergence of diversified demographic groups in rural areas are fairly well documented, but the impacts of such change have been less explored. This study aims to identify separate impacts of the Comprehensive Rural Village Development Project (CRVDP) on farmers' agricultural income, by birth and farming experience cohorts. For the empirical analysis, the study employs propensity score matching (PSM) and the double cohort method of Myers and Lee (1996), based on the age-period-cohort (APC) model. Unlike policy evaluation studies that draw empirical generalizations, this study combines two methods to reveal the causal mechanisms under which the empirical generalization may hold.

4.2. Literature Review

Demographic changes in rural areas is a topic of increasing interest in the rural demographic literature on urban-to-rural migration and farm succession. These studies have highlighted the potential of rural in-migrants and farm successors as active agents of change in rural communities (Jauhiuainen, 2009; Koutsou et al., 2014; Zagata and Suterland, 2015).

Studies that explore urban-to-rural migration have generally investigated migration motivations, destination choices and migrants' socioeconomic characteristics. Many of these studies have attempted to identify rural pull factors in the context of the retirement period of the baby boomer generation. Overall, urban-to-rural migration is led by birth cohorts comprised of individuals in their 50s and 60s who migrate in search of idyllic surroundings to improve their quality of life. Stockdale and Catney (2014) observe that the age groups around retirement have led this trend of counter-urbanization. Regarding their motivations, Jauhiainen (2009) examines the pull and push factors for baby boomers' returning to peripheral rural areas and finds that natural amenities are a general pull factor. Saint Onge et al. (2007) also posit that natural amenities are a significant factor affecting the internal migration decision; they assert that rural population gains in areas endowed with natural amenities potentially impact long-term residents through land-use management and demands, cultural and sociodemographic differences, and changing economies and socioeconomic status.

In Korea, a steep increase in the number of urban-to-rural migrants has occurred since 2009 and overlaps with the retirement period of the 7.1 million baby boomers born between 1955 and 1963. As noted by Jeong and Kim (2019), the main driver of the movement has been retirees in pursuit of the natural environment. Park and Kim (2016) describe this generation as better educated and wealthier than prior generations. More importantly, these authors find that the elderly individuals who moved to rural areas had a strong preference for various regional attractions, and contrary to a common perception, the level of natural amenity was not a significant factor. In either case, for this particular generation, farming is not a main or supplementary reason for moving to rural areas (Kim and Lee, 2017). This accords with a general observation that economic opportunities as stimuli decline with a migrant’s age and that amenity effects have the strongest influence (Millington, 2000).

An emerging strand of urban-to-rural migration studies has explored the urban, young adults migrating to rural areas to become farmers. Together with young farming heirs, young entrepreneur farmers are being studied under the concept of the ‘young farmer problem.’ This problem is related to the perceived role of young farmers in the economic revitalization of rural areas (Zagata and Sutherland, 2015). Milone and Ventura (2019) define these farmers as a ‘new generation of farmers’ and highlight that their choice to become farmers is in contrast with that of the outwardly migrating young adults expecting to increase their prospects. In their study, the authors emphasize that this new group is highly educated and has both knowledge and ability to manage scarce resources strategically and collaborate with fellow farmers and consumers (Milone and Ventura, 2019).

Some studies have attempted to analyze the farming behavior of these young farmers. Zagata and Sutherland (2015) report that unlike the previous generation, young farmers chose farming over other possibilities, and such decision affect their farming behavior. These authors reveal that compared with the elder farmers, these young farmers possess stronger economic motivations, are more involved in value-added farming activities, and can better capitalize on their urban networks and experiences and embrace multifunctionality. Inwoods et al. (2013) sub-categorize young farmers into first-generation and multi-generation farmers and demonstrate their differences in the economic and social values that shape farming behavior. These authors find that first-generation young farmers cherish innovation and have a lower level of economic motivation, while multi-generation young farmers place more emphasis on profits but are less willing to take an innovative stance.

Some studies have solely analyzed traits of young farm successors. For instance, Cavicchiolo et al. (2018) analyze factors that affect the willingness of potential heirs to take over the family farm. Evaluated against the employment options outside the agricultural sector, factors that affect the decision are, for example, not only characteristics of the successor child and local labor market conditions, but also the physical and economic dimensions of the farm; the succession probability is higher among larger, thriving, and more efficient farms.

Studies have often emphasized that today's young farmers are distinguished from prior generations of farmers by deciding to engage in farming against the odds of the decline of agriculture. Young farmers are identified as entrepreneurial, oriented toward high-income activities, highly educated, self-confident in using sophisticated information technology, and likely to prioritize socio-environmental values such as organic farming. Among young farmers, farm successors are likely to be heirs of large-scale, profitable farms.

In Korea, agriculture-related motivations were reported as the biggest pull factor for the younger generation (those in their 20s to 40s), which starkly contrasts with that of the older generations who were mostly attracted to rural areas by natural amenities (MAFRA, 2016). Few studies have examined the disparate characteristics of young farmers in Korea in an attempt to draw policy implications to attract young adults to rural communities, where the aging population is the biggest problem. According to Jeong et al. (2019), Korean young farmers (aged 18 to 39 years) have higher levels of education and income, larger-sized farmland, and a higher propensity to use information technology than older farmers (aged 40 or higher). Ma and Kim (2019) highlight that young farmers generally have a high level of education, for example, 85.3% holding at least a bachelor's degree. These authors identified farm inheritance, large initial capital, experience in farming, and farm record keeping as determinants of young farmers' agricultural income.

In summary, studies have observed a gradually changing rural demographic landscape led by the inflow of internal migrants from urban areas and the emergence of young farmers. As noted by Saint Onge et al. (2007), new migrants to rural regions often do not follow the conventional economic theories of migration. This group is well educated and practices non-traditional farming behavior, and this observation also applies to young farm successors. The unique background, experience, and social and cultural values of this group contribute to the heterogeneousness of rural societies. However, an understanding of how such differences may shape outcomes of a rural policy has notably absent from literature.

4.3. Conceptual Framework

As it was observed in chapter 2 that provided an introduction to the CRVDP, the income generation activities of the CRVDP emphasized sustainable farming practices and interactions with the urban community. Moreover, the CRVDP was the first attempt to adopt a new concept of endogenous rural development, and as a result, values put forward by the CRVDP may have created conditions that either facilitated or constrained the participation of particular groups within rural societies.

Among rural residents in the project supported areas, some might have regarded the project as an invaluable opportunity while others may have remained apathetic or found the same project a nuisance which tries to interrupt their serene neighborhood; the level of compliance will be higher for the former whereas that of the latter is likely to be lower. As observed by Anderson (1984), group membership is one determinant that contributes to one's compliance with a particular policy. It is because group membership is related to the attachment to particular values and practices. Based on the account by Coombs (2005) that policy outcomes are shaped by the policy compliance of the target population, the present study posits that the effects of the project could differ by the cohort membership.

A cohort is a group of individuals who experience a common event together within the same time period (Ryder, 1965). As a result, each cohort has a distinctive character reflecting circumstances of its unique origination and history. Cohorts are typically specified by an individual's birth year, but also by the initial time period that establishes a status to which certain patterns of experience emerge. In this study, cohorts are identified by birth and the level of experience in farming.

Both birth year and farming experience are closely related to farmers' disposition and farming behavior that may affect one's degree of compliance with a rural policy. For instance, young farmers today are generally highly educated, innovative, oriented towards high-income activities, and adapt to using information and communications technology (ICT) through which they create a new networking culture with customers, suppliers, and fellow farmers. However, innovation is restricted for older generation of farmers by their unwillingness and inability to adopt technological devices (Mckillop et al., 2018).

The level of experience in farming is simultaneously considered. New entrants differ from experienced farmers as they encounter a considerable learning curve for the sake of the biological nature of farming and the time it takes to be skillful in production (Inwood et al., 2013). As career in farming increases, it becomes easier to use personal networks or acquire agriculture-related information, and accordingly, making changes or expanding market channels or changing crops to increase net earnings. Also, farmers who entered farming during the productivist agricultural regime will strikingly differ from those who began farming in the post-productivism multifunctional agricultural regime.[13] Farmers who stepped into the agricultural sector in the recent era tend to show higher uptake of environmentally friendly farming practices (Cavicchioli et al., 2018; Zagata and Suterland, 2015).

Compliance results when private interests are in align with policy prescriptions because such harmony ensures positive rewards from participation (Anderson, 1984). On the contrary, individuals of certain groups may resolve to noncompliance if their values, mores and beliefs conflict with policy or if sufficient resources to comply are not available (Anderson, 1984; Coombs, 2005). The specific values emphasized by the CRVDP were much more favorable to the young than older generations. Thus, the young generation are more likely to have an affirmative attitude toward the project driven by their social values, motivations and ability to take advantage of the government support.

In a rural setting where new groups of farmers with distinguished life values and experiences are emerging, a cohort analysis allows an elaborated interpretation of empirical findings. For this purpose, the study concerns specific cohorts as in Table 4-1.

[13] Productivist agriculture refers to an intensive and expansionist farming driven by state support geared towards output and increased productivity which predominated from the period from the end of the Second World War to the beginning of the 1990s (Lowe et al., 1993).

Table 4-1. Categorization of Cohorts

Cohort		Definition
Birth Cohort (BC)	25-34	Young farmers
	35-44	
	45-54	Mid-aged farmers
	55-64	
	65-74	Elderly farmers
Experience Cohort (EC)	1-5	Beginning farmers
	6-10	Early-career farmers
	11+	Experienced farmers

The exact location of sub-populations highlighted in the literature review is difficult to discern by using the aforementioned categorization, but it nonetheless is useful to determine the composition of certain cohorts. The birth cohort aged 55-64 years in our initial study period in 2010 who are also beginning farmers are likely to be recent in-migrants of the baby boomer generation. A majority of them were likely to born in rural areas but moved to cities for their education or career in later years; they are natural amenity-seekers who returned to rural settings with urban life styles and culture. Similarly, farmers in the birth cohort aged 65-74 years of age and also belong to the experienced cohort as of 2010 can be defined as elderly traditional farmers.

Most young entrepreneurial farmers are in the birth cohort aged 25-45 years in 2010 and also simultaneously belong to the entrant level cohorts. It is likely that they were born and grew up in urban areas and moved to a countryside motivated primarily by a career in agriculture. They chose to become farmers which remarkably contrast with the yearly outmigration of young adults (Milone and Ventura, 2019). Individuals in the cohort aged 25-34 years with more than 11 years of farming experience in 2010 are likely to be young successor farmers. They are individuals of rural origin, but some of them might have returned to their hometown after higher education in urban centers. Their choice to either remain or return to rural areas runs counter to the intention of young potential heirs in the present era to abandon agricultural activity (Cavicchioli et al., 2018).

4.4. Theoretical Framework: The Double Cohort Model

In this study, the cohort effects are defined as the simultaneous effects of the birth and experience cohorts over time. To analyze such effects, the study adopts the double cohort model that Myers and Lee (1996) developed to study immigration.

The double cohort model is based on the traditional APC model, a regression model designed to explain a socioeconomic phenomenon with respect to effects of age, period, and cohort membership. Age effects describe a specific result associated with the process of aging or changes in lifecycle trajectory. Period effects are the result of population-wide exposures at a specified point in time. The cohort effects are variations over time among a specific group of individuals with a shared initial event unique to each cohort.

A valid APC model requires simultaneous identification of each effect; however, three variables are collinear because each effect is calculated as a function of the two other variables, such as period = age + cohort. This restricts a simultaneous estimation of three linear effects by a conventional multivariate regression model. Many approaches have been developed to overcome this identification problem (Holford, 1983; Fienberg and Mason, 1985; Myers and Lee, 1996; Yang et al., 2008).

The double cohort model overcomes the identification problem by defining cohort effects as the effects of multiple interaction terms among time periods and two types of cohort variables. The essence of the double cohort model applied in Myers and Lee (1996; 1998) is to nest birth cohorts within immigration cohorts. Likewise, this study conceives that birth cohorts are nested within experience cohorts. Unlike the traditional APC model that includes a cross-sectional age variable, the application of the double cohort model allows for the recognition that cohorts increase in both age and experience in farming in tandem over time (Myers and Lee, 1996). Changes in various outcomes such as agricultural income over the study periods are then attributable to the change between period conditions, change in age, and change in farming experience.

The double cohort model applied in this study uses the experienced farmers (EC3) as a reference group that represents the career role model toward which the farmers of each entry cohort (ECk) would converge as they catch up (e.g., skills, knowledge, networks). Changes in attributes of the experienced cohort are the result of the incremental changes in age and career length. Then, the difference between the changes experienced by the beginning and early-career farmer groups of each birth cohort (EC3BCj) and experienced farmer group of the same birth cohort (ECkBCj) represents the portion of change in the criterion measure because of the convergence in career experience in farming. Thus, net effects on agricultural income (AI) of the increase in farming experience, exclusive of aging and holding the period effects the same for the study population ($\gamma_n = \gamma_i$), can be represented as the following equations:

$$Aging\ Effect^{t_0 \to t_5} = AI^{t_0 \to t_5}_{EC_3 BC_j} = AI^{t_5}_{EC_3 BC_j} - AI^{t_0}_{EC_3 BC_j} \quad \cdots(1)$$

$$Experience\ Effect^{t_0 \to t_5} = AI^{t_0 \to t_5}_{EC_k BC_j} - AI^{t_0 \to t_5}_{EC_3 BC_j} \quad \cdots(2)$$

$$Experience + Aging\ Effect^{t_0 \to t_5} = AI^{t_0 \to t_5}_{EC_k BC_j}$$

$$= AI^{t_5}_{EC_k BC_j} - AI^{t_0}_{ncome EC_k BC_j} \quad \cdots(3)$$

where EC_k refers to experience cohorts with EC_3 representing experienced farmers, and BC_j refers to birth cohorts.

Suppose we pool two cross-sectional data to estimate agricultural income (AI) for birth cohort *j* and experience cohort *k*:

$$AI_{jk} = f(Y, X, YSF, BC_j, EC_k) \quad \cdots(4)$$

where *Y* is a census year, with 2010=1 and 2015 as the reference category (=0); *X* is a vector of individual attributes between 2010 and 2015; *YSF* indicates years since entry into farming; BC_j indexes a series of birth cohorts; and EC_k indexes a series of experience cohorts with experienced farmers as the reference group. By including the equations (1) to (3) into the equation (4), equation (5) is obtained such that,

$$AI_{jk} = f(Y,\ X,\ BC_j,\ EC_k,\ Y \times BC_j,\ Y \times EC_k,\ Y \times EC_k \times BC_j) \quad \cdots(5)$$

In equation (5), the *YSF* and EC_k terms are combined into an interaction term, $Y*EC_k$, along with $Y*BC_j$ and $Y*EC_k*BC_j$. Thus, using the equation (5), the net effects of the policy in question for different cohorts by the interactions of aging, farming experience accumulation and period effects.

4.5. Data and Variables

The main data used for empirical analysis are from Korea Agricultural Census of 2010, when the CRVDP was being implemented, and 2015, after the termination of the project. Using the internal data of MAFRA with a full list of villages (*ri*) that received support from the CRVDP, a total of 301 rural villages in higher administrative units of *eup* and *myeon* were identified as the project implemented areas.

The variable used as an indicator of agricultural income levels is the gross revenue of farms from the total amount of agricultural sales, and this information is coded in a categorical format in the census. Using this information, the dependent variable is the probability of making agricultural income greater than KRW 50 million, an indication of a ‘high level’ of agricultural income. The average gross revenue from the sales of agricultural products in Korea has been maintained between the range of KRW 26 million and 35 million in the last 10 years (Statistics Korea, 2019).

Table 4-2 summarizes the variables used in the analysis and their definitions. In addition to the cohort variables of age and experience, and demographic variables indicating life cycle such as marital status and household size, selected explanatory variables are the probable determinants of agricultural income levels. The literature has demonstrated that the probability of farm households earning higher income is more likely among those headed by males with a high level of formal education (López and López, 2015; Reimers and Klasen, 2011; Luh, 2017).

Regarding regions, Jeolla province, the southern-most province of mainland Korea, where agriculture is characterized by fertile soil and warm temperatures, is the reference group. Because crop type is one important determinant of gross sales earnings, different regions specialize in different types of crops. For example, rice, the staple food in Korea, is mostly cultivated in parts of the capital region and Kyungsang province and throughout Jeolla and Chungcheong provinces; a high proportion of farms in Kwangwon province, in the eastern part of Korea, cultivates food crops such as potatoes, and vegetables and fruits are mainly cultivated in Kyungsang province. Jeju Island was excluded from analysis because of the limited number in the birth and experience cohorts.

For the analysis, agriculture-related variables that affect the capacity to sell agricultural products were used. These variables include computer use, type of main marketing channel, and crop type and variables that affect the extent of farming such as involvement in nonfarm activities and agribusiness.

Table 4-2. Definition of Variables

Variable		Definitions
Dependent Variable		
A high-level agricultural income		Total amount of sales greater than KRW 50 million
Independent Variables		
Demographic		
Year	Year	2015=1, 2010=0
Age of householder	AC1	25-34 years of age
	AC2	35-44 years of age
	AC4	45-54 years of age
	AC4	55-65 years of age
	AC5	65-74 years of age (Ref.)
Gender	Male	Male=1, Female=0
Marital status	Married	Married=1, Otherwise=0
Household Size	HHNUM	Number of household members
Socioeconomic		
Education	Eduy	Years of education
	Eduy_sq	Eduy*eduy
Experience in farming	EXP1	1-5 years of farming experience
	EXP2	6-10 years of farming experience
	EXP3	11 or more years of farming experience (Ref.)
Region	Capital	Capital region
	Kyungsangdo	Kyungsan province
	Chungcheondo	Chungcheong province
	Kangwondo	Kangwon province
	Jeollado	Jeolla province (Ref.)
Agricultural		
Farm household characteristics	Computer	Utilize computer for work=1, otherwise=0
	Nonfarm	Has nonfarm income=1, otherwise=0
	Agribiz	Participate in agribusiness=1, otherwise=0
Marketing channel	Wholesale	Wholesale, joint market
	Coop	Agricultural cooperatives and corporations
	Distributor	Government, collector, large distributors
	Processing	Processing companies, traditional markets
	Direct	Direct sales (Ref.)
Crop type	Rice	Rice
	Fruits	Fruits
	Others	Vegetables, flowers, medicinal and other special crops
	Livestock	Livestock
	Upland	Upland crops (Ref.)

Note: Ref.=reference group

4.6. Methodology

4.6.1. Propensity Score Matching

The effectiveness of a policy can be assessed by comparing either the outcome variable before and after policy intervention or the outcomes between policy participants and non-participants; for the latter approach to be valid, an assumption is required, that is, non-participants are equivalent to participants, ensuring their equal probability of being selected as policy beneficiaries.

For the case of the CRVDP, the likelihood to attain high levels of agricultural income between households of participants and non-participants can be compared by dichotomizing farm households into those that belong to the project implemented areas and those that do not (i.e., not-implemented areas). One may randomly choose a certain number of farm households in the project implemented areas and a comparable number of those in not-implemented areas. However, such an approach can be problematic in a case under which an individual household with specific attributes holds a relatively higher probability to be located in the project recipient areas. This is related to the problem of not randomly assigning subjects to a certain treatment, causing selection bias. The randomization is important because it minimizes systematic differences between the treated and not-treated groups; outcome differences between the two groups can then be attributed to the causal impact of the project participation (Rubin, 1974).

In the absence of a random assignment, one possible approach to mimic randomization is propensity score matching (PSM), designed to reduce the possible sample selection bias (Rosenbaum and Rubin, 1983). PSM was applied in this study to form a treatment group of farm households in the project implemented areas and a comparison group of farm households in the project not-implemented areas. The two groups are comparable because their members are farm households with similar traits except for the residential location in the project implemented areas.

PSM relies on two assumptions that render the treatment assignment to be ‘strongly ignorable’: the conditional independence assumption and common support assumption. In this study, the conditional independence assumption posits that all household-level variables relevant to the probability of living in the project implemented areas are observable and included in the set of observed covariates. The common support assumption implies that for each household in the project implemented areas, there is another matched household with a similar set of observed covariates in the project not-implemented areas.

In this study, a farm household’s residential location in the project implemented areas is used as the treatment. Based on the aforementioned reasoning, one-to-one nearest neighbor matching with replacement was applied which selects the *m* comparison units found in the not-treated areas whose propensity scores are closest to farm households located in the treated areas. The regression equation takes the following form:

$$Propensity\ Score = \Pr(T_i = 1) = \beta_0 + \beta_1 Z_i + \varepsilon_i \quad \cdots(6)$$

where *T* is a dummy capturing whether the household is located in implemented or nonimplemented areas, with *T=1* if the household is in the project implemented area and 0 otherwise; *i=1,…,n* is the number of observations; *Z* is a vector of observed variables, for example, age, gender, and family size, that may affect the household's location; and ε is an error term.

The description of variables by policy implementation for the two study periods of 2010 and 2015 after applying the PSM is presented in Table 4-3.

Table 4-3. Description of Variables Based on the PSM Modelling

Variable	2010				2015			
	Implemented		Not-implemented		Implemented		Not-implemented	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age								
AC1	0.0066	0.0809	0.0064	0.0800	0.0092	0.0953	0.0086	0.0921
AC2	0.0638	0.2443	0.0621	0.2413	0.0707	0.2563	0.0691	0.2536
AC3	0.2248	0.4174	0.2249	0.4175	0.2485	0.4321	0.2486	0.4322
AC4	0.3378	0.4730	0.3392	0.4734	0.3518	0.4775	0.3540	0.4782
Male	0.8800	0.3249	0.8830	0.3215	0.8687	0.3377	0.8708	0.3355
Married	0.8443	0.3625	0.8470	0.3600	0.8164	0.3871	0.8161	0.3874
Household size	2.5823	1.2485	2.5759	1.2165	2.2950	1.0824	2.2847	1.0526
Eduy	8.7364	3.1243	8.7450	3.1137	8.7911	3.0799	8.7998	3.0733
Eduy_sq	86.0856	61.0290	86.1703	60.6775	86.7689	58.9560	86.8821	58.8899
Experience								
EXP1	0.0511	0.2202	0.0510	0.2199	0.1103	0.3133	0.1104	0.3134
EXP2	0.0860	0.2803	0.0867	0.2814	0.0570	0.2318	0.0566	0.2311
Region								
Capital	0.0073	0.0853	0.0156	0.1241	0.0080	0.0890	0.0157	0.1243
Kyungsangdo	0.3028	0.4595	0.3432	0.4748	0.3019	0.4591	0.3434	0.4749
Chungchungdo	0.2085	0.4062	0.2160	0.4115	0.2076	0.4056	0.2201	0.4143
Kangwondo	0.1764	0.3812	0.1758	0.3807	0.1793	0.3836	0.1772	0.3819
Computer	0.2430	0.4289	0.2225	0.4159	0.2111	0.4081	0.1974	0.3980
Nonfarm	0.4463	0.4971	0.4591	0.4983	0.4006	0.4900	0.4191	0.4934
Agribiz	0.1733	0.3785	0.1573	0.3641	0.1886	0.3912	0.1850	0.3883
Marketing channel								
Wholesale	0.1218	0.3270	0.1284	0.3345	0.1269	0.3329	0.1227	0.3281
Coop	0.3663	0.4818	0.3718	0.4833	0.3930	0.4884	0.3914	0.4881
Distributor	0.4404	0.4964	0.4358	0.4959	0.4092	0.4917	0.4232	0.4941
Processing	0.0622	0.2416	0.0589	0.2354	0.0568	0.2315	0.0549	0.2278
Crop type								
Rice	0.4115	0.4921	0.4542	0.4979	0.4110	0.4920	0.4493	0.4974
Fruits	0.1509	0.3580	0.1473	0.3544	0.1616	0.3681	0.1580	0.3647
Others	0.2699	0.4439	0.2542	0.4354	0.2715	0.4447	0.2542	0.4354
Livestock	0.1017	0.3023	0.0859	0.2802	0.0722	0.2589	0.0604	0.2382
Number of observations	138,294		138,294		127,209		127,209	

Note: See Appendix C for number of observations by cohort.
Source: Statistics Korea (2010, 2015).

4.6.2. Ordered Logit Model

The dependent variable in this study is ordinal with ten categories (see Table 4-4). Therefore, for both the treatment and comparison groups, an ordered logit model is employed respectively for the estimation of the double cohort analysis. The regression equation of the ordered logit model is expressed as below:

$$y^* = \sum_{k=1}^{N} X_k \beta_k + \varepsilon \quad \cdots(7)$$

where y^* is the unobserved dependent variable, X_k is the vector of independent variables, β is the vector of regression coefficients to be estimated, and ε is an error term. $y^*$is an unobservable response variable that determines the observed variable y_i. The continuous latent variable y^* has various threshold or cutoff points expressed by μ_i. In this model, F is the cumulative distribution function for the error term, which is assumed to be distributed logistically. The mathematical expression of the relationship can be described as follows:

$$y_i = \begin{cases} 0 \; if \; y^* \le \mu_1 \\ 1 \; if \; \mu_1 < y_i^* \le \mu_2 \\ 2 \; if \; \mu_2 < y_i^* \le \mu_3 \\ \vdots \\ J \; if \; \mu_j < y_i^* \end{cases} \cdots(8)$$

In the ordered logit model, μ_1 is normalized to zero to satisfy the proportional odds (parallel lines) assumption. The underlying logic of the proportional odds assumption is that all the coefficients except the intercept should be the same across the response categories (Lee et al., 2005; Williams, 2016). Using the value that makes μ_1 equal to zero as the constant, μ_i is then estimated by adding the constant value to each intercept coefficient as in Table 4-4.

By combining the equations (7) and (8), the probability of observed variables to be in categories of the dependent variable is shown in equation (9).

$$\Pr(y_t = 1) = F(-\sum_{k=1}^{K}\beta_k x_k)$$
$$\Pr(y_t = 2) = \mathrm{F}(\mu_2 - \sum_{k=1}^{K}\beta_k x_k) - F(-\sum_{k=1}^{K}\beta_k x_k)$$
$$\vdots$$
$$\Pr(y_t = 10) = 1 - F(\mu_9 - \sum_{k=1}^{K}\beta_k x_k) \quad \cdots(9)$$
$$\text{where, } \mathrm{F}(\theta) = \frac{1}{1+e^{-\theta}} = \frac{e^{\theta}}{1+e^{\theta}}$$

Using the ordered logit model, the probability to attain the high levels of agricultural income exceeding KRW 50,000,000 or equivalently, $P(y_i \geq 8)$ is estimated, for both the project implemented group and not-implemented group in 2010 and 2015.

