The Institute of Food Economics and Consumption Studies

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The Impact of Agricultural Cooperatives on the Adoption of Technologies and Farm Performance of Apple Farmers in China

Dissertation

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Kiel, 2016

Wanglin Ma

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List of Abbreviations

ATE	Average Treatment Effects
ATT	Average Treatment Effects on the Treated
ATU	Average Treatment Effects on the Untreated
BFG	Bourguignon, Fournier and Gurgand
FAO	Food and Agriculture Organization
FFS	Farmer Field School
FIML	Full Information Maximum Likelihood
FTC	Fixed Transaction Costs
IPM	Integrated Pest Management
MNL	Multinomial Logit
ESR	Endogenous Switching Regression
ESP	Endogenous Switching Probit
OLS	Ordinary Least Square
PCS	People's Commune System
PSM	Propensity Score Matching
PTC	Proportional Transaction Costs
PRC	People's Republic of China
RBP	Recursive Bivariate Probit
ROI	Return on Investment
SUBP	Seemingly Unrelated Bivariate Probit

Abstract in English

In many developing countries, agricultural cooperatives constitute a major vehicle that can be used to enhance the adoption of new agricultural technologies and output marketing among smallholder farmers. Despite the efforts made by the Chinese government to accelerate the systematic promotion of agricultural cooperatives, cooperative participation rate remains significantly low. Understanding and identifying the constraints and incentives that influence smallholder farmers' decisions to join agricultural cooperatives and evaluating the economic impact of cooperative membership can provide significant evidence to policy makers for further agricultural policy design, aimed at enhancing sustainable agricultural development and improving rural household welfare. However, very few studies have empirically examined the impact of agricultural cooperative membership on the adoption of technologies and farm performance of smallholder farmers in China. The dissertation attempts to fill in the research gaps by providing a comprehensive understanding of how agricultural cooperative is systematically correlated with the system of food production and marketing in China. The empirical analyses are based on a dataset collected from 481 apple farmers in Gansu, Shaanxi and Shandong provinces, where covered the majority of apple orchards in China.

The study first examines the determinants of cooperative membership and the impact of cooperative membership on investment in organic fertilizer, farmyard manure and chemical fertilizer using a recursive bivariate probit model that accounts for endogeneity of cooperative membership and selection bias. Second, the causal link between agricultural cooperative membership and adoption of integrated pest management technology is analyzed by employing an endogenous switching probit model to address the issue of selection bias. Meanwhile, a treatment effects model is employed to analyze the impact of integrated pest management technology adoption on apple yields, net returns and agricultural income. Third, this study examines the impact of cooperative membership on household welfare, measured by apple yields, net returns and household income. An endogenous switching regression model that accounts for selection bias is employed in the analysis. In order to understand the profitability of a number of different investments in apple production, this study also analyzes the impact of agricultural cooperative membership on return on investment. Finally, the determinants of marketing contract choices including written contracts, oral contracts and no contracts, as well as the impact of marketing contracts on net returns from apple production in China are analyzed. In particular, a two-stage selection correction BFG approach is employed to conduct the empirical analysis. On the basis of the BFG estimation, this study also uses an endogenous switching regression model to analyze the causal effect of written contract choice on net returns from apple production and a propensity score matching technique to estimate the causal effects of oral contract choice on net returns from apple production.

The empirical results show that agricultural cooperative membership exerts a positive and statistically significant impact on the probabilities of investing in soil-improving measures such as organic fertilizer and farmyard manure, but does not significantly influence the likelihood of investing in chemical fertilizer. The estimates also reveal that cooperative membership exerts a positive and significant impact on the adoption of integrated pest management technology, and integrated pest management technology adoption has positive and significant effects on apple yields, net returns and agricultural income. With respect to household welfare and investment profitability, the results reveal that cooperative membership exerts a positive and statistically significant impact on apple yields, farm net returns and household income, and small-scale farms tend to benefit more from cooperatives than medium and large farms. Also cooperative membership tends to exert a positive and significant impact on the return on investment. The further estimations show that selling apples primarily through cooperative organizations have positive and statistically significant impacts on net returns of both written and no contract users, but positive and insignificant impact on that of oral contract users. In particular, written contracts increase apple farmers' net returns, while oral contracts exert the opposite effect. On the factors that influence farmers' decision to join agricultural cooperatives, the findings show that education, household size, farm size, labor input, asset ownership and access to credit exert positive and significant effects on the choice of cooperative membership.

Abstract in German

In vielen Entwicklungsländern stellen landwirtschaftliche Genossenschaften ein zentrales Instrument dar, welches die Annahme neuer landwirtschaftlicher Technologien und den Produktionsabsatz kleinbäuerlicher Betriebe fördern kann. Trotz der Bemühungen der chinesischen Regierung, die systematische Förderung von landwirtschaftlichen Genossenschaften zu beschleunigen, verbleibt die Beteiligungsrate an Genossenschaften gering. Das Verständnis und die Identifikation von Hemmnissen und Anreizen, welche kleine landwirtschaftliche Betriebe in ihrer Entscheidung, einer landwirtschaftlichen Genossenschaft beizutreten, beeinflussen und die Bewertung des ökonomischen Einflusses dieser Mitgliedschaften können Entscheidungsträgern signifikante Anhaltspunkte für agrarpolitische Strategien zur Steigerung einer nachhaltigen landwirtschaftlichen Entwicklung sowie zur Wohlfahrtssteigerung von ländlichen Haushalten liefern. Derzeit liegen jedoch wenige Studien vor, die den Einfluss der Mitgliedschaft in landwirtschaftlichen Genossenschaften auf die Annahme von Technologien und die rentabilität von kleinbäuerlichen Farmen in China untersuchen. Die Dissertation unternimmt einen Versuch, die Forschungslücken zu füllen, indem ein umfassendes Verständnis darüber vermittelt wird, wie landwirtschaftliche Genossenschaften systematisch mit dem System der Nahrungsmittelproduktion und des -absatzes in China korrelieren. Den empirischen Analysen liegt ein Datensatz von 481 apfelproduzierenden Landwirten der Regionen Gansu, Shaanxi und Shandong, in denen der überwiegende Anteil des chinesischen Apfelanbaus stattfindet, zugrunde.

Die Studie untersucht zunächst unter der Verwendung eines rekursiven, bivariaten Probit-Modells, welches Endogenität von Genossenschaftsmitgliedschaften und Selektionsverzerrungen berücksichtigt, die Determinanten von Genossenschaftsmitgliedschaften, sowie deren Einfluss auf das Investitionsverhalten in organische, chemische und Wirtschaftsdünger. Im nächsten Schritt wird der kausale Zusammenhang zwischen Mitgliedschaft in einer landwirtschaftlichen Genossenschaft und der Annahme von integrierten Pflanzenschutzsystemen (Integrated-Pest-Management) analysiert. Hierbei findet ein endogenes Switching-Probit-Modell Anwendung, um Selektionsverzerrungen entgegenzuwirken. Drittens untersucht die Studie, unter Verwendung eines endogenen Switching-Regressions-Modells, welches Selektionsverzerrung berücksichtigt, den Einfluss von Genossenschaftsmitglied-schaften auf die Wohlfahrt der Haushalte, gemessen an Apfelerträgen, Nettorenditen und Haushaltseinkommen. Um die Effizienz verschiedener Investitionsmöglichkeiten in der Apfelproduktion zu erfassen und zu verstehen, untersucht diese Studie außerdem den Einfluss von landwirtschaftlichen Genossenschaftsmitgliedschaften auf die Kapitalrendite. Abschließend

werden die Einflussfaktoren auf Entscheidungen über Vermarktungsverträge, einschließlich schriftlicher und mündlicher Verträge und der Abwesenheit von Verträgen, und der Einfluss von Vermarktungsverträgen auf die Nettoerträge der Apfelproduktion in China untersucht. Für die Durchführung der empirischen Analyse wird dabei auf einen zweistufigen, selektionskorrigierenden BFG Ansatz zurückgegriffen. Basierend auf der BFG Schätzung verwendet die Studie des Weiteren ein endogenes Switching-Regressions-Modell, um den Kausalzusammenhang zwischen der Entscheidung für schriftliche Verträge und der Nettorenditen aus der Apfelproduktion zu analysieren. Eine Propensity-Score-Matching-Methode wird angewandt, um den Zusammenhang zwischen der Entscheidung für mündliche Verträge und der Nettorenditen der Apfelproduktion zu schätzen.

Die empirischen Ergebnisse belegen, dass die Mitgliedschaft in einer landwirtschaftlichen Genossenschaft einen positiven und statistisch signifikanten Einfluss auf die Wahrscheinlichkeit ausübt, Investitionen in bodenverbessernde Maßnahmen wie die Verwendung von biologischen oder Wirtschaftsdüngern zu tätigen. Die Wahrscheinlichkeit in chemische Dünger zu investieren wird hingegen nicht signifikant beeinflusst. Zudem ergeben die Schätzungen, dass Genossenschaftsmitgliedschaften einen positiven und signifikanten Einfluss auf Annahme von Integrated-Pest-Management Technologien haben. Hinsichtlich der Wohlfahrt von Haushalten und der Effizienz von Investitionen, geben die Ergebnisse Aufschluss darüber, dass Genossenschaftsmitgliedschaften einen positiven und statistisch signifikanten Einfluss sowohl auf die Ernteerträge, die Nettorenditen, als auch das Haushaltseinkommen haben, und dass kleine landwirtschaftliche Betriebe dazu tendieren, in größerem Ausmaß als mittelgroße oder große Höfe von einer Genossenschaft zu profitieren. Darüber hinaus hat eine Genossenschaftmitgliedschaft einen positiven, signifikanten Einfluss auf die Kapitalrendite (Return On Investment). Weitere Schätzungen ergeben, dass der vorwiegende Verkauf von Äpfeln über genossenschaftliche Organisationen einen positiven und statistisch signifikanten Einfluss auf die Nettorenditen von Landwirten hat, die schriftliche oder keine Verträge nutzen. Bei Nutzern von mündlichen Verträgen ist der Einfluss auf die Nettorenditen zwar auch positiv, aber nicht statistisch signifikant. Insbesondere schriftliche Verträge erhöhen die Nettorenditen apfelanbauender Landwirte, während mündliche Verträge einen gegenläufigen Effekt aufweisen. In Bezug auf die Determinanten, die einen Landwirt in seiner Entscheidung, einer Genossenschaft beizutreten, beeinflussen, kann gezeigt werden dass Bildung, Haushaltsgröße, Hofgröße, Arbeitsaufwand, Vermögensbesitz und der Zugang zu Krediten einen positiven und statistisch signifikanten Einfluss auf die Entscheidung über eine Genossenschaftsmitgliedschaft nehmen.

Chapter 1 General Introduction

1.1 Motivation and Problem Setting

In most developing countries, the smallholder farmers are facing a range of problems in agro-food production and marketing such as lack of production and marketing information and lack of voice in decision-making. Thus, government programs have emerged to help smallholder farmers benefit from modern agricultural production and marketing. Among them, agricultural cooperatives, which constitute a major vehicle to improve the performance of smallholder agricultural producers, have been promoted. Agricultural cooperatives offer members a wide range of services and opportunities. Providing market information, facilitating smallholder farmers' participation in decision-making at all levels, and negotiating better terms of trade in contract farming and inputs purchase are a few examples (World Bank 2006; Zheng et al. 2012). Given the important role of agricultural cooperatives in supporting smallholder farmers' agricultural production and marketing, the promotion of cooperative organization has increasingly attracted attention of donors, governments and researchers in developing countries (Abebaw and Haile 2013; Deng et al. 2010).

Previous studies have analyzed the impact of cooperative membership on the investment in static inputs such as chemical fertilizers (Abebaw and Haile 2013; Verhofstadt and Maertens 2014b). Crop yields normally increase with higher rates of application of yield-enhancing measures such as chemical fertilizer, yields may decline over time due to soil degradation, if no organic material is added to the soil (Abdulai et al. 2011). Therefore, investment in organic inputs that build up the soil structure plays an important role in mitigating the negative impact of soil degradation on crop yields and the environment. Thus, there is a need to look at how cooperative membership influences smallholder farmers' investment in soil-improving measures such as organic fertilizer and farmyard manure.

In addition to analyzing the impact of cooperative membership on the adoption of chemical fertilizers, previous studies have also examined the impact of cooperative membership on the adoption of chemical pesticides with respect to pest management (Abebaw and Haile 2013; Verhofstadt and Maertens 2014b). Although the enhanced pesticide use due to cooperative membership may increase crop yields, the overuse or misuse of chemical pesticides has caused a range of environmental and food safety problems. For instance, Calvin et al. (2006) noted that farm households in China depended on the heavy use of chemicals to deal with the pest pressure, which challenges the food safety supply. Thus, it is significant to facilitate the adoption of alternative pest management technology that is less harmful to the environment and human health. Existing evidence has suggested that the adoption of integrated pest management (IPM) technology significantly lowered pesticide use, saved production costs and maintained farm productivity for adopters (Carrión Yaguana et al. 2015; Dasgupta et al. 2007; Fernandez-cornejo 1996). Some studies have revealed that agricultural cooperatives have the potential to improve the safety and quality of the products of members through technical assistance (Jin and Zhou 2011; Moustier et al. 2010; Naziri et al. 2014). Given the fact that agricultural cooperative enhances technology adoption and food safety and quality and IPM adoption minimizes pesticide use, it is significant to understand whether cooperative organizations can promote the adoption of IPM technology.

Several studies have evaluated the impact of cooperative membership on smallholder market participation, crop price, farm income and poverty reduction (Bernard and Spielman 2009; Bernard et al. 2008; Fischer and Qaim 2012; Francesconi and Heerink 2011; Ito et al. 2012; Verhofstadt and Maertens 2014a; Wollni and Zeller 2007; Yang and Liu 2012). Most researchers found modest positive impacts of cooperative participation on farm outcomes of interest, using various measures and econometric approaches. However, farm income can only provide a partial picture of income effects, because higher farm income may be realized by reallocating resources from other important economic activities occasioned by the choice of cooperative membership (Kabunga et al. 2014; Rao and Qaim 2011). Moreover, focusing on the impact on farm income may be misleading and leas to spurious conclusions, since there are also differences in the aspects of output levels, prices and costs of variable inputs. It is therefore necessary to examine the impacts of cooperative membership on crop yield, net returns, household income and return on investment, which are more accurate and comprehensive to reflect the benefits of membership in agricultural cooperatives.

Marketing contracts play a vital role in linking smallholder farmers to advanced supply chains (e.g., supermarkets, restaurants, processors, and international markets), and leading to rural income growth and poverty reduction (BlandonHensonand Cranfield 2009; Mangala and Chengappa 2008; Miyata et al. 2009). Several studies have examined the nature and determinants of the choices of different types of marketing contracts (Abdulai and Birachi 2009; Guo and Jolly 2008; Jia et al. 2012; Katchova and Miranda 2004; Sartwelle et al. 2000). In the situation with different types of marketing contracts available, farmers choose the most appropriate one to maximize their net returns from crop production. Thus, it is significant to understand the linkages between different marketing contract choices and farm net returns. In the crop supply chain, farmers may choose agricultural cooperative as a primary marketing channel to maximize farm profit. However, the knowledge on how cooperative membership affects farmers' net returns and decisions on the choice of marketing contracts is currently lacking in the literature.

Agricultural cooperative membership is not randomly distributed among farming households. Farmers choose to join the cooperatives themselves. Therefore, in examining the impact of cooperative membership, many of previous studies have employed propensity score matching method to address the issue of selection bias, assuming that cooperative members and nonmembers are systematically different only in observed characteristics (e.g., age, education, farm size, and asset ownership). However, unobserved characteristics (e.g., farmers' innate abilities, motivations to improve soil conditions and supply food to meet food safety standards) may also simultaneously influence farmers' decisions to choose cooperative membership and outcomes of interest. Ignoring such factors tends to produce biased estimates of the impact of cooperative membership on the adoption of technologies and farm performance. Hence, there is a need to analyze the impact of cooperative membership by addressing the sample selection bias issue accounting for both observable and unobservable factors.

The present dissertation attempts to fill in those research gaps and contribute to the literature by examining the impact of cooperative membership on the adoption of agricultural technologies and farm performance of smallholder apple farmers in China. Apple farmers are considered as an interesting case in this dissertation, since apple is an important fruit historically cultivated in China. Although apple production and marketing plays a critical role in improving the livelihoods of farming households, small-scale farmers are facing difficulties in adopting agricultural technologies and benefiting from output marketing. The agricultural policy design aimed at enhancing agricultural performance and rural household welfare requires understanding the impact of agricultural cooperatives on technology adoption and farm performance of smallholder farmers.

In the next section, background information about China's agricultural sector, apple production and marketing, and agricultural cooperatives is presented.

1.2 Background

1.2.1 The Profile of China

China, officially the People's Republic of China (PRC), is located in the east and middle of Asia and on the west shore of the Pacific, which covers a land area of about 9.6 million square kilometers and a sea area of about 4.73 million square kilometers, with a mainland coastline about 18 thousand kilometers. The territory of China lies between latitudes 18° and 54° N, and longitudes 73° and 135° E. China is bordered to the east by Korea (Dem Rep), the Yellow Sea, and the South China Sea; to the south by Vietnam, Laos, Myanmar, India, Bhutan, and Nepal; to the west by India, Pakistan, Afghanistan, Tajikistan, Kyrgyzstan and Kazakhstan; to the north by Russia and Mongolia.

The climate in China differs from region to region because of the country's highly complex topography. There are primarily four seasons including spring, summer, autumn, and winter. Summer and winter in China have a subtropical climate and the temperatures can reach extremes, and spring and autumn are very pleasant periods in almost all the regions.

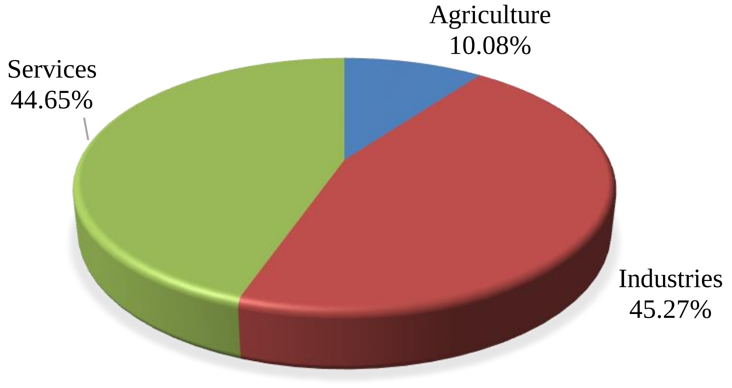
Source: National Administration of Surveying, Mapping and Geoinformation of China

Figure 1.1 Map of the People's Republic of China

China is the world's most populous country. The population is about 1.35 billion and is growing at a rate of 19% between 1990 and 2012 (CSA 2013). It has 34 provincial-level administrative units including 23 provinces, 4 municipalities (Beijing, Tianjin, Shanghai and Chongqing), 5 autonomous regions (Guangxi, Inner Mongolia, Tibet, Ningxia and Xinjiang) and 2 special administrative regions (Hong Kong and Macau). It is officially reported that there are 56 nationalities living in China, and Han Chinese account for more than 90% of the total population. The languages and customs in other groups such as Mongolians, Uyghurs, Zhuang, Miao, and Bai are quite different from those of the Han. Standard Chinese, which is also referred to as "Mandarin", is the official language of China.

Beijing and Shanghai are the two best known cities in China. Beijing is the capital, which is well-known for its mixture of ancient culture and modernization. The ancient culture is represented by the Great Wall, the Forbidden City, and the Summer Palace. It is a political, educational, and cultural center, with light industries (science, technology and research) dominating over mass manufacturing. Shanghai is the undisputed largest and wealthiest city in China, which features a combined culture of East and West. Shanghai has the largest and busiest port in terms of containers and cargo tonnage, with a grand business district, two large airports (Pudong and Hongqiao), the world's fastest train (the Maglev), and a network of elevated highways.

1.2.2 Overview of Agricultural Sector in China

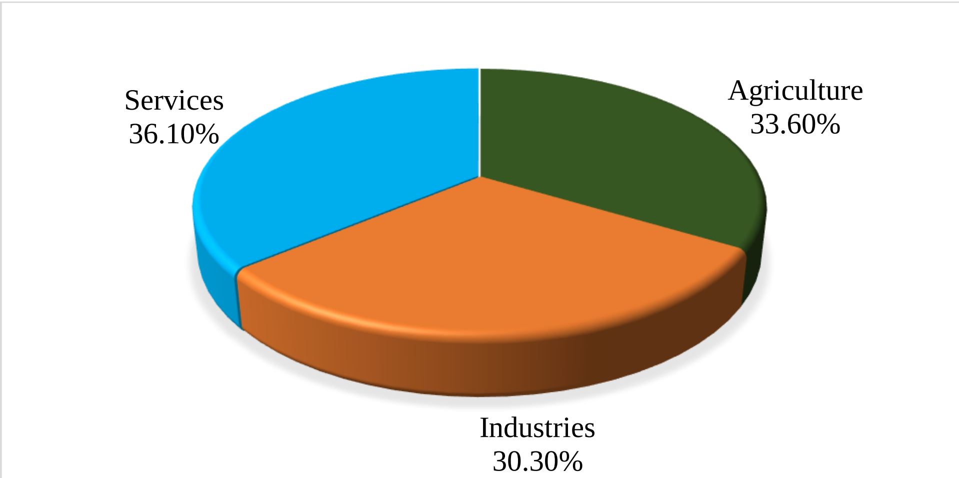


Source: Compiled from the data of China Statistical Abstract 2013

Figure 1.2 Sectional contribution of China's GDP in 2012

Agriculture is at the heart of China's rural economy, and most rural people rely on agriculture for their livelihoods. It contributed about 10.08% of GDP in 2012, while industries and services sectors contributed 45.27% and 44.65%, respectively (see Figure 1.2). Agriculture is still by far the most important sector of China's economy, employing over 257 million workers. In 2012, about 33.60% of the Chinese labor force was involved in agricultural sector, and the labor force distributed to industries and services accounted for 30.30% and 36.10%, respectively (see Figure 1.3).

In China, around 47.43% of the population lives in rural areas, who are directly or indirectly dependent on agricultural activities for their livelihoods (CSA 2013). Despite the recent rapid increase of Chinese income, rural income falls far behind urban income. In 2012, per capita rural disposable income was 7,917 yuan, only one third of its urban counterpart of 24,565 yuan (CSA 2013). The Chinese government has encouraged farmers to grow higher-valued agricultural products to raise rural incomes.

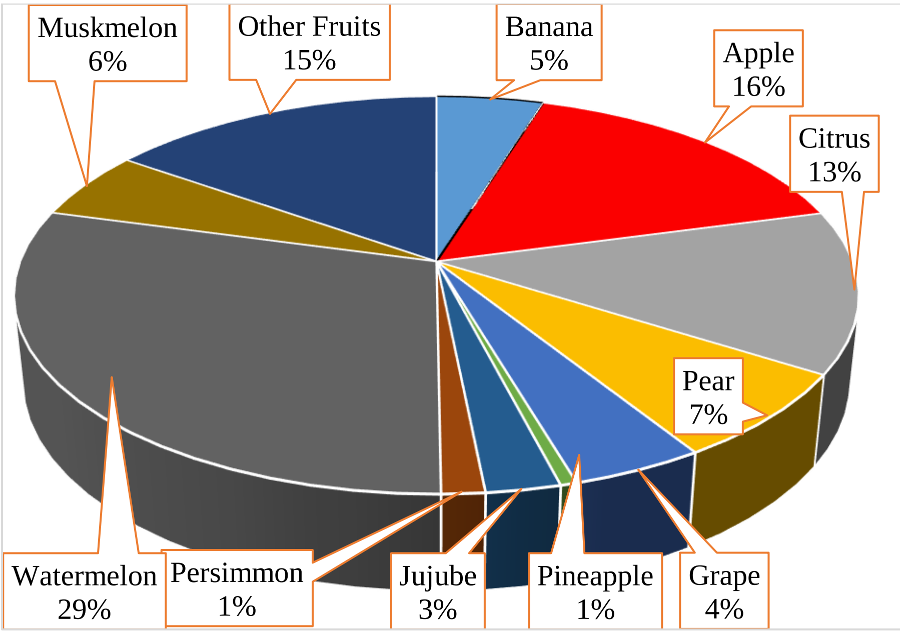


Source: Compiled from the data of China Statistical Abstract 2013

Figure 1.3 Sectional contribution of China' labor force employment in 2012

China has 12.172 million hectares of arable land, but it is burdened with a fifth of the world's population and insufficient resources. The average size of Chinese farm is less than 0.5 ha, which is much smaller than other Asian developing countries such as India (1.5 ha), Thailand (3.4 ha), and South Korea (1.5 ha) (Fan and Chan-Kang 2005). Even so, China is among the most affected countries in the world in terms of the extent, intensity and economic impact of land degradation (Bai and Dent 2009). Land degradation is a serious threat to food production and rural livelihoods. Only 1.3 million square meters' land is suitable for agricultural production. Since the land degradation will directly influence the potential and productivity, more yield-enhancing inputs such as fertilizers, pesticides and irrigation water are needed to maintain or enhance the productivity, which result in higher production costs. The government has attempted to enhance smallholder farmers' investment in soil-improving measures to mitigate the negative impact of soil degradation on crop yields and the environment.

In China, around 75% of cultivated land is used for grain crops. Rice and wheat are the two most important crops. The majority of rice is grown in Yunnan, Guizhou and Sichuan provinces, in the Zhujiang delta, and the south of the Huai River. Wheat is grown in almost all parts of China. Crops like millet and corn are also grown in various places in China. Potatoes are also considered as an important part in China's agricultural production, and various species of potatoes have cultivated in the country. Oil seeds are also cultivated in a large quantity and are often exported as well.



	Output/million tons
Banana	11.56
Apple	38.49
Citrus	31.68
Pear	17.07
Grape	10.54
Pineapple	1.29
Jujube	5.89
Persimmon	3.42
Watermelon	70.71
Muskmelon	13.32
Other Fruits	36.61
Total output	240.57

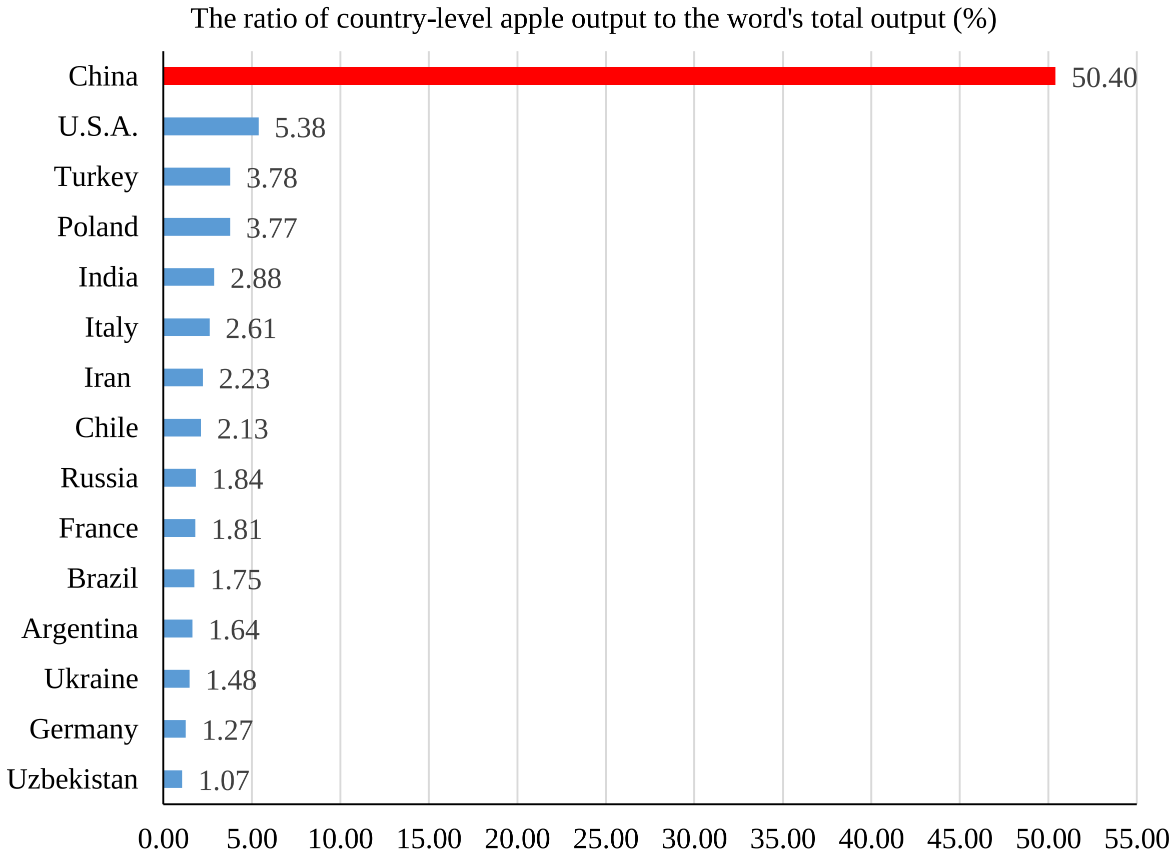
Source: Compiled from the data of China Rural Statistical Yearbook 2013

Figure 1.4 Major fruits produced in China in 2012

In China, fruit sector is one of the most important parts in agricultural sector. Due to geographical and climate advantages, and its importance to human health and nutrition, the fruit production has been increasing. The fruit cultivation area in China rose from 8.93 million hectares in 2000 to 12.14 million hectares in 2012, while output grew from 62.25 million tons to 240.57 million tons over the same years (CRSY 2001, 2013). Apple and watermelon have the largest production quantities. In 2012, 38.49 million tons of apples and 70.71 million tons of watermelons were produced in China, accounting for 29% and 16% of the total fruit output, respectively (see Figure 1.4). Other commonly produced fruits are pear, grape, muskmelon, citrus, pineapple, persimmon and jujube.

1.2.3 Apple Production and Marketing in China

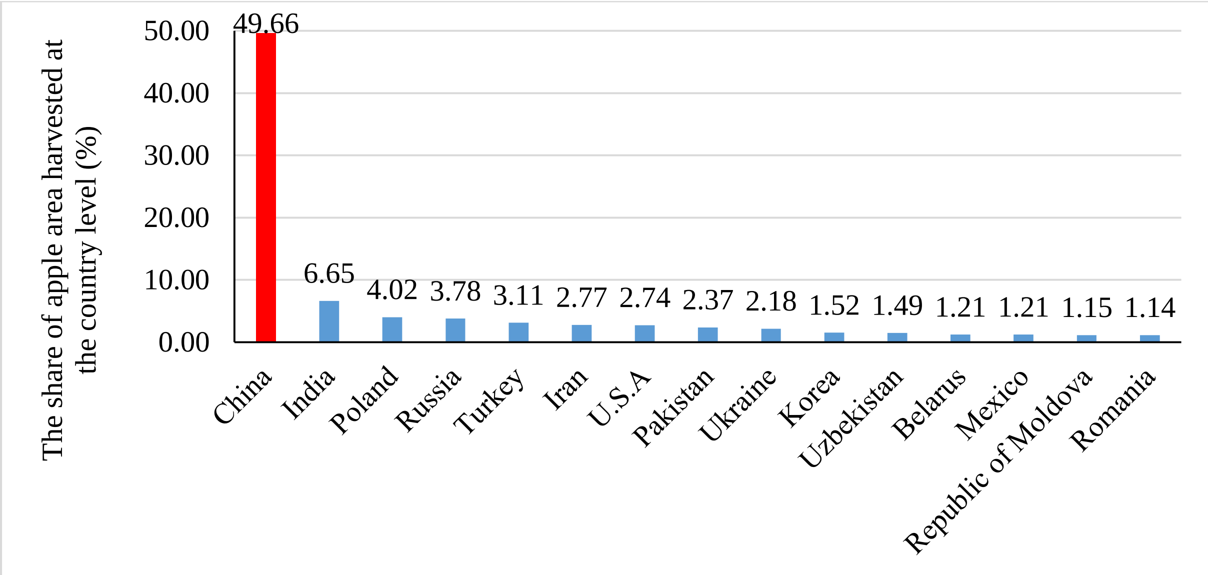
China is by far the largest apple producer in the world. About 76.38 million tons of apples were grown worldwide in 2012, 38.49 million tons in China, 4.11 million tons in U.S.A and 2.89 million tons in Turkey. It can be seen in Figure 1.5, apples produced in China, U.S.A and Turkey account for 50.40%, 5.38% and 3.78% of the world's total output in 2012, respectively. Uzbekistan ranks fifteenth in terms of apple output, contributing 1.07% of the world's total apple production. In terms of varieties, Fuji is the primary apple variety in China, with production area accounting for 70% of apple production. Fuji apple was developed in Japan in the 1930s and was popularly grown in many countries since then, given its nutritious value. Other commonly cultivated apple varieties in China include Delicious, Golden Deli, Gala and Jiaona Jin. Apple consumption occupies a more and more important place in China. According to the data released by Helgi library, the per capita consumption of apples grew from just 14.6 to 21.3 kg per year between 2008 and 2012. China's population is rapidly urbanizing and apple consumption fits into this changing lifestyle that emphasizes convenience.



Data source: Compiled from the data of FAO

Figure 1.5 Top 15 apple producing countries by total output in 2012

In recent years, the amount of land for apple production has been increasing in China. The agricultural land covered by apple orchards had expanded to 2.4 million hectares by the end of 2012, which accounted for 49.66% of the world's total apple areas cultivated (see Figure 1.6). The land used for apple production in China is significantly higher than other major apple producing countries such as U.S.A, Turkey, Poland, India, and Italy. For instance, the land used for apple cultivation in India was 0.32 million hectares, ranking the second among the major apple producing countries in the world. However, it only accounts for 13.39% of China's total apple areas.

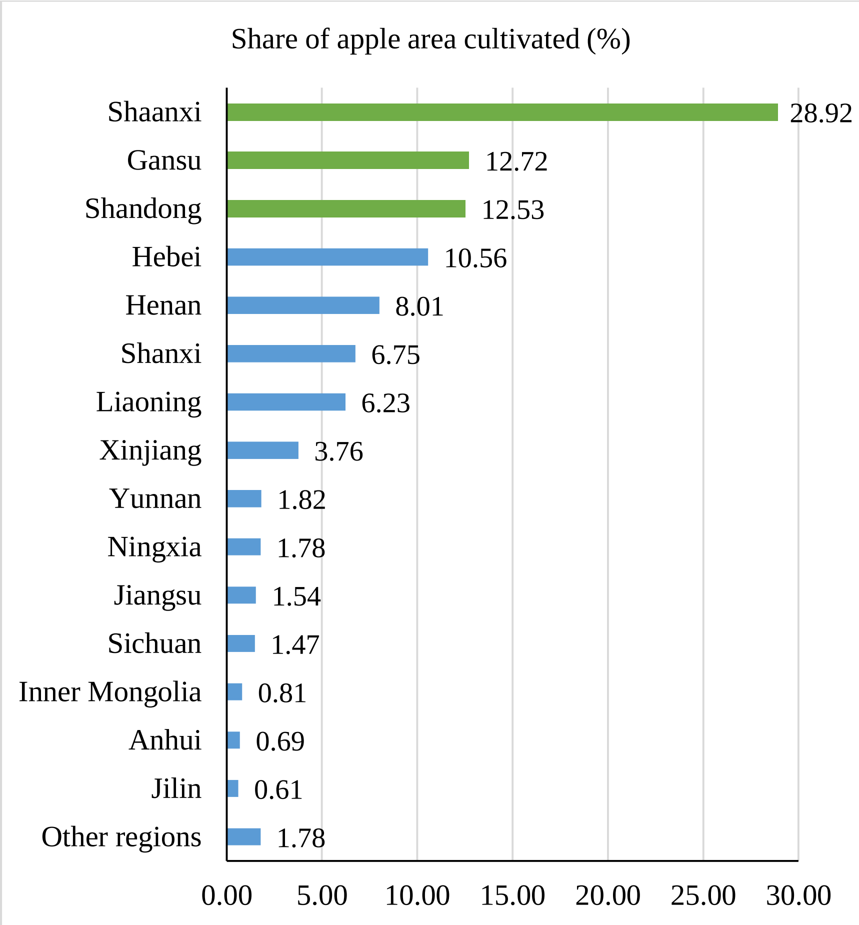


Source: Compiled from the data of FAO

Figure 1.6 Top 15 apple producing countries by area harvested in 2012

Apples are grown in many regions across China. The main apple production areas are Bohai Gulf region (Shandong, Liaoning and Hubei provinces) and Northwest Loess Plateau region (Shaanxi, Shanxi, Henan and Gansu provinces) due to the favorable climate conditions there. More than half of the country's apple orchards was located in Shaanxi, Gansu and Shandong provinces, having an orchard area of 645.2, 283.9 and 279.6 thousand hectares respectively in 2012 (see Figure 1.7). Apples play an important role in improving rural incomes in Gansu, Shaanxi and Shandong provinces where local governments place high importance on apple production. For instance, Yantai government in Shandong province published the "Guidelines on Facilitating the Upgrade of Apple Industry" on February 21, 2014, with the aim of promoting Fuji varieties and facilitating high density planting systems. In particular, the guidelines encourage standardized apple production and promote land transfers to consolidate the production. In Shaanxi province, the government issued "Shaanxi Fruit Regulations" on May

1, 2014, aimed at addressing fruit quality issues. The regulations allow local authorities to establish fruit production standards and call for the establishment of fruit testing and traceability system.

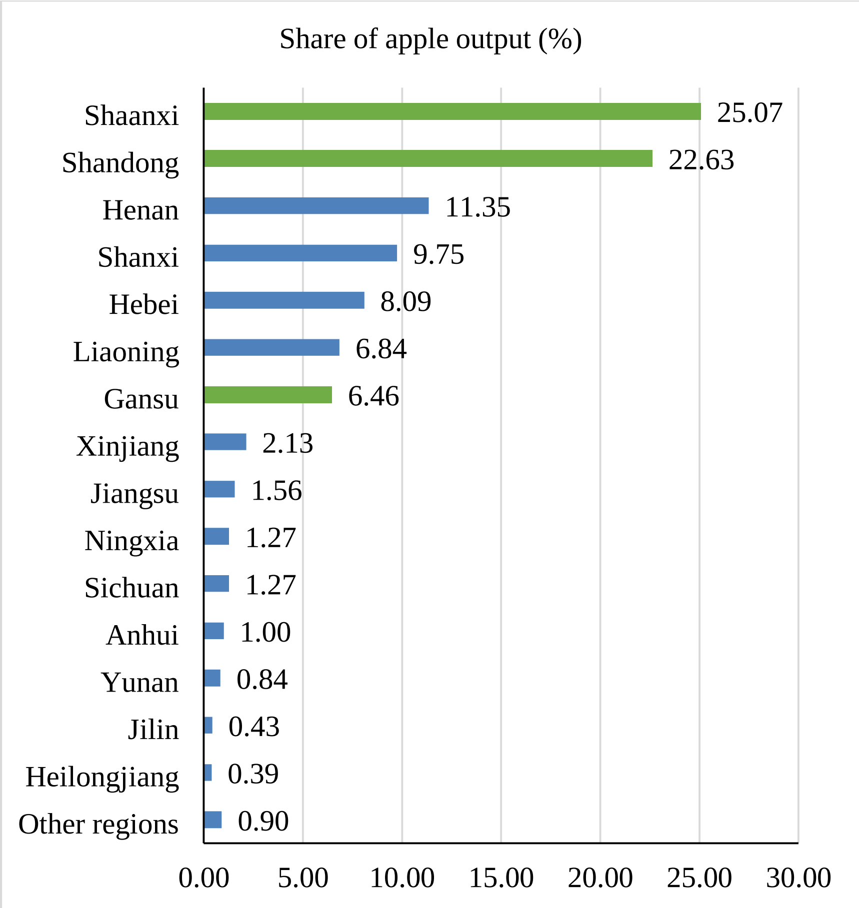


Area cultivated (thousand hectares)	
Shaanxi	**645.2**
Gansu	**283.9**
Shandong	**279.6**
Hebei	235.7
Henan	178.8
Shanxi	150.7
Liaoning	139.0
Xinjiang	83.9
Yunnan	40.6
Ningxia	39.8
Jiangsu	34.3
Sichuan	32.9
Inner Mongolia	18.1
Anhui	15.5
Jilin	13.6
Other regions	39.7
Total areas	**2231.1**

Source: Compiled from the data of China Rural Statistical Yearbook 2013

Figure 1.7 Top 15 apple producing provinces by area cultivated in China in 2012

However, due to the differences in soil and climate conditions, the total apple output varies among those regions. For instance, although Gansu ranks the second largest in terms of apple orchard areas, the total apple output only ranks the seventh among major apple producing regions, showing a relatively low productivity (See Figure 1.8). Although Shaanxi, Gansu and Shandong provinces have better conditions for apple production relative to other areas, they are obviously different in terms of agro-climates and agro-food market environments, resulting in different levels of apple productivity and profitability. For instance, Shandong is a coastal province with favorable annual rainfall, and farmers there produce several types of cash crops including pears, peaches, cherries, peanuts, corns, and apricot. In contrast, Gansu and Shaanxi are inland provinces and characterized by low rainfall and poor infrastructure, and farmers there only grow corns and potatoes as extra income sources.

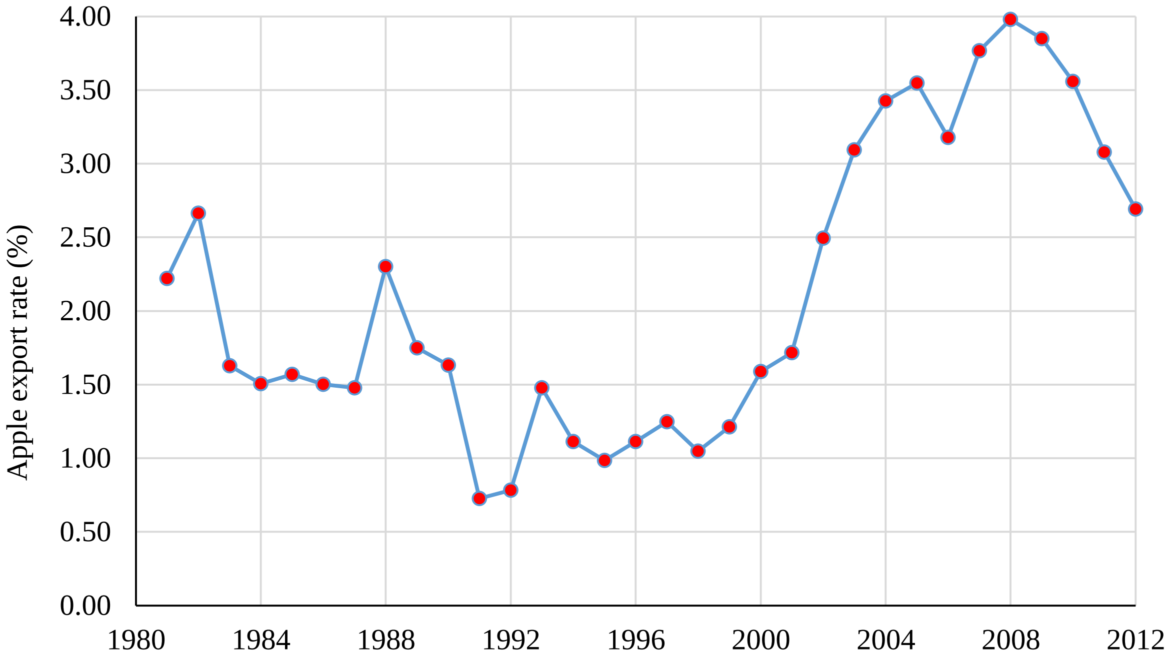


Output/thousand tons	
Shaanxi	9,651
Shandong	8,710
Henan	4,367
Shanxi	3,752
Hebei	3,115
Liaoning	2,634
Gansu	2,488
Xinjiang	821
Jiangsu	601
Ningxia	489
Sichuan	488
Anhui	387
Yunan	322
Jilin	167
Heilongjiang	151
Other regions	347
Total areas	**38,491**

Source: Compiled from the data of China Rural Statistical Yearbook 2013

Figure 1.8 Top 15 apple producing provinces by output in China in 2012

Although apple production in China has a compelling advantage in terms of growing areas and total output, apple farmers' participation in domestic and international markets is severely constrained as a result of market imperfection, information asymmetry, and high transaction costs. In particular, apple export rate remains below 4% since 1981, and the potential for expansion is large (see Figure 1.9). Several factors such as low yields, inadequate cold storage and packing plant capacity, high pesticide residues, and phytosanitary problems prevent apple exports to some high-income markets such as European countries and the United States (Miyata et al. 2009). The main markets for Chinese apples are Southeast Asia and Russia.



Source: Compiled from the data of FAO

Figure 1.9 Apple export rate from 1981 to 2012 in China

1.2.4 The Role of Agricultural Cooperatives in China

According to the definition of International Labor Organization, a cooperative is an autonomous association of women and men, who unite voluntarily to meet their common economic, social and cultural needs and aspirations through a jointly owned and democratically controlled enterprise. Agricultural cooperatives enable farmers to realize economic benefits that they could not otherwise achieve alone.

In China, the systematic development of agricultural cooperatives is supported by the government. In 1998, a directive was issued by the State Council to support the agricultural cooperatives that were voluntary organizations established by farmers themselves. In 2002, the Ministry of Agriculture developed a pilot project with 100 agricultural cooperatives throughout the country, and provided them with marketing information, technical assistance and management training. In 2007, the Law of Farmers' Professional Cooperatives was promulgated, with the aim of facilitating the development of agricultural cooperatives, standardizing organization and behaviors of them, protecting legal interests of cooperatives and members, and fostering the growth of agriculture and rural economy. As a new institutional innovation, agricultural cooperatives in China are expected to promote higher incomes for its members, to enhance access to modern supply chains and technology adoption, and to help lower production and marketing costs (Zheng et al. 2012).

Agricultural cooperatives play an important role in food production and marketing. They can help improve smallholder farmers' bargaining power in the marketplace and reduce costs by pooling capital. Through cooperatives, farmers can achieve economies of scale by reducing the unit costs of inputs and services. Moreover, agricultural cooperatives can provide technical assistance to their members and collectively purchase production inputs for their members, contributing to a reduction in transaction costs and an increase in farm income. Agricultural cooperatives enable farmers to participate in high value supply chain, particularly in fresh produce markets. Even so, cooperative membership participation rate remains low in the country.

In addition to the provision of production and marketing services, another interesting emerging role that agricultural cooperatives play is the enhancement of agro-food safety and quality. Enhancing the small-scale farmers' participation in the growing domestic and global markets for safer food can reduce rural poverty (Weinberger and Lumpkin 2007; World Bank 2008). With rapid income growth, the food consumption is shifting from staple grains toward high-value commodities such as meat, fish, dairy, and fruit and toward processed foods (Minot and Roy 2007). Farmers are facing good opportunities if they can supply safer food to both domestic and international markets. The role of cooperatives in enhancing food safety and quality has been discussed in previous studies (see Jia et al. 2012; Moustier et al. 2010; Narrod et al. 2009). In combination with the domestic agricultural practice and food safety situation, the government proposed organic food standard, green food standard and pollution-free food standard, aims at meeting domestic and international requirements for quality and safety products (Yu et al. 2014). The government is encouraging the adoption of food safety and quality standards by agricultural cooperatives to ensure improved quality of the foods produced. The certified agricultural cooperatives are responsible for guiding and supervising their members to produce products in accordance with the corresponding food safety standards.

1.3 Objectives of the Study

The present study attempts to analyze the impact of membership of agricultural cooperatives on the adoption of technologies and farm performance of apple farmers in China. The specific objectives of the study are:

- To analyze the factors that influence farmers' decisions to join agricultural cooperatives;

- To examine the impact of cooperative membership on investment in soil-improving measures such as organic fertilizer and farmyard manure, as well as yield-enhancing measure such as chemical fertilizer;

- To illustrate the causal relationship between cooperative membership and adoption of integrated pest management (IPM) technology, as well as examine the impact of IPM adoption on apple yields, net returns and agricultural income;

- To evaluate the impact of cooperative membership on apple yields, net returns and household income;

- To estimate the impact of agricultural cooperative membership on return on investment;

- To understand the factors that influence farmers' decisions to choose different types of marketing contracts used in apple supply chain, as well as analyze the causal relationship between the marketing contract and net returns from apple production;

- To draw policy recommendations to improve the status of apple production and marketing based on the findings, and thus enhance rural income and reduce poverty in China.

1.4 Significance of the Study

Since the present study is the first study to provide the comprehensive understanding of the relationship between agricultural cooperatives and apple production and marketing in China, the findings of this paper could contribute important implications for policy-makers in their effort to develop sustainable agriculture and improve rural household welfare. The information from this study can significantly contribute to the literature on the impact of cooperative membership. The findings from this dissertation can assist policymakers in their efforts to design and implement polices, laws, regulations and projects that take the needs and concerns of smallholder farmers into consideration.

The role of agricultural cooperatives in influencing farmers' decisions to adopt agricultural technologies with respect to soil-improving measures and integrated pest management technology also has important implications for policy makers. On one hand, soil erosion and desertification are considered two most serious environmental degradation problems in China, which impact adversely on environmental sustainability and productivity of apple production. On the other hand, only 3% of apples produced in China is exported due to pesticide residue issue. The existing evidence has shown that agricultural cooperative can facilitate farmers' adoption of yield-enhancing measures such as chemical fertilizers and pesticides, and it has potential to improve farmers' food safety performance. Thus, understanding how agricultural cooperatives influence farmers' adoption of soil-improving measures and product safety-enhancing technology can help adjust the role of agricultural cooperatives in enhancing sustainable and environmentally-friendly agricultural production.

The issues whether agricultural cooperative can increase rural household welfare are also relevant to food policy decisions. If agricultural cooperative has a pro-poor impact, it can attract and motivate more farmers without the membership to join agricultural cooperatives, and policies and programs to support the development of cooperative organizations could be justified on equity grounds. If not, the policymakers would be better to allocate resources to other agricultural development strategies.

1.5 Outline of the Thesis

Chapter 1 of the dissertation gives general introduction, chapter 2 to chapter 6 are a collection of five journal articles, and chapter 7 presents conclusions and policy implications. Specifically, chapter 2 develops a dynamic model to show how membership in agricultural cooperatives influences smallholder farmers' decisions to invest in soil-improving and yield-enhancing measures such as organic fertilizer, farmyard manure and chemical fertilizer, as well as empirically examines the impact of cooperative membership on investment in those measures. Chapter 3 presents a conceptual framework to show the link between agricultural cooperative membership and IPM adoption. It also empirically examines the causal relationship between cooperative membership and IPM adoption, as well as assesses the impact of IPM adoption on apple yields, net returns and agricultural income. Chapter 4 assesses the impact of cooperative membership on apple yields, net returns, and household income. Chapter 5 analyzes how membership in agricultural cooperatives affects return on investment of smallholder apple farmers. Chapter 6 investigates the determinants of marketing contract choices including written contracts, oral contracts and no contracts, as well as examines the impact of marketing contracts on net returns from apple production in China. The last chapter summarizes the results and suggests policy implications based on the findings in the dissertation.

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Chapter 2 The Role of Agricultural Cooperatives in Promoting Sustainable Soil Management Practices in Rural China

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Abstract

In this article, we develop a dynamic model to show how membership in agricultural cooperatives influences smallholder farmers' decisions to invest in soil-improving and yield-enhancing measures. We then use farm-level data from three provinces in China to empirically examine the impact of cooperative membership on investment in organic fertilizer, farmyard manure and chemical fertilizer. A recursive bivariate probit model that accounts for endogeneity of cooperative membership and selection bias is employed in the empirical analysis. The empirical results are largely consistent with the theoretical specification, and the findings show that cooperative membership exerts a positive and statistically significant impact on the probabilities of investing in soil-improving measures such as organic fertilizer and farmyard manure, but does not significantly influence the likelihood of investing in chemical fertilizer. The findings also reveal that farm size, asset ownership and access to credit tend to significantly influence the probability of a farmer joining a cooperative and the likelihood of investing in soil quality measures.

Keywords: Agricultural cooperative; Investment; Soil quality; Impact assessment; China

JEL codes: C83; F61; J54; P52; Q01

2.1 Introduction

In many developing countries, agricultural cooperatives constitute a major vehicle that can be used to improve smallholder agricultural performance, particularly through services that enhance the adoption of new agricultural technologies, sustainable farm practices, and output marketing. Several studies have highlighted positive and significant impacts of cooperative membership on farm income and profits, producer prices and output market participation (e.g., Bernard and Spielman 2009; Hellin et al., 2009; Ito et al., 2012; Wollni and Zeller 2007; Vandeplas et al., 2013; Chagwiza et al., 2016). To the extent that output marketing efficiency is promoted by improved investment in agricultural production, an understanding of the effect of cooperative membership on investment decisions of smallholder farmers should be as important as that of the effect of cooperative membership on marketed output. However, little effort has gone into investigating how cooperative organizations influence the adoption of agricultural technologies by smallholder farmers. In particular, although land degradation due to soil erosion and loss of soil quality has been identified as one of the most serious ecological and economic problems facing developing countries (Rozelle et al. 1997; Pender et al. 2001; Antle and Diagana 2003), the issue of whether agricultural cooperative can help facilitate farmers' investment in sustainable land management practices has been overlooked.

Land degradation does not only contribute to a reduction in crop yields, but also increases crop production costs in the long-run (Barbier 2000; Rozelle et al. 1997). Thus, from a sustainable agriculture perspective, investment in soil improvement measures is an inevitable choice for smallholder farmers facing land degradation problems. Empirical evidence using micro-level data indicates that investment in soil improvement measures helps increase farm productivity (Byiringiro and Reardon 1996; Ersado et al. 2004; Holden et al. 2009).

Some studies have analyzed the impact of cooperative membership on investment in static inputs such as pesticides and chemical fertilizers (Abebaw and Haile 2013; Verhofstadt and Maertens 2014). In their investigation of the impact of cooperative membership on adoption of agricultural technologies in Ethiopia, Abebaw and Haile (2013) found that agricultural cooperatives have a positive and significant impact on application of chemical fertilizers such as Dibasic Ammonium Phosphate and Urea. A recent study by Verhofstadt and Maertens (2014) on Rwanda also found a positive and significant relationship between agricultural cooperatives and adoption of chemical fertilizer. Although crop yields normally increase with higher rates of application of yield-enhancing measures such as chemical fertilizer, yields may decline over time due to soil degradation, if no organic material is added to the soil. Given the importance of investing in organic inputs that build up the soil structure and naturally replenish nutrients in the soil, examining the impact of cooperative membership on investment in soil-improving measures such as organic fertilizer and farmyard manure would definitely provide significant information for agricultural policy design.

Agricultural cooperative membership is not randomly distributed, but farmers choose to belong to cooperatives themselves. Therefore, in their efforts to examine the impact of cooperative membership on outcomes of interest, the studies mentioned above employed propensity score matching (PSM) model to address the issue of selection bias (Abebaw and Haile 2013; Verhofstadt and Maertens 2014). However, the PSM model addresses the issue of selection bias by controlling for only observable factors, which is a well-known shortcoming of the model (Dehejia and Wahba 2002). Within the context of heterogeneous populations, farmers with similar observed characteristics (e.g., age, education, household size and farm size) might have different levels of innate abilities and motivations to improve soil conditions. Such characteristics cannot be observed directly, but they may significantly influence farmers' decisions of choosing cooperative membership and investing in cultivated land simultaneously. Hence, addressing the issue of selection bias should also take into account unobserved factors. Moreover, the past studies mentioned above did not attempt to systematically develop a coherent theoretical framework that links cooperative membership to investment in soil quality and yield-enhancing measures.

This study contributes to the literature on agricultural cooperatives and soil investment decisions by developing a dynamic model that relates cooperative membership to investment in soil quality measures. We identify conditions under which cooperative membership helps in reducing costs and enhancing investments in soil quality measures. We also employ farm-level data of 481 households from major apple producing provinces including Gansu, Shaanxi and Shandong of China to examine the factors influence farmers' decisions to join cooperatives, and the impact of cooperative membership on investment in organic fertilizer, farmyard manure and chemical fertilizer. We use a recursive bivariate probit model to account for selection bias that arises from both observed and unobserved heterogeneities (Thuo et al. 2014; Vall Castello 2012).

The rest of the article is structured as follows. In the next section, we present the theoretical framework and analysis from the model developed in the study. We then outline the empirical specification, and then proceed to describe the data used in the empirical analysis. This is followed by a presentation of the empirical results. The final section presents some concluding remarks.

2.2 Theoretical Framework

The theoretical framework presented in this article analyzes the link between the decision to join an existing agricultural open-membership cooperative and to invest in soil-improving measures. Let ξ denote the outcome of the decision to join a cooperative or not, where $\xi = 1$ indicates the farmer joining and $\xi = 0$ not joining. Given that current investment decisions tend to affect the evolution of soil quality over time, we analyze the decision problem of an individual farmer within a dynamic context. Household and farm-level characteristics are specific for each farmer and include variables like age, education, household size, farm size, asset ownership, and soil types. Following the concept of the so-called location or address models (Fulton and Giannakas 2013), we consider that household and farm-level characteristics, which form the basis of an index, denoted by θ, are specific for each farmer. Let the index be scaled such that it is distributed over the interval $[0,1]$, with $\theta = 0$ indicating the characteristics with the lowest, and $\theta = 1$ having the highest effect on the net returns of production.[1]

We assume that the farmer cultivates a unit of land and combines investment in soil-improving and yield-enhancing measures such as organic fertilizer and farmyard manure $O(t)$, and chemical fertilizer $M(t)$, which is considered as a yield-enhancing input, where t indicates calendar time.[2] To simplify the analysis, we also assume that farmers do not change their status of cooperative membership from the initial period to the end of the planning horizon T.

The quality of the agricultural product is a distinctive characteristic and influences the price P that farmers can obtain for their product. However, the production of higher quality is more

[1] Let the lowest and the highest values of the unscaled index be denoted by l and h, respectively. Hence, the lowest and highest values of the scaled index θ are given by $(l-l)/(h-l) = 0$ and $(h-l)/(h-l) = 1$, respectively. Any in between value i of the unscaled index is transformed by the equation $(i-l)/(h-l) \in (0,1)$ to the scaled index.

[2] Organic fertilizer refers to commercial products that farmers can purchase in the market, and farmyard manure refers to the manure fertilizer that is either from the family yard or bought from livestock farms.

costly, as it requires employing more inputs and following a more stringent production protocol. To focus on the fundamental characteristics of the driving forces, we consider only high and low qualities as characteristics of the products. Let the high quality product be indicated by H and the low quality one by L, and the associated prices by P^H and P^L, respectively. The agricultural production function per unit of land, $Y^j(\cdot)$, $\mathrm{j}=L,H$ can be specified as a function of soil-improving and yield-enhancing inputs $O(t)$, yield-enhancing input $M(t)$, soil quality $S(t)$ and the household and farm-level characteristics θ. This is given as $Y^j\left(O(t),M(t),S(t);\theta\right)$, $j=L,H$. To simplify notation, we suppress for the remaining part of the text the information $j=L,H$, whenever no unambiguity can arise. We assume that the function $Y^j(\cdot)$ is strictly concave in the arguments O, M, S and additive separable in O and M, because these two inputs are in the short-run nearly perfect substitutes with respect to production. Consequently, the cross derivative with respect to these variables is equal to zero. The costs of production of nonmembers of the cooperative are denoted by the functions $C^j\left(O(t),M(t);\theta\right)$. Given a higher productivity index, the same amount of output can be produced with less fertilizers or manure. Thus, we assume that the production costs and the net returns index are negatively related, i.e., $C^j_\theta(\cdot;\theta)<0$ and that $C^j_{\theta\theta}(\cdot;\theta)>0$.[3]

Widespread empirical evidence shows that members of agricultural cooperatives may have a relative advantage over nonmembers with respect to production efficiency, as well as input and output market operations (Abebaw and Haile 2013; Hendrikse and Bijman 2002; Vandeplas et al. 2013). These benefits may include lower search costs for input and output markets; better bargaining position for lower input and higher output prices; screening of the market partners in the presence of asymmetric information with respect to quality of the inputs, and better access to credit and management information. In particular, a number of studies have shown that agricultural cooperatives play a significant role in supplying markets with high quality products (e.g., Moustier et al. 2010; Naziri et al. 2014). We therefore assume that farmers with cooperative membership have lower productions costs over a wide range of θ. Let us denote the cost function of members of the cooperative by $CO^j(\cdot;\theta)$. The difference between the cost

[3] Throughout the text the subindex of a function by a variable indicates the partial derivative of the function with respect to the variable.

functions $C^j(\cdot;\theta)-CO^j(\cdot;\theta)$ represents the individual share of the cooperative benefits that members of the cooperative with characteristics θ can realize exclusively as members. Without loss of generality, we only consider cooperative benefits resulting from cost savings, and not from premium sale prices. It is significant to mention that a different formulation of the theoretical model would not alter the results of the analysis, since the magnitude of the cooperative benefits is the determining factor for the farmer's participation decision and not the origin of the benefits.

As indicated previously, being a member of a cooperative does not only bring along advantages, but also a number of obligations. These may include paying an annual fixed fee, following a stricter and more expensive production protocol, as well as being subjected to frequent contacts/controls in order to ensure that members meet the quality standards laid down by the cooperative.[4] The population of farmers is heterogeneous and the farmer's household and farm-level characteristics, θ, follow a distribution function $\Gamma(\theta)$. We consider that farmers whose value of θ is below a threshold $\bar{\theta}^j$ incur lower production costs, if they are members of the cooperative. Beyond this limit value, we assume that the potential of the farmer's net returns is so high that being a member of a cooperative does not lead to any reduction in the costs of production, i.e., for $\theta<\bar{\theta}^j$ we have $CO^j(\cdot;\theta)<C^j(\cdot;\theta)$, and for $\theta>\bar{\theta}^j$ we have $CO^j(\cdot;\theta)>C^j(\cdot;\theta)$. Based on the introduced notation, the net returns function for low and high quality production is given by:

$$P^jY^j(\cdot;\theta)-\xi CO^j(\cdot;\theta)-(1-\xi)C^j(\cdot;\theta) \tag{2.1}$$

As an illustration, we present the evolution of the returns and cost functions $P^HY^j(\cdot;\theta)$, $C^j(\cdot;\theta)$ and $CO^j(\cdot;\theta)$ with changes in θ in Figure 1. It is assumed that both types of cost functions are linear in $O(t)$ and $M(t)$, so that C_O^j, CO_O^j and C_M^j, CO_M^j depend exclusively on θ. Without loss of generality, we focus our analysis on the production of high quality products

[4] The obligations of cooperative members in developing countries including China may be different from that in Western countries. For instance, in the United States, cooperative members are expected to contribute equity or risk capital in proportion to their patronage and are recipients of the surplus or residual claims in proportion to their patronage, and they must meet specific qualifications that are stated in the cooperatives' bylaws (Gijselincks et al., 2014).

and base our graphical analysis on the specification of the cost functions, given by $C^j = \left(\alpha^j - \beta^j\theta\right)\left(O(t)+M(t)\right)$ with $\alpha,\beta > 0$ and $\alpha - \beta\theta > 0$. The cost function of the members of the cooperative has the same mathematical structure but, as formulated above, its value is greater or lower than $C^j(\cdot)$. Consequently, Figure 2.1 reflects the cost function of high quality producing cooperative members, $CO^H(\cdot;\theta)$ and the cost functions of low and high quality producing nonmembers; $C^L(\cdot;\theta)$ and $C^H(\cdot;\theta)$, respectively. The analysis of the cases of low quality, or of qualities in between low and high is identical to the discussed case of high quality. Figure 2.1 shows that low quality farmers with characteristics $\theta < \underline{\theta}^L$ do not break even, and thus production of low quality is only profitable for nonmembers if $\theta \geq \underline{\theta}^L$. Similarly, Figure 2.1 also shows that high quality producing nonmembers only make profits if their individual characteristics are at least as high as $\underline{\theta}^H$. For cooperative members, Figure 2.1 demonstrates that they make profits if their characteristics are at least as high as $\underline{\theta}^H_C$. However, if the characteristics are higher than $\bar{\theta}^H_C$, cooperative members still make profits but less than nonmembers. It would therefore be optimal for farmers producing high quality to join the cooperative if their characteristics fall within the range of $\left[\underline{\theta}^H_C, \bar{\theta}^H_C\right]$. Within this range, the individual net returns of members are higher than those of nonmembers. The dotted area in Figure 2.1 indicates the share of the cooperative net returns that accrue to its members with characteristics $\theta \in \left[\underline{\theta}^H_C, \bar{\theta}^H_C\right]$, while the striped area shows the net returns that are realized by all farmers independently whether they belong to the cooperative or not. It is important to note that the dotted area in Figure 2.1 does not illustrate the aggregate cooperative benefits because the density function $\Gamma'(\theta)$ has not been specified so far and thus, the number of farmers with $\theta \in \left[\underline{\theta}^H_C, \bar{\theta}^H_C\right]$ is not known. Given that the specification of the distribution function $\Gamma(\theta)$ does not provide any additional insights for the purposes of this study, we do not provide this specification here.[5]

[5] If the total number of farmers was given by N, every farmer had a different θ, and if the density function was given by $1/N$, the dotted area in Figure 2.1 would correspond approximately to the total aggregate cooperative benefits.

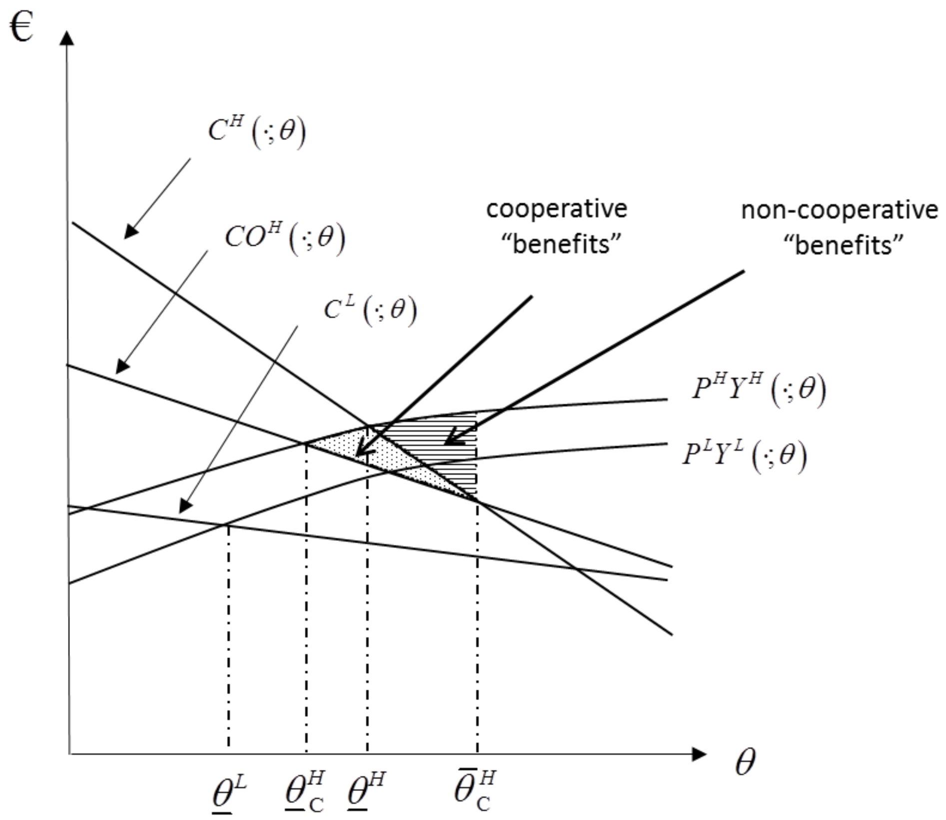

Figure 2.1 Returns and cost for farmers of type θ

Drawing the returns and cost functions differently would yield distinct results. Depending on the location of the values $\underline{\theta}^L, \underline{\theta}^H, \underline{\theta}_C^H, \overline{\theta}_C^H$, situations could emerge where it is beneficial for none of the farmers, or for all the farmers to join the cooperative. Thus, Figure 2.1 presents an intermediate case and is consistent with our empirical analysis, where we observe segmentation with respect to the decision to join or not to join.

After analyzing the decision to join or not to join an existing cooperative, we now examine how cooperative membership impacts on investment in soil-improving and productivity-enhancing measures. For this purpose, it is significant to note that the continuous application of organic fertilizer or farmyard manure improves the soil quality over time, while the application of chemical fertilizer, considered as a static input, does not influence soil quality directly, but indirectly through the withdrawal of nutrient by crop harvest. Thus, we assume that the application of organic inputs improves soil quality by the factor α_O and the harvest reduces soil quality by the factor α_Y, with $\alpha_O, \alpha_Y > 0$. Hence, the evolution of the soil quality over time can be represented by:

$$\dot{S}=\alpha_O O(t)-\alpha_Y Y\left(O(t),M(t),S(t);\theta\right) \text{, with } S(0)=S_0 \tag{2.2}$$

where $\dot{S}$ denotes the operator d/dt and S_0 is the given soil quality at time 0. To avoid additional notation, we assume that the soil quality is initially identical for all farmers. The parameter α_Y represents the decrease in soil quality in proportion to the harvested output resulting from soil degradation in the absence of any soil-improving investment.

It is assumed that farmers maximize their farm net returns over the planning horizon T. We assume that the present value of the soil quality at the end of the planning horizon is given by $S(\mathrm{T},\theta)\mathrm{e}^{-\delta(\mathrm{T})}$, where δ represents the value of the intertemporal discount rate. The farmer's decision problem with characteristics θ is then given by:

$$\mathrm{J}^*=\max_{O,M,\xi}\int_0^T\left\{\begin{array}{l}P^H Y\left(O(t),M(t),S(t);\theta\right)-\xi CO^H\left(O(t),M(t);\theta\right)\\ -(1-\xi)C^H\left(O(t),M(t);\theta\right)+\xi\mu_0-\xi\mu_1\end{array}\right\}e^{-\delta t}dt+S(T)e^{-\delta T} \tag{2.3}$$

subject to $O,M>0$, $\xi\in[0,1]$, and $\dot{S}=\alpha_O O-\alpha_Y Y(\cdot;\theta)$, with $S(0,\theta)=S_0$

where the Lagrange multipliers μ_0 and μ_1 are associated with the lower and upper limit of the decision variable ξ and α_O, α_Y are as defined earlier. To simplify notation, we suppress the argument t of the variables O, M, S, unless necessary for an unambiguous notation. Equation (2.3) indicates that households maximize the discounted farm net returns over the planning horizon.

The definition of the current value Hamiltonian of the farmer's decision problem yields:

$$\begin{aligned}H&=P^H Y(O,M,S;\theta)-\xi CO^H(O,M;\theta)-(1-\xi)C^H(O,M;\theta)+\xi\mu_0-\xi\mu_1\\&+\lambda\left(\alpha_O O-\alpha_Y Y(O,M,S;\theta)\right)\end{aligned} \tag{2.4}$$

The first-order conditions for an interior solution with respect to O,M are given by:

$$H_O=P^H Y_O-\xi CO_O^H-(1-\xi)C_O^H+\lambda\left(\alpha_O-\alpha_Y Y_O\right)=0 \tag{2.5}$$

$$H_M=P^H Y_M-\xi CO_M^H-(1-\xi)C_M^H-\lambda\alpha_Y Y_M=0 \tag{2.6}$$

$$H_{\xi} = -CO^{H} + C^{H} + \mu_0 - \mu_1 = 0 \tag{2.7}$$

$$\dot{\lambda} = \delta\lambda - H_S = \left(\delta + \alpha_Y Y_S\right)\lambda - P^H Y_S \tag{2.8}$$

$$\dot{S} = \alpha_O O - \alpha_Y Y, \ \ S\left(0\right) = S_0 \tag{2.9}$$

The variable ξ is defined as a continuous variable in the interval $\left[0,1\right]$, but since the Hamiltonian (H) is linear in ξ, the optimal value is given at the boundary of the domain of ξ. If the net returns are strictly positive, the maximization of H requires choosing $\xi = 1$, and if not, it is optimal to choose $\xi = 0$. Hence, the possible solution is either to join, or not to join a cooperative. Finally, the transversality condition requires that $\lambda\left(T\right) = dS\left(T\right)e^{-\delta T} / dS$. The solution to equation (2.8), $\lambda(t)$ which determines the shadow value of the soil quality at time t, is given as:

$$\lambda\left(t\right) = \int_t^T e^{-\int_t^u \delta + \alpha_y Y_S(\vartheta) d\vartheta} P^H Y_S\left(u\right) du + \lambda\left(T\right) > 0 \tag{2.10}$$

Equation (2.9) indicates that the reduction in soil quality resulting from agricultural production can only be compensated by applying soil-improving measures such as organic inputs. The solution to equation (2.9) is given by:

$$S\left(t\right) = S_0 + \int_0^t \left(\alpha_O O\left(\vartheta\right) - \alpha_Y Y\left(O\left(\vartheta\right), M\left(\vartheta\right)\right)\right) d\vartheta \tag{2.11}$$

As mentioned above the initial soil quality $S\left(0\right) = S_0$ is identical for all farmers, i.e., it is identical for both cooperative members and nonmembers. Let the steady state value of the soil quality be denoted by S^{∞}. Given that soil quality is likely to evolve over time, we further assume that the soil quality S(t) at a specific time t is not identical for the two groups of farmers, due to different optimal investment behaviors in the long-run. Note that when the soil quality is above a threshold denoted by S_C, the soil-improving measure O and yield-enhancing measure M are substitutes with respect to S. We consider that economically viable agricultural production requires that $S > S_C$, and therefore we assume that the variables O and

M are substitutes, i.e., $Y_{MS} < 0$, $Y_{OS} < 0$, for $S > S_C$. In this case, an increase in S decreases the marginal productivity of O and M. Given these assumptions, we now show graphically in Figures 2.2 and 2.3 farmers' short-run and long-run investment behavior determined by the first-order conditions in equations (2.5) and (2.6).

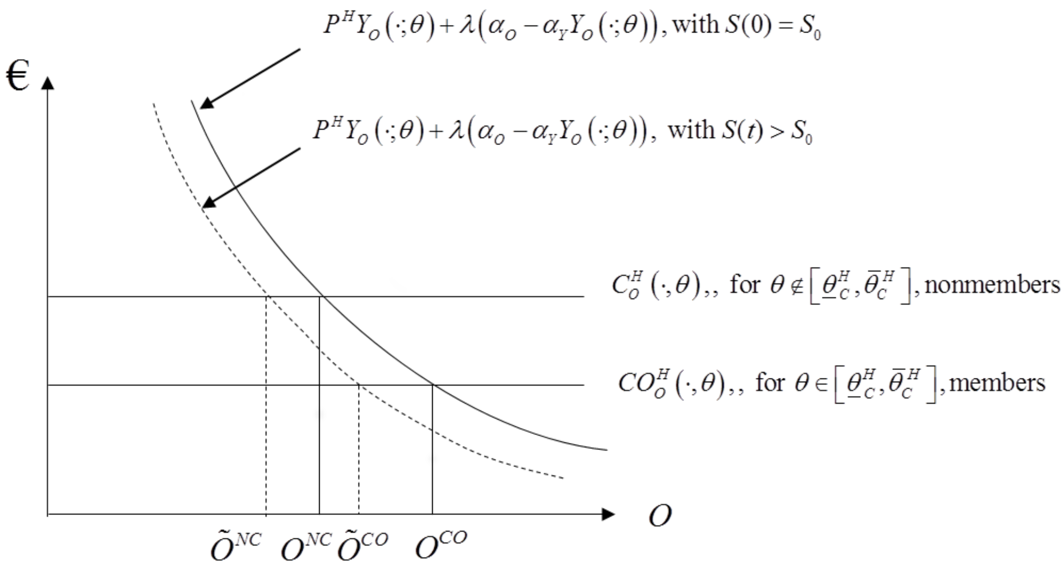

Figure 2.2 The optimal level of organic fertilizer applied by farmers with and without cooperative membership given the farm characteristics θ and different level of soil quality

As shown in Figure 2.2 (continuous lines), the solution to equation (2.5) demonstrates that the efficient level of organic inputs O^{CO} applied by cooperative members will be higher than the efficient level by nonmembers, O^{NC}. With respect to the optimal investment behavior of farmers in the long-run, we analyze it for the cases where $S_0 < S^\infty$ and $S_0 > S^\infty$, where S^∞ denotes the value of the steady state equilibrium of soil quality. For the case of $S_0 < S^\infty$, it is optimal for farmers to build up soil quality over time so that $S(t) > S_0$. However, for, $S_0 > S^\infty$ it is optimal to reduce soil quality so that $S(t) < S_0$ holds. Given the situation that farmers build up soil quality $S(\mathrm{t}) > \mathrm{S}_0$, an increase in $S(\mathrm{t})$ decreases the marginal productivity $Y_O(t)$. Thus, the curve $P^H Y_O + \lambda(\alpha_O - \alpha_Y Y_O)$ shifts to the left as indicated by the discontinuous line in Figure 2.2. Therefore, it is optimal for farmers to reduce the level of organic inputs over time so that $O^{CO} \to \tilde{O}^{CO}$ and $O^{NC} \to \tilde{O}^{NC}$. For the case where it is optimal to reduce $S(t)$, i.e.,

$S(t) < S_0$, a decrease in $S(t)$ will decrease the marginal productivity $Y_O(t)$. Thus, it is optimal for both cooperative members and nonmembers to increase the level of organic inputs. This case is not shown in Figure 2.2 in order to make the Figure more tractable.

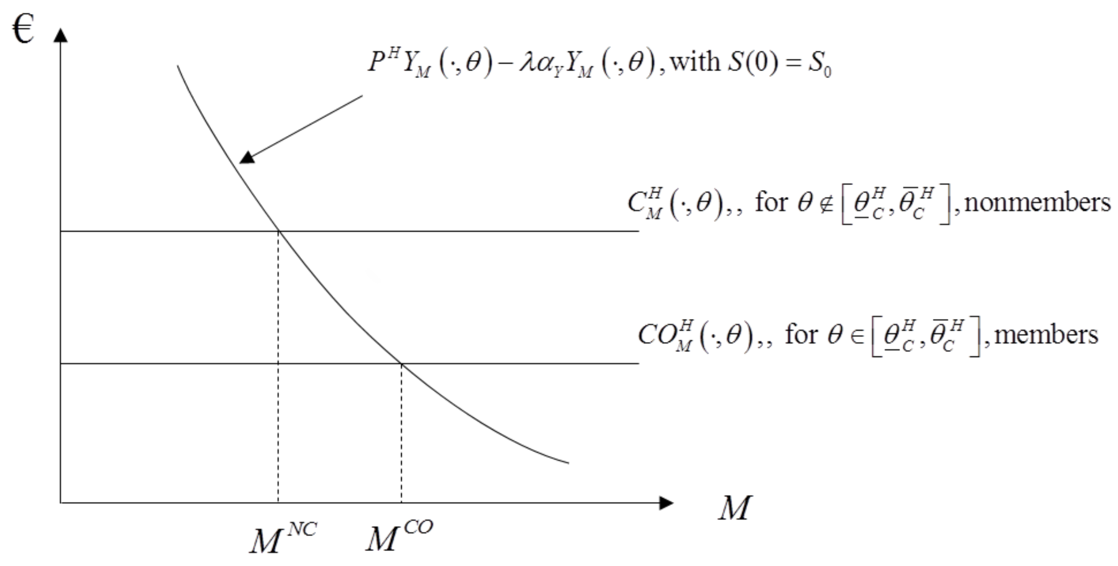

Figure 2.3 The optimal level of mineral fertilizer applied by farmers with and without cooperative membership given the farm and household characteristics θ and the same level of soil quality

By solving equation (2.6), Figure 2.3 shows that it is more efficient for cooperative members and farmers with characteristics $\theta \in [\underline{\theta}_C^H, \overline{\theta}_C^H]$ to apply more chemical fertilizer, M^{CO}, than nonmembers, M^{NC}. On the other hand, if the characteristics of nonmembers are fulfilled, i.e., $\theta \notin [\underline{\theta}_C^H, \overline{\theta}_C^H]$, it would be beneficial for farmers not to join cooperatives, and the applied amount of chemical fertilizer M^{NC} is below the amount of fertilizer applied by members. The qualitative attributes of the transitory behavior for the optimal level of chemical fertilizer are identical to the ones of organic inputs and can be obtained by the same arguments for an increase or decrease in $S(\mathrm{t})$. However, for the same reason as in Figure 2.2, these cases are not shown in Figure 2.3.

The theoretical analysis generally reveals that farmers whose household and farm-level characteristics fall within the range of $[\underline{\theta}_C^H, \overline{\theta}_C^H]$ are better off joining the cooperative and investing in soil-improving measures than those whose characteristics do not fall within this specified range. Thus, farmers may self-select into cooperatives depending on their characteristics.

Our analytical results are consistent with the empirical results reported by Verhofstadt and Maertens (2014) who found a positive and significant impact of cooperative membership on the use of chemical fertilizer. However, to what extent this positive impact is due to changes in the household and farm-level characteristics θ, and to what extent it is due to the cooperative membership, has received little attention in the previous literature. A change in the household and farm-level characteristics can be interpreted in different ways. One way would be to interpret them as completely immovable, so that an analysis of a change in θ explains behavioral changes between farmers with different θ. However, we do not follow this line of argument and consider the household and farm-level characteristics to a certain degree variable and interdependent. Obviously, some characteristics like education or the size of the farm will not vary with the outcome of the farmer's decision to join or not to join a cooperative. However, other characteristics like access to credit, access to expertise or networking capabilities are likely to increase with a change in the characteristic of being a member of a cooperative. Thus, it is possible to interpret changes in the farmer's characteristics with changes in the farmer's input and investment decisions.

Figures 2.2 and 2.3 have shown that the impact of the cooperative membership on the production intensity. We now show the impact of changes in the household and farm-level characteristics and its interaction with the cooperative membership. In order to disentangle the effects of the two underlying forces on the farmer's investment behavior, we conduct a comparative static analysis. For this purpose, we consider the soil quality as given, in order to concentrate on the effect of an increase in θ on the optimal amount of chemical fertilizer $M^*(\theta)$ and organic inputs $O^*(\theta)$ of the members of a cooperative. As detailed in the Appendix 1, the calculations show that an increase in the household and farm-level characteristics may magnify, moderate or even reverse the intensification of the production intensity resulting from joining the cooperative. The precise results depend on the signs and magnitude of the changes in marginal productivity and in the marginal costs in relation to the cooperative benefits. The signs of $Y_{M\theta}$ and $Y_{O\theta}$ and their magnitude cannot be determined on theoretical grounds. The index θ encompasses a wide range of factors and depending on the particular situation of each farmer, different factors may be most influential for the determination of the value of θ. Thus, if for some farmers, education or the size of the farm is most influential for the determination of θ, one can imagine that $Y_{I\theta}, I = M, O$ is strictly positive, i.e. M and O are complements with respect to θ. On the other hand, if the soil quality is the most important factor for the calculation of the index, it seems reasonable to assume that M and O are substitutes with respect to θ, i.e., $Y_{I\theta} < 0, I = M, O$.

Despite the indeterminacy with respect to the magnitude of $Y_{I\theta}$ and $C_{I\theta}$ and the sign of $Y_{I\theta}$, the analysis in the Appendix 1 allows the identification of three situations that govern the farmers' behavior with respect to production intensity and relate them with the cooperative membership effect. Yet, the relative importance of each of these three situations is important for policy analysis and can only be evaluated empirically, given a specific population of farmers located at a concrete region. The empirical part of the study addresses this issue.

2.3 Empirical Specification

As indicated in the theoretical model, the soil investment decision of the farmer is determined by the expected farm net returns. However, the expected farm net return is unobservable, since it is subjective. What is observed in the data is the farmer's decision to invest or not to invest. Let R_{ik}^{*} represent the unobserved or latent variable, the observed variable R_{ik} can be used to represent a household's decision to invest in soil-improving measures $(\mathrm{R}_{ik} = 1)$, or not to invest $(\mathrm{R}_{ik} = 0)$. Following the maximization problem outlined in equation (2.3), the unobserved variable would be positive, if the conditions $\partial J^{*}/\partial O$ and $\partial J^{*}/\partial M$ are all positive. Moreover, equations (2.5) and (2.6) imply that the farmer's decision to invest in organic inputs and chemical fertilizer is influenced by the choice of cooperative membership, as well as household and farm-level characteristics.

It is worth mentioning here that the application of farmyard manure is not sufficient to maintain soil quality due to missing markets in most locations. Hence, farmers normally depend on investment in organic fertilizer, or combine farmyard manure with organic fertilizer to improve the soil quality. Although organic fertilizer and farmyard manure are considered together and denoted as $O(\mathrm{t})$ in the theoretical framework, the two inputs will be analyzed separately in the empirical analysis. Given that the main goal of the empirical analysis is to examine how cooperative membership ξ_i and the household and farm-level characteristics θ_i influence the investment decisions of farmers, we express farmers' investment decisions as a latent variable function[6]:

$$R_{ik}^{*} = \omega\xi_i + \gamma\theta_i + \mu_{ik}\ , \quad R_{ik} = 1 \text{ if } R_{ik}^{*} > 0 \tag{2.12}$$

where R_{ik} is a binary indicator variable which equals 1 if the household i chooses to invest in a particular type of soil-improving and yield-enhancing measure (i.e. organic fertilizer $(\mathrm{k}=1)$, farmyard manure $(\mathrm{k}=2)$, and chemical fertilizer $(\mathrm{k}=3)$), if the expected farm net returns (R_{ik}^{*}) to investment is positive, and 0 otherwise; ξ_i is a dummy variable for the choice of cooperative membership; ω and γ are parameters to be estimated; and μ_{ik} is an error term assumed to be normally distributed.

In line with our theoretical model, a household chooses to belong to a cooperative, if the expected farm net returns derived from cooperative membership (ξ_{i1}^{*}) are greater than that derived from non-membership (ξ_{i0}^{*}). Households are then assumed to choose to join cooperatives if the difference in farm net return is positive, i.e. $\xi_i^{*} = \xi_{i1}^{*} - \xi_{i0}^{*} > 0$.[7] However, ξ_i^{*} cannot be directly observed, but can be expressed as a function of observed elements in the following latent variable function:

$$\xi_i^{*} = \beta Z_i + \varepsilon_i\ , \ \xi_i = 1 \text{ if } \xi_i^{*} > 0 \tag{2.13}$$

where ξ_i equals 1 if a household is a member of a cooperative, and 0 otherwise; Z_i represents a vector of factors that influence farmers' decisions to choose to belong to a cooperative; β is the parameters to be estimated and ε_i is the error term assumed to be normally distributed and zero mean.

If the same unobservable factors (e.g., farmers' innate ability and motivation to improve soil quality by virtue of cooperative organization) influence both the error term (ε_i) in the

[6] It is significant to note that θ_i, which is used to denote household and farm-level characteristics, is an index in the theoretical section, but a vector in the empirical specification.

[7] This is in line the with previous studies that have assumed that the farmer's decision to choose to belong to a cooperative is based on a comparison between the utility derived from choosing cooperative membership and the utility derived from not choosing the membership (Abebaw and Haile 2013; Ito et al. 2012).

cooperative membership choice equation and the one (μ_{ik}) in the investment equation, selection bias occurs, resulting in a correlation of the two error terms in the two specifications, such that $corr(\varepsilon_i, \mu_i) = \rho_{\varepsilon\mu}$. In this case, any standard regression technique such as probit or logit model applied to estimate equation (2.12) produces biased results when $\rho_{\varepsilon\mu} \neq 0$. Thus, rigorous assessment of the effect of cooperative membership on investment decisions of farmers should take into account the endogeneity of the cooperative membership variable.

Although endogenous switching probit (ESP) model suggested by Lokshin and Sajaia (2011) is an option to estimate the average treatment effects of cooperative membership on the probabilities of investing in soil investment measures to control for both observable and unobservable heterogeneities, it fails to estimate the marginal effects of cooperative membership and other controlling variables on investment measures. Given our interest in estimating both the marginal effects and average treatment effects of cooperative membership on investment in soil-improving and productivity-enhancing measures, this study employs a recursive bivariate probit (RBP) model as an empirical strategy (Vall Castello 2012; Lanfranchi and Pekovic 2014). The RBP model estimates the cooperative membership choice equation and the investment equation simultaneously, using full information maximum likelihood (FIML) approach.

In estimating the RBP model, the variables in the vector θ_i in equation (2.12) and Z_i in equation (2.13) are allowed to overlap. However, to identify the bivariate probit, we need at least one exclusion restriction, i.e., an additional instrumental variable, that explains the probability of choosing to belong to a cooperative but that is not correlated with the outcome variabls. In this study, the presence of a cooperative in a farmer's village of residence is used as an identifying instrument.[8] As noted by Deng et al. (2010), one of the primary reasons for low cooperative membership rate in China is due to the absence of agricultural cooperatives in many villages. Thus, the presence of a cooperative in a village is justifiably related to the choice of cooperative membership, but should not influence the investment decisions of farmers.

[8] In China, a farmer can choose to either join a cooperative in the village of residence, or join a cooperative in a different village, town or county. In this study, the randomly selected members either have the membership in village cooperatives or cooperatives in towns or counties. We expect that farmers are more likely to join a cooperative if a cooperative is present in the village of residence.

We also estimate the average treatment effects on the treated (ATT), using the method proposed by Chiburis et al. (2011) to provide a better understanding of the causal effects of cooperative membership on the likelihood of investing in soil quality and yield-enhancing measures. The ATT is calculated using the following expression:

$$ATT = \frac{1}{N_{\xi}} \sum_{i=1}^{N_{\theta}} \left\{ \Pr(\mathrm{Y}_{ik} = 1) \middle| \xi_i = 1) - \Pr(\mathrm{Y}_{ik} = 0 \middle| \xi_i = 1) \right\} \tag{2.14}$$

where N_{ξ} denotes the total sample for the treated; $\Pr(\mathrm{Y}_{ik} = 1) | \xi_i = 1)$ represents the predicted investment probability for cooperative members in an observed context, while $\Pr(\mathrm{Y}_{ik} = 0) | \xi_i = 1)$ represents the predicted probability that a farmer belonging to a cooperative (in a counterfactual context) will not invest.

2.4 Data and Descriptive Statistics

The data used in the analysis are from a household survey of apple farmers conducted in Gansu, Shaanxi and Shandong provinces in China between September and December 2013. We selected apple farmers in those provinces as the focus of our analysis for a number of reasons. First, although China produces around half of the world's total apple output (FAOSTAT), the majority of apple orchards are primarily in the Bohai Gulf region (Shandong, Liaoning and Hubei provinces) and Northwest Loess Plateau region (Shaanxi, Shanxi, Henan and Gansu provinces). In particular, more than half of the country's apple orchards are located in Gansu (12.72%), Shaanxi (28.92%) and Shandong (12.53%) (CRSY 2013). Apple production plays an important role in determining smallholder farmers' livelihood in the surveyed regions. Second, soil erosion and desertification are considered two of the most serious environmental degradation problems in China, which impact adversely on environmental sustainability and productivity of apple production. Soil erosion in China's Loess Plateau region, including Gansu and Shaanxi, is cited as one of the most severely degraded areas in the world, with over 60% of its land subjected to soil degradation (Hou et al. 2014; Rozelle et al. 1997). Hence, facilitating investment in soil quality measures among smallholder apple farmers can help enhance apple productivity and promote rural economic growth in the long-run.

Considering our interests in analyzing the impact of cooperative membership on apple farmers' soil-improving and yield-enhancing investment decisions, we focus on cooperatives specialized in apple production and marketing in this study. These cooperatives are located either in farmers' village of residence or in other places (towns or counties), but they share similar attributes in helping members across different provinces. The cooperatives' behaviors are regulated by the national law on Farmers' Professional Cooperatives. In the surveyed regions, farmers are intensively producing apples on their cultivated land. Among other things, the cooperatives assist members in orchard management approaches (e.g., pruning, branch drawing), efficient use of both organic and chemical fertilizers for sustainable soil management, efficient use of pesticides for pest management and apple quality control, and collectively purchasing inputs at reasonable prices. They also provide members with marketing information (e.g., prices, channels) with the aim of enhancing members' participation in output markets.[9]

A multistage sampling procedure was used to select 208 cooperative members and 273 nonmembers. First, Gansu, Shaanxi and Shandong provinces were purposively selected due to the intensive apple production in these provinces. Second, we selected representative districts with significant apple output in each province. In particular, Jingning county in Gansu, Luochuan county in Shaanxi, and Qixia and Laiyang cities in Shandong were selected. Third, six agricultural cooperatives were randomly selected from these districts. Fourth, three villages affiliated to each cooperative in the selected district were randomly selected. Finally, around 25-30 households including both cooperative members and nonmembers in each village were randomly selected. A structured questionnaire was used to collect information from households with and without cooperative membership, with specific purpose of interviewing household heads. The questionnaire covered a range of topics including socioeconomic and farm-level factors (e.g., age, education, household size and farm size), soil characteristics, financial situation (e.g., access to credit), as well as asset ownership (e.g., rotary cultivator and livestock).

The dependent variable used in the analysis refers to the farmer's choice of cooperative

[9] Agricultural cooperatives in China usually provide members with both production and marketing services, although they do not fully supply inputs to members, or purchase members' farm produce due to loose management structures. Moreover, they provide very little help with respect to credit facilities to its members (Deng et al. 2010). In comparison, cooperatives in the United States are classified by responsibility and function (marketing, supply, processing, bargaining and service) (Gijselincks et al., 2014). For instance, U.S. agricultural service cooperatives provide farmers with a wide variety of services including credit, utilities, insurance, irrigation and others, while agricultural marketing cooperatives emphasize the marketing of farm products supplied by their members. With respect to food production and marketing, members in the U.S. transact with a cooperative by buying materials and inputs or selling raw materials (Gijselincks et al. 2014).

membership, which takes the value of one, if a farmer had cooperative membership, and zero otherwise. The questionnaire also includes dichotomous dummy variables that indicate whether farmers apply any of the soil-improving and yield-enhancing measures such as organic fertilizer, farmyard manure and chemical fertilizer. Given that the focus of this study is to examine how cooperative membership influences farmers' decisions to invest in cultivated land while controlling for other exogenous variables, we draw on the existing literature on cooperative membership to identify explanatory variables (Ito et al. 2012; Abebaw and Haile 2013; Bernard and Spielman 2009; Marenya and Barrett 2009; Chagwiza et al. 2016). Table 2.1 presents descriptive statistics for the selected variables.

Table 2.1 Definition of variables and descriptive statistics

Variable	Definition	Mean (S.D.)
Dependent variables		
Membership	1 if farmer is a cooperative member, 0 otherwise	0.43 (0.50)
Organic fertilizer	1 if farmer applies organic fertilizer, 0 otherwise	0.84 (0.37)
Farmyard manure	1 if farmer applies farmyard manure, 0 otherwise	0.28 (0.45)
Chemical fertilizer	1 if farmer applies chemical fertilizer, 0 otherwise	0.93 (0.26)
Organic material	1 if farmer applies organic fertilizer and/or farmyard manure, 0 otherwise	0.87 (0.34)
Organic fertilizer expenditure	Expenditure on organic fertilizer (yuan/100/mu)[a]	5.53 (4.75)
Chemical fertilizer expenditure	Expenditure on chemical fertilizer (yuan/100/mu)	9.36 (5.81)
Net returns	Apple gross revenue minus variable costs (yuan/1,000/mu)	7.54 (3.91)
Independent variables		
Age	Age of farmer (years)	48.63 (10.25)
Education	Years of formal education of farmer	7.60 (2.87)
Household size	Total number of household members	4.33 (1.44)
Farm size	Total farm size of apple orchard (mu)	5.07 (3.24)
Farming vehicle	1 if farmer owns farming vehicle, 0 otherwise	0.92 (0.28)
Rotary cultivator	1 if farmer owns rotary cultivator, 0 otherwise	0.53 (0.50)
Access to credit	1 If farmer is not liquidity constrained, 0 otherwise	0.53 (0.50)

Sandy soil	1 if land has sandy soil, 0 otherwise	0.38 (0.49)
Clay soil	1 if land has clay soil, 0 otherwise	0.45 (0.50)
Loam soil	1 if land has loam soil, 0 otherwise	0.17 (0.37)
Livestock	1 if farmer raises livestock, 0 otherwise	0.23 (0.42)
Irrigation	1 if farmer has access to irrigation facilities, 0 otherwise	0.61 (0.49)
Road condition	1 if farmer reports that road condition from orchards to village/market is good, 0 otherwise	0.60 (0.49)
Tree age	Age of fruiting apple trees (years)	15.45 (6.56)
Tenure security	1 if farmer perceives that land will be readjusted within five years, 0 otherwise	0.48 (0.50)
Shandong	1 if farmer resides in Shandong province, 0 otherwise	0.43 (0.50)
Gansu	1 if farmer resides in Gansu province, 0 otherwise	0.17 (0.37)
Shaanxi	1 if farmer resides in Shaanxi province, 0 otherwise	0.40 (0.49)
Village cooperative	1 if there is a cooperative in farmer's residing village, 0 otherwise	0.09 (0.28)

Note: [a] 1 mu=1/15 hectare; 1$=6.14 yuan.

Age and education are two important proxies for human capital. As noted by Schultz (1982), human capital increases people's abilities to perceive, interpret and respond to new events. Previous studies have found that both age and education have positive impacts on farmers' decisions to choose cooperative membership (Bernard and Spielman 2009; Chagwiza et al. 2016). We expect similar influences of these variables on the likelihood of cooperative membership. Sufficient labor availability is required for participating in direct cooperative activities (Abebaw and Haile 2013), so we expect a positive link between household size and cooperative membership choice. Larger farm size contributes to lower average fixed costs of cooperative membership. Consistent with previous studies (Ito et al. 2012), farm size is expected to have a positive impact on cooperative membership.

With regards to physical assets, transportation costs and household wealth, previous studies have shown that ownership of radio, ox, cattle, and farm equipment exerts positive impacts on the probability of cooperative membership (Bernard et al., 2008; Abebaw and Haile 2013). In this study, we use ownership of farming vehicle, rotary cultivator and livestock, and access to convenient road as proxy variables for ownership of physical assets, transportation costs and household wealth, and expect similar positive impacts on cooperative membership choice. Although agricultural cooperatives can distribute technologies to farmers, the efficiency of technology use (e.g., absorption rate of fertilizer) depends on irrigation conditions. Thus, access to irrigation is expected to increase the probability of cooperative membership.

With technical assistance of cooperatives for sustainable soil management, farmers may maintain or enhance crop productivity. Thus, cooperative membership may be correlated with soil quality of cultivated land. We include soil quality dummies in the analysis to account for soil conditions. In different plantation periods of apple trees, the requirements of orchard management technology may differ. Nevertheless, we expect that farmers cultivating fruiting young trees will be more likely to choose cooperative membership for the purpose of obtaining yield-enhancing technology. A number of studies have shown that land tenure security influences farmers' decisions to invest in soil-improving measures (Gao et al, 2012; Rao et al. 2016; Ma et al. 2013; Abdulai and Goetz 2014). We therefore expect a positive relationship between tenure security and investment in soil-improving measures. Finally, a set of location dummies are included to account for unobserved agro-climate and socioeconomic heterogeneities among the sample districts.

It can be observed from the Table 2.1 that 43% of farmers had cooperative membership. Mean use rates for the soil-improving measure outcome variables range from 28% for farmyard manure to 84% for organic fertilizer, while the mean use rate for chemical fertilizer variable is 93%. The average age of household head was almost 48.63 years, whereas the mean number of years of schooling was about 7.6 years. Farmers in the sample are smallholders with an average farm size of 5.07 mu. We also present in Table 2.4.A1 in Appendix 2 a comparison of the mean characteristics between cooperative members and nonmembers. The figures show that cooperative members tend to be more likely to invest in organic fertilizer and farmyard manure, and also obtained higher farm net returns than nonmembers. However, since cooperative membership was not randomly assigned to farmers, a rigorous assessment of the impact of cooperative membership on investment in soil-improving and yield-enhancing measures needs to account for possible selection bias that may arise from unobserved factors (e.g., Thuo et al. 2014; Vall Castello 2012).

2.5 Results and Discussion

The primary interest of this study is to investigate how cooperative membership and other household and farm level characteristics affect farmers' decisions to invest in soil-improving and yield-enhancing measures. Before presenting the results for the Recursive Bivariate Probit (RBP) model, we will first present the estimates from a seemingly unrelated bivariate probit (SUBP) model and the goodness-of-fit test for the justification of the RBP model.

2.5.1 Results for SUBP Estimates and Goodness-of-fit Test

The main reason for estimating the SUBP model is to ascertain whether the decision to choose cooperative membership is correlated with the outcome variables through unobserved heterogeneities, and whether these two decisions are substitutes or complements (Thuo et al. 2014; Amare et al. 2012). The SUBP model estimation requires that cooperative membership variable is left out in the investment equation. Results for three groups of model specifications are reported in Table 2.5.A2 in Appendix 2. The *P*-values for the null hypothesis that $\rho'_{\varepsilon\mu}$ in models 1-3 (three outcome variables) are all significantly different from zero, indicating that the unobserved heterogeneities of both decisions are correlated. These findings suggest that the probability that a farmer chooses to belong to a cooperative is related to the probability of investing in soil-improving and yield-enhancing measures through unobserved effects captured in the model's error terms. That is, unobserved effects such as farmers' innate abilities and motivations to improve soil quality are not captured by the data, but may have an indirect influence on farmers' decisions to join a cooperative and invest in soil-improving and yield-enhancing measures. Moreover, the sign for $\rho'_{\varepsilon\mu}$ is positive in Models 1 and 2, suggesting that cooperative membership and investment in organic fertilizer and farmyard manure are complementary decisions (Huth and Allee 2002; Thuo et al. 2014). By contrast, as pointed out by Thuo et al. (2014), the negative sign for $\rho'_{\varepsilon\mu}$ in Model 3 indicates that cooperative membership and investment in chemical fertilizer are substitutes in terms of decisions.

Note that maximizing the joint density of the observed dependent variables in RBP model does not guarantee a good fit (Chiburis et al. 2012). We therefore run both Murphy's (2007) score test and Hosmer-Lemeshow's (1980) test, using the methods proposed by Chiburis et al. (2011) to check misspecification of the RBP model. In particular, the null hypothesis of the Murphy's score test is that the error terms in equations (2.12) and (2.13) are bivariate standard joint normal, and the null hypothesis of the Hosmer-Lemeshow test is that the sample frequency of the dependent variables is the same as the sample frequency of the fitted probabilities of observation subgroup. The results are presented in Table 2.6.A3 in the Appendix 2. The *P*-values are all not significant at the 10% level in the three groups of model specifications, indicating that the null hypothesis of normality is not rejected, confirming the validity of the RBP model.

2.5.2 Results for RBP Estimates

The estimates of the determinants of cooperative membership and its impacts on soil-improving and yield-enhancing measures using RBP model are presented in Table 2.2.[10] As indicated previously, the FIML approach jointly estimates the cooperative membership choice equation and three soil investment equations, respectively. The results for the three model specifications are presented in Table 2.2. The lower parts of Table 2.2 show that all estimated correlation coefficients $\rho_{\varepsilon\mu}$ in Models 1-3 are significantly different from zero, indicating the presence of selection bias arising from unobserved factors. In particular, the negative correlation coefficients $\rho_{\varepsilon\mu}$ indicate negative selection bias, suggesting that farmers having lower probabilities of investing in organic fertilizer, farmyard manure and chemical fertilizer are more likely to choose to belong to cooperatives. Moreover, the results of the Wald tests for $\rho_{\varepsilon\mu} = 0$ in Models 1-3 are significantly different from zero, indicating that the null hypothesis that the cooperative membership variable is exogenous can be rejected. That is, farmers are jointly making decisions to choose to belong to a cooperative and investing in soil quality and yield-enhancing measures.

In the sections below, we first discuss the determinants of cooperative membership based on the first-stage estimates of the RBP model. The second-stage estimates of the RBP model that examine the impact of cooperative membership on farmers' decisions to invest in organic fertilizer, farmyard manure and chemical fertilizer are then discussed. Finally, the estimates for the marginal effects and average treatment effects on the treated of cooperative membership are presented.

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[10] The estimates of multivariate probit model also show that the likelihood ratio test of the join significance of the correlation coefficients of error terms accept the null hypothesis that there is no correlation between the three investment specifications, suggesting it is more efficient to estimate the impact of cooperative membership on investment in organic fertilizer, farmyard manure and chemical fertilizer separately using RBP model. The results are presented in Table 2.7.A4 in Appendix 2.

Determinants of Cooperative Membership and Investment Decisions

The results from the first-stage estimates of the RBP model, which show the determinants of farmers' decisions to choose cooperative membership, are presented in the second, fourth and sixth columns in Table 2.2. Given that the variables having the same name show similar signs and significance levels in the three model specifications, we have chosen to discuss the results from the cooperative membership choice equations in Models 1-3 together. In the three specifications, the coefficients of the education variable are positive and significantly different from zero, suggesting that well-educated farmers are more likely to join cooperatives, a finding that is in line with the results reported by Bernard and Spielman (2009), who found that the probability of choosing cooperative membership is increased by 8% if the household head is literate. The household size variable is also positively and significantly associated with the choice of cooperative membership in all three models, indicating that larger households with more labor endowments are more likely to choose to belong to a cooperative.

Consistent with the finding from Ito et al. (2012), farm size tends to increase the probability of being a cooperative member. Asset ownership such as having farming vehicle and rotary cultivator appears to increase the probability of joining cooperatives. The results in Table 2.2 show that farmers' decisions to choose cooperative membership are also related to soil quality. Specifically, farmers cultivating land on sandy soil and loam soil are more likely to be cooperative members. Road condition also appears to be an important determinant of cooperative membership choice. Tenure security appears to be an important determinant of cooperative membership. In particular, farmers who perceive that land will be adjusted within five years are less likely to choose cooperative membership. Relative to the reference province (Shaanxi), farmers living in Gansu are more likely to join cooperatives.

Table 2.2 The RBP model estimates for the impact of cooperative membership on investment in organic fertilizer, farmyard manure and chemical fertilizer

	Model 1		Model 2		Model 3	
	Membership	Organic fertilizer	Membership	Farmyard manure	Membership	Chemical fertilizer
Membership		1.550 (0.272)***		1.313 (0.398)***		0.378 (0.428)
Age	0.08 (0.007)	-0.002 (0.009)	0.011 (0.008)	0.002 (0.010)	0.010 (0.008)	-0.027 (0.011)**
Education	0.047 (0.026)*	0.002 (0.027)	0.051 (0.027)*	0.014 (0.032)	0.056 (0.028)**	-0.056 (0.030)*
Household size	0.105 (0.050)**	-0.163 (0.059)***	0.115 (0.052)**	-0.119 (0.068)*	0.114 (0.053)**	0.023 (0.077)
Farm size	0.099 (0.027)***	-0.057 (0.028)**	0.095 (0.026)***	0.011 (0.033)	0.100 (0.026)***	0.094 (0.045)**
Farming vehicle	0.749 (0.263)***	0.564 (0.295)*	0.755 (0.258)***	0.596 (0.309)*	0.765 (0.269)***	0.244 (0.373)
Rotary cultivator	0.293 (0.130)**	0.467 (0.182)**	0.320 (0.131)**	0.522 (0.183)***	0.307 (0.130)**	0.174 (0.209)
Access to credit	0.169 (0.130)	0.380 (0.156)**	0.209 (0.129)	0.381 (0.175)**	0.221 (0.130)*	0.155 (0.177)
Sandy soil	1.382 (0.373)***	0.059 (0.390)	1.309 (0.362)***	-2.466 (0.457)***	1.583 (0.420)***	0.240 (0.428)
Loam soil	0.374 (0.192)*	0.757 (0.299)**	0.387 (0.195)**	0.518 (0.221)**	0.437 (0.200)**	0.423 (0.313)
Livestock	0.062 (0.191)	0.001 (0.226)	0.092 (0.193)	0.444 (0.224)**	0.124 (0.192)	-0.371 (0.212)*
Irrigation	0.192 (0.145)	0.378 (0.189)**	0.150 (0.146)	0.559 (0.225)**	0.164 (0.143)	0.317 (0.184)*
Road condition	0.416 (0.154)***	0.037 (0.174)	0.399 (0.159)**	0.192 (0.219)	0.417 (0.158)***	0.227 (0.250)
Tree age	-0.017 (0.012)	0.017 (0.014)	-0.016 (0.012)	0.025 (0.016)	-0.015 (0.012)	-0.001 (0.018)
Tenure security	-0.445 (0.143)***	0.229 (0.161)	-0.448 (0.146)***	0.078 (0.187)	-0.437 (0.145)***	0.352 (0.218)
Shandong	-0.019 (0.406)	-0.050 (0.397)	0.014 (0.408)	0.010 (0.395)	-0.227 (0.443)	-0.279 (0.484)
Gansu	0.488 (0.268)*	0.087 (0.295)	0.501 (0.279)*	0.732 (0.335)**	0.466 (0.269)*	-0.453 (0.339)
Village cooperative	0.956 (0.237)***		0.974 (0.244)***		1.006 (0.241)***	
Constant	-3.509 (0.565)***	-0.255 (0.731)	-3.729 ***	-2.751 (0.826)***	-3.822 (0.594)***	1.835 (0.801)**
$\rho_{\varepsilon\mu}$	-0.763 (0.141)***		-0.530 (0.255)**		-0.734 (0.155)***	
Log-likelihood	-424.197		-412.288		-360.022	
Wald test of $\rho_{\varepsilon\mu}$=0	8.886***, with Prob= 0.003		2.775*, with Prob=0.096		7.731***, Prob = 0.005	
ATT	0.459 (0.187)**		0.225 (0.091)**		0.080 (0.116)	
Sample size	481		481		481	

Note: Asterisk *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. Robust standard errors are in parentheses. The reference region is Shaanxi and the reference soil type is clay soil. ATT refers to average treatment effects on the treated, which is estimated by equation (2.14).

The results regarding the impacts of cooperative membership on investment in soil-improving measures are presented in the third and fifth columns in Table 2.2. The estimates show that cooperative membership has a positive and statistically significant impact on the probabilities of investing in organic fertilizer and farmyard manure.[11] The other coefficient estimates in the third and fifth columns in Table 2.2 show that investments in organic fertilizer and farmyard manure are also affected by several other factors. The coefficients of the household size variable are negative and significantly different from zero in the organic fertilizer and farmyard manure specifications, suggesting that larger households are less likely to invest in soil quality measures. Although larger household size normally results in increased labor endowments, it could also result in reduced financial resources to purchase organic fertilizer and farmyard manure for soil improvement. Farmers cultivating larger farms appear to be less likely to invest in organic fertilizer. This is possible, because as farm size increases, it becomes less feasible for farmers to meet the organic fertilizer requirement of the land (Abdulai et al., 2011). The asset ownership such as farming vehicle and rotary cultivator tends to increase the probabilities of investing in soil-improving measures. The variable for access to credit is positive and significantly different from zero in the soil quality outcome equations, suggesting that farmers who are not liquidity constrained are more likely to invest in organic fertilizer and farmyard manure. Sufficient credit enables farmers to purchase organic fertilizer from the markets and farmyard manure from livestock farms.

The soil variables appear to have differential impacts on the probabilities of investing in soil-improving measures. In particular, the variable for sandy soil has a negative and significant impact on the probability of investing in farmyard manure, while the variable for loam soil has positive and significant impacts on the likelihood of investing in both organic fertilizer and farmyard manure. These findings probably suggest that farmers tend to invest more in fertile soils such as loam soils, and less in sandy soils. Access to irrigation facilities tends to have significant and positive effects on investment in organic fertilizer and farmyard manure. Raising livestock tends to increase the likelihood of investing in farmyard manure. There is a well-functioning manure market in the surveyed areas, such that farmers are able to buy and sell

[11] Given that organic fertilizer and farmyard manure are substitutes with respect to soil management practices, we also estimated a specification that combined both into one variable. The results are presented in Table 2.8.A5 in the Appendix 2, and show that cooperative membership has a positive and significant impact on the probability of investing in organic material. We thank an anonymous reviewer for suggesting this to us.

manure from the markets. Hence, possessing livestock is not a sufficient condition for investment in manure (Abdulai and Goetz 2014). The results also reveal that location fixed effects may be significant in explaining differences in investment decisions of farmers. In particular, farmers located in Gansu appear to be more likely to invest in in farmyard manure.

The estimates of the impact of cooperative membership on investment in chemical fertilizer are presented in the last column of Table 2.2. The results show that cooperative membership has a positive but insignificant impact on the probability of investing in chemical fertilizer. Among other factors that influence chemical fertilizer investment, the variable representing age is negative and significantly different from zero, suggesting that older farmers are less likely to invest in chemical fertilizer, a finding that is consistent with the results of Marenya and Barrett (2009) for Kenya. Education variable is also negative and significantly different from zero, indicating that more educated farmers are less likely to invest in chemical fertilizer, a finding that contrasts with the results reported by Asfaw and Admassie (2004) for Ethiopia. However, the negative relationship between education and investment in chemical fertilizer is not implausible in our case, given the fact that some surveyed cooperatives are involved in food safety practices. Thus, it is possible that educated farmers who aim at increasing their market sales through improved product quality are more likely to be food safety oriented cooperative members, resulting in a lower probability of investing in chemical fertilizer. The farm size variable is positive and statistically significant, suggesting that farmers having larger farms are more likely to invest in yield-enhancing measures such as chemical fertilizer. This is probably because larger farm size represents wealth, such that wealthier farmers can better afford chemical fertilizers. The negative coefficient of livestock variable suggests that farmers raising livestock are less likely to invest in chemical fertilizer, while access to irrigation facilities tends to increase the likelihood of investing in chemical fertilizer.

Given the high application rates of both organic fertilizer and chemical fertilizer, we also analyzed the impact of cooperative membership on expenditures on organic fertilizer and chemical fertilizer using a Tobit model.[12] We employ a two-stage residual inclusive (2SRI) approach suggested by Rivers and Vuong (1988) to address the endogeneity of cooperative membership. In the first-stage of 2SRI, the cooperative membership variable is specified as a function of all other explanatory variables including the instrumental variable used in the RBP

[12] We thank an anonymous reviewer for suggesting this to us.

model. In the second-stage regression, the residual predicted from the first-stage estimation is included as an additional regression in the expenditure equation. The results, which are presented in Table 2.9.A6 in the Appendix 2, show that cooperative membership does not significantly affect expenditures on organic and chemical fertilizer.

Marginal Effects and Average Treatment Effects

Given that the estimated coefficients of the explanatory variables in Table 2.2 cannot be directly interpreted, we calculate the marginal effects to provide a better understanding about the magnitudes of the coefficients. We are particularly interested in the marginal effects of variables that influence farmers' soil investment decisions, so the marginal effects from first-stage estimation of RBP model are not presented for the sake of brevity. The results are presented in Table 2.3. The estimates of marginal effects reveal that being a cooperative member increases the probabilities of investing in organic fertilizer by 31.4% and farmyard manure by 29.5%, respectively. Among other variables, the results show that farmers with larger household size are 3.6% and 2.4% less likely to invest in organic fertilizer and farmyard manure, respectively. Farmers with access to credit are 8.5% and 7.6% more likely to invest in organic fertilizer and farmyard manure, respectively. Moreover, farmers cultivating land with sandy soil are 40.9% less likely to invest in farmyard manure. Access to irrigation increases the probabilities of investing in organic fertilizer, farmyard manure and chemical fertilizer by 8.7%, 10.5% and 3.8%, respectively.

With respect to the theoretical part of this study it is significant to mention that the marginal effects of the empirical study represent average values of the θ discussed in the theoretical section. In light of this interpretation, the results of the empirical analysis support the theoretical findings that cooperative membership tends to favor investment in yield-enhancing and soil improving measures.

Table 2.3 Marginal effects of RBP model estimation on the marginal probability of investing in organic fertilizer, farmyard manure and chemical fertilizer (in %)

Variables	Organic fertilizer	Farmyard manure	Chemical fertilizer
Membership	0.314***	0.295***	0.042
Age	-0.0004	0.0004	-0.003**
Education	0.0004	0.003	-0.006*
Household size	-0.036***	-0.024*	0.003
Farm size	-0.013**	0.002	0.011**
Farming vehicle	0.156*	0.088*	0.032
Rotary cultivator	0.105**	0.103***	0.020
Access to credit	0.085**	0.076**	0.018
Sandy soil	0.013	-0.409***	0.026
Loam soil	0.126**	0.126**	0.039
Livestock	0.0001	0.102**	-0.049*
Irrigation	0.087**	0.105**	0.038*
Road condition	0.008	0.038	0.027
Tree age	0.004	0.005	-0.0001
Tenure security	0.051	0.016	0.040
Shandong	-0.011	0.002	-0.033
Gansu	0.019	0.190**	-0.065
Sample size	481	481	481

Note: Asterisk *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. The reference region is Shaanxi and the reference soil type is clay soil.

To the extent that marginal effects only estimate partial effects of cooperative membership on investment in soil-improving and yield-enhancing measures in the case of changing cooperative membership variable from zero to one, we also follow Chiburis et al. (2011) to estimate the ATT to provide a better and more comprehensive understanding of the effects of cooperative membership on investment decisions of smallholder farmers. As suggested by Chiburis et al. (2011), we used 199 bootstrap replications in each of our simulations to reduce sampling noise. Unlike the mean differences presented in Table 2.4.A1 in the Appendix 2, these ATT estimates account for selection bias arising from the fact that members and nonmembers are systematically different in terms of both observed and unobserved characteristics. The results are presented in the lower part of Table 2.2. Our findings show that the causal effect of cooperative membership was to significantly increase the probabilities of investing in organic fertilizer by 45.9% and farmyard manure by 22.5%. However, no statistically significant impact was found for cooperative membership on investment in chemical fertilizer. Although the RBP model estimation reveals some differences in the magnitudes of the marginal effects and average treatment effects of cooperative membership, both reveal highly positive and statistically significant impacts. As pointed out by Lanfranchi and Pekovic (2014), these differences are expected, since they are calculated based on two different evaluation parameters. In particular, the marginal effect shows how the probability of investing in a particular soil quality measure changes as the cooperative membership variable changes from zero to one, while ATT measures the causal effect of cooperative membership on the investment probability.

2.6 Conclusion

Although agricultural cooperative is considered to be an important institutional arrangement that enhances agricultural production and marketing, empirical evidence on the link between cooperative membership and adoption of agricultural technologies is quite scarce in the literature. To bridge this gap, this article contributes to the literature by examining the impact of cooperative membership on investment in soil-improving and yield-enhancing measures such as organic fertilizer, farmyard manure and chemical fertilizer. Specifically, we developed a dynamic model to show how cooperative membership and household and farm-level characteristics impact on farmers' decisions to invest in soil-improving and yield-enhancing measures. We then used survey data from apple producing households in Gansu, Shaanxi and Shandong provinces in China to examine the impact of cooperative membership and household and farm-level variables on investment in these soil-improving and productivity-enhancing measures. A recursive bivariate probit model was used to address the issue of selection bias that arises from both observed and unobserved heterogeneities.

The theoretical analysis provides a model that illustrates the influence of household and farm-level characteristics on a farmer's decision to join or not to join an agricultural open-membership cooperative. Moreover, it identifies two situations where farmers with cooperative membership are more likely to invest in soil-improving and yield-enhancing measures than those without membership. Finally, the theoretical analysis characterizes a third situation where members of a cooperative are less likely to invest in yield-enhancing and soil-improving measures than nonmembers. The econometric estimates revealed that a number of factors tend to drive farmers' decisions to join contemporary agricultural cooperatives, including education, household size, farm size, asset ownership such as farming vehicle and rotary cultivator, and road condition. With respect to the investment decisions, our findings showed that cooperative membership tend to positively and significantly impact on investment in organic fertilizer and farmyard manure, but no statistically significant impact on investment in chemical fertilizer. Furthermore, access to credit was found to increase the propensity to invest in soil quality measures.

Our findings generally confirm the significant role of agricultural cooperatives in facilitating adoption of soil-improving measures among smallholder farmers, which actually enhance environmental sustainability and agricultural productivity. This suggests that the government should step up its efforts to encourage smallholder farmers to join cooperatives. In addition to building up farmers' apple production capacities with sustainable input use, agricultural cooperatives can also enhance farmers' access to inputs and output markets by reducing transaction costs involved. Therefore, enhancing the development of agricultural cooperatives is of great importance in promoting rural development and poverty alleviation policies. Moreover, given the crucial role of access to credit and irrigation facilities in facilitating investment in soil quality measures, it is apparent that policies that improve farmers' access to credit and accelerate the development of rural infrastructure such as irrigation system would help enhance investment in soil-improving measures, and contribute to sustainable agriculture.

Despite the interesting theoretical and empirical findings, the study still has some limitations, which could be considered in future research in the area. While we found that agricultural cooperatives increase the probabilities of investing in organic fertilizer and farmyard manure, little is known on whether cooperative members are more cost and profit efficient than nonmembers with respect to agricultural technology adoption. In addition, it is still not clear how agricultural cooperatives influence the soil investment decisions of farmers cultivating other products, since this study focuses on apple farmers in China due to a limited survey budget.

Appendix 1

Comparative static analysis:

We start out by determining the determinant of the Hessian Matrix $\tilde{H}$ of the first-order conditions (5) and (6) that is given by[13]:

$$\left|\tilde{H}\right| = \begin{vmatrix} \tilde{H}_{OO} & \tilde{H}_{OM} \\ \tilde{H}_{MO} & \tilde{H}_{MM} \end{vmatrix} = \begin{vmatrix} (-) & 0 \\ 0 & (-) \end{vmatrix} = \tilde{H}_{OO}\tilde{H}_{MM} > 0 \tag{2.15}$$

where the positive sign is the result of the previous assumptions that the production function Y is strictly concave and additive separable in M and O. Application of Cramer's rule yields:

$$\frac{dO^*}{d\theta} = \frac{\begin{vmatrix} \tilde{H}_{OO} & -\tilde{H}_{O\theta} \\ \tilde{H}_{MO} & -\tilde{H}_{M\theta} \end{vmatrix}}{\left|\tilde{H}\right|} = \frac{\begin{vmatrix} (-) & (\pm) \\ 0 & (\pm) \end{vmatrix}}{+} \gtreqless 0 \tag{2.16}$$

$$\frac{dM^*}{d\theta} = \frac{\begin{vmatrix} -\tilde{H}_{O\theta} & \tilde{H}_{OM} \\ -\tilde{H}_{M\theta} & \tilde{H}_{MM} \end{vmatrix}}{\left|\tilde{H}\right|} = \frac{\begin{vmatrix} (\pm) & 0 \\ (\pm) & (-) \end{vmatrix}}{+} \gtreqless 0 \tag{2.17}$$

To analyze equations (2.16) and (2.17) in more depth we need to determine the signs of:

$$\begin{aligned} \tilde{H}_{O\theta} &= \left(P - \lambda\alpha_Y\right)Y_{O\theta} - CO_{O\theta} \gtreqless 0 \\ \tilde{H}_{M\theta} &= \left(P - \lambda\alpha_Y\right)Y_{M\theta} - CO_{M\theta} \gtreqless 0 \end{aligned} \tag{2.18}$$

The indeterminacy of the signs of the equations (2.16), (2.17) and (2.18) results from the fact that the sign of $Y_{I\theta}, I = M, O$ cannot be determined unambiguously. Depending on the sign of $Y_{I\theta}$ and the magnitude of $Y_{I\theta}$ and $CO_{I\theta}$, we can isolate three situations which are depicted in Figure 2.4.A1 which is based on equation (2.18) . In order to simply notation but without loss of generality we concentrate on the case of mineral fertilizer. Let us assume that the index increases from θ_1 to θ_2. The first case considers an increase in $Y_{M\theta} > 0$. Hence, an increase in

[13] Without loss of generality we suppress the superscript H (high quality) of the equations (2.5) and (2.6) in order to simplify notation.

θ shifts the function $(P-\lambda\alpha_Y)Y_M(\cdot,\theta_1)$ to the right so that it is given by $(P-\lambda\alpha_Y)Y_M(\cdot,\theta_2)$, with $Y_{M\theta}>0$. Likewise the cost function $CO_M(\cdot,\theta_1)$ shifts downward so that the new cost function is given by $CO_M(\cdot,\theta_2)$. As a result of these two shifts, the optimal amount of fertilizer increases from M_1^{CO} to M_2^{CO}. The second case considers an decrease in $Y_{M\theta}<0$. Hence, an increase in θ shifts the function $(P-\lambda\alpha_Y)Y_M(\cdot,\theta_1)$ to the left so that it is given by $(P-\lambda\alpha_Y)Y_M(\cdot,\theta_2)$, with $Y_{M\theta}<0$. Provided that the cost function $CO_M(\cdot,\theta_1)$ shifted downward and were given by $CO_M(\cdot,\theta_2)$, then it would be optimal to increase the optimal amount of fertilizer from M_1^{CO} to M_3^{CO}. For the third case we consider the situation where the cost function $CO_M(\cdot,\theta_1)$ shifted downward but only up to $\underline{CO}_M(\cdot,\theta_2)$, then it would be optimal to decrease the optimal amount of fertilizer from M_1^{CO} to M_4^{CO}. Apart from the three cases, Figure 2.4.A1 also show the increase in input use as a result of the cooperative membership. It is driven by the reduction of the costs from $C_M(\cdot,\theta_1)$ to $CO_M(\cdot,\theta_1)$ which in turn leads to an increase in mineral fertilizer from M_1^{NC} to M_1^{CO}. According to Figure 2.4.A1, this increase can be magnified (case 1 or 2) or moderated (case 3). The case where the increase from M_1^{NC} to M_1^{CO} as a result of the cooperative membership is more than offset by the decrease in mineral fertilizer as a result of an increase in θ is not shown in Figure 2.4.A1 in order to keep it trackable. As presented in the main text, the previous discussion can be summarized in the following way:

$$\frac{dO^*}{d\theta}=\begin{pmatrix} >0,\ \text{if } Y_{O\theta}>0, \\ >0, \text{if } Y_{O\theta}<0, \text{ and } |Y_{O\theta}|<|C_{O\theta}| \\ <0, \text{if } Y_{O\theta}<0, \text{ and } |Y_{O\theta}|>|C_{O\theta}| \end{pmatrix} \tag{2.19}$$

$$\frac{dM^*}{d\theta}=\begin{pmatrix} >0,\ \text{if } Y_{M\theta}>0, \\ >0, \text{if } Y_{M\theta}<0, \text{ and } |Y_{M\theta}|<|C_{M\theta}| \\ <0, \text{if } Y_{M\theta}<0, \text{ and } |Y_{M\theta}|>|C_{M\theta}| \end{pmatrix} \tag{2.20}$$

Summarized briefly, these results show that it is optimal for famers to increase the use of inputs/investment if the farmer's characteristics reinforce the marginal productivity with respect to M and O, i.e., $Y_{I\theta}>0$. Since an increase in θ leads to a reduction in

$CO_I^j, I = M, O$ and to an increase in $Y_I^j, I = M, O$, it is unambiguously optimal to intensify production. On the other hand, if the decrease in the marginal productivity is in absolute terms less than the decrease in the costs, it is optimal for farmers to produce only slightly more intensively. However, if the farmer's characteristics moderate the marginal productivity with respect to M and O, i.e., $Y_{I\theta} < 0$, and the decrease in the marginal productivity is in absolute terms greater than the decrease in the costs, then it is optimal for farmers to produce less intensively.

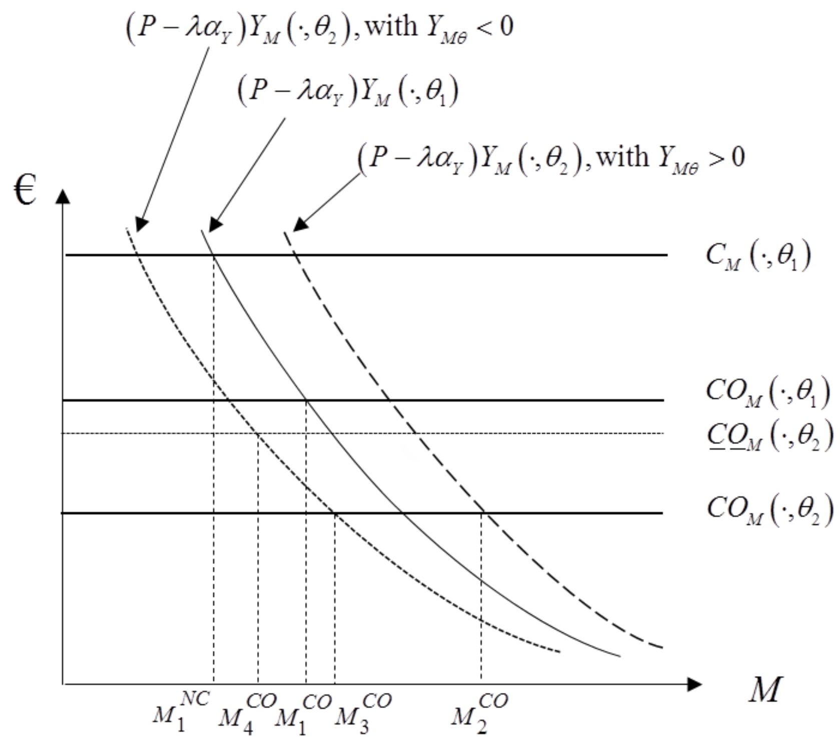

Figure 2.4.A1 The optimal level of mineral fertilizer applied by farmers that are cooperative members given an increase in the characteristics from θ_1 to θ_2, with $\theta_2 > \theta_1$

Appendix 2

Table 2.4.A1 Mean differences in characteristics between cooperative members and nonmembers

Variables	Members (208)	Nonmembers (273)	Diff.
Age	48.45 (0.66)	48.77 (0.66)	-0.326
Education	8.05 (0.17)	7.27 (0.19)	0.781***
Household size	4.57 (0.10)	4.14 (0.08)	0.433***
Farm size	5.51 (0.24)	4.73 (0.18)	0.778***
Farming vehicle	0.96 (0.01)	0.88 (0.02)	0.079***
Rotary cultivator	0.63 (0.03)	0.46 (0.03)	0.177***
Access to credit	0.57 (0.03)	0.51 (0.03)	0.067
Sandy soil	0.44 (0.03)	0.34 (0.03)	0.093***
Loam soil	0.20 (0.03)	0.15 (0.02)	0.051
Livestock	0.27 (0.03)	0.20 (0.02)	0.068*
Irrigation	0.64 (0.03)	0.59 (0.03)	0.058
Road condition	0.70 (0.03)	0.52 (0.03)	0.185***
Tree age	14.96 (0.46)	15.83 (0.39)	-0.871
Tenure security	0.41 (0.03)	0.53 (0.03)	-0.126***
Shandong	0.45 (0.03)	0.41 (0.03)	0.042
Gansu	0.20 (0.03)	0.14 (0.02)	0.063*
Village cooperative	0.14 (0.02)	0.04 (0.01)	0.095***
Organic fertilizer	0.92 (0.02)	0.78 (0.03)	0.147***
Farmyard manure	0.38 (0.03)	0.21 (0.02)	0.175***
Chemical fertilizer	0.89 (0.02)	0.96 (0.01)	-0.062***
Organic material	0.94 (0.02)	0.82 (0.02)	0.117***
Organic fertilizer expenditure	6.60 (0.32)	4.71 (0.29)	1.897***
Chemical fertilizer expenditure	8.81 (0.40)	9.79 (0.35)	-0.976*
Net returns	8.65 (0.30)	6.69 (0.20)	1.963***

Note: Asterisks * and *** denote significance at the 10% and 1% levels, respectively. Standard errors are in parentheses.

Table 2.5.A2 Estimation results of SUBP model for joint decisions of cooperative membership and soil investments

	Model 1		Model 2		Model 3	
Variables	Membership	Organic fertilizer	Membership	Farmyard manure	Membership	Chemical fertilizer
Age	0.010 (0.008)	0.004 (0.010)	0.009 (0.008)	0.004 (0.010)	0.010 (0.008)	-0.028 (0.012)**
Education	0.054 (0.027)**	0.025 (0.031)	0.052 (0.027)*	0.035 (0.033)	0.055 (0.028)**	-0.053 (0.032)*
Household size	0.109 (0.053)**	-0.132 (0.068)*	0.106 (0.052)**	-0.078 (0.072)	0.111 (0.0525)**	0.038 (0.080)
Farm size	0.098 (0.026)***	-0.008 (0.032)	0.098 (0.027)***	0.054 (0.030)*	0.099 (0.026)***	0.113 (0.052)**
Farming vehicle	0.775 (0.255)***	1.022 (0.296)***	0.777 (0.258)***	0.949 (0.286)***	0.782 (0.263)***	0.369 (0.320)
Rotary cultivator	0.309 (0.130)**	0.739 (0.167)***	0.307 (0.130)**	0.699 (0.173)***	0.308 (0.130)**	0.240 (0.202)
Access to credit	0.215 (0.130)*	0.561 (0.165)***	0.208 (0.130)	0.497 (0.171)***	0.215 (0.129)*	0.189 (0.185)
Sandy soil	1.312 (0.365)***	0.739 (0.366)**	1.330 (0.367)***	-2.097 (0.472)***	1.520 (0.392)***	0.428 (0.378)
Loam soil	0.411 (0.193)**	1.083 (0.299)***	0.410 (0.193)**	0.732 (0.205)***	0.423 (0.195)**	0.504 (0.348)
Livestock	0.121 (0.193)	0.086 (0.256)	0.127 (0.192)	0.532 (0.227)**	0.126 (0.192)	-0.380 (0.226)*
Irrigation	0.142 (0.144)	0.557 (0.185)***	0.167 (0.145)	0.633 (0.216)***	0.164 (0.144)	0.362 (0.196)*
Road condition	0.403 (0.159)**	0.283 (0.185)	0.411 (0.158)***	0.398 (0.210)*	0.416 (0.159)***	0.306 (0.243)
Tree age	-0.014 (0.012)	0.016 (0.015)	-0.014 (0.012)	0.027 (0.016)*	-0.016 (0.012)	-0.003 (0.018)
Tenure security	-0.450 (0.146)***	0.001 (0.174)	-0.452 (0.147)***	-0.131 (0.184)	-0.441 (0.145)***	0.326 (0.230)
Shandong	0.0002 (0.405)	-0.004 (0.442)	-0.018 (0.402)	-0.032 (0.417)	-0.172 (0.423)	-0.312 (0.491)
Gansu	0.490 (0.272)*	0.404 (0.324)	0.469 (0.269)*	0.963 (0.327)***	0.472 (0.271)*	-0.440 (0.362)
Village cooperative	0.888 (0.243)***		0.846 (0.239)***		0.997 (0.242)***	
Constant	-3.734 (0.581)***	-1.428 (0.721)**	-3.684 (0.578)***	-3.706 (0.745)***	-3.790 (0.587)***	1.713 (0.878)*
$\rho'_{\varepsilon\mu}$	0.208 (0.110)*		0.257 (0.110)**		-0.581 (0.090)***	
Log-likelihood	-427.230		-414.937		-360.259	
Wald test: $\rho'_{\varepsilon\mu}$=0	3.395*, with Prob=0.065		5.042***, with Prob =0.005		24.077***, Prob=0.000	
Sample size	481		481		481	

Note: Asterisk *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. Robust standard errors are in parentheses. The reference region is Shaanxi and the reference soil type is clay soil.

Table 2.6.A3 Goodness-of-fit tests for RBP model

Groups	Murphy's score test	Hosmer-Lemeshow test
Membership and organic fertilizer use	chi2(9) =11.52 with Prob > chi2 =0.2419	chi2(9) =29.22 with Prob > chi2 =0.1089
Membership and farmyard manure use	chi2(9) =2.64 with Prob > chi2 =0.9767	chi2(9) =12.57 with Prob > chi2 =0.9229
Membership and chemical fertilizer use	chi2(9) =5.59 with Prob > chi2 =0.7804	chi2(9) =20.11 with Prob > chi2 =0.5146
Membership and organic material use	chi2(9) =14.53 with Prob > chi2 =0.1048	chi2(9) =17.95 with Prob > chi2 =0.6521

Table 2.7.A4 Multivariate probit estimates for determinants of soil investments

Variables	Organic fertilizer	Farmyard manure	Chemical fertilizer
Membership	0.404 (0.183)**	0.531 (0.189)***	-0.989 (0.232)***
Age	0.003 (0.010)	0.002 (0.010)	-0.028 (0.013)**
Education	0.021 (0.031)	0.026 (0.033)	-0.043 (0.034)
Household size	-0.149 (0.069)**	-0.103 (0.072)	0.070 (0.086)
Farm size	-0.022 (0.032)	0.040 (0.031)	0.152 (0.054)***
Farming vehicle	0.958 (0.297)***	0.846 (0.300)***	0.623 (0.343)*
Rotary cultivator	0.714 (0.170)***	0.655 (0.177)***	0.362 (0.221)
Access to credit	0.550 (0.166)***	0.472 (0.173)***	0.274 (0.192)
Sandy soil	0.605 (0.380)	-2.344 (0.480)***	0.829 (0.390)**
Loam soil	1.041 (0.300)***	0.681 (0.210)***	0.619 (0.364)*
Livestock	0.064 (0.257)	0.496 (0.231)**	-0.358 (0.243)
Irrigation	0.538 (0.189)***	0.626 (0.221)***	0.443 (0.215)**
Road condition	0.238 (0.187)	0.340 (0.213)	0.505 (0.267)*
Tree age	0.018 (0.0151)	0.029 (0.016)*	-0.009 (0.020)
Tenure security	0.054 (0.178)	-0.056 (0.185)	0.208 (0.248)
Shandong	-0.022 (0.443)	-0.021 (0.420)	-0.376 (0.495)
Gansu	0.354 (0.320)	0.925(0.333)***	-0.404 (0.393)
Constant	-1.205 (0.742)	-3.393 (0.767)***	1.331 (0.931)
Cross-equation correlations			
ρ_{OF}		-0.082 (0.110)	
ρ_{OC}		-0.068 (0.137)	
ρ_{FC}		0.005 (0.127)	
Log-likelihood		-398.256	
Likelihood ratio test: $\rho_{OF} = \rho_{OC} = \rho_{FC} = 0$		0.669, with Prob=0.881	
Sample size	481	481	481

Note: Asterisk *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. The reference region is Shaanxi and the reference soil type is clay soil.

Table 2.8.A5 The RBP model estimates for the impact of cooperative membership on organic material

Variables	Membership	Organic Material
Membership		1.551 (0.278)***
Age	0.008 (0.007)	0.003 (0.009)
Education	0.045 (0.026)*	0.035 (0.029)
Household size	0.107 (0.050)**	-0.204 (0.062)***
Farm size	0.102 (0.026)***	-0.063 (0.029)**
Farming vehicle	0.735 (0.261)***	0.749 (0.314)**
Rotary cultivator	0.300 (0.129)**	0.455 (0.189)**
Access to credit	0.170 (0.128)	0.432 (0.165)***
Sandy soil	1.320 (0.368)***	-0.284 (0.411)
Loam soil	0.344 (0.197)*	0.401 (0.317)
Livestock	0.015 (0.202)	0.109 (0.268)
Irrigation	0.200 (0.145)	0.561 (0.210)***
Road condition	0.414 (0.153)***	0.121 (0.182)
Tree age	-0.018 (0.012)	0.020 (0.015)
Tenure security	-0.443 (0.143)***	0.120 (0.168)
Shandong	0.065 (0.408)	0.032 (0.420)
Gansu	0.523 (0.272)*	0.362 (0.323)
Village cooperative	0.992 (0.233)***	
Constant	-3.487 (0.573)***	-0.652 (0.815)
$\rho_{\varepsilon\mu}$	-0.830 (0.118)***	
Log-likelihood	-396.347	
Wald test of $\rho_{\varepsilon\mu}$=0	9.887***, with Prob= 0.002	
ATT	0.456 (0.142)***	
Sample size	481	

Note: Asterisk *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. Robust standard errors are in parentheses. The reference region is Shaanxi and the reference soil type is clay soil. ATT refers to average treatment effects on the treated, which is estimated by equation (14).

Table 2.9.A6 Tobit model estimation of impact of cooperative membership on expenditures of organic fertilizer and chemical fertilizer

Variables	Organic fertilizer expenditure	Chemical fertilizer expenditure
Membership	0.151 (0.217)	-0.184 (0.175)
Age	0.007 (0.003)*	0.006 (0.003)**
Education	0.013 (0.012)	-0.008 (0.010)
Household size	-0.007 (0.027)	0.016 (0.020)
Farm size	-0.040 (0.015)***	-0.012 (0.012)
Farming vehicle	-0.030 (0.130)	0.163 (0.107)
Rotary cultivator	0.094 (0.061)	0.131 (0.051)**
Access to credit	0.010 (0.065)	-0.025 (0.054)
Sandy soil	0.306 (0.167)*	0.257 (0.163)
Loam soil	0.233 (0.118)**	-0.039 (0.078)
Livestock	0.094 (0.091)	0.127 (0.067)*
Irrigation	-0.143 (0.0662)**	0.121 (0.056)**
Road condition	0.133 (0.086)	0.130 (0.065)**
Tree age	-0.005 (0.005)	0.003 (0.005)
Tenure security	0.090 (0.059)	0.082 (0.052)
Shandong	0.290 (0.175)*	-0.756 (0.174)***
Gansu	-0.080 (0.127)	-0.450 (0.100)***
Residual (membership)	0.029 (0.100)	0.063 (0.079)
Constant	5.682 (0.278)***	6.423 (0.236)***
Sigma	0.554 (0.023)***	0.483 (0.017)***
Sample size	481	481

Note: Asterisk *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

The reference region is Shaanxi and the reference soil type is clay soil.

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Chapter 3 Adoption of Integrated Pest Management Technology and Farm Economic Performance

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Abstract

Despite widespread evidence of health and environmental benefits associated with integrated pest management (IPM) technology, the adoption rate of this technology remains significantly low. Using survey data from a sample of 481 apple households, this paper employs an endogenous switching probit model that accounts for selectivity bias to analyze the impact of agricultural cooperative membership on farmers' decisions to adopt IPM technology. The impact of IPM adoption on farm performance indicators such as apple yields, net returns and agricultural income is also investigated using a treatment effects model to address the sample selection problem. The empirical results show that cooperative membership exerts a positive and significant impact on the adoption of IPM, a finding that is consistent with our theoretical analysis. In addition, IPM adoption has positive and significant effects on apple yields, net returns and agricultural income. Generally, our findings indicate that agricultural cooperatives can be a transmission route in the efforts to facilitate IPM technology, and increased IPM adoption tends to improve the economic performance of farm households.

Keywords: IPM Adoption; Agricultural Cooperatives; Farm Performance; Endogenous Switching Probit; Treatment Effects Model; China

JEL Classification C52 · J54 · Q56

3.1 Introduction

While pesticide use has increased agricultural production and productivity, its use, overuse and misuse have caused negative externalities on human health and the environment, as well as food safety (Dasgupta et al., 2007; Fernandez-Cornejo et al., 1998; Kabir & Rainis, 2014; Wilson & Tisdell, 2001). In particular, the overuse of chemical pesticides has led to pest resistance, resurgence and secondary outbreaks, which push farmers to use more new pesticides. To ease the negative issues associated with pesticide use, integrated pest management (IPM) technology is introduced and implemented in agricultural production in many developing countries.

IPM refers to an ecologically based approach that makes the best use of all available technologies to manage pest problems sustainably. The primary objective of IPM technology is to minimize chemical pesticide use in relation to pest management, while maintaining or enhancing farm net returns with minimal environmental degradation. Previous studies have shown that IPM adoption significantly lowers pesticide use, saves production costs and maintains farm productivity for adopters (Carrión Yaguana et al., 2015; Dasgupta et al., 2007; Fernandez-cornejo, 1996). In view of the significant benefits associated with IPM technology, many government and FAO programs have been developed to spread the technology. One such effective approach is the introduction of Farmer Field School (FFS) (Kabir & Rainis, 2014; Sanglestsawai et al., 2015; Van Den Berg & Jiggins, 2007). However, IPM adoption rate remains low worldwide (Dasgupta et al., 2007; Kabir & Rainis, 2014). On the one hand, FFS is still not available in most regions (Kelly, 2005). On the other hand, due to low education levels, most small-scale farmers cannot understand the complex interrelationship between the pests/diseases existing in the cultivated crop and the knowledge-intensive IPM technology (Carrión Yaguana et al., 2015). Therefore, from a development policy perspective, it is particularly important to facilitate IPM adoption not only by FFS, but also through other institutional mechanisms.

Among agricultural programs, agricultural cooperative, as an important institutional innovation that promotes the adoption of agricultural technologies among smallholder farmers, has been well developed in developing countries. The studies by Abebaw & Haile (2013) for Ethiopia and Verhofstadt & Maertens (2014) for Rwanda have reported that cooperative membership has a positive and significant impact on adoption of pesticides with respect to pest management. Moreover, the existing literature has also recorded that agricultural cooperatives improve food safety and quality among members due to technical assistance (Jin & Zhou, 2011; Moustier et al., 2010; Naziri et al., 2014). In their investigation of 60 farmer organizations in Vietnam, Naziri et al. (2014) found that farmer organizations provide members with technical assistance and monitoring for pest management, which help improve members' food safety performance. Nevertheless, agricultural cooperative may play a much larger role in managing pest problems, since its goal in influencing agricultural production differs across countries and regions due to differences in natural resources and economic development conditions.

Given the importance of IPM adoption in minimizing pesticide use and the significant role of agricultural cooperatives in disseminating agricultural technologies and enhancing food safety practices, it is significant to understand whether cooperative organizations can promote IPM adoption. IPM is an information-intensive technology, and agricultural cooperatives may directly provide information to farmers through collective actions. However, there is lack of knowledge on how agricultural cooperatives affect the adoption of IPM technology by smallholder farmers. Moreover, IPM adoption may influence agricultural performance of farm households. For instance, adoption of IPM technology may increase farm profitability since it saves production costs. Understanding the issue is of great importance, since the effectiveness of agricultural policies that promote IPM adoption might be improved by taking into account the economic performance of farm households. However, much less is known about the farm-level economic performance associated with IPM adoption.

This study attempts to fill the research gap and contribute to the literature in threefold. First, we present a conceptual framework to show the link between agricultural cooperative membership and IPM adoption. Second, we employ an endogenous switching probit model to address the issue of selection bias in the process of choosing cooperative membership. The decision to join an agricultural cooperative is not a random event and depends on a number of observable factors (e.g., age, education and farm size) and unobservable factors (e.g., farmers' innate abilities, and motivations to enhance food safety and improve environmental performance). Although previous studies have employed propensity score matching method to analyze the causal effect of cooperative membership on agricultural technology adoption, the approach addresses the self-selection issue accounting for only observable factors, and it fails to capture the factors that influence farmers' decisions to adopt IPM (Abebaw & Haile, 2013; Verhofstadt & Maertens, 2014). Third, we employ a treatment effects model to analyze the impact of IPM adoption on crop yields, net returns and agricultural income. The treatment effects model adjusts for heterogeneity of IPM adoption by taking into consideration covariates affecting selection bias (Cong & Drukker, 2000). Fernandez-cornejo (1996) has employed a standard Heckman two-step model to analyze the impact of IPM adoption on pesticide use, tomato yields, and farm profits. However, the standard Heckman model emphasizes modeling structures of selection bias rather than assuming mechanisms of randomization work to balance data between IPM adopters and non-adopters.

The study utilizes a cross-section survey data of 481 households in three major apple producing provinces (Gansu, Shaanxi and Shandong) in China. Apple sector in China is an interesting example. Being the largest apple producer in the world, China produces almost half of the world's total apple output. However, only 3% of apples produced in the country are exported due to pesticide residual issues (FAOSTAT). The total pesticide use has increased from 0.73 million tons in 1990 to 1.81 million tons in 2012, and the total pesticide expenditure rose more than 11-fold between this period (CRSY, 2013). Particularly, fruit and vegetable production is intensive in pesticides, and apple has no exception. The rising use of chemical pesticides has increased farmers' production costs and posed serious food safety, health and environmental problems. IPM technology is therefore being promoted intensively among apple producers to help reduce these adverse environmental impacts of conventional agriculture.

This paper proceeds as follows. We present the theoretical model in section 3.2 and the empirical specification in section 3.3. Section 3.4 presents the data and descriptive statistics. The empirical results and discussion are presented in section 3.5, and the final section concludes.

3.2 Theoretical Model

To illustrate the relationship between cooperative membership and IPM adoption, the theoretical model presented in this section modifies the farm household model suggested by Fernandez-Cornejo et al. (2007). The model expands the farm household model developed by Huffman (1991) with several conditions to allow for IPM adoption. To begin with, we assume that an agricultural household maximizes utility over consumption of goods (G) and leisure (L):

$$Max\ U = U(G, L; H) \tag{3.1}$$

where U is the household utility function, which is assumed to be strictly concave and to possess continuous second partial derivatives; H represents a vector of individual, household and location characteristics. Utility is maximized subject to time, technology and income constraints. The time constraint is:

$$T = F(\tau) + N + L \tag{3.1a}$$

where T denotes the total household time, which consists of the time allocated to farm work (F), off-farm work (N) and leisure (L). F is assumed to be a function of the intensity of IPM adoption, τ. The household faces a technology constraint specified as:

$$Q = Q[I(\tau), F(\tau), H, \tau, R] \tag{3.1b}$$

where Q is the output level; I captures input use such as pesticides, which is a function of the intensity of IPM adoption, τ; F and H are as defined above; R is a vector of exogenous factors that shift the production function.

Utility maximization is also subject to income constraint. Previous studies have generally revealed that agricultural cooperatives promote smallholder commercialization by overcoming entry barriers in accessing input and output markets and mitigating transaction costs associated with poor access to market information and transport (e.g., Deng et al. 2010; Holloway et al. 2000; Vandeplas et al. 2013). Lowering transaction costs through agricultural cooperatives may increase farmers' net incomes due to better market access. For instance, agricultural cooperatives may help members deliver the products to (or inputs from) the markets, which finally lower members' transportation costs due to collective action. We therefore present the income constraint in the presence of transaction costs. Let PTC_θ^I and PTC_θ^Q represent proportional transaction costs per unit of input and output, respectively, with θ distinguishing the transaction costs for cooperative members ($\theta = 1$) and nonmembers ($\theta = 0$). In essence, the proportional transaction costs increase the real price of input P^I, and decrease the real price received for output P^Q (Key et al. 2000). The adjusted input price is then given as $P_I' = P^I + PTC_\theta^I$, while that for output price is $P_Q' = P^Q - PTC_\theta^Q$. Meanwhile, let FTC_θ^I represent fixed transaction costs for input market participation and FTC_θ^Q the costs for output market participation. Finally, the income constraint can be expressed as:

$$P_g G = \left(P^Q - PTC_\theta^Q\right)Q - \left(P^I + PTC_\theta^I\right)I - \ FTC_\theta^Q - FTC_\theta^I + WN + E \tag{3.1c}$$

where P_g and G denote the prices and quantities of purchased goods; P^Q is output price and P^I is price for input; Q is the output level and I represents the level of input use; W represents off-farm wages paid to the farmer, and N is the amount of time allocated to off-farm work; E is the income from other sources such as rents, interest and dividends.

Following Huffman (1991), the technology-constrained measure of household income is obtained by substituting equation (3.1b) into equation (3.1c). Then, the Lagrangian of the household's maximization problem is:

$$\mathcal{L} = U(G, L; H) + \lambda\{(P^Q - PTC_\theta^Q)Q[I(\tau), F(\tau), H, \tau, R] - (P^I + PTC_\theta^I)[I(\tau)] - FTC_\theta^Q - FTC_\theta^I + WN + E - P_g G\} + \mu[T - F(\tau) - N - L] \quad (3.2)$$

where λ is the Lagrangian multiplier for income constraint, and μ is the Lagrangian multiplier associated with the time constraint. The first-order conditions associated with maximizing utility subject to these constraints yield the following optimal choices of the household:

$$\partial\mathcal{L}/\partial I = \lambda(P^Q - PTC_\theta^Q)(\partial Q/\partial I) - (P^I + PTC_\theta^I) = 0 \quad (3.3a)$$

$$\partial\mathcal{L}/\partial F = \lambda(P^Q - PTC_\theta^Q)(\partial Q/\partial F) - \mu = 0 \quad (3.3b)$$

$$\partial\mathcal{L}/\partial \tau = \lambda\{(P^Q - PTC_\theta^Q)[(\partial Q/\partial I)(dI/d\tau) + (\partial Q/\partial F)(dF/d\tau) + dQ/d\tau] - (P^I + PTC_\theta^I)(dI/d\tau)\} - \mu(dF/d\tau) = 0 \quad (3.3c)$$

$$\partial\mathcal{L}/\partial N = \lambda W - \mu \leq 0, N \geq 0, N(\lambda W - \mu) = 0 \quad (3.3d)$$

$$\partial\mathcal{L}/\partial G = U_G - \lambda P_g = 0 \quad (3.3e)$$

$$\partial\mathcal{L}/\partial L = U_L - \mu = 0 \quad (3.3f)$$

where $U_G = \partial U/\partial G$ and $U_L = \partial U/\partial L$ are the partial derivatives of the function U.

The optimal time allocation decisions for farm work, off-farm work and leisure can be obtained from the optimality conditions, equations (3.3b), (3.3d), (3.3e) and (3.3f):

$$\mu/\lambda = (P^Q - PTC_\theta^Q)(\partial Q/\partial F) \geq W \quad (3.4)$$

where μ/λ is equal to the marginal rate of substitution between leisure and consumption goods (from equations (3.3e) and (3.3f)); $(P^Q - PTC_\theta^Q)(\partial Q/\partial F)$ represents the value of the marginal product of farm labor. In equation (3.4), $\mu/\lambda = (P^Q - PTC_\theta^Q)(\partial Q/\partial F) > W$ implies that the marginal value of an individual's leisure or farm work exceeds his or her off-farm wage opportunities, and optimal time for off-farm work is zero. When $\mu/\lambda = (P^Q - PTC_\theta^Q)(\partial Q/\partial F) = W$, then the marginal value of an individual's leisure or farm work equals to his or her off-farm wage, and the optimal time that households allocated to off-farm work may be positive (Huffman 1991). When the interior solution for off-farm work occurs, equations (3.3a) and (3.3b) can be solved together to obtain the demand functions for on-farm labor. The derivation of off-farm work can be employed to relate off-farm work to IPM adoption, since the off-farm wage determines the value of the household's time ($W = \mu/\lambda$). In particular, earnings from off-farm work may relax farmers' liquidity constraint and enable them to purchase IPM components (e.g., yellow sticky mobile, fixed traps, insect-trap light and trap band). The effectiveness of IPM adoption might be improved by taking into account the different demands on managerial time and the relative ability of the farm households to accommodate those demands (Fernandez-Cornejo et al. 2007).

The optimal IPM adoption decision can be obtained from the optimality conditions, equations (3.3c), (3.3e) and (3.3f):

$$(P^Q - PTC_\theta^Q)dQ/d\tau - (P^I + PTC_\theta^I)(dI/d\tau) - P_g(U_L/U_G)(dF/d\tau) = 0 \quad (3.5)$$

where the total derivative of $dQ/d\tau$ is equal to $(\partial Q/\partial I)(dI/d\tau) + (\partial Q/\partial F)(dF/d\tau) + dQ/d\tau$; $\mu/\lambda = P_g(U_L/U_G)$, which represents the marginal rate of substitution between leisure and consumption goods, can be derived based on equations (3.3e) and (3.3f). In equation (3.5), $(P^Q - PTC_Q^\theta)dQ/d\tau$ may be interpreted as the marginal benefit of IPM adoption, $(P^I + PTC_\theta^I)(dI/d\tau)$ represents the marginal cost of production inputs from IPM adoption, and $P_g(U_L/U_G)(dF/d\tau)$ denotes the marginal cost of the farm work from IPM adoption and valued at the marginal rate of substitution between leisure and consumption of goods. Equation (3.5) indicates that it is beneficial for farmers to adopt IPM technology when the marginal benefit of adoption is higher than the marginal cost of adoption, and the net benefit from IPM adoption is maximized when the marginal benefit of adoption is equal to the marginal cost of adoption.

Given the cross-sectional nature of the data, one can use the implicit function theorem to derive the expression for IPM adoption that is a function of off-farm wages, prices, the choice of cooperative membership that determines the transaction costs, human capital, and other exogenous factors. These factors are replaced in reduced-form representations of IPM adoption by observable farm and household level characteristics.

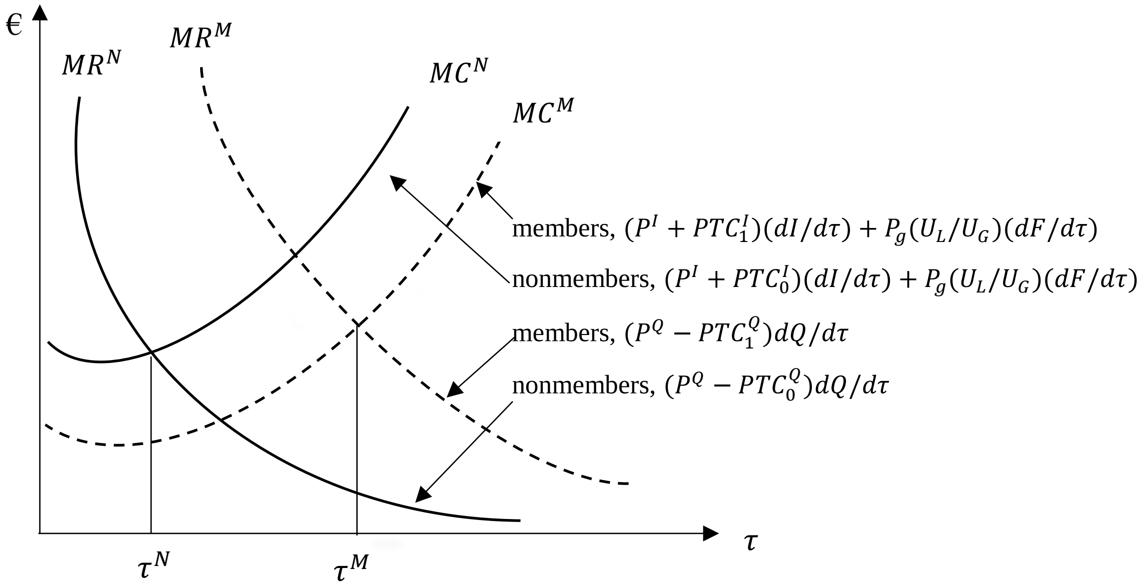

Figure 3.1 Determinants of the optimal level of IPM adoption for cooperative members and nonmembers

As an illustration, we provide a graphical analysis for intuitive understanding on how agricultural cooperative membership influences farmers' behavior in the IPM adoption process. Specifically, based on equation (3.5), we demonstrate in Figure 3.1 the curves that represent the marginal benefit (MR^N) and the marginal cost (MC^N) of IPM adoption for nonmembers ($\theta = 0$) (continuous lines), which determine the optimal level of IPM adoption for this group of farmers, τ^N. As indicated earlier, agricultural cooperatives help members reduce the transaction costs involved. If this is the case, the proportional transaction costs per unit of input and output for cooperative members ($\theta = 1$) presented in equation (3.5) are lower than that for nonmembers, i.e. $PTC_1^I < PTC_0^I$ and $PTC_1^Q < PTC_0^Q$. Thus, due to lower PTC_1^I and PTC_1^Q contributed by cooperative membership, the curves of MR^N and MC^N rotate clockwise. After rotation, the curves of MR^M and MC^M that represent the marginal benefit and the marginal cost of IPM adoption for members can be obtained (discontinuous lines), which determine the optimal level of IPM adoption for members, τ^M. As evident in Figure 3.1, cooperative members tend to adopt higher levels of IPM technology τ^M, compared to nonmembers τ^N.

IPM adopters and non-adopters may be systematically different since they themselves choose to adopt IPM technology (Fernandez-cornejo, 1996; Fernandez-Cornejo, 1998). For instance, farmers with favorable characteristics (e.g., environmental and health perceptions associated with IPM technology) may be more likely to choose to adopt IPM technology. These differences may manifest IPM adopters and non-adopters in farm performance. Therefore, in addition to analyzing the impact of cooperative membership on IPM adoption, it is also significant to understand how IPM adoption affects economic performance of farm households, and the empirical part of this study provides the evidence.

3.3 Empirical Specification

3.3.1 Impact Evaluation Issues

The theoretical model presented above indicates that it is profitable for farmers to adopt IPM technology if the net benefit of IPM adoption is positive. However, the expected net benefit from IPM adoption is not observable, since it is subjective. What is observed in the cross-sectional data is the farmer's decision to adopt IPM technology ($Y_i = 1$) or not to adopt ($Y_i = 0$). For the analytical setting, let Y_i^* represent the net benefit acquired from adopting IPM technology, we observe Y_i, if the underlying latent variable Y_i^* exceeds a certain threshold. Given our interest of exploring the impact of cooperative membership on IPM adoption, while controlling for other factors that may influence farmers' decisions to adopt, we express farmers' IPM adoption decisions as a latent variable function:

$$Y_i^* = \alpha X_i + \eta C_i + \vartheta_i \text{ with } Y_i = 1 \; if \; Y_i^* > 0 \tag{3.6}$$

where Y_i^* is a latent variable that represents the propensity to adopt IPM technology for household i, which gives the value of one, if the farmer adopted IPM technology, and zero otherwise; X_i is a vector of observable characteristics (e.g., age, education, household size and off-farm work participation) that are assumed to influence IPM adoption; C_i is an indicator representing the farmers' binary choices of cooperative membership; α and η are parameters to be estimated; and ϑ_i is a random error term.

Following the empirical literature that examines the impact of cooperative membership on technology adoption (e.g., Abebaw and Haile 2013; Ito et al. 2012), it is assumed that a farmer's decision to choose to belong to a cooperative is based on a comparison between the utility derived from choosing cooperative membership (C_{1i}^*) and the utility derived from not choosing the membership (C_{0i}^*). The utility maximizing household is then assumed to join an agricultural cooperative if the utility difference is positive, i.e. $C_i^* = C_{1i}^* - C_{0i}^* > 0$. However, C_i^* cannot be observed directly, but can be expressed by a latent variable function with observed characteristics (Z_i) that determine the choice of cooperative membership and an error term (ε_i):

$$C_i^* = \psi Z_i + \varepsilon_i > 0 \quad \text{with} \quad C_i = 1 \; if \; C_i^* > 0 \tag{3.7}$$

where C_i is a binary indicator variable that equals one if a farmer joined an agricultural cooperative, and zero otherwise, and ψ is a vector of parameters to be estimated; The error term ε_i is assumed to be normally distributed with zero mean.

Note that farmers themselves decide (self-selection) whether to join a cooperative, the decision is likely influenced by unobserved characteristics (e.g., farmers' innate abilities, awareness of dangers of pesticides, and motivations to improve food safety and environmental performance) that may be correlated to the IPM adoption. In the regression framework, this is equivalent to saying that the error term ϑ_i in equation (3.6) and the error term ε_i in equation (3.7) are correlated. In this case, estimation of equation (3.6) using a probit or logit model that fails to account for this self-selection is likely to produce biased estimates of the impact of cooperative membership on IPM adoption.

The standard approaches for dealing with the problem of self-selection are propensity score matching (PSM) model, recursive bivariate probit (RBP) model and endogenous switching probit (ESP) model. The ESP model has some advantages over other methods, and employed among them in this study (Lokshin and Sajaia 2011). First, the method addresses the issue of selection bias accounting for both observable and unobservable factors. PSM model addresses the issue of selection bias accounting for only observed heterogeneities, and fails to estimate the factors that influence IPM adoption (Abebaw and Haile 2013). Second, the ESP approach analyzes the determinants of IPM adoption separately for cooperative members and nonmembers. Although RBP model estimation that is inclusive of instrumental variables takes into account both observed and unobserved heterogeneities to address the selection bias issue, it only simultaneously estimates selection equation with one outcome equation, which fails to capture the factors that separately influence cooperative members and nonmembers' decisions to adopt IPM technology. However, efforts at enhancing IPM adoption through cooperative organizations require understanding and identifying the constraints and incentives that influence cooperative members and nonmembers' decisions separately.

3.3.2 Endogenous Switching Probit Model

Modeling the impact of cooperative membership on IPM adoption under the ESP framework proceeds in two stages: the first stage is the decision to join agricultural cooperatives as represented by equation (3.7); in the second-stage, a probit model is used to examine the relationship between IPM adoption variable and a set of explanatory variables conditional on the choice of cooperative membership. The two outcome equations, conditional on the choice of cooperative membership, can be expressed as:

$$Y_{1i}^* = \beta_1 X_{1i} + \xi_{1i} \quad \text{with} \qquad Y_{1i} = \begin{cases} 1 & if\ Y_{1i}^* > 0 \\ 0 & if\ Y_{1i}^* \le 0 \end{cases} \quad \text{if } C_i = 1 \tag{3.8a}$$

$$Y_{0i}^* = \beta_0 X_{0i} + \xi_{0i} \quad \text{with} \qquad Y_{0i} = \begin{cases} 1 & if\ Y_{0i}^* > 0 \\ 0 & if\ Y_{0i}^* \le 0 \end{cases} \quad \text{if } C_i = 0 \tag{3.8b}$$

where Y_{1i}^* and Y_{0i}^* are two latent IPM adoption variables for cooperative members and nonmembers, respectively; Y_{1i} and Y_{0i} are observed adoption choices, which take the value of one if cooperative members and nonmembers adopted the IPM technology, and zero otherwise; X_i is a vector of observable variables (e.g., age, education, household size and off-farm work) that determine IPM adoption; β_1 and β_0 are parameters to be estimated; ξ_{1i} and ξ_{0i} are two error terms that represent unobservable factors related to IPM adoption for members and nonmembers, respectively.

Previous analysis shows that IPM adoption is influenced by off-farm work participation, since additional income acquired from off-farm work activities enables farmers to purchase more agricultural inputs used in the IPM (e.g., yellow sticky mobile, fixed traps, insect-trap light and trap band). However, it is also significantly noted that allocating household labor and capital to off-farm work may constraint sustainable IPM technology management, resulting in the lost-labor effect as emphasized in the new economics of labor migration literature (Shi et al. 2011; Taylor et al. 2003). Given that the income effect of off-farm work participation is opposite to the lost-labor effect, the income effect may, or may not compensate for the lost-labor effect. The joint relationship between off-farm work participation and IPM adoption suggests potential endogeneity of off-farm work in IPM adoption equations, which should be addressed in estimating the IPM adoption specifications. Since off-farm work variable considered in this study is dichotomous, we employ a two-stage residual inclusive (2SRI) approach suggested by Rivers and Vuong (1988) to address its potential endogeneity. In the first-stage of 2SRI, the off-farm work variable is specified as a function of all other explanatory variables with inclusive of one instrumental variable. In this study, a variable representing access to local nonfarm work is identified and employed as an instrument in the estimation, which is required to strongly influence the off-farm work variable, but not IPM adoption.

[1] In the second-stage regression, the residual predicted from the first-stage estimation is included as an additional regressor in IPM adoption equations (3.8a) and (3.8b).

We assume that ε_i in equation (3.7), and ξ_{1i} and ξ_{0i} in equations (3.8a) and (3.8b) are jointly normally distributed, with a mean-zero and correlation matrix:

$$\Omega = \begin{bmatrix} 1 & \rho_0 & \rho_1 \\ & 1 & \rho_{10} \\ & & 1 \end{bmatrix} \tag{3.9}$$

where ρ_1 is the correlation between ε_i and ξ_{1i}; ρ_0 is the correlation between ε_i and ξ_{0i}; ρ_{10} is the correlation between ξ_{1i} and ξ_{0i}. Here, ρ_{10} cannot be estimated, since Y_{1i} and Y_{0i} are never observed simultaneously and the joint distribution of (ξ_{1i}, ξ_{0i}) is not identified. The full information maximum likelihood (FIML) approach estimates the selection equation (3.7) and outcome equations (3.8a) and (3.8b) simultaneously (Lokshin and Sajaia 2011). In ESP estimation, ρ_1 and ρ_0 are automatically created and respectively included in IPM adoption equation (3.8a) for members and the equation (3.8b) for nonmembers to correct for selectivity bias arising from unobservable factors. Using ESP model, Gregory and Coleman-Jensen (2013) analyzed food security effects of low-income households participating in the Supplemental Nutrition Assistance Program in the United States and Ayuya et al. (2015) evaluated the effects of certified organic production on poverty in smallholder production systems in Kenya.

3.3.3 Average Treatment Effects

The estimates of equations (3.7), (3.8a) and (3.8b) can provide understanding of the important factors that influence farmers' decisions to choose cooperative membership and the determinants of IPM adoption separately for cooperative members and nonmembers. Importantly, the estimated coefficients can be used to calculate the average treatment effects of cooperative membership on IPM adoption, which account for selection bias issue arising from

[1] The employed instrument is a dummy variable which takes the value of one, if the farmer self-reported that he/she has opportunity to engage in nonfarm work in the surrounding area, and the value zero, otherwise. We expect that farmers with local employment opportunities are more likely to participate in off-farm work.

both observed and unobserved heterogeneities. Following Lokshin and Sajaia (2011), we calculate the average treatment effects on the treated (ATT) and average treatment effects on the untreated (ATU) in this study. In particular, ATT compares the IPM adoption probability of cooperative members with and without the choice of cooperative membership, while ATU is a comparison of IPM adoption probability of nonmembers with and without the choice of cooperative membership. In particular, the ATT and ATU can be calculated as follows:

$$\text{ATT} = \frac{1}{N_1}\sum_{i=1}^{N_1}[Pr(Y_1 = 1|C = 1, X = x) - Pr(Y_0 = 1|C = 1, X = x)]$$

$$= \frac{1}{N_1}\sum_{i=1}^{N_1}\left[\frac{\Phi_2(\beta_1 X_1,\ Z\psi,\ \rho_1) - \Phi_2(\beta_0 X_0, Z\psi, \rho_0)}{F(Z\psi)}\right] \tag{3.10a}$$

$$\text{ATU} = \frac{1}{N_0}\sum_{i=1}^{N_0}[Pr(Y_1 = 1|C = 0, X = x) - Pr(Y_0 = 1|C = 0, X = x)]$$

$$= \frac{1}{N_0}\sum_{i=1}^{N_0}\left[\frac{\Phi_2(\beta_1 X_1,\ -Z\psi,\ -\rho_1) - \Phi_2(\beta_0 X_0, -Z\psi, -\rho_0)}{F(-Z\psi)}\right] \tag{3.10b}$$

where N_1 and N_0 represent the sample numbers of cooperative members and nonmembers, respectively; $Pr(Y_1 = 1|C = 1, X = x)$ and $Pr(Y_0 = 1|C = 0, X = x)$ predicted probabilities of IPM adoption for cooperative members and nonmembers in an observed context, while $Pr(Y_0 = 1|C = 1, X = x)$ and $Pr(Y_1 = 1|C = 0, X = x)$ are predicted IPM technology probabilities for those two groups of farmers in a counterfactual context; Φ_2 is the cumulative function of a bivariate normal distribution; and F is a cumulative function of the univariate normal distribution.

3.3.4 Treatment Effects Model

The relationship for examining the impact of IPM adoption on economic performance of farm households assumes a linear specification for farm performance indicator (e.g., crop yields, net returns or agricultural income) as a function of a vector of explanatory variables (X_i) along with a dummy variable for IPM adoption (Y_i). The regression equation for farm performance (H_i) can be specified as:

$$H_i = \omega Y_i + \nu X_i + \delta_i \tag{3.11}$$

where H_i represents farm performance indicators such as crop yields, net returns or agricultural income; Y_i is a 0 or 1 dummy variable for IPM adoption; X_i summarizes observed individual and household characteristics (e.g., age, education, farm size, household size, and asset ownership) that may influence the farm performance indicators; ω and ν are parameters to be estimated; and δ_i is an error term.

As indicated earlier, farmers choose to adopt IPM technology themselves. Farmers who choose to adopt IPM technology are therefore likely to have characteristics that could allow them to be more successful in using the technology than the average farmers. Therefore, due to self-selection bias, it would be incorrect to employ OLS regression to directly estimate the impact of IPM adoption on economic performance indicators, as evidenced in equation (3.11). In this study, we employ a treatment effects model to analyze the impact of IPM adoption on farm performance indicators. This approach addresses the issue of selection bias accounting for both observable and unobservable factors, as well as estimates the direct impact of cooperative membership on crop yields, net returns and agricultural income (Cong & Drukker, 2000).

By using treatment effects model, the selection mechanism for IPM adoption by the probit model can be explicitly specified as:

$$Y_i^* = \zeta X_i + \kappa T_i + \varpi_i \quad \text{with} \quad Y_i = 1 \; if \;\; Y_i^* > 0 \tag{3.12}$$

where Y_i^* is a latent variable and Y_i is its proxy variable in an observed context, as defined in equation (3.6); X_i is a vector of explanatory variables (e.g., age, education, household size and off-farm work participation); T_i is a vector of instrumental variables that are expected to influence farmers' decisions to adopt IPM technology, but do not directly have impacts on crop yields, net returns and agricultural income; ζ and κ are parameters to be estimated; and ϖ_i is a random error term.

In treatment effects model, the error term (ϖ_i) in IPM adoption equation (3.12) and the error term (δ_i) in farm performance equation (3.11) are assumed to have a correlation $\rho_{\delta\varpi}$. In particular, if $\rho_{\delta\varpi}$ is statistically significant, there is the presence of selection bias and the coefficient estimate ω of using OLS regression is biased (Cong & Drukker, 2000). Positive $\rho_{\delta\varpi}$ reveals a positive selection bias, suggesting that farmers with higher than average crop yields, net returns and agricultural income have higher probabilities to adopt IPM technology. Negative $\rho_{\delta\varpi}$ suggests a negative selection bias. In treatment effects model estimation, the potential endogeneity of off-farm work in IPM adoption equation is also addressed using the approach proposed by Rivers & Vuong (1988), as it is discussed previously.

3.4 Data and Descriptive Statistics

The data used in this paper come from a farm household survey of apple farmers conducted between September and December 2013 in Gansu, Shaanxi and Shandong provinces in China. We chose to collect data from those provinces since they are top three apple producing regions with respect to the orchard areas cultivated in the country. Out of a total of 481 surveyed farmers, the number of farmers having cooperative membership is 208 and of farmers without membership is 273. The members were randomly selected from a list of farmers provided by randomly selected agricultural cooperatives using the information provided by local agricultural bureau in each purposively selected provinces, while the nonmembers were randomly selected in the same region. Information from these households was gathered through pre-tested questionnaire interview. The questionnaire covered a range of topics including socioeconomic and farm level factors, IPM practices, yields, gross income and production costs associated with apple production, off-farm work, income from other on-farm activities , farmers' environmental and health perceptions associated with continuous use of chemical pesticides, as well as asset ownership.

In this study, the first objective aims to analyze the impact of cooperative membership on IPM adoption. However, as noted by Fernandez-cornejo (1996), the development of IPM programs is so different across pest class, crops and regions that it is difficult to provide a general operational definition of IPM. Our operational definition of IPM adoption follows the studies by Fernandez-cornejo (1996) and Dasgupta et al. (2007), who defined IPM adoption as a dichotomous decision. Specifically, a farmer is defined as a IPM adopter: (i) if the farmer reports having used both scouting for pests and economic thresholds in making pest treatment decisions; (ii) if the farmer reports adjusting application rates, time, and frequency of pesticide use; and (iii) if the farmer uses any of the following methods: yellow sticky mobile, fixed traps, insect-trap light, trap band, cardboard traps to target adult, purchasing beneficial insects that prey on insects damaging to the crop. IPM non-adopters refer to those farmers who only depend on pesticides for pest management.[2]

The second objective of this study is to analyze the impact of IPM adoption on apple yields, net

[2] Unlike the findings of lower adoption rates of pesticide reported by Abebaw & Haile (2013) on Ethiopian and Verhofstadt & Maertens (2014) on Rwanda, all apple farmers in our survey used different levels of pesticides (either chemical or biological pesticides, or both).

returns and agricultural income. In particular, apple yields refer to apple yields per mu (1 mu=1/15 hectare). Net returns measure the difference between gross income of apple yields and variable investment costs (including fertilizers, pesticides, bags, irrigation, hired labors and agricultural films) per mu. Agricultural income measures per capita agricultural income. The total agricultural income includes the income from apple production and the income from other farm activities such as raising livestock and growing other crops such as corns, potatoes, pears, peaches, cherries, peanuts, corn, and apricot.

The definitions and descriptive statistics for the variables used in the empirical analysis are presented in Table 3.1. The independent variables were selected based on past studies on determinants of cooperative membership and IPM adoption (e.g., Abebaw & Haile, 2013; Carrión Yaguana et al., 2015; Dasgupta et al., 2007; Verhofstadt & Maertens, 2014). The survey showed that the households with cooperative membership represented 43% of the total sample. The average apple yields and net returns are 2,220 kg/mu and 7540 yuan/mu, respectively. The mean value of agricultural income is 13,460 yuan per capita. Only 21% of households adopted IPM technology, showing a lower adoption rate. The average number of years of schooling of the household head is about 7.6 years. Around 15% of surveyed household heads participated in off-farm work, suggesting agricultural production is the primary profession for most of the farmers. The data also show that about two thirds of households are aware of the negative health effects of chemical pesticide use.

Table 3.1 Definition of variables and descriptive statistics

Variable	Definition	Mean (S.D.)
Dependent variables		
Membership	1 if farmer had agricultural cooperative membership, 0 otherwise)	0.43 (0.50)
IPM adoption	1 if farmer adopted integrated pest management (IPM) technology, 0 otherwise	0.21 (0.41)
Apple yields	Apple output (kg/1,000/mu)[a]	2.22 (8.20)
Net returns	Apple gross revenue minus variable investments costs (yuan/1,1000/mu)[b]	7.54 (3.91)
Agricultural income	Per capita agricultural income (yuan/1000)	13.46 (7.50)
Independent variables		
Age	Age of the household head (years)	48.63 (10.25)

Gender	1 if farmer is male, 0 otherwise	0.86 (0.35)
Education	Formal education of farmer (years)	7.60 (2.87)
Farm size	Total size of fruiting apple orchards (mu)	5.07 (3.24)
Household size	Number of people residing in household	4.33 (1.44)
Off-farm work	1 if farmer participates in non-farm work, 0 otherwise	0.15 (0.36)
Asset ownership	1 If farmer owns farming vehicle, 0 otherwise	0.92 (0.28)
Warehouse	1 if farmer reports there is apple refrigerated warehouse in local areas, 0 otherwise	0.54 (0.50)
Price knowledge	1 if farmer perceives that food produced under food safety standards (i.e. organic food standard, green food standard or pollution-free food standard) may be sold at a higher price than conventional food, 0 otherwise	0.43 (0.50)
Environmental perception	1 if farmer considers continuous use of chemical pesticides as a threat to environmental performance, 0 otherwise	0.47 (0.50)
Health perception	1 if farmer considers continuous use of chemical pesticides as a threat to human health, 0 otherwise	0.55 (0.47)
Gansu	1 if farmer is located in Gansu, 0 otherwise	0.17 (0.37)
Shaanxi	1 if farmer is located in Shaanxi, 0 otherwise	0.40 (0.49)
Shandong	1 if farmer is located in Shandong, 0 otherwise	0.43 (0.50)
PCS perception	1 if farmer perceives that contemporary agricultural cooperative is more effective than people's commune system (PCS), 0 otherwise	0.42 (0.49)
Information availability	The availability of IPM information determines my decision to adopt IPM technology (1=Strongly disagree; 2=general; 3=agree; 4=strongly agree)	2.79 (0.96)
Benefit availability	My tuition tells me that I can benefit from the adoption of IPM technology (1=Strongly disagree; 2=general; 3=agree; 4=strongly agree)	1.95 (0.86)
PCS perception	1 if farmer perceives that contemporary agricultural cooperative is more effective than people's commune system (PCS), 0 otherwise	0.42 (0.49)

[a] 1 mu=1/15 hectare; [b] 1 $=6.14 yuan.

Table 3.2 presents differences in means in the characteristics of cooperative members and nonmembers. In particular, cooperative members are more educated than nonmembers. They have larger farm sizes, and are more likely to own assets such as farming vehicle. Compared with nonmembers, cooperative members are more likely to believe that food produced under organic food standard, green food standard or pollution-free food standard receives higher prices than conventional food.[3] The mean comparisons in Table 3.2 also show that cooperative members and nonmembers are also distinguishable in terms of environmental perception and health perception. In particular, members are more likely to be aware of negative health and environmental effects associated with continuous use of chemical pesticides than nonmembers. With regards to the variable that represents IPM adoption, we find that cooperative members are more likely to adopt IPM technology than nonmembers.

Table 3.2 Mean differences in characteristics between cooperative members and nonmembers

Variables	Members (N=208)	Nonmembers (N=273)	Diff.
Age	48.45 (0.66)	48.78 (0.66)	-0.326
Gender	0.89 (0.02)	0.84 (0.02)	0.051
Education	8.05 (0.17)	7.27 (0.19)	0.781***
Farm size	5.51 (0.24)	4.73 (0.18)	0.778***
Household size	4.57 (0.10)	4.14 (0.08)	0.433***
Off-farm work	0.14 (0.02)	0.16 (0.02)	-0.013
Asset ownership	0.96 (0.01)	0.88 (0.02)	0.079***
Warehouse	0.57 (0.03)	0.52 (0.03)	0.048
Price knowledge	0.50 (0.03)	0.37 (0.03)	0.130***
Environmental perception	0.55 (0.03)	0.41 (0.03)	0.141***
Health perception	0.64 (0.03)	0.48 (0.03)	0.160***
PCS perception	0.60 (0.03)	0.29 (0.03)	0.312***
IPM adoption	0.32 (0.03)	0.13 (0.02)	0.190***

Note: Standard errors in parentheses; *** p<0.01.

[3] In combination with the domestic agricultural practice and food safety situation, the Chinese government proposed three food safety standards that include organic food standard, green food standard and pollution-free food standard (or known as safe food in some literature). In comparison with the unified international standard of organic food, the latter two safer food standards are unique in China. The requirements of these three safer food standards can be found in Yu et al. (2014).

Table 3.3 presents the mean differences in characteristics between IPM adopters and non-adopters. It shows that IPM adopters are younger than non-adopters. IPM adopters are better educated, and have larger farm size and household size, compared with non-adopters. The mean comparisons also indicate that IPM adopters and non-adopters are significantly different with respect to off-farm work participation, price knowledge, environmental perception, and health perception. In relation to outcomes of interest, Table 3.3 shows that apple yields for IPM adopters are significantly lower than that for non-adopters. There is, however, no significant difference in net returns between IPM adopters and non-adopters. With regard to agricultural income, the descriptive analysis in Table 3.3 shows that agricultural income obtained by IPM adopters are significantly higher than that received for non-adopters.

Table 3.3 Mean differences in characteristics between IPM adopters and non-adopters

Variables	IPM adopters (N=108)	Non-adopters (N=378)	Diff.
Age	44.10 (0.88)	49.87 (0.53)	-5.771***
Gender	0.87 (0.03)	0.86 (0.02)	0.017
Education	8.77 (0.27)	7.29 (0.15)	1.479***
Farm size	7.00 (0.34)	4.54 (0.15)	2.460***
Household size	5.05 (0.13)	4.13 (0.07)	0.919***
Off-farm work	0.29 (0.04)	0.11 (0.02)	0.178***
Asset ownership	0.95 (0.02)	0.91 (0.01)	0.044
Warehouse	0.71 (0.04)	0.35 (0.02)	0.360***
Price knowledge	0.70 (0.05)	0.50 (0.03)	0.196***
Environmental perception	0.80 (0.04)	0.38 (0.02)	0.418***
Health perception	0.84 (0.04)	0.47 (0.03)	0.376***
Information availability	3.06 (0.08)	2.71 (0.05)	0.344***
Benefit availability	2.35 (0.09)	1.84 (0.04)	0.514***
Apple yields	1.93 (0.08)	2.24 (0.04)	-0.306***
Net returns	7.15 (0.39)	7.65 (0.20)	-0.494
Agricultural income	15.38 (0.86)	12.94 (0.36)	2.441***

Note: Standard errors in parentheses; *** $p<0.01$.

Overall, the descriptive statistics presented in Tables 3.2 and 3.3 show that cooperative members and nonmembers, IPM adopters and non-adopters are systematically different in observed household and farm level characteristics. However, given that farmers choose to join agricultural cooperatives themselves, the differences in IPM adoption between cooperatives members and nonmembers presented in Table 3.2 are inconclusive to understand the impact of IPM adoption on IPM adoption. Similarly, due to farmers self-select into IPM programs, the differences in apple yields, net returns and agricultural income between IPM adopters and non-adopters presented in Table 3.3 are also not sufficient to help understand the impact of IPM adoption on farm outcomes of interest. Thus, rigorous impact evaluation methods including ESP model and a treatment effects model are respectively employed to estimate the true effect of cooperative membership on IPM adoption, as well as the effect of IPM adoption on apple yields, net returns and agricultural income.

3.5 Results and Discussion

3.5.1 Results of ESP Model Estimation

The ESP estimation results for the IPM adoption equations of cooperative members and nonmembers are shown in the third and fourth columns of Table 3.4. The coefficient estimates for the cooperative member and nonmember regimes differ notably with respect to some of the variables, indicating that ESP model is preferred over a RBP model. The estimates of the residuals of the off-farm work variable, derived from the first-stage regression of off-farm work, are not significantly different from zero in IPM adoption specifications for cooperative members and nonmembers, suggesting that there is no simultaneity bias and the coefficients are consistently estimated (Wooldridge, 2002). The finding confirms the exogeneity of off-farm participation in IPM adoption equations.

The results in Table 3.4 show that age is an important factor in explaining lower probability of adopting IPM technology among cooperative members. This is possibly because that older farmers are more used to traditional methods for pest management rather than learning the knowledge-intensive IPM technology. The negative and significant coefficient of gender variable for nonmembers suggests that male nonmembers are less likely to adopt IPM technology. The education variable shows a positive and statistically significant effect on the probabilities of IPM adoption for both cooperative members and nonmembers, suggesting that well-educated farmers are more likely to adopt IPM technology. Good knowledge makes farmers better able to understand the importance and benefits associated with IPM technology. The finding on education is consistent with other empirical studies on the effect of education on adoption of IPM strategies (e.g., Dasgupta et al., 2007; Fernandez-Cornejo, 1998). The estimates reveal that farm size has a positive and significant impact on the probability of adopting IPM technology for cooperative members, but a negative and insignificant effect on

IPM adoption for nonmembers. Larger farm size may help members obtain higher benefit from IPM adoption, contributing to a higher likelihood of IPM adoption. However, IPM adoption may involve risks such as productivity loss for nonmembers in the absence of technical assistance, resulting in decreasing adoption likelihood with increasing farm size for this group of farmers. The variable representing household size has a positive and significant effect on IPM adoption for members, suggesting that larger households with potentially more labor supply are more likely to adopt labor-intensive IPM technology under the cooperatives' guidance.

The coefficients of the variable representing off-farm work are positive for both cooperative members and nonmembers, but only statistically significant for nonmembers. The positive and significant impact is consistent with the income effect of off-farm work participation, since off-farm earnings help farmers overcome credit and insurance market constraints by providing liquidity for the purchase of equipment such as fixed traps, insect-trap light, and yellow stick mobile for IPM technology. However, the finding contradicts with the result reported by Shi et al. (2011), who found that income effect of off-farm work participation cannot compensate for the lost-labor effect, contributing to a negative relationship between off-farm work participation and the levels of chemical input use in rice production in Jiangxi Province of China. Ownership of assets such as farming vehicle and the availability of apple refrigerated warehouse appears to increase the probability of IPM adoption for cooperative members. The positive and significant coefficients of price knowledge variable for cooperative members and nonmembers suggest that farmers who perceive that food produced under food safety standards obtains a higher price than conventional food are more likely to adopt IPM technology. To the extent that IPM adoption improves food safety due to the reduction of chemical pesticide use, the high quality product is expected to obtain favorable price (Moustier et al., 2010; Naziri et al., 2014).

The coefficients of environmental perception variable are positive and statistically significant, suggesting that farmers who are aware of pesticide pollution on the environment are more likely to adopt IPM technology. Cooperative members with health perception associated with chemical pesticide use tend to have a higher probability of adopting IPM technology. The finding supports the study by Dasgupta et al. (2007) who found that farmers who attribute their poor health to pesticide use may be more likely to adopt IPM, since IPM adoption may well improve health. The results in Table 3.4 also reveal that location fixed effects may be significant in explaining differences in IPM adoption. In particular, nonmembers located in Shaanxi are more likely to adopt IPM technology. The significance of location variable reflects variation in cropping systems, temperature, humidity and regional pest populations in determining farmers' decisions to adopt IPM technology.

Table 3.4 Determinants of cooperative membership and determinants of IPM adoption: ESP model estimation

		IPM adoption	
Variable	Selection	Members	Nonmembers
Constant	-2.903 (0.601)***	-7.998 (2.846)***	-4.187 (1.136)***
Age	0.003 (0.007)	-0.042 (0.017)**	0.012 (0.015)
Gender	0.150 (0.190)	0.624 (0.432)	-0.914 (0.298)***
Education	0.053 (0.027)**	0.196 (0.074)***	0.137 (0.056)**
Farm size	0.063 (0.028)**	0.140 (0.051)***	-0.064 (0.041)
Household size	0.173 (0.052)***	0.291 (0.126)**	-0.003 (0.106)
Off-farm work	-0.146 (0.180)	2.847 (2.076)	1.535 (0.667)**
Asset ownership	0.683 (0.258)***	1.280 (0.695)*	0.026 (0.318)
Warehouse	0.150 (0.131)	0.679 (0.333)**	0.292 (0.243)
Price knowledge	0.325 (0.143)**	0.884 (0.301)***	0.547 (0.271)**
Environmental perception	0.269 (0.136)**	0.914 (0.480)*	0.643 (0.251)**
Health perception	0.226 (0.135)*	1.934 (0.666)***	0.242 (0.211)
Shaanxi	-0.953 (0.238)***	0.483 (0.777)	1.485 (0.522)***
Gansu	-0.251 (0.256)	0.909 (0.711)	0.422 (0.538)
Residual (off-farm work)		0.471 (0.690)	-0.039 (0.197)
PCS perception	0.736 (0.130)***		
ρ_1		-0.166 (0.518)	
ρ_0			-0.909 (0.107)***
Log pseudolikelihood	-382.374		
Wald test of indep. eqns. ($\rho_1 = \rho_0$)	Chi2 (2)=7.36, Prob>chi2=0.025		
Observations	481	481	481

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

The results presented in the second column of Table 3.4 generally show that education, farm size, household size, asset ownership, price knowledge, environmental perception and health perception are important factors that influence farmers' decisions to choose cooperative membership. Note that the primary objective of the selection equation in ESP model is not to perfectly explain the determinants of cooperative membership, but to account for unobserved heterogeneity that could bias the treatment effects of cooperative membership on IPM adoption. For this purpose, the selection equation needs to include at least one valid instrument, which should be excluded in IPM adoption equations. As noted by Lokshin & Sajaia (2011), missing instrumental variable in the selection equation may make the ESP model be identified by nonlinearities.

In this study, a variable representing a farmer's perception whether contemporary agricultural cooperative is more effective than people's commune system (PCS) is used as the instrument. PCS was a collective farming regime that was practiced between 1958 and 1984, which resulted in stagnation of agricultural production. Ito et al. (2012) found that farmers who were perceived as having been influenced by an image of the PCS when making the participation decisions are significantly less likely to choose cooperative membership. Thus, the perception variable is expected to significantly influence farmers' decisions to choose cooperative membership. Particularly, we expect that farmers who perceive the effectiveness of contemporary agricultural cooperatives are more likely to join cooperatives. To test the validity of the perception variable as an instrument, we run simple probit models for the cooperative membership choice equation and the IPM adoption equation with inclusive of the instrumental variable as a regressor. The results, which are not presented for the sake of brevity, show that the coefficient of the perception variable is positive and significant in the cooperative membership choice specification, but statistically insignificant in IPM adoption specification. Furthermore, Pearson correlation analysis also reveals that the perception variable is significantly correlated with the cooperative membership variable, but uncorrelated with IPM adoption variable. The findings confirm the validity of the perception variable as an instrument.

In the lower part of Table 3.4, we present the estimates of correlation coefficients (ρ_0 and ρ_1) of covariance terms between the error term in equation (3.7) and the error terms in the outcome equations (3.8a) and (3.8b). The significance of ρ_0 confirms the presence of selection bias arising from unobservable factors, suggesting that addressing the self-selection bias issue by accounting for both observable and unobservable factors is a prerequisite for obtaining consistent and unbiased treatment effect of cooperative membership on IPM adoption. Of particular interest here is the negative coefficient of ρ_1, which measures the correlation between the error terms of the selection equation and the outcome equation for the cooperative members. It clearly indicates negative selection bias, implying that farmers with lower probabilities of adopting IPM technology are more likely to join cooperatives (Ayuya et al., 2015; Gregory & Coleman-Jensen, 2013). Moreover, the results also show that the Wald test of the joint significance of the correlation coefficient rejects the null hypothesis that there is no correlation between cooperative membership choice equation and IPM adoption equation, indicating that it is more efficient to use the ESP model than a simple probit model.

Table 3.5 Average treatment effects of cooperative membership on IPM adoption

Category	ATT	*t*-value [a]	ATU	*t*-value [b]
Full sample	0.30 (0.02)***	11.93	0.10 (0.01)***	6.60
Gansu	0.51 (0.05)***	9.61	0.19 (0.05)***	3.81
Shaanxi	0.39 (0.04)***	9.46	0.09 (0.02)***	3.96
Shandong	0.13 (0.03)***	4.31	0.07 (0.02)***	3.89

Note: Standard errors in parentheses; *** $p<0.01$

[a] and [b]: *t*-values are calculated based on the immediate form of the *ttest* command in Stata 13.1.

We now use the estimated coefficients from the ESP model in combination with equations (3.10a) and (3.10b) to calculate the average treatment effects (ATT and ATU) of cooperative membership on IPM adoption. The results are presented in Table 3.5. Unlike the mean values predicted in Table 3.2, these ATT and ATU estimates account for selection bias arising from both observable and unobservable factors. Specifically, the ATT estimate shows that the causal effect of cooperative membership was to significantly increase the probability of adopting IPM technology by 30%. The ATU estimate in Table 3.5 is also statistically significant, which suggests that farmers without cooperative membership would be 10% more likely to adopt IPM technology if they were involved in cooperative organizations.

To gain further understanding of the impact of cooperative membership on IPM adoption, we also present in Table 3.5 the ATT and ATU estimates based on surveyed regions. The results generally show that the causal effects of cooperative membership were to increase the probabilities of adopting IPM technology, and agricultural cooperative in Gansu plays the largest effect. In particular, cooperative members in Gansu are 51% more likely to adopt IPM technology. Overall, the findings of positive relationship between cooperative membership and IPM adoption in Table 3.5 are consistent with our theoretical model, suggesting that agricultural cooperative can be a transmission route in the efforts to spread IPM technology that may contribute to the improvements of food safety, health and environmental performance.

3.5.2 Results of Treatment Effects Model Estimation

The empirical results of the impact of IPM adoption on farm economic performance indicators such as apple yields, net returns and agricultural income are presented in Table 3.6. As indicated previously, treatment effects model was employed to jointly estimate the IPM adoption equation and three farm performance equations, respectively.

The lower parts of Table 3.6 show that the estimates of the correlation coefficients $\rho_{\delta\varpi}$ in Models 1-3 are significantly different from zero, suggesting the precence of selection bias due to unobservable factors. In particular, the negative correlation coefficients $\rho_{\delta\varpi}$ indicate negative selection bias. This would suggest that farmers having lower than average apple yields, net returns and agricultural income have higher probabilities of adopting IPM technology. In other words, farmers who expect that IPM adoption may improve the efficiency of pest management and save production costs are more likely to be IPM adopters, since the improvement of pest management efficiency may contribute to increased yields and the reduction of investment costs is closely associated with higher net returns and agricultural income. Thus, failing to account for such negative selection bias would lead to underestimated effects of IPM adoption on apple yields, net returns and agricultural income, and treatment effects model is preferred than other approaches such as propensity score matching or OLS regression. The results of the Wald tests for $\rho_{\delta\varpi} = 0$ in Models 1-3 are significantly different from zero, suggesting that the null hypothesis that the IPM adoption variable is exogenous in three farm performance equations can be rejected.

The results from the first-stage estimates of the treatment effects model, which show the determinants of farmers' decisions to adopt IPM technology, are presented in the second, fourth and sixth columns in Table 3.6. Given that the primary objective of IPM adoption equation estimation is to account for unobserved heterogeneities that may bias the impact of IPM adoption on apple yields, net returns and agricultural income, detailed interpretation of the results are not provided here. The statistically insignificant coefficients of the off-farm work residual variables in Models 1 to 3 in Table 3.6 also confirm the exogeneity of off-farm participation in IPM adoption equations (Wooldridge, 2002).

Table 3.6 Impact of IPM adoption on apple yields, net returns and agricultural income: Treatment effects model estimation

	Model 1		Model 2		Model 3	
Variable	IPM adoption	Apple yields	IPM adoption	Net returns	IPM adoption	Agricultural income
IPM adoption		0.154 (0.091)*		0.272 (0.104)***		0.222 (0.128)*
Age	0.006 (0.013)	-0.003 (0.002)	0.006 (0.012)	-0.008 (0.003)***	0.012 (0.013)	-0.007 (0.002)***
Gender	-0.207 (0.277)	0.086 (0.045)*	-0.214 (0.276)	0.130 (0.067)*	-0.204 (0.268)	0.129 (0.067)*
Education	0.156 (0.048)***	-0.006 (0.006)	0.150 (0.047)***	-0.007 (0.010)	0.149 (0.048)***	-0.004 (0.009)
Farm size	0.069 (0.032)**	-0.055 (0.006)***	0.066 (0.031)**	-0.055 (0.010)***	0.040 (0.036)	0.127 (0.008)***
Household size	0.089 (0.094)	0.032 (0.011)***	0.102 (0.084)	0.019 (0.019)	0.110 (0.088)	-0.187 (0.017)***
Off-farm work	1.803 (0.624)***	-0.165 (0.051)***	1.952 (0.579)***	-0.293 (0.073)***	1.931 (0.576)***	-0.116 (0.066)*
Asset ownership	0.730 (0.319)**	0.055 (0.052)	0.721 (0.330)**	0.117 (0.082)	0.735 (0.326)**	0.052 (0.076)
Warehouse	0.729 (0.188)***	0.048 (0.035)	0.748 (0.179)***	0.062 (0.055)	0.682 (0.188)***	0.072 (0.048)
Price knowledge	0.627 (0.180)***	0.091 (0.031)***	0.635 (0.179)***	0.204 (0.049)***	0.592 (0.177)***	0.119 (0.045)***
Environmental perception	0.904 (0.219)***	-0.083 (0.035)**	0.903 (0.214)***	-0.083 (0.057)	0.957 (0.205)***	-0.064 (0.049)
Health perception	0.677 (0.211)***	-0.012 (0.032)	0.675 (0.205)***	-0.017 (0.053)	0.685 (0.206)***	0.075 (0.045)*
Shaanxi	0.611 (0.419)	-0.210 (0.054)***	0.654 (0.403)	-0.214 (0.094)**	0.818 (0.421)*	-0.245 (0.070)***
Gansu	0.728 (0.398)*	-0.290 (0.058)***	0.770 (0.393)*	0.118 (0.094)	0.831 (0.385)**	-0.100 (0.079)
Residual (off-farm work)	0.087 (0.195)		0.034 (0.173)		0.057 (0.186)	
Information availability	0.284 (0.100)***		0.291 (0.0968)***		0.287 (0.095)***	
Benefit availability	0.238 (0.127)*		0.253 (0.116)**		0.208 (0.111)*	
Constant	-7.574 (1.094)***	7.942 (0.153)***	-7.690 (1.097)***	9.175 (0.228)***	-7.795 (1.034)***	9.721 (0.196)***
$\rho_{\delta\varpi}$	-0.333 (0.173)*		-0.455 (0.107)***		-0.511 (0.174)***	
$\mathrm{Ln}(\sigma_{\delta\varpi})$	-1.195 (0.034)***		-0.703 (0.037)***		-0.880 (0.047)	
Wald test ($\rho_{\delta\varpi} = 0$)	chi2(1) =3.17, Prob > chi2 = 0.075		chi2(1) =13.15, Prob > chi2 = 0.000		chi2(1) =5.73, Prob > chi2 = 0.017	
Observations	481		481		481	

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; The reference region is Shandong;

The dependent variables in the second-stage estimation of treatment effects model include log form of apple yields measured in kg/mu in Model 1, log form of net returns from apple production measured in yuan/mu in Model 2, and log form of agricultural income measured in yuan/capita in Model 3.

Focusing on the variable of primary interest, IPM adoption, controlling for selection bias arising from observable and unobservable factors has positive and statistically significant impacts on apple yields, net returns and agricultural income. Such effects could not be observed when only comparing descriptive statistics between IPM adopters and non-adopters, due to the mentioned negative selection bias. The findings of positive impact of IPM adoption on apple yields and net returns are consistent with the finding by Fernandez-Cornejo (1998) who found that IPM adoption for diseases significantly increases yields and profits for grape growers in the United States. Dasgupta et al. (2007) also found that IPM rice farming is more profitable than conventional rice farming, while there is no significant productivity difference between IPM and conventional rice farming.

Among other variables in Table 3.6, the coefficients of variables representing gender and price knowledge are positive and statistically significant in Models 1-3, suggesting that apple yields, net returns and agricultural income are higher for male farmers and the farmers who perceive that food produced under food safety standards obtain higher prices than conventional food, compared with their counterparts. The results also reveal that household size tends to increase apple yields, and farm size and health perception tend to increase agricultural income. The significance of location variables suggests that farmers located in Shaanxi and Gansu tend to have lower apple yields, while farmers located in Shaanxi have lower net returns.

For model identification, treatment effects model requires the inclusion of valid instrumental variables. In this study, two variables including information availability and benefit availability are used in the analysis. The validity of the employed instrumental variables are tested using the approaches mentioned in ESP model. As shown in Table 3.6, information availability and benefit availability variables are significantly different from zero, suggesting that information acquisition and benefits associated with IPM technology play important roles in determining farmers' decisions to adopt the technology.

3.6 Conclusion and Policy Implications

Although IPM technology is promoted as a preferred approach for both sustainable intensification of crop production and pesticide risk reduction, its adoption rate remains low in China. There is still a need to facilitate the adoption of the technology. While recent studies have shown that agricultural cooperative is an efficient institutional innovation that enhances farmers' adoption of agricultural technologies, there is hardly any work that has looked at the question whether agricultural cooperatives can promote IPM adoption. In this paper, we have addressed the research gap by analyzing the impact of cooperative membership on IPM adoption. We employed an endogenous switching probit model that accounts for sample selection bias and structural differences between cooperative members and nonmembers to analyze the adoption behaviors of 481 apple farmers in China. To further understand how IPM adoption influences the economic performance of farm households, we also employed a treatment effects model to analyze the impact of IPM adoption on apple yields, net returns and agricultural income.

The empirical results did suggest the presence of selection bias arising from unobserved heterogeneities. After controlling for this bias, the ATT estimate showed that the causal effect of cooperative membership was to increase the probability of IPM adoption by 30%. On the other hand, the positive and significant ATU suggested that farmers without cooperative membership would be 10% more likely to adopt IPM technology if joined cooperatives. The empirical finding is generally consistent with our theoretical finding that it is optimal for cooperative members to adopt IPM technology to maximize the expected profit. Overall, our results suggest that agricultural cooperative could be an important transmission route in the government's efforts of spreading IPM technology.

The ESP estimates also provide a better understanding of the factors that influence farmers' decisions to join cooperatives and adopt IPM technology. In particular, the results showed that farmers' cooperative membership choice decisions are driven primarily by farmers' education, farm size, household size, asset ownership, price knowledge, environmental perception and health perception. With respect to IPM adoption, the results showed that cooperative members' decisions to adopt IPM technology are influenced by education, farm size, household size, asset ownership, price knowledge, the establishment of refrigerated warehouse, environmental and health perceptions, while IPM adoption decisions of nonmembers are influenced by education, off-farm work, price knowledge and environmental perception.

With respect to the relationship between IPM adoption and farm outcomes (apple yields, net returns and agricultural income), the simple mean value comparisons revealed apple yields of IPM adopters were significantly lower than that of non-adopters, and there was no significant difference in net returns between these two groups of farmers. However, econometric estimation with a treatment effects model revealed negative selection bias, implying that farmers with lower than average apple yields, net returns and agricultural income are more likely to adopt IPM technology. Controlling for this bias resulted in positive and significant impacts of IPM adoption on apple yields, net returns and agricultural income.

Generally, the empirical results presented in this paper support the notion that membership in agricultural cooperatives can play a positive role by serving as a catalyst for spreading IPM technology. The finding that price knowledge tends to influence farmers' decisions to join cooperatives and adopt IPM technology suggests that the enhancement of farmers' price knowledge about food produced under organic food standard, green food standard and pollution-free food standard and the establishment of food safety markets would step up the promotion of farmers' decisions to join cooperatives and adopt IPM technology. In particular, the Chinese government should continue to encourage the adoption of food safety and quality standards by agricultural cooperatives and enhance market mechanism of high price for high quality products. The positive and significant impacts of environmental perception on IPM adoption suggest that promoting effective measures to improve farmers' understanding of negative environmental effects associated with continuous use of chemical pesticides would help increase farmers' adoption of IPM technology. This could be achieved through cooperatives' collective activities. Finally, the positive impact of IPM adoption on apple yields, net returns and agricultural income underscores the importance of efforts by policy makers to promote IPM adoption through agricultural cooperative.

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Chapter 4 Does Cooperative Membership Improve Household Welfare? Evidence from Apple Farmers in China

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Abstract

This paper examines the impact of cooperative membership on farm performance indicators such as apple yields, net returns and household income, using cross-sectional data from a survey of farmers in China. An endogenous switching regression model that accounts for selection bias is employed in the analysis. The empirical results reveal that cooperative membership exerts a positive and statistically significant impact on apple yields, farm net returns and household income. A disaggregated analysis also reveals that small-scale farms tend to benefit more from cooperatives than medium and large farms.

Keywords: Agricultural cooperatives; Impact assessment; Apple farmers; China

4.1 Introduction

The emergence of agricultural cooperatives is widely viewed as an important institutional arrangement that can help overcome the constraints that impede smallholders in developing countries from taking advantages of agricultural production and marketing opportunities (World Bank 2006). For instance, they can strengthen farmers' negotiation abilities in the markets to gain more competitive prices for both inputs and outputs, reduce transaction costs and information asymmetry, and improve agro-food safety and quality standards (Hellin et al. 2009; Holloway et al. 2000; Jia et al. 2012; Markelova et al. 2009; Moustier et al. 2010; Trebbin 2014; Valentinov 2007). Given its significance in enhancing agricultural growth, the promotion of agricultural cooperatives has increasingly attracted attention of donors, governments and researchers in developing countries (Abebaw and Haile 2013; Deng et al. 2010).

The Chinese government has made efforts to accelerate the systematic promotion of agricultural cooperatives through financial and policy support. One of such efforts in the promulgation of the Law of Farmers' Professional Cooperatives in 2007, with the aim of developing sustainable cooperatives. Despite the efforts made by the government, the Ministry of Agriculture in China reported that only 25.2% of farm households were involved in agricultural cooperatives in the country in 2013. This is partly because of the high transaction costs involved in contracting with small-scale farmers in the villages, resulting in the absence of agricultural cooperatives in many villages (Deng et al. 2010; Francesconi and Wouterse 2015; Ito et al. 2012).

Several studies have shown that agricultural cooperatives influence the adoption of improved agricultural technology by farmers and household welfare (e.g., Abebaw and Haile 2013; Fischer and Qaim 2012; Francesconi and Heerink 2011; Ito et al. 2012; Verhofstadt and Maertens 2014a, 2014b). In their study on Ethiopia, Abebaw and Haile (2013) find that cooperative membership exerts a positive and significant impact on fertilizer adoption, while a recent study by Verhofstadt and Maertens (2014a) on Rwanda finds a positive and significant effect of cooperative membership on the likelihood of using improved seeds, mineral fertilizer and pesticide. The study by Ito et al. (2012) shows that cooperative membership exerts a positive and significant effect on farm income of watermelon farmers in China. In examining the impact of cooperative membership, most of the studies have employed propensity score matching (hereinafter, PSM) technique to account for selection bias (Abebaw and Haile 2013; Bernard et al. 2008; Fischer and Qaim 2012; Ito et al. 2012; Verhofstadt and Maertens 2014a). For example, in the recent study on Rwanda, Verhofstadt and Maertens (2014b) employ the

PSM approach to examine the impact of cooperative membership on farmers' welfare, measured by farm income and poverty incidence, and find that agricultural cooperatives are effective in improving rural incomes and reducing rural poverty. However, a well-known shortcoming of PSM method is its inability to account for unobservable factors such as innate skills and risk perception, which may result in biased estimates.

This paper aims to contribute to the growing literature on the role of agricultural cooperatives by identifying the factors that influence farmers' decisions to join cooperatives, as well as estimating the impact of cooperative membership on crop yields, net returns and household income. The study employs recent survey data of 481 apple farmers in Gansu, Shaanxi and Shandong provinces of China for empirical analysis.

We model farmers' choice of cooperative membership as a selection process, where the expected higher net returns to the cooperatives drive farmers' decisions of choosing to belong to agricultural cooperatives. This study employs an endogenous switching regression approach to account for selection bias (Lokshin and Sajaia 2004). This approach allows us to analyze both the determinants of cooperative membership and the impact of membership on farm performance indicators such as apple yields, net returns, as well as household income, separately for members and nonmembers.

The remainder of the study is structured as follows: The next section gives an overview of the apple sector and agricultural cooperatives in China. Section 4.3 presents the data and corresponding descriptive statistics. Section 4.4 outlines the empirical specifications employed in the analysis. The empirical results and discussions are presented in section 4.5. The final section provides conclusion and policy implications.

4.2 Overview of Apple Sector and Agricultural Cooperatives in China

China is the world's largest apple producing country, recording a total of 38.49 million MT (49.67% of the world's total) in 2012, followed by the United States and Turkey, who produced 4.11 and 2.89 million MT, respectively (FAOSTAT). Apple production in China is mainly in its Bohai Gulf region (Shandong, Liaoning and Hebei provinces) and Northwest Loess Plateau region (Shaanxi, Shanxi, Henan and Gansu provinces). In particular, Gansu, Shaanxi and Shandong provinces cover more than half of the country's total apple orchards, accounting for 54.17% of total production in 2012. These three provinces are characterized by hilly and mountainous lands, and endowed with suitable soil and weather conditions for top quality apple production.

Gansu, Shaanxi and Shandong have obvious differences in terms of agro-climates and agro-food market environments, although they have better conditions for apple production over other areas in China. Shandong is a coastal province with favorable annual rainfall and well developed infrastructure for exports. Farmers in this province also produce other crops like pears, peaches, cherries, peanuts, corn, and apricot as cash sources, which they sell to international markets. In contrast, Gansu and Shaanxi are inland provinces that are characterized by low rainfall and poor infrastructure (e.g., road and telecommunication). As a result, the farmers there only grow corn and potatoes as extra income sources, or for household consumption, and apple output is mostly for domestic sales.

Despite being the highest apple producing country, China faces constraints on the world markets, with only about 3% of apples produced finding their way into international markets (FAOSTAT). The primary reason is the difficulty in meeting food safety and quality standards, since farmers use large quantities of agro-chemicals in the production process. Moreover, farmers engaged in apple production and marketing are severely constrained by high transaction costs and information asymmetry, particularly those living in remote areas.

Given the constraints facing apple production and marketing in China, the government has strived to facilitate the development of agricultural cooperatives in the apple sector. As a new institutional innovation, agricultural cooperatives are expected to enhance its members' access to modern supply chains, promote the adoption of new technologies, help lower production and marketing costs, as well as raise farmers' incomes (Zheng et al. 2012). The cooperative organizations take on responsibilities for providing production technologies and/or marketing information to its members. In exchange for their role in enhancing agricultural performance, these agricultural cooperatives receive support and subsidies from the government. The production technologies promoted by cooperatives include orchard management approaches (e.g., pruning, branch drawing), efficient use of inputs (e.g., fertilizer and pesticide), quality control, and pest management. In addition, cooperatives provide some services by collectively purchasing inputs for its members at reasonable prices. The typical marketing services include provision of information with respect to prices and access to marketing channels, aimed at enhancing smallholders' output market participation. The service provision of agricultural cooperatives differs across regions. For instance, in Gansu and Shaanxi provinces, apple cooperatives are mainly providing production services to its members, with limited services on farm produce distribution. In contrast, cooperatives in Shandong province provide both technical guidance and distribution services.

4.3 Data and Descriptive Statistics

The data used in the study come from a farm household survey that was conducted from September to December 2013 in China. A multistage sampling procedure was used for the selection of observation units. First, Gansu, Shaanxi and Shandong provinces were purposively selected based on the national intensity of apple production. In a second stage, four county-level districts where apples are intensively produced at the provincial level were chosen. These include Jingning county in Gansu, Luochuan county in Shaanxi, and Qixia and Laiyang cities in Shanong.[1] Third, six agricultural cooperatives were randomly selected from those districts, using information provided by the local agricultural bureau. Fourth, three villages affiliated to each cooperative in the selected district were randomly selected.[2] Finally, around 25-30 households including both cooperative members and nonmembers in each village were randomly selected, resulting in a total of 481 households. The data collected include information on apple production and marketing (e.g., input use, costs, yields, and output price), household income, as well as household and farm-level characteristics (e.g., age, education, farm size, and asset ownership).

Table 4.1 presents the definition and summary statistics of the variables used in the analysis. The dependent variable used in the study is a dummy variable that takes the value of one, if the household belonged to an agricultural cooperative, and the value zero, if no cooperative membership was recorded. The outcome variables used in the study are apple yields, net returns, and household income. Net returns are measured as the difference between the value of apple yields and variable input costs per mu. The inputs included fertilizer, pesticide, hired labor, bags, irrigation and films for land moisture conservation and apple coloring. It can be observed from the Table 4.1 that about 43% of households in the sample belong to agricultural cooperatives. The average age of farmers is almost 49 years. The average farm size is 5.07 mu,

[1] Qixia and Laiyang are county-level cities that belong to Yantai city, according to administrative division in China.

[2] In China, village is the basic administrative unit, and there are cooperatives who organize farmers in more than one village, especially those with certain scale and who are well operated.

showing that the majority of households are small-scale apple producers. The average household includes 4-5 household members.

Table 4.1 Definition and summary statistics of selected variables

Variable	Description	Mean	S.D.
Membership	1 If farmer belonged to a cooperative, 0 otherwise	0.43	0.50
Apple yields	Apple output (kg/mu[a])	2,218.46	820.29
Net returns	Apple gross revenue minus variable costs (yuan[b]/mu)	7,540.34	3,911.82
HH incomes	Annual household income per capita (yuan)	15,884.81	8,566.27
Age	Age of household head (years)	48.63	10.25
Education	Farmer’s maximal education level (years)	7.60	2.87
Household size	Number of people residing in household	4.33	1.44
Labor	Labor use (labor days/mu)	101.26	42.95
Farm size	Total fruiting apple orchards (mu)	5.07	3.24
Computer	1 If farmer owns computer, 0 otherwise	0.32	0.47
Extension contact	1 If farmer visited government extension service, 0 otherwise	0.38	0.49
Access to credit	1 If farmer is not liquidity constrained, 0 otherwise	0.53	0.50
Sandy soil	1 if orchard land has sandy soil, 0 otherwise	0.38	0.49
Clay soil	1 if orchard land has clay soil, 0 otherwise	0.45	0.50
Loam soil	1 if orchard land has loam soil, 0 otherwise	0.17	0.37
Gansu	1 If farmer is located in Gansu province, 0 otherwise	0.17	0.37
Shaanxi	1 If farmer is located in Shaanxi Province, 0 otherwise	0.40	0.49
Shandong	1 If farmer is located in Shandong province, 0 otherwise	0.43	0.50
Neighbor membership	1 if any neighbor has cooperative membership, 0 otherwise	0.33	0.47

[a] 1 mu=1/15 hectare;

[b] yuan is Chinese currency unit ($1=6.14 yuan).

The mean differences in the characteristics of cooperative members and nonmembers are presented in Table 4.2. Cooperative members tend to be better educated than nonmembers. They have larger household size and farm size. Particularly, members have larger probability to own computer, which represents wealth and convenience of access to production and marketing information. Cooperative members tend to have a stronger link with the government extension agents, compared to nonmembers. Other household and farm-level characteristics such as household's age and access to credit hardly differ between members and nonmembers.

Table 4.2 Mean differences in characteristics between cooperative members and nonmembers

Variables	Members	Nonmembers	Diff.
Age	48.45 (0.66)	48.78 (0.66)	-0.33
Education	8.05 (0.17)	7.27 (0.19)	0.78***
Household size	4.57 (0.10)	4.14 (0.08)	0.43***
Farm size	5.51 (0.24)	4.73 (0.18)	0.78***
Computer	0.38 (0.03)	0.27 (0.03)	0.11**
Extension contact	0.50 (0.03)	0.29 (0.03)	0.21***
Access to credit	0.57 (0.03)	0.51 (0.03)	0.07
Sandy soil	0.44 (0.03)	0.34 (0.03)	0.09**
Clay soil	0.37 (0.03)	0.51 (0.03)	-0.14***
Loam soil	0.20 (0.02)	0.15 (0.03)	0.05
Neighbor membership	0.56 (0.03)	0.16 (0.02)	0.40***
Labor (days/mu)	105.58 (3.05)	97.98 (2.54)	7.61*
Apple yields (kg/mu)	2310.81 (64.07)	2148.10 (43.90)	162.71***
Net returns (yuan/mu)	8654.38 (301.88)	6691.55 (199.87)	1962.84***
Household income (yuan/capita)	17538.88 (620.79)	14624.57 (487.22)	2914.31***

Note: Standard deviations in parentheses;
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Differences in apple yields, net returns from apple production and household income between members and nonmembers are presented in the lower part of Table 4.2. As evident from the Table, the average apple yield for members is 162.71 kg/mu higher than that of nonmembers, which is statistically significant in mean difference. Moreover, the average net returns per mu and per capita household income are both significantly higher for members. These descriptive comparisons seem to suggest that agricultural cooperatives play a significant role in enhancing agricultural productivity and welfare of members, relative to nonmembers. However, the findings in Table 4.2 cannot be used to make inferences regarding the impact of cooperative membership on apple yields, net returns and household income, as the simple comparison of mean differences does not account for confounding factors such as observed household and farm-level characteristics (e.g., age, education, farm size, and asset ownership) and unobserved factors (e.g., farmers' innate skills, risk perception and motivations of membership choice).

4.4 Empirical Specifications

4.4.1 The Choice of Cooperative Membership

The conceptual framework employed here is based on the assumption that apple farmers choose to belong and not to belong to an agricultural cooperative. We assume here that farmers are risk neutral, and take into account the potential net returns (D_M^*) derived from apple production from belonging to an agricultural cooperative and the expected net returns (D_N^*) derived from not belonging. If we define the difference between the expected net returns from joining a cooperative and not joining as D_i^*, that is $D_i^* = D_M^* - D_N^*$, then a farmer would choose to belong to a cooperative if $D_i^* > 0$. However, D_i^* cannot be observed, but can be expressed as a function of observable elements in the following latent variable model:

$$D_i^* = Z_i\beta + \mu_i, \quad D_i = 1 \ \ if \ D_i^* > 0 \tag{4.1}$$

where D_i is a binary indicator variable that equals 1 for household i, in case of membership in an agricultural cooperative and 0 otherwise; Z_i is a vector of household and farm-level characteristics such as age, education, farm size and household size; β is a vector of parameters to be estimated; and μ_i is an error term assumed to be normally distributed with zero mean. The probability of being a member of an agricultural cooperative can be expressed as:

$$\Pr(D_i = 1) = \Pr(D_i^* > 0) = \Pr(\mu_i > -Z_i\beta) = 1 - F(-Z_i\beta) \tag{4.2}$$

where F is the cumulative distribution function for μ_i.

To link the cooperative membership with the potential outcome, we assume that rational farmers maximize net returns (π) from apple production. This can then be expressed as:

$$\pi_{max} = PQ(R, Z) - OR \tag{4.3}$$

where P is apple price and Q is the total apple output; O is a vector of input prices and R is a vector of input variables (e.g., fertilizer, pesticide, and labor); Z is a vector of explanatory variables as defined above. Output Q is described by a well-behaved production function in which $\partial \mathrm{Q}/ \partial \mathrm{R} > 0$ and $\partial^2 \mathrm{Q}/\partial^2 \mathrm{R} < 0$. Net returns can be expressed as a function of inputs and outputs prices, the choice of cooperative membership *D*, and the household and farm-level characteristics as follows:

$$\pi = \pi(P, O, D, Z) \tag{4.4}$$

The first-order condition of the maximization problem of the net returns function (3) yields a reduced-form apple output supply function:

$$Q = Q(P, O, D, Z) \tag{4.5}$$

The specifications in equations (4.4) and (4.5) show that the net returns of apple production (π) and apple yields (Q) are determined by the input and output prices, the choice of cooperative membership, as well as household and farm-level characteristics.

4.4.2 Impact Assessment and Selection Bias

The focus of this study is to analyze the impact of cooperative membership on apple yields, net returns and household income. Considering that the vector of outcome variables (apple yields, net returns or household income) is a linear function of a vector of explanatory variables X_i, we can specify an outcome equation as:

$$Y_i = X_i\alpha + D_i\eta + \varepsilon_i \tag{4.6}$$

where Y_i represents a vector of outcome variables; X_i is a vector of explanatory variables such as household characteristics (e.g., age, education and household size), farm and location characteristics (e.g., farm size), and financial capital and institutional variables (e.g., extension contact and access to credit); D_i is an indicator of cooperative membership dummy as defined above; α and η are parameters to be estimated, and ε_i is a random error term.

In equation (4.6), the choice of cooperative membership is exogenously determined. However, farmers may self-select into cooperatives, depending on their inherent characteristics, rather than being randomly selected. Therefore, ordinary least square (OLS) method might generate biased estimates. Furthermore, unobservable factors may influence the error term μ_i in the selection equation (4.1) and the error term ε_i in the outcome equation (4.6) simultaneously, resulting in a correlation between the two error terms, i.e. $\mathrm{corr}(\mu_i, \varepsilon_i) \neq 0$. Failing to account for such selectivity bias may result in inconsistent estimates. For instance, if farmers, who have lower than average outcomes such as apple yields, net returns or household income, but higher motivations to improve apple quality and safety, are more likely to belong to cooperatives, this may result in negative selection bias and underestimated treatment effects. On the other hand, if farmers who have higher than average outcomes are more likely to belong to a cooperative and their choice of cooperative membership is influenced by the neighbors' membership situation, it may result in positive selection bias and overestimated treatment effects.

In non-experimental research work with survey data, the econometric approach such as PSM method has been widely applied to address the issue of selection bias. However, as indicated earlier, PSM method estimates the treatment effects of cooperative membership accounting for only observed heterogeneities. In this paper, we employ an endogenous switching regression (hereinafter, ESR) model to address the issue of selection bias by accounting for both observed and unobserved heterogeneities (Lokshin and Sajaia 2004; Narayanan 2014; Shiferaw et al. 2014). This approach employs the full information maximum likelihood (FIML) method to estimate one selection and two outcome equations simultaneously.

4.4.3 The ESR Model

The ESR model consists of two stages. The first-stage is a selection equation based on a dichotomous criterion function for the choice of cooperative membership, as shown by equation (4.1). In the second stage, two regime equations for cooperative members and nonmembers can be specified for the outcomes of interest. The model is specified as:

Regime 1: $Y_{iM} = X_i'\beta_{iM} + \varepsilon_{iM} \quad if\ D_i = 1$ (4.7a)

Regime 2: $Y_{iN} = X_i'\beta_{iN} + \varepsilon_{iN} \quad if\ D_i = 0$ (4.7b)

where Y_{iM} and Y_{iN} are outcomes such as apple yields, net returns or household income for cooperative members and nonmembers, respectively; X_i' represents a vector of exogenous variables that may influence the outcomes employed; ε_i is random disturbance term associated with the outcome variables.

While the variables Z_i in equation (4.1) and X_i' are allowed to overlap, proper identification requires at least one variable in Z_i that does not appear in X_i'.[3] Therefore, the selection equation (4.1) is estimated based on all explanatory variables specified in the outcome equations plus one or more instruments. The valid instrument is required to influence farmer's choice of cooperative membership but have no effect on outcomes. In this study, we employ neighbor's membership variable as an identifying instrument, since previous studies have shown that farmers' choice of cooperative membership is positively and significantly influenced by their neighbor's membership (e.g., Ito et al. 2012). However, neighbor's membership is not expected to affect agricultural productivity and incomes. For the validity check of this instrument, we have run simple probit model for selection equation and OLS regression for outcome equations separately and we have checked that this variable is, in effect, significant when included in the cooperative membership choice equation but not significant when included in the outcome equations. A further test of correlation analysis also reveals that the selected instrument is uncorrelated with apple yields, net returns and household income, respectively, suggesting the validity of the instrument.

The variable X_i' in specifications (4.7a) and (4.7b) takes into account observable factors to address the issue of selection bias. However, unobservable factors could still create a correlation between the error terms in the selection and outcome equations. i.e. $\mathrm{corr}(\mu_i, \varepsilon_i) \neq 0$. The ESR model addresses the selection bias issue resulting from unobservable factors as a missing variable problem. In particular, after estimating the selection equation, the inverse Mills ratios λ_{iM} and λ_{iN} and the covariance terms $\sigma_{\mu M} = cov\ (\mu_i, \varepsilon_{iM})$ and $\sigma_{\mu N} = cov\ (\mu_i, \varepsilon_{iN})$ are calculated and plugged into equations (4.7a) and (4.7b):

$$Y_{iM} = X_i'\beta_{iM} + \sigma_{\mu M}\lambda_{iM} + \gamma_{iM} \quad if\ \ D_i = 1 \tag{4.8a}$$

$$Y_{iN} = X_i'\beta_{iN} + \sigma_{\mu N}\lambda_{iN} + \gamma_{iN} \quad if\ \ D_i = 0 \tag{4.8b}$$

where λ_{iM} and λ_{iN} control for selection bias resulting from unobservable factors; the error terms γ_{iM} and γ_{iN} have conditional zero means. The FIML method suggested by Lokshin and Sajaia (2004) is used to simultaneously estimate the selection and outcome equations.

In ESR estimation, the correlation coefficients $\rho_{\mu M}(\sigma_{\mu M}/\sigma_\mu \sigma_{iM})$ and $\rho_{\mu N}(\sigma_{\mu N}/\sigma_\mu \sigma_{iN})$ of the

[3] The variables X_i and variables Z_i are usually expected to have similar variables, and the only difference is that there is at least one instrumental variable which is included in Z_i but excluded in X_i'.

covariance terms between the error terms in selection equation (4.1) and outcome equations (4.7a) and (4.7b) have econometric interpretations. First, if $\rho_{\mu M}$ or $\rho_{\mu N}$ is statistically significant, this would indicate the presence of selection bias arising from unobservable factors. Hence, taking into account both observable and unobservable factors is a prerequisite to derive unbiased estimates of treatment effects. Second, if $\rho_{\mu M}$ and $\rho_{\mu N}$ have alternative signs, it means that farmers choose to belong to cooperatives on the basis of their comparative advantage, while the same sign implies "hierarchical sorting", i.e., members have an above-average outcomes, compared to nonmembers, independent of the membership choice decision. Third, $\rho_{\mu M} > 0$ implies negative selection bias, indicating farmers who have below than average outcomes are more likely to choose to belong to agricultural cooperatives. Conversely, if $\rho_{\mu M} < 0$, this would suggest positive selection bias.

4.4.4 Estimating Treatment Effects

Following Lokshin and Sajaia (2004), the coefficients from the ESR model can be employed to derive average treatment effect on the treated (ATT). Specifically, the observed and unobserved counterfactual outcomes for cooperative members can be calculated as follows:

Farmers with membership (observed):

$$\mathrm{E}[Y_{iM}|D=1] = X_i\beta_{iM} + \sigma_{\mu M}\lambda_{iM} \tag{4.9a}$$

Farmers without membership (counterfactual):

$$\mathrm{E}[Y_{iN}|D=1] = X_i\beta_{iN} + \sigma_{\mu N}\lambda_{iM} \tag{4.9b}$$

Thus, the expected outcomes in equations (4.9a) and (4.9b) are used to derive unbiased treatment effects (ATT).

$$\mathrm{ATT} = \mathrm{E}[Y_{iM}|D=1] - \mathrm{E}[Y_{iN}|D=1] = X_i(\beta_{iM} - \beta_{iN}) + \lambda_{iM}(\sigma_{\mu M} - \sigma_{\mu N}) \tag{4.10}$$

4.4.5 Method for Addressing Potential Endogeneity

In estimating equation (4.1), some of the employed explanatory variables such as extension contact and access to credit are potentially endogenous. In particular, agricultural extension agents may disseminate new technologies to farmers, and also encourage them to join cooperative organizations. Some cooperatives normally help their members to obtain credit from financial institutions, thus making access to credit a potentially endogenous variable. Thus, extension contact and access to credit variables may be jointly determined with the decision of choosing to belong to cooperatives.

Given the dichotomous nature of the dependent variables, this study employs the approach suggested by Rivers and Vuong (1988) to address these potential endogeneity problems. The approach involves specifying the potential endogenous variables (extension contact, and access to credit) as functions of all other explanatory variables given in the cooperative membership choice equation, in addition to a set of instruments in the first stage regression, such as:

$$G_i = Z_i\beta + S_i\omega + \xi_i \tag{4.11}$$

where G_i is a vector of observed potential endogenous variables such as extension contact and access to credit, Z_i is as defined previously, and S_i is a vector of instruments. It is worth noting here that the employed instruments should strongly influence the given potential endogenous variables, but not the choice of cooperative membership. Therefore, two instruments are excluded in estimating equation (4.1). The two variables include the perception of the usefulness of extension service and the distance to the farmer's source of capital, which are not expected to influence the choice of cooperative membership. These variables are employed in the extension contact and access to credit equations, respectively.[4] It is significant to note that the two instrumental variables are required not to be correlated with the variable (i.e. neighbor membership) used for ESR model identification. Finally, both the observed factors and the residuals predicted from equation (4.11) are used in the cooperative membership choice specification as follows:

$$D_i^* = Z_i\delta + G_i\eta + R_i\kappa + \vartheta_i \tag{4.12}$$

where R_i is a vector of the residual terms predicted from equation (4.11) for the endogenous variables (Wooldridge 2002). The endogenous variables become appropriately exogenous in a second-stage estimating equation by adding appropriate residuals since these residuals serve as the control functions. The approach leads to robust, regression-based Hausman test for endogeneity of the suspected variables (Wooldridge 2015)

[4] The distance to the capital source variable measures the distance between farmer's residence and available capital source (e.g., banks, friends and relatives).

4.5 Results and Discussion

The estimates of the factors that influence a farmer's decision to belong to an agricultural cooperative, and the impact of cooperative membership on apple yields, net returns and household income are presented in Tables 4.3 to 4.5. As indicated previously, the FIML approach estimates both the selection and outcome equations jointly. The selection equations that represent the determinants of choosing cooperative membership are given in the second columns of Tables 4.3, 4.4 and 4.5. The outcome equations that represent the impact of cooperative membership on apple yields, net returns and household income for both members and nonmembers are given in the third and fourth columns of Tables 4.3-4.5, respectively. Moreover, the estimates of the residuals derived from the first-stage regression for the potential endogenous variables that include extension contact and access to credit are also presented in the second columns of Tables 4.3-4.5. These residuals are not significantly different from zero, suggesting that the coefficients have been consistently estimated (Wooldridge 2002). In the next sections, we first discuss the determinants of cooperative membership based on selection equations in Tables 4.3-4.5 together. The impact of cooperative membership on apple yields, net returns and household income are then discussed. Finally, the estimates for the average treatment effects on the treated (ATT) are presented.

4.5.1 Determinants of Cooperative Membership

In the selection specifications of Tables 4.3-4.5, variables having the same name have statistically similar effects on the choice of cooperative membership. The farm size variable is positive and significantly different from zero, suggesting that farmers with larger farm sizes are more likely to belong to cooperatives, a finding that is consistent with the results reported by Bernard and Spielman (2009) and Ito et al. (2012). The variable for labor input is positive and significant, indicating that households devoting more labor inputs to apple production are more likely to have cooperative membership. Computer ownership seems to be an important determinant of cooperative membership, a finding that is in line with Fischer and Qaim (2012), who pointed out that efficient means of communication can facilitate the formation of farmer organizations. The coefficients of the variables representing soil types and regional variables are also significantly different from zero, indicating significant cluster effects and probably revealing agro-climate variance, and differences of environment resources, access to local agricultural institutional arrangements and infrastructure.

4.5.2 Yield Effects

We now interpret the impact of cooperative membership on apple yields, using the estimates presented in Table 4.3. The variable representing labor input shows a significant and positive impact on apple yields for both members and nonmembers, suggesting that labor is a vital determinant of higher apple yields. Farm size variable tends to have negative and statistically significant impacts on apple yields for both cooperative members and nonmembers, suggesting that larger farms obtained significantly lower apple yields. The finding of the inverse relationship between farm size and productivity is consistent with the results obtained by Abdulai and Huffman (2014) and Kleemann et al. (2014). The ownership of computer tends to have a positive and significant impact on apple yields for members. Computer network may be crucial in reducing information search costs that are associated with input markets and uncertainties of new technologies recommended by agricultural cooperatives.

Extension contact variable has a positive and significant impact on apple yields for members, reflecting the important role of government extension services in enhancing agricultural productivity. The variable representing access to credit exerts a positive and significant effect on apple yields for members, which is a finding that is in line with the notion that access to capital allows members to purchase productivity-enhancing inputs suggested by cooperatives. Soil types tend to have different impacts on apple yields for members and nonmembers. In particular, sandy soil tends to have a significantly positive effect on apple yields for members, while clay soil exerts a significantly negative impact on productivity for nonmembers. The significant influence of soil variables suggests that productivity estimates may be biased if environmental variables are omitted (Abdulai and Huffman, 2014).

Table 4.3 Determinants of cooperative membership and their impact on apple yields

		Apple yields	
Variables	Selection	Members	Nonmembers
Constant	-5.392 (1.518)***	6.578 (0.604)***	6.860 (0.405)***
Age	0.023 (0.050)	-0.022 (0.016)	0.007 (0.013)
Age squared	-0.0002 (0.001)	0.0003 (0.0002)*	-0.0001 (0.0001)
Education	0.058 (0.027)**	0.013 (0.009)	-0.015 (0.007)**
Household size	0.071 (0.061)	0.030 (0.017)*	0.023 (0.016)
Labor (log)	0.380 (0.183)**	0.192 (0.059)***	0.187 (0.053)***
Farm size	0.130 (0.029)***	-0.029 (0.010)***	-0.052 (0.009)***
Computer	0.395 (0.169)**	0.184 (0.048)***	-0.067 (0.048)
Extension contact	0.856 (0.404)**	0.137 (0.054)**	0.017 (0.050)
Access to credit	0.148 (0.653)	0.268 (0.040)***	0.008 (0.037)
Sandy soil	1.419 (0.386)***	0.272 (0.133)**	0.085 (0.089)
Clay soil	-0.427 (0.234)*	-0.034 (0.065)	-0.096 (0.056)*
Gansu	1.444 (0.401)***	0.018 (0.148)	-0.136 (0.101)
Shaanxi	0.226 (0.369)	-0.230 (0.126)*	0.153 (0.088)*
Neighbor membership	0.433 (0.137)***		
Res (Extension contact)	-0.092 (0.166)		
Res (Access to credit)	0.018 (0.323)		
$Ln\sigma_{\mu M}$		-1.229 (0.101)***	
$\rho_{\mu M}$		0.620 (0.188)**	
$Ln\sigma_{\mu N}$			-1.145 (0.078)***
$\rho_{\mu N}$			-0.784 (0.106)***
LR test of indep. eqns.	9.14***		
Log likelihood	-301.229		
Observations	481	481	481

Note: The dependent variable is log form of apple yields measured in kg/mu;
The reference region is Shandong;
The reference soil type is loam soil;
*** p<0.01, ** p<0.05, * p<0.1.

4.5.3 Net Returns Effects

Table 4.4 presents the estimates of the impact of cooperative membership on net returns. The coefficient of the age variable is negative and significant, suggesting that younger farmers obtain higher net returns from the products. The education variable appears to have differential impacts on net returns for members and nonmembers. The positive and significant coefficient for members indicates that better education may help members acquire sufficient market information and identify the appropriate marketing channels provided by cooperatives to sell their products at lower costs. The computer variable has a positive and significant impact on net returns for members, but no impact for nonmembers. To some extent, the convenient modern equipment such as computer can enhance interactive communication between members and agricultural cooperatives regarding market information, leading to lower input costs and higher output prices, and finally higher net returns from apple production. This result is consistent with the finding by Mishra et al. (2009), who concluded that computer is an important management tool in the production process. The variables representing extension contact and access to credit appear to have positive and statistically significant effects on net returns for both members and nonmembers. With regards to the location variables, the results show that both members and nonmembers located in Gansu tend to obtain higher net returns relative to their counterparts in Shandong.

Table 4.4 Determinants of cooperative membership and their impact on net returns

		Net returns	
Variables	Selection	Members	Nonmembers
Constant	-5.247 (1.507)***	9.101 (0.878)***	9.163 (0.678)***
Age	0.025 (0.051)	-0.055 (0.026)**	-0.009 (0.020)
Age squared	-0.0002 (0.001)	0.001 (0.0003)**	-0.00002 (0.0002)
Education	0.036 (0.028)	0.033 (0.014)**	-0.017 (0.012)
Household size	0.107 (0.062)*	0.009 (0.028)	0.019 (0.025)
Labor (log)	0.445 (0.182)**	-0.035 (0.093)	0.013 (0.090)
Farm size	0.132 (0.031)***	-0.051 (0.015)***	-0.047 (0.019)**
Computer	0.468 (0.174)***	0.338 (0.075)***	-0.026 (0.084)
Extension contact	0.793(0.463)*	0.159 (0.087)*	0.228 (0.096)**
Access to credit	-0.621 (0.739)	0.437 (0.066)***	0.105 (0.058)*
Sandy soil	1.387 (0.439)***	0.492 (0.205)**	0.126 (0.148)
Clay soil	-0.492 (0.244)**	-0.048 (0.104)	-0.206 (0.092)**
Gansu	1.429 (0.440)***	0.691 (0.226)***	0.346 (0.172)**
Shaanxi	0.226 (0.402)	0.045 (0.205)	0.173 (0.135)
Neighbor membership	0.514 (0.140)***		
Res (Extension contact)	-0.063 (0.194)		
Res (Access to credit)	0.391 (0.365)		
$Ln\sigma_{\mu M}$		-0.751 (0.088)***	
$\rho_{\mu M}$		0.596 (0.164)***	
$Ln\sigma_{\mu N}$			-0.781 (0.063)***
$\rho_{\mu N}$			-0.239 (0.390)
LR test of indep. eqns.	4.12**		
Log likelihood	-548.694		
Observations	481	481	481

Note: The dependent variable is log form of net returns of apple production measured in yuan/mu;
The reference region is Shandong;
The reference soil type is loam soil;
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.5.4 Household Income Effects

To the extent that the sampled farmers are not exclusively engaged in apple production, but in other agricultural activities, we also examined the impact of cooperative membership on per capita household income. This is because cooperatives may bring benefits to other crops, which would not be captured by net returns from apple production. Table 4.5 presents the estimates of the impact of cooperative membership on per capita household income. The estimates reveal that farm size exerts positive and significant impacts on household income of members and nonmembers. The significance of the variable representing farm size suggests that apple production is lucrative for smallholder farmers. The coefficients of the household size variable are negative and significantly different from zero for both members and nonmembers, suggesting that larger household size may increase the farming labor supply, but reduce the per capita household income. Access to credit has a positive and significant effect on household income of cooperative members.

Table 4.5 Determinants of cooperative membership and their impact on household income

		Household income	
Variables	Selection	Members	Nonmembers
Constant	-6.109 (1.589)***	8.183 (0.664)***	8.754 (0.545)***
Age	0.041 (0.053)	-0.024 (0.019)	0.035 (0.017)**
Age squared	-0.0004 (0.001)	0.0003 (0.0002)	-0.001 (0.0002)***
Education	0.035 (0.029)	0.011 (0.011)	-0.014 (0.010)
Household size	0.089 (0.062)	-0.167 (0.021)***	-0.202 (0.020)***
Labor (log)	0.441 (0.188)**	0.231 (0.073)***	0.080 (0.069)
Farm size	0.137 (0.030)***	0.118 (0.011)***	0.126 (0.0135)***
Computer	0.352 (0.180)*	0.287 (0.057)***	-0.025 (0.067)
Extension contact	0.468 (0.486)	0.295 (0.066)***	0.072 (0.066)
Access to credit	-0.261 (0.732)	0.211 (0.050)***	0.017 (0.049)
Sandy soil	1.289 (0.425)***	0.583 (0.154)***	0.175 (0.119)
Clay soil	-0.318 (0.248)	-0.093 (0.079)	-0.140 (0.075)*
Gansu	1.104 (0.428)***	0.577 (0.172)***	0.180 (0.135)
Shaanxi	0.376 (0.408)	0.223 (0.155)	0.202 (0.115)*
Neighbor membership	0.848 (0.160)***		
Res (Extension contact)	0.136 (0.206)		
Res (Access to credit)	0.194 (0.366)		
$Ln\sigma_{\mu M}$		-1.039 (0.079)***	
$\rho_{\mu M}$		0.547 (0.178)**	
$Ln\sigma_{\mu N}$			-0.922 (0.058)***
$\rho_{\mu N}$			-0.354 (0.221)
LR test of indep. eqns.	4.95**		
Log likelihood	-439.18		
Observations	481	481	481

Note: The dependent variable is log form of household income measured in yuan/capita;
The reference region is Shandong;
The reference soil type is loam soil;
*** p<0.01, ** p<0.05, * p<0.1.

The lower parts of Tables 4.3-4.5 present the estimated correlation coefficients ($\rho_{\mu M}$ and $\rho_{\mu N}$) of covariance terms between the error term μ_i in the selection equation (4.1) and the error terms ε_i in the outcome equations (4.7a) and (4.7b), and they have econometric interpretations (Abdulai and Huffman 2014; Michael Lokshin and Sajaia 2004). First, the results show that $\rho_{\mu M}$ or $\rho_{\mu N}$ is statistically significant in Tables 4.3-4.5, indicating the presence of selection bias. The results confirm that both observable and unobservable factors influence the farmers' decisions of choosing to belong to agricultural cooperatives and the outcomes, given the choice of cooperative membership. Thus, failing to correct for selectivity effects may give biased coefficients of the results. Second, $\rho_{\mu M}$ and $\rho_{\mu N}$ have the opposite signs, suggesting that farmers choose to belong to cooperatives based on their comparative advantage. Third, the signs of $\rho_{\mu M}$ are all positive in Tables 4.3-4.5, suggesting negative selection bias. These results suggest that farmers with below than average apple yields, net returns and household income are more likely to choose to belong to agricultural cooperatives. It is significant to mention that the negative selection bias in our example is quite plausible, since cooperative organizations are expected to enhance agricultural performance and welfare of farm households.

4.5.5 Estimating Treatment Effects (ATT)

The estimates for the average treatment effects on the treated (ATT), which show the effects of cooperative membership on apple yields, net returns and household income, are presented in Table 4.6. Unlike the simple mean differences presented in Table 4.2, these ATT estimates account for selection bias resulting from both observable and unobservable characteristics. The results reveal that cooperative membership significantly increases apple yields by 5.36%. With respect to income gains, the results show that cooperative membership tends to increase net returns by 6.06% and household income by 4.66%. Consistent with the earlier studies by Bernard and Spielman (2009) for Ethiopia and Verhofstadt and Maertens (2014b) for Rwanda, the findings in Table 4.6 imply that contemporary cooperative organizations play an important role in enhancing agricultural performance and raising rural income.

Table 4.6 Impact of cooperative membership on apple yields, net returns and household income

	Mean Outcome[a]				
	Members	Nonmembers	ATT	*t*-value	Change (%)
Yields	7.66 (0.33)	7.27 (0.27)	0.39***	22.25	5.36
Net Returns	8.92 (0.39)	8.41 (0.28)	0.51***	21.37	6.06
Household Income	9.66 (0.36)	9.23 (0.42)	0.43***	22.26	4.66

Note: ATT, average treatment effect on the treated;

[a] As the dependent variables in the ESR outcome equations are the logs of apple yields (kg/mu) , net returns (yuan/mu), household income (yuan/capita), the predictions are also given in log forms. Converting the means back to kg and yuan would lead to inaccuracies, due to the inequality of arithmetic and geometric means (AM-GM inequality);

*** p<0.01.

To gain insight into the impact of cooperative membership on different groups of farmers, we also examined the impact of membership on apple yields, net returns and household income for different farm size categories. The results presented in Table 4.7 generally reveal that even within the different farm size groups, cooperative membership tends to positively and significantly affect farm productivity and household income. In particular, the estimates reveal that belonging to an agricultural cooperative increases apple yields by 6.29% when farm size is less than 6 mu. However, apple yields tend to increase by 4.81% and 4.66% for medium and large farm sizes, respectively, when they belong to cooperatives. The finding is consistent with the earlier observation of negative relationship between farm size and productivity. Moreover, the results in Table 4.7 also reveal that the effects of cooperative membership on net returns and household income tend to decrease with increasing farm size from small, medium to larger. Generally, the results in Table 4.7 suggest that small-scale farmers stand to benefit more from agricultural cooperatives, compared to medium and large-scale farmers. These findings are in line with the findings by Ito et al. (2012) for China and Fischer and Qaim (2012) for Kenya who show that cooperative membership is more rewarding for smaller farms, but contradict the findings by Verhofstadt and Maertens (2014b) for Rwanda, who found that mean income and poverty effects of cooperative membership are largest for larger farms.

Table 4.7 Impact of cooperative membership on apple yields, net returns and household income by farm sizes

Outcomes	Category	Mean Outcomes		ATT	*t*-value	Change (%)
		Members	Nonmembers			
Apple Yields	Small (<=6 mu)	7.94 (0.20)	7.47 (0.15)	0.47***	19.36	6.29
	Medium (6-10 mu)	7.64 (0.27)	7.27 (0.19)	0.37***	12.06	4.81
	Large (>10 mu)	7.41 (0.26)	7.08 (0.27)	0.33***	9.96	4.66
Net Returns	Small (<=6 mu)	9.18 (0.25)	8.49 (0.16)	0.69***	20.96	8.13
	Medium (6-10 mu)	8.92 (0.33)	8.49 (0.30)	0.43***	10.99	5.06
	Large (>10 mu)	8.68 (0.40)	8.27 (0.31)	0.41***	9.58	4.96
Household Income	Small (<=6 mu)	9.59 (0.25)	9.07 (0.27)	0.52***	16.97	5.73
	Medium (6-10 mu)	9.58 (0.35)	9.16 (0.37)	0.42***	12.90	4.59
	Large (>10 mu)	9.80 (0.41)	9.44 (0.32)	0.36***	10.29	3.81

*** $p<0.01$.

4.6 Conclusion and Policy Implications

This paper examined the factors that influence apple farmers' decisions of choosing to belong to agricultural cooperatives, as well as the impact of cooperative membership on apple yields, net returns and household income in China. The study utilized cross-sectional farm household level data of apple farmers collected from Gansu, Shaanxi and Shandong provinces in 2013 from a randomly selected sample of 481 households. Simple comparisons of average apple yields, net returns and household income between cooperative members and nonmembers revealed some significant differences. Given that these comparisons are merely descriptive, without accounting for confounding factors that affect the differences, we also employed an endogenous switching regression model that accounts for both observed and unobserved factors to address the issue of selection bias. The results did reveal that sample selection bias would result if the outcome specifications (apple yields, net returns and household income) were estimated without taking into consideration the membership decision. Specifically, we found a negative selection bias, implying that farmers with below than average apple yields, net returns and household income are more likely to choose to belong to an agricultural cooperative.

The empirical results showed a positive and significant relationship between membership and apple yields, farm net returns and household income. In particular, belonging to a cooperative tends to increase apple yields by 5.36%, net returns by 6.06% and household income by 4.66%. The estimates, differentiated by farm size, revealed that productivity and income gains of cooperative membership were higher for small-scale farmers, compared to medium and large-scale farmers. This finding suggests that cooperatives can play a significant role in increasing the incomes of smallholders to reduce rural poverty in China. On the factors that influence farmers' decision to belong to agricultural cooperatives, the results show that farm size, labor input and asset ownership such as computer exert positive and significant effects on the choice of cooperative membership.

The findings from this study show that contemporary agricultural cooperatives can contribute to the enhancement of agricultural productivity as well as improvement in farm household income. Therefore, the government should continue supporting the development of contemporary cooperatives. Moreover, government could intensify support for cooperatives to improve their marketing strategies in a way that would ensure higher prices for their products. These measures could encourage other farmers to join these cooperatives to produce for the international markets, where food safety and quality standards are quite high.

The finding that farmers' access to computers tend to influence their decisions to join cooperatives suggests that government policy to improve rural internet routing infrastructure would go a long way to increase the number of farmers joining cooperatives, which could make the products more competitive on the world markets. The positive and significant impacts of extension contact and access to credit suggest that promoting effective measures to improve farmers' access to extension service and credit would help improve farm household welfare. As pointed out by Deng et al. (2010), agricultural cooperatives provide very little help with respect to credit facilities to its members in China. The government could therefore put in place policy measures to support farmers in this area.

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Chapter 5 Impact of Agricultural Cooperative Membership on Return on Investment in China

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Abstract

This paper examines the impact of agricultural cooperative membership on return on investment (ROI) utilizing a recent household survey data of 481 apple producers in China. We employ a treatment effects model to address the issue of selection bias, admitting that cooperative members and nonmembers are systematically different in terms of both observable and unobservable factors. The empirical results show that cooperative membership exerts a positive and significant impact on the ROI, whilst membership choice is found to be significantly influenced by education, farm size, asset ownership and social network.

Keywords: Agricultural cooperatives; Return on investment; Selection bias; China

JEL Classification: C35, D71, Q12, Q13

5.1 Introduction

In most developing countries, the smallholder farmers face a systematically unfavorable situation regarding agricultural technology adoption, access to modern supply chain, input use efficiency and various other uncertainties (World Bank, 2008). These barriers make it difficult for smallholder farmers to benefit from agricultural production and marketing, and tend to widen the income gap between rural and urban residents. Available evidence suggests that average incomes of smallholder farmers in China are just about one third of their urban counterparts (Grain, 2012). Government programs have thus emerged to enhance smallholder farmers' performance in modern agricultural production. Among others, agricultural cooperatives have been promoted based on their strong potential to improve smallholders' farm performance (Chagwiza, Muradian, & Ruben, 2016; Hellin, Lundy, & Meijer, 2009; Liang, Hendrikse, Huang, & Xu, 2015). Generally, the development of cooperative organization in developing countries is expected to facilitate smallholder farmers' market participation, increase farm incomes, enhance crop productivity, and lower production costs (Abebaw & Haile, 2013; Hellin et al., 2009; Zheng, Wang, & Awokuse, 2012). Hence, from a development policy perspective, it is essential to empirically evaluate the impact of agricultural cooperative membership on the profitability of smallholder agricultural investments, aimed at finding evidence to design sustainable agri-environmental policies.

A growing literature related to agricultural cooperatives has emerged recently. The first strand has focused on the impact of cooperative membership on technology adoption. For instance, the studies by Abebaw & Haile (2013) for Ethiopia and Verhofstadt & Maertens (2014) for Rwanda show that farmers with cooperative membership are more likely to adopt agricultural technologies such as fertilizer and pesticide than those without membership. The second strand of literature addresses the role of agricultural cooperatives in influencing smallholder farmers' access to both input and output markets and prices obtained (e.g., Hellin et al., 2009; Piesse, Doyer, Thirtle, & Vink, 2005; Trebbin, 2014). Wollni & Zeller (2007) find that cooperative membership has positive impacts on prices and participation in specialty markets among coffee growers in Costa Rica, while Fischer & Qaim (2012) find a positive impact of membership on banana prices of farmers in Kenya. Agricultural cooperatives can enhance smallholder farmers' access to advanced production factor markets and modern supply chains (e.g., supermarkets, restaurants, processors and international markets), contributing to lower input prices and higher output prices for members.

The third strand of the literature has analyzed the impact of cooperative membership on farm performance, employing indicators such as farm income or farm revenue (Bernard & Spielman, 2009; Bernard & Taffesse, 2012; Ito, Bao, & Su, 2012; Yang & Liu, 2012; Zheng, Wang, & Song, 2011). The studies by Zheng et al. (2011), Yang & Liu (2012) and Ito et al. (2012) have found that cooperative members in China obtain higher agricultural income or farm income than nonmembers. In a recent study, Chagwiza et al. (2016) report a positive and significant impact of cooperative membership on dairy farmers' income in Ethiopia.

Most of the studies mentioned above have separately examined the impact of agricultural cooperative membership on technology adoption, output prices or farm income. However, using farm income as a farm performance measure may be incomplete, since there are also significant differences in terms of production investment costs, which need to be taken into account. Identifying the relationship between cooperative membership and the performance of a number of different investments can help stakeholders to understand how well their current investments are utilized and then enable them to adjust future investments. However, empirical evidence on the impact of agricultural cooperative membership on the profitability of different investments is currently lacking in the literature.

The present study contributes to the literature by analyzing the impact of cooperative membership on return on investment. Return on investment is a preferred indicator than others such as farm income or farm revenue to proxy farm performance, since it not only concentrates on improving net returns from crop production, but also takes the profitability of agricultural investments into account (Kleemann et al., 2014). We use a treatment effects model to conduct the empirical analysis (Cong & Drukker, 2000). The approach addresses the selection bias issue that arises from the fact that cooperative members and nonmembers are systematically different in terms of both observable factors (e.g., age, education and farm size) and unobservable factors (e.g., farmer's entrepreneurial ability, managerial ability or motivations), and also estimates direct marginal effect and average treatment effect of cooperative membership on return on investment.

The study utilizes a recent farm household survey data of 481 apple farmers in Gansu, Shaanxi and Shandong provinces of China. In China, the agricultural sector is a key engine for economic development and rural income growth, contributing 10.08% of GDP and around 33.60% to total employment (CSA, 2013). In the surveyed regions, farmers including both cooperative members and nonmembers are primarily engaged in apple production and marketing for their livelihoods. The empirical findings have important implications for policy-makers in China and other countries in their efforts to promote sustainable agricultural development and increase rural incomes in the apple sector through farm organizations.

This paper proceeds as follows. In following section, we present the econometric approach. In section 5.3, data and descriptive analysis are presented. We give the empirical results in section 5.4. Section 5.5 concludes.

5.2 Econometric Approach

5.2.1 Conceptual Framework

The conceptual framework employed in this study is based on the assumption that farmers maximize net returns from apple production and marketing. For analytical convenience, let Y_i denote the total apple output for household i, P_i is the price of the output; I_{ik} refers to a vector of input variables, and R_{ik} refers to corresponding prices of used inputs, with k indicating m types of considered inputs including fertilizers, pesticides, labor, agricultural films for apple coloring and land moisture conservation, irrigation, bags, plantlet costs and farm equipment costs that are required for apple production; L_i refers to farm size used for apple production; X_i represents a vector of variables representing household and farm-level characteristics (e.g., age, education and farm size) that may influence net returns from apple production; D_i represents the choice of agricultural cooperative membership. Under these assumptions, the net returns function can be expressed as:

$$\pi(P,R,L;X,D) = P_i Y_i - \sum_{k=1}^{k=m} I_{ik} R_{ik}\,, \quad k = 1,2,\dots,m \tag{5.1}$$

Considering land endowment (L_i) as a fixed input for farmers and using the homogeneity conditions, the restricted net returns function can be expressed as:

$$\pi(P,R,L;X,D) = L_i \cdot \tilde{\pi}(P,R;X,D) \tag{5.2}$$

where $\tilde{\pi}(P,R;X,D)$ denotes net returns per unit of land, defined as the difference between the value of apple yield and per unit costs of inputs. Thus, apple yield per unit of land and input use per unit of land can be expressed as $\tilde{Y}_i = Y_i/L_i$ and $\tilde{I}_i = I_i/L_i$, respectively, which can be obtained by direct application of Hotelling's lemma to equation (5.2):

$$\tilde{Y}_i = \partial\tilde{\pi}(P,R;X,D)/\partial P_i \tag{5.3a}$$

$$\tilde{I}_i = \partial\tilde{\pi}(P,R;X,D)/\partial R_i \tag{5.3b}$$

The specifications in (5.2), (5.3a) and (5.3b) show that net returns from apple production, apple yield per unit of land, input use per unit of land are influenced by input and output prices, farm and household level characteristics, as well as the choice of cooperative membership. In particular, the above analysis reveals that agricultural cooperative membership (D) affects net returns ($\tilde{\pi}$) from apple production through directly influencing apple yields ($\tilde{Y}$) and input use ($\tilde{I}$) per unit of land. For instance, agricultural cooperatives may assist farmers in the efficient use of yield-enhancing technologies such as fertilizers and pesticides, contributing to higher apple yields obtained by members; they may purchase production inputs (e.g., fertilizers, pesticides and agricultural films) collectively for their members and/or rent out farm equipment (e.g., sprayers and rotary cultivators) to members at lower costs, contributing to a reduction in investment costs for their members (Abebaw & Haile, 2013; Liang et al., 2015; Verhofstadt & Maertens, 2014). Moreover, agricultural cooperatives may bargain with apple buyers on behalf of the members for a better price and provide members with timely marketing information, which tend to help increase farmers' sales prices. Therefore, we expect that agricultural cooperative membership will tend to increase the net returns from apple production by improving farmers' apple output, sales prices, while lowering investment costs. Given that the primary objective of this study is to analyze the impact of cooperative membership on return on investment, which is a relative profitability indicator, we will relate the return to investment in the empirical specification.

5.2.2 Empirical Specification

The present study aims to examine the impact of agricultural cooperative membership on return on investment (ROI). The ROI is a preferred indicator to measure farm performance, since it relates net returns from apple production to farmers' investment costs and consequently indicates how well the available assets have been used (Asfaw, Mithöfer, & Waibel, 2009; Kleemann et al., 2014). The empirical investigation of the impact of agricultural cooperative membership on the ROI assumes a linear specification for the ROI as a function of a vector of individual and household characteristics (X_i) and a cooperative membership dummy variable (D_i). The ROI (V_i) regression can be expressed as:

$$V_i = \beta X_i + \delta D_i + \varepsilon_i \tag{5.4}$$

where β and δ are parameters to be estimated, ε_i is an error term. V_i represents the ROI outcome. In particular, the ROI can be calculated as follows:

$$ROI = \frac{Return - Total\ cost\ of\ investment}{Total\ cost\ of\ investment}$$

$$= \frac{L_i(P_i\tilde{Y}_i) - L_i(\sum_{k=1}^{k=m}\tilde{I}_{ik}R_{ik})}{L_i(\sum_{k=1}^{k=m}\tilde{I}_{ik}R_{ik})} = \frac{P_i\tilde{Y}_i - \sum_{k=1}^{k=m}\tilde{I}_{ik}R_{ik}}{\sum_{k=1}^{k=m}\tilde{I}_{ik}R_{ik}}, k = 1, 2, \ldots, m \tag{5.5}$$

where *Return* refers to total gross revenue from apple production and marketing, which is determined by apple farm size (L_i), apple price (P_i) and apple yield per unit of land ($\tilde{Y}_i$) for household i; *Total cost of investment* refers to the costs incurred during apple production, which is determined by apple farm size (L_i), a vector of inputs ($\tilde{I}_{ik}$) per unit of land and the related input prices (R_{ik}), with k representing a particular type of input from m available choices, as indicated previously. ROI from apple production and marketing compares the magnitude of investment gains directly with the magnitude of investment costs for a specific time period.

The empirical literature on impact assessment of cooperative membership shows that whether an individual chooses to join a cooperative or not is dependent on the individual and household characteristics (self-selection), rather than random assignment (e.g., Abebaw & Haile, 2013; Fischer & Qaim, 2012; Ito et al., 2012). Thus, we model individual decision to become a cooperative member in a random utility framework. Within this framework, a farmer chooses to join a cooperative if the expected utility gained from choosing membership (U_i^m) is larger than that obtained from not choosing (U_i^n), i.e. $D_i^* = U_i^m$-U_i^n>0, with D_i^* denoting the utility difference between these two options. However, the actual utility level of D_i^* cannot be observed directly, but can be expressed by a latent variable function, such as:

$$D_i^* = \lambda Z_i + \mu_i,\ D_i = \begin{cases} 1 & if\ D_i^* > 0 \\ 0 & if\ D_i^* \leq 0 \end{cases} \tag{5.6}$$

where λ is a vector of parameters to be estimated; μ_i is an error term, with zero mean and normal distribution; Z_i is a vector of explanatory variables that are assumed to influence the choice of cooperative membership, including age, education, dependency ratio, farm size, sprayer ownership, computer ownership, income specialization, marketing contract, labor availability, risk attitude, social networks and location variables. The choice of these explanatory variables is primarily based on previous studies on cooperative membership (e.g., Bernard & Spielman, 2009; Chagwiza et al., 2016; Fischer & Qaim, 2012; Ito et al., 2012; Zheng et al., 2011).

Given that farmers choose to join agricultural cooperatives by themselves, the same unobservable factors (e.g., farmers' innate abilities and motivations) may simultaneously influence the choice of cooperative membership and the ROI. In this case, the error term (ε_i) in equation (5.4) and the error term (μ_i) in equation (5.6) may be correlated such that $\mathrm{corr}(\varepsilon_i, \mu_i) \neq 0$, leading to potential endogeneity of cooperative membership variable in the analysis. Thus, applying standard regression technique such as ordinary least square (OLS) to estimate equation (5.4) tends to produce biased estimates. Instead, propensity score matching (PSM) approach is widely used. However, the PSM technique fails to account for unobservable factors when serving to address the issue of selection bias (Chagwiza et al., 2016; Fischer & Qaim, 2012; Ito et al., 2012). In this study, we employ a treatment effects model to conduct the empirical analysis.

5.2.3 Treatment Effects Model

The treatment effects model estimates the cooperative membership choice equation (5.6) and the ROI equation (5.4) jointly (Cong & Drukker, 2000). The advantages of using treatment effects model over PSM approach include that (i) it removes the selection bias due to observed and unobserved covariates; (ii) conditional on the inverse Mills' ratio, the exposure to treatment becomes random; and (iii) the factors determining the ROI are identified in the second stage.

In the treatment effects model, the error term ε_i in equation (5.4) and the error term μ_i in equation (5.6) are assumed to have a bivariate normal distribution with mean zero, and a correlation such that $\rho_{\varepsilon\mu} = \mathrm{corr}(\varepsilon_i, \mu_i)$. In particular, if $\rho_{\varepsilon\mu}$ is significantly different from zero, this would suggest the presence of selection bias arising from unobservable factors (Cong & Drukker, 2000). In particular, negative $\rho_{\varepsilon\mu}$ indicates negative selection bias, which implies that farmers with lower than average ROI are more likely to join agricultural cooperatives. In contrast, positive $\rho_{\varepsilon\mu}$ implies positive selection bias. In addition, the presence of positive or negative selection bias also implies that simple OLS regression may either overestimate or underestimate the impact of cooperative membership on the ROI.

Using a formula for the joint density of bivariate normally distributed variables, the expected ROI for farmer i conditional on the presence of the treatment (i.e. in a context of having cooperative membership) is expressed as (Cong & Drukker, 2000):

$$\mathrm{E}(V_i|D=1) = \beta X_i + \delta + E(\varepsilon_i|D=1) = \beta X_i + \delta + \rho_{\varepsilon\mu}\sigma_{\varepsilon\mu}\frac{\phi(\lambda Z_i)}{\Phi(\lambda Z_i)} \quad (5.7a)$$

where $\phi(\cdot)$ is the standard normal density function, and $\Phi(\cdot)$ refers to the standard normal cumulative distribution function; $\sigma_{\varepsilon\mu}$ is the covariance term between the error term ε_i in equation (5.4) and the error term μ_i in equation (5.6); The ratio of $\phi(\cdot)$ and $\Phi(\cdot)$ is termed as the inverse Mill's ratio; β and δ are parameters to be estimated and X_i is a vector of explanatory variables as defined previously. The expected ROI for farmer i conditional on the absence of the treatment (i.e. in a context of having no cooperative membership) is expressed as:

$$\mathrm{E}(V_i|D=0) = \beta X_i + E(\varepsilon_i|D=0) = \beta X_i - \rho_{\varepsilon\mu}\sigma_{\varepsilon\mu}\frac{\phi(\lambda Z_i)}{1-\Phi(\lambda Z_i)} \quad (5.7b)$$

Thus, the average treatment effect (ATE) of cooperative membership on the ROI for the sample size N can be calculated by comparing the expected ROI in equation (5.7a) and that in equation (5.7b):

$$\mathrm{ATE} = \frac{1}{N}\sum_{i=1}^{N}[\mathrm{E}(V_i|D=1) - \mathrm{E}(V_i|D=0)] \quad (5.8)$$

For proper model identification, the treatment effects model requires that there is at least one variable in Z_i of cooperative membership equation that does not appear in X_i of ROI equation. The additional variable in cooperative membership equation serves as an instrumental variable to control for unobservable factors (e.g., farmers' innate abilities) that may bias the impact of cooperative membership on the ROI, which is expected to affect the choice of cooperative membership but should not affect the ROI directly. In this study, a friend membership variable representing whether a farmer's neighbors, friends or relatives have cooperative membership is used as an identifying instrument. Ito et al. (2012) found that farmers are more likely to be enrolled in the agricultural cooperatives if more neighbors are cooperative participants. To test the validity of the employed instrumental variable, we run a probit model for the cooperative membership equation and OLS model for the ROI equation including the friend membership variable in both regressions. The results, which are not presented for the sake of simplicity but are available on request, show that the friend membership variable has a statistically significant impact on the choice of cooperative membership, while it has no significant impact on the ROI. The findings confirm the validity and efficiency of the employed instrumental variable.

5.3 Data and Descriptive Analysis

The data were collected from a primary filed survey in the major apple growing areas (Gansu, Shaanxi and Shandong provinces) between September and December 2013 in China. The data set comprises two types of apple farmers: those who are members of agricultural cooperatives and those who do not belong to any cooperative. We used a multistage sampling procedure for data collection. At first, three provinces were purposively selected, namely Gansu, Shaanxi and Shandong. These provinces cover more than half of the country's total apple orchards (54.17%), with 283,900 hectares in Gansu, 645, 200 hectares in Shaanxi and 279, 600 hectares in Shandong, respectively (CRSY, 2013). In the second stage, the regions with intensive apple production in each province were purposively selected using the information from Statistical Yearbook at the provincial level. In particular, Jingning county in Gansu, Luochuan county in Shaanxi, and Laiyang and Qixia cities in Shandong were selected. In the third stage, six agricultural cooperatives that are specialized in apple production and marketing were randomly selected, using the information provided by the local agricultural bureau. In the fourth stage, three villages affiliated to each cooperative were randomly selected. In the last stage, 25-30 households including both cooperative members and nonmembers were randomly selected in each village. A total of 481 households were finally selected as a sample for this study. Of these, 208 were formal members of agricultural cooperatives. Face-to-face interviews were conducted by enumerators who spoke local languages and supervised by one of the authors, using a detailed structured questionnaire. The enumerators were hired from local universities. The survey gathered information on socioeconomic and farm level factors, apple production and marketing practices, asset ownership, as well as other structural characteristics.

Table 5.1 presents definitions and descriptive statistics for the variables used in the analysis. The survey showed that about 43% of households had membership in agricultural cooperatives. The average age of farmers was about 48.63 years, whereas the mean number of schooling years was about 7.60 years. The mean farm size of apple orchards was 5.07 mu (1 mu=1/15 hectare). Apple incomes contributed around 75% of total household incomes, indicating apple production and marketing are the main source of household income in the surveyed regions.

Table 5.1 Definition of variables and descriptive statistics

Variable	Definition	Mean (S.D.)
Membership	1 if farmer is a member of cooperative, 0 otherwise	0.43 (0.50)
ROI	Return on investment (%)	2.43 (1.54)
Age	Age of HH in years	48.63 (10.25)
Education	Schooling of HH in years)	7.60 (2.87)
Dependency ratio	Proportion of household members under the age of 15 and over the age of 64	0.31 (0.19)
Farm size	Total fruiting apple orchard area (mu[a])	5.07 (3.24)
Sprayer ownership	1 If farmer owns power sprayer, 0 otherwise	0.86 (0.34)
Computer ownership	1 If farmer owns computer, 0 otherwise	0.32 (0.47)
Specialization	The value of total apple yields divided by the total household incomes (%)	0.75 (0.21)
Marketing contract	1 if famer uses formal written contract to sell produce, 0 otherwise	0.41 (0.49)
Labor availability	1 if labor is available during apple season, 0 otherwise	0.48 (0.50)
Risk attitude	Self-stated openness to innovation and risk: 1 if farmer is risk-loving; 0 otherwise	0.52 (0.50)
Social network	1 if farmer acquired input or output market information from neighbors, 0 otherwise	0.60 (0.49)
Gansu	1 if household is located in Gansu, 0 otherwise	0.17 (0.37)
Shandong	1 if household is located in Shaanxi, 0 otherwise	0.40 (0.50)
Shaanxi	1 if household is located in Shandong, 0 otherwise	0.43 (0.50)
Friend membership	1 if farmer reports if he/she has neighbors, friends or relatives joining cooperatives, 0 otherwise	0.69 (0.46)
Information availability	1 if farmer reports that he/she can acquire sufficient information to understand the functions of contemporary cooperatives, 0 otherwise	0.49 (0.50)

Note: [a] 1mu=1/15 hectare

Table 5.2 presents differences in means in the characteristics of cooperative members and nonmembers. In particular, members are more educated than nonmembers. They have larger farm size, and are more likely to own assets such as power sprayer and computer. On average, both members and nonmembers depend highly on apple production as income source, although the income specialization variable is not statistically different in means between these two groups. Members are more likely to have the issue of labor shortage, compared with nonmembers. In addition, the mean comparison in social network variable shows that cooperative members are more likely to acquire input or output market information from neighbors, relative to nonmembers.

Table 5.2 Descriptive statistics of selected variables by cooperative membership status

Variables	Members (208)	Nonmembers (273)	Diff. in Mean
Age	48.45 (0.66)	48.77 (0.66)	-0.326
Education	8.05 (0.17)	7.27 (0.19)	0.781***
Dependency ratio	0.31 (0.01)	0.30 (0.01)	0.011
Farm size	5.51 (0.24)	4.73 (0.18)	0.778***
Sprayer ownership	0.93 (0.02)	0.81 (0.02)	0.123***
Computer ownership	0.38 (0.03)	0.27 (0.03)	0.109**
Specialization	0.75 (0.01)	0.74 (0.01)	0.013
Marketing contract	0.41 (0.03)	0.40 (0.03)	0.014
Labor availability	0.41 (0.03)	0.53 (0.03)	-0.126***
Risk attitude	0.55 (0.03)	0.51 (0.03)	0.043
Social network	0.71 (0.03)	0.52 (0.03)	0.190***
Gansu	0.20 (0.03)	0.14 (0.02)	0.063*
Shaanxi	0.35 (0.03)	0.45 (0.03)	-0.104**
Shandong	0.45 (0.03)	0.41 (0.03)	0.042
Friend membership	0.75 (0.03)	0.65 (0.03)	0.093**
Information availability	0.55 (0.03)	0.44 (0.03)	0.110**

Note: Standard deviations in parentheses.

Differences in ROI components are presented in Table 5.3. It shows that average apple price for cooperative members is significantly higher than that for nonmembers. Members are more likely to have higher costs on labor, agricultural films, and irrigation, compared to nonmembers. With respect to farm equipment costs, the information presented in Table 5.3 reveals that cooperative members paid less for agricultural equipment than nonmembers, potentially suggesting the role of agricultural cooperatives in providing members with some farm equipment for free, or renting them to members at lower costs. Although total production costs for members are 12.77% higher than that for nonmembers, the net returns from apple production for members are 31.53% higher than that for nonmembers. The information presented in Tables

5.2 and 5.3 generally shows that cooperative members and nonmembers are systematically different. Finally, the value of ROI is also higher for members compared to nonmembers, which is statistically significant at 1% level in mean difference. However, to the extent that this comparison is only descriptive, a potential selection bias should be accounted for to obtain true effect of cooperative membership on the ROI.

Table 5.3 Mean difference of production costs and profits between members and nonmembers

Variables	Mean (481)	Members (N=208)	Nonmembers (N=273)	Diff. in Mean
ROI components				
Gross return (yuan/mu)[a]	10,536.52	11,895.97	9,500.76	2,395.208***
Quantity Sold (kg)	2,886.29	3,033.36	2774.24	259.129**
Average price (yuan/kg)	3.73	3.99	3.54	0.454***
Fertilizer (yuan/mu)	1,510.18	1,562.76	1,470.11	92.658
Pesticide (yuan/mu)	262.25	258.73	264.94	-6.212
Labors (yuan/mu)	524.35	682.96	403.50	279.463***
Agricultural films (yuan/mu)	88.77	98.59	81.28	17.304**
Irrigation (yuan/mu)	49.04	62.22	39.00	23.225***
Bags (yuan/mu)	524.31	534.97	516.19	18.772
Plantlet costs (yuan/mu)	202.49	193.21	209.57	-16.361
Farm equipment costs (yuan/mu)	194.34	165.74	216.14	-50.400**
Total production costs (yuan/mu)	3,368.17	3,600.49	3,192.41	407.628***
Net return (yuan/mu)	7,168.44	8,295.88	6,309.42	1,987.577***
ROI	2.43	2.67	2.25	0.421***

[a] yuan is Chinese currency: 1 US $=6.21 yuan in 2013.

5.4 Empirical Results

The estimates for the impact of cooperative membership on the ROI using the treatment effects model are presented in Table 5.4. The maximum likelihood approach estimates both the cooperative membership choice equation (5.6) and the ROI equation (5.4) jointly. The empirical analysis was conducted using the Stata 13.0 statistical package.

5.4.1 ROI Effects of Cooperative Membership

An interesting finding in Table 5.4 is the sign and significance of $\rho_{\varepsilon\mu}$. The results show that the coefficient of $\rho_{\varepsilon\mu}$ is significantly different from zero, indicating the presence of sample selection bias arising from unobservable factors (Cong & Drukker, 2000). The negative $\rho_{\varepsilon\mu}$ implies negative selection bias, which suggests that farmers with lower than average ROI are more likely to join cooperatives. This is plausible, as agricultural cooperatives are expected to promote higher returns to members' investments in comparison to nonmembers (Ito et al., 2012; Zheng et al., 2011). The negative $\rho_{\varepsilon\mu}$ also implies that OLS model would underestimate the impact of cooperative membership on the ROI, since OLS regression ignores the non-random nature of cooperative membership choice in the ROI equation. Moreover, the Wald test for $\rho_{\varepsilon\mu} = 0$ is statistically significant, which suggests the rejection of the null hypothesis that there is no correlation between cooperative membership choice specification and the ROI specification (Cong & Drukker, 2000). That is, cooperative membership is an endogenous variable in equation (5.4). Generally, these findings suggest that accounting for selectivity effects is essential to obtain unbiased and consistent estimation of the impact of cooperative membership on the ROI.

The results regarding the impact of cooperative membership on the ROI using treatment effects model are presented in the third column in Table 5.4, which is shown next to the estimates from OLS model for comparison. It shows that cooperative membership has a positive and significant impact on the ROI, with a marginal effect of 1.739. This translates into an increase of 71.56% in ROI, using the sample mean value as the reference. Such effects could not be observed when only comparing descriptive statistics of the ROI means between cooperative members and nonmembers, due to the previously mentioned negative selection bias. The marginal effect of cooperative membership on the ROI in the OLS model estimate (0.363) is much smaller than that in the treatment effects model, although the coefficient of membership variable in the OLS model is also positive and significant. The finding that OLS model underestimates the ROI effect of cooperative membership is due to the fact that OLS model treats cooperative membership as an exogenous variable in regression.

Table 5.4 Impact of cooperative membership on the ROI

	Treatment effects model		OLS
Variable	Selection	ROI	ROI
Membership		1.739 (0.505)***	0.363 (0.135)***
Age	0.002 (0.007)	-0.018 (0.009)**	-0.017 (0.008)**
Education	0.043 (0.025)*	-0.055 (0.028)**	-0.035 (0.024)
Dependency ratio	0.190 (0.322)	-1.045 (0.367)***	-0.967 (0.333)***
Farm size	0.084 (0.026)***	-0.151 (0.032)***	-0.107 (0.028)***
Sprayer ownership	0.788 (0.193)***	-0.119 (0.227)	0.185 (0.178)
Computer ownership	0.390 (0.148)***	0.201 (0.170)	0.388 (0.142)***
Specialization	0.032 (0.325)	1.543 (0.353)***	1.572 (0.320)***
Marketing contract	0.118 (0.172)	0.545 (0.185)***	0.596 (0.166)***
Labor availability	-0.426 (0.153)***	0.741 (0.190)***	0.545 (0.153)***
Risk attitude	-0.073 (0.128)	0.329 (0.140)**	0.280 (0.127)**
Social network	0.420 (0.129)***	-0.065 (0.154)	0.156 (0.128)
Gansu	0.055 (0.237)	0.703 (0.267)***	0.684 (0.253)***
Shaanxi	-1.044 (0.238)***	-0.087 (0.285)	-0.613 (0.218)***
Friend membership	0.319 (0.121)***		
Constant	-1.803 (0.602)***	2.169 (0.639)***	2.144 (0.562)***
$\text{ath}(\rho_{\varepsilon\mu})$	-0.655 (0.243)***		
$\rho_{\varepsilon\mu}$	-0.575 (0.163)***		
$\text{Ln}(\sigma)$	0.381 (0.078)***		
R-squared			0.262
Wald test ($\rho_{\varepsilon\mu} = 0$)	7.27***, with Prob > chi2 = 0.007		
ATE (PSM)[a]	0.304 (0.162)*		
Sample size	481		481

Note: In selection equation, dependent variable is a 1-0 dummy; Robust standard errors in parentheses;

*** p<0.01, ** p<0.05, * p<0.1;

[a] ATE (PSM) refers to average treatment effects estimated by propensity score matching model, which is calculated using *teffects psmatch* command in Stata 13.0.

Turning to the other factors that influence the ROI, the results show that the variable representing household head age tends to have a negative and significant impact on the ROI, a finding that suggests that elder farmers are unfavorable for apple production and marketing probably due to a number of factors such as poor health condition and outdated technology, resulting in a lower ROI. Education has a negative and significant impact on the ROI. The possible reason for this may be that well-educated farmers have higher incentives to invest in organic fertilizers and green pesticides that are more expensive than chemical alternatives, with the aim of winning the markets by improving apple quality and safety. However, the increased fertilizer and pesticide costs cannot be compensated by increased prices due to lagged market for high-quality apples, finally leading to lower ROI.

The variable representing dependency ratio is negative and statistically significant, suggesting that lower farm labor ratio in a household is associated with lower ROI. Higher dependency ratio requires a trade-off between taking care of family members and focusing on apple production and marketing. Allocating more labor to the household work results in insufficient labor being allocated to farms, which may result in production and marketing efficiency loss, and then lower ROI. The variable representing farm size appears to have a negative and significant coefficient, indicating that households with large farm size obtained significantly lower ROI than small farms. The finding is consistent with the finding by Chen et al. (2011) who also found a negative relationship between farm size and farm returns, but contradicts with the finding by Zheng et al. (2011), who found that larger farm size contributes to higher agricultural incomes. The coefficient of income specialization variable is positive and significantly different from zero, suggesting that specialized apple production is a lucrative profession. The finding is consistent with the results reported by Yang and Liu (2012), who also noted the positive relationship between agricultural specialization and rural income in their study on China. Farmers who depend on incomes from apple production and marketing as main income source may have higher incentives to identify markets in order to purchase inputs and sell their products at lower costs.

The results show that marketing contract variable has a positive and significant impact on the ROI. Marketing contracts can help overcome imperfect markets and reduce transaction costs involved, contributing to a higher ROI. The finding is consistent with the finding by Escobal & Cavero (2012), who pointed out that marketing contracts tend to increase farm profits. The coefficient of labor availability variable is positive and significant, suggesting that sufficient labor tend to increase the ROI. Apple production is a labor-intensive profession, and sufficient labor can enhance the efficiency of farm input investment and output marketing, contributing to an increase in ROI. The coefficient of risk attitude variable is positive and significant, suggesting that risk-loving farmers obtained higher ROI. Among location dummies, the results in Table 5.4 show that farmers located in Gansu tend to have higher ROI, relative to farmers in

Shandong (reference region). The finding suggests the presence of location fixed effects in influencing the ROI.

The results estimated from cooperative membership equation show that education, farm size, sprayer ownership, computer ownership and social network are main factors that drive farmers' decisions to choose cooperative membership, which are generally consistent with the findings in previous studies (Bernard & Spielman, 2009; Fischer & Qaim, 2012; Ito et al., 2012; Yang & Liu, 2012; Zheng et al., 2012). It is worth mentioning that the primary objective of cooperative membership equation estimation is to control for unobserved factors that may bias the impact of cooperative membership on the ROI. Finally, the friend membership variable is significantly and positively associated with the choice of cooperative membership. We hereby do not expect the friend membership variable to be correlated with the ROI, hence it functions as an identifying instrumental variable in the treatment effects model as explained previously.

5.4.2 Average Treatment Effects

In addition to the marginal effect of cooperative membership on the ROI presented in Table 5.4, we are also interested in estimating the average treatment effects (ATE) of cooperative membership on the ROI. The ATE measures the difference in the predicted ROI for sampled households in the contexts with and without cooperative membership, which is calculated based on equation (5.8) (Cong & Drukker, 2000). This ATE estimate accounts for selection bias arising from both observable and unobservable factors. The results are presented in Table 5.5. As one can note, the ATE estimate reveals that the causal effect of cooperative membership was to increase the ROI by 14% on average.

To gain further understanding of the ROI effects of cooperative membership, disaggregation of the ATE by regions and membership years are also presented in Table 5.5. The results show that cooperative membership has a larger effect on the ROI for farmers in Shaanxi, while it has a smaller effect on the ROI for farmers in Gansu. Specifically, for farmers living in Shaanxi, Shandong and Gansu provinces, cooperative membership appears to increase the ROI by 16.37%, 14.43% and 9.87% on average, respectively. With respect to ROI effects of cooperative membership differentiated by membership years, the results in Table 5.5 show that the ROI effect of cooperative membership increases with increasing membership years.

Table 5.5 Average treatment effects of cooperative membership on the ROI

	Sample size	Mean outcome		ATE [a]	*t*-value	Change (%)
		Members	Nonmembers			
ROI (Full sample)	481	2.605	2.285	0.320***	63.56	14.00
ROI effects by regions						
ROI (Gansu)	80	3.594	3.271	0.323***	34.39	9.87
ROI (Shaanxi)	195	2.118	1.820	0.298***	29.11	16.37
ROI (Shandong)	206	2.681	2.343	0.338***	64.98	14.43
ROI effects by membership status						
ROI (Nonmembers)	273	2.557	2.249	0.308***	40.39	13.69
ROI (Members)	208	2.668	2.333	0.335***	58.02	14.36
ROI effects by membership years [b]						
ROI (0<membership<=3)	85	2.617	2.320	0.297***	30.30	12.80
ROI (3<membership<=5)	87	2.687	2.329	0.358***	47.28	15.37
ROI (6<membership<=8)	36	2.743	2.373	0.370***	39.97	15.59

Note: *** p<0.01;

[a] ATE refers to average treatment effects;

[b] Among sampled 208 cooperative members, the average membership is 4.03 years, with minimum value of 1 year and maximum value of 8 years.

As comparison, the ATE estimate from PSM method is reported in the lower part of Table 5.4. The result reveals that the ATE value (0.304) estimated by PSM model is slightly lower than that estimated by treatment effects model (0.320), as shown in Table 5.5. This finding suggests that in our case, the omission of unobservable factors (e.g., farmers' innate abilities) that influence both the decision of cooperative membership and the ROI results in negative selection bias, leading to underestimated ATE in PSM model estimation.

For robustness check, we estimated the impact of cooperative membership on the ROI, using treatment effects model, and including an information availability variable representing whether a farmer can acquire sufficient information to understand the functions of contemporary cooperatives as an identifying instrumental variable. We used the same method to check the validity of friend membership variable to test the validity of information availability variable as an instrument. The results, which are presented in Table 5.6.A1 in the Appendix, show that the marginal effect of cooperative membership is 1.604, which is similar to that (1.739) presented in Table 5.4. Moreover, the ATE value of cooperative membership is 0.318 in Table 5.6.A1 in the Appendix, which is quite similar to the ATE value (0.320) presented in Table 5.5. These findings generally confirm the robust estimates for the impact of cooperative membership on the ROI.

5.5 Conclusion

The paper has examined the impact of cooperative membership on the ROI. A treatment effects model was applied to address the issue of selection bias and explore a survey data of 481 apple producing households in China. A negative selection bias was identified in our analysis, suggesting that farmers with lower than average ROI are more likely to choose cooperative membership. The implication is plausible, as cooperative organization is expected to benefit smallholder farmers that are in unfavorable conditions. Also, the presence of selection bias confirms the use of the treatment effects model to estimate the effect of cooperative membership on the ROI.

The empirical results showed that the impact of cooperative membership was to increase the ROI by 14% on average. Moreover, farmers located in Shaanxi province obtained higher ROI than their counterparts in Shandong and Gansu. We also found that ROI effects of cooperative membership increased with increasing membership years. With respect to the factors that influence cooperative membership, the results revealed that education, farm size, asset ownership such as power sprayer and computer, and social network are vital determinants of cooperative membership. The higher ROI was found to be positively and significantly influenced by income specialization, marketing contract, labor availability and risk attitude.

For development program designers, this analysis provides empirical evidence for a vital role of agricultural cooperative in enhancing the agricultural performance of smallholder farmers. As revealed by the results, smallholder farmers in unfavorable conditions are more likely to be included in the agricultural cooperatives. The development of cooperative organization is thus beneficial for smallholder farmers and promotes a more equitable and sustainable agricultural development in rural areas. The agricultural cooperatives deserve more public investment and guidance in the near future. In practice, the development of such organization could be promoted through spreading cooperative information to well-educated farmers and enhanced by the construction of rural internet infrastructure, as education, social network and the internet were found to facilitate smallholder farmers' participation in agricultural cooperative. Finally, a development strategy of production specialization and marketing contract transaction could further improve the performance of smallholder farmers, by significantly increasing their return on investment.

Appendix

Table 5.6.A1 Impact of cooperative membership on the ROI: Robustness check

Variable	Selection	ROI
Membership		1.604 (0.418)***
Age	0.005 (0.008)	-0.018 (0.008)**
Education	0.054 (0.026)**	-0.053 (0.027)**
Dependency ratio	0.103 (0.325)	-1.037 (0.359)***
Farm size	0.089 (0.025)***	-0.147 (0.030)***
Sprayer ownership	0.738 (0.194)***	-0.089 (0.213)
Computer ownership	0.339 (0.150)**	0.220 (0.164)
Specialization	0.048 (0.337)	1.546 (0.347)***
Marketing contract	0.071 (0.170)	0.550 (0.181)***
Labor availability	-0.429 (0.153)***	0.721 (0.183)***
Risk attitude	-0.078 (0.129)	0.324 (0.137)**
Social network	0.418 (0.128)***	-0.044 (0.144)
Gansu	0.209 (0.251)	0.701 (0.264)***
Shaanxi	-0.946 (0.238)***	-0.139 (0.262)
Information availability	-0.356 (0.130)***	
Constant	-1.615 (0.605)***	2.167 (0.626)***
$\mathrm{ath}(\rho'_{\varepsilon\mu})$	-0.590 (0.201)***	
$\rho'_{\varepsilon\mu}$	-0.530 (0.145)***	
Ln(σ)	0.364 (0.066)***	
Wald test ($\rho'_{\varepsilon\mu} = 0$)	8.62***, Prob > chi2 = 0.0033	
ATE (treatment effects model)[a]	0.318***, with *t*-value=63.56	
ATE (PSM)[b]	0.304 (0.162)*	
Sample size	481	

Note: In selection equation, dependent variable is a 1-0 dummy; Robust standard errors in parentheses;

*** p<0.01, ** p<0.05, * p<0.1;

[a] ATE (treatment effects model) refers to average treatment effects estimated by treatment effects model;

[b] ATE (PSM) refers to average treatment effects estimated by propensity score matching model, which is calculated using *teffects psmatch* command in Stata 13.0.

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Chapter 6 Linking Apple Farmers to Markets: Determinants and Impacts of Marketing Contracts in China

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Abstract

Purpose-The objective of this paper is to investigate the determinants of marketing contract choices including written contracts, oral contracts and no contracts, as well as to examine the impact of marketing contracts on net returns from apple production in China.

Design/methodology/approach-A two-stage selection correction approach (BFG) for the multinomial logit model is employed to estimate the impact of marketing contracts on net returns from apple production. On the basis of the BFG estimation, we also use an endogenous switching regression model and a propensity score matching technique to estimate the causal effects of marketing contract choices on net returns from apple production.

Findings-The results reveal significant selectivity correction terms in the choices of both written contracts and no contracts and insignificant selectivity correction terms in the choice of oral contract, indicating that accounting for selection bias is a prerequisite for unbiased and consistent estimation. The findings also indicate written contracts increase apple farmers' net returns, while oral contracts exert the opposite effect.

Originality/value-To the best of our knowledge, this study is the first to examine the impact of marketing contract choices on net returns from apple production, accounting for selectivity effects.

Keywords: Marketing Contracts; Multinomial Logit; Selectivity Correction; China

6.1 Introduction

Marketing contracts are pre-harvest agreements between producers and contractors, in which only prices and quantities are agreed between the contracting parties (MacDonald et al. 2004; Wang et al. 2014). Agro-food marketing on a contractual basis is a common arrangement in agricultural sector all around the world. The coordination mechanisms through marketing contract arrangements play a vital role in linking smallholder farmers to advanced supply chains (e.g., supermarkets, restaurants, processors, and international markets), and contributing to rural income growth and poverty reduction (Islam 2009; Mangala and Chengappa 2008; Miyata et al. 2009). For small farmers living in remote rural areas in particular, agro-food marketing with marketing contracts is an option that may help overcome imperfect markets, improve access to credit, and reduce transaction costs and income risks (Goodwin and Schroeder 1994; Katchova and Miranda 2004; Musser et al. 1996). However, despite the benefits associated with marketing contracts, surveys have found that farmers use fewer marketing contracts in developing countries. For instance, in a survey of the fruit sector in 2005, Huang et al. (2008) found that only 22.86% and 4.76% of grapes are respectively sold with written and oral contracts in Shandong province in China.

The significance of marketing contracts in promoting smallholders' market participation and improving their welfare in developing countries has attracted considerable attention of policy analysts. In particular, several studies have examined farmer's binary choice between participating in advanced agro-food supply chains such as supermarkets through the contractual arrangements and selling at spot markets (e.g., Blandon et al. 2009; Bourguignon et al. 2007; Escobal and Cavero 2012; Franken et al. 2014; Goodwin and Schroeder 1994; Miyata et al. 2009; Paulson et al. 2010; Roe et al. 2004). Furthermore, an emerging body of research reveals that participation in high-value markets such as supermarkets through marketing contracts leads to higher net incomes (Escobal and Cavero 2012; Neven et al. 2009).

A number of authors have also examined the nature and determinants of the choices of different types of marketing contracts (Abdulai and Birachi 2009; Guo and Jolly 2008; Jia et al. 2012; Katchova and Miranda 2004; Sartwelle et al. 2000). For instance, Katchova and Miranda (2004) investigated farmers' choices of marketing contracts such as cash sales, forward contracts, and futures/options. Abdulai and Birachi (2009) noted that the choice of written contracts, verbal contracts and spot market contracts used in Kenyan fresh milk supply chain are determined by location, information source, travel time, gender and distance to markets. In addition to examining the factors that influence farmers' choices of different types of marketing contracts, understanding the linkages between marketing contract choices and farm outcomes can also provide significant information to agro-food producers and policy makers on whether a particular choice of marketing contract is an effective option for smallholder farmers who are gradually shifting from traditional spot markets to advanced supply chains. The issue is critical, given the increasing significance of contractual arrangements in linking smallholder farmers to modern supply chains in developing countries (Schipmann and Qaim 2011). However, to the best of our knowledge, the impact of marketing contract choices on farm performance has not been previously analyzed.

The present study therefore contributes to the debate on contractual arrangements and net returns, by investigating the determinants of different types of marketing contract choices, as well as estimating the impact of marketing contract choices on net returns from crop production. In particular, net returns from crop production are employed to provide an indication of income effect as it rules out possible differences in the aspect of output level, prices and variable input costs. The study utilizes a cross-sectional survey data of 422 apple farmers collected in Gansu, Shaanxi and Shandong provinces of China between September and December 2013. In the survey regions, farmers are primarily engaged in apple production for their livelihoods, and they are involved in contractual arrangements including written contracts, oral contracts and no contracts for apple marketing.

We model farmers' choices of marketing contracts as a selection process, where the expected higher net returns from apple production (hereafter, also known as the "net returns" for brevity) drive their choices of particular types of marketing contracts from available alternatives. Specifically, we employ a selectivity based approach for the multinomial logit (MNL) model to examine the impact of the choice of written contracts, oral contracts, or no contracts on net returns. This approach was proposed by Bourguignon et al. (2007), which can identify the direction of the bias related to the choice of a given marketing contract, as well which type of marketing contract is the source of the bias. We also use an endogenous switching regression model and a propensity score matching technique to estimate the causal effects of marketing contract choices on net returns, as robustness checks.

The rest of the paper is structured as follows: Section 6.2 gives an overview of apple production and marketing in China. This is followed by the empirical specification and estimation technique used in the analysis. Section 6.4 presents a description of the data used, while the estimated results are given in Section 6.5. Conclusions are discussed in the final section.

6.2 Overview of Apple Production and Marketing in China

China is the largest apple producer in the world. Apple output reached 37 million metric tons in 2012, accounting for nearly 48.44% of the world's total apple output (FAOSTAT). Although apple is widely grown in China, the major producing areas are concentrated in Bohai Gulf region (Shandong, Hebei and Liaoning provinces) and Northwest Loess Plateau region (Gansu, Shaanxi, Shanxi and Henan provinces). In particular, around 54.17% of the country's total apple orchards are located in Gansu, Shaanxi and Shandong provinces. The agro-food market in China is dominated by a large number of smallholder farmers, traders and wholesalers (Huang et al., 2007), and apple marketing is no exception. Apple farmers' participation in domestic and international markets is severely constrained as a result of market imperfection, information asymmetry and high transaction costs, especially those producing apples in hilly and mountainous areas. For instance, farmers have better information about apple quality, while buyers have more information about the markets. However, the information asymmetry between farmers and buyers prevents the apple transactions from operating efficiently. Although the Chinese government has made efforts in the development of farm associations and agricultural cooperatives in order to facilitate vertical coordination with the agro-food market, farmers continue to make their own marketing decisions (Huang et al. 2009).

As indicated previously, three main types of contractual arrangements are used in the fresh apple supply chain in China. These include written contracts, oral contracts and no contracts, or spot market contracts. Written contracts are formal agreements between farmers and buyers with regards to price, quantity, timing, and product attributes. They are normally signed by farmers and buyers from different marketing channels, after negotiation of the contract terms, which are backed by the law. Oral contracts are informal agreements, in which the transaction terms similar to written contracts are verbally agreed. Deposits may be given to farmers to seal the deal. Finally, no contract refers to spot market transactions, in which the transaction agreements are made on the market at prices fixed according to demand and price changes, without any advanced commitments.

6.3 Empirical Specification and Estimation Technique

6.3.1 The Empirical Specification

The framework used in the analysis is based on the assumption that farmers choose between mutually exclusive marketing contracts. For analytical convenience, it is assumed that farmers are risk neutral, and normally consider the net benefits from a marketing contract in their decision-making process.[1] In the present setting, we refer to the net benefits as net returns from apple production, derived under transaction costs (TC). These marketing contract alternatives could be: (1) written contracts; (2) oral contracts; and (3) no contracts (i.e. spot market sales). In essence, the proportional transaction costs increase the real price of inputs (O_i) and decrease the real price received for output (P_q) (Iliopoulos 2013; Key et al. 2000). Let TC_i^p and TC_q^p represent proportional transaction costs per unit of input (*I*) and output (*Q*), respectively. The adjusted input price is then given as $O_i' = O_i + TC_i^p$, while that for output price is $P_q' = P_q - TC_q^p$. Meanwhile, let TC_i^f and TC_q^f denote fixed transaction costs for input and output market participation, respectively. Given these assumptions, farmers are assumed to maximize their net returns (π^*) as:

$$\pi^* = max\left[Q(P_q - TC_q^p) - (O_i + TC_i^p)I - TC_q^f - TC_i^f\right] \tag{6.1}$$

From equation (6.1), a reduced-form of net returns function, in which the net returns from apple production are determined by the output and variable input prices, proportional transaction costs for input and output market participation, and household and farm level characteristics (*Z*), can be expressed as:

$$\pi = \pi(P_q, \mathrm{O}, TC_i^p, TC_q^p, Z) \tag{6.2}$$

As indicated previously, we assume that farmer *i* compares the expected net returns from choosing a specific marketing contract (C_{ij}^M) to that obtained from using no contract (C_{ij}^N), and the rational individual finally chooses to use the marketing contract, if $C_{ij}^M - C_{ij}^N > 0$. Although the preferences of the farmers are not known to the analysts, the farm and household-level characteristics of the individual farmers, as well as the attributes of the marketing contracts

[1] This assumption is consistent with previous work on the determinants of marketing contracts by Katchova and Miranda (2004).

were observed during the survey. Based on the information available, we can represent the net returns from a marketing contract by a latent variable C_{ij}^*, such that:

$$C_{ij}^* = Z\gamma_{ij} + \eta_i$$

$$C_{ij} = 1, \;\; if \; C_{ij}^* > 0$$

$$C_{ij} = 0, \;\; if \; C_{ij}^* \leq 0 \tag{6.3}$$

where C_{ij} is a binary indicator variable that equals 1, if the individual uses the marketing contract, and 0 if the individual uses no contract, or sells at spot market; in particular, *j*=1 if the farmer chooses written contract, while *j*=2 if the individual chooses oral contract. Thus, the farmer only uses marketing contract if the perceived net returns are positive.

6.3.2 The Issue of Impact Analysis

In order to examine the impact of marketing contract choice on net returns, we assume that net returns from apple production is a linear function of a vector of explanatory variables (X_{ij}) and a marketing contract choice dummy (C_{ij}). Thus, the net returns function can be specified as:

$$Y_{ij} = \beta X_{ij} + \delta C_{ij} + \mu_i \tag{6.4}$$

where Y_{ij} is net returns for choosing written contracts (*j*=1) and oral contracts (*j*=2); β and δ are parameters to be estimated; μ_i is an error term that satisfies $\mu_i \sim N(0, \sigma)$. The issue of selection bias arises if unobservable characteristics affect both the error terms in equations (6.3) and (6.4), resulting in a correlation between the two error terms, i.e. $\mathrm{corr}(\eta_i, \mu_i) \neq 0$.

When selection is over a large number of mutually exclusive choices (e.g., selling apples using written contracts, oral contracts or no contracts), a two-step method is normally employed to address the issue of selection bias based on a multinomial logit model. Two traditional approaches are suggested by Lee (1983) and Dubin and McFadden (Hereinafter DMF, 1984). However, Lee's method estimates a single selectivity effects for all choices together and DMF method establishes *M*-1 selection terms for the *M* choices, which cannot fully address the selection bias issue arising from multiple choices of marketing contracts. Therefore, this study employs a selectivity correction approach proposed by Bourguignon, Fournier and Gurgand

(Hereinafter BFG, 2007), which is more accurate in capturing selectivity effects generated by alternative choices (Khanal and Mishra 2014).

6.3.3 BFG Method

The BFG method is a two-step estimation model, accounting for selection bias and systematic differences across groups. The first-step applies an unordered multinomial logit (MNL) model aimed at studying farmers' choices of different types of marketing contracts, as well as creating selectivity terms for unbiased estimation of net returns equations. Since three types of marketing contracts are identified in this study, there are three selectivity correction terms that can be derived. Given that the first type of marketing contract is chosen (*j*=1), the MNL model is given as:

$$P_1(\varepsilon_1 < 0|Z) = \frac{exp(Z\gamma_1)}{\sum_{j=1}^{3} Z\gamma_j}\ , j = 1, 2, 3 \tag{6.5}$$

where $\varepsilon_1 = max_{j\neq 1}(C_j^* - C_1^*) = max_{j\neq 1}(Z\gamma_j + \eta_j - Z\gamma_1 - \eta_1)$; P_1 is the probability of choosing the first type of marketing contract; j is a categorical variable describing farmers' choices of written contracts (*j*=1), oral contracts (*j*=2) and no contracts (*j*=3); γ_j are the consistent maximum likelihood estimates; *Z* is a set of explanatory variables for all marketing contract alternatives. In a non-linear model such as the MNL, the estimated coefficients are not interpreted directly, we thus calculate the marginal effects to provide a better understanding about the magnitudes of the coefficients (Greene 2003).

The second-step of the BFG method involves the estimation of the net returns equations for the different types of marketing contracts, using ordinary least square (OLS) regression, where the selectivity correction terms estimated in the first-step are simultaneously included to obtain unbiased and consistent estimation. Given that the marketing contract option one is chosen (*j*=1), the outcome equation for net returns, y_1 is specified as:

$$y_1 = X\beta_1 + \sigma_1\left[\rho_1^* m(P_1) + \rho_2^* m(P_2)\frac{P_2}{P_2 - 1} + \rho_3^* m(P_3)\frac{P_3}{P_3 - 1}\right] + w_1 \tag{6.6}$$

where $m(P_1)$, $m(P_2)$ and $m(P_3)$ are the conditional expectations of η_1^*, η_2^* and η_3^*, which are used to correct for selectivity effects; ρ represents correlation coefficients between μ and η; σ is the standard deviation of the disturbance term from the net returns equation; and w_1 is the error term. The net returns equations for choosing the other marketing contracts can be written in a similar way.

The selectivity correction terms in equation (6.6) have econometric interpretations. Specifically, if at least one of them is significant, this would suggest the presence of sample selectivity effects arising from unobservable factors. The estimated coefficients would be biased and inconsistent if these terms are not included in the related net returns equations. Moreover, for each net returns specification, a positive (negative) coefficient of the selectivity term indicates higher (lower) net returns for the farmers, relative to a randomly chosen producer. This is because farmers with better (worse) unobserved endowments are more likely to choose this given type of marketing contract rather than other alternatives (Bourguignon et al. 2007). Insignificant selectivity terms indicate the absence of selectivity effects.

The BFG estimation investigates the factors that influence the choices of different types of marketing contracts and the impact of contractual choice on net returns. As robustness checks, we also employ two impact assessment methods that account for selectivity bias to complement the results from the BFG analysis. These methods are endogenous switching regression (ESR) model, which accounts for both observable and unobservable factors, and propensity score matching (PSM), which accounts only for observable factors (Dehejia and Wahba 2002; Lokshin and Sajaia 2004). In particular, if at least one of the selectivity correction terms is significant for the given type of marketing contract, this would suggest the presence of selection bias arising from unobservable factors, in which case the ESR model is appropriate in analyzing the causal effect of the given marketing contract choice. If none of the selectivity correction terms is significantly different from zero in the net return specification for the given type of marketing contract, this would indicate the absence of selection bias arising from unobservable factors. In such a case, we use PSM technique to assess the related casual effects.

6.3.4 The ESR Model

The ESR is a parametric approach that uses two different estimation equations for a given marketing contract option and other alternatives, while accounting for selection process by including an inverse Mills ratio that is calculated from the selection equation presented in equation (6.3) (Lokshin and Sajaia 2004). The outcome equations are then based on equation (6.4), separately for each regime, conditional on the marketing contract selection decision, which is estimated by a probit model.

Given the marketing contract choice and outcome equations specified in (6.3) and (6.4), respectively, the relationship between the choice of marketing contract and the two regimes can be specified as:

$$C_1^* = Z\gamma_1 + \eta_1 \tag{6.7}$$

$$Y_1 = X\beta_1 + \varphi_1 \quad if\ \ C_1 = 1 \tag{6.7a}$$

$$Y_0 = X\beta_0 + \varphi_0 \quad if\ \ C_0 = 0 \tag{6.7b}$$

where Y_1 represents net returns, if the first marketing contract option is chosen (*j*=1), and Y_0 is net returns derived from choosing other marketing contract options ($j \neq 1$); X is a vector of exogenous variables that affect the net returns; φ_1 and φ_0 are error terms, with zero mean and normal distribution. The ESR model addresses the issue of selection bias resulting from unobservable factors as a missing variable problem. In particular, after estimating a probit model using the selection equation (6.7), the inverse Mills ratios λ_1 and λ_0 and the covariance terms, $\sigma_{\eta 1} = cov(\eta_1, \varphi_1)$ and $\sigma_{\eta 0} = cov(\eta_1, \varphi_0)$ can be calculated and plugged into equations (6.7a) and (6.7b):

$$Y_1 = X\beta_1 + \sigma_{\eta 1}\lambda_1 + \xi_1 \quad if\ \ C_1 = 1 \tag{6.8a}$$

$$Y_0 = X\beta_0 + \sigma_{\eta 0}\lambda_0 + \xi_0 \quad if\ \ C_0 = 0 \tag{6.8b}$$

where λ_1 and λ_0 control for selection bias resulting from unobservable factors such as the local institutional environment for the produce market and farmers' inherent ability; the error terms ξ_1 and ξ_0 have conditional zero means. The full information maximum likelihood (FIML) method suggested by Lokshin and Sajaia (2004) is used to estimate the selection and outcome equations simultaneously. The approach overcomes the drawback of estimating the equations separately, which generates residuals that are heteroskedastic.

The correlation coefficients, $\rho_{\eta 1}(\sigma_{\eta 1}/\sigma_\eta \sigma_1)$ and $\rho_{\eta 0}(\sigma_{\eta 0}/\sigma_\eta \sigma_0)$ of covariance terms between the error terms η_1, φ_1 and φ_0 have econometric interpretations. If $\rho_{\eta 1}$ or $\rho_{\eta 0}$ is significant, this would indicate the presence of selection bias arising from unobservable factors. Moreover, $\rho_{\eta 1} > 0$ implies negative selection bias, suggesting that farmers with below average net returns are more likely to choose the given marketing contract, while $\rho_{\eta 1} < 0$ implies positive selection bias (Lokshin and Sajaia 2004). The consistent estimation also requires that the correlation coefficient $\rho_{\eta 1}$ in ESR model and the coefficients of the significant selectivity bias terms $m(P_j)$ in BFG model for the given marketing contract option have opposite signs. The effect of marketing contract on net returns is examined by specifying expected values of the outcomes. The change in net returns due to a specific marketing contract relative to another contract is specified as the difference between the marketing contracts. These estimates are termed average treatment effects on the treated (ATT).

The ATT τ_{ATT}^{ESR} in this case is:

$$\tau_{ATT}^{ESR} = E[Y_1|C_1 = 1] - E[Y_0|C_1 = 1] = X(\beta_1 - \beta_0) + \lambda_1(\sigma_{\eta 1} - \sigma_{\eta 0}) \tag{6.9}$$

6.3.5 The PSM Technique

PSM compares outcomes between a specific type of marketing contract users ("treated") and those using other marketing contract alternatives ("controlled") that are similar in terms of observable characteristics, thus reducing the bias that would otherwise occur when the two groups are systematically different (Dehejia and Wahba 2002). It involves two stages. First, we generate propensity score (i.e. the probability) of choosing the given marketing contract using a probit model. Second, we calculate the average treatment effect on the treated (ATT) based on the estimated propensity score. PSM can be expressed as:

$$\Pr(X_1) = \Pr(C_1 = 1|Z_1) = E(C_1|Z_1) \tag{6.10}$$

where $C_1 = \{0, 1\}$ is an indicator for choosing the given type of marketing contract (*j*=1) and Z_1 is a vector of pre-choice characteristics.

After estimating the propensity scores, the ATT, τ_{ATT}^{PSM} can then be estimated as:

$$\tau_{ATT}^{PSM} = E_{P(Z_1)|D_1=1}\{E[(Y_1|D_1 = 1, P(Z_1)] - E[(Y_0|D_1 = 1, P(Z_1)]\} \tag{6.11}$$

Several techniques have been developed to match the given marketing contract users and non-users of similar propensity score. In this study, we employ the most commonly used techniques including nearest neighbor matching (NNM), kernel-based matching (KBM) and radius matching methods to estimate the ATT.

6.4 Data and Description

The data employed in the present study come from a farm household survey that was conducted between September and December 2013 in three main apple growing provinces (Gansu, Shaanxi and Shandong) in China. A multistage random sampling procedure with purposive selection of provinces and counties based on the intensity of apple production and random selection of villages and households was employed to select 422 farmers for the survey. Farmers were asked to provide detailed information on personal and farm level characteristics, asset ownership, financial situation, access to information, as well as marketing activities. Only 7.58% of the farmers who used marketing contracts choose different types of contracts. In these cases, we classify their contract type as the type of the contracts with larger proportion of production contracted in order to simplify the analysis. The final dataset of marketing contracts includes records for 179 written contract users, 71 oral contract users and 172 no contract users (i.e. spot market sellers).

The dependent variables considered include written contracts, oral contracts and no contracts, which gives the value of 1 if a given marketing contract was chosen, and 0 otherwise. The outcomes refer to net returns from apple production, which are measured as the difference between the value of apple yields and variable input costs per mu[2]. The inputs included fertilizer, pesticide, hired labor, films for land moisture conservation and apple coloring, bags, and irrigation. The independent variables employed to explain the determinants of marketing contract choices are based on the existing literature (Katchova and Miranda 2004; Wang et al. 2014).

Table 6.1 presents descriptive statistics for the survey households. It can be observed that 42% and 17% of farmers choose written contracts and oral contracts, respectively. The rest opted for spot market contracts. Farmers in the sample are smallholders with an average orchard size of 5.22 mu. Apple production and marketing contribute 75% of total household incomes averagely, and the average net returns per mu is 7110 yuan[3]. In our sample, only 19% of farmers use cooperative organization as a primary marketing channel. 30% of households are observed to acquire output marketing information from their neighbors. More than half of the households

[2] 1 mu=1/15 hectare.

[3] yuan is Chinese currency unit (1$=6.14 yuan).

are not credit constrained in the survey year. These are households that did not require additional credit for the farming activities.

Table 6.1 The definitions of the variables used in the analysis

Variables	Description	Mean (S.D.)
Written contract	1 if farmer chose written contract for apple marketing, 0 otherwise	0.42 (0.49)
Oral contract	1 if farmer chose oral contract for apple marketing, 0 otherwise	0.17 (0.37)
No contract	1 if farmer sold apples with no contract, 0 otherwise	0.41 (0.49
Net returns	Gross revenue from apple production minus variable input costs (yuan/1000/mu[a])	7.11 (3.69)
Age	Age of respondent (years)	48.47 (10.46)
Education	No. of years of schooling	7.48 (2.95)
Orchard size	Total fruiting apple orchards (mu)	5.22 (3.27)
Specialization	The value of total apple yields divided by the total household incomes (%)	0.75 (0.22)
Farming vehicle	1 if farmer owns farming vehicle, 0 otherwise	0.91 (0.29)
Computer	1 if farmer owns computer, 0 otherwise	0.29 (0.45)
Cooperative sales	1 if farmer sold apples mainly through agricultural cooperatives, 0 otherwise	0.19 (0.39)
Extension contact	1 If farmer visited extension service, 0 otherwise	0.39 (0.49)
Access to credit	1 If farmer is not liquidity constrained, 0 otherwise	0.52 (0.50)
Timely payment	1 if farmer received timely payment, 0 otherwise	0.82 (0.38)
Neighbors	1 if farmer acquired output marketing information from neighbors, 0 otherwise	0.30 (0.46)
Market perception	Apple market demand situation last year (1=Bad; 2=Fair; 3=Good)	2.24 (0.85)
Distance	Distance to markets (km)	0.72 (2.66)
Quantity	Quantity of total apple sold (kg/1000)	18.02 (10.67)
Price	Average apple selling price (yuan/kg)	3.72 (0.83)
Shandong	1 if farmer is located in Shandong province, 0 otherwise	0.37 (0.48)
Gansu	1 if farmer is located in Gansu province, 0 otherwise	0.19 (0.39)
Shaanxi	1 if farmer is located in Shaanxi province, 0 otherwise	0.44 (0.50)

[a] yuan is Chinese currency (1$=6.14 yuan); 1 mu=1/15 hectare.

Table 6.2 presents differences in the characteristics between written contract users, oral contract users and no contract users. In particular, both written and oral contract users are younger than no contract users. The orchard size of oral contract users is about 84% larger compared to no contract users. The orchard size of written contract users is much larger, which is more than double that of no contract users. Compared with no contract users, written contract users are 31% less likely to be credit constrained, while oral contract users are 27% more likely to be capital constrained. Both written and oral contract users have lower market perception of apple demand, compared with no contract users. There are also marked differences in output price and supply quantity between marketing contract users and no contract users. In particular, both written and oral contract users tend to obtain higher prices and sell larger quantities of the produce. The lower part of Table 6.2 also reveals that the average net returns from apple production for written contract users is 2.71% lower than that for no contract users, while the average net returns for oral contract users is much lower than that for the counterpart by 14.38%. Overall, the results presented in Table 6.2 indicate that written contract users, oral contract users and no contract users are systematically different.

Table 6.2 Difference in characteristics between the users of written contracts, oral contracts and no contracts

Variables	Written contract (N=179)	Oral contract (N=71)	No contract (N=172)
Age	45.17 (10.31)	46.44 (8.51)	52.75 (9.88)
Education	7.80 (2.66)	7.21 (3..32)	7.24 (3.05)
Orchard size	6.97 (3.09)	5.82 (2.80)	3.17 (2.36)
Specialization	0.84 (0.17)	0.70 (0.22)	0.68 (0.22)
Farming vehicle	0.89 (0.31)	0.92 (0.28)	0.92 (0.27)
Computer	0.41 (0.49)	0.31 (0.47)	0.15 (0.36)
Cooperative sales	0.11 (0.31)	0.38 (0.49)	0.20 (0.40)
Extension contact	0.55 (0.50)	0.51 (0.50)	0.19 (0.39)
Access to credit	0.63 (0.49)	0.35 (0.48)	0.48 (0.50)
Timely payment	0.80 (0.40)	0.73 (0.46)	0.89 (0.31)
Neighbors	0.22 (0.41)	0.25 (0.44)	0.40 (0.49)
Market perception	2.05 (0.85)	1.92 (0.92)	2.58 (0.68)
Distance	0.58 (2.23)	0.97 (3.80)	1.26 (3.07)
Quantity	23.51 (11.39)	17.54 (9.61)	12.52 (6.73)
Price	3.83 (1.01)	3.86 (0.60)	3.55 (0.64)
Net returns	7.17 (37.27)	6.31 (3.86)	7.37 (3.54)

Note: Standard deviation in parentheses.

6.5 Empirical Results

6.5.1 Determinants of Marketing Contract Choices: First-stage BFG Estimation

The parameter estimates of the choices of marketing contracts used by apple farmers are presented in Table 6.3. Note that the base group for comparison is farmers selling with no contracts. The MNL regression was used to model the farmer's choice of marketing contracts such as written contracts, oral contracts or no contracts. As indicated previously, the magnitudes of the coefficients from MNL model are difficult to interpret, we therefore use the marginal effects to interpret the determinants of farmer's choices of marketing contracts.

The marginal effect of cooperative sale variable is positive and statistically significant for oral contracts, indicating that trust mechanism developed between apple farmers and cooperative organizations contribute to the use of informal oral contracts. