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MEASURING TECHNICAL EFFICIENCY IN AGRICULTURAL EXTENSION SERVICES

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Abstract

With rapid technological advances in the second half of last century, the increasing dependence on science-based agriculture has placed greater importance on the fast and efficient transfer of the advanced knowledge to farmers. For most of countries, without an efficient agricultural sector, a country is severely constrained in its ability to feed itself and in consuming other goods and its development.

Agricultural extension is one of the most common forms of public support to enhance the agricultural productivity. With costs rising, limited resources available, decreasing proportion of agricultural sector in the economy and changes in the prevailing philosophy of the appropriate extent of government intervention, it becomes more imperative to improve the performance of agricultural extension.

Our research focuses on quantifying these changes brought up by agricultural extension. Existing literature on this quantification work on agricultural extension is scarce and inconclusive. Measuring the technical efficiency in a variety of fields has achieved rapid progress via the newly adopted econometric toolboxes; however, the corresponding work in agricultural extension failed to keep in pace. One particular aspect that has been overlooked in agricultural extension literature is the possibility of sample selectivity.

Given the public goods nature of agricultural extension, one should distinguish between the two production processes that are involved. In the first stage, an intermediate output is produced using only discretionary inputs (i.e.,variable and controllable by the decision making unit). In the second stage, final outcomes are determined by the level of the intermediate output and by environmental (i.e.,fixed) variables.

In quantifying the technical efficiency levels present at the farm level, we extend the existing framework on measuring technical efficiency to account for sample selectivity. Stochastic production frontier approach with accommodations for sample selectivity is used to measure technical efficiency and technical efficiency scores of individual farm. In addition, we test for sample selectivity from the statistical causal effect perspective.

An empirical study is conducted based on this extended framework and some hypothesis testing of our interest will be done as well. Our study confirms the existence of sample selectivity from both econometrical and statistical approaches. Efficiency scores are calculated based on our econometrical estimation procedure. Comparisons between farms receiving and those not receiving extension visits are made. We find that there is no significant difference in the level of technical efficiency between these two types of farms. However, farms receiving the extension services have higher productivity level than those not receiving extension services. This finding is consistent with the existence of sample selection. Farms' herd behavior, debt/asset ratio and education level are identified as possible sources of sample selectivity. We also reinforce the conclusion of the existence of sample selectivity following causal inference approach. Several matching algorithms are conducted. Similar conclusions are drawn as in the econometric approach.

At the macro level, a static game theoretic model with incomplete information adapted from mechanism design is developed to characterize the interactions among all participants in the two production processes. Extension agents are assumed to have up to three different types characterized by productivity levels. The government's objective is to maximize social welfare by setting up a truth-telling mechanism subject to a set of constraints. Equilibrium results and policy implications are discussed. To our knowledge, this is the first attempt to analyze the interactions of the government, extension agents and farms using game theoretic model. A simulation study is conducted to learn the comparative statics, which is based on the two nonlinear equation systems provides us insight into the impact of productivity difference among agents on economic variables of our interest.

Based on our study, policy implications can be multi-fold. At the micro level, policy makers should alleviate the possible influence of sample selection in farm's choices of extension services. Several instruments identified in our analysis including educational level, debt status can serve for such a purpose. At the macro level, we establish a solid foundation that government should be less involved in specific production process of extension service. Our findings are consistent with the decreasing resource allocation to agricultural sector and the increasing financial, human resource input by nongovernment organization and many other private sectors. In addition, the different reaction patterns to the changes in relative productivity may guide policy makers to design mechanisms suitable to different types of extension agencies. In particular, the different price reaction curves to the change in relative productivity may be studied so that extension agencies charger different prices to different farm types. In this case, the true demand rather than the demand distorted by sample selectivity can be more accurately identified.

Following future research is of our particular interest. Our estimation of stochastic production frontier function is limited due to data availability in several aspects. In particular, farm types are classified as receiving and not receiving extension services. The exploration may go deeper if we can further distinguish between private and public extension service provision. Increasing the number of individual farms in our data set would make it possible to compare the performance of private extension services to that of public extension services.

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Chapter 1

Background Introduction

With the emergence of rapid technological advances in the second half of last century, the increasing dependence on science-based agriculture has placed greater importance on the fast and efficient transfer of these advances to farmers. Farmers and society, in general, benefit from access to and adoption of improved information because it is likely to result in increased productivity and possibly other benefits, such as improved environmental quality. Moreover, rapid advances achieved in information technology further accelerate and expand the avenues for knowledge transmission.

Agricultural extension service is one of the mechanisms of transferring knowledge from research community to practitioners. Originally, it was a publicly funded activity using resources from federal, state and local governments. This service converts the results from agricultural research into practice and thus agricultural research will be more demand-driven as feedback from farms can be transmitted back via agricultural extension services.

1.1 Agricultural Extension: Definition and Its Functions

The goals of agricultural extension service delivery has evolved over time. Some definitions are broad and specific, and others are abstract. The traditional concept of agricultural extension includes as agents a professional body of agricultural experts(generally governments, nonprofit organizations, and private enterprises) who teach improved methods of farming, demonstrate innovations, and organize farmer meetings and field days on a wide range of topics. Extension also functions informally as farmers transfer their best practices to one another. Namely, it serves as a link between farmers to transfer the "best practices", and as a channel to introduce and sometimes enforce agricultural policies.

A commonly cited definition of agricultural extension is from the Food and Agricultural Organization (FAO) of the United Nations, where it is defined as a service assisting farmers through educational programs in improving their farming methods and techniques, increasing production efficiency and income as well as improving their standard of living and lifting their social and educational standards (Maunder, 1973). At the outset, it is a tool by which technical information is passed to the farmers to promote the development of agriculture. In contrast to other definitions, the FAO definition is more comprehensive in the sense that it covers not only the objective but how to achieve it.

A more recent definition is provided by Leeuwis and den Ban (2004) where agricultural extension is defined as "a series of embedded communicative interventions that are meant, among others, to develop and/or induce innovations which supposedly help to resolve(usually multi-actors) problematic situations". This definition focuses on innovation transmitted by agricultural extension services.

In all these definitions, we find that agricultural extension services encompass a wide range of activities, but the exchange of information continues to be the primary focus of extension activities (Hayward, 1989; Lafourcade, 1988). However, extension service provision has been criticized as inherently emphasizing the "top-down" dissemination of information while ignoring other types of information flows between farmers, extension and research, particularly activities involving farmers as equal partners in the process. A second criticism is that it is important to distinguish between agricultural research and agricultural extension services. Although the linkage between agricultural research and agricultural extension services is apparent, the former focuses on "the technical aspects for generating useful technologies and the latter mainly deals with the acceptance and adoption of those technologies by the users"(Qamar, 2005).

Along with a variety of definitions, the pace of change in the extension services organization, functions, strategies, and approaches of agricultural extension is clearly accelerating. Conventionally, extension services comprise of the following functions (van den Ban and Hawskins, 1996):

(1) Diagnosis of farmers' demographic conditions of their strength and weakness.

(2) Information transfer via training courses/seminars and mass media, and through direct visits to farms. Enable farmers to clarify their own goals and possibilities.

(3) Feedback to researchers on farmers' reactions to new technology to modify future research.

(4) Development of linkages with researchers, government planners, non-governmental organizations, banks and the private commercial sector. In remote areas, extension agents take on a number of input supply functions directly.

These functions are of continuous interest in the contemporary dialogue, as is evident in workshop on public extension services convened by the World Bank, the U.S. Agency for International Development, and the Neuchatel Group to review recent approaches to revitalizing extension services (World Bank, USAID, and the Neuchatel Group, 2002).

1.2 Agricultural Extension: Past and Present

1.2.1 Origins

Agricultural extension has a long history. The term extension was first introduced in England to describe adult education programs in the second half of the 19th century. These programs helped extend the work of universities beyond the campus and into the neighboring communities. The term was later adopted in the United States, while in Britain it was replaced with "advisory service" in the 20th century. A number of other terms were used in different parts of the world to describe this similar concept. In most developing countries, the terminology used to establish agricultural extension is generally associated with the donor agency that helped establish the service(Swanson, 2008). The literature uses both terminologies of extension services and advisory services, especially in sub-Saharan Africa. Advisory services reflects the official closeness of extension systems with Ministries of Agriculture. Our study does not make a clear distinction between these terms and uses the terminology agricultural extension services provision.

In its formative stage in the early years of the 20th century, agricultural extension was relatively small in scale, limited in the scope of the work and contact with farmers, and its organization was often somewhat haphazard even though it was based on legislation(Swanson, 2008). It was organized predominantly by (a) central or local governments, (b) by agricultural colleges, usually in close association with experiment stations, (c) by farmers' organizations (agricultural societies, cooperatives, farmers' unions, or chambers of agriculture), or (d) combinations of these parent bodies. The organizations became well established later on. Changes often occurred to its parent affiliations, objectives became broader and the extension personnel are better trained and more professional.

In most countries, agricultural extension did not become institutionalized until the 1950s. Several countries which gained independence in the post World War II period viewed agricultural extension services as essential for promoting agricultural growth and enhancement of the use of modern inputs necessary to support government import substitution and industrialization policies. Thus, agricultural ministries were reorganized to include extension units (Prawl et al., 1984).

In addition, several other organizations developed comparable activities: agriculture-related commercial companies, agricultural commodity marketing boards to manage the supply and quality of their specific product, agricultural development projects involving considerable territorial scale, and a variety of nongovernmental organizations(especially religious and charitable) involved in agricultural and rural development. In many countries in the 1950s and 1960s, extension was linked to specific capital investments to ensure that farmers had sufficient access to inputs and technical information to make optimal use of, for example, irrigation infrastructure. Support for extension was broadened via integrated rural development projects in the 1970s.

There are several forces driving the change of agricultural extension services provisions, in terms of its definition, functions and participants, etc. The following forces appear to be necessary for the initiation and organized development of agricultural extension work. The first condition is that information has been assembled, systematized, and made available to certain agricultural practices, and is based on either the accumulation of experience or findings from research. Second, this information is used to educate extension agents who may further enlarge or refine this body of knowledge or become active promoters and disseminators of the information. Third, an appropriate administrative or organizational structure exists by and within which the dissemination activities may be established and conducted. Fourth, there is a legislative, other official mandate or influential proponent which prescribes or enables that agricultural extension work is desirable and must occur. All or several of these conditions have been present in the evolution of modern forms of agricultural extension.

These conditions hold when there are positive externalities to innovation or market failure in agricultural service provision. Market failure is often due to unorganized demand and supply. Unorganized demand arises from small scale farmers not recognizing potential benefits, having limited purchasing power, and are not organized to access services. Unorganized supply takes into consideration that few individuals or institutions are capable of providing technical services or there is limited opportunity for private firms to charge for provision of easily disseminated information.

Public sectors has been playing the dominant role in transmitting information including extension services to farmers. The rationale behind the strong role of public extension services is summarized by Farrington (1995), where five major roles are discussed. A major reason is that much of the information related to technological innovation and transfer is public good in nature. Therefore, it is argued that farmers will receive less than optimal level of information as long as it is inappropriate by the private sector. Other compelling reasons include agricultural production involves greater risk and uncertainty than other production activities. Public provision of information is one way of reducing such risk and therefore enhancing overall production stability. Another argument is related to regional balance. In particular, public action is needed to enhance the incomes and, ultimately, participation in civil society of people on the periphery. Public action is needed to enhance incomes and ultimately participation of people in civil society. The fourth argument is that the institutional and physical infrastructure for information provision is often poorer in areas beyond the immediate radius of administrative and commercial centers. The last reason is the potential adverse selection problem; in particular, when the quality of the input and the locally appropriate levels of application are uncertain, public provision of information allied with the application of technical standards can reduce these.

In pursuit of the above arguments, public sectors have been dominant in agricultural extension services provision until the 1980s. One extreme example was that the World Bank committed over US$\$1000m$ during the 1970s to smallholder projects involving research and extension (mostly in terms of Training and Visit), rising to US$\$4700m$ in the 1980s. Huffman and Evenson (2006) estimates that in excess of 1 billion US dollars is spent annually on agricultural extension by government agencies in the US and 6 billion dollars per year (and 600,000 extension workers) spent globally on servicing the extension needs of farmers. The involvement of the World Bank in funding Green World Technology in developing countries has resulted in studies that attempt to directly evaluate the effectiveness of extension services to farmers in these countries. Of course many successes are attributed to public sector extension as a return to investment.[1]

Between 1950s and 1990s, most countries expanded the size of their extension staff and the extension staff to farmer ratio differs dramatically across countries. However, the number of agents working to provide extension services has uneven distribution around the world. About 95 percent of extension staff work in public agricultural extension systems (Umali and Schwartz, 1994), and 90 percent of extension workers in the world are located in developing countries, over 70 percent in Asia alone. Extension coverage (the ratio of extension personnel to farmer population) by public extension services in developing countries varies from $1 : 1,800$ to $1 : 3,000$. Developed countries of Europe, North America, and Asia have ratios averaging about $1 : 400$. Although staff numbers are high in many developing countries, staff quality is often low. Fiscal constraints face managers of public extension systems, forcing them to hire staff with low skills to cut operational costs. FAO found 40 percent of extension personnel had only a secondary school education, and another 33 percent with an intermediate diploma or certificate.

[1]An example is the Plum Pox Eradication program which requires a team engage in research and education. In October 1999, plum cox was discovered in Adams County peach trees. State and federal officials, Penn State researchers and extension educators, and local growers cooperated together and finally get the virus eliminated.

In the near future, the need for agricultural and rural information and advisory services is likely to intensify. In much of the world, agriculture faces the challenge of keeping pace with rapidly increasing population with few reserves of potentially cultivable land. Farmers will have to become more efficient and specialized. Combined with the forces discussed above, these together become the motivation of the new trend in agricultural extension services provision.

1.2.2 New Trend toward privatization

With costs rising, resources limited, the declining proportion of agricultural sector in the economy and changes in the prevailing philosophy of the appropriate extent of government intervention, governments have been slow to increase appropriations for many publicly funded activities. Some functions of government have been curtailed, and others have been privatized. Such changes have been particularly significant in the formerly centrally managed economies (Swanson et al., 1990).

The private sectors have been taking on more responsibilities of providing agricultural extension services to farms. In particular, agro-processing and marketing firms worldwide have provided agricultural extension services to their farmer suppliers as a means of reducing input supply risks. Extension services are typically an integral component of contract growing schemes involved in the production of high value commodities. These firms generally supply farmers with information on new techniques and technologies to increase output, reduce postharvest losses and improve quality, consistency, and timeliness of output (Schwartz, 1994). Moreover, opportunities for small farm operators to acquire technical information from sources other than public sectors have been expanded rapidly, which include improved transport networks, widely used telecommunication technologies and improved literacy levels which make both hard and soft copy more popular.

In most industrialized countries private investment in agricultural research has surpassed that of the government. Several countries have fully or partially privatized their agricultural extension services in different ways. For example, Denmark, France and Finland received most of support from private sources . The emergence in agricultural biotechnology has given even greater impetus to private investments in agricultural research. In developing countries, private investment in research is growing faster than spending on public research but still appears to play a relatively small and limited role as a source of agricultural productivity growth (Rivera et al., 2000).

The organizational forms taken by private extension services provision vary over spaces. At the beginning, private research in developing countries was in the agricultural sector itself. In Asia, an early example was the tea industry in the colonial period of eastern India, where tea leaf production was affected by an insect pest. Tea planters self financed themselves so that they could hire an entomologist to develop solutions to the problem. In Latin American, agricultural research was initiated by some of the haciendas, or large estates and ranches. These private enterprises were large enough that they could afford to have their own crop and animal breeders who could develop improved varieties and breeds, as well as to sell seed and breeding stock to neighboring farms. In 1992, Chile launched an extension project that included subcontracting extension services to private consulting firms(Umali-Deininger, 1997). To qualify subcontractors under the plan, private firms must meet technical and professional staffing criteria. Similar programs have also been launched in Mexico(World Bank Operations Evaluation Department, 1994).

However, it is noted that the increasing role of the private sector(whether for profit or not for profit) in agricultural extension can not completely take the place of public extension services. Indeed, both economic and social reasons justify some public financing of extension. Kidd et al. (2000) discusses that there are some important extension functions and topics which will not be absorbed by the private sector. For instance, extension projects dealing with issues with long-term consequences such as the conservation and stabilization of the natural resources, assignments in remote areas, unattractive subjects and work with the most disadvantaged groups in a society will remain in the public domain. Cary (1993) refers to these as the social determinants of the government level support.

These perceivable facts indicate that private extension services provision is not completely supplementary to public extension and vice versa. In the future, it is unlikely that private sectors be in place of public sectors. FAO(2005) discusses the pros and cons of public and private extension services. The benefits of private extension include increased efficiency, improved quality, client-orientation, job satisfaction for staff, and expanded marketing opportunities for farmers. The problems include loss of government authority, the government's inability to keep financial promises, and weaker communication with the stakeholders because of creation of competition among them.

1.3 Efficiency and Sample Selection

We have established the importance of the provision of agricultural extension services and its status quo. Efficient agricultural extension can bridge the gap between progress in the laboratory and feedback in the individual farmer's field. In addition to information about cropping techniques, optimal input use, high-yielding varieties, and prices, extension agents can inform farmers about improved record keeping and aid in the development of their managerial skills, and thus facilitate a shift to more efficient methods of production.

A natural question to ask is how well agricultural extension services perform. The performance of agricultural extension services is an important subject of study mainly due to the policy implications. In the framework of economics, researchers usually quantify the performance by efficiency and productivity. There are several methodological issues in the impact measurement of the agricultural extension services. Moreover, the evaluation is subject to problems that also appear in the evaluation of other public sector investments.

First, it is noted that the dynamics of information diffusion which might make the extension services efficient in the early stage and then less efficient later on. If the analysis focuses on a later period in which knowledge has already been fully diffused and no new technology is generated, the impact of extension may be judged as small while, in fact, it has been very effective in earlier stages(Birkhaeuser et al., 1991). A second relevant issue is the distortions that result from other policies. The diffusion of improved technology may be slowed down by policies that discriminate against agriculture and thus causes a low return to investment in extension, which could be high in the absence of such distortions.

Second, current studies on the performance of agricultural extension service provision have not rigorously considered the potential sample selection issue. Ideally, the extension impact should be evaluated in a framework resembling a random experiment. However, it is difficult to find situations where an actual experiment has been undertaken. Thus, there are potential biases in the estimation of the effect of extension on production depending on the level of analysis. On the one hand, extension agents may choose certain class of farms based on a profit maximization criteria. On the other hand, individual farms with different productivity/efficiency levels may have different demand elasticities of extension service. Both of these possibilities may create potential sample selection bias. Efficiency measurement with possible sample selection issues will be one of our main focuses.

1.4 Motivation and Justification

Agricultural extension services provision is a subject of interest for government and non-governmental extension agents as well as for farm operators, the main beneficiary of the services. Considerable research regarding the basic description of agricultural extension services provision, its current situation and its future prospects, as well as its performance either on the country level or on a regional basis. The foundation and basis are well established and our study will follow these notions on definition, and functions of agricultural extension services. However, the study on the performance of agricultural extension services needs further development.

Birkhaeuser et al. (1991) reviewed hundreds of papers on the evaluation of the productivity(efficiency) of the extension services using individual and aggregate farm data. Nonetheless, the methodology in evaluating the efficiency of providing extension services is limited in the sense that the literature tends to adopt a similar approach to quantify the efficiency of extension services. A detailed review on the paradigm of efficiency studies is presented in Chapter 2. Most performance-evaluation research focuses on moderate modifications as the main qualitative tool in empirical econometrics including assessing the efficiency of extension services. Under this general approach, farm operators are assumed implicitly to operate at their respective production frontier. Agricultural extension studies had a stagnating period characterized by a passive response approach via measuring a shadow value of the presence of extension.[2] The gap between the econometric approaches and the previous studies on efficiency measurement of extension provides us with a motivation to incorporate the new methodology into measuring the performance of extension services. In particular, this study contributes to the literature of measuring the performance of agricultural extension by addressing the sample selectivity issues in the framework of stochastic production frontier models.

Another important aspect in agricultural extension services missing from the literature is that as the privatization of extension services develops, it becomes more imperative to study the interactions among all the participants in agricultural extension services, including the government, agricultural extension agencies and farms. A feasible perspective is to develop a game theoretical framework to characterize each participant's equilibrium strategy. If an equilibrium solution for all players exists, policy makers will have solid ground to design a policy scheme so that the resources of extension agencies can be allocated more efficiently.

1.5 Goals and Objectives

This dissertation takes on both microeconomic and macroeconomic perspectives of the provision of agricultural extension services. At the micro level, a case study of how extension service provision impacts farm decision making in the presence of sample selection is explored with a case study of Greek agriculture. At the macro level, a mechanism is designed where the government can provide a set of optimal policies to help extension services achieve higher social welfare given a fixed budget.

With two different production processes involved, it is important to distinguish the two types of productivity in the production of extension services. First, the extension agents use capital, labor and other inputs to produce information and expertise. Second, farm operators use the traditional inputs together with the technical knowledge transmitted by the extension agents to produce the final outputs. Both processes involve

[2] Dinar et al. (2007) is an exception: stochastic production frontier approach is implemented to evaluate the performance of agricultural extension service provision.

a production efficiency issue which is important to the extension agents. Analyzing the productivity of the first production process addresses the problem of the extension agents to make full use of the available resources. For the second process, with the knowledge of farms' performance, the extension agents can have a better understanding of the demand from the farmers.

Not all producers are technically efficient. As opposed to conventional microeconomic theory, such a statement implies that not all producers are able to utilize the minimum quantity of required inputs to produce the desired quantity of output given the available technology. Similarly, not all producers are able to minimize necessary costs for the intended production of outputs. Specifically our goals in this study are:

1. Construct an empirical model to estimate the efficiency of agricultural extension services on farm's output using stochastic frontier production framework.

2. Based on the stochastic frontier framework, develop the specification of sample selection that can emerge in the process of providing extension services to farms. A causal effect estimation is adapted from the statistics literature to provide extra evidence of our econometric analysis on the existence of sample selectivity.

3. Based on the estimation results, generate the efficiency score of each farm, and then conduct a series of hypothesis testing to explore some underlying relationships among the parameters. Moreover, we conduct a robustness check on sample selectivity.

4. Build a game-theoretic framework to address the interaction between government, extension agencies and farmers. My main focus is on the provision of private extension service. The government funds but does not provide the extension services directly. Instead, they act as a central planner deciding what the prices of extension services are and the tax rate. Extension agents now charge a fee for what they provide to the farms. Farms productivity is assumed to be impacted by extension contacts. Under this set up, we analyze the equilibrium number of the extension contacts and optimal quantities of other variables in the model.

5. Given the equilibrium quantities derived in the game framework, a series of simulation studies will be conducted and the relationships between the productivity

and other economic variables of interest will be analyzed based on which policy implications can be drawn.

1.6 Dissertation organization

The plan for this dissertation proceeds as follows. Chapter 2 reviews the literature regarding how to define technical efficiency and measure the technical efficiency including the econometric issues involving in the measurement. General public goods provision is reviewed first, followed by defining technical efficiency, and the review on agricultural extension provision. We distinguish two different production processes and investigate each of the processes subsequently.

In Chapter 3, the theoretical framework on extension service provision is developed. A stochastic frontier model with sample selectivity is developed to examine the technical efficiency of extension services. Also, a causal effect model is proposed to provide a robustness check on the sample selectivity issue from a statistical perspective.

Chapter 4 presents an empirical application of the model proposed in Chapter 3. In particular, a specific estimation procedure will be used to obtain the estimation results, on which we based the hypothesis testing. Meanwhile, several procedures are provided to estimate the causal effect and identify the extent of sample selectivity.

Chapter 5 focuses on the first production process described in Chapter 2. A game theoretic framework is developed to analyze behavior of each participant. Simulation study will be conducted to understand the equilibrium outcomes and to learn the comparative statics.

Chapter 2

Literature Review

2.1 Efficiency Measurement Overview

Producer efficiency is a comparison between observed and optimal values of its output and input. The contemporary literature usually distinguishes technical efficiency and allocative efficiency. The technical component refers to the ability to avoid waste by producing as much output as possible using a given input bundle or by utilizing the minimum input bundle for a given level of output. Therefore, the analysis of technical efficiency can have output-augmenting or input-augmenting orientation. Formally, Koopmans (1951) provides a definition of technical efficiency: a producer is technically efficient if an increase in any output requires a reduction in at least one other output or a reduction in any input requires an increase in at least one other input. The allocative component refers to the ability to combine inputs and outputs in optimal proportions and follows from the specification of an economic objective and information on relevant prices (Farrell, 1957) and (Debreu, 1951).

Investigation into efficiency measurement has been evolving over the last 50 years. This is partially due to the assumption of full technical efficiency made in neoclassical production theory contributed by (Debreu, 1951), (Farrell, 1957) and (Leibenstein, 1966). Moreover, when technical inefficiency exists, it is possible that allocative efficiency will be influenced which produce a negative cumulative overall inefficiency

(Kalirajan and Shand, 1992). Consequently, technical efficiency measurement has been the focus of considerable research and policy. Quantification of these measures can be useful in several ways. First, they facilitate comparisons across similar economic units, i.e. relative efficiency. Second, while measurement reveals variations in efficiency among economic units, further analysis can be conducted to identify factors causing such variations. Third, such analyses imply policy implications for the improvement of inefficiencies.

The canonical measurement of technical efficiency usually starts with descriptions of production technology, cost functions or profit functions. These representations of production technology can lead to several different tools to measure technical efficiency providing similar results in essence. Among them, a common tool is the primal production function (Kalirajan and Shand, 1992). In practice, efficiency measurement involves a comparison of actual performance with optimal performance located on the relevant frontier. Since the true frontier is unknown, an empirical estimation is needed, which is regarded as a best practice frontier.

The empirical estimation of the technical efficiency falls into two main categories: (i) data envelopment analysis (DEA) or deterministic approach, and (ii) statistical or stochastic production frontier approach. Farrell (1957) and Charnes et al. (1981) pioneered the work on deterministic approach of measuring technical efficiency. The full development of stochastic frontier production estimation was first proposed by Aigner et al. (1977). Besides these two main approaches,The Bayesian approach was discussed in detail by van den Broeck et al. (1994). The discussion on advantages and disadvantages of these approaches can be found in Chapter 2 of Fried et al. (2008).

DEA, outlined by Farrell (1957) and operationalized by Charnes et al. (1981), is a non-parametric method for estimating production frontiers and evaluating the relative efficiency of Decision Making Units (DMUs). The advantages of DEA over parametric stochastic frontier methods (Aigner et al., 1977) and (Meeusen and van den Broeck, 1977) are its flexibility in multiple inputs and multiple output environment, and robustness with respect to the specification of the functional relationships between inputs and outputs (Aigner et al., 1977) and (Meeusen and van den Broeck, 1977). However, since DEA relies on identifying best practice reference units, it can be extremely sensitive to outliers in the data.

To calculate the efficiency of a particular DMU in the basic CCR models [1], mathematical programming techniques are used to determine weights for the relative value of various outputs and inputs that maximize a specific DMU's efficiency score. Therefore, the weights turn out to be the primal variables in the programming. Given the constraint that all other DMU's efficiency scores using that particular DMU's weights are less than or equal to one, a particular DMU may utilize any combination of inputs and outputs to maximize its own efficiency score. Technical inefficiencies are identified with failures to achieve best possible output levels and/or usage of excessive amounts of inputs using a separate linear programming formulation. [2] This approach is widely used in comparing efficiencies of departments, public sectors, organizations, etc.

An alternative to DEA is the stochastic production frontier approach. The classic stochastic model of the frontier production approach assumes that any deviation of the observed production from the theoretical microeconomic production function is caused by purely random disturbances and inefficiency. The deviation is characterized by the composite error term in the stochastic frontier model. The purely random component captures the effect of variables that are beyond the control of the production unit being analyzed (eg., weather, bad luck and other random shocks). A main advantage of the stochastic frontier approach over DEA is that it isolates the influence of factors other than inefficient behavior, thus correcting the possible upward bias of inefficiency from the deterministic methods. The stochastic production models of Aigner et al. (1977) and Meeusen and van den Broeck (1977) are motivated by these considerations. These path-breaking papers introduced the composed error model that allows not only inefficiency, but also stochastic factors. Firm-specific estimates of inefficiency were provided by Jondrow et al. (1982), who suggested estimating the expected value of the inefficiency component conditional on the measured overall error.

The concept of stochastic production frontier has received tremendous amount of attention among researchers and policy makers. Since the work by Aigner et al. (1977)

[1]DEA was first introduced by Charnes et al. (1981),the so-called "CCR" model was named after these authors.

[2]It is important to note that DEA models produce only relative efficiency scores in comparison to all other DMUs.

and Meeusen and van den Broeck (1977), several alternative models for estimating productive efficiency have been developed, extending the stochastic production frontier methodology to account for different theoretical issues in frontier modeling context. Efforts have focused on studying the specification of functional forms and the approaches of estimations and also the derivations of technical efficiency scores.

Also, extensions were implemented to accommodate more sophisticated production activities. To study the production process where multiple outputs are produced, a parametric version of distance functions was introduced. It can be used to estimate the characteristics of multiple-output production technologies in cases where we have no price information and/or it is inappropriate to assume firms minimize costs or maximize revenues (Coelli and Perelman, 1999).

Another extension is that the stochastic production frontier approach was used to analyze cross-sectional data, and later on panel data (repeated observations on each producer) was applied under the framework. Pitt and Lee (1981) is one of the early studies using panel data analyzing technical efficiency in the Indonesian weaving industry. Most of these have used long-standing extensions of the stochastic frontier model to fixed effects and random effects specifications. They also maintained a strong assumption that technical efficiency is constant over time.

Cornwell et al. (1990) and Kumbhakar (1990) are among the first to propose a stochastic production frontier model with panel data structure and time-varying technical efficiency assumption. They provided a few estimation procedures, including a fixed-effects approach and a random-effect approach. One difference between fixed-effects and random-effect model is that time-invariant regressors cannot be included in the fixed-effects model with time-invariant technical inefficiency. Therefore, a GLS random effects estimator for their time-varying technical efficiency model was developed by Cornwell et al. (1990). They also proposed an efficient instrumental variables estimation procedure to overcome the shortcoming of inconsistency due to the possible correlation between technical efficiencies and regressors. Some other changes to the modeling framework based on Cornwell et al. (1990) can be found in Kumbhakar and Lovell (2000). Greene (2005) identified another problem in the previous literature in addition to the solution to the time-invariant technical efficiency assumption, which is the possibility of other unmeasured heterogeneity that is unrelated to inefficiency.

There are two common approaches to the estimation methodology of stochastic production frontier models: the maximum likelihood estimation (MLE) and the Bayesian approach. Maximum likelihood estimation was the one that originally implemented together with the estimation of parametric specification of stochastic frontier models. However, an analytical solution of the targeted loglikelihood function is not always available. Many variants were developed to get a numerical solution. Among them, simulated maximum likelihood estimation proposed by Greene (2003) is one of the common methods. Two practical issues need to be addressed, generation of random draws from the truncated distribution and the problem of producing the primitive draws for the simulation.

A second widely adopted approach is Bayesian. van den Broeck et al. (1994) was among one of the first research using the Bayesian framework. Koop et al. (1999) generalized the following advantages of Bayesian approach over MLE.

i) obtain exact small sample results in a way that is particularly appropriate for the treatment of very small data set;

ii) focus on any quantity of interest and derive its full posterior distribution. In particular, the full posterior distribution of any individual efficiency or any function of the parameters and the data;

iii) integrate out easily nuisance parameters since each is assigned a probability distribution.

iv) impose economic regularity conditions on the production easily.

Kim and Schmidt (2000) provided an empirical comparison of various methods of estimation for technical inefficiency. The conclusion there is not much difference is found between MLE and Bayesian approach, in the sense that the classical MLE based on a distributional assumption for efficiencies gives results that are similar to a Bayesian analysis with the corresponding prior function.

Most efficiency analysis focuses on private DMU's making decisions under their full control. However, efficiency of DMUs where public goods are considered does not follow exactly the same pattern as in the private sector. In the following section, the efficiency analysis of public goods provision is discussed.

2.2 Efficiency Measurement in public goods provision

Public goods provision covers a wide range of production processes including, for example, health care, libraries, education, police, fire protection, utilities. Given that tax and deficit increases are often politically costly, one way to deal with increasing tasks and tightening budget requirements is to improve allocative and technical efficiency (e.g., Geys and Vermeir (2008)). In much the same way that concerns over allocative efficiency are at the heart of micro-economic theory (e.g., (Leibenstein, 1966) and (Frantz, 1992)), allocative efficiency in the public sector has always been a major concern in public finance. Numerous studies, for example, analyze whether local governments, which often have important responsibilities with respect to education, housing, health care, social welfare, recreation, infrastructure and the environment(including refuse collection), have a tendency to over or under provide public goods (e.g., Brueckner (1979), Brueckner (1982), and Brueckner (1983)). Moreover, scholars studying the decentralization of tasks from higher level governments to the local level often evaluate this evolution in terms of allocative efficiency. Smaller jurisdictions with more homogeneous populations are argued to increase allocative efficiency as they are more capable of matching the provision of public goods with the preferences of their constituents (Musgrave, 1959), while numerous "informal and formal versions of the Tiebout model demonstrate that private allocative efficiency tends to be increased by Tiebout choice"[3] (Hoxby, 2000).

Compared with the study on allocative efficiency, the study on technical efficiency of public services provision has received less attention[4]. In line with the definition of technical efficiency provided, an efficient public services production is one producing the maximum possible output given its input allocation, or one producing a target level

[3]According to WIKIPEDIA, "Tiebout model" is a positive political theory model first described by economist Charles Tiebout in his article titled "A Pure Theory of Local Expenditures" in 1956. The essence of the model is that there is in fact a non-political solution to the free rider problem in local governance.

[4]For some important exceptions, see Hoxby (1999) and Hoxby (2000)

of output with the minimum input allocation.

Methodologically, when researchers analyzed the technical efficiency of public services provision in the early stage until early 1980's, simple ratio measures(such as pupil/teacher ratios) through to regression based measures and data envelope analysis (see Jesson et al. (1987)) are typical metrics.

Under DEA, individual units are designated as efficient when they outperform not only all other individuals in the sample, but also all possible linear combinations of all other individuals. Again, like the DEA framework in any other settings, non-parametric approaches share the common feature that all deviations from the frontier are designated as inefficiency. More recently, the frontier approach is widely used in the efficiency measurement of private sector goods, however, DEA is widely used in the study on efficiency in public sectors. There are only a few studies on public services provision using stochastic production frontier approach. [5] Hemmeter (2006) uses stochastic production frontier approach to study the efficiency of public libraries. Partially, this is due to the fact that not too many DMU's are available for study. Therefore, DEA may be more appropriate in such an environment where each DMU is taken into consideration.

The inputs associated with production can be easily identified in the production process of public goods. But in many cases the direct and immediate output is difficult to quantify in the public sector. A key characteristic of many public services is that without the productive activities of consumers, public services will not produce any virtual value(Parks et al., 1981b). For example, schools require students' (and parents') effort to produce favorable exam results, health care provision can only succeed if doctors' and nurses' orders are followed by patients, waste collection proceeds faster when citizens appropriately bag material and transport it to the curb, and unemployment assistance programs stand or fall with the active engagement of the (long-term) unemployed. Urban scholars discuss the relevance of citizen involvement for a wide and varied range of local public services including fire and police protection, libraries, tax collection, recreation, and among others (Percy, 1984). A second reason is that consumers' welfare (for example, quality of the life) is difficult to quantify, which is the result of public services provision. The technical efficiency measurement is not as straightforward as it is in the

[5]For instance, as reviewed by Hemmeter (2006), nine out of ten studies on efficiency measurement of public libraries used DEA.

case of private goods. There is a built-in tendency for measures of efficiency to be better at comparing the costs of input than the equivalence of outputs (leung Tang, 1997).

In practice, the single output specification was first used by many studies in studying the performance of public services. In the case of public libraries, most studies recognize that libraries provide a range of services, but due to limitations of the methodology, the emphasis focused on attempts to fit an empirical production function in which output is represented by one variable. Although many studies identify and discuss the nature of library outputs, a common practice is to argue that the several outputs are strongly correlated and that one may be used to represent them all. For libraries, the common approach is to use the annual circulation of books (House, 1984).

Later, modern production economics provides a more robust framework for the analysis of multi-product technologies. This richer methodology is applied in several recent studies on public goods provision. Multiple outputs were used as a proxy for the outputs of the public services. For example, passengers and freight services are used in the case of efficiency study on railway systems(Coelli and Perelman, 2000). A sequence of value added test scores are used as multiple outputs in analyzing public school efficiency by Grosskopf et al. (1992). Fernandez et al. (2000) used a parametric aggregator of the outputs and to model the aggregate output through a univariate frontier. The multivariate model is then completed by specifying a Dirichlet distribution on the output shares. Another approach in modeling and estimating multiple output production activities is to construct a multivariate distribution through a copula function which allows for separate modeling of the marginal inefficiency distributions and the dependence (Carta and Steel, 2012).

However, these studies fail to distinguish between the final output of consumer's interest and the direct "potential" output directly produced. Instead, the focus is on treating the provision of public service as simply one production process, focusing on finding appropriate proxies for output(s) and developing a variety of empirical tools to quantify the technical efficiency. As Parks et al. (1981a) point out, a key characteristic of many public services is that "without the productive activities of consumers nothing of value will result". This view of the importance of citizens-consumers as "co-producers" of public service production and delivery was first developed among urban governance and public administration scholars in the early 1980s ((Whitaker, 1980), (Parks et al., 1981b), Kiser (1984) and (Percy, 1984)).

Citizens' co-production indicates that public goods have consumers in their production function. Consequently, it has important implications for measuring public service providers' technical or productive efficiency. As discussed by Cordero-Ferrera et al. (2008), active involvement by the recipient of the service implies that observable outcomes (e.g., library circulation, school results, crimes resolved, fires extinguished) are not really "produced" in a strict sense by the public service provider and thus are inappropriate measures to evaluate their technical efficiency. Given the importance of demand-side factors in the service production process, relying on observable outcomes in productive efficiency analysis may lead to strongly biased inferences of efficiency.[6]

To make sure that one concentrates on the part of production processes that is fully under the control of service provider, a two-stage production process of public goods is developed. The idea was originally adapted from Bradford et al. (1969) in the context of local public services where a careful distinction between the services directly produced and the services of primary interest to the citizen-consumer was made. Hence, the public production process is divided into two stages. In the first stage, local governments produce an intermediate output. In the second stage, the private production uses the intermediate product to produce final outputs. This distinction has important implications for measuring technical efficiency of public services provision. Two technical efficiency measures can be generated from the process since there are two production stages. Duncombe and Yinger (1993) adapted this idea to estimate returns to scale for fire protection where consumers(or voters) care about the saving of lives and property, not about the number of fire companies available.

[6] As an example, when observed library circulation (i.e., the final output) is low, a relatively high-cost library will appear inefficient when using circulation as the output variable in the analysis. Yet, it may at the same time be very efficient in translating its basic inputs (such as labor and capital) into books, opening hours and so on. If so, using circulation as an output measure will lead it to be unduly described as productively inefficient simply because it suffers from low-demand in its area.

2.3 Efficiency in the context of agricultural extension provision

Our study addresses the efficiency study of agricultural extension service provision. As in the case of all other public service provision, we ask what is produced as output from extension provision and how to measure technical efficiency. However, public extension services do differ from public goods provision in the sense that farm operators have the choice whether to receive the extension services. In general, public goods provision is somewhat mandatory. For example, transportation, police services and education, all of which are imperative for consumers' economic/social needs. This mandatory characteristic of the extension service provision makes efficiency measurement more complex.

Like any other public service provision, extension agents provide information as an intermediate output and farm operators use the information to produce final outputs. The first process happens within the agricultural extension agencies, which utilize conventional inputs to produce products or services that are of value to farm operators. This leads to an efficiency measure associated with the information production process. The subsequent process involves farm decisions which allocate inputs with the aid from the services produced in the first production process. Therefore, the second stage involves an efficient measurement for each individual farm. Farmers and rural stakeholders are interested in how information on new technologies, more effective management options and better farming practices are transmitted to farm operators. They are not concerned with the number of extension agencies available per se (Owens et al., 2003).

Our study revisits Bradford et al. (1969) to make the distinction between the two production stages and try to characterize technical efficiencies for both stages through both an empirical investigation and a simulation study. Given the distinction of two production stages, we need to be clear on which production process is being addressed. Given a less efficient agricultural extension agency in producing extension services, its services could help farms improving their technical efficiency by significant amount and vice versa.

2.3.1 Measuring farm's efficiency

It is widely accepted that farmers' performance is affected by human capital, which encompasses both innate and learned skills, including the ability to process information (Jamison and Lau, 1982). Extension service is an important instrument that provides human-capital enhancing inputs, as well as flows of information that can improve farmers' and other rural peoples' welfare, an importance long recognized in the development dialog. The goals of extension include the transferring of knowledge from researchers to farmers, advising farmers in their decision making and educating farmers on how to make better decisions, enabling farmers to clarify their own goals and possibilities, and stimulating desirable agricultural development(den Ban and Hawkins, 1996).

Extension helps to reduce the differences between farmer's potential and actual yields by accelerating technology transfer and helping farmers become better farm managers. It also plays an important role in helping the research establishment tailor technology to the agro-ecological and resource circumstances of farmers. Thus, extension has a dual function in bridging blocked channels between scientists and farmers by facilitating both the adoption and the adaptation of technology to local conditions. The first involves translating information from the store of knowledge and from new research to farmers, and the second by helping to articulate for research workers the problems and constraints faced by farmers.

Because many factors impact the performance of agriculture in complex and contradictory ways, it is difficult to trace the relationship between extension inputs and their impact at the farm level. This difficulty, in turn, exacerbates other inherent problems related to political support, budget allocation, incentives of extension employees, and their accountability, both upstream(to the managers) and downstream (to their clients). The literature on the measurement of agricultural extension services mainly focuses on how extension services provision improves farm performance either represented by final outputs, productivity or household income. It is a natural response of the objectives of agricultural extension services to improve farm productivity and reduce poverty.

Methodologically, the literature can be classified into the following categories. One is the experimental approach, where the performance of groups of farms which have contact with extension service is compared to the performance of farms without the benefits of contact. In a pure experiment, farms are assigned randomly to the two groups. Leavy (1991) and Leavy et al. (1998) assess a farm improvement program in West Ireland by finding the impact of improvement program on regional resource use. These studies indicate that contact with the extension service is a positive factor in increasing gross margin on farms participating in this specific program. The main shortcomings of this approach is that, in practice, researchers are often faced with two self-selected groups. This creates difficulty in interpreting results since researchers cannot determine how much the self-selection biases the outcomes observed.

Aside from experimental approach, the remaining literature generally follows econometric approach. Dinar et al. (2007) provided a summary on the literature analyzing the impact of agricultural extension. One branch of the literature accounts for the differences in farm's output(or in some cases, quality of the output) across individuals in terms of differences in the use of conventional inputs(land, labor and capital) and non-conventional inputs(R&D expenditure, education and extension services, etc) by fitting a production function to data on output and inputs.

Birkhaeuser et al. (1991) summarized fifteen studies using farm level data for both productivity and extension variables, where extension is typically some form of contact by the farmer with an extension agent. Among 35 coefficients relevant to extension impact, only nine are statistically significant. Additionally, farm level data for productivity but village/area specific data for extension variables and aggregate level data(country level for example)are also used in several studies. Birkhaeuser et al. (1991) concluded that the majority of studies showed that a significant and positive extension seem to be significantly affected by extension with rate of return ranging from 20 to 100 percent. However, these studies have their own problems, including data issues such as measurement error and aggregation bias, and conceptual issues to do with the nature of the precise relationship between extension expenditure (or the number of extension visits) and the increase in output. Anderson (2007) updated the study to account for the emerging evaluations of the newer approaches since Birkhaeuser et al. (1991). These studies share the following characteristics:

a) Farms are operated efficiently at their own production frontier;

b) The estimation coefficients for the extension variables can suffer from sample selectivity which will bias the coefficients.

c) There is no distinction between the production stages that is particular to public goods of any type.

However, concerns over data quality, along with difficult methodological issues regarding causality and quantification of all benefits, must be important qualifiers to the prevailing evidence of positive economic returns from extension.[7]

In light of the first common characteristic, more recent research uses another framework which attempts to define the best practice stochastic frontier production function and measure the distance of each individual farm from its frontier. This distance is interpreted as a measure of the technical inefficiency of the individuals. Under this general framework, agricultural extension is included along with other socioeconomic and demographic variables in the inefficiency effect function as a factor influencing technical inefficiency.

As laid out in the previous sections, the frontier production is an extension of the familiar regression model based on the theoretical premise that a production function, its dual(the cost function), or the convex conjugate of the two(the profit function), represents an ideal, maximum output attainable given a set of inputs, the minimum cost of producing that output given the prices of the inputs, or the maximum profit attainable given the inputs, outputs, and the prices of the inputs (Fried et al., 2008). While still allowing for technical inefficiency, they also acknowledge that some external events such as an unusually high number of random equipment failures, or even bad weather can be separated from the contribution of variation in technical inefficiency. This leads to the more appealing formulation where a particular farm faces its own production frontier, and that frontier is placed randomly by the whole collection of stochastic elements that enter the model outside the control of each individual.

The characteristic of sample selectivity has received little attention in the stochastic production frontier approach. The issue of selectivity bias was first brought up in a

[7]For example, in Kenya, although previous evaluations had indicated remarkably high positive economic returns to extension investments, a comprehensive evaluation based on improved and new data revealed a disappointing performance of extension (Gautam, 2000).

framework to identify the determinants of wages and labor supply behavior of females (Heckman, 1979). Studies evaluating the impact of extension services at the individual farm level by utilizing a farm-level measure of extension may also be affected by problems of sample selection. Overlooking these problems potentially leads to biased estimators.

The sources of parameter bias may be multi-fold. Suppose the government decides to concentrate extension resources in highly productive areas and that this fixed locality characteristic is not controlled for in the linear regression.

Moreover, some of the extension contacts are farmer-initiated. If one observes that more efficient farms have more extension contact, one cannot conclude that extension contact caused the efficiency difference. It may simply reflect the demand for information by the more efficient farmers. Alternatively, extension contact with more productive farmers may reflect a herd effect approach where the productive producers can serve as models for others.

General approaches to deal with the sample selection issues include:

a) Controlling for unobserved household fixed effects by using the unique characteristic of longitudinal data. The differentiating process eliminates the specification of the correlation between extension and the disturbance term.

b) Using a location dummies in the regression equation, if we consider the possible correlation between location and extension service variable.

c) Combing fixed effects and different matching methods to isolate program effects is another option. Pedro Cerdan-Infantes (2008)used the matching technique as an identification of a proper counterfactual scenario; that is what would have happened to the beneficiaries of the extension services in the absence of the extension program. A usual technique is the propensity score, which is a probit estimation, in essence.

d) Applying a standard heckit model to deal with the selection bias, which is discussed in greater detail in Chapter 3. We revisit Greene (2010) where sample selectivity is taken into consideration in the context of stochastic production frontier approach.

e) Adapting causal effect analysis which is broadly used in statistics to study sample selectivity in a variety of fields. Details will be provided in Chapter 3.

At present, the literature is sparse addressing the sample selectivity issue especially in the context of agricultural extension[8], although the problem of sample selection was pointed out by Birkhaeuser et al. (1991). The analyses of agricultural extension services using quantified approaches are still at an initial stage with very few empirical investigations. Chapter 3 focuses on measuring the technical efficiency of the individual farms and takes on the problem of sample selectivity rigorously.

2.3.2 Measuring agencies' efficiency

Compared to the farms' efficiency measurement, measuring extension agents' efficiency has received less attention. One of the reasons is that it is empirically hard to quantify the elements needed for the efficiency analysis. Very few rigorous impact evaluations are conducted until now.

However, as agricultural extension organizations have grown and changed, they have invariably become more bureaucratic with distinct hierarchical structures. The work of dispersed extension workers had to be administered and controlled so that one or more levels of intermediary structure (for example, district, region) have been created between the field-level agents and their headquarters. Thus the management of extension activities has become a major preoccupation. Many of these organizations are open to the criticism of being top heavy and top-down in their approach. Moreover, with funding derived largely from government revenues (or international donors), senior managers have necessarily had to account for and justify their organization's activities.

We do not find relevant research attempting to quantify the efficiency level for this first production process. This has much to do with the fact that researchers were not able to measure the output produced from this process. However, if we take all participants in the agricultural extension into consideration and specify an objective for each of the participants, we may be able to work back toward efficiency measurement of extension

[8]One exception is Dercon et al. (2009) where they deal with sample selectivity in the context of agricultural extension via Generalized Methods of Moments.

provision. Although there is difficulty in attempting to analyze the issue empirically, we can develop a theoretical framework based on which we can conduct simulation studies. A game theory model on mechanism design is adapted to serve our goal.

Mechanism design theory has its origins in the seminal work of Hurwicz (1973). In Hurwicz's formulation, a mechanism is a communication system in which participants exchange messages with each other, messages that jointly determine the outcome. These messages may contain private information, such as an individuals (true or pretend) willingness to pay for a public good. Each agent strives to maximize his or her expected payoff (utility or profit), and may decide to withhold disadvantageous information or send false information (hoping to pay less for a public good, say).

The key concepts underlying this framework are incentive compatibility and the revelation principle. Hurwiczs (1972) notion of incentive compatibility can be expressed as follows: the mechanism is incentive compatible if it is a dominant strategy for each participant to report his private information truthfully. In addition, we may want to impose a participation constraint: no agent should be made worse off by participating in the mechanism. The revelation principle states that any equilibrium outcome of an arbitrary mechanism can be replicated by an incentive compatible direct mechanism. Myerson (1979)developed the the concept further in the 1970s and 1980s so that moral hazard phenomenon can be analyzed using the same framework.

The mechanism design frame has been used widely in public goods provision where market mechanisms fails to provide public goods efficiently. This raises the possibility of government provision to improve efficiency. If the government is going to provide the public goods efficiently, however, the government needs information on the demand for extension services. If that information is assumed to be privately held, then the government must setup an incentive system that induces individuals to reveal their true demand.

Studies using mechanism design in the context of agriculture mainly focus on policy designs such as production subsidies and supply control. A common assumption is that farmers have better information regarding their own productivity than the government (Sheriff, 2004). Chambers (1992) assumes asymmetric information between government and farms regarding the latter's cost structure, based on which the motivations underlying the choice of agricultural policy mechanisms are examined using mechanism design. By assuming the asymmetric information in farm types ,Hueth (2000) examined the motivations for three different specific government objectives.

Our study will resume the tradition of information asymmetry. However, in the context of agricultural extension provision, the players in the design are not merely government and farm operators. Extension agents also participate in the game. Hence, adaptations are needed. In Chapter 5, a game theoretical model is built to explain the interactions among the participants and a simulation study will be conducted.

2.4 Concluding Comments

In Chapter 2, we present the literature review on efficiency measurement in general, efficiency measurement on public goods provision, and efficiency measurement on agricultural extension services provision. Under the efficiency measurement of agricultural extension services provision, agents' and farms' efficiency are reviewed separately. Moreover, sample selection issues under the econometric framework of stochastic production models are investigated. Aggregating from the farm to the macro setting implies a game involving as players the extension agency, the government and farms.

Chapter 3

Modeling Public Service Provision and Private Production under Sample Selection

3.1 Introduction

Public services provide public goods that private sectors are unable to provide or services that are insufficiently provided by the private sector. Production in the public sector has been modeled by Bradford et al. (1969) as a two-stage process where an intermediate output is produced in the first stage by a production process involving only discretionary inputs that are variable and controllable by the decision making unit. In the second stage, final outputs are determined by the level of intermediate output and by environmental variables. Empirical studies of public sector production find that environmental variables have a substantial impact on the final outputs.[1]

[1] A good example is the provision of the fire services (measured perhaps by the number of lives saved and/or the dollar amount of property damage prevented) by local communities. We would expect that a community with a higher proportion of brick houses would be able to provide a higher level of services than a community consisting primarily of old wood houses, assuming the same usage of inputs. In this case residential structure is exogenous to the decisions of the fire departments.

Bartik (1991) identifies three ways on how intermediate outputs exert impacts on the second stage production. Public services may be an unpriced input to production. The expansion of public services may reduce the prices paid by business for those services. Some public services may work to reduce the cost of private inputs used by business. For instance, public highways serve as an input (usually unpriced) to many businesses, expansion of public airports may reduce the full price business must pay for air transport, and public education may reduce quality-adjusted prices of labor by increasing the supply of workers of a given quality (either by increasing average skills everywhere or by attracting additional workers to a specific location). In all these cases, the idea is that public input reduces production costs directly or increases the productivity of a private input and thus increases output. In the underlying model, firms are passive recipients of public services.

Efficiency analysis in public section has gained renewed attention, as there is an interest in linking budgets to performance measures (see Duncombe et al. (1997) for a detailed discussion). One relevant question is how to quantify the output from public goods provision. Bradford et al. (1969) suggested three alternative ways to characterize public output. These are spending on inputs, the directly produced output or facilities that result from those inputs (such as hours of police patrols), and the consumer output or consumption service that results partly from the directly produced output or facility. Based on the two-stage production process, parametric and nonparametric approaches to studying the efficiency of public services have been developed and empirically applied. Studies also focus on the the efficiency of the second stage production. Among them, performance of public safety (police, fire department, etc), education and transportation are frequently studied.

Public extension is a special kind of public goods provision. It behaves like other regular producers using traditional inputs (capital, labor, etc) to produce information as their product. Information transmitted to and from farmers through the agricultural extension system can be divided into two broad categories: pure information and information that is embodied in new products or equipment (Ruttan, 1987). In particular, pure information includes all types of advice on practical farming in cultural and production techniques, farm management, marketing and processing information and community development. Embodied agricultural information includes new agricultural equipment, chemicals, seeds and livestock breeds, etc.

Similar to other public goods provision, a distinction between the information directly produced and the attributes of primary interest to the citizen consumers must be made. In our study, neither pure information and embodied information will go directly into citizens' consumption. Instead, they are "consumed" by next stage producers as an input augmenting technique. Hence, we treat the information as intermediate output. On the other hand, farms produce final outputs that are consumed by citizen consumers using the intermediate output (information).

Another aspect in common with other public goods provision is that the second stage production of final outputs is also affected by environmental factors. Consider two rural communities of equal size but having different general environmental conditions (e.g., road network, farm specialization, quality of extension agents, proximity). We expect these two areas will experience differences in receiving extension services. With the role of public service provision, we treat the environmental factors of different areas as exogenous upon entering the second stage production.

However, agricultural extension provision is not merely a replicate of any other public goods production. What makes public extension service distinct from other public goods are the characteristics of the information produced by extension agencies. The first characteristic is that the information will not only enter the second stage production as a nonconventional input but help augment farms' labor to make them more productive, given the same amount of labor. Secondly, the information flow is a two-way interaction. Farmers are not merely a passive information receiver. Instead, they will convey information back to extension agencies helping the first stage production develop more targeted information in the future.

Given the distinction between the two-stage production process, the efficiency evaluation of extension provision must proceed with caution. We must specify clearly which stage of production is the focus. Considerable research has analyzed the efficiency of the second stage; that is, the changes have been made by the introduction of the intermediate output into the final output production.

Moreover, the speciality of agricultural extension provision makes the analysis of production efficiency more complex. The extension service provider will not treat each farming area equally. Agencies may tend to allocate resources to areas with high agricultural potential to be persuasive for getting more budgets from the government. On the other hand, some of the extension services are farmer initiated. If one observes that more efficient farms have more extension contact, one cannot conclude that extension contact caused the efficiency difference. It may simply reflect the demand for information by the more efficient farmers.

Our objective is to characterize the process of the agricultural extension service, from which we generalize the two production stages and address technical efficiency while giving sample selectivity serious consideration.

In this chapter, our focus is to measure the technical efficiency of agricultural extension services in the second stage of the production process. We extended the classic stochastic production frontier framework to allow the mean of the pre-truncation distribution to depend on a set of exogenous factors, which is implemented via a non-neutral stochastic frontier production model and also allow for sample selectivity. The model coincides with the definition of "best practice" frontier production technology and to measure the distance individual farms are from this frontier. Based on this framework, we also introduce how to measure the efficiency score of individuals. As a last consideration, we provide a statistical perspective to address sample selection issue.

The organization of Chapter 3 is as follows. In Section 3.2, we briefly describe the first production stage (i.e. the production of public services) followed by discussion about the second production stage in Section 3.3. In Section 3.4, we address two issues. An econometric modeling framework is developed to provide evaluation of technical efficiency of the production processes. Then we proceed with the causal effect approach to identify the sample selectivity problem statistically. Section 3.5 describes the decomposition of the efficiency measurement in the production processes. Section 3.6 offers concluding comments.

3.2 The Production of Public Services

3.2.1 Defining the Process

Like production of any private goods, in the first stage, public services are produced by local governments or extension agencies via a well behaved production technology. To define the technology, denote the vector of nonnegative conventional inputs as:

$$\mathbf{x} = \{x_1, \cdots, x_J\} \in \mathbb{R}_+^J. \tag{3.1}$$

Let $Q \in \mathbb{R}_+$ be the nonnegative intermediate output. The production possibilities set is $T^Q(t) \subseteq \mathbb{R}_+^{J+1}$ and defined as:

$$T^Q(t) = \{(\mathbf{x}, Q) : \text{x can produce Q at time t}\}. \tag{3.2}$$

As a consequence, the intermediate output production function $f(\mathbf{x}, t) : \mathbb{R}_+^J \rightarrow \mathbb{R}_+$ is defined as:

$$f(\mathbf{x}; t) \equiv \max_Q \{Q : (\mathbf{x}, Q) \in T^Q(t)\}. \tag{3.3}$$

Accordingly, the input requirement set of this first stage public extension services provision is:

$$L^Q(Q, t) = \{\mathbf{x} \in \mathbb{R}_+^J : Q \leq f(\mathbf{x}; t)\} \tag{3.4}$$

One can find all possible input combinations capable of producing intermediate output Q given the technology in period t.

The inputs are the same at this stage as any production processes. Extension agents will need capital, labor, and materials to get started. The total capital equipment includes buildings, office equipment, transportation vehicles, etc. Labor will include both seasonally hired labor and permanent extension agents.

What is directly produced from this production process? There is no standard answer to the question, since the definition of the extension variable is usually confounded by measurement problems. In practice, extension provides both technical and economic information, which can have different impacts on farm efficiency. However, the data available to the analyst usually can not separate these two types of information. The number of contacts made by agents is a typical output identified in the literature which is measured by both number of extension visits made and number of telephone calls received by the extension agency.

3.2.2 Cost Minimization Problem

We will characterize the cost minimization problem in the first stage of the public service provision. Using the input requirement set defined in (3.4, the first stage production of public extension services provision can be represented by the input distance function $D^I(\mathbf{x}, Q; t) : \mathbb{R}_+^J \times \mathbb{R}_+ \longrightarrow \mathbb{R}_+ \cup +\infty$:

$$D^I(\mathbf{x}, Q; t) \equiv \sup_{\lambda}\{\lambda > 0 : \frac{\mathbf{x}}{\lambda} \in L^Q(Q, t), \forall Q \in \mathbb{R}_+\}. \tag{3.5}$$

The input distance function defined in (3.5) has the following properties (Kumbhakar and Lovell, 2000):

a non-decreasing, linearly homogeneous in **x**;

b decreasing in Q;

c $D^I(\mathbf{x}, Q) \geq 1$ if $Q \in L^Q(Q, t)$, the equality holds if the input combinations are on the isoquant of Q.

As an illustration, see figure 3.1. For point A, $D^I(A) = \frac{0A}{0B} > 1$; For point B, $D^I(B) = 1$.

When producers face input prices $w = (w_1, \cdots, w_J) \in \mathbb{R}_{++}^J$ and seek to minimize cost, the cost frontier, is defined as:

$$c(w, Q; t) = \min_{x}\{w'x : D^I(\mathbf{x}, Q; t) \geq 1\}. \tag{3.6}$$

If the input requirement set $L^Q(Q, t)$ is closed and convex, and if inputs are freely disposable, then the cost frontier in (3.6) is dual to the input distance function (see

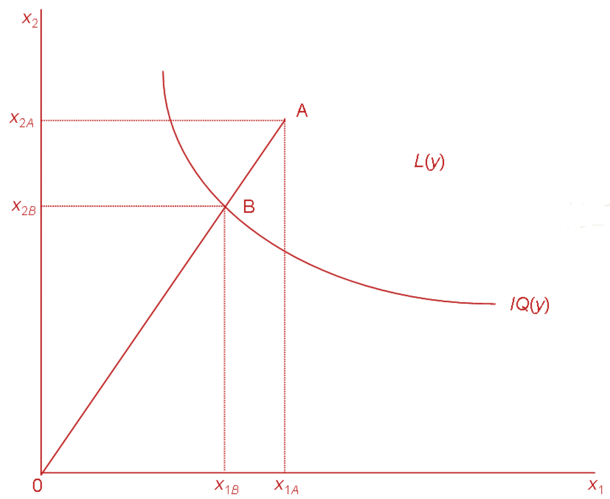


Figure 3.1: Illustration of Distance Function

Chapter 7 in Kumbhakar and Lovell (2000)).

$$D^I(\mathbf{x}, Q; t) = \min_w \{w'\mathbf{x} : c(w, Q; t) \geq 1\}. \tag{3.7}$$

3.3 Private Production with Public Service as Input

3.3.1 Defining the production process

3.3.1.1 Formal specification of a production technology

The second production stage is a natural extension of the first production stage in the sense that the second production stage will use the the intermediate output from the first stage to produce final output. Let Y be the output of farms, where $Y \in \mathbb{R}_+$. Consider two rural areas of similar size which receive extension services from two extension outlets of equal size, it is possible that these two rural areas will experience differences in receiving extension services. The reason for this is mainly attributed to the fact that these areas differ in the general environmental conditions that will have an impact on extension provision. For example, these environmental conditions include the road network, farm specialization, quality of extension agents and farm proximity.

Denote Q as the first stage intermediate output, N as the population of farmers in the rural area and, $\mathbf{z} = \{z_1, \cdots, z_s\} \in \mathbb{R}^s_+$ as a vector of environmental conditions assumed to affect the quality of extension provision. In this case, the second stage technological constraints may be represented by the following set $T^Y(N, \mathbf{z}) \subseteq \mathbb{R}^{S+3}_+$,

$$T^Y(N, \mathbf{z}) = \{(Q, Y) : Q \text{ can produce } Y \text{ given } N, \mathbf{z}\}. \tag{3.8}$$

Based on the production possibility set defined in (3.8), conditional on the environmental conditions **z**, the second stage production process can be represented by the following well-behaved production function $h(Q; N, \mathbf{z}) : \mathbb{R}^{s+2}_+ \longrightarrow \mathbb{R}_+$:

$$h(Q; N, \mathbf{z}) \equiv \max_Y \{Y : (Q, Y) \in T^Y(N, \mathbf{z})\} \tag{3.9}$$

3.3.1.2 Neutral Stochastic production frontier

An implicit assumption of the above production function is that all farms are producing in a technically efficient manner, and therefore the representative (average) firm defines the frontier. Variations from the frontier are assumed to be random, and are likely to be associated with mis-measured or omitted production factors.

In contrast, estimation of the production frontier assumes that the boundary of the production function is defined by "best practice" firms. Therefore, it indicates the maximum potential output for a given set of inputs along a ray from the origin point. Some white noise is accommodated, since the estimation procedures are stochastic by appending an additional term representing other reasons why firms would be away from (within) the boundary. Observations within the frontier are "inefficient". So it is possible to measure the relative efficiency of certain groups from an estimated production frontier. It is also possible to evaluate a set of practices from the relationship between observed production and some ideal or potential production (see Greene (1993)). In our specification, we adopt a stochastic production frontier specification and define the relevant environmental variables.

We start with the loglinear Cobb-Douglas production specification:

$$\ln y_i = \beta_0 + \sum_n \beta_n \ln x_{ni} + v_i - u_i \tag{3.10}$$

where v_i is “two-sided” noise component and u_i is the nonnegative technical inefficiency component, leading to the composite error model, with $\varepsilon_i = v_i - u_i$.

In the basic specification above, both components of the compound disturbance are generally assumed to be independent and identically distributed (iid) across observations. Normal and half normal distributions are among the frequently studied error specifications.

Given the basic model set up in (3.10), one can begin with a general formulation of the model and then narrow the specification to some particular models that have been proposed in the literature (Fried et al., 2008). The simplest assumptions to start with areFried et al. (2008):

a) $f_v(v_i)$ is a symmetric distribution;

b) v_i and u_i are statistically independent of each other; and

c) v_i and u_i are iid across observations.

As a starting point, u and v are assumed to have mean 0 and variances σ_u and σ_v respectively, over all observations.

To form the likelihood function on $\ln y_i$, the independence assumption a) leads to:

$$f_{v,u}(v_i, u_i) = f_v(v_i) f_u(u_i)$$

Using $\epsilon_i = v_i - u_i$, one derives:

$$f_{\epsilon,u} = f_u(u_i) f_v(\epsilon_i + u_i);$$

To obtain the marginal density of ϵ_i, we integrate u_i out of the joint density:

$$f_\epsilon(\epsilon_i) = \int_0^\infty f_u(u_i) f_v(\epsilon_i + u_i) du_i$$

Finally, if all the information in each of the observation i is reflected in the log-likelihood function, we have:

$$\ln L_i(\ln y_i, x_i \mid \alpha, \beta, \sigma_u^2, \sigma_v^2) = \ln f_\epsilon(y_i - \alpha - \beta' x_i \mid \sigma_u^2, \sigma_v^2)$$

If there exists closed-form solution for the parameter estimates based on either the usual MLE or Bayesian approach, the estimation becomes standard exercises. In the absence of closed-form solution, simulation techniques will play an important role.

3.3.1.3 Nonneutral Stochastic production frontier

A wide range of extensions to the traditional stochastic production frontier are addressed in the literature. These include Greene (2010):

a) enriching the specification of the functional forms of the production function; for example, from the most frequently used translog specification to Box-Cox functional form to incorporate zero values for some outputs and to Fourier flexible function.

b) enriching the error structure; for example, moving from the original normal-half normal error structure to normal-Gamma and normal-exponential.

c) seeking alternative approaches to estimate the targeted parameters; for example, Bayesian applications and Markov Chain Monte Carlo of maximizing the likelihood function.

Among all the variants to the original stochastic production frontier approach, the extension from neutral to non-neutral technical inefficiency term is our main interest. Kumbhakar et al. (1991), Huang and Liu (1994) and Battese and Coelli (1992) allow the mean of the pre-truncation distribution to depend on a set of exogenous factors. As argued by Huang and Liu (1994), the original specification suffers from a serious drawback where it is implicitly assumed that the efficiency index shifts the average observed output downward and the unit isoquant upward in such a way that the marginal rates of technical substitution(MRTS) at any input combination remain unchanged. However, the effects of technical inefficiency on productivity may be greater on some inputs than on others, Therefore, we usually end up with a production that is a non-neutral shift of observed output from the frontier. Consequentially, not only the productivity of inputs change, but so will the marginal rates of technical substitution.

This non-neutral technical change in the context of the stochastic frontier model involves specifying two regressions. The unobserved stochastic frontier output is the same as before:

$$\ln y_i = \alpha + \beta' x_i + v_i - u_i = \alpha + \beta' x_i + \epsilon. \tag{3.11}$$

The technical efficiency, u, is specified as:

$$u = \gamma \ln z_i + \xi_i \tag{3.12}$$

where the z variables are covariates such as physical factors influencing production, and/or the farm's characteristics and policy variables. The technical inefficiency is mostly explained in (3.12). ξ_i is a random error in explaining the residual efficiency. The derivation of the log-likelihood function is then a straightforward exercise.

3.3.2 Together With Public Service: Sample Selection Problem

As an intermediate output from the first production stage, public service presents some special features when treated as an input of the second production stage. Firstly, traditional inputs like capital and labor are treated as fixed when carrying out any analysis. However, the level of public extension services provided is not fixed. As an output from the first stage, one cannot control the exact level of services entering the second stage of production. Local governments may choose to provide services to regions with high agricultural potential. Furthermore, the delivery of extension services is not mandatory to all farms. Instead, farms choose whether or not to consume extension services. Farms with lower skills may have a higher demand for the extension services.

In the context of sample selection, the structural equation or the primary equation is specified as:

$$y_1 = x_1\beta_1 + u_1 \tag{3.13}$$

where x_1 is a vector of explanatory variables, all of which are exogenous in the population, and u_1 is an error term.

Let selection be determined by the equation:

$$y_2 = I\{x\delta_2 + v_2 \geq 0\}. \tag{3.14}$$

where the vector x is assumed to contain all variables in the vector x_1 plus some more variables (unless otherwise stated), v_2 is an error term. We assume we always observe x, regardless of the value of y_2.

Given the specification in (3.13) and (3.14), can the parameters β_1 in (3.13 be unbiasedly estimated based on the selected sample? When there is selection bias, what can be done about it? The fundamental issue is why some individuals are not included in the sample.

The following assumptions are made:

a) sample selection: (x, y_2) are always observed, but y_1 is only observed when $y_2 = 1$;

b) x is exogenous in the population: $(u_1; v_2)$ is independent of x with zero mean;

c) distributional assumption: $v_2 \sim N(0, 1)$;

d) correlations among residuals: $E(u_1 \mid v_2) = \gamma_2 v_2$, which is bivariate normality. Given $v(v_2) = 1$, γ measures the covariance between u_1 and v_2.

Given the specified model, sample selection bias arises when the residual v_2 in the selection equation is correlated with the residual u_1 in the primary equation; i.e., $\gamma_2 \neq 0$. Several methods have been developed for the estimators of the model parameters.

Heckman (1979)'s two step limited information methods calculates the Inverse Mills ratio λ_i for each observation as $\lambda_i = \frac{\phi(x_i\delta_2)}{\Phi(x_i\delta_2)}$. The fully parametric expression for the expected value of y_1 conditional on observable variables x, and selection into the sample ($y_2 = 1$) becomes:

$$E(y_1 \mid x, y_2 = 1) = x_1\beta_1 + \gamma_1\lambda(x\delta_2).$$

The regressor is augmented to include $\lambda(x\delta_2)$ as an additional regressor which corrects for the selection bias.

This limited information approach has received criticism. The distribution of the observed random variable conditioned on the selection will generally not be the same as the case without sample selection. Therefore, the addition of the Inverse Mill's ratio to the original likelihood function generally does not produce the appropriate log-likelihood in the presence of sample selection.

A second approach contributed to Maddala (1983) develops the full information maximum likelihood estimator for sample selection. The log-likelihood function for the sample selection model is:

$$\begin{aligned}
&\log L(\beta_1, \sigma_{u_1}, \delta_2, \gamma) \\
=&\Sigma \log \left[y_2 \left\{ \frac{\exp\left(-\frac{1}{2}((y_{1i} - \beta_1' x_{1i})^2)/\sigma_{u_1}^2\right)}{\sigma_{u_1}\sqrt{2\pi}} \Phi\left(\frac{(\gamma(y_{1i} - \beta_1' x_{1i})/\sigma_{u_1}) + \delta x}{\sqrt{1-\gamma^2}}\right) \right\} \right. \\
&\left. + (1 - y_2)\Phi(-\delta_2 x) \right]
\end{aligned}$$

Our approach to deal with sample selection will be built partially upon this full information MLE frame. Some modifications will be made to accommodate the composite error in the primary function and also the non-neutrality in the technical inefficiency specification.

3.3.3 The Context For efficiency In Private Production

Given our specification of non-neutral stochastic production frontier technology, the technical inefficiency term u_i cannot be estimated directly. The estimates from this specification provide only estimates of the composite error $\epsilon_i = v_i - u_i$. Therefore, u_i has to be estimated indirectly.

A solution to this problem was proposed by Jondrow et al. (1982) where distributional assumptions were imposed on both error components, and then the conditional distribution of $u_i \mid \epsilon_i$ was derived. Since ϵ_i contains information on u_i , the conditioning will extract this information.

A second approach is proposed by Battese and Coelli (1988). The parameters in the model can be estimated using the Maximum Likelihood method or Method of Moments. Fried et al. (2008) notes that these two estimators of u_i proposed by Jondrow et al. (1982) and Battese and Coelli (1988) are consistent estimates.

3.4 Modeling Framework

3.4.1 Stochastic Production Frontier Approach

Huang and Liu (1994) combined a stochastic production frontier function and a truncated regression. The truncated regression specifies a non-neural shifting of the average production function to reveal the sources of inefficiencies. The advantage of using this specification instead of the original stochastic production frontier is that the assumptions made by non-neutral stochastic production frontier specification are more realistic. An assumption of the traditional stochastic production frontier is that the marginal rates of technical substitution at any input combination remain unchanged. However, the effects of technical inefficiency on production may be greater for some inputs than others.

Following Dinar et al. (2007), part of our proposed framework is built on a simplified version of non-neutral frontier model. In particular, it is assumed that the degree of technical efficiency depends on the methods of application of inputs and the number of extension visits, but not the quantities of conventional inputs. In addition, we deal with the problem of sample selection via the approach suggested by Greene (2010).

Consider the following models (Huang and Liu, 1994; Dinar et al., 2007) with

$$\ln y_i = D_i \ln \tilde{y}_i^1 + (1 - D_i) \ln \tilde{y}_i^0$$

and

$$\ln \tilde{y}_i^D = \alpha^D \ln x_i + v_i^D - u_i^D, \quad u_i^D = |\beta^D \ln z_i + \sigma_{\xi_i} \xi_i^D|,$$

where D is a dummy indicator, with $D_i = 0$ corresponding to the observations without extension service, while $D_i = 1$ corresponding to the observations with extension service; $\{y_i, x_i, z_i\}$ is a random sample; x and z are regressors for inputs, and environmental variables respectively; and y is the dependent variable, farm output.

The stochastic frontier is $\alpha^D \ln x_i + v_i^D$, with v_i^D being a symmetric i.i.d. error term representing those factors that cannot be controlled by farmers as well as omitted variables and measurement errors in the dependent variable. $u_i^D \geq 0$ represents the shortfall of output from the production frontier due to technical inefficiency, measuring the distance of actual output from production frontier. In our specification, u_i^D is replaced by the above linear form with $(u_i^D, \tilde{y}_i^D)$ not observed and (α^D, β^D) are parameter vectors of interest. The two sets of farms have different coefficients; i.e., receiving extension service changes their production function. Policy makers want to compare α^0 against α^1, or compare β^0 against β^1.

The sample selection problem arises because

$$D_i = \mathbf{I}[\gamma w_i + \epsilon_i \leq 0],$$

where $\{w_i\}$ is another set of regressors that influence whether extension visit takes place and ϵ_i is correlated with $(v_i^0, v_i^1, \xi_i^0, \xi_i^1)$.

We extend the framework of Dinar et al. (2007) by allowing for the sample selection in the extension service. If there is unobserved heterogeneity across farms and if the heterogeneity affects farms' decision, then receiving extension services or not is not randomly determined. Ignoring the selection bias can lead to inconsistent estimates for the parameters in the production function.

Following Greene (2010), the endogenous extension service is incorporated by allowing for the correlation between the error terms in the selection equation and in the production functions. This model uses the information from the observations not receiving extension service, which are missing in Greene (2010) data set. The extension service is specified as a 0-1 treatment[2].

This model can be estimated using MLE. For the subsample with $D_i = 1$, consider the following likelihood,

$$\begin{aligned}
&f\left\{y = y_i, D = 1 | x = x_i, z = z_i, w = w_i; \alpha^1, \beta^1, \gamma\right\} \\
=&f\left\{\alpha^1 x + v^1 - u^1 = y_i, D = 1 | x = x_i, z = z_i, w = w_i\right\} \\
=&f\left\{v_i^1 = y_i - \alpha^1 x_i + \beta^1 z_i, \epsilon_i \leq -\gamma w_i | x = x_i, z = z_i, w = w_i\right\} \\
=&\Pr\left(\epsilon_i \leq -\gamma w_i | v_i^1 = \Delta_i^1, x = x_i, z = z_i, w = w_i\right) f_v(\Delta_i^1)
\end{aligned}$$

where we use a change of variable of $y = \alpha^1 x + v^1 - u^1$, and $D = 1 \Leftrightarrow \epsilon_i \geq -\gamma w_i$. The last equality is from the Bayes formula.

We assume

$$(\epsilon_i, v_i^1) \sim N\left(0, \begin{bmatrix} 1 & \rho^1\sigma_v \\ \rho^1\sigma_v & \sigma_v^2 \end{bmatrix}\right)$$
$$(\epsilon_i, v_i^0) \sim N\left(0, \begin{bmatrix} 1 & \rho^0\sigma_v \\ \rho^0\sigma_v & \sigma_v^2 \end{bmatrix}\right)$$

The conditional density of ϵ conditional on v^1 is:

[2]It would be interesting to consider extension service as a continuous (as in Dinar et al. (2007)) and endogenous random variable. I leave this for future exploration.

$$\epsilon|v^1 \sim N\left(\mu_\epsilon + \frac{\sigma_\epsilon}{\sigma_v}\rho(v^1-\mu_v), (1-\rho^2)\sigma_\epsilon^2\right)$$

and when $\mu_v = \mu_\epsilon = 0$ and $\sigma_v = 1$, the standardized distribution is:

$$\frac{\epsilon - \sigma_\epsilon\rho^1 v^1}{\sigma_\epsilon\sqrt{1-(\rho^1)^2}}|v^1 \sim N(0,1)$$

Continuing the derivation using the normalized conditional density yields the following:

$$\begin{aligned}
&\Pr\left(\epsilon_i \le -\gamma w_i | v_i^1 = \Delta_i^1, x = x_i, z = z_i, w = w_i\right) f_v(\Delta_i^1)\\
=&\Pr\left(\frac{\epsilon - \sigma_\epsilon\rho^1 v^1}{\sigma_\epsilon\sqrt{1-(\rho^1)^2}} \le \frac{-\gamma w_i - \sigma_\epsilon\rho^1 v^1}{\sigma_\epsilon\sqrt{1-(\rho^1)^2}}|v_i^1 = \Delta_i^1, x = x_i, z = z_i, w = w_i\xi^1\right) f_v(\Delta_i^1)\\
=&\Phi\left[\frac{-\gamma w_i - \sigma_\epsilon\rho^1 v^1}{\sigma_\epsilon\sqrt{1-(\rho^1)^2}}\right] \times \exp\left\{-\frac{(\Delta_i^1)^2}{2\sigma_v^2}\right\}
\end{aligned}$$

Similarly, we can obtain the likelihood for the subsample with $D = 0$,

$$\begin{aligned}
&\Pr\left\{y = y_i, D = 1 | x = x_i, z = z_i, w = w_i; \alpha^1, \beta^1, \gamma\right\}\\
=&\int_{-\gamma w_i}^{\infty} f_{v^1-\xi^1,\epsilon}(\ln y_i - \alpha^1 \ln x_i + \beta^1 \ln z_i, e)de.
\end{aligned}$$

Let θ represent the vector of all parameters, then

$$\hat{\theta}_{MLE} = \text{argmax} \sum_{i=1}^{n} \ln\left(\Pr\left\{y = y_i, D = D_i | x = x_i, z = z_i, w = w_i; \alpha^D, \beta^D, \gamma\right\}\right. \tag{3.15}$$

Depending on the joint distributional assumption of $(v_i^0, v_i^1, \xi_i^0, \xi_i^1, \epsilon)$, one can derive the expression for the likelihood function distributions, but closed form expressions are not always guaranteed. In these cases, one can use the simulated MLE instead, as suggested by Greene (2010).

3.4.2 Causal Inference Approach

3.4.2.1 Literature review: estimating causal effects

In this section, we proceed with investigating the sample selectivity issue from a statistical perspective, namely, the causal effect approach. This approach can serve as a robustness check on conclusion drawn via the stochastic framework. A cause is viewed as a manipulation or treatment that brings about a change in the variable of interest, compared to some baseline, called the control(Cox, 1992). The basic problem in identifying a causal effect is that the variable of interest is observed under either the treatment or control regimes, but never both. In a randomized experiment, treated and control groups are guaranteed to be only randomly different from one another on all covariates, both observed and unobserved. However, with observational data, it is well recognized that the estimate of a causal effect obtained by comparing a treatment group with a non experimental comparison group could be biased because of problems such as self-selection or some systematic judgment by the researcher in selecting units to be assigned to the treatment.

One of the widely used approaches to estimate the treatment effect is through matching. We define "matching" broadly to be any method that aims to equate (or "balance") the distribution of covariates in the treated and control groups. In particular, we would like to compare treated and control groups that are as similar as possible in terms of the covariates distribution. The relevant differences between any two units are captured in the observable (pretreatment) covariates, which occurs when outcomes are independent of assignment to treatment conditional on pretreatment covariates. Matching methods can yield an unbiased estimate of the true treatment effects.

Considerable work has investigated various matching schemes. The first generation of matching methods paired observations based on either a single variable or weighting several variables (Bassi, 1984) and (Czajka et al., 1992). However, the dimensions of the covariates are high in many applications. In such cases, it is difficult to determine along which dimensions to match units or which weighting scheme to adopt. Propensity score matching methods are especially useful under such circumstances because they provide a natural weighting scheme yielding unbiased estimates of the treatment impact (Dehejia and Wahba, 2002). Rosenbaum and Rubin (1983) introduced multivariate matching based on the propensity score, and (Rubin and Thomas, 1992) presented additional theoretic work. An early example by Rosenbaum and Rubin (1985) illustrates and compares three methods of multivariate matching on a single set of data: nearest available matching on the estimated propensity score, Mahalanobis metric matching including the propensity score, and nearest available Mahalanobis metric matching within calipers defined by the propensity score. (Rosenbaum, 2002) contrasted greedy and optimal matching and discussed matching with a fixed number of controls versus a variable number of controls. Another method of adjusting treatment effects used by researchers involves weighting on the propensity score. For example, Hirano and Imbens (2001) analyzed the data on right-heart catheterization using a procedure that reweights observations by the inverse of the estimates of the propensity score.

Matching methods have a few key advantages compared to adjusting for background variables in a regression model (ANCOVA), instrumental variables, or selection models. However, matching methods should not be seen as a conflict with ANCOVA and, in fact, the two methods are complementary and best used in combination. Readers will find that ANCOVA models are performed on the post-matched dataset. Second, matching methods highlight areas of the covariate distribution where there is not sufficient overlap between the treatment and control groups, such that the resulting treatment effect estimates would rely heavily on extrapolation. Selection models and regression models have been shown to perform poorly in checking this overlap (Dehejia and Wahba, 1999). The pre-diagnosis check in matching methods in part serves to make researchers aware of the quality of resulting inferences. Third, matching methods have straightforward post-match diagnostics by which their performance can be assessed.

In the following subsection, we will focus on several matching algorithms that are suitable for our purposes and assess whether the results strengthen or weaken our findings in the econometrical estimation.

3.4.2.2 Estimate Average Causal Effect

A propensity score is the conditional probability that a person will be in one condition rather than in another given a set of observed covariates used to predict the person's condition. Like all probabilities, a propensity score ranges from 0 to 1. Typically each person's true propensity score is known for randomized experiments, given that an equal probability assignment mechanism was used to assign people to treatment or control. But estimated propensity scores are derived from observed covariates. Consequently, omitting relevant covariates may result in hidden bias that propensity scores cannot accommodate.

Let Y_i be the output of farmer i, which is observed in the data. Let $D_i = 1$ if farmer i receives extension service, and $D_i = 0$ if he does not. Let Y_i^1 be the output of farmer i if he receives extension service and Y_i^0 be the output if he does not.For all the farmers with $D_i = 1$, the output is recorded as $Y_i^1 = Y_i$, but Y_i^0 is not observed in the data; for all the farmers with $D_i = 0$, $Y_i^0 = Y_i$, but Y_i^1 is not observed in the data. So $Y_i = Y_i^1 D_i + Y_i^0(1 - D_i)$. For every i, we only observe either Y_i^1 or Y_i^0. Let z_i be exogenous covariates (instruments) of farmer i.

However, the simple difference between Y_{i0} and Y_{i1} is not a true causal effect. In a regression approach, we are comparing two different groups of farms. But causality is about changes in the response variable when different treatments are applied to the same individuals.

Rubin (1974) introduced a notation of potential outcomes, which is commonly known as Rubin's Causal Model (RCM):

1) D_i = treatment received by farm i (0 or 1);

2) Y_{i0} = output for farm i, if $D_i = 0$;

3) Y_{i1} =output for farm i, if $D_i = 1$;

4) $D_i = Y_{i1} - Y_{i0}$ = causal effect for farm.

The fundamental problem of causal inference is that D_i can never be observed; thus, one of the two potential outcomes is missing (Holland, 1986). By making certain assumptions, however, it becomes possible to estimate the average causal effect for the population,

$ACE = E(D_i) = E(Y_{i1}) - E(Y_{i0})$.

If all potential outcomes were seen, we would estimate the ACE by

$$A\hat{C}E = \frac{1}{n}\sum D_i = \frac{1}{n}\sum Y_{i1} - \frac{1}{n}\sum Y_{i0}$$

In an observational study, it is unlikely that D_i will be independent of Y_{i0} and Y_{i1}. It is crucial to have good pretreatment covariates to help understand and adjust for baseline differences between the groups.

An alternative to the ACE for the entire population is the ACE for the treated group,

$$ACE_1 = E(Y_{i1}|D_i = 1) - E(Y_{i0}|D_i = 1)$$

which measures how much extension service provision helped or hurt the farms who actually received it. Therefore, it can be more relevant than ACE for discussing policy implications.

Several key assumptions are needed to estimate ACE.

Assumption A. *Unconfoundedness. A treatment mechanism is said to be unconfounded given a set of covariates z_i if the treatment D_i is independent of the potential outcomes Y_{i0} and Y_{i1} conditional on the covariates z_i;*

Assumption B. *No interference between the subjects, in the sense that the treatment applied to one subject does not affect the outcome from any other subject. This is called the "the stable unit treatment value assumption" (Rubin, 1980).*

This assumption may be violated if subjects interact in close proximity and the treatment given to one subject impacts others.

Finally, we will have to assume:

Assumption C. *The probabilities of receiving each treatment are bounded away from 0* *and 1. Namely, Y_{i0} and Y_{i1} should both exist, at least in principle.*

To obtain an estimate, we have to propose a least one model. That is, we will have to model the treatment mechanism. Specifically, the distribution of D_i given z_i or model the potential outcome involving the distributions of Y_{i1} and Y_{i0} given z_i or both. The above estimation of ACE and ACE1 is trying to model the potential outcomes Y_{i0} and Y_{i1}. The other body of methods for estimating ACE's that make few or no assumptions about the distribution of potential outcomes. Rather, they make assumptions about the distribution of the treatment indicator D_i. These methods are based on propensity scores.

3.4.2.3 Propensity Score Matching

The introduction of propensity score in matching is a great advance in the history of matching approaches. With more than just a few covariates it becomes very difficult to find matches with close or exact values of all covariates. For example, Chapin (1947) finds that with initial pools of 671 treated and 523 controls there are only 23 pairs that match exactly on six categorical covariates. The propensity score facilitates the construction of matched sets with similar distributions of the covariates, without requiring close or exact matches on all of the individual variables.

Rosenbaum and Rubin (1983) defined the propensity score as:

$$\pi_i = P(D_i = 1|z_i, Y_{i0}, Y_{i1})$$

which can be modeled by regressing D_i on z_i. When the treatment mechanism is unconfounded, the propensity scores depend only on z_i:

$$\pi_i = P(D_i = 1|z_i)$$

which can be modeled by regressing D_i on z_i. The most popular way is by fitting a logistic regression. There are many different ways to use propensity scores to estimate ACE. The key property of propensity scores is that that they balance the distributions of the covariates in the following sense: treated and untreated persons with identical propensity scores have identical distributions for all the covariates. If we divide the population into groups of constant propensity, then subjects in each group can be treated as if they had participated in a randomized experiment. This is the basic consideration behind any matching algorithm.

Matching involves selecting matched subsamples of treated and untreated farms whose covariates distributions are similar enough that selection bias is not an issue. Matching works best when one group in smaller than the other, and the distribution of the propensities in the smaller group is well covered by the distribution in the larger group.

Stuart (2010) notes four key steps in implementing any matching algorithms.

(1) defining “closeness”: the distance measure used to determine whether an individual is a good match for another;

(2) choosing an algorithm that assigns units to matched sets to make the distance small;

(3) assessing the quality of the resulting matched samples, and perhaps iterating with Steps (1) and (2) until well-matched samples result;

(4) analyzing the outcome and estimation of the treatment effect, given the matching done in Step (3).

In the first step, two questions must be addressed. Which covariates need to be specified? How to convert the differences of each individual computed from the corresponding covariates into a scalar distance measure? Let D_{ij} denote the distance between i and j for matching, four ways to define closeness are suggested in Stuart (2010):

(1) Exact distance:

$$D_{ij} = \begin{cases} 0 & \text{if} \quad z_i = z_j \\ \infty & \text{if} \quad z_i \neq z_j \end{cases}$$

(2) Mahalanobis: $D_{ij} = (z_i - z_j)' \sum^{-1} (z_i - z_j)$.

If interest is in the ACE1, $\sum^{-1}$ is the variance covariance matrix of X in the full control group; if interest is in the ACE then $\sum^{-1}$ is the variance covariance matrix of X in the pooled treatment and full control groups.

(3) Propensity score: $D_{ij} = |e_i - e_j|$, where where e_k is the propensity score for individual k.

(4) Linear propensity score: $D_{ij} = |\operatorname{logit} e_i - \operatorname{logit} e_j|$.

In the second step, a chosen matching algorithm assigns controls to treated units using the distance. In current statistical practice, the common approach is a greedy algorithm called "nearest neighbor matching". The treated units are randomly ordered and the first is paired with the nearest of the m controls, the second is paired with the nearest of the remaining $m - 1$ controls, and so on (Rubin, 1976). This algorithm is well established in R, SAS, STATA among other statistical software packages and has a spectrum of variants, such as matching with replacement and without replacement. In the former case, an untreated individual can be used more than once as a match, whereas in the latter case it is considered only once. Replacement involves a trade-off between bias and precision.

Nearest neighbor matching faces the risk of bad matches, if the closest neighbor is far away. This can be avoided by imposing a tolerance level on the maximum propensity score distance (known as a calliper). Imposing a calliper works in the same direction as allowing for replacement. Bad matches are avoided and hence the matching quality rises. However, if fewer matches can be performed, the variance of the estimates increases.

Applying calliper matching means that an individual from the comparison group is chosen as a matching partner for a treated individual because it lies within the calliper and is closest in terms of propensity score. A possible drawback of calliper matching is that it is difficult to know a priori what choice for the tolerance level is reasonable.

A second class of matching is subclassification, full matching, and weighting. Compared to nearest neighbor matching algorithms, this class uses all of the data from both control and treatment groups. These three methods discussed here represent a continuum in terms of the number of groupings formed, with weighting as the limit of subclassification as the number of observations and subclasses go to infinity (Rubin, 2001) and full matching in between.

When there are many covariates (or some covariates can take a large number of values), finding sufficient exact matches will often be impossible. The goal of subclassification is to form subclasses, such that in each the distribution (rather than the exact values) of covariates for the treated and control groups are as similar as possible. Full matching is a particular type of subclassification forming the subclasses in an optimal way. A fully matched sample is composed of matched sets, where each matched set contains one treated unit and one or more controls (or one control unit and one or more treated units). Full matching is optimal in terms of minimizing a weighted average of the estimated distance measure between each treated subject and each control subject within each subclass. The weighting schemes typically uses the propensity score as each individual's weight. For instance, inverse probability of treatment weighting is a widely used scheme serving to weight both the treated and control groups up to the full sample, in the same way that survey sampling weights weight a sample up to a population (Lunceford and Davidian, 2004). Mathematically, the weight $W_i = \frac{T_i}{\hat{e}_i} + \frac{1-T_i}{1-\hat{e}_i}$, where e_k is the estimated propensity score for the individual k. A potential drawback of the weighting approaches is that the variance can be very large if the weights are extreme, i.e., if the estimated propensity scores are close to 0 or 1(Stuart, 2010).

3.5 Concluding Comments

In this chapter, we have laid out a framework for analyzing the technical efficiency for the second stage of public extension service provision. Stochastic production frontier approach is adopted. In the framework, the sources of inefficiency have been identified. The sample selectivity issue that has never been addressed in agricultural extension literature is taken care of. We also provide a statistical perspective to validate our analysis about sample selectivity.

At this point, we have derived the maximum likelihood function that is needed for empirical estimation in the next chapter. We will carry out an empirical application to evaluate how individual farms perform in four areas in Crete, Greece in Chapter 4.

Chapter 4

Empirical Investigation of Public Service and Private Production: The Case of Extension in Crete

4.1 Introduction

Chapter 3 established the basic modeling framework of studying the economic performance of agricultural extension service provisions. In this chapter, empirical applications of our modeling framework are undertaken to evaluate this economic performance for the case of Crete, Greece based on a broad survey. In particular, two approaches are explored to investigate the performance of agricultural extension services provision in this chapter. The first is the econometric approach framed in Chapter 3 employing non-neutral stochastic production frontier model with accommodations for sample selectivity. The second approach is causal inference, which revisits the same data from a statistical perspective. We will testify whether the empirical results from the two approaches coincide and therefore support each other or produce conflicts to each other.

As discussed in Section 3.3, selection bias is caused by preferential exclusion of samples from the data which is a major obstacle to valid causal and statistical inferences. We proposed to use an indicator function and impose correlations on the error structure of sample indicator function and that of the stochastic production frontier function to identify the possible sample selection bias. Conclusions can be drawn based on the estimation via simulated maximum likelihood.

More broadly, sample selection problem can be studied in the context of causal inference framework. As a special case of causal effect estimation, sample selection problem is a major concern for causal inference from observational data. In an observational study, treatment status is not controlled by the researcher but can be related to various background variables. Thus systematic differences in these variables can exist between farms receiving extension services and those that do not; thus direct comparisons of observed outcomes from the two groups of farms are not appropriate. Other reasons making causal inference not easy to draw include: there are units that always take the treatment, and others that never takes it; there are also units take treatment when assigned and control when not assigned, and units take treatment when not assigned and control when assigned.

In this chapter, we first explore sample selectivity problem by extending the current literature of stochastic production frontier. Subsequently, we adopt potential outcome framework as well as various matching methods to estimate the true causal effect as a second way to identify sample selectivity.

4.2 Background on Agricultural development in Crete, Greece and Data Description

4.2.1 Background on Agricultural Development in Crete, Greece

The empirical study focuses on the case of Crete, Greece. Agricultural development of rural area in Crete is facing particular challenges requiring special attention from policy makers and researchers. An OECD background report on place-based policies for rural development in Crete identified three concerns. First, primary industries create fewer jobs. Second, the population structure exhibits a tendency of aging in some places and also outmigration of young people and immigration of retirees to rural areas may create problems in agricultural development. Finally, the lack of the necessary critical mass of facilities in most rural areas, producer services and investments to support economic development make entrepreneurs have difficulty starting up enterprises in the area (OECD, 2005). For the other reason, Greek government-debt crisis makes it imperative to enhance the efficiency of government expenditure.

The Region of Crete is bordered to the north by the Sea of Crete and to the south by the Libyan Sea. It has a total area of 8335 sq. km. and covers 6.3 $\%$ of the country's total area, composed of four prefectures which are of focus: Chania, Rethymno, Herakilo and Lasithi. The morphology of Crete is characterized by three basic zones: the high or mountainous zone at an altitude of 400 m. and above, the middle zone from 200 to 400 m. and the low zone, comprising areas rising from sea level to 200 m. Crete has 7.4% of agricultural land in Greece that is specialized in traditional cultivations such as olive and viticulture. The rural population consistently accounts for 58% of the total population in 1991 and 57.98% in 2001(Source, National Statistical Service of Greece and (OECD, 2005)). The highest concentration of rural population appears in Rethymnon (61.56 %) and Lassithi (50.26 %) prefectures. In Heraklion and Chania prefectures, the rural population rates are 35.5% and 39.89% prefectures, respectively. Our data covers all these four prefectures.

4.2.2 Data Description

Data used in this study are the same set analyzed by Dinar et al. (2007), with some accommodations for the sample selection issues. The data is composed of two different surveys addressing the structural characteristics of agricultural sectors in the island of Crete on the structural characteristics. The surveys were financed by the Regional Directorate of Crete in the context of 1995-99 Regional Development Program.

Data on farm population and its characteristics were obtained from an extensive survey on agricultural sector in Crete by the Regional Development Program for year 1995-96. The survey is composed of farm individual-level characteristics including output, input use on land, capital, labor, and demographic variables, socioeconomic variables and the number of extension visits from both public and private extension agents.

The farms were selected randomly and 265 farms participated the survey. Summary statistics for these data are presented in table 4.1.

From table 4.1, 31 farms did not participate in either public or private extension program, 188 farms reports receiving public extension services and 134 farms receive private extension services. This leaves 88 farms receiving both types of extension services. Farms did not use public/private extension services more often than private/public extension services. They account for a similar but considerable share among the overall farms. Therefore, we treat public and private extension services as one general category of farms receiving extension services and do not differentiate these different types of services in the empirical investigation that follows. As a consequence, 234 farms receive extension services of either type.

Total cultivated land is measured in stremmas, with 1 stremma equals to 0.1 hectare(ha). Total labor consists of total hired and family(paid and unpaid) labor, measuring in hours. The variable materials in table 4.1 represents pesticides, fertilizers, fuel expenses, which are measured in euros. Capital includes machinery and equipment, measured by its end of the year value in euros.

In addition, a schooling-based index is used to augment the labor input. Disregarding quality differences will lead to biases in the estimated parameters. Farm managers' years of schooling is used to construct the education index. As a purposively designed experiment, stratification guarantees these values can be seen as a reasonable proxy for education level. Moreover, we include an interaction term of labor$\times$eduation following (Griliches, 1963) that both quantity and quality dimensions of the labor can be combined before estimating the model.

An aridity index is calculated, defined as the ratio of the average annual temperature in the region over the total annual precipitation to account for regional heterogeneity that may exist among farms on the four different islands. The altitude of farm's location is measured in meters. Soil quality is distinguished into four categories, i.e., sandy, limestone, marly and dolomites.

Farmer's age is measured in years. Farm's tenancy status is measured by the share of leased or rented land to total farm land. Farm's debts, the total amount of subsi-

Table 4.1: Summary statistics for farms receiving both private and public services

	no service		**only public service**		**only private service**		**either service**		**all**	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
output	6065.13	4775.18	4632.09	4877.75	4574.19	4764.45	5272.95	5159.69	5365.65	5113.94
land	51.58	31.52	48.87	32.65	46.29	29.34	49.95	35.40	50.14	34.92
labxedu	2729.16	2796.05	1894.34	1611.80	1803.81	1900.20	2121.89	2556.81	2192.99	2596.41
labor	298.45	235.72	221.53	183.35	231.29	210.69	241.55	219.14	248.23	221.42
education	8.06	3.21	8.66	3.40	7.98	3.89	8.52	3.30	8.46	3.29
materials	898.16	852.36	675.62	913.95	735.55	703.46	814.96	907.76	824.70	900.30
capital	905.94	656.48	791.83	549.67	915.55	568.27	1113.04	895.30	1088.82	872.27
aridity	0.79	0.33	0.97	0.46	0.96	0.45	0.83	0.42	0.82	0.41
altitude	262.13	233.01	345.36	278.91	381.21	282.70	298.93	282.94	294.63	277.42
rainfall	939.64	363.86	1166.49	524.14	1126.36	444.31	1007.99	441.52	1000.00	435.81
temperature	17.65	0.98	17.39	0.83	17.35	0.83	17.59	0.92	17.59	0.93
sandy	0.35	0.49	0.19	0.40	0.17	0.38	0.26	0.44	0.27	0.45
limestones	0.23	0.43	0.28	0.45	0.33	0.48	0.32	0.47	0.31	0.46
marly limestone	0.32	0.48	0.28	0.45	0.31	0.47	0.24	0.43	0.25	0.44
age	58.68	11.76	50.15	14.09	51.19	13.09	50.64	13.00	51.58	13.10
tenancy	0.98	0.09	0.91	0.17	0.89	0.21	0.91	0.18	0.92	0.18
debts	833.13	2527.34	145.28	363.80	465.98	1582.16	685.88	1899.05	703.10	1977.62
subsidies	1090.29	1110.18	1159.43	1008.57	1340.31	1193.18	1319.73	1245.73	1292.89	1230.91
offfarm	1572.87	2005.44	1096.13	1581.23	1580.95	1817.27	1409.57	1822.92	1428.68	1841.91
selfcons	0.22	0.25	0.33	0.34	0.31	0.35	0.21	0.28	0.21	0.27
spec	0.80	0.29	0.85	0.29	0.87	0.25	0.86	0.25	0.86	0.26
intensity	133.84	98.31	96.19	57.84	110.14	74.54	123.63	125.68	124.83	122.65
sample	31		188		134		234		265	

dies(SUB) received by framers in the context of the EU's Common Agricultural Policy (CAP), and the total off-farm income arising from nonfarm activities of the household are measured in euros. Self-consumption is a percentage measure for the proportion of self-consumption of farm output.

Farms' specialization is measured by the Herfindhal index. Each farm's output level is used to generate respective weight in computing the index. The Herfindhal index is considered to affect farm's performance due to the following reasons. First, specialization may matter for farms' efficiency. There is an emerging consensus that technical efficiency and overall performance of farms are influenced by farm size so that larger and more diversified farms are more productive or efficient than small farms (Key et al., 2008). Second, farm specialization may affect farms' choice of extension services and therefore might be associated with sample selection issues.

4.3 Stochastic Production Frontier Approach with Sample Selection

4.3.1 Algorithm

We empirically investigate the farm performance in the four districts in Crete. Denote y_i as the dependent variable (output of the farm). D_i is a dummy indicator, where $D_i = 0$ corresponds to the observations without extension service, and $D_i = 1$ corresponds to the observations with extension service. $\{y_i, x_i, z_i\}$ is a random sample: x and z are regressors (input, environmental variables). $\tilde{y}_i$ denotes the farm output for the corresponding type of farm i. α^D represents the coefficient estimator for the parameter in the stochastic production frontier equation. β^D represents the coefficient estimator for the parameter in the equation specifying non-neutrality. γ is the coefficient estimator in the sample selection equation. u_i represents the shortfall of output from the production frontier due to technical inefficiency, measuring the distance of actual output from production frontier. The distribution of u_i is specified as $u_i \sim N^+(0, \sigma_u^2)$. v_i is the symmetric i.i.d. error term representing those factors that cannot be controlled by farmers as well as omitted variables and measurement errors in the dependent variable. The distribution of v_i is specified as $v_i \sim N(0, \sigma_v^2)$.

Based on the log likelihood function (3.15) and the data, the algorithm to estimate the production function are based on the following model framework:

$$\ln y_i = D_i \ln \tilde{y}_i^1 + (1 - D_i) \ln \tilde{y}_i^0 \tag{4.1}$$

$$\ln \tilde{y}_i^D = \alpha^D \ln x_i + v_i^D - u_i^D \tag{4.2}$$

$$u_i^D = |\beta^D \ln z_i + \sigma_{\xi_i} \xi_i^D| \tag{4.3}$$

$$D_i = \mathbf{1}[\gamma w_i + \epsilon_i \leq 0] \tag{4.4}$$

Let $\hat{\theta}$ be the set of parameters to be estimated. Then the generic form for our objective function is formulated in (3.15).

Building on Greene (2010), we use the simulated MLE as a general guideline to construct the algorithm.

Let R be the number of replications. The optimization of log likelihood function is carried out in the following steps.

Step 1: Choose a set of initial values: $\theta_1 = (\alpha_1^0, \alpha_1^1, \beta_1^0, \beta_1^1, \gamma_1)$.

Step 2: Draw $(\xi_r^1, \xi_r^0) \sim N(0, \mathbf{I}_2)$ for $r = 1, \cdots, R$, where $\mathbf{I}_2$ is an identity matrix of order 2.

Step 3: Compute likelihood function $\hat{P}_i(\theta_1)$ for observation i, where $\hat{P}_i(\theta_1) = D_i \hat{f}^1 + (1 - D_i)\hat{f}^0$.

At this stage, we derive $\hat{f}^1$ and $\hat{f}^0$.

Assume that v_i and ϵ_i are jointly normally distributed, which is the source of our selection bias. That is:

$$(\epsilon_i, v_i^1) \sim N\left(0, \begin{bmatrix} 1 & \rho^1\sigma_v \\ \rho^1\sigma_v & \sigma_v^2 \end{bmatrix}\right)$$

$$(\epsilon_i, v_i^0) \sim N\left(0, \begin{bmatrix} 1 & \rho^0\sigma_v \\ \rho^0\sigma_v & \sigma_v^2 \end{bmatrix}\right)$$

For $D_i = 0$:

$$f^0(y_i \mid x_i, z_i, w_i, \xi_i^0) = \int_{\xi_i^0} A_i(\xi^0) f(\xi_i^0) d\xi_i^0 \tag{4.5}$$

where

$$A_i(\xi^0) = \frac{1}{\sigma_v} \exp\left[-\frac{1}{2}\frac{(\ln y_i - \alpha^0 \ln x_i + |\beta^0 \ln z_i + \sigma_u \xi_i^0|)^2}{\sigma_v^2}\right] \times \Phi\left(\frac{\frac{\rho(\ln y_i - \alpha^0 \ln x_i + |\beta^0 \ln z_i + \sigma_u \xi_i^0|)}{\sigma_v} + \gamma w_i}{\sqrt{1-\rho^2}}\right) \tag{4.6}$$

Similarly, for $D_i = 1$:

$$f^1(y_i \mid x_i, z_i, w_i, \xi_i^1) = \int_{\xi_i^1} B_i(\xi^1) f(\xi_i^1) d\xi_i^1 \tag{4.7}$$

where

$$B_i(\xi^1) = \frac{1}{\sigma_v} \exp\left[-\frac{1}{2}\frac{(\ln y_i - \alpha^1 \ln x_i + |\beta^1 \ln z_i + \sigma_u \xi_i^1|)^2}{\sigma_v^2}\right] \times \left[1 - \Phi\left(\frac{\frac{\rho(\ln y_i - \alpha^1 \ln x_i + |\beta^1 \ln z_i + \sigma_u \xi_i^1|)}{\sigma_v} + \gamma w_i}{\sqrt{1-\rho^2}}\right)\right] \tag{4.8}$$

Given the above two derivations,we approximate the two integrals as:

$$\hat{f}_0 = \frac{1}{R}\sum_{r=1}^{R} A_i(\xi^0)$$

$$\hat{f}_1 = \frac{1}{R}\sum_{r=1}^{R} B_i(\xi^1)$$

Step 4: Compute the loglikelihood function as follows:

$$Ln(\theta_1) = \frac{1}{n}\sum_i \left[D_i \ln \hat{f}_{1i} + (1-D_i)\ln \hat{f}_{0i}\right]$$

Step 5: for another set θ_2 which is estimated from the first optimization, replicate steps 1 to 4, and obtain $Ln(\theta_2)$. This algorithm is repeated K times, leading to the estimated set of θ_K. The maximum likelihood estimator of θ is chosen based on:

$$\hat{\theta}_{MLE} = \text{argmax}_\theta\{Ln(\theta_1), \cdots, Ln(\theta_K)\}$$

Based on this algorithm, the following parameters are estimated.

a) Two sets of $\alpha^D, D = 0, 1$ in the stochastic production frontier equation 4.1, one for farms receiving extension services and the other for farms not receiving extension services. It will include a constant and covariates in the production function.

b) Two sets of $\beta^D, D = 0, 1$ in the equation indicating technical inefficiency, one for farms receiving extension services and the other for farms not receiving extension services. It will include a constant term and variables that explain the technical inefficiency.

c) One set of γs in the sample selection equation, same for all farms. It will include a constant term and variables accounting for sample selection.

MATLAB is used to execute this algorithm. In finding an efficient way to obtain the parameter estimates, the speed of convergence is a major concern. Several alternative approaches are explored. We use the package "global maximization" in MATLAB(2011b) to deal with the convergence issue [1].

[1]The package has some advantages over other existing packages. It can automatically avoid the local optimization which is a great improvement over other packages (for example, "fminsearch" or a third party package "Knitro"). Moreover, it successfully takes care of the simultaneous estimation of the variance components and the self-selection parameter ρ. In "fminsearch" and "Knitro", one has to use grid search to estimate ρ instead. In our application, "fminsearch" fails due to the local optimization problem. "Knitro" produces similar results as the "global maximization" package but it requires extra steps to obtain the estimator of ρ. Therefore, only the results from "global maximization" are reported.

4.3.2 Empirical Results

From (4.1), it is known that both public and private extension services are provided. However, in the following analysis, the farms not receiving either type of extension services are treated as 0, and farms not receiving any extension services are treated as 1. Distinction between public and private extension services is meaningful as well. It would be an interesting exercise if we adapt the probit scenario to logit scenario so that public and private extension can be treated separately.

Table 4.2: choices of regressors

	X	Z	W
Scenario 1	land, capital, materials, labor	age, education, tenancy, debts,	subsidy, aridity, altitude,education
Scenario 2	land, capital, materials, labor	age, education, tenancy, debts,	subsidy, aridity, altitude
Scenario 3	land, materials,labor, capital,education	age, tenancy, debts, specification	subsidy, aridity, altitude
Scenario 4	land, materials,labor, education, capital	age, tenancy, debts, off-farm, self-consumption, specification	subsidy, aridity, altitude

Table 4.2 summarizes possible sets of regressors specified for the parameter estimation. These four scenarios do not constitute an exhaustive list of choices. Each scenario represents a possible hypothesis. Capital, labor, land and materials are specified as factors that have an impact on production activities of any kind. These four variables are specified in the primary stochastic production frontier stated in (4.1).

Two alternatives are proposed on how labor and education can be modeled in the stochastic production frontier equation, the Mincerian approach and the Welch approach. According to Mincerian approach, education appears to be a labor augmenting factor using some functional specifications. Following the specification used in Chatzimichael and Tzouvelekas (2013), we attempt to use the exponential specification. In particular, $L \exp \phi(E)$, with $\phi(E)$ being a Mincerian piecewise linear function with zero intercept and slope varying along the time span. Following the Psacharopoulos (1994) survey on the evaluation of the returns to education, those slopes are defined as being 0.134 for the first four years, 0.101 for the next four years and 0.068 for education beyond the eighth year. In the Welch approach, human capital is treated as a separate factor of production (Welch, 1970).

A formal statistical test is suggested by Griliches (1970) to examine both hypothesis. The production frontier model is first estimated using the Welch approach and then utilizing a simple t-test one can examine the hypothesis that the coefficients of human capital and labor are equal. If it is rejected, we proceed with the Mincerian approach. Empirical investigation on how labor and education are modeled in our case suggests that education functions via its impact on farm's non-neutral inefficiency and its role of possible sources of sample selectivity.

A summary of parameter estimates for Scenario 1 where ρ and the variance components from the production function and the non-neutrality function are all freely estimated. Capital, labor, intermediate inputs and land are specified as explanatory variables in the stochastic production frontier equation. Farm-specific characteristics including education, age, tenancy and debts are hypothesized to impact farm non-neutral inefficiencies. Subsidy, aridity, education and altitude capturing both geographic and farm-specific characteristics are used as possible factors that lead to sample selectivity. Hausman test for endogeneity of tenancy and debts are conducted, suggesting that the issue of endogeneity should not be a concern in our case.

A range of starting values are used when implementing the algorithm. In the "global maximization" package, the different choices of starting values do not make a difference. All the data is standardized and taking logs as standard estimation of Cobb-Douglas form production function. Tables 4.3 through 4.5 present the corresponding parameter estimates, standard deviations and p-values. Table 4.3 presents the parameter estimates in the stochastic production frontier equation (4.1). Table 4.4 presents the parameter estimates in the non-neutrality equation (4.2). In tables 4.3 and 4.4, panel A of each table indicates farms which receive the extension service, while Panel B in these tables report the parameters for farms not receiving extension services. Table 4.5 provides parameters in the sample selection estimation and variance components.

Some notation clarifications in reading tables 4.3 through 4.5 are needed. The first subscript for α indicates whether a farm receives extension service or not. The second subscript for α refers to the chosen variables. For example, α_{01} is the coefficient for the constant among farms who do not receive extension services. The first subscript for β indicates whether a farm receives extension service or not. The second subscript for β refers to the chosen variables. For example, β_{01} is the coefficient for the constant among farms not receiving extension services.

Table 4.3: Parameters in the stochastic production frontier estimation

	Parameters	Variables	coefficient	p value
Panel A: receiving extension service	α11	constant	2.4885	0.000
	α12	land	0.4304	0.000
	α13	materials	0.3333	0.000
	α14	capital	0.1448	0.018
	α15	labor	0.1485	0.010
Panel B: not receiving extension service	α01	constant	2.0041	0.000
	α02	land	0.3446	0.022
	α03	materials	0.1680	0.299
	α04	capital	0.2921	0.065
	α05	labor	0.0767	0.575

Table 4.4: Parameters in the Non-neutral inefficiency estimation

	parameters	variables	coefficient	p value
Panel A: receiving extension service	$\beta 11$	constant	-4.5590	0.000
	$\beta 12$	age	0.3765	0.010
	$\beta 13$	tenancy	0.6115	0.000
	$\beta 14$	debts	-0.0119	0.362
	$\beta 15$	education	-0.0228	0.337
Panel B: not receiving extension service	$\beta 01$	constant	-2.7508	0.038
	$\beta 02$	age	-0.0250	0.962
	$\beta 03$	tenancy	1.4379	0.082
	$\beta 04$	debts	-0.1559	0.073
	$\beta 05$	education	-0.5355	0.103

Table 4.5: Parameters in the sample selection estimation and variance components

parameters	variables	coefficient	p value
$\gamma 1$	constant	-1.2391	0.000
$\gamma 2$	subsidy	-0.0509	0.271
$\gamma 3$	aridity	0.0291	0.879
$\gamma 4$	altitude	-0.0303	0.610
$\gamma 5$	education	-0.458	0.102
ρ	sample correlation	0.7368	0.000
σ_u	variance	0.6012	0.000
σ_v	variance	0.6138	0.000

As is demonstrated by table 4.5, the correlation coefficient $\rho = 0.7368$ is highly significant suggesting a substantive selection mechanism exists in the farmer's choices of whether to receive extension services. The selectivity issue confirms our hypothesis of whether other factors related to the choices of getting extension services are correlated with the stochastic element in the production function.

Given the fact that sample selectivity does play a significant role in the empirical analysis, one possible explanation to the sample selection mechanism from the supply side is that extension service provision is targeting more productive farms. This is analogous to the tradition of "herd behavior" (Banerjee, 1992), defined as the social phenomenon that everyone is doing everyone else is doing, even when their private information suggests doing something quite different. In the case of agriculture, less productive farmers seek to imitate the successful farmers; the implication for extension is to seek out the successful farmers and show them the cutting edge practices, so that the less successful farmers will imitate them and adopt it.

Another possible explanation from the demand side is that farms with higher productivity levels are more eager to receive extension services. These farms are usually larger in scale, having lower debt/asset ratio and thus more ready to get technical help from extension services agencies. For farms receiving extension services, the capital on average(which includes machinery and equipment) is 22.9% higher than those who do not receive any extension services. While intermediate inputs(which include fertilizer, pesticides, fuel expenses) utilized by farms receiving extension services are 10% less than those not receiving any extension services.

Table 4.3 provides a comparison of the coefficients in the stochastic production frontier estimation. Allowing for land, intermediate inputs, capital and labor, farms receiving extension services present a returns to scale measure of 1.057 compared to 0.8854 for farms not receiving extension. The relative contribution of intermediate inputs is twice as much as capital for farms receiving extension services, while for farms not receiving extension services, capital is contributing twice as much as that of intermediate inputs.

This finding is consistent with our data. The law of diminishing returns is playing an important role, which states that in all productive processes, adding more of one factor of production, while holding all others constant, will at some point yield lower per-unit returns.

The total factor productivity level of two types of farms is revealed in the constant terms in the stochastic production equation with the estimates presented in (4.1). The farms receiving extension services are approximately 60% more productive than those not receiving extension services. [2]

This finding is also consistent with the existence of sample selection. Farms having lower debt/asset ratio are potentially those with higher productivity. On the other hand, farms with more intermediate inputs may indicate that these farms substitute extension services with their own choices of fertilizer, pesticides and other machinery inputs, etc. In the presence of sample selectivity, those farms with better financial situation and fewer intermediate inputs are more motivated to have the demand for extension services.

The estimation results presented in table 4.4 have the following implications. First, education's role is positive for farms not receiving extension and insignificant for farms receiving extension services. Extension service provision, as a channel of continuing education to farms, dilutes the role of education in improving technical efficiency of farms. It functions as a substitute of education not aiming at farming expertise.

Second, the impact of farmer's age as a possible source of technical inefficiency is different for these two types of farms. For the farms receiving extension services, a larger percent of older farmers have a negative effect on improving technical efficiency. However, the coefficient associated with older farmers does not significantly impact the non-neutral inefficiency of farms. The rationale behind the observation is that young farmers are more ready to accept and act in response to new techniques and other information transmitted from extension agencies.

Finally, table 4.5 implies that education serves as a source of sample selection in agricultural extension service provision. The longer years of schooling increases the possibility of farmers to receive extension services. Education can support these farms to be identified by extension agencies; Alternatively, more educated farmers are possibly more eager to self-identify receiving extension service.

[2]The constant, $A_i = e^{\alpha_{i1}}, i = 0, 1$, reflects the farm productivity level. For the farms which receive extension services, the productivity level $A_1 = e^{2.4885} = 12.04$, and for the farms not receiving extension services, the productivity level is $A_0 = e^{2.0041} = 7.42$.

4.3.3 Estimating Observation-Specific Inefficiency

The above procedures lay the groundwork for estimation of inefficiency in the sample, u_i or technical efficiency $TE_i = \exp(u_i)$. Upon estimating α and β, only the difference $v_i - u_i$ is recoverable in the basic model $\ln y_i = \alpha + \beta x_i + v_i - u_i$. Hence, the best predictor of farm-specific technical efficiency is the expected value of u_i given the composite error.

Based on an approximation of $u_i = -\ln(\exp(u_i)) \approx 1 - \exp(u_i)$, Jondrow et al. (1982) compute $E(u_i|\epsilon_i) = E(u_i|(v_i - u_i))$ as a prediction for the technical inefficiency. The result is:

$$E(u_i|\epsilon_i) = \frac{\sigma\lambda}{1+\lambda^2}\left[\mu_i + \frac{\phi(\mu_i)}{\Phi(\mu_i)}\right] \tag{4.9}$$

where $\mu_i = \dfrac{-\lambda(v_i - u_i)}{\sigma}$. To simplify notations, denote $\sigma^2 = (\sigma_u^2 + \sigma_v^2)$ and $\lambda = \dfrac{\sigma_u}{\sigma_v}$. Fried et al. (2008) presents the derivation of the formula before any simplifications. Alternatively, one can avoid using the above approximation and calculate the conditional expected value of $\exp(u_i)$, as suggested in Battese and Coelli (1988).

In our framework, the computation of technical inefficiency requires more effort since we also have the function which explains the non-neutrality. However, the general principle of the computation carries over.

Recall that we have:

$$\ln \tilde{y}_i^D = \alpha^D \ln x_i + v_i^D - u_i^D, \quad u_i^D = |\beta^D \ln z_i + \sigma_{\xi_i}\xi_i^D|,$$

Hence, $\ln \tilde{y}_i = \alpha \ln x_i - \beta \ln z_i + v_i - \xi_i$. For notational convenience, denote $\tau_i = v_i - \xi_i$, where τ_i is estimable directly after we generate the parameter estimates, i.e. $\tau_i = \ln \tilde{y}_i - \alpha \ln x_i + \beta \ln z_i$. Given the joint distribution of v_i and ξ_i, we use equation (4.15) where non-neutrality was not considered to calculate $E(\xi_i|\tau_i)$. Consequently, $\hat{u}_i = E(\xi_i|\tau_i) + \hat{\beta} z_i$.

An alternative approach proposed by Greene (2010) takes advantage of the simulated values of u_i during estimation. Denoting $u_i = \sigma_u|U_i|$, where $|U_i|$ is the standard normal random variable, and using Bayes theorem, the desired expectation is:

$$E[u_i|\epsilon_i] = E[(\sigma_u U_i)|\epsilon_i]$$
$$= \frac{\int_{\sigma_u|U_i|} (\sigma_u|U_i|)\, p(\epsilon_i \Big| (\sigma_u|U_i|)) p(\sigma_u|U_i|) d(\sigma_u|U_i|)}{\int_{\sigma_u|U_i|} p(\epsilon_i(\sigma_u|U_i|)) p(\sigma_u \Big| U_i|) d(\sigma_u|U_i|)}. \quad (4.10)$$

The simulated denominator would be:

$$\hat{A}_i = \frac{1}{R}\sum_{r=1}^{R} \frac{1}{\hat{\sigma_v}} \exp\left[-\frac{1}{2}\frac{(\ln y_i - \hat{\alpha}\ln x_i + |\hat{\beta}\ln z_i + \hat{\sigma_u}\xi_i|)^2}{\hat{\sigma_v}^2}\right] \times$$
$$\Phi\left(\frac{\hat{\rho}(\ln y_i - \hat{\alpha}\ln x_i + |\hat{\beta}\ln z_i + \hat{\sigma_u}\xi_i|)/\hat{\sigma_v} + \hat{\gamma}w_i}{\sqrt{1-\hat{\rho}^2}}\right)$$
$$= \frac{1}{R}\sum_{r=1}^{R} \hat{f_{ir}} \quad (4.11)$$

where R is the number of replications. The numerator is simulated by
$\hat{B}_i = \frac{1}{R}\sum_{r=1}^{R}\left(|\hat{\beta}\ln z_i + \hat{\sigma_u}\xi_i|\right)\hat{f_{ir}}$.

The estimated $E(u_i|\epsilon_i) = \hat{B}_i/\hat{A}_i$ is computed for each observation using the estimated parameters. The efficiency scores are computed for each individual farm based on equation (4.6). Figure 4.1 illustrates the distribution of these efficiency scores. The horizontal axis stands for the output level for farms, while the vertical axis stands for the efficiency scores. The circles represent distribution of efficiency scores for farms without any type of extension services. The asterisks represent distribution of efficiency scores for farms which receive extension services.

The efficiency scores are computed for each individual farm based on (4.10). Figure 4.1 illustrates the distribution of these efficiency scores. The horizontal axis stands for the output level for farms, while the vertical axis stands for the efficiency scores. The circles represent distribution of efficiency scores for farms without any type of extension services. The asterisks represent distribution of efficiency scores for farms which receive extension services. No clear distinction between the two types of farms is apparent by inspection on Figure 4.1. Within the range of low technical inefficiency scores, there

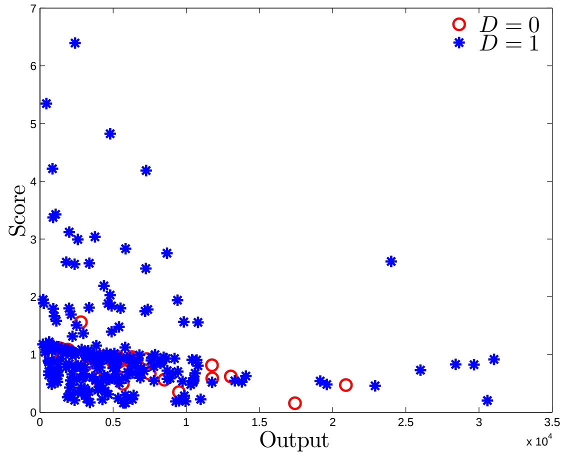
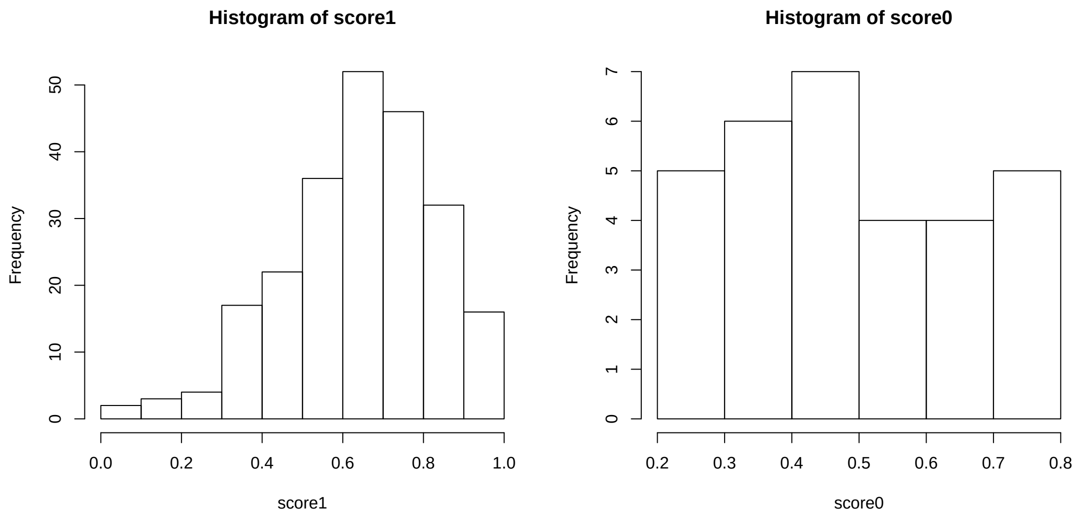


Figure 4.1: Distributions of efficiency scores

is some degree of overlapping between these two types of farms. But the farms with higher efficiency scores are generally those who receive extension services and with lower output level.



(a) Farms receiving extension services (b) Farms not receiving extension services

Figure 4.2: Frenquency distribution of efficiency scores

Figure 4.2 presents the raw histograms of efficiency scores for each farm type. Score 0 stands for the efficiency scores of farms not receiving extension services, while score

1 represents the farms receiving any extension services. As demonstrated, most farms receiving extension services are performing at a relatively high efficiency level, while most farms not receiving extension services have a lower efficiency scores.

We conduct here a formal test to see whether the distribution of the efficiency scores for these two types of farms differ following the approach proposed by Simar and Zelenyuk (2004) and investigate the possibility of adapting existing Li's tests for the equality of two distributions in the context of efficiency scores (Li, 1999).

Let $\{U^{A,k} : k = 1, \ldots, n_A\}$ and $\{U^{Z,k} : k = 1, \ldots, n_Z\}$ representing the efficiency scores for the two groups of farms respectively. n_A is the number of observations for farms which do not receive extension service, while n_Z is the number of observations for farms who receive extension service. Letting f_l denote the density of the distribution of a random variable $U^l(l = A, Z)$, our null and alternative hypotheses are:

$$H_0 : f_A(u^A) \quad = \quad f_Z(u^Z) \tag{4.12}$$

$$H_a : f_A(u^A) \quad \neq \quad f_Z(u^Z) \tag{4.13}$$

To test such hypothesis, Li (1999) considered the integrated square difference criterion:

$$I \equiv \int (f_A(u) - f_Z(u)^2 du = \int (f_A^2(u) + f_Z^2(u) - 2f_A(u)f_Z(u))du. \tag{4.14}$$

A particular convenient statistic was proposed by Li (1999) who showed that a consistent and asymptotically normal estimator of Equation (4.14) is obtained using the empirical distribution functions. The nonparametric kernel density estimators are defined as:

$$\hat{f}_{l.n_l}(u) \equiv \frac{1}{n_l h_l} \sum_{k=1} n_l K(\frac{u - u^{l,k}}{h_l}), l = A, Z, \tag{4.15}$$

where $h_l = h(n_l)$ is a bandwidth such that $h_l \to 0, n_l h_l \to 0$ as $n_l \to \infty$, K is an appropriate kernel function, and u is a point at which the density will be estimated. As suggested by Li (1999), we choose the u's to be the observed points and $h = \min{(h_A, h_Z)}$.

The test statistic to compute is:

$$\widehat{J}^{nd}_{n_A,n_Z,h} \equiv \frac{n_A h^{1/2} \widehat{I}^{nd}_{n_A,n_Z,h}}{\hat{\sigma}_{\hat{\lambda},}} \to N(0,1) \tag{4.16}$$

where $\widehat{I}^{nd}_{n_A,n_Z,h}$ can be computed using the kernel density functions, bandwidth and the number of observation in each subgroup.

However, the properties of the limiting distribution is difficult to handle. In such situations, bootstrap techniques often provide a practical way of obtaining inferences. Li (1999) provides convincing Monte Carlo evidence that the bootstrap techniques is a practical way of obtaining inferences and it is preferred to using normal tables.

Our test here is based on bootstrapping the adapted tests of Equation (4.16). The p-values of the Li test in its standard context are given by:

$$\hat{p} = \frac{1}{B} \sum_{b=1}^{B} I\{\widehat{J}^{nd,b}_{n_A.n_Z} > \widehat{J}^{nd}_{n_A,n_Z}\}. \tag{4.17}$$

The p-value we generate for this test is 0.053, a strong evidence against the null hypothesis; namely, the distributions of the efficiency scores among two groups are significantly different from each other.

Upon implementing the simulated maximum log likelihood estimation procedure, the stochastic production frontier model with correction for sample selectivity provides us several insights. We explored the existence of sample selectivity in the extension service provision program in Crete. The mechanisms behind sample selectivity are also identified from two possible channels, both demand and supply side of extension services provision. In particular, we find that farms receiving extension services have higher productivity level than those which do not receive extension services. This finding supports either of the following two hypotheses. One of them is that extension agents are aiming to provide extension services to farms with higher extension agents. The other hypothesis is that farms with high productivity level are more motivated to get extension services.

We further investigated the efficiency scores based on the simulated maximum log likelihood estimation results. The distributions of the efficiency scores for two farm types are significantly different as suggested by Li's statistical test. Applying the stochastic production frontier modeling framework, we empirically find the existence of sample selection in the case of extension service provision in the case of Crete agriculture. Possible sources of technical inefficiency are identified. Moreover, they are different for different farm types. Sample selection may stem from herd behavior, farms' scale, asset/debt ratio, etc. After correcting for the sample selection, farms receiving extension services have a better performance in terms of both productivity and technical efficiency than those not receiving any extension services.

The next section continues with an investigation from the causal inference perspective which analyzes the sample selectivity problem in statistical setting. Ideally, we can evaluate the conclusion drawn from stochastic production frontier framework with correction for sample selection if data structure permits us to do so.

4.4 The Causal Inference Perspective

From the perspective of the stochastic production frontier approach, we establish that sample selectivity is playing a role in agricultural extension services provision. Causal inference approach presented in Section 3.4 is empirically conducted to provide a second perspective of investigating the true causal effect of agricultural extension service provision on the farm output level. Several methods are proposed to estimate this effect. Different from the direct estimation of average causal effect, various matching algorithms are used to eliminate the pre-treated discrepancies between two types of farms. Outcome analysis based on the matched samples is conducted.

The empirical results of average causal effect estimation and matching algorithms are presented and discussed below. These results are not comparable with the conclusion drawn in stochastic production frontier model. In particular, in the stochastic production frontier approach, farms are grouped by whether they received any type of extension services. It would be ideal if we can use the same grouping rule in the causal inference approach. However, the number of farms is quite different by the grouping rule used in stochastic production frontier model. The results from causal inference approach will not be convincing in such a scenario. Instead, we group of the farms by wether they receive any public extension services. Consequently, the purpose of causal inference approach is not to provide a comparison of these two perspectives, but rather proposing a alternative possibility of handling group comparisons.

Before proceeding with any matching scheme, we first check the covariate imbalance which gives us a statistical description of the covariates. By comparing to the post-match data, we evaluate whether matching can balance an observed covariate between treated and control observations. The formula for computing the standardized difference is:

$$SD = \frac{\text{difference in the mean outcomes between groups}}{\text{standard deviation of the outcome among paticipants}} = \frac{100(\bar{x}_{\text{treated}} - \bar{x}_{\text{control}})}{\sqrt{\frac{s^2_{\text{treated}} + s^2_{\text{control}}}{2}}}$$

Table 4.6: Standardized difference before matching

Variable	standardized diff	Variable	standardized diff
Labour	-12.32	Marlylimestones	9.43
Education	-9.71	Altitude	3.87
Other	-21.55	Subsidies	12.27
Capital	-11.25	Age	5.31
Aridity	16.16	Rainfall	18.09
ClayeySandy	-15.07	Offfarm	15.37
Spec	-2.37	Temperature	-2.86
Debts	-20.16	SelfCons	24.55
Clayeylimestones	0.47	Intensity	18.23
tenancy	187.68		

From Table 4.6, we find that some covariates are classified as unbalanced before matching since the standardized differences are larger than 20. These covariates are tenancy, debts, self-consumption, others which represents intermediate inputs, consisting of pesticides, fertilizers, fuel expenses. Other covariates with a standardized difference close to 20 include aridity, rainful, clayeysandy, offfarm and intensity. [3]

Several algorithms are implemented to match the treatment group (farms who receive extension services) with the control group (farms not receiving extension services). These include: linear regression estimates with robust standard errors, Mahalanobis-metric matching within calipers defined by the estimated logit-propensity score, propensity score matching (nearest neighbor with 1 to 1 ratio), full matching, inverse propensity score matching, and propensity-subclassified estimates.

Table 4.7 reports the average causal effects and average causal effects for the treatment group using five different approaches. Standard errors are in parenthesis. We find that neither average treatment effects and average treatment effects for the treatment group is significant. The ordinary least square regression of farm output on indicator variable of public extension services based on the matched samples also leads to an insignificant coefficient on the indicator variable. These findings assure the credibility of our conclusion using the stochastic production frontier approach where farm technical efficiency scores do not significantly differ between the two types of farms [4].

Table 4.7: Average causal effect for the population and for the treated

Algorithm	ACE	ACE1
Regression with Robust SE	584.2(411.2)	611.3(459.3)
full matching	1175.2(702.5)	1175.2(677.0)
inverse propensity score matching	646.1(440.9)	671.1(498.8)
genetic matching	646.1(440.9)	671.1(498.8)
subclassification	1175.2(702.5)	1175.2(677.0)

Table 4.8 presents another set of matching algorithms. The number of matched samples, ordinary mean comparisons based on matched samples and the variance of the

[3] The cutoff might be different in different settings. The chosen cutoff value (20) refers to the following source: http://cran.r-project.org/web/packages/nonrandom/vignettes/nonrandom.pdf.

[4] The results of stochastic production frontier approach using the same grouping rule is not reported in the dissertation.

estimators are reported. Bootstrapping is used to compute the variance of these ordinary mean comparisons. The conclusion drawn here again shows that there is no significant impact of public agricultural extension on farm output.

Table 4.8: Matching Algorithms and ordinary mean comparison

Algorithm	Matched pairs	ordinary mean comparison	bootstrapping standard error
Mahalanobis with calipers	69/69	1219.5	440.1
nearest neighbor	77/77	1478	126 .3
full matching	77/188	558	107.4
genetic matching	57/188	365	205.9
subclassification	77/188	558	107.4

4.5 Concluding Comments

In this chapter, we build a stochastic production frontier model framework allowing for inputs non-neutrality and giving sample selectivity a consideration. An empirical investigation into the farm performance is conducted in the case of Crete, Greece. Our main objectives include checking for the existence of sample selectivity and measuring the technical efficiency of individual farms in the context of agricultural extension provision. Upon implementing the simulated maximum log likelihood estimation procedure, the stochastic production frontier model with correction for sample selectivity provides us several insights.

By adopting stochastic frontier framework, farms are no longer assumed to perform production in their respective production frontiers. The distance of each individual farm from its frontier is measured and interpreted as technical inefficiency of the individuals. Under our general framework, sources of technical inefficiencies can also be identified. Along with other socioeconomic and demographic variables, agricultural extension service provision was included in the inefficiency effect function as factors influencing technical inefficiency. Farmers' age, tenancy, debt status, farm specialization, share of self-consumption and land types exert significant effects on the technical inefficiency of both farm types. However, direction of the effects on these two types of farms varies. Moreover, our empirical results suggest that there is a clear distinction between farms receiving and those not receiving extension services on the basis of efficiency performance. The effect of agricultural extension services on improving technical efficiencies is positive even after correcting for sample selection bias. Moreover, farms' choices of extension services also relate to their productivity levels. Farms choosing to receive extension services are those with higher average productivity.

In addition, the results show that sample selection bias does exists, therefore justifying the choice of our modeling framework. To our knowledge, this is a first attempt in studying the sample selectivity in the context of agricultural extension service provision. In contrast, estimation grouping as one farm type will provide biased results in the parameter estimation of the production technology , as well as farm-specific technical efficiency scores. The mechanisms behind sample selectivity are also identified from two possible channels, both demand and supply side of extension services provision. In particular, we find that farms receiving extension services have higher productivity level than those which do not receive extension services. This finding supports either of the following two hypotheses. One of them is that extension agents are aiming to provide extension services to farms with higher productivity extension agents. The other hypothesis is that farms with high productivity level are more motivated to get extension services.

The performance of extension agencies in the first production stage was not analyzed in this chapter in the absence of relevant data. However, we can study the first stage theoretically and put it in a larger picture where local governments distribute budgets to different extension agency according to some mechanism designed by the government. Chapter 5 will try to answer the question of how the mechanism can be designed. Equilibrium solution concepts and corresponding simulations will be conducted as well.

Chapter 5

Public or Private Extension: A Macro Perspective

5.1 Introduction

Chapters 3 and 4 focus on the micro level provision of agricultural extension services, by econometrically measuring the technical efficiency of agricultural extension services in the second production stage for the case of Crete, Greece. Extension services provided via private and public extension services are not distinguished in this micro perspective.

From a macro perspective, policy makers are interested in designing a suitable mechanism for all the participants in the extension service system given all economic and social conditions. Who should sit in the driver's seat in the extension system, public sector, private sector or some combinations of both? How should one characterize efficiency in the first production stage where an intermediate service is produced? Both private and public extension agencies play an important role in providing extension services. Private extension service takes on greater responsibilities, and even public extension service breaks with tradition to allow for fee-for-service projects as part of the extension program. Therefore, how much to charge for extension services? To address these questions, the demand side of the extension service system should not be ignored.

Theoretically, the demand for agricultural extension services and therefore the willingness to pay for these services depend on the expected benefits from the services. The objective in this chapter is to develop a game theoretical framework incorporating both supply and demand of the agricultural extension system, where extension agents are classified into several types according to their productivity performance. The chapter organization is as follows. In the next section, we lay out the mechanism framework with government, extension agents and farms as players. The government's objective is to maximize the social welfare via mechanism design to reveal the true information of extension agents. In the third and fourth sections, numerical methods are implemented to solve the equilibrium systems for two-type and three-type agents respectively. The last section presents concluding comments.

5.2 Model Setup

One basic characteristic of agricultural extension service is its public goods nature. By the market mechanism alone, the private supply of extension services is not sufficient to meet the demand from farms. Hence, government enters and plays a role. In particular, the government subsidizes the extension agents by designing a mechanism where farm operators and others pay for the services via taxes subject to a budget constraint.

The environment of our model is as follows. It is a static one-period game with incomplete information. There are three players in the game: the central planner (government), N extension agencies and M farms, with $1 < N << M$. Some players are uncertain about the characteristics of some other parties. The formal definition of a game with incomplete information is:

Definition 1. *For $i = 1, \cdots, I$, where I is the number of players, a game with incomplete information $G = (\Theta, S, P, u)$ consists of (Mas-Colell et al., 1995):*

1) *A set $\Theta = \Theta_1 \times \Theta_2 \times \cdots \Theta_I$, where Θ_i is the (finite) set of possible types. for player i.*

2) *A set $S = S_1 \times S_2 \times \cdots S_I$, where S_i is the set of possible strategies for player i.*

3) A joint probability distribution $p(\theta_1, \theta_2, \cdots, \theta_I)$ over types. For finite type space, assume that $p(\theta_i) > 0$ for all $\theta_i \in \Theta_i$.

4) Payoff functions $u_i : S \times \Theta \to \mathbb{R}$.

Let B be the fixed government budget. Government has two specific roles in the mechanism design. One is to set a price for the extension visits by agencies. [1] The second role is to design a contract for the N extension agents. The complete contract is composed of a set of quantity requirements by the government for the extension visits and a set of subsidies summing to B that are allocated to the N extension agents.

Each farm i has a production function which is also its payoff function. To incorporate the property of public goods, an externality is included in the farm's production function; that is, each farm i's production is affected by the aggregate level of the technology that all farms currently adopt. The technology is specified as:

$$U^i = \eta_i \ln \sum_{i=1}^{M} v_i + \alpha_i \ln v_i + r_i \tag{5.1}$$

where v_i denotes the number of extension visits a farm receives. The marginal productivity of extension visits is different across farms given the heterogeneity in farm endowments. The constant term r_i is also farm specific. The summation term reflects the externality of extension services as each farm's current payoff function is affected by the aggregate technology level of farming practices. For simplicity, this specification neglects the farms' inputs to produce output and the cost of production, which are reflected in the constant term.

The utility of the extension agents depends on the wealth and leisure they consume. It is specified as:

$$u^j(m, \delta) = \ln m + \theta_j \ln \delta_j \tag{5.2}$$

[1] Extension visits are used loosely as a proxy for the intensity of extension service delivered or demanded. Of course, a multitude of delivery opportunities exist. In this chapter, I focus on an aggregate service delivered.

where m denotes the endowment wealth and δ denotes the leisure level. Without loss of generality, the total time available to an extension agent is normalized to unity. θ_j denotes the productivity type of extension agent, which is private information for each agent. However, we assume that its distribution is common knowledge to all players. The government and the farmers know the distribution of θ_j, but neither knows what exactly each agent adopts.

The production function of the extension visits is specified as:

$$G^j = A^j k_j^{\beta} l_j^{1-\beta} \tag{5.3}$$

where k_j and l_j are the capital and labor utilized by extension agent j in producing extension visits. A^j captures the total factor productivity of each agent. It is assumed to be an increasing function of total factor productivity. Since the total time available to the extension agent is normalized as unity, and A^j is a decreasing function of the leisure of extension agent. The more leisure an agent consumes, the less time will be allocated to production. For simplicity, assume $A_j = \frac{1}{\delta_j}$. Hence, $G^j = \frac{1}{\delta_j} k_j^{\beta} l_j^{1-\beta}$. From the specification, the smaller the δ_j is, the greater effort an extension agent undertakes, and the higher productivity level the extension agent achieves.

Based on the Cobb-Douglas specification of extension agents' production function, one can derive the corresponding cost function for each agent:

$$\min(Rk_j + wl_j) \qquad \text{(Programming 1)}$$
$$\text{s.t.: production constraint} \quad \frac{1}{\delta_j} k_j^{\beta} l_j^{1-\beta} \geq v$$

Here v can be the number of extension visits designed for either the high or low productivity type of extension agent.

The corresponding cost function is of the form(see Appendix A1 for a derivation):

$$c(v, r, w, \delta_j) = v\delta^j \phi \tag{5.4}$$
$$\text{where } \phi = R\left[\frac{(1-\beta)r}{w\beta}\right]^{1-\beta} + w\left[\frac{(1-\beta)R}{w\beta}\right]^{\beta} \tag{5.5}$$

Given the cost structure of the extension agents, the extension agent j's payoff function is derived as:

$$\ln(B_j - v_j\delta_j\phi) + \theta_j \ln \delta_j$$

where B_j is the budget that agent j receives from the government. The choice variable in agent j's objective is the level of leisure consumption δ_j.

The first part in the payoff function represents the payoff from the "profit", which equals the government budget minus the cost incurred by extension agent j to produce v_j extension visits. The second component captures the negative payoff to extension agent j due to her effort to produce v_j extension visits. Since $\delta_j \in (0, 1)$, the second component is negative. We now have a nonlinear payoff function for all extension agents, which satisfies the Inada condition.[2] Consequently, the initial efforts made by the extension agents have higher payoff than those of the later efforts.

The agent j's choice variable is the leisure consumption level, which can be formulated as:

$$\max_{\delta_j \in (0,1)} \ln(B_j - v_j\delta_j\phi) + \theta_j \ln \delta_j \tag{5.6}$$

Her payoff function is (see derivations in Appendix A2):

$$\ln(B_j - v_j\delta_j\phi) + \theta_j \ln \delta_j = \ln \frac{1}{1+\theta_j} + \theta_j \ln \frac{\theta_j}{1+\theta_j} - \theta_j \ln \phi \tag{5.7}$$

Under the assumption of incomplete information, some agents choose not to report the true type to gain extra benefits. It is the government's goal to design a truth-telling mechanism where every agent has the incentive to report her true parameters θ_j. The government pays the information rent.

Take the case $\theta_j, j = L, H$ for example, assuming that $\theta_H < \theta_L$; i.e., agent H has high productivity while agent L has low productivity. It is possible that agent H makes a greater effort to produce the extension visits since he/she values leisure as much as the the θ_L does. They have relatively high productivity consequently. In this case, agent L has a binding participation constraint, while agent H's participation constraint is not

[2]In particular, any function $f(x)$ such that $f'(0) = \infty$ and $f'(\infty) = 0$ is said to satisfy the Inada condition. Our specification for the payoff function of the extension agent satisfies this condition obviously.

binding and this non-binding part becomes the information rent for agent H to report its true type to the government.

The choice variables of the extension agents are the contract sets offered by the government. They need to choose the best contract sets possible to maximize their profit given the technology constraint, the participation constraint and the incentive compatibility constraint. The participation constraint indicates that for the extension agents to engage in the game, the profit realized from the game must be nonnegative (assuming the profit earned in the outside option is 0). The incentive compatibility constraint guarantees that the contract chosen by the extension agent maximizes its profit.

The government decides the price for extension visits. Given a fixed budget B, its objective is to maximize total output of all farms minus the cost of making extension visits and the subsidy, given that all farms and extension agents are incentive compatible (maximizing their respective profit) and the farms' demand equals the extension agents' supply of extension visits. Formally, this problem is:

$$\max_{p_v,\{B^j,v_j\}} \left\{ \sum_{i=1}^{M} \left(\eta_i \ln \sum_{i=1}^{M} v_i + \alpha_i \ln v_i + r_i \right) - p_v \sum_{i=1}^{M} v_i - B \right\} \qquad \text{(Programming 2)}$$

s.t.:

(1) Farm's profit max:

$$\max_{v_i} \{\eta_i \ln \sum_{i=1}^{M} v_i + \alpha_i \ln v_i + r_i - p_v v_i\} \tag{5.8}$$

(2) Extension agent payoff max:

(5.9)

$$\{B^j, v^j\} = \arg\max\{(1+\theta_j)\ln B_j - \theta_j \ln v_j + \varphi(\theta_j)\}$$

where $(1+\theta_j)\ln B_j - \theta_j \ln v_j + \varphi(\theta_j) \geq 0$.

(3) Market Clearing Condition (demand=supply):

(5.10)

$$\sum_{j=1}^{N} v_j = \sum_{i=1}^{M} v_i$$

(4) The government budget-balanced condition:

$$\sum_{j=1}^{N} B_j = B + p_v \sum_{i=1}^{M} v_i \tag{5.11}$$

In the next two sections, we proceed with solution concepts for this mechanism design and some simulation studies are performed accordingly.

5.3 Two-type agent case: Solution Concepts and simulation study

5.3.1 Solution Concepts

Upon laying out the set of possible agent strategies and the outcome rule to implement the government's goal of maximizing social welfare in the last section, we start with the two-agent case to analyze the solution concepts. In practice, we need to analyze the constraints in Programming 2.

The constraint for the farm is straightforward. The profit maximization condition for farm i is derived via the standard first order condition. Taking the derivative with respect to v_i leads to:

$$\eta_i \frac{1}{\sum\limits_{i=1}^{M} v_i} + \frac{\alpha_i}{v_i} = p_v \tag{5.12}$$

When M is sufficiently large, the term $\sum_{i=1}^{M} v_i$ is not significantly influenced by individual behavior. Since individual farms have very little power contributing to the aggregate level of technology, (5.12) reduces to:

$$\frac{\alpha_i}{v_i} = p_v \tag{5.13}$$

Extension agent j chooses a contract set composed of subsidy and number of extension visits requirements:

$$\{B^j, v^j\} = \arg\max\{(1+\theta_j)\ln B_j - \theta_j \ln v_j + \varphi(\theta_j)\}$$

In the two extension agents case, the high-type extension agent has a productivity advantage over the low-type agent. The goal of the government is to reveal each agent's true type via the mechanism design. An ideal contract therefore satisfies the following incentive compatibility constraints:

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H + \varphi(\theta_H) \geq (1+\theta_H)\ln B_L - \theta_H \ln v_L + \varphi(\theta_H) \quad (5.14)$$

$$(1+\theta_L)\ln B_L - \theta_L \ln v_l + \varphi(\theta_L) \geq (1+\theta_L)\ln B_H - \theta_L \ln v_H + \varphi(\theta_L) \quad (5.15)$$

For the high-type extension agent, the incentive compatibility constraint in (5.14) guarantees that the gain from reporting the high-type (the left hand side of the inequality) is greater than or equal to the gain from reporting low-type technology when it is actually the high-type.

For the low-type extension agent, the incentive compatibility constraint in (5.15) guarantees that the gain from reporting the low-type (the left hand side of the inequality) is greater than or equal to the gain from reporting high-type technology when it is actually the low-type.

These two incentive compatibility constraints can be managed as:

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H \geq (1+\theta_H)\ln B_L - \theta_H \ln v_L \quad (5.16)$$

$$(1+\theta_L)\ln B_L - \theta_L \ln v_l \geq (1+\theta_L)\ln B_H - \theta_L \ln v_H \quad (5.17)$$

The next two constraints are the participation constraints:

$$(1+\theta_L)\ln B_L - \theta_L \ln v_L + \varphi(\theta_L) \geq 0 \quad (5.18)$$

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H + \varphi(\theta_H) \geq 0 \tag{5.19}$$

To summarize, the five constraints (5.12),(5.16)-(5.19) must be satisfied for Programming 2. We can further remove the following constraints:

i) (5.17) and (5.19) are redundant, and

ii) (5.16) and (5.18) must be binding.

These constraints (see the proof in Appendix A3) also have implications on the optimal budget allocations and optimal extension visits; that is, $B_H > B_L$ and $V_H > V_L$. The government will design a contract portfolio such that the subsidies and extension visits requirement for the high type agent are greater than those for the low type agent (see the proof in Appendix A4).

The government's objective function is now subject to three equality constraints:

$$\max_{p_v,\{B^j,v_j\}} \{\sum_{i=1}^{M}(\eta_i \ln \sum_{i=1}^{M} v_i + \alpha_i \ln v_i + r_i) - p_v \sum_{i=1}^{M} v_i - B\} \tag{Programming 3}$$

s.t.:

$$\frac{\alpha_i}{v_i} = p_v \tag{5.20}$$

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H + \varphi(\theta_H) = (1+\theta_H)\ln B_L - \theta_H \ln v_L + \varphi(\theta_H) \tag{5.21}$$

$$(1+\theta_L)\ln B_L - \theta_L \ln v_l + \varphi(\theta_L) = 0 \tag{5.22}$$

together with market clearing condition (5.10) and the government budget-balanced condition (5.11).

We can simplify further by using the government's budget-balanced equation (5.11) to obtain:

$$B = \sum_{j=1}^{N} B_j - p_v \sum_{i=1}^{M} v_i = B_H + B_L - p_v \sum_{i=1}^{M} v_i \tag{5.23}$$

From (5.20), we have $v_i = \frac{\alpha_i}{p_v}$, and the demand = supply constraint implies $\sum_{j=1}^{N} v_j = v_H + v_L = \sum_{i=1}^{M} v_i$.

These two simplifications imply that the government's problem further leads to:

$$\begin{aligned}
&\max\left\{\sum_{i=1}^{M}(\eta_i \ln \sum_{i=1}^{M}\frac{\alpha_i}{p_v} + \alpha_\mathrm{i}\ln\frac{\alpha_i}{p_v} + \mathrm{r_i}) - p_v\sum_{i=1}^{M}\frac{\alpha_i}{p_v} - B_H - B_L - p_v\sum_{i-1}^{M}\frac{\alpha_i}{p_v}\right\} \\
&= \max\left\{\sum_{i=1}^{M}(\eta_i \ln \sum_{i=1}^{M}\frac{\alpha_i}{p_v} + \alpha_\mathrm{i}\ln\frac{\alpha_i}{p_v} + \mathrm{r_i}) - \sum_{i=1}^{M}\alpha_i - B_H - B_L - \sum_{i-1}^{M}\alpha_i\right\} \\
&\equiv \max\{\Omega - \Phi\ln p_v - B_H - B_L\}
\end{aligned}$$

where $\Omega = \sum\limits_{i=1}^{M}\left(\eta_i \ln \sum\limits_{i=1}^{M}\alpha_i + \alpha_i \ln \alpha_i + r_i\right) - 2\sum\limits_{i=1}^{M}\alpha_i$ and $\Phi = \sum\limits_{i=1}^{M}(\eta_i + \alpha_i)$ are irrelevant to the solution concept and can be viewed as constants.

Our programming problem now becomes:

$$\max_{p_v,\{B^j, v_j\}}\{\Omega - \Phi\ln p_v - B_H - B_L\} \qquad \text{(Programming 4)}$$

s.t.:

$$p_v(v_H + v_L) = \sum_{i=1}^{M}\alpha_i$$

$$\begin{aligned}
&(1+\theta_H)\ln B_H - \theta_H \ln v_H = (1+\theta_H)\ln B_L - \theta_H \ln v_L \\
&(1+\theta_L)\ln B_L - \theta_L \ln v_l + \varphi(\theta_L) = 0
\end{aligned}$$

Now we are ready to construct the Lagrangian function:

$$\begin{aligned}
L &= \Omega - \Phi\ln p_v - B_H - B_L + \lambda_1\left[p_v(v_H+v_L) - \sum_{i=1}^{M}\alpha_i\right] \\
&+ \lambda_2\left[(1+\theta_H)\ln B_H - \theta_H\ln v_H + \varphi(\theta_H) - \ (1+\theta_H)\ln B_L + \theta_H \ln v_L - \varphi(\theta_H)\right] \\
&+ \lambda_3\left[(1+\theta_L)\ln B_L - \theta_L \ln v_L + \varphi(\theta_L)\right]
\end{aligned}$$

After some manipulations (see Appendix A5), the problem is summarized as a system with 5 nonlinear equations and 5 unknowns, B_H, B_L, v_H, v_L, p_v,

$$\Phi = (v_H + v_L)\frac{\theta_H B_H}{v_H(1+\theta_H)} \tag{5.24}$$

$$\frac{\theta_H}{v_H(1+\theta_H)} + \frac{\theta_H}{v_L(1+\theta_H)} = \frac{\theta_L}{v_L(1+\theta_L)} \tag{5.25}$$

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H = (1+\theta_H)\ln B_L - \theta_H \ln v_L \tag{5.26}$$

$$(1+\theta_L)\ln B_L - \theta_L \ln v_L + \varphi(\theta_L) = 0 \tag{5.27}$$

$$p_v(v_H + v_L) = \sum_{i=1}^{M} \alpha_i \tag{5.28}$$

The above system has a closed form solution. After solving the above system, we use the solution of p_v to solve another M-equation system (where M refers to the number of farms in the model) and eventually compute the number of extension visits each farm demands.

5.3.2 Simulation Study

Based on the above five equations/five unknowns equation systems, we conduct a simulation study in this section to characterize the solution behavior and the associated economic implications. The parameters in the above system are:

- farm's production function: η, α and r
- Agent's utility function: θ_H, θ_L.
- Agent's production function: β.
- Agent's cost function: wage w and interest rate R.

In solving the system, the following specifications for these parameters are explored. First, we generate three random vectors of η, α and r from the positive part of a normal distribution on (0,1).

The parameters θ_H, θ_L are of the main focus. These two parameters represent the productivity differences between different types of agents. In the computation, θ_H is chosen to be fixed at 1, and θ_L ranges from 1.1 to 5 which makes it possible to see how final results change according to different ratios of the technology level for two different types of agents.

The parameter β in the production function of extension agent refers to the fraction of capital income and a common specification in the literature is 1/3 Islam and Nazara (2000). The wage level w is normalized to be 1 and the interest rate R is set at 5% .

Figures 5.1 to 5.4 provide the equilibrium results for the model. The horizontal axis reflects the productivity dispersion (or the relative productivity). The vertical axis reflects several different variables with economic implications. The relative productivity of the high-type agent, by definition, is calculated by A_H/A_L. We have established before that $\delta_L = 1/A_L$ and $\delta_H = 1/A_H$. The relative productivity can therefore be represented by δ_L/δ_H.

Figures 5.1 and 5.2 provide the number of extension visits and subsidies for both the high-type agent and low-type agent in equilibrium. Both types of agents provide fewer extension visits as the relative productivity increases. The high productivity type agents are always producing more than the low productivity agents regardless of the change in relative productivity. But the high type agent has a flatter slope than that of the low-type agent. The economic rational behind this phenomenon is that the high-type agent has more technology advantages over the agent with low-type as θ_L increases. Therefore, a incentive compatible mechanism should be designed so that the high-type agent takes more economic benefits. This is also reflected in budget allocations demonstrated in Figure 5.2. Meanwhile, the individual rational condition should guarantee that the low-type agent remains active. Hence, the equilibrium extension visits also decrease for the high-type agents but not as steep as that for the low-type agent. Figure 5.2 can be explained via a similar economic rationale.

With θ_H treated as a constant, we let θ_L increase, implying that the leisure becomes more important. In theory, we would expect that δ_L will increase due to the increase in

θ_L, which means that extension visits produced in equilibrium will decrease accordingly.

This is exactly what we find in the simulation result. The equilibrium leisure consumption is increasing as extension agents attach more importance to leisure. However, this observation is not the result of increasing importance of leisure alone. Instead, it results from two opposing forces. The dominant side wins and determines the direction of movement for the equilibrium leisure consumption.

The government is mostly interested in designing the unit price of the extension visits. From (5.27), given v_L, for the equality to hold, the larger θ_L, the smaller B_L. It can be shown that $\varphi(\theta_L)$ is also a decreasing function of θ_L. Given v_L, θ_H, the smaller B_L, the smaller the right hand side of (5.26), which is the expression for the information rent. That is, greater θ_L implies the smaller the restriction for the government to design a contract and therefore the smaller the information rent. If the force that increases δ_L is positive as θ_L increases, then we can view the decrease in information rent as the negative force. In the simulation scenario, the positive force dominates, and we notice a increase in the leisure consumption as θ_L increases.

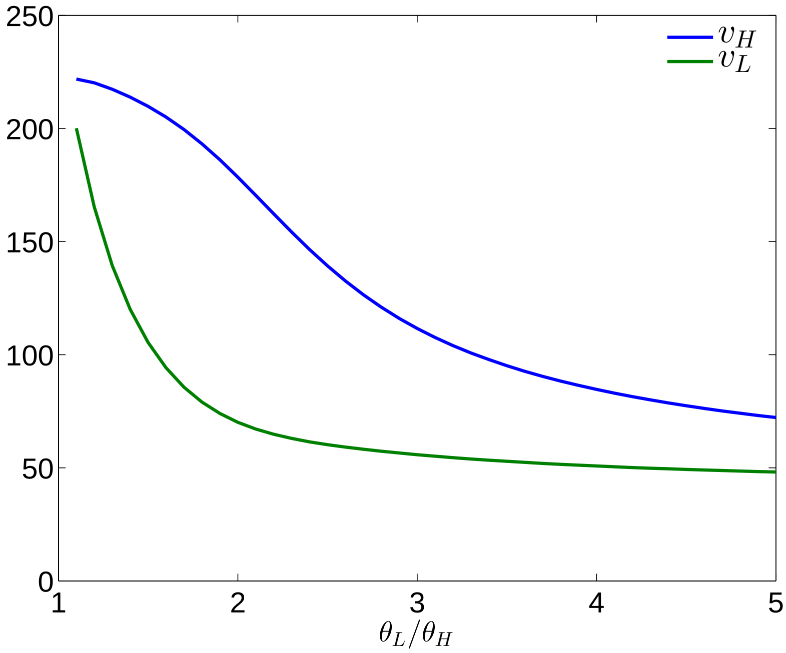


Figure 5.1: Number of Extension Visits

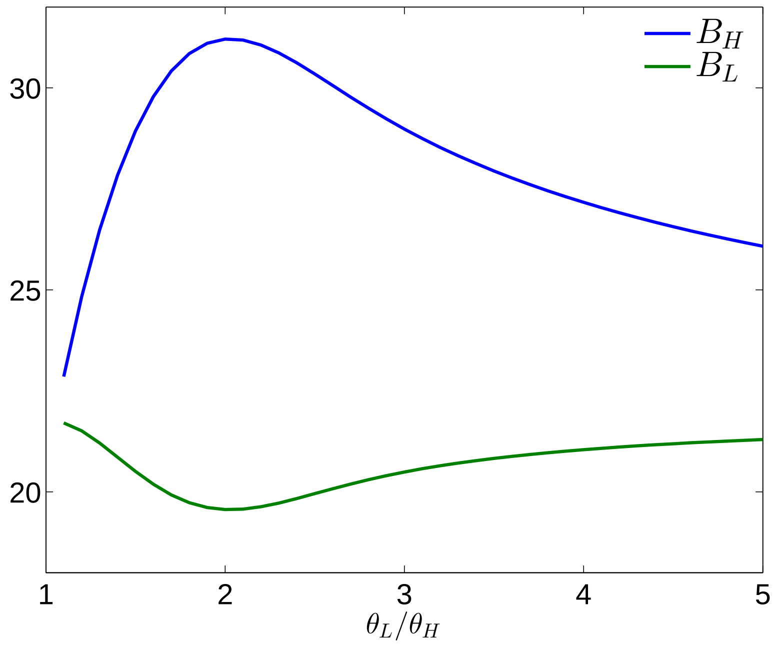
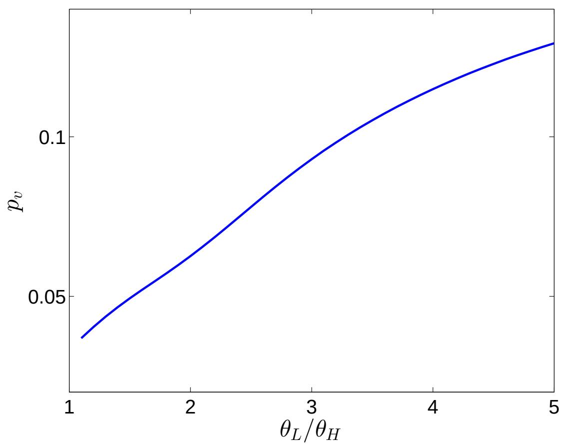
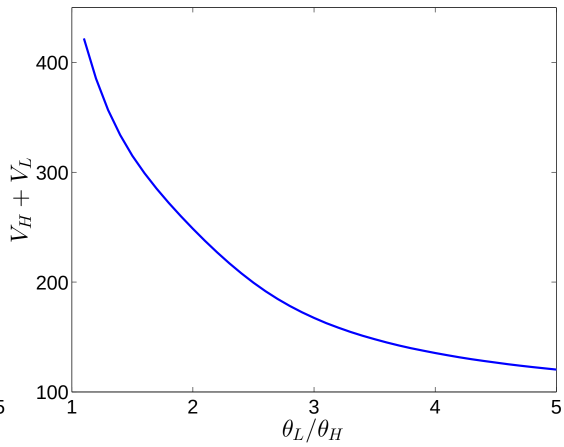


Figure 5.2: Subsidy Allocation

Figure 5.3a depicts the equilibrium price of the extension visits. Figure 5.3b characterizes the total number of extension visits in equilibrium. The equilibrium price increases as the relative efficiency increases. The rationale behind this phenomenon is straightforward: the fewer extension visits produced, the higher the price one would expect in equilibrium for a normal goods like extension visits.



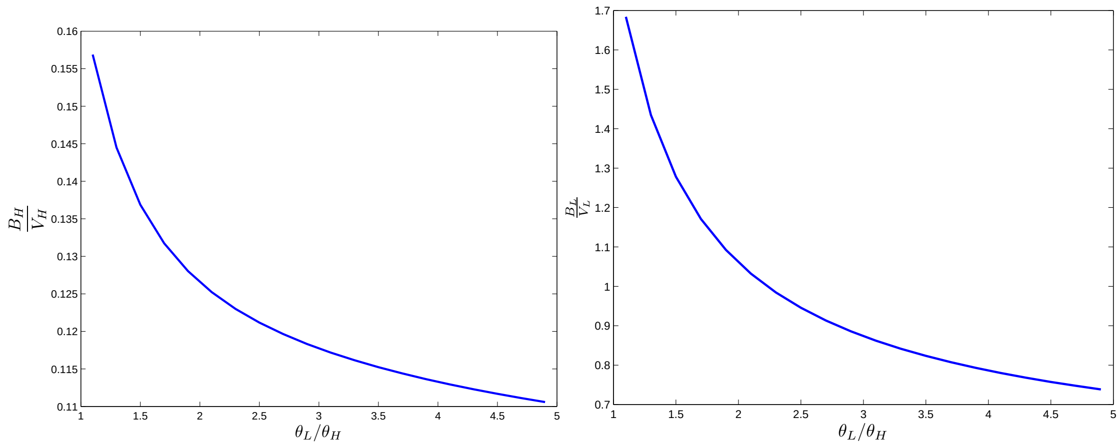
(a) Price for extension visits



(b) Total number of Extension Visits

Figure 5.3: Equilibrium Outcome

Figure 5.4 represents the subsidy utilization rate for the high and low type of extension agents, respectively. The subsidy utilization rate is computed as the ratio of subsidy and the number of extension visits produced. In some sense, this variable reflects how efficiently government allocates the social resources. From these two figures, we find that as the relative efficiency of extension agent increases, the government allocates subsidies less efficiently. Thus if the agents are homogeneous, government will be able to allocate the social resources more efficiently. When agents are heterogeneous and information is incomplete, the larger the differences between agents, the more difficult it is for the government to identify the true type of each agent and to design an efficient allocation.



(a) High type (b) Low type

Figure 5.4: Subsidy per visit

5.4 Three-type agent case: Solution Concepts and simulation study

5.4.1 Solution Concepts

In the last two sections, we set up the mechanism design problem with agents of two types. Solution concepts are discussed and simulation studies are implemented. The simulation results are reasonable and strengthen our insights into economic theories. Our next investigation is the scenario of three-type agents. The expression for the government's decision problem and the farm's problem remain unchanged. The budget balance and market clearing conditions are also the same as in the two-type agent case. However, the extension agents are specified to have three possible types instead of the previous two.

For notational convenience, let's denote the three types as $\theta_H,\ \theta_0,$ and $\theta_L,$ where $\theta_H < \theta_0 < \theta_L$; that is, the type L agent is endowed with the lowest productivity while type H agent has the highest productivity. θ_H has the lowest the negative utility brought by making effort while θ_L has the highest numerical value.

The extension agents face the same objective function as before, but they have more choices regarding which type to report to the government. Therefore, to enforce the truth telling mechanism, the government faces a more complicated contract design where all types of agents satisfy both the incentive compatibility and individual rationality constraints.

We adopt the following tradition regarding the revelation principle with more than two types by assuming: if θ_L chooses not to pretend to be its adjacent type θ_0, then he/she will not choose to report θ_H to the government, either (Mas-Colell et al. (1995)). An optimal contract therefore satisfies the following constraints:

The individual participation constraints:

$$
\begin{aligned}
(1+\theta_L)\ln B_L - \theta_L \ln v_L + \varphi(\theta_L) \geqslant 0 \quad (P_L)\\
(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 + \varphi(\theta_0) \geqslant 0 \quad (P_0)\\
(1+\theta_H)\ln B_H - \theta_H \ln v_H + \varphi(\theta_H) \geqslant 0 \quad (P_H)
\end{aligned}
$$

It is assumed that the payoff of the outside options is 0 for all three types. To force participation in the game, the payoff for all agents has to be at least 0.

The incentive compatibility constraints make agents compare the gain from telling their own true type to that of reporting the other two alternatives. Therefore, for each agent, there are two comparisons:

$$(1+\theta_L)\ln B_L - \theta_L \ln v_L + \varphi(\theta_L) \geqslant (1+\theta_L)\ln B_0 - \theta_L \ln v_0 + \varphi(\theta_L) \quad (IC_L^1)$$
$$(1+\theta_L)\ln B_L - \theta_L \ln v_L + \varphi(\theta_L) \geqslant (1+\theta_L)\ln B_H - \theta_L \ln v_H + \varphi(\theta_L) \quad (IC_L^2)$$

A further manipulation to these two constraints yields:

$$(1+\theta_L)\ln B_L - \theta_L \ln v_L \geqslant (1+\theta_L)\ln B_0 - \theta_L \ln v_0 \tag{5.29}$$
$$(1+\theta_L)\ln B_L - \theta_L \ln v_L \geqslant (1+\theta_L)\ln B_H - \theta_L \ln v_H \tag{5.30}$$

Constraints (5.29) and (5.30) are for the low-type agent. When the low type agent reports to the government its true type, the contract should be designed such that the payoff is greater than either deviating to report the adjacent 0-type or the high-type. The superscript in the parenthesis refers to the ordering of the constraint. The subscript in the parenthesis refers to the type. Therefore, IC_L^1 denotes the first constraint for the type θ_L agent, while IC_L^2 denotes the second constraint for the type θ_L agent. The same notation carries over to the constraints for the 0-type and the high-type agent.

Incentive compatibility constraints for the 0-type and high-type agents are stated as:

$$(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 + \varphi(\theta_0) \geqslant (1+\theta_0)\ln B_L - \theta_0 \ln v_L + \varphi(\theta_0) \quad (IC_0^1)$$
$$(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 + \varphi(\theta_0) \geqslant (1+\theta_0)\ln B_H - \theta_0 \ln v_H + \varphi(\theta_0) \quad (IC_0^2)$$

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H + \varphi(\theta_H) \geqslant (1+\theta_H)\ln B_L - \theta_H \ln v_L + \varphi(\theta_H) \quad (IC_H^1)$$
$$(1+\theta_H)\ln B_H - \theta_H \ln v_H + \varphi(\theta_H) \geqslant (1+\theta_H)\ln B_0 - \theta_H \ln v_0 + \varphi(\theta_H) \quad (IC_H^2)$$

After simplification:

$$(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 \geqslant (1+\theta_0)\ln B_L - \theta_0 \ln v_L$$
$$(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 \geqslant (1+\theta_0)\ln B_H - \theta_0 \ln v_H$$

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H \geqslant (1+\theta_H)\ln B_L - \theta_H \ln v_L$$
$$(1+\theta_H)\ln B_H - \theta_H \ln v_H \geqslant (1+\theta_H)\ln B_0 - \theta_H \ln v_0$$

The similar interpretation for the type θ_L agent applies to these four constraints. In the case of the two-type agents, there are four IC and IR constraints. Now we have nine such constraints, which greatly complicates the contract system.

The six incentive constraints IC_L^1 through IC_H^2 can be classified into local and global incentive constraints. Local incentive constraints involve adjacent types, such as the downward incentive constraints (deviating to report the next lower efficiency type). For example: IC_H^2 and IC_0^1, or the upward incentive constraints such as IC_0^2 and IC_L^1 are possible. Global incentive constraints involve nonadjacent types, such the downward incentive constraint IC_H^1 or the upward incentive constraint IC_L^2.

To analyze these constraints, we can proceed in two steps. The high-type agent has a motivation to lie downward and claim it is less efficient. Therefore, we can momentarily ignore the upward incentive constraints. We are left with the remaining downward incentive constraints: IC_H^2, IC_H^1 and IC_0^1.

Second, the incentive constraints IC_H^2 and IC_L^2 imply some implementability conditions on the schedule of the outputs. Adding the incentive constraints for two adjacent types yield:

$$v_H \geqslant v_0, \text{ using } IC_H^2 \text{ and } IC_0^2$$
$$v_0 \geqslant v_L, \text{ using } IC_0^1 \text{ and } IC_L^1$$

Therefore, we obtain the monotonic constraint $v_H \geq v_0 \geq v_L$. For proof, see Appendix A6.

Using IC_2^H and IC_1^0 , this monotonicity condition further simplifies the set of relevant incentive constraints by eliminating the global incentive constraints IC_1^H.

To see this, adding IC_2^H and IC_1^0, we obtain:

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H \geqslant (1+\theta_H)\ln B_0 - \theta_H \ln v_0$$
$$(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 \geqslant (1+\theta_0)\ln B_L - \theta_0 \ln v_L$$

We want to show that:

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H \geqslant (1+\theta_H)\ln B_L - \theta_H \ln v_L$$

which is equivalent to

$$\begin{aligned}
&(1+\theta_H)\ln B_L - \theta_H \ln v_L + (1+\theta_0)\ln B_0 - \theta_0 \ln v_0 - \\
&(1+\theta_H)\ln B_0 + \theta_H \ln v_0 - (1+\theta_0)\ln B_L + \theta_0 \ln v_L \leqslant 0 \\
\Leftrightarrow &(\theta_H - \theta_0)\ln B_L - (\theta_H - \theta_0)\ln v_L - (\theta_H - \theta_0)\ln B_0 + (\theta_H - \theta_0)\ln v_0 \leqslant 0
\end{aligned}$$

Using the fact that $\theta_H - \theta_0 \leqslant 0$, we obtain $\ln B_L - \ln v_L \geqslant \ln B_0 - \ln v_0$ which was shown before.

But the last inequality is the global incentive constraint IC_1^H, which is implied by the two local incentive constraints IC_2^H and IC_1^0 when the monotonicity constraint holds.

To design an optimal contract, we only need to consider two downward local incentive constraints with the monotonicity constraint on outputs: IC_2^H and IC_1^0. We also need to check ex post that the upward incentive constraints are also satisfied (i.e.,IC_1^L, IC_2^L, and IC_2^0). To summarize, our constraints are IC_2^H and IC_1^0 and p_L.

Claim: the government's objective is subject to the following set of constraints:

$$\begin{aligned}
(1+\theta_L)\ln B_L - \theta_L \ln v_L + \varphi(\theta_L) = 0 \qquad & (P_L) \\
(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 = \ (1+\theta_0)\ln B_L - \theta_0 \ln v_L \qquad & (IC_0^1) \\
(1+\theta_H)\ln B_H - \theta_H \ln v_H = \ (1+\theta_H)\ln B_0 - \theta_H \ln v_0 \qquad & (IC_H^2)
\end{aligned}$$

As the first step, we show the redundancy of the participation constraint for 0-type and high-type. Given that the low-type agent has a binding participation constraint, then it must be the case that the 0-type agent and high-type agent have a nonbinding constraint, and the nonbinding part becomes their information rent. The argument is similar as in the case of two type agents.

More rigorously, we impose an additional assumption of fixed cost structure for the extension agents. Adding the participation constraint for the low-type agent and IC_0^1, IC_H^1 respectively, we can easily show the participation constraints for 0-type and high-type agents can be satisfied automatically.

Next we show that IC_2^H and IC_1^0 are binding. From the perspective of the government, as long as these two constraints are nonbinding, there is always a small positive change that can be made by the government which still guarantees the 0-type and high-type agent to remain in the game. The inequality constraints will hold at equality when achieving the maximum. In particular, suppose the strict inequality holds, then the government can decrease subsidy B_H by a small amount such that it does not change the direction of the inequality, while the third constraint still holds.

Given the above analysis on the constraints, the government's problem and corresponding constraint reduces to:

$$\max_{p_v,\{B_j,v_j\}} \{\Omega - \Phi \ln p_v - B_H - B_L - B_0\} \qquad \text{(Progamming 5)}$$

s.t.:

$$\begin{cases} p_v(v_H + v_L + v_0) = \sum_{i=1}^{M} \alpha_i \\ (1+\theta_L)\ln B_L - \theta_L \ln v_L + \phi(\theta_L) = 0 \\ (1+\theta_0)\ln B_0 - \theta_0 \ln v_0 = (1+\theta_0)\ln B_L - \theta_0 \ln v_L \\ (1+\theta_H)\ln B_H - \theta_H \ln v_H = (1+\theta_H)\ln B_0 - \theta_H \ln v_0 \end{cases}$$

The Lagrangean function for this maximization problem is:

$$\begin{aligned} L = \Omega - \Phi \ln p_v - B_H - B_L - B_0 + \lambda_1 \left[p_v(v_H + v_L + v_0) - \sum_{i=1}^{M} \alpha_i \right] \\ + \lambda_2[(1+\theta_L)\ln B_L - \theta_L \ln v_L + \phi(\theta_L)] \\ + \lambda_3[(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 - (1+\theta_0)\ln B_L + \theta_0 \ln v_L] \end{aligned}$$

$$+ \lambda_4[(1+\theta_H)\ln B_H - \theta_H \ln v_H - (1+\theta_H)\ln B_0 + \theta_H \ln v_0]$$

The standard first order conditions with respect to seven choice variables are given in Appendix A7. These seven unknowns are $B_H, B_0, B_L, v_H, v_0, v_L$ and p_v.

As a result, the seven equations and seven unknown nonlinear equation system is:

$$\frac{\Phi}{v_H + v_L + v_0} = \left(\frac{B_H}{1+\theta_H}\right)\frac{\theta_H}{v_H} \tag{5.31}$$

$$\frac{\Phi}{v_H + v_L + v_0} - \left(\frac{B_0 + B_L + B_H}{1+\theta_L}\right)\frac{\theta_L}{v_L} + \left(\frac{B_0 + B_H}{1+\theta_0}\right)\frac{\theta_0}{v_L} = 0 \tag{5.32}$$

$$\frac{\Phi}{v_H + v_L + v_0} + \left(\frac{\theta_H}{v_0}\right)\frac{B_H}{1+\theta_H} - \left(\frac{B_0 + B_H}{1+\theta_0}\right)\frac{\theta_0}{v_0} = 0 \tag{5.33}$$

$$p_v(v_H + v_L + v_0) = \sum_{i=1}^{M}\alpha_i \tag{5.34}$$

$$(1+\theta_L)\ln B_L - \theta_L \ln v_L + \varphi(\theta_L) = 0 \tag{5.35}$$

$$(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 = (1+\theta_0)\ln B_L - \theta_0 \ln v_L \tag{5.36}$$

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H = (1+\theta_H)\ln B_0 - \theta_H \ln v_0 \tag{5.37}$$

The parameters in this system are nearly the same as before when we have two type agents except that now we have three parameters in the agent's utility function.

- farm's production function: η, α and r
- Agent's utility function: $\theta_H, \theta_0, \theta_L$.
- Agent's production function: β.
- Agent's cost function: wage w and interest rate R.

5.4.2 Simulation Study

Based on the equations system we laid out in the last section, simulation study is carried out here. We adopt similar specifications as in the two-type agent case. However, we need to specify θ_H, θ_0 and θ_L for the agent types. In the two agent case, only θ_H and

θ_L are specified. In the computation, θ_H is again chosen to be fixed at unity, θ_0 ranges from 1.1 to 3 and θ_L ranges from 3.1 to 6. We are interested to investigate how final results change according to different ratios of technology level for three different types of agents.

Equilibrium outcomes for extension visits produced by each type of agent, subsidy allocation, equilibrium price are presented in the following figures. In each figure, contour plot for different variables of interest is drawn. The x-y plane denotes the relative efficiency of low-type agents and 0-type agents with respect to the high-type agents, respectively.

Figures 5.5 to 5.7 demonstrate the extension visits produced by the three types of agents, respectively. Fixing the relative productivity of 0-type agent, as the productivity difference between low- and high-type agents enlarges, high-type agent decreases its production of extension visits. On the other hand, the 0-type and low-type agent increase their production. The same tendency is true for subsidy allocation as shown in Figures 5.8 to 5.10. The rationale behind this result is similar to that in the two-type agent case for the high-type agent. To the contrary of the two-type agents case, the extension visits provided by the other two types are increasing possibly as a consequence of increased market competition when more agents are in the market.

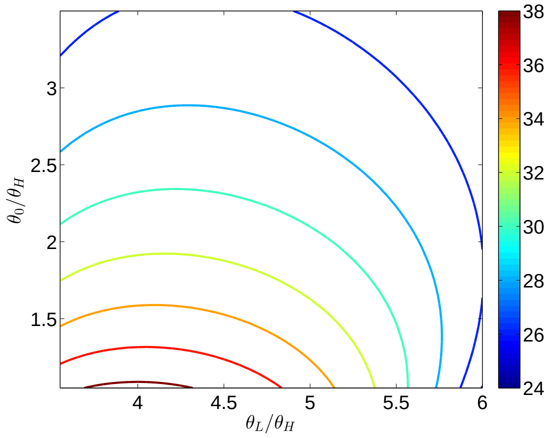


Figure 5.5: Extension visits: high type agents

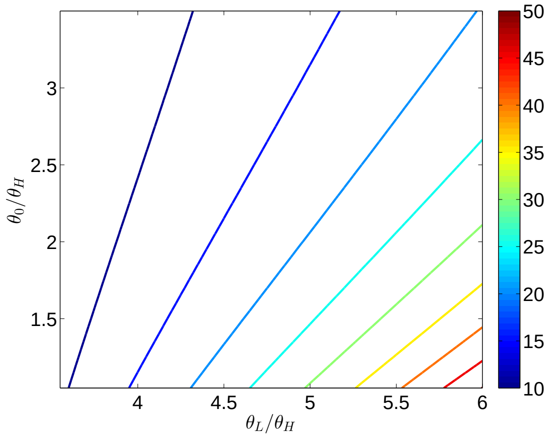


Figure 5.6: Extension visits: medium type agents

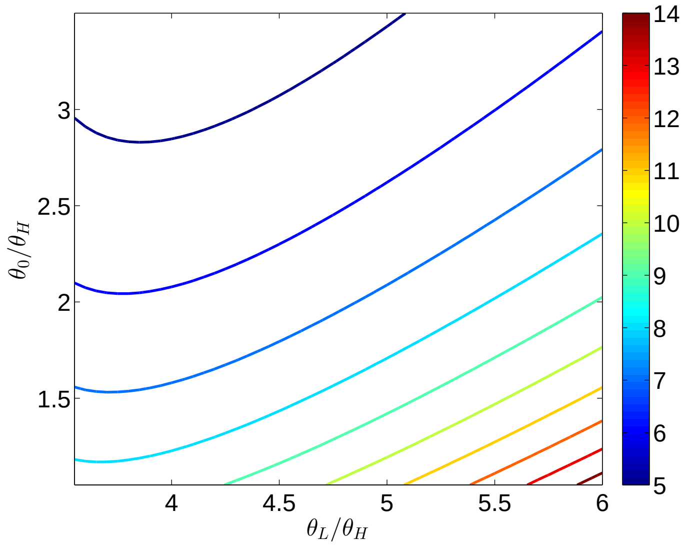


Figure 5.7: Extension visits: low type agents

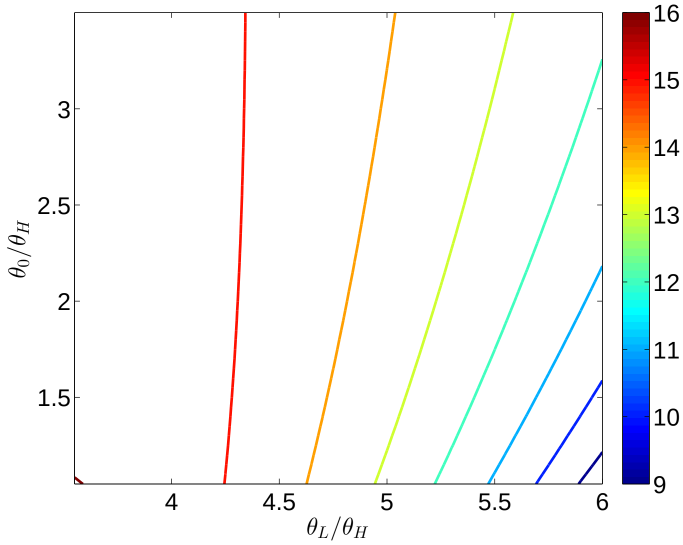


Figure 5.8: Subsidy allocation: high type agents

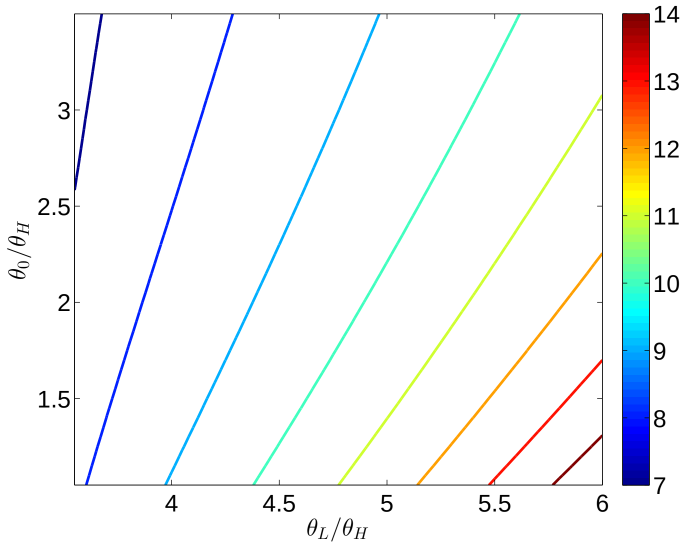


Figure 5.9: Subsidy allocation: medium type agents

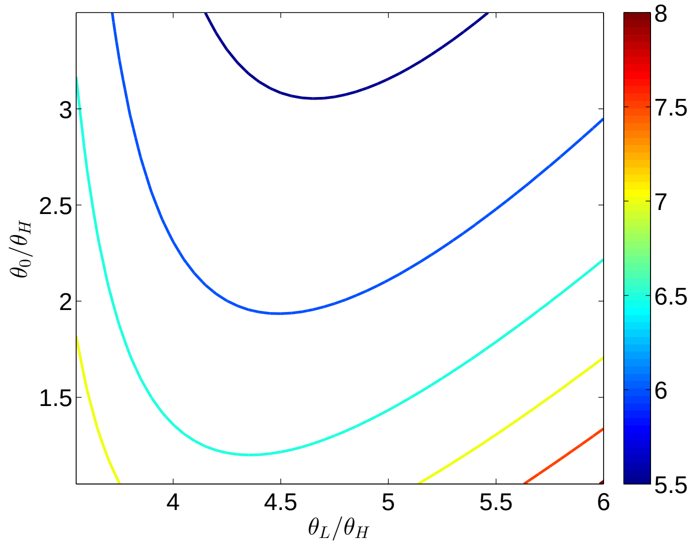


Figure 5.10: Subsidy allocation: low type agents

Figures 5.11 and 5.12 characterize the total number of extension visits production and the equilibrium price. The findings are different from the two-type agent case. The total number of extension visits are increasing, while the price of the extension visits in equilibrium decreases. It is consistent with our conjecture of increasing market competition as well.

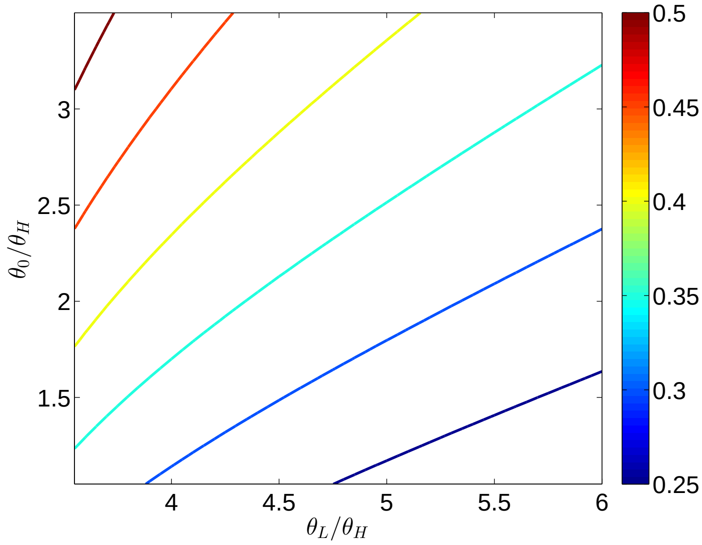


Figure 5.11: Price for extension visits

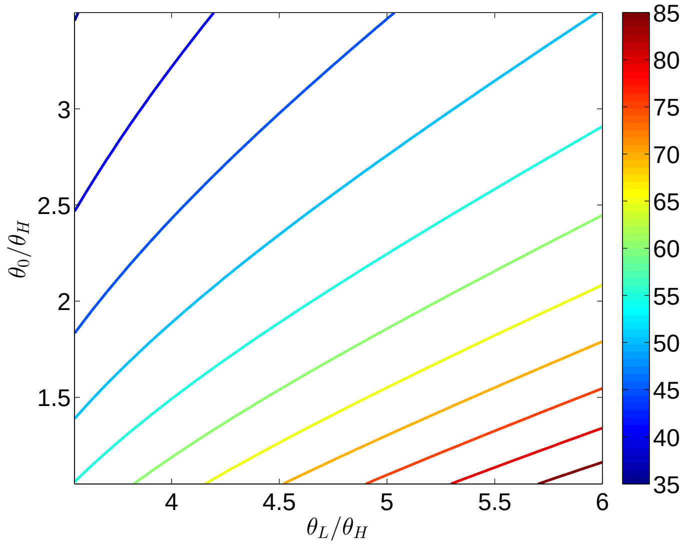


Figure 5.12: Total number of visists

5.5 Concluding Comments

In Chapter 5, we build a game theoretic framework to analyze the provision of agricultural extension services from the macro perspective. Equilibrium results and policy implications are discussed. To our knowledge, this is the first attempt to analyze the interactions of the government, extension agents and farms using game theoretic model.

We address both two-type agents and three-type agents cases where the types are defined based on extension agents' productivity level. In each case, a model is set up which demonstrates the government's objective and its constraints. To maximize social welfare, the government uses principles of mechanism design to motivate extension agents revealing their true productivity type to the public. Its specific instruments are sets of contracts including the subsidy allocation and number of extension visits requirements available to extension agents. Extension agents and farms are incorporated in the model via their respective profit maximization interests. The nature of public goods aspect of extension visits is captured in the farms' decision problem. Extension agents choose a contract from the government to maximize their profit based on the cost structure. As the solution concept, a set of nonlinear equations is derived.

The simulation study based on the two nonlinear equation systems provides insight into the impact of productivity difference among agents on economic variables of our interest. In particular, we investigate the patterns of extension visits, price, subsidy allocations in response to changes in the productivity difference. In the case of two-type agents, the increase in the productivity difference among agents increases the aggregate production level while decreasing the price of extension visits in equilibrium. Moreover, both types of extension agents produce more extension visits. The subsidy allocated to the high productivity type increases while it decreases for the low productivity type agent as the productivity difference grows. The subsidy utilization rate represented by subsidy per visit decreases as the observed productivity difference increases due to two reasons. One is the difficulty for the government to motivate the more heterogeneous extension agents increases. The fixed budget constraint constitutes a second reason.

In the case of three-type agents, the price and aggregate level of extension visits produced and the equilibrium price exhibit different patterns from in the two-type agent case. The introduction of the additional type of extension agent brings changes to economic behaviors of individual agent with the lowest productivity and also increases market competition. In particular, the extension visits produced by the lowest productivity type agent tend to increase which is different from the two-type agent case. The total number and the price of extension visits also display different tendencies.

To conclude, we provide a framework where private extension agents take on more responsibilities of providing agricultural extension services to farms. The proposed framework characterizes the transition government's role from operator to planner. It is a rational way to improve welfare for the government and society as a whole when government itself is less able to provide extension services to satisfy all the needs from farms. The mechanism laid out here can identify extension agents' true productivity types and therefore provide the best combination of extension visits production and subsidies allocation. Extension visits production incorporates the demand information from farms and subsidies are allocated to their best use according to extension agents' characteristics. Further research can be conducted to study the behavior of all participants in the game when the types of extension agents become N.

Chapter 6

Summary and Conclusion

6.1 Overview

The challenges facing agriculture today are considerable. Global food supplies are under pressure from expanding demand for food, feed, and biofuels; the rising price of energy; increasing land and water scarcity; and the effects of global warming. While 75% of the world's poor live in rural areas, only 4% of official development assistance (ODA) goes to agriculture in developing countries. The share of agriculture in ODA has declined sharply in the last two decades, and this neglect of agriculture is even more striking because it was in the face of rising rural poverty (World Bank, 2008).

Agricultural extension, as our main subject of study, has exerted greater importance on transferring knowledge between agencies and farms. Therefore, it is imperative to learn more about the performance of agricultural service provision. Efficiency is a widely used indictor of farmer operator performance. Both technical efficiency and allocative efficiency are widely studied among researchers using either parametric or linear programming approaches.

The public goods nature of agricultural service provision guided our theoretical and empirical study. A key characteristic of many public services is that without the productive activities of consumers, public services will not produce any virtual value. In practice, researchers and policy makers use proxies in quantifying the final output(s), treating the provision of public services as a simply one production process. We make a careful distinction between the services directly produced and the services of primary interest to the citizen-consumer. Hence, the public production process is divided into two stages. In the first stage, local governments produce an intermediate output. In the second stage, the private production uses the intermediate product to produce final outputs. This distinction has important implications for measuring technical efficiency of public services provision. In terms of efficiency measurement, Chapter 4 focuses on measurement in the first production stage and Chapter 5 focuses mainly on the second production stage.

Stochastic production frontier approach is widely adopted as the parametric families in measuring technical efficiency. Efficiency scores for each individual farm can be computed based on estimating a stochastic production frontier model. Studies have applied this approach for production activities of both public goods and private goods. Under this general framework, farms are not longer assumed to be technically efficient. Agricultural extension is included along with other socioeconomic and demographic variables in the inefficiency effect function as a factor influencing technical inefficiency. While still allowing for technical inefficiency, they also acknowledge that some random external events can be separated from the contribution of variation in technical inefficiency. This leads to the more appealing formulation where a particular farm faces its own production frontier, and that frontier is placed randomly by the whole collection of stochastic elements that enter the model outside the control of each individual.

Sample selection problem has received considerable amount of attention in many subjects of social science. However, in evaluating the performance of agricultural extension service provision, possible sample selectivity issue has not yet been rigorously studies. The sources of sample selection bias may be multi-fold. Suppose the government decides to concentrate extension resources in highly productive areas and that this fixed locality characteristic is not controlled for in the linear regression. Moreover,some of the extension contacts are farmer initiated. If one observes that more efficient farms have more extension contact, one cannot conclude that extension contact caused the efficiency difference. It may simply reflect the demand for information by the more efficient farmers. To correct for this bias, two accommodations are made in our analysis. Econometrically, we add a sample selectivity equation to the classical stochastic production frontier frame. Statistically, we adopt the causal inference approach serving a possible alternative and robustness check for our conclusion drawn from the econometric approach if the same grouping rule is applied.

The macro study on agricultural extension service provision has focused on description of economic facts. The mechanism behind economic phenomenon is more or less ignored. We aim to incorporate both demand and supply side of agricultural extension service provision into a game theoretical framework. Extension agents are classified into different productivity types. The government acts a social planner to maximize social welfare and reveal each extension agent's true productivity type. Farm's profit maximization is also part of the government's objective. The interactions between different economic variables are studied based on simulation studies.

6.2 Summary of Empirical Findings

We take on both micro and macro perspectives of the technical efficiency measurement of agriculture extension. Within the micro framework, econometrical and statistical models are constructed to investigate the technical efficiency of agricultural service extension provision from the demand side. Within the macro perspective, a game theoretical framework incorporating both the supply and demand of the agricultural extension system is developed. Simulations are then conducted to characterize the interactions between economic variables of our interest.

Our contributions to the existing studies are multi-fold. We enrich the studies on the efficiency of agricultural extension with a focused investigation of the stochastic production frontier approach allowing for possible sample selection problems. Robustness check for sample selectivity is conducted via the statistical causal effect estimation approach.

The empirical example uses the data from farms in Crete. The data is composed of two different surveys addressing the structural characteristics of agricultural sectors in the island of Crete on the structural characteristics. In the stochastic production frontier approach, simulated maximum likelihood estimation procedure is implemented to get the numerical estimates for the parameters in the equations. In the causal effect approach, we conducted several matching algorithms for treatment and control group of farms. Average causal effect is then computed based on the match samples. Both the stochastic production frontier approach and statistical causal inference approach draw the same conclusion that sample selectivity is playing a role in the extension service provisions. Formal tests are conducted to identify the strength of the sample selection and how does it influence individual farms' performance. Technical efficiency scores are then computed for each individual farms. We find that there are no significant differences in terms of score distributions for these two types of farms. This may due to the fact that the extension agencies' objective is in improving productivity instead of efficiencies.

A classical game theory modeling framework is developed, embedding mechanism design to characterize agricultural extension service provision from macro perspective. As the first attempt using game theoretic model to analyze the interactions of the government, extension agents and farms, equilibrium results are derived for two scenarios with different number of extension agents. It provides us a way to study the efficiency of extension agents in the first production stage. In accordance with the tendency of government's role change from operators to policy makers, we propose private extension agencies to take greater and more direct responsibilities in agricultural extension service provision. In particular, the government subsidizes the extension agents by designing a mechanism where farm operators and others pay for the services via taxes subject to a budget constraint. Each farm is a profit maximization entity choosing the number of extension visits consumed. The extension agents, classified by different productivity levels, are characterized to comply with incentive compatibility and participation constraint. The solution concepts of the game result in two sets of nonlinear equation systems, one for two-agent case, the other for three-agent case.

The simulation study based on the nonlinear equation systems provides us insight into the impact of productivity difference among agents on economic variables of our interest. In particular, we investigate the patterns of extension visits, price, subsidy allocations in response to changes in the productivity difference. In the case of two-type agents, the increase in the productivity difference among agents increases the aggregate production level while decreasing the price of extension visits in equilibrium. Moreover, both types of extension agents produce more extension visits. The subsidy allocated to the high productivity type increases while it decreases for the low productivity type agent as the productivity difference grows. The subsidy utilization rate represented by subsidy per visit decreases as the observed productivity difference increases due to two reasons. One is the difficulty for the government to motivate the more heterogeneous extension agents increases. The fixed budget constraint constitutes a second reason.

6.3 Policy Implications and Future Research

Several policy implications can be drawn based on the theoretical work and empirical results from our analysis. First, we establish a solid foundation that government may be involved in production process of extension service via the mechanism designed in Chapter 5. Our findings are consistent with the decreasing resource allocation to agricultural sector and the increasing financial, human resource input by nongovernment organization and many other private sectors. Hence, government's role in agricultural service extension provision should target at maximizing social welfare and guarantee a smooth implementation of the contract between government and the extension agents. As long as the designed contract is a truth telling mechanism and the enforcement of the contract is smooth, extension agent's profit maximization behavior should be consistent with farm's profit maximization and therefore achieve the maximum social welfare.

In the policy design, resource allocation can be much closer to the target if sample selection issue can be addressed. In particular, if the objective is to improve well being of the low productivity farms, more resources can be allocated to these low productivity farms accordingly. The demand for extension visits may serve as a signal to the agencies and government of the possible productivity distribution pattern. Before, the policy on agricultural extension service provision overlooked the demand side from farms to some extent. The inefficiency sources identified for different farm types in Chapter 4 (education level, soil types, debt status, etc) may serve as instruments for government/extension agencies to pick up farms in need of extension services.

The simulation results presented in Chapter 5 provide a possible guideline for policy makers if certain economic variables are of their particular interest. The more accurately policy makers know about the economic behaviors of extension agencies, the higher possibility for them to achieve their policy targets. The different reaction pattern to the changes in relative productivity may also guide policy makers to design mechanisms suitable to different types of extension agencies. In particular, the different price reaction curves to the change in relative productivity may be studied so that extension agencies charger different prices to different farm types. In this case, the true demand rather than the demand distorted by sample selectivity can be more accurately identified.

Following future research is of our particular interest. It is possible for us to add the distance measure between farms into our analysis, allowing for spatial consideration. Meanwhile, our estimation of stochastic production frontier function is limited due to data availability in several aspects. In particular, farm types are classified as receiving and not receiving extension services. The exploration may go deeper if we can further distinguish between private and public extension service provision. Increasing the number of individual farms in our data set would make it possible to compare the performance of private extension services to that of public extension services.

Furthermore, the number of extension visits is treated as discrete variable in our empirical investigation in Chapter 4. More information can be revealed if we treat this variable as continuous. It is plausible that intensity of extension visits to individual farm matters. The probit model adopted to incorporate extension visits variable fails to study on the possible effect of intensity of extension visits. A continuous version of stochastic production frontier model with accommodation for sample selectivity will be an interesting exploration.

Another possible direction is an application to panel data setting, which will help learn more about the true effect of agricultural extension service provision and also the technical efficiency dynamics. With panel data, the technical efficiency comparison between two types of farms will be more accurate. Our analysis can incorporate the dynamic choices of whether or not to receive extension service for a particular year. The following scenario might be the case: in the past year, farms receiving and not receiving extension services differ in terms of technical efficiency scores. This might lead to a different choice of whether continuing to receive extension service. Consequently, the technical efficiency score might be similar for next year.

It is also a natural extension to study the game with the number of extension agencies going to N. We can investigate whether the simplifications for individual rationality and individual participation constraints still carry over to the case of N extension agencies. The simulation can serve to check how the patterns of economic variables of our interest change as a response to different number of extension agencies. In addition, the dynamic version of mechanism design is brought up by researchers which is worthwhile for us to incorporate dynamics into the game framework.

Derivations in CH 5

Deriving cost function for extension agents

This is a standard exercise in microeconomics.

$$\min(Rk_j + wl_j) \qquad \text{(programming 1)}$$
$$\text{s.t.: production constraint} \quad \frac{1}{\delta_j} k_j^{\beta} l_j^{1-\beta} \geq v$$

Notice here v can be either the number of extension visits designed for the high type or for the low type depending on what type of extension agents we are considering.

First order condition yields:

$$\frac{\beta k^{\beta-1} l^{1-\beta}}{r\delta_j} = \frac{(1-\beta)k^{\beta} l^{1-\beta}}{w\delta_j}$$
$$\Rightarrow \frac{\beta}{rk} = \frac{1-\beta}{wl} \Rightarrow \frac{k}{l} = \frac{(1-\beta)r}{w\beta} \equiv \Delta$$

The production function of extension visits can be rewritten as:

$$\frac{1}{\delta_j}(\frac{k}{l})^{\beta} l = v \Rightarrow l = \frac{v\delta_j}{(\frac{k}{l})^{\beta}} = \frac{v\delta_j}{\Delta^{\beta}}$$

and $k = l\Delta = v\delta_j \Delta^{1-\beta}$

Given the optimal solution of capital and labor respectively, we can now get the correct form of cost function:

$$\begin{aligned}
c(v, r, w, \delta_j) &= Rk + wl \\
&= Rv\delta_j\Delta^{1-\beta} + w\frac{v\delta^j}{\Delta^\beta} \\
&= v\delta_j(R\Delta^{1-\beta} + \frac{w}{\Delta^\beta}) = v\delta^j\phi \\
\text{where } \phi &= R\left[\frac{(1-\beta)r}{w\beta}\right]^{1-\beta} + w\left[\frac{(1-\beta)R}{w\beta}\right]^\beta
\end{aligned}$$

Deriving the payoff function for extension agents

$$\max_{\delta_j \in (0,1)} \ln(B_j - v_j\delta_j\phi) + \theta_j \ln \delta_j \tag{.1}$$

F.O.C with respect to δ_j gives:

$$-\frac{v_j\phi}{B_j - v_j\delta_j\phi} + \frac{\theta_j}{\delta_j} = 0$$

Rearranging and collecting terms:

$$\delta_j v_j \phi = \theta_j(B_j - v_j\delta_j\phi) = \theta_j B_j - \theta_j v_j \delta_j \phi \Rightarrow \delta_j = \frac{\theta_j B_j}{(1+\theta_j)v_j\phi}$$

Substituting the optimal choice of δ_j back into agent j's objective function, we will have:

$$\begin{aligned}
&\ln(B_j - v_j\delta_j\phi) + \theta_j \ln \delta_j \\
=&\ln\left(B_j - \frac{\theta_j B_j}{(1+\theta_j)}\right) + \theta_j \ln \frac{\theta_j B_j}{(1+\theta_j)v_j\phi} \\
=&\ln \frac{B_j}{1+\theta_j} + \theta_j \ln \frac{B_j\theta_j}{1+\theta_j} - \theta_j \ln v_j\phi \\
=&(1+\theta_j)\ln B_j - \theta_j \ln v_j + \ln\frac{1}{1+\theta_j} + \theta_j \ln\frac{\theta_j}{1+\theta_j} - \theta_j \ln \phi \\
=&(1+\theta_j)\ln B_j - \theta_j \ln v_j + \varphi(\theta_j)
\end{aligned}$$

where $\varphi(\theta_j) = \ln \frac{1}{1+\theta_j} + \theta_j \ln \frac{\theta_j}{1+\theta_j} - \theta_j \ln \phi$

To show bindingness and redundantness of constraints 9-12

Let's first show that constraint 12 is redundant;

Denote

$$\delta^*_{\theta_L} = \arg\max[\ln(B_j - v_j\delta_j\phi) + \theta_j \ln \delta_j]$$
$$\text{where } \delta_{\theta_L} \in (0,1)$$

Then from constraint 9, we have:

$$\ln(B_L - v_L\delta^*_{\theta_L}\phi) + \theta_L \ln \delta^*_{\theta_L} \geq 0$$

Using the fact that $\theta_H < \theta_L$ and also $\delta^*_{\theta_L} \in (0,1)$, we will have that:$\theta_H \ln \delta^*_{\theta_L} < \theta_L \ln \delta^*_{\theta_L}$, and therefore,

$$\ln(B_L - v_L\delta^*_{\theta_L}\phi) + \theta_H \ln \delta^*_{\theta_L} \geq \ln(B_L - v_L\delta^*_{\theta_L}\phi) + \theta_L \ln \delta^*_{\theta_L} \geq 0 \tag{.2}$$

To be more specific, the first line is a maximization problem that given B_L and v_L, the high type agent is facing. We don't need to solve for the optimal solution, while it is enough to know that $\delta^*_{\theta_L}$ is feasible.

Therefore, constraint 12 is satisfied as well. Furthermore, constraint 5 will not be binding unless $v_L = 0$, which means the government does not use the low-type extension agent production which is usually not the case.

On the other hand, constraint 11 must be binding, i.e. $(1+\theta_L)\ln B_L - \theta_L \ln v_l + \varphi(\theta_L) = 0$. To see this, if neither constraint 11 and 12 are binding, the government could decrease the B_H and B_L by the same small positive amount, which would keep the incentive compatibility constraint satisfied and would not violate the individual rationality (i.e. the participation constraint) and increase the payoff for government. Hence, constraint 11 must be binding.

Next, constraint 9 must be binding unless $v_L = 0$. That is:

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H + \varphi(\theta_H) = (1+\theta_H)\ln B_L - \theta_H \ln v_L + \varphi(\theta_H) \qquad (.3)$$

If constraint 9 were not binding, the government would decrease slightly and keep all constraints satisfied.

The relationship for equilibrium extension visits and budgets allocation: I

First, adding the two incentive compatibility constraints together, we can have,

$$(\theta_H - \theta_L)\ln B_H - (\theta_H - \theta_L)\ln B_L - (\theta_H - \theta_L)\ln v_H + (\theta_H - \theta_L)\ln v_L \geq 0$$
$$(\theta_H - \theta_L)(\ln B_H - \ln B_L) \geq (\theta_H - \theta_L)(\ln v_H - \ln v_L)$$
$$\ln B_H - \ln B_L \geq \ln v_H - \ln v_L$$
$$\ln B_H - \ln V_H \leq \ln B_L - \ln v_L$$

Adding the incentive compatibility constraint to the above inequality, we have,

$$(1+\theta_H)\ln B_H - \theta_H \ln v_H + \phi(\theta_H) \geq (1+\theta_H)\ln B_L - \theta_H \ln v_H \geq (1+\theta_H)\ln B_L - \theta_H \ln v_L$$
$$\Rightarrow (1+\theta_H)\ln B_H - \theta_H \ln v_H \geq (1+\theta_H)\ln B_L - \theta_H \ln v_L$$
since $\ln B_H - \ln v_H \leq \ln B_L - \ln v_L$
$$\Rightarrow \ln B_H \geq \ln B_L \Rightarrow B_H \geq B_L$$
$$\ln B_H - \ln B_L \leq \ln v_H - \ln v_L \Rightarrow \ln v_H \geq \ln v_L \Rightarrow v_H \geq v_L$$

Solving the government's objective function in two-type agents' case

Taking derivatives with respect to p_v, v_H, v_L, B_H, B_L respectively, we have the following five equations:

With respect to p_{v}, we have:

$$-\Phi\frac{1}{p_v} + \lambda_1(v_H + v_L) = 0 \tag{.4}$$

With respect to B_H, we have:

$$-1 + \lambda_2(1+\theta_H)\frac{1}{B_H} = 0 \tag{.5}$$

With respect to B_L, we have:

$$-1 - \lambda_2(1+\theta_H)\frac{1}{B_L} + \frac{\lambda_3(1+\theta_L)}{B_L} = 0 \tag{.6}$$

With respect to v_H, we have:

$$\lambda_1 p_v - \lambda_2\theta_H\frac{1}{v_H} = 0 \tag{.7}$$

With respect to v_L, we have:

$$\lambda_1 p_v + \lambda_2\frac{\theta_H}{v_L} - \lambda_3\frac{\theta_L}{v_L} = 0 \tag{.8}$$

From (.5): we can have:

$$\lambda_2 = (1+\theta_H)B_H \tag{.9}$$

Using the expression of λ_2 and (.7):

$$\lambda_1 p_v = \frac{\theta_H}{v_H}(1+\theta_H)B_H \tag{.10}$$

From (.4):

$$\Phi = (v_H + v_L)\frac{\theta_H(1+\theta_H)B_H}{v_H} \tag{.11}$$

From (.8):

$$\frac{\theta_H}{v_H}(1+\theta_H)B_H + (1+\theta_H)B_H\frac{\theta_H}{v_L} = \lambda_3\frac{\theta_L}{v_L} \tag{.12}$$

From (.6):

$$1 + (1+\theta_H)^2\frac{B_H}{B_L} = \lambda_3(1+\theta_L) \tag{.13}$$

Therefore,

$$\lambda_3 = \frac{\left[1+(1+\theta_H)^2\frac{B_H}{B_L}\right]}{(1+\theta_L)} = \frac{B_L+(1+\theta_H)^2 B_H}{B_L(1+\theta_L)} \tag{.14}$$

(.13) together with (.14) gives us:

$$\frac{\theta_H}{v_H(1+\theta_H)} + \frac{\theta_H}{v_L(1+\theta_H)} = \frac{\theta_L}{v_L(1+\theta_L)} \tag{.15}$$

Given that we can solve for $\lambda_1, \lambda_2, \lambda_3$ in terms of the five unknowns, we are now having five equations to solve for these five choice variables.

The relationship for equilibrium extension visits and budgets allocation: II

To show,$v_H \geqslant v_0$, adding IC_H^2 and IC_0^2:

$$\begin{aligned}
&(1+\theta_H)\ln B_H - \theta_H \ln v_H \geqslant (1+\theta_H)\ln B_0 - \theta_H \ln v_0 \\
&(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 \geqslant (1+\theta_0)\ln B_H - \theta_0 \ln v_H \\
\Rightarrow &(\theta_H-\theta_0)\ln B_H - (\theta_H-\theta_0)\ln v_H - (\theta_H-\theta_0)\ln B_0 + (\theta_H-\theta_0)\ln v_0 \geqslant 0 \\
\because\ &\theta_H - \theta_0 \leqslant 0 \\
\therefore\ &\ln B_H - \ln v_H \leqslant \ln B_0 - \ln v_0
\end{aligned}$$

On the other hand, from IC_H^2:

$$\begin{aligned}
(1+\theta_H)\ln B_H - \theta_H \ln v_H &\geqslant (1+\theta_H)\ln B_0 - \theta_H \ln v_0 \\
\ln B_H + \theta_H(\ln B_H - \ln v_H) &\geqslant \ln B_0 + \theta_H(\ln B_0 - \ln v_0)
\end{aligned}$$

We already established that:

$$\theta_H(\ln B_H - \ln v_H) \leqslant \theta_H(\ln B_0 - \ln v_0)$$

Hence to make the above "$\geq$ " work, we must have, $\ln B_H \geq \ln B_0$ and therefore $B_H \geq B_0$.

In addition, we have $\ln B_H - \ln v_H \leq \ln B_0 - \ln v_0$, together with $B_H \geq B_0$, The following must be true:

$$\ln v_H \geq \ln v_0$$

And therefore, $v_H \geq v_0$.

Similarly, we can show $v_0 \geq v_L$: adding IC_L^1 and IC_0^1:

$$\begin{aligned}
&(1+\theta_0)\ln B_0 - \theta_0 \ln v_0 \geqslant\ (1+\theta_0)\ln B_L - \theta_0 \ln v_L \\
&(1+\theta_L)\ln B_L - \theta_L \ln v_L \geqslant\ (1+\theta_L)\ln B_0 - \theta_L \ln v_0 \\
\Rightarrow &(\theta_0-\theta_L)\ln B_0 - (\theta_0-\theta_L)\ln v_0 - (\theta_0-\theta_L)\ln B_L + (\theta_0-\theta_L)\ln v_L \geqslant 0 \\
\because &\theta_0 \leqslant \theta_L \\
\therefore &\ln B_0 - \ln B_L \leqslant \ln v_0 - \ln v_L \\
\therefore &\ln B_0 - \ln v_0 \leqslant \ln B_L - \ln v_L
\end{aligned}$$

Together with IC_0^1,

$$\ln B_0 + \theta_0(\ln B_0 - \ln v_0) \geqslant \ln B_L + \theta_0(\ln B_L - \ln v_L)$$

We have established that $\ln B_0 - \ln v_0 \leq \ln B_L - \ln v_L$.

So by the same logic before when we show $v_H \geq v_0$, we now have $v_0 \geq v_L$.

Solving the government's objective function in three-type agents' case

W.r.t p_v:

$$-\frac{\Phi}{p_v} + \lambda_1[v_H + v_L + v_0] = 0; \tag{.16}$$

W.r.t B_H:

$$-1 + \lambda_4(1+\theta_H)\frac{1}{B_H} = 0 \tag{.17}$$

W.r.t B_L:

$$-1 + \lambda_2(1+\theta_L)\frac{1}{B_L} - \lambda_3(1+\theta_0)\frac{1}{B_L} = 0 \tag{.18}$$

W.r.t B_0:

$$-1 + \lambda_3(1+\theta_0)\frac{1}{B_0} - \lambda_4(1+\theta_H)\frac{1}{B_0} = 0 \tag{.19}$$

W.r.t v_H:

$$\lambda_1 p_v - \lambda_4 \frac{\theta_H}{v_H} = 0 \tag{.20}$$

W.r.t v_L:

$$\lambda_1 p_v - \lambda_2 \frac{\theta_L}{v_L} + \lambda_3 \frac{\theta_0}{v_L} = 0 \tag{.21}$$

W.r.t v_0:

$$\lambda_1 p_v + \lambda_4 \frac{\theta_H}{v_0} - \lambda_3 \frac{\theta_0}{v_0} = 0 \tag{.22}$$

From p_v: we have

$$\lambda_1 p_v = \frac{\Phi}{v_H + v_L + v_0} \tag{.23}$$

From B_H, we have

$$\lambda_4(1+\theta_H) = B_H \tag{.24}$$

From v_H, we have

$$\lambda_1 p_v = \lambda_4 \frac{\theta_H}{1+\theta_H}\frac{\theta_H}{v_H} \tag{.25}$$

From the above three, we get:

$$\frac{\Phi}{v_H + v_L + v_0} = \frac{B_H}{v_H}\frac{\theta_H}{1+\theta_H} \tag{.26}$$

From B_0, we have

$$\lambda_3(1+\theta_0)\frac{1}{B_0} = 1 + \lambda_4(1+\theta_H)\frac{1}{B_0} = 1 + \frac{B_H}{B_0} \tag{.27}$$

Therefore,

$$\lambda_3 = \frac{B_0 + B_H}{1+\theta_0} \tag{.28}$$

From B_L, we have

$$\lambda_2(1+\theta_L)\frac{1}{B_L} = 1 + \lambda_3(1+\theta_0)\frac{1}{B_L} = 1 + \frac{B_0 + B_H}{B_L} \tag{.29}$$

Therefore,

$$\lambda_2 = \frac{B_0 + B_L + B_H}{1 + \theta_L} \tag{.30}$$

From v_L, we have:

$$\lambda_1 p_v - \lambda_2 \frac{\theta_L}{v_L} + \lambda_3 \frac{\theta_0}{v_L} = 0 \tag{.31}$$

Which is:

$$\frac{\Phi}{v_H + v_L + v_0} - \frac{B_0 + B_L + B_H}{1 + \theta_L} \frac{\theta_L}{v_L} + \frac{B_0 + B_H}{1 + \theta_0} \frac{\theta_0}{v_L} = 0 \tag{.32}$$

Fromv_0, we have:

$$\lambda_1 p_v + \lambda_4 \frac{\theta_H}{v_0} - \lambda_3 \frac{\theta_0}{v_0} = 0 \tag{.33}$$

Which is:

$$\frac{\Phi}{v_H + v_L + v_0} + (\frac{\theta_H}{v_0}) \frac{B_H}{1 + \theta_H} - (\frac{B0 + B_H}{1 + \theta_0}) \frac{\theta_0}{v_0} = 0 \tag{.34}$$

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