Table 4-4. Definition of the Dependent Variable and Estimated Values of Thresholds (μ_i)

Indicator (y_i)	**Classification by agricultural income**	**Implemented** Intercept Coef.	μ_i	**Not-implemented** Intercept Coef.	μ_i
1	Less than 1.2 M	-0.8484	0.0000	-0.9016	0.0000
2	1.2 –3 M	0.4541	1.3025	0.3430	1.2446
3	3 to 5 M	1.2661	2.1145	1.1509	2.0525
4	5 to 10 M	2.1542	3.0026	2.0095	2.9111
5	10 to 20 M	3.0118	3.8602	2.8309	3.7325
6	20 to 30 M	3.7051	4.5535	3.4965	4.3981
7	30 to 50 M	4.5756	5.4240	4.3497	5.2513
8	50 to 100 M	5.9187	6.7671	5.6679	6.5695
9	100 to 200 M	7.1912	8.0396	6.9014	7.8030
10	Over 200 M				

Unit: KRW, M=million

The general specification of the double cohort model under the ordered logistics framework is then expressed as,

$$\begin{aligned}\mathrm{INC}_i = {} & \beta_0 + \beta_1\mathrm{Year} + \beta_2\sum_{i=1}^{4} Age_i + \beta_3 Male + \beta_4 Married + \beta_5 Hhsize \\ & +\beta_6 Eduy + \beta_7 Eduy^2 + \beta_8\sum_{j=1}^{3} Exp_j + \beta_9\sum_{k=1}^{5} Region \\ & +\beta_{10} Computer + \beta_{11} Nonfarm + \beta_{12} Agribiz + \beta_{13}\sum_{l=1}^{5} Marketing \\ & +\beta_{14}\sum_{m=1}^{5} Crop + Year\,[\sum_{i=1}^{4}\beta_{14i} Age_i] + Year \times [\sum_{j=1}^{3}\beta_{15j} Exp_j] \\ & +Year \times [\sum_{i=1}^{4}\sum_{j=1}^{3}\beta_{16ij} Age_i Exp_j] + \varepsilon_i \quad \cdots(10)\end{aligned}$$

where INC_i is the probability of agricultural income being in a certain income level category, and ε_i is assumed to follow a logistic distribution.

4.7. Empirical Results

4.7.1. Determinants of Agricultural Income

Analysis of the pooled sample from the datasets of 2010 and 2015 reveals the determinants of agricultural income. These determinants are indicated by the coefficients of independent variables without time effects in Table 4-5. Regardless of the project implementation, a higher agricultural income is more likely for a farm household headed by a married male that has a high number of householders. Householder's educational level depicted by years of education is also positively correlated with agricultural income, although the negative sign of its squared term suggests diminishing returns to education.

The probability of earning high levels of agricultural income will probably be the highest for households located in Jeolla province, as suggested by the negative coefficients in the remaining provinces in comparison to this reference region. Farm households that use a computer for agricultural activity and participate in agribusiness are more likely to earn high levels of agricultural income. Conversely, participation in nonfarm activity was negatively correlated to agricultural income; this finding is reasonable because farmers engaging in nonfarm activities might focus less on farming.

In terms of agricultural marketing channels, the probability to attain a high-income level is more likely for farm households that sell agricultural products directly to consumers than those that trade through distribution channels. After direct sales, wholesale markets and cooperatives are the next preferred marketing channels of the most affluent farm households. Moreover, for the main type of cultivation, the positive coefficients for all types of crops show that the upland crop has the lowest probability to attain an upper level of agricultural income. This finding coincides with those for the typical Korean agricultural scene, under which upland crops earn the lowest income followed by rice, and the highest average agricultural income is among livestock farmers.

Among the cohort groups, a high income probability was the highest for the experienced farmers, the reference category. Among the age cohorts, the youngest birth cohort (aged 25-34 years) had the highest likelihood to make a high-level agricultural income, followed by the mid-age cohort (aged 45-54 years). Considering the inverse relationship between age and farm productivity with peak earnings at age ranges between 35 and 44 years (Tauer, 1995), such a contrasting result supports the necessity to jointly consider the effects of both experience accumulation and aging.

Overall, the signs of the coefficients in the project implemented and not-implemented areas are the same; however, a relatively larger magnitude of the coefficients suggest that the probability to reach the upper-tier agricultural income level was more likely in the project implemented areas. Moreover, the variable year can be interpreted as the probability of making high levels of agricultural income in 2010 vis-à-vis 2015. The result indicates that attaining a high-level agricultural income was more difficult in 2010 than in 2015 in the project implemented and not-implemented areas. Thus, the economic recession initiated in 2008 probably affected the probability of making a higher level agricultural income. The magnitude of the coefficient is greater with statistical significance at the 1% level where the project was not implemented. This finding may imply that in 2010, the conditions to generate agricultural income were more unfavorable for the areas that were not supported by the CRVDP. All things being equal, the CRVDP initiated in 2004 may have improved overall conditions of the project supported regions such that households in these areas were less affected by the recession than those in the not-implemented regions.

Table 4-5. Interaction of Birth and Experience Cohort Membership and the Likelihood of Earning a High-level Agricultural Income (Y≧8), 2010-2015

	Project Implemented Areas		**Project Not-implemented Areas**	
Variable	Coeff.	Std. Err.	Coeff.	Std. Err.
Year	-0.0110	0.0121	-0.0650***	0.0121
Male	0.6121***	0.0137	0.5787***	0.0139
Married	0.4212***	0.0124	0.4039***	0.0125
Family	0.1248***	0.0034	0.0950***	0.0036
Eduy	0.1264***	0.0066	0.1481***	0.0068
Edu_sq	-0.0064***	0.0003	-0.0084***	0.0004
Capital	-0.4444***	0.0398	-0.0902***	0.0284
Kyungsangdo	-0.1848***	0.0090	-0.1646***	0.0092
Chungchungdo	-0.1451***	0.0098	-0.0332***	0.0101
Kangwondo	-0.3532***	0.0105	-0.2801***	0.0109
Computer	0.6783***	0.0091	0.6476***	0.0092
Nonfarm	-0.6719***	0.0076	-0.6661***	0.0077
Agribiz	0.6217***	0.0095	0.6650***	0.0096
Wholesale	-0.2293***	0.0334	-0.3078***	0.0438
Coop	-0.5226***	0.0323	-0.6319***	0.0431
Distributor	-1.2738***	0.0323	-1.5191***	0.0431
Processing	-2.0722***	0.0351	-2.3114***	0.0453
Rice	0.4730***	0.0144	0.5642***	0.0149
Fruits	1.3425***	0.0163	1.1999***	0.0169
Others	0.9639***	0.0147	1.1643***	0.0155
Livestock	2.3192***	0.018	2.5282***	0.0193
EXPERIENCE COHORT IN 2010 (EC, Reference = Experienced farmers)				
Beginning farmers	-1.1802***	0.0228	-1.2222***	0.0229
Early-career farmers	-0.8195***	0.0179	-0.8631***	0.0180
BIRTH COHORT (AGE IN 2010) (BC, Reference = 65-74)				
25-34	1.0682***	0.0606	1.2614***	0.0614
35-44	0.6916***	0.0228	0.7256***	0.0231
45-54	0.7547***	0.0140	0.7162***	0.0140
55-64	0.6014***	0.0117	0.5593***	0.0116
EXPERIENCE EFFECT WITH TIME				
Beginning farmers	0.3645***	0.0497	0.3111***	0.0506
Early-career farmers	0.2918***	0.0559	0.2567***	0.0567
AGING EFFECT WITH TIME (For experienced farmers)				
25-34 to 30-39	-0.2011	0.1412	-0.5560***	0.1507
35-44 to 40-49	0.2272***	0.0343	0.1430***	0.0347
45-54 to 50-59	0.3181***	0.0194	0.3017***	0.0194
55-64 to 60-69	0.1253***	0.0171	0.1062***	0.0171
AGING AND EXPERIENCE EFFECT WITH TIME (Relative to experienced farmers)				
For beginning farmers:				
25-34 to 30-39	0.6668***	0.1505	1.0338***	0.1601
35-44 to 40-49	0.1217**	0.0616	0.2338***	0.0626
45-54 to 50-59	-0.2652***	0.0528	-0.2628***	0.0536
55-64 to 60-69	-0.2603***	0.0524	-0.2516***	0.0532
For early-career farmers:				
25-34 to 30-39	0.8752***	0.1738	0.9118***	0.1835
35-44 to 40-49	0.3375***	0.0738	0.4004***	0.0750
45-54 to 50-59	-0.1872***	0.0652	-0.1408**	0.0659
55-64 to 60-69	-0.2406***	0.0673	-0.3004***	0.0679
Chi-squared	17286.3612***		21617.0984***	
Degrees of freedom	328		328	
Adj. R-square	0.3317		0.3243	
-2LL: intercept only	1137447.2		1135927.4	
-2LL: intercept and covariates	1032253.6		1033614.7	
Number of Observation	265,503		265,503	

Note: ***p<0.01, **p<0.05, *p<0.1.

4.7.2. Effects of Experience Accumulation and Aging

The *EC* term establishes the 2010 effect of the career length of a farmer across all age cohorts. The *Year*EC* term then estimates the effect of further accumulation of farming experience from 2010 to 2015 for each of beginning and early-career cohorts, relative to the experienced cohort. This term then measures relative convergence or catch-up between beginning or early-career farmers and experienced farmers.

The relatively disadvantaged position of beginning or early-career farmers is reflected in the *EC* terms related to the base year, 2010. The set of coefficients for *Y*EC* that represent interaction with census year traces the effect if five years of experience is added for beginning and early-career farmers. The results indicate that the effects of experience are the biggest for farmers with the least experience in farming (i.e., beginning farmers). The magnitude of the coefficients in the project implemented and not-implemented areas are similar, suggesting that the project did not influence this effect. This finding might suggest a tendency of low-skilled farmers to more actively use farming-related knowledge, techniques, and networks accumulated over time through experience. The experienced farmers, however, already possess an adequate level of such resources; thus, they are less likely to learn and adopt new skills.

The *BC* term establishes the 2010 effect of birth cohort on agricultural income across all experience cohorts. The *Year*BC* term then specifies a unique trajectory of agricultural income for each birth cohort from 2010 to

2015, as farmers age. Using the experienced farmers as the career role model, the aging effects represent the changes over time for each birth cohort within the experienced cohort; it captures the effects of aging over five years on the premise that all farmers are endowed with an adequate level of farming resources. The net aging effects measure the change in agricultural income with an individual's status change according to the life-cycle trajectory.

The greatest aging effects were in the birth cohort of the middle-aged parenting generation, who are likely to have school-aged children (45-54→55-59). The birth cohort with the second greatest aging effects is the young cohort in the life cycle of family formation (35-44→45-54). The other mid-age cohort (55-59→60-64) has positive aging effects in reference to the elderly cohort, but the magnitude of the effects was relatively lower. The labor-intensive aspects of agriculture make age a fundamental constraint; thus, despite experience level, the probability of making a higher level of agricultural income is often restricted by age.

The effects of the aging analysis are notable for the youngest cohort (25-34→35-44). Farmers who are in their 20s with more than 11 years of farming experience are quite exceptional and highly likely to be young farmers who inherited family farms. Thus, if we identify them as farm successors, the negative coefficients suggest that the five-year term will probably overlap with the period to become self-reliant; their agricultural income would decrease as they become less dependent on inherited capital and, possibly, as they attempt to adopt new farming techniques or varieties. Another important observation of this cohort is the difference in the implementation of the CRVDP. The negative coefficient was statistically significant only for the case of the project not-implemented areas, suggesting that the strong negative effect was undermined by the project implementation for the case of farm households in this cohort that belonged to the supported areas.

4.7.3. Estimation of Agricultural Income Trajectories

4.7.3.1. Agricultural income trajectories by birth and experience cohort

Next, let us take a look at the cohort effects implicit in the interaction of *Year*EC*BC*. This term can be used to evaluate the rate of change for each birth cohort within specific experience cohorts. Because the experienced farmers form the reference group for two cohorts of entry-level farmers, the interaction term can be interpreted as representing the changes, over the five years of project implementation, of beginning and early-career farmer groups relative to experienced farmers in the same birth cohort. For this purpose, the coefficients from the ordered logit regression model were used to compute expected values of making high levels of agricultural income for each cohort (see Table 4-6). The results are shown in the format of double cohort plots in Figure 4-1. Separate figures are provided for the project implemented areas and not-implemented areas. For each area, the agricultural income trajectories of birth cohorts within the beginning cohort, early-career cohort, and experienced cohort are displayed.

It is observed that the initial probability of attaining high levels of agricultural income in 2010 differ for three types of experience groups. The main interest from the result is the slopes of the arrows that indicate the rate of change in attaining a high level agricultural income over the study periods. For both groups of areas, the highest probability is observed for the experienced farmers in all age cohorts, and the lowest probability is likely for those with the least experience. Positive trajectories are found for all birth cohorts in the beginning cohort and early-career cohort, while the steeper slopes of the young farmers in the early-career cohort suggest the higher potential holds for these particular groups. Although of less intensity, relatively steeper slopes among young birth cohorts in the beginning farmer group are likely to be related to entrepreneurial traits of the young generation of farmer.

The agricultural income trajectories for the experienced cohort slightly differ from those of the two other experience cohorts. The young farmers in the youngest birth cohort experience a considerable decline in the probability to earn a high income over five years. However, a substantial loss in the probability is then followed by a recovering trend of agricultural income for the case of young farmers who were in their mid-30s to mid-40s in 2010. This observation is analogous to the findings of previous studies, that is, farm successors possess a unique advantage at the beginning of the settlement due to the ‘succession effect,’[14] but their background may be an obstacle to discovering new markets or adopting innovation (Barclay et al., 2007; Koh, 2001; Sharma and Rao, 2000). The trajectories depict that as young farm successors attempt to implement more innovative approaches and decrease the influence from their parents, the probability of earning an income declines; a rebound suggests that this probability recovers as they become self-reliant.

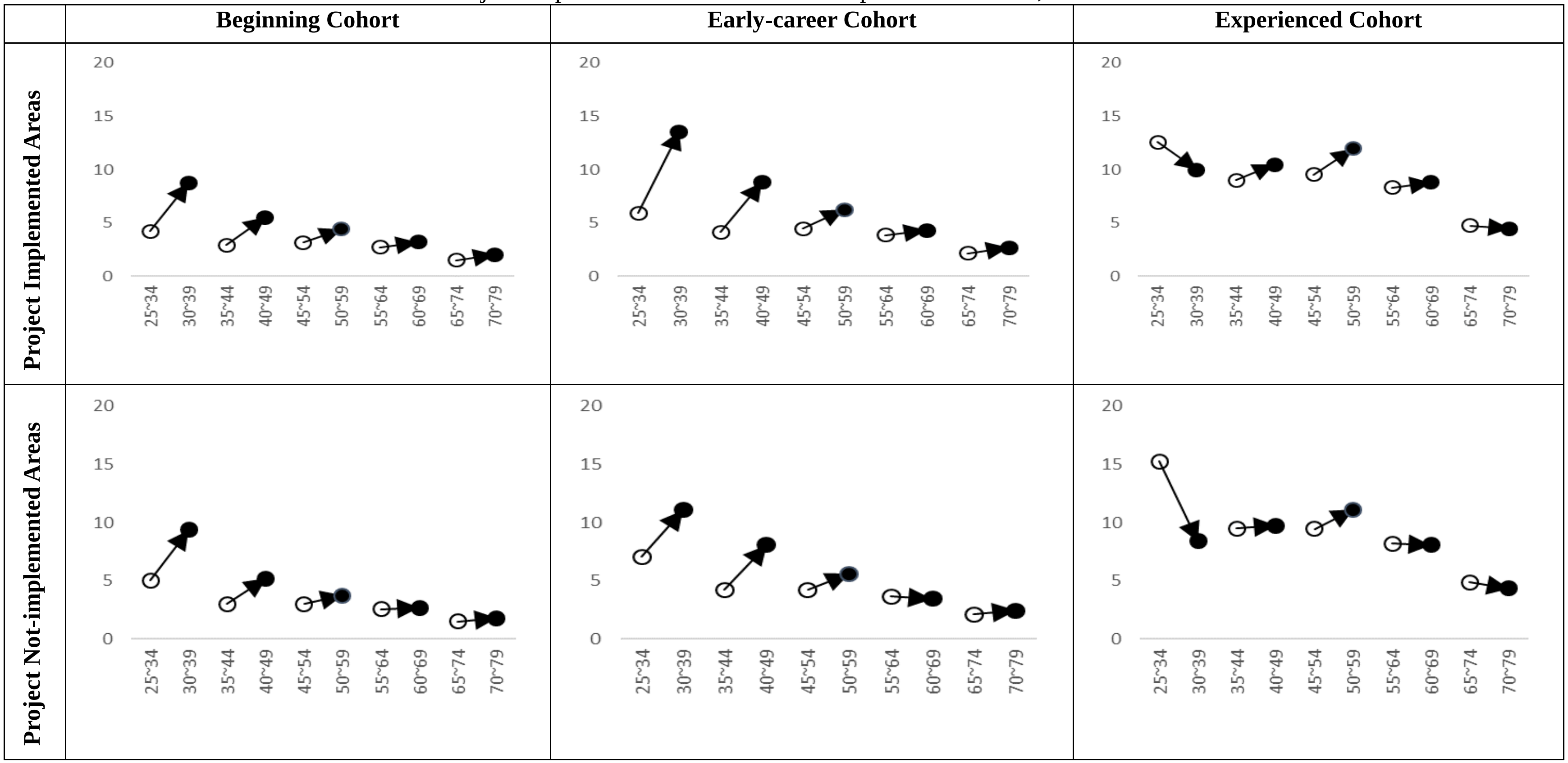
Table 4-6. Expected Values of Making a High-level Agricultural Income

	Project Implemented					
	EXP1		EXP2		EXP3	
AC	2010	2015	2010	2015	2010	2015
1	4.24	8.72	5.98	13.57	12.61	9.98
2	2.95	5.51	4.18	8.81	9.01	10.46
3	3.14	4.42	4.44	6.25	9.54	11.99
4	2.7	3.18	3.83	4.28	8.3	8.79
5	1.5	2.02	2.14	2.68	4.72	4.45
	Project Not-implemented					
	EXP1		EXP2		EXP3	
AC	2010	2015	2010	2015	2010	2015
1	5.03	9.39	7.05	11.06	15.25	8.39
2	3.01	5.19	4.25	8.07	9.52	9.74
3	2.98	3.73	4.21	5.6	9.44	11.13
4	2.56	2.68	3.62	3.43	8.19	8.09
5	1.48	1.79	2.1	2.41	4.85	4.33

Unit: Percent (%)

[14] Potter and Lobley (1996) suggested that succession is more likely to occur on profitable farms.

Figure 4-1. The Change in the Expected Value of Making a High-level Agricultural Income
in the Project Implemented Areas and Not-implemented Areas, 2010 to 2015



4.7.3.2. Comparison of agricultural income trajectories between the project implemented areas and not-implemented areas

The figure 4-1 is particularly useful in comparing changes in trajectories of agricultural income attainment between the project implemented and not-implemented areas, to draw implications on the project's effectiveness. All things being equal, the results of the comparison group show what would have occurred in the absence of the project implementation.

Discernable changes over the analysis periods are observed among four groups in the project implemented areas: young farmers in their mid-20s to early 30s (in 2010) in either the early-career or experienced cohort, and young farmers aged in their mid-30s to early 40s (in 2010) in the early-career or experienced cohort. Of all the cohorts, the youngest farmers of the early-career cohort gained the most from the project, suggested by the steepest slope.

The youngest farmers of the experienced cohort are likely to have gained substantial benefits from the project because the same group of farmers in the project not-implemented areas underwent a serious loss in the probability to attain a high income, as indicated by a comparatively steep downward slope. The likely explanation for this finding is that although the rate of change is negative for the same cohort groups in both areas, the flatter slope in the project implemented areas suggests that the project produced a cushioning effect that prevented a further decline for this particular group. Young farmers in the upper age range with more than six years of experience (early-career and experienced cohorts) in the project implemented areas are also likely to have an increase in agricultural income with the implementation of the CRVDP; although the rate of change less obvious, the slopes of projection are relatively steeper than those of the other birth and experience cohorts.

The change in slope among the older birth cohorts (mid-age cohorts and elderly cohort) at all levels of experience is imperceptible compared with that of the two areas, suggesting that gains from the project are less obvious for older birth cohorts. This includes mid-aged farmers in the beginning and early-career cohorts identified as in-migration baby boomers. This result is probably associated with their reasons for becoming farmers, of which income was not a major motivation. Furthermore, although the differences in the two areas are not obvious, the flattening slopes with the increase in the age range of cohorts show that senior farmers in all groups of experience did not benefit much from the project implemented in their villages.

4.8. Conclusion

A number of existing studies have demonstrated a change in demographic patterns in rural societies. The main drivers of the change are the rural turnaround, urban-to-rural migration, and emergence of young entrepreneurial and successor farmers. These new demographic groups in rural society chose to migrate or remain in rural areas to become farmers despite the general perception of agriculture as a declining industry. This background allows us to identify them as new groups of farmers distinct from traditional farmers of previous generations. The young farmers today have the will and ability to exploit both internal and external resources, in contrast with the general traits of elderly traditional farmers.

The study attempted to analyze how changing demographic trends may have shaped the outcomes of a rural policy in Korea. With respect to the CRVDP, the effectiveness was measured by its effect on raising the level of agricultural income. In addition to birth cohort, sub-groups of farmers were further defined by experience in farming. To incorporate two types of cohorts into the empirical analysis, the double cohort model developed from the traditional APC model was employed.

All things being equal, between the two study areas (i.e. policy implemented areas and not-implemented areas), the major differences in the probability to attain high levels of agricultural income are because of the policy implementation over the studied years. Young farmers in their early-career stage experienced a significant increase in the probability of making a higher agricultural income because of the implementation of the CRVDP. The generational traits of young cohorts seemed to have facilitated their participation as they shared values promoted by the project. On the other hand, mid-aged and elderly birth cohorts of all experience levels were less able to take advantage of the project because the same values emphasized by the project may have worked as a barrier to their participation.

This study contributes to a deeper understanding of the recent changes in rural demography, which significantly deviates from past trends. The CRVDP was terminated in 2014, and now there are various small-scale village development projects with different goals. The lessons from the CRVDP revealed in this chapter suggest that rural revitalization projects should be able to incorporate the changing dynamics of rural demography by providing a project that is more equally accessible or motivational to various demographic groups. Moreover, such project should also be able to encourage the formation of an environment under which a benefit-sharing mechanism can be developed within the community.

Chapter 5.
Micro- and Macro-Level Investigations of the Impact of Transportation Infrastructure on Agricultural Income, 2005-2015

5.1. Introduction

Access to reliable, well-connected transportation infrastructure is a cornerstone of economic activities. Transportation infrastructure not only facilitates a cost-effective production process by lowering transportation costs and increasing mobility but also removes geographic barriers to competition. Since the pioneering work by Aschauer (1989), the contribution of transportation infrastructure to economic growth has long been debated, but overall, empirical findings confirm the presence of a strong linkage between public investment in core infrastructure and economic growth.

In recent years, the importance of transportation infrastructure has been reviewed from the perspective of its role in reducing income inequality through generalized access to economic opportunities and social services. Evidence shows that public investment in transportation geared toward less-affluent individuals and underdeveloped areas reduce income disparities (Lopéz, 2003; Calderón and Servén, 2014; Chen and Vickerman, 2016). The expansion in transportation infrastructure allows poorer individuals to become connected to diverse economic activities and helps poorer regions reduce production and transaction costs. Thus, investments in transportation infrastructure are often adopted by a central government as one of its key strategies for narrowing regional economic disparities. Ideally, if public resources are judiciously mobilized to implement pro-poor expansion of transportation infrastructure, then the result can be a more egalitarian income distribution and spatially balanced growth.

In the agricultural sector, adequate and efficient transportation infrastructure is an indispensable factor upon which farm products rely on for the creation and preservation of their value (Kohls and Uhl, 2002). The remoteness of rural communities underscores the potential of transportation infrastructure as an effective policy instrument to resolve problems associated with the ever-declining agricultural sector. Thus, a general expectation is that investments in transportation infrastructure in rural areas would be highly beneficial for the farmers. Despite a common belief regarding a positive association between the expansion of transportation infrastructure and agricultural income, a thorough establishment of such a link with empirical findings remains surprisingly understudied.

This study aims to explore this fundamental yet under-investigated question: “Does investment in transportation infrastructure result in positive benefits for farm household income?” This question is examined in relation to the role of transportation infrastructure in ensuring equal access to market opportunities under the context of the widening regional economic disparity in Korea. As the quantitative measurement of transportation infrastructure incorporating both quantity and quality, this study adopts space-time utility accessibility measures.

The main novelty of our approach is the attempt to introduce an accessibility measurement for evaluating the benefits of transportation infrastructure to a rural setting, which has been limitedly applied in urban-centered studies. An accessibility approach is particularly suitable because it quantifies the welfare benefits of gaining access to markets for firms and households (Vickerman 2008; Rokicki and Stepniak, 2018). To fulfill the task, multilevel and spatial econometrics models are employed to evaluate the ex-post impact of transportation accessibility on agricultural income from the perspectives of, primarily, farmers and, subsequently, local autonomies. Along with a micro-level analysis of farm households' agricultural income, a macro-level analysis at the district level is helpful in drawing broader implications for balanced regional development.

5.2. Literature Review

5.2.1. Economic Impacts of Transportation Infrastructure

In general, investments in public infrastructure are known to have a positive effect on national and regional economic development by increasing productivity. Aschauer's seminal work incorporated publicly provided infrastructure into the production function model as an input and found that core public capital including transportation infrastructure had made a significant contribution to increasing national productivity in the United States (Aschauer, 1989). Subsequent studies have examined the contribution of transportation infrastructure on the economy of a single country or state, with a more elaborate methodology, and confirmed the positive association (Munnel, 1990; García-Milá and MacGuire, 1992; Morrison-Schwartz, 1996).

Similarly, many empirical studies have recognized transportation infrastructure as a driver of regional economic growth because it produces positive effects on expanding markets, reducing production costs and facilitating economic activities. On the demand side, transportation infrastructure improves physical accessibility, thereby increasing demand for various products and services (Qi et al., 2020). On the supply side, transportation infrastructure reduces production costs by lowering storage and logistics expenses (Litman, 2015; Speranz, 2018). In addition, the expansion of transportation infrastructure improves inter-regional accessibility, increasing flexibility in employment and enhancing the overall reliability of the distribution system (Rokicki and Stepniak, 2018).

Despite the proven effects, the interaction of transportation infrastructure and economic growth is complex. A large body of literature has presented contrasting views with empirical results that show the negative or insignificant effects of transportation infrastructure investments. Transportation infrastructure entails so-called 'network effects' that occur when increased productivity in a beneficiary region affects productivity in other locations. In this respect, there are studies that highlighted the positive spillover effects of transportation infrastructure in resolving regional income gaps (Hulten and Schwab, 1991), but the countervailing evidence has become more prominent, which emphasizes that negative externalities are usually greater than positive externalities (Baiard, 2005; Boarnet, 1998).

Evans and Karras (1994) and Holtz-Eakin and Schwartz (1995) have found no significant correlation between highway investments and the level of regional productivity. According to Boarnet (1998), highway investments have a positive effect on the level of output in the region where investments in infrastructural capital are made, but this is premised on the loss of outputs in neighboring regions. Transportation infrastructure investments produce the possibility of an unbalanced spatial system by increasing comparative advantage in beneficiary locations at the expense of other locations (Boarnet, 1998). Similarly, Raphann and Isserman (1994) emphasize that the regional economic growth effect of highway investments is only valid in the vicinity of large cities and produced little effect in other areas.

A high proportion of the literature has focused on the aggregate contribution of transportation infrastructure to the large economy, usually measured by gross domestic product (GDP) or gross regional product. In contrast to the vast literature on the gross output contribution, studies of the impact of transportation infrastructure on specific industries are much less abundant. However, most of the earlier research with a sectorial focus has attempted to study the linkage between transportation infrastructure and productivity or the locational choice of firms in the manufacturing sector (Hulten and Schwab, 1984; Morris and Schwartz, 1996; Holl, 2004; Kim et al., 2018).

In the agricultural sector, despite the importance of transportation infrastructure as a key medium for agricultural development (FAO, 2017; Kohls and Uhl, 1998), only a handful of studies have explored the correlation between transportation infrastructure and agricultural performance. Antle (1983) finds that transportation infrastructure has a positive effect on the agricultural sector’s GDP in both developed and developing countries and that such effects were more pronounced among the developing countries. The subsequent studies that have explored such a linkage were mostly conducted in developing countries with an inadequate level of transportation infrastructure. For instance, Felloni et al. (2001) demonstrate that road expansion in China facilitated the adaptation of high-yield crops, increasing the overall level of agricultural productivity and yield. Studies conducted in India and Africa have also confirmed that newly constructed or expanded roads in rural areas had a positive effect on agricultural productivity (Fakayado et al., 2008; Llanto, 2012; Fan et al., 2000).

Some studies have investigated the effect of transportation infrastructure on the agricultural sector in terms of labor mobility. An empirical analysis by Fan et al. (2000) concludes that investments in rural roads are critical not only for enhancing agricultural productivity but also for employment and income generation in the case of India. Edeme et al. (2020) also reported positive effects of transportation infrastructure on job creation, whereas its effect on agricultural productivity was found to be negative and not statistically significant.

Some studies that have investigated the agricultural sector assess regional spillover effects generated by transportation infrastructure. Tong et al. (2013) highlight that road investments produced a positive effect on agricultural productivity in the beneficiary areas and adjacent areas in the United States; however, they find that, although statistically insignificant, railways had negative direct effects on the beneficiary areas whereas its indirect effects on the neighboring regions were positive. Cantos et al. (2005) find that the network effects of roads, ports, and railways were more pronounced in agriculture than in other sectors.

Despite the importance of transportation infrastructure as an essential input for agricultural productivity and agricultural income, little attention has been paid to empirically testing such a nexus. According to the review of the literature, this study might be the first to attempt to assess the direct effects of transportation infrastructure investments on agricultural income by utilizing farm-level micro data and regional-level aggregated data.

5.2.2. Methodological Concerns: Micro- or Macro-Level Investigation

Most of the earlier studies on the economic impacts of transportation infrastructure investment have used capital stock or density as a measurement of the quantity of transportation infrastructure. Because capital stock data are usually available at the macro-level, analyses have estimated the impact on aggregated outputs such as GDP. Thus, little is known of the benefits at the disaggregated level.

This chapter aims to explore the effect of enhanced accessibility to transportation infrastructure on farm households' agricultural income. Thus far, no attempts have been made to analyze the effect of transportation infrastructure on household-level benefits. This study uses a multilevel model to reflect the hierarchical structure of data, namely, household and region. Because of the structural feature of the data, there are advantages to using multilevel modeling.

When variables from different levels are analyzed at a single-level, there is a possibility of fallacious reasoning associated with a cross-level inference (Hox and Kreft, 1994). In such a case, identifying the proper level to which variables are aggregated or disaggregated requires careful deliberation. A fallacy will probably arise if data are analyzed at one level while inferences are drawn at another level. For instance, if we aggregate household-level variables and analyze the effect of transportation accessibility at the regional level, interpretation of the results at the household-level would lead to a fallacious conclusion known as the ecological fallacy (Robinson, 1950).

Moreover, in geographical analyses, incorporating contextual variables by using multilevel models can improve estimates by reflecting spatial heterogeneity and spatial dependency, to acknowledge spatial variation in the effects of determinants on agricultural income and to reflect the fact that agricultural income of households in close locations are more likely to be alike than households in distant areas are. Cohen (2010) observes that ignoring spatial effects can lead to inaccurate estimation of infrastructure effects caused by the omitted variable bias.

Despite the advantages, multilevel modeling does not allow the interpretation of the results in a wider context at the region level. If inferences are drawn at the regional level based on observations at the household level, there is a risk of committing the atomistic fallacy (Alker, 1969). Therefore, in addition to the multilevel model, this study also employs a spatial econometrics model to cross-check the results and to draw implications on balanced regional development.

5.3. Data and Variables

Three types of datasets were used in this study: (i) microdata of the Korean Agricultural Census for 2005, 2010, and 2015 that contain information on household attributes and residential areas; (ii) various statistics on regional attributes at the district level *si/gun/gu* of Korea; and (iii) transportation accessibility data for each *si/gun/gu* district. The census data and regional statistics are publicly available on the websites of the Korean National Statistics Office, and the accessibility data were obtained from the Korea Transportation Institute (KOTI).

A combination of household-level variables from the original agricultural censuses, district-level statistics, and transportation accessibility measures by districts was used for the multilevel analysis. Using 20% of randomly sampled households, the multilevel model was used to analyze the effects of transportation infrastructure on agricultural income at the micro-level of farm households. For the analysis of the effects at the macro-level of districts based on the spatial econometrics modeling, variables from the agricultural census data were aggregated to derive the regional average and those data were integrated with regional statistics and the accessibility data.

Some municipalities had undergone administrative changes by being either integrated with neighboring municipalities or promoted to an upper tier (i.e., from a village to a city) from 2005 to 2015. Thus, the datasets were re-aligned to match the municipalities as of 2015, considering spatial conformity before and after the reorganization. Studies of rural areas in Korea commonly classify urban and rural regions by administrative units according to *si/gun/gu*. *Si* contains both urban and rural areas, *gun* are solely rural areas, and *gu* refers to urban towns. Among the 226 *si/gun/gu* districts in Korea, all rural areas and some cities where agricultural activities take place are extracted for the analysis by excluding metropolitan cities and islands in the final datasets. As a result, 157 *si* and *gun* municipal districts (cities and rural villages) were the study areas.

Various types of factors that determine agricultural income were abstracted from the empirical evidences of other empirical studies. The description of all variables used in this study is presented in Table 5-1. Model (1) refers to the multilevel model, and model (2) refers to the spatial econometrics model. In both models, the dependent variable is agricultural income (INCOME), using the gross revenue of farms from the sales of agricultural products from the agricultural census; because this information is originally coded in a categorical format, the data was linearized by the median value of the total amount of agricultural sales by using a natural logarithm.

Table 5-1. Definition of Variables

Category	Model (1)	Model (2)	Definition
Dependent Variable			
Agricultural income	INCOME	INCOME	Log (total amount of sales/10,000)
Independent Variables			
Demographic			
Age		MIDAGE	Proportion of farmers aged 35-54
	AGE		Householder's age (linear)
	AGE_SQ		AGE*AGE (linear)
Gender		FEMALE	Proportion of female householders
	GENDER		Male=0, Female=1
Number of household members	HHNUM	HHNUM	Number of household members (linear)
	HHNUM_SQ		HHNUM*HHNUM (linear)
Socioeconomic			
Level of education		LOWEDU	High school diploma or below
	SCH1		Below high school
	SCH2		High school diploma (ref.)
	SCH3		Bachelor's degree or higher
Experience in farming	CAREER		Years of farming experience (linear)
	CAREER_SQ		CAREER*CAREER (linear)
Agricultural			
Principal income source		FARM	Earn income only from farming
	AGBIZ		Participate in agribusiness
Computer	COMP		Utilize computer for work
Crop type	RICE	RICE	Cultivate rice
	FRUIT		Cultivate fruits
	OTHER		Cultivate other types of crops (ref.)
	VEGE		Cultivate vegetables
	LIVESTOCK		Raise livestock
Marketing channel	WHOLESALE		Wholesale market, joint market
	COOP		Agricultural cooperatives (ref.)
	DISTRIBUTOR		Collector, distribution company
	DIRECT	DIRECT	Direct sales to consumers
	PROCESSING		Agricultural processing company
Regional			
	P_LAND	P_LAND	Land price index
	P_NET	P_NET	Number of net migrants
	UTILITY	UTILITY	Log(utility accessibility)

Notes: 1. ref.=reference group.
2. Model (1) = multilevel model, Model (2) = spatial econometrics model

The main predictor factor of the focus of this study is transportation accessibility. The full accessibility database obtained from KOTI includes accessibility measured in terms of roads, railways, and utility. Our analysis adopted the utility measure of accessibility (UTILITY) as the indicator of improvements in transportation infrastructure. Based on random utility theory (Domencich and McFadden, 1975), the utility measure assumes that individuals select the best alternative with the highest utility and treats utility as a random variable.

In economic appraisal, the conventional approach to estimate accessibility benefits of transportation policies is to use the rule-of-half measure; this method computes the change in user benefits as the sum of the full benefit obtained by the original travelers and half the benefit obtained by the new travelers, using travel times or costs as input. Although more complicated to derive, the utility-based benefit measure, or so-called logsum accessibility, provides a more accurate benefit estimate of transportation policies than the rule-of-half approach does (Guers et al., 2010). The logsum accessibility was derived based on the multi logit model that is expressed as:

$$L_{piz} = \log(\textstyle\sum_j \exp(\mu_p V_{piz}))$$
$$V_{piz} = \beta_p T_{zj} + \chi_{ph} \ln\left(C_{zj}\right) + \delta_p D_{pj} + \cdots \cdots(1)$$

where μ_p is the logsum coefficient travel purpose *p*, *V* is utility, *T* is travel time, *C* is the travel cost, and *D* is a variable representing the attractiveness of the destination zone (destination utility) for a specific activity. The cost coefficient χ differs between travel purposes but also between income groups h per travel purpose.

The advantage of using the logsum accessibility in this paper is that it expresses a traveler's utility from a choice set of travel alternatives (i.e. different modes of transportation) but also considers welfare effects from changes in land use that result from transportation strategies. Therefore, this method is more comprehensive than using a single-mode accessibility such as roads or railways and captures a more complete picture of spatial interactions than other measurements often used to estimate the benefits of transportation investments.

In addition to transportation accessibility, demographic, socioeconomic, agricultural, and regional contextual variables are input in the analytic models as control variables. For the multilevel model analysis, the demographic-related control variables included householder’s age (AGE) and its squared term (AGE_SQ), gender (GEDER), and number of family members (HHNUM). The socioeconomic variables included householder’s level of education (SCH1-SCH3), years of farming experience (CAREER), and its squared term (CAREER_SQ).

Households’ agricultural characteristics were reflected by participation in off-farm agribusiness (AGBIZ), use of a computer for work (COMP), type of major farming activity (RICE, FRUIT, VEGE, LIVESTOCK, OTHER), and the main type of marketing channel (WHOLESALE, COOP, DISTRIBUTOR, DIRECT, PROCESSING). For district-level contextual variables, the land price index (P_LAND) and number of net migrants (P_NET) were used as indicators of the vitality of a local economy. All the continuous variables were deviated around their mean for the sample to perform the multilevel modeling effectively (see Bryk and Raudenbush, 1992; Kreft et al., 1995). Similarly, control variables for the spatial econometric analysis were constructed such that the variables applied to two different models were the most alike.

5.4. Methodology

5.4.1. Multilevel Model for Micro Data

The study applied the multilevel model to the analysis of our micro data. The multilevel model recognizes the existence of data hierarchies by allowing for residual components at each level in the hierarchy (Goldstein, 2003). Studies have shown that multilevel modeling is almost always superior to ordinary least squares regression (Bryk and Raudenbush, 1992; Duncan et al., 1993; Lee and Myers, 2003).

In this study, the household-level variables reflect characteristics of an individual farm household and the district-level variables are the utility accessibility and two variables of district characteristics. If the analysis is conducted in a manner that generalizes that all districts have analogous traits, there is a risk of oversimplification. The employment of the multilevel model reduces such possibility by allowing district-level regional variations.

Given the hierarchical structure of data, it is reasonable to assume that the household-level variables in some way depend on district-level attributes and that the effects of the household level determinants may vary systematically as a function of idiosyncratic district attributes. Suppose there are n_j -element household-level dependent variable vector y_j , explanatory variable matrix X_j defined by m groups (*j*=1 to *m*) of districts and p household level independent variables (s=1 to p) with the total number of observations $N = \sum_{j-1}^{j-m} n_j$. A household-level equation of each district can then be defined as:

$$y_j = X_j\beta_j + \varepsilon_j \;\cdots(2)$$

where β is a $p \times 1$ vector of unknown regression parameter and $j = 1, \cdots, J$ higher level districts are allowed to have different numbers of individual observations. It is assumed that ε_j is independently distributed as $N(O_j, \Sigma_j)$ and observations are independent and have a constant variance as $\Sigma_j = \sigma_j^2 I$. Equation (2) then is a standard linear model also known as the fixed effects regression model.

A more realistic model can be explored by letting intercept and slope vary in the district level by allowing a more flexible specification of the covariance matrix ε_j. Assuming β_j is a random sample from a multivariate normal, $\beta_j \sim N_p(\beta, \Xi)$ uncorrelated with ε_j, an extended form of the standard linear model is called as the random coefficient model. This model is expressed as:

$$y_j = X_j\beta + Z_j\gamma_j + \varepsilon_j \;\cdots(3)$$

where the matrix Z_js a random-effects design matrix and $\gamma_j = \beta_j - \beta$ is a vector of deviations of the regression coefficients β_j from the their expectation β. In this case, the matrix Z contains the intercept (=1) as its first column and its variance is presented by σ_γ^2. Also, σ_ε^2 denotes to household-level intercept variance term.

There are two special cases of the random coefficient model that corresponds to the analysis of this study. A random effects analysis of variance model (ANOVA) is obtained by setting all of the coefficients of X_j and Z_j to zero except intercepts at both levels:

$$y_j = \beta_1 + \gamma_j + \varepsilon_j \quad \cdots(4)$$

where β_1 is a constant term indicating the grand mean of *y*. This model includes no capacity for explaining variability in y_j at either the household or district-level, but it incorporates two sources of random variability in y_j.

Another important case is a random intercept model that specifies Z_j as a column vector of ones which is embodied by the following equation:

$$y_j = X_j\beta + \gamma_j + \varepsilon_j \quad \cdots(5)$$

This model depicts a picture as a series of parallel lines with the fixed slope and varying intercepts $(\beta_1 + \gamma_j)$.

5.4.2. Spatial Econometrics Model for Aggregated Data

The use of regional datasets implies the necessity to consider the possibility that observations are not independent as a result of the inter-connections between neighboring regions (Anselin, 1988). The multilevel model as one approach to control such spatial autocorrelation in the micro-level analysis. For the macro-level analysis, the issue of spatial autocorrelation can be managed by applying spatial econometrics techniques. Spatial regression methods identify groups of nearest neighbors and incorporate dependence between close regions (Anselin, 1988; LeSage, 2005).

There is a class of spatial autoregressive models that captures the effects of spatial dependence and spatial heterogeneity, which are built on the standard linear regression model. All spatial models are based on the following benchmark expression:

$$y = \rho W_1 y + X\beta + u \quad \cdots (6)$$
$$u = \lambda W_2 u + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2 I_n)$$

where y is the n x 1 vector of the dependent variable, and X is the n x k matrix of independent variables. W_1 and W_2 are a spatial weighted matrix that formally incorporates spatial dependence into the model; ρ and λ are spatial autoregressive coefficients that express the strength of spatial interaction, and ε is a vector of error terms considering iid.

Spatial correlation can be incorporated as an additional regressor in the form of a spatially lagged dependent variable, or in the error structure (Anselin, 1988). When both the spatial lag term and a spatially correlated error structure are included in the model as in equation (6), it is called the spatial autoregressive combined (SAC) model. Because the SAC model restricts the spatial effects parameters to 0, other models can be derived. When $\rho = 0$, a spatial error model (SEM) with spatial autocorrelation in the disturbances can be derived. When $\lambda = 0$, a mixed regressive-spatial autoregressive model (SAR) can be derived.

In this study, the SAR model is used as the most appropriate among the three models. The SAR model takes the following form:

$$y = \rho W y + X\beta + \varepsilon \quad \cdots(7)$$
$$\varepsilon \sim N(0, \sigma^2 I_n)$$

The spatial weights matrix *W* is the building block of spatial econometrics, which is most commonly specified by contiguity (spatial neighbors) or distance functions. Contiguity weights matrices define relations of two spatial units by specifying a binary relationship with weights 1 and 0. For instance, if district *i* is contiguous to district *j*, then $d_{ij} = 1$ and, otherwise, $d_{ij} = 0$. In this case, *W* is given by the following formula:

$$W_{ij} = d_{ij} / \sum_{j=1, i \neq j}^{n} d_{ij} \quad \cdots(8)$$

W can be constructed based on the rook, bishop, and queen contiguity matrix. There is no set of criteria for selecting weights matrix, and it is usually chosen in a manner that conforms to the data structure, applicability, and economics theory (Cliff and Ord, 1981; Anselin, 1988). The row standardized queen contiguity matrix grants $W_{ij} = 1$ if two districts share a border or a corner; otherwise, $W_{ij} = 0$ is used for the quantification of the location under study.

5.5. Empirical Results

A bivariate analysis was performed to identify co-related trends in transportation accessibility and the average agricultural income of all study districts by using the Pearson correlation test. The results in 2005, which reflect mainly the effects of transportation infrastructure built in the 1990s and early 2000s, show a positive correlation with statistical significance between transportation infrastructure measured in terms of road, train, and utility accessibilities and agricultural income. In 2010, however, all three transportation indexes show a markedly low correlation with agricultural income, resulting in a substantial loss of statistical significance. Deviating from the positive trends in 2005 and 2010, the correlation between agricultural income and road accessibility (-0.1513), railway accessibility (-0.1622), and utility accessibility (-0.1598) in 2015 were shown to be negative, and the results of which are proven to be statistically significant at conventionally acceptable test levels.

Table 5-2. Bivariate Correlation Analysis (Pearson's r)

	2005	2010	2015
Road accessibility	0.2003**	0.0563	-0.1513*
Train accessibility	0.1883**	0.0141	-0.1622**
Utility accessibility	0.1373*	0.0067	-0.1598**

Note: ***p<0.01, **p<0.05, *p<0.1.

Such trends may imply that much of transportation infrastructure built since the 2000s has been promoted without consideration for the agricultural sector and rural communities at large; despite the government's endeavor to achieve balanced regional growth through transportation infrastructure, the results indicate that transportation policy has been promoted in a manner that adversely affects agricultural income. The results of the two types of multivariate analyses employing the multilevel and spatial econometrics models corroborate the results of the bivariate analysis.

5.5.1. Multilevel Model

Table 5-3 presents the estimation results for the multilevel model. In multilevel modeling, the ANOVA model forms the base model, which is useful in determining the appropriateness of the model. Model 1 in Table 5-3 displays the results of the base model that compares the relative contribution of household-level and district-level effects on agricultural income. With the household effects entered as fixed parameters, the district-level intercept indicates the remaining variation due to inter-district differences. The relatively low district-level variance indicates that agricultural income can be explained primarily by the discrepancies between households. Nevertheless, variations among farm households (σ_{ε}^2) and those among districts (σ_{γ}^2) were highly significant at 1% level. This finding illustrates that if the analysis were conducted by single-level regression models, ignoring the multilevel structure of the data would have decreased the accuracy of the results.

In model 2, or the random intercept model, intercepts are allowed to vary in their slopes. Considering random effects, the variances represented by both household-level and district-level random intercepts decrease with the introduction of independent variables in all three years. The Bayesian information criterion (BIC), one of the most used indicators to assess the model fit, is also lessened. Thus, knowledge of specific household-level and district-level attributes helps reduce agricultural income differences across households and districts.

Despite the little direct interest in this work, the estimated coefficients for control variables provide relevant insights into the determinants of agricultural income. The results of the random coefficient model show the same signs and similar values as coefficients in 2005, 2010, and 2015, except for the education-level dummy variables. Concerning the educational background, farm households who did not complete the high school (SCH1) or attain a bachelor’s degree or higher level of education (SCH3) showed a lower level of agricultural income than those with a high school diploma (SCH2) in the case of 2005, with statistical significance found only for SCH1. In 2010 and 2015, however, a statistically significant negative agricultural income effect was found for farm households whose householder has at least a bachelor’s degree (SCH3) compared with those who are high school graduates (SCH2).

The age of farm householder (AGE) seems to negatively affect agricultural income, and it will probably be related to the general trend of rural aging, for example, the average age of farmers has gradually increased over the past years. Agricultural income would decrease with age, and the negative coefficient of the age squared term (AGE_SQ) indicates the negative marginal effect. In terms of gender effect (GENDER), farm households led by women showed lower agricultural income than those headed by men, which is in accordance with common observations.

Householders with a larger family size (HHNUM) are likely to earn higher agricultural income, but the negative sign of its squared term (HHNUM_SQ) presents that the effect has a decreasing and non-linear trend. Considering a householder’s career length in farming (CAREER), agricultural income increases as the householder’s experience in farming increases, and its squared term (CAREER_SQ) shows a negative sign through which one can postulate that the effect of farming is non-linear.

Participation in agribusiness (AGBIZ) and the use of a computer for work (COMP) were found to be negatively associated with agricultural income. As for the participation in agribusiness (AGBIZ), the coefficients in 2010 and 2015 decreased in comparison to that of in 2005, indicating that the negative effect of this particular variable has become stronger since

2005.

Participation in agribusiness indicates whether a household earns income solely from farming or also from off-farm activities. This information can be understood in the general context that farm households engaged in both farming and off-farm activities make a lower level of agricultural income because they allocate fewer resources to farming. The negative coefficient of the use of a computer (COMP) means agricultural income of households that use a computer for economic activities earn less from farming than those who do not use computers. Thus, it can be interpreted that farm households tend to use a computer for distribution and service-related activities such as marketing and rural tourism rather than for farming.

The estimates of major crop type indicate that farmers who produce fruit (FRUIT) and other types of crops including cash crops (OTHER) or are engaged in the livestock industry (LIVESTOCK) have higher agricultural income than those who cultivate mainly rice (RICE). A contrasting result was evident for upland crops (VEGE), which was found to earn less than rice.

Concerning the results for the variable indicating the major marketing channel, farm households that trade in agricultural products through the wholesales market (WHOLESALE) have a higher income compared with those who mainly trade through agricultural cooperatives (COOP). By contrast, farmers who sell through government and distributors

(DISTRIBUTOR), direct sales (DIRECT), and retailers and processing companies (PROCESSING) had lower income than the reference group (COOP). Furthermore, the effects of regional attributes such as land price index (P_LAND) and net migrants (P_NET) had no significant effect on agricultural income.

Most importantly, this study aims to test the hypothesis concerning the effect of transportation accessibility on agricultural income. The effect of the main predictor variable, utility accessibility (UTILITY), was positive in 2005 but had a negative effect in 2010 and 2015. In 2005, the coefficient value of 0.02 was attained, whereas the value decreased in 2010 and 2015 from -0.02 to -0.08, indicating that the effect of transportation accessibility on agricultural income had been undermined by the lapse of time. Most notably, the statistical significance at 1% level was only observed in 2015. This result signifies that despite the increased investments in transportation infrastructure over time, the level of improvements in transportation accessibility remain inadequate in rural areas, thereby causing a negative consequence on farm households' agricultural income.

Table 5-3. Results of Multilevel Model

Variable	2005			
	Model 1		Model 2	
Fixed effect				
INTERCEPT	15.4303***	0.0340	16.3613***	0.2375
AGE			-0.0285***	0.0004
AGE_SQ			-0.0006***	0.0000
GENDER			-0.6642***	0.0079
HHNUM			0.0616***	0.0030
HHNUM_SQ			-0.0078***	0.0010
SCH1			-0.0490***	0.0073
SCH3			-0.0569	0.0156
CAREER			0.0081***	0.0003
CAREER_SQ			-0.0005***	0.0000
AGBIZ			-0.2427***	0.0095
COMP			-0.5717***	0.0088
FRUIT			0.6163***	0.0099
OTHER			0.4121***	0.0072
VEGE			-0.3671***	0.0099
LIVESTOCK			1.1252***	0.0104
WHOLESALE			0.2395***	0.0102
DISTRIBUTOR			-0.1135***	0.0069
DIRECT			-1.1930***	0.0082
PROCESSING			-0.1525***	0.0096
P_LAND			0.0080	0.0080
P-NET			0.0000	0.0000
UTILITY			0.0206	0.0208
Random effect				
Level1				
INTERCEPT(σ_{ε}^{2})	2.1080***	0.0064	1.3351***	0.0041
Level2				
INTERCEPT(σ_{γ}^{2})	0.1774***	0.0204	0.1049***	0.0122
-2RLL	769152.6		671412.1	
BIC	769162.7		671422.2	
N	214431		214431	

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 5-3. Results of Multilevel Model (Cont'd)

Variable	2010			
	Model 1		Model 2	
Fixed effect				
INTERCEPT	15.5686***	0.0324	17.3858***	0.2762
AGE			-0.0238***	0.0004
AGE_SQ			-0.0004***	0.0000
GENDER			-0.5029***	0.0074
HHNUM			0.0569***	0.0031
HHNUM_SQ			-0.0113***	0.0011
SCH1			0.0162	0.0069
SCH3			-0.1207***	0.0126
CAREER			0.0094***	0.0003
CAREER_SQ			-0.0005***	0.0000
AGBIZ			-0.9364***	0.0078
COMP			-0.4188***	0.0070
FRUIT			0.6815***	0.0089
OTHER			0.5600***	0.0069
VEGE			-0.0571***	0.0109
LIVESTOCK			1.3905***	0.0102
WHOLESALE			0.2314***	0.0095
DISTRIBUTOR			-0.0610***	0.0073
DIRECT			-1.2193***	0.0079
PROCESSING			-0.6376***	0.0091
P_LAND			-0.0410	0.0360
P-NET			0.0000	0.0000
UTILITY			-0.0241	0.0217
Random effect				
Level1				
INTERCEPT(σ_{ε}^{2})	1.9639***	0.0063	1.1941***	0.0038
Level2				
INTERCEPT(σ_{γ}^{2})	0.1620***	0.0187	0.0858***	0.0100
-2RLL	682743.0		586324.9	
BIC	682753.1		586335	
N	194161		194161	

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 5-3. Results of Multilevel Model (Cont'd)

Variable	2015			
	Model 1		Model 2	
Fixed effect				
INTERCEPT	15.5800***	0.0343	17.9687***	0.2599
AGE			-0.0277***	0.0004
AGE_SQ			-0.0004***	0.0000
GENDER			-0.4630***	0.0085
HHNUM			0.0776***	0.0040
HHNUM_SQ			-0.0161***	0.0014
SCH1			-0.0033	0.0076
SCH3			-0.1123***	0.0134
CAREER			0.0114***	0.0002
CAREER_SQ			-0.0005***	0.0000
AGBIZ			-0.6101***	0.0079
COMP			-0.3687***	0.0087
FRUIT			0.5648***	0.0096
OTHER			0.3282***	0.0078
VEGE			-0.2206***	0.0110
LIVESTOCK			1.5811***	0.0132
WHOLESALE			0.1916***	0.0104
DISTRIBUTOR			-0.0329***	0.0087
DIRECT			-1.1794***	0.0083
PROCESSING			-0.7766***	0.0105
P_LAND			-0.0363	0.0289
P-NET			0.0000	0.0000
UTILITY			-0.0753***	0.0191
Random effect				
Level1				
INTERCEPT(σ_ε^2)	2.1432***	0.0072	1.3717***	0.0046
Level2				
INTERCEPT(σ_γ^2)	0.1812***	0.0209	0.0774***	0.0091
-2RLL	642274.3		562885.7	
BIC	642284.5		562895.8	
N	178209		178209	

Note: ***p<0.01, **p<0.05, *p<0.1.

5.5.2. Spatial Econometrics Model

To diagnose the existence of spatial patterns in respect to agricultural income, the global Mora's I test was performed with the help of ArcGIS software. The results are summarized in Table 5-4. Global Moran's I statistics is one of the most preferred methods to test for spatial autocorrelation in a dataset. This spatial diagnostic tool measures the level of clustering patterns across districts. If Moran's I index is statistically positive, there is a positive correlation in the spatial distribution, indicating a spatial clustering effect; otherwise, a negative spatial correlation would exist.

The Moran's I statistic for the aggregated agricultural income by district presents a strong positive direction in all years. This finding rejects the null hypothesis that states the average agricultural income is randomly distributed across rural districts. The result therefore confirms the necessity to control spatial effects because of the presence of autocorrelation in the datasets in which the average agricultural income in one district is highly likely to be influenced by that of neighboring districts.

Table 5-4. Global Moran's I

Year	Moran's I	Z-score
2005	0.2738***	5.1244
2010	0.2065***	3.9067
2015	0.2021***	3.8199

Notes: 1. Queen contiguity-based spatial weight matrix is used.
2. *** $p<0.01$.

The estimated results of the SAR, SEM, SAC models find statistical evidence that both rho (for spatial lagged model) and lambda (for spatial error model) have a significant impact on agricultural income. Among different spatial econometrics models, one common approach to select the most appropriate model is to select the model with the highest log likelihood coefficient. Although the SAC model presented the highest log likelihood value, the coefficients of log likelihood, adjusted R-squared, and the effects of independent variables were relatively similar for the SAR model when the degrees of freedom were considered. Based on this reasoning, the interpretation of the results is limited to the SAR model, which emphasizes the spatial autocorrelation of the dependent variable, namely, aggregate agricultural income.

The results of the SAR model are presented in Table 5-5. In all years under study, the more farmers there are at mid-age (MIDAGE) and engaged only in farming (FARM), the higher the average agricultural income of those districts. What was particularly notable was the drastic increase in the coefficient value of MIDAGE in 2015. A reasonable interpretation for this finding is that the proportion of farm householders in the most economically active age group has been reduced because of the acceleration of rural aging, and thus, their relative contribution to local agricultural outcomes has been enlarged.

Likewise, the direction and magnitude of the effect of direct sales (DIRECT) were relatively constant from 2005 to 2015. It is observed that when more farmers sold agricultural outputs directly to consumers, the average agricultural income of those districts decreased. The proportion of farmers primarily engaged in rice cultivation (RICE) is negatively associated with the district's average agricultural income in all the study periods, but statistical significance was not attained. The number of net migrants in a region (P_NET) was proven to be positively related to the average agricultural income, but the strength was weak.

The proportion of households headed by a woman had a negative association with the district-level average agricultural income in 2005 and 2010, and in 2015, its effect was positive but with a loss of statistical significance. The average number of household members (HHNUM) in each district was proven to be positively correlated with the average agricultural income in 2005 and 2015, a negative correlation was found in the case of 2010. However, statistical significance was observed only in 2015, which is also likely to be associated with the recent acceleration of rural aging; more populated districts have become more likely to have a higher level of agricultural income. Concerning the level of education, the greater the number of farm householders with an educational level below high school (LOWEDU), the higher the average agricultural income of that district in 2005 and 2015, and a negative but statistically insignificant result was obtained in 2010.

The volatility in land price measured by land price fluctuation rate (P_LAND) shows a positive correlation with agricultural income in 2005 and 2010, and the sign turns negative in 2015. Land price change was most sensitive in areas with attributes such as a central location and often followed grand-scale development projects (Albouy et al., 2018). The switch in the direction of the sign from 2010 to 2015 and the statistical significance attained only in 2015 are most likely to reflect the effect of national-level spatial planning to develop non-capital regions, which was implemented in the mid-2000s. Innovation Cities were newly constructed throughout Korea, and subsequently, public agencies originally located in the capital region were relocated to achieve geographically balanced development (see Seo, 2009). The relocation project would have increased the price of some rural lands, which would probably have had a significant impact on agricultural activities.

Utility accessibility (UTILITY), the variable of most interest in this study, had a positive effect on agricultural income in 2005, but the effect turned negative starting in 2000. In the case of 2005, the coefficient was not statistically significant, but the negative effect was highly significant in 2010 and 2015. These results suggest that public investments in transportation infrastructure had a meager or negative impact on agricultural income at the district-level. In conjunction with the results found at the disaggregate household-level based on the multilevel modeling, the aggregate district-level analysis implies that the transportation network has been extended in a manner that is highly irrelevant for agricultural activities in rural areas.

Table 5-5. Results of Spatial Econometrics Model (SAR)

Variable	2005		2010		2015	
	Coef.	T-test	Coef.	T-test	Coef.	T-test
CONSTANT	1.5817	0.9606	4.7123***	3.7954	3.9524***	3.7395
MIDAGE	0.064***	5.5368	0.0500***	5.6677	2.3477***	3.7838
FEMALE	-0.0022	-0.2936	0.0043	0.6130	-0.0017	-0.2148
HHNUM	0.0767	0.4074	-0.0028	-0.0139	0.6787***	3.5372
LOWEDU	0.0017	0.1450	-0.0002	-0.0312	0.0116**	2.0070
RICE	-0.0002	-0.1987	-0.0016	-1.3110	-0.0004	-0.3620
DIRECT	-0.0156***	-7.1005	-0.0156***	-8.5775	-0.0150***	-8.8073
AGINCONLY	0.0158***	6.0876	0.0140***	4.7352	0.0167***	6.0349
P_LAND	0.0027	0.4193	0.0467	1.6416	-0.0653***	-2.7870
P_NET	0.0000*	1.8280	0.0000*	1.7428	0.0000	1.5114
UTILITY	0.0019	0.7867	-0.1009***	-4.0125	-0.0599***	-2.6969
ρ	0.0540***	2.6668	0.0400**		0.0540***	3.5701
R^2	0.6674	0.9606	0.6963		0.7305	3.7395
Adj. R^2	0.6447		0.6755		0.7120	
Log Likelihood	56.1835		71.9502		77.4951	

Note: ***p<0.01, **p<0.05, *p<0.1.

As aforementioned, the SAR model reflects the spatial autocorrelation of agricultural income across districts. In this model, the spatial lagged term of the dependent variable defined by the spatial weight matrix is added as an independent variable, which enables separate estimates of direct, indirect, and total effects. The direct effects measure the effect that a change in an independent variable in district *i* has on the dependent variable (average agricultural income) in that district. The indirect or spillover effects capture the effect of a change in an independent variable in district *i* on the dependent variable in all other districts. The total effects are calculated by summing the two effects. The direct, indirect, and total effects of utility accessibility on the aggregate agricultural income by district derived based on the SAR model is presented below.

Table 5-6. Direct, Indirect, and Total Effects of Utility Accessibility on Agricultural Income (SAR)

Year	**Direct Effects**	**Indirect Effects**	**Total Effects**
2005	0.0192	0.0011	0.0203
2010	-0.1001***	-0.0042*	-0.1051***
2015	-0.0600***	-0.0034**	-0.0634***

Note: ***p<0.01, **p<0.05, *p<0.1.

In all the years under study, the coefficients of direct effects are much bigger than those of indirect effects. In 2010 and 2015, a high level of statistical significance is observed for the direct effects, and the level of significance is comparatively lower for the indirect effects. Considering both the magnitude and strength, the effects of utility accessibility on agricultural income are more closely related to the direct or within-district effects. Thus, the impact of improved transportation accessibility in district *i* on agricultural income in the same district is greater than the spillover effects on neighboring districts.

The results reveal a negative effect of transportation infrastructural investments on agricultural income in Korea from the 2010s, which is also analogous to the findings based on bivariate correlation analysis and multilevel modeling. These overall negative results contradict the general expectation that the expansion of transportation infrastructure in rural areas would have contributed to raising agricultural income by lowering production costs and securing price competitiveness of agricultural products.

Instead, it implies more transportation infrastructure investments are still being allocated to a few selected urban centers, causing negative consequences in rural districts.

5.6. Conclusion

Transportation infrastructure is an indispensable factor that has a profound influence on the production and consumption of various actors in the economy and the overall industry. Abundant literature has assessed the impact of transportation infrastructure on the gross product of a country or region. However, studies that have examined the relationship between transportation infrastructure and agricultural outcomes, particularly that of income, have been limited. The likely reasons for such a limitation might be the academic prejudice that transportation infrastructure is a variable principally related to urban attributes and the difficulty in obtaining datasets in an appropriate format that can be applied in conjunction with rural data.

The findings of this study can be summarized as follows. First, in the multilevel model, transportation infrastructure showed a positive but non-significant association with agricultural income in 2005, but the sign then turned negative in 2010 and 2015 while the statistical significance at 1% level was only observed in 2015. These results suggest that despite the continued expansion of investment in transportation infrastructure, such public investment had no effect on farm households' agricultural income.

Instead of providing benefits, transportation infrastructure constructed after 2000 is either unrelated or hindering agricultural activities in rural areas.

Second, the spatial econometrics model analyzed at the macro-level by using aggregated data corroborated the results of the micro-level findings. The district-level impact demonstrates that transportation infrastructure had a non-significant but positive effect on the average agricultural income in 2005, but a negative and highly significant relationship was revealed in 2010 and 2015. The results suggest that although the general accessibility to transportation infrastructure has continuously enhanced annually, transportation accessibility necessary for agricultural production has been relatively deteriorated, and consequently, it has become a driver that exerts a negative influence on agricultural income in rural areas.

The results of this study indicate that if the current direction of transportation policy continues without much consideration for agriculture as an industry and rural areas as living spaces, the economic alienation of the agricultural industry and farm households can be intensified. Opportunities for market access provided by the immense public investments in transportation infrastructure should be fairly distributed to farmers and local autonomies based in rural areas.

Chapter 6.
Concluding Remarks

6.1. Summary of Findings and Policy Implications

The decline of rural areas is causing the problems of the rural exodus and aging, which, in turn, further exacerbates rural economic crises at an unprecedented rate. Such problems in rural areas are rapidly showing up on government policy agendas around the world. In Korea, the vast sum of investment has been allocated to the agricultural and rural sector in an effort to revive rural communities. Despite the consensus on the necessity of rural revitalization, economic efficiency or value for money has been called into question both at home and abroad. This is related to the tendency of policymakers to give lower priority to objective assessment of policy outcomes once the policy intervention is terminated. However, an accurate and valid assessment of a precedent policy is fundamental in designing future policies to ensure their quality and effectiveness.

This study attempted to empirically analyze the effectiveness of large-scale public funds invested in rural areas by applying various econometric techniques for rigorous policy evaluation. Farm households' agricultural income was chosen as the study's ex-post quantifiable indicator of the impact. Agricultural income was chosen not only because it is one of the implicit goals of the policies in question but also because attaining higher agricultural income is important in a broader rural context.

The widening gap in rural-urban income in Korea is largely attributed to the decreasing level of farm households' income that accompanied the steady decline of the agricultural sector, which is losing its competitiveness to urban-centered industrial sectors. Korean farm household income remains slightly above 60% of urban household income over a decennium. When only agricultural income is considered, it has continuously decreased over the past decade.

In Korea, there is a public consensus that agriculture is an indispensable industry not only for national food security but also for the virtue of preserving the rural landscape and the nostalgic sense of hometowns. However, the low-level of income has made agriculture not only the least preferred industry to work in but also a driver of rural flight and the subsequent aging problem in rural areas. As in many other countries, nonfarm income has become a significant source of income for Korean rural households, but agricultural income is still crucial for improving sustainability of agriculture and attractiveness of rural areas. Therefore, achieving a higher agricultural income is also an imperative element in achieving balanced regional development.

Against this backdrop, in Chapter 3, the empirical results indicate that the CRVDP had generated a significant positive impact on enhancing farm households' chance to make agricultural income. The study also finds that the selection of beneficiary areas was appropriate. If there had been no government support, the project implemented areas could have been exposed to a difficult situation in terms of income earning. Such results highlight the positive potential of the community-led, multi-sectoral rural development approach.

The CRVDP was a meaningful attempt; however, the project was limited by the inability to engage diverse stakeholders in collaboration as it was presented in Chapter 4. The young cohorts comprised of farmers in their mid-20s to mid-40s gained the most from the project implementation. By contrast, mid-aged and elderly farmers did not benefit much from the project. A majority of the rural population is elderly farmers and many are living in poverty, but the CRVDP did not assist much for this important segment of the rural population. The evidence of project effects on agricultural income in Chapter 3 was probably led by the young farmers with more than 6 years of farming experience.

Today's young farmers are innovative, adapt to using IT technology, and practice sustainable eco-friendly farming, all traits that well match with the values promoted by the CRVDP. Moreover, young farmers chose to become farmers against other career options available in the non-agricultural sector; such experience may reflect their tendency and ability to cope actively with new circumstances introduced by the project. On the other hand, despite the elderly farmers' professional knowledge in agriculture and long-founded personal networks, they were less likely to take advantage of this particular government policy. Their tendency to embrace traditional values and inability to use IT technology are some of the traits that contrast with those of young farmers. Such tendency may have made it difficult for elderly farmers to comply with the new policy, leading to a low level of participation.

Members of today's rural societies in Korea are no longer bonded by a strong sense of community. New, diverse demographic groups are now the neighbors of traditional farmers, who are in the senior age group, and such change is becoming more pronounced in recent years. As a result, a sense of community has become further weakened, and implementing community-based action and planning requires additional efforts to motivate the participation of diverse stakeholders. The effects of a community-based policy such as the CRVDP should be realized at the overall level of the community, and the benefits of such a project should be equitably distributed to the majority of residents. However, from the outset, the CRVDP was designed in a way that participation was easier for a specific group of the rural population. A discriminatory distribution of economic surpluses and monopolization of accrued benefits by certain groups can threaten rural communities and undermine the legitimacy of a government policy.

Prospects of economic gains provided by external resources such as the CRVDP can divide a community in the absence of either a sense of community or a benefit-sharing mechanism. Therefore, rural village development projects should be designed to be more inclusive with respect to demographic characteristics and promote an environment under which an equitable benefit-sharing mechanism emerges within the community. Additionally, a more fundamental effort should be directed at incorporating strategies that can generate a sense of community and social cohesion in rural societies.

Chapters 3 and 4 dealt with strengthening the viability of rural societies using endowed or internal resources. Chapter 5, on the other hand, is concerned with external resources that are being heavily invested in urban areas vis-à-vis rural areas. In Chapter 5, the study explored the benefits of transportation infrastructure by examining the subsequent change in agricultural income after the improvements in transportation accessibility from 2005 to 2015 in Korea. The effects were analyzed from both the micro- and macro-levels from the perspectives of individual farmers and rural districts.

The lack of access to transportation infrastructure, in particular, hinders rural residents from participating in labor and agricultural markets. That is, access to transportation infrastructure generates benefits to the agricultural sector. The linkage of such benefits is straightforward because the increase in market accessibility and the expansion of markets facilitate farmers earning a fair return for their product while the reduction in travel time and distance decreases freight and logistics costs. Because better access to markets bolsters agricultural productivity and profitability, transportation infrastructure that specifically targets the development of the agricultural sector and rural areas should result in positive benefits to farmers by raising their income from farming.

However, the negative empirical results lead to a discourse on economic efficiency versus equity in transportation policy in the wider context of the deepening regional economic inequality in Korea. Until today, Korea's transportation infrastructure policy has been promoted as a driver of economic growth by maximizing gross outputs. Thus, the effectiveness of transportation policy has been evaluated based on overall efficiency. Regarding the effectiveness for the agricultural sector, however, the efforts to improve transportation accessibility with the expansion of transportation infrastructure are observed to be not much help in enhancing agricultural outcomes in rural autonomies.

This observation is more pronounced after the 2010s, suggesting that it is closely related to the construction of satellite cities around Seoul and so-called the innovative cities in the non-capital region. It is observed that creating a greater number of growth poles in the non-capital region has been the strategy implemented by the Korean government to achieve balanced regional development. Despite the recognition of past failures caused by the promotion of the growth pole strategy, the overall direction of transportation policy has been unchanged, and the emphasis of which has been efficiency-oriented spatial planning.

As a result, transportation infrastructure investments have been heavily concentrated in urban areas, whereas considerations for the agricultural and rural sectors have been highly inadequate. People in Korea expect that the provision of transportation services by the government should, most of all, be efficient, that is, it should be geared toward maximizing the overall welfare benefits for the country as a whole. As a result, the mobilization of the massive budget for transportation infrastructure has been highly concentrated in the capital region and some industrial centers.

However, if investments in transportation infrastructure are being promoted to achieve balanced regional growth, the policy should be strategically favorable to the agricultural sector because the low level of agricultural income is one of the drivers of the gap in regional economic inequality. Therefore, it is recommended that a paradigm shift in transportation policy to remedy past failures should be an equity-oriented policy aimed at inclusive growth targeting farm households for balanced regional development.

6.2. Limitations of the Studies and Future Research

The significance of this study comes from its academic and methodological contributions. Findings from the three empirical essays help to seek directions for future rural policies, and the methods applied in the three essays suggest pragmatic policy evaluation approaches to support realization of evidence-based policymaking. Nonetheless, there are still a number of limitations mostly related to the data availability.

The first essay has an academic significance in that its empirical findings prove the positive impact of the CRVDP, the assessments of which have remained controversial in the absence of a scientific evidence. Nevertheless, the CRVDP was implemented at the village level (*ri*), but the data was available at a higher district level of towns and townships (*eup* and *myeon*). As a consequence, the study conducted the analysis at the level of towns and townships under which the CRVDP-implemented villages form a part. Also, the CRVDP was a community-driven project which renders it necessary to control regional characteristics but the study was not able to reflect such variables in the model due to data limitation. Moreover, although this study narrowed down the target indicator of the project effectiveness to agricultural income, future studies that explore the project effectiveness with respect to quality of life, the explicit goal of the project, as well as indirect societal effects such as in and out-migration would allow the estimation of broader project impacts.

The change in rural demography in Korea over the last decade is increasingly noted, but how such change affect rural policy outcomes remains understudied. The second essay explored such a timely issue by analyzing the effectiveness of the CRVDP by birth and experience cohorts. Large enough sample sizes for each birth and experience cohorts were obtained, but in 2010, the number of rural in-migrants were not as large as today. Reflecting that the flow of urban-to-rural migrants had grown significantly since 2011 and the flow of in-migrants who are less than 40 years of age has evidently increased since 2016, future studies on the recently implemented projects using more recent data would be able to capture more dynamic picture of changing rural demographic trend.

The third essay appears to be the first academic attempt to analyze the impact of transportation infrastructural investments on farm households' income. The findings are highly reliable as similar results were derived at different levels of analysis using two different econometric models. Also, it has an academic significance in that it adopted transportation accessibility data on a rural topic since the application of such data has been limited to urban studies. However, if it was possible to obtain a set of regional data at a lower level such as *eup* and *myeon* instead of *si* and *gu*, more specified results that solely concern rural areas could have elucidated the impact of improved transportation accessibility on farm households' agricultural income at a more rigorous level. For the purpose of this study, its impact on agricultural income was examined, but it seems necessary to extend the study incorporating nonfarm income to conduct an empirical study of the impact of transportation infrastructural investments on the overall income of farm households.

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Appendix

Appendix A.

Table A-1. Number of Rural-to-Urban Migrated Farm Households, 2009-2019

Year	Number of Households
2009	4,080
2010	4,067
2011	10,075
2012	11,220
2013	10,923
2014	11,144
2015	11,959
2016	12,875
2017	12,630
2018	11,961
2019	11,422

Source: Statistics Korea

Appendix B.

Table B-1. Descriptive Statistics of Project Implemented and Not-implemented Areas in 2005 and 2015

	2005				**2015**			
	Implemented		**Not-Implemented**		**Implemented**		**Not-Implemented**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D
Ag. INCOME	15.5567	1.4909	15.5004	1.5118	15.8342	1.4908	15.6327	1.5225
AGE	61.4844	11.0334	60.8388	11.0930	65.9798	10.9077	64.9052	10.9964
AGE_SQ	3902.06	1313.56	3824.41	1315.25	4472.30	1402.48	4333.60	1398.09
GENDER	0.8270	0.3782	0.8380	0.3684	0.8202	0.3840	0.8314	0.3744
MARRY	0.7883	0.4086	0.8021	0.3984	0.7665	0.4231	0.7887	0.4083
HHNUM	6.5789	4.1412	7.2310	4.2797	7.7809	4.1896	8.5965	4.2956
EDUY	60.4305	56.8310	70.6038	63.7423	78.0942	64.3175	92.3516	71.1499
EDUY_SQ	2.5427	1.3052	2.7299	1.3952	2.2221	1.0922	2.3779	1.1620
NEW	0.0395	0.1947	0.0538	0.2256	0.0560	0.2300	0.0644	0.2454
INFO	0.1128	0.3163	0.1118	0.3151	0.1877	0.3905	0.2014	0.4011
OTHER	0.0864	0.2809	0.0866	0.2813	0.1762	0.3810	0.1852	0.3885
CROP2	0.4814	0.4997	0.5125	0.4998	0.3889	0.4875	0.4252	0.4944
CROP3	0.1164	0.3207	0.1211	0.3263	0.1718	0.3772	0.1755	0.3804
CROP4	0.2322	0.4222	0.2124	0.4090	0.2859	0.4518	0.2572	0.4371
CROP5	0.0678	0.2515	0.0696	0.2545	0.0574	0.2326	0.0510	0.2199
S_PLACE1	0.0991	0.2988	0.1058	0.3076	0.1197	0.3246	0.1091	0.3117
S_PLACE2	0.3065	0.4611	0.2617	0.4396	0.3847	0.4865	0.3602	0.4801
S_PLACE3	0.3474	0.4762	0.3184	0.4659	0.1902	0.3925	0.1579	0.3646
S_PLACE5	0.0924	0.2896	0.1103	0.3132	0.0852	0.2791	0.0967	0.2955
N	21,951		47,062		17,686		39,344	

Table B-2. Descriptive Statistics of Project Implemented Areas in 2005 and 2015

	2005		**2015**	
	Mean	S.D.	Mean	S.D.
Ag. INCOME	15.8159	1.4812	15.8448	1.4875
AGE	61.5581	10.9929	65.8776	10.9604
AGE_SQ	3910.23	1308.42	4459.99	1406.17
GENDER	0.8261	0.3790	0.8177	0.3861
MARRY	0.7864	0.4099	0.7646	0.4243
HHNUM	6.5969	4.1304	7.7987	4.1864
EDUY	60.5789	56.9942	78.3436	64.2047
EDUY_SQ	2.5484	1.3222	2.2204	1.0925
NEW	0.0382	0.1916	0.0520	0.2220
INFO	0.1094	0.3121	0.1883	0.3910
OTHER	0.0861	0.2805	0.1774	0.3820
CROP2	0.4761	0.4994	0.3844	0.4865
CROP3	0.1179	0.3225	0.1727	0.3780
CROP4	0.2322	0.4222	0.2812	0.4496
CROP5	0.0696	0.2545	0.0619	0.2410
S_PLACE1	0.0989	0.2985	0.1138	0.3176
S_PLACE2	0.3067	0.4611	0.3913	0.4881
S_PLACE3	0.3445	0.4752	0.1859	0.3890
S_PLACE5	0.0931	0.2905	0.0885	0.2840
N	22,114		17,376	

Appendix C.

Table C-1. Number of Observations by Age and Experience Cohorts in Policy Implemented Areas

Experience Cohort	**Age Cohort**					
	AC1	AC2	AC3	AC4	AC5	Total
Beginning	1,045	3,985	6,681	6,747	2,640	21,098
Early-career	698	4,163	5,986	5,080	3,207	19,134
Experienced	335	9,662	50,027	79,639	85,608	225,271
Total	2,078	17,810	62,694	91,466	91,455	265,503

Table C-2. Number of Observations by Age and Experience Cohorts in Policy Not-implemented Areas

Experience Cohort	**Age Cohort**					
	AC1	AC2	AC3	AC4	AC5	Total
Beginning	1,010	3,943	6,737	6,860	2,543	21,093
Early-career	672	4,087	6,080	5,169	3,187	19,195
Experienced	296	9,338	49,909	79,913	85,759	225,215
Total	1,978	17,368	62,726	91,942	91,489	265,503

국문초록

농촌 및 공간정책의 농업소득 성과에 관한 선험적 고찰

- 농촌마을종합개발사업과 교통SOC를 중심으로 -

최 은 지

농경제사회학부 지역정보전공

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본 연구의 목적은 체계적이고 과학적인 정책평가모형을 구축하고, 우리나라 농촌지역에서 시행된 대규모 공공정책의 효과성을 실증적으로 분석하는 데에 있다. 본 연구에서는 농정 전환기에 시행된 대표적 농촌정책인 농촌마을종합개발사업과 교통SOC 투자에 따른 교통접근성 개선이 농업소득 증진에 미치는 영향을 정량적 평가기법을 활용하여 사후적으로 분석하였다. 본 논문은 3개의 실증분석으로 구성된다.

첫 번째 실증분석에서는 가용자료를 고려하여 헤크만선별모형(Heckman Selection Model)을 이용해 선택편의를 보정하고, 해체기법(Decomposition Method)을 활용하여 농촌마을종합개발사업 시행에따른 농업소득 증대효과를 분석하였다. 분석 결과 사업시행지역은 미시행지역에 비해 농업소득 증대효과가 존재하는 것으로 나타났으며, 사업시행지역은 사업시행 이전보다 농업소득이 증가하여 정책효과가 있는 것으로 평가되었다.

두 번째 실증분석은 성향점수매칭(Propensity Score Matching)과 APC(Age-Period-Cohort) 모형에 기초한 이중코호트 모형(Double Cohort Model)을 적용하여 농업인의 연령과 영농 경력에 의해 분류된 코호트별로 농촌마을종합개발사업의 농업소득 증진 효과를 분석하였다. 분석 결과 농촌마을종합개발사업은 경력 초기단계 청년 농업인의 고소득 가능성을 높인 것으로 나타난 반면, 중년 및 노년기 농업인 코호트에 있어서는 그 효과가 미미했던 것으로 분석되었다.

세 번째 실증분석은 다층모형(Multilevel Model)과 공간계량모형

(Spatial Econometrics Model)을 활용하여 교통SOC 투자에 의한 교통접근성 개선이 농업소득에 미치는 영향을 미시적 수준의 농가단위와 거시적 수준의 지역단위 측면에서 분석하였다. 결과에 따르면 2005년에는 교통접근성의 변화가 농업소득에 긍정적인 방향으로 작용한 것으로 분석되었으나, 2010년 이후에는 별다른 영향이 없거나 부정적인 방향으로 작용하는 것으로 나타났다.

본 연구는 공공정책의 중장기적 성과 및 재정 투입 효율성 평가에 대한 객관적이고 과학적인 분석이 요구되는 상황에서 이용 가능한 객관적 통계자료를 기반으로 체계적이고 정량적인 평가모형 방법을 제시하였다는데 일차적 의미가 있다. 또한, 기초통계 및 정성적 지표 위주의 정책평가가 주를 이루었던 농촌정책 부문에 정량적 사후평가모형을 적용하여 평가결과의 통계적 타당성을 제고하였다는 점에서 의의가 있다.

Keyword : 정책평가, 준실험설계, 헤크만선별모형, 코호트분석,
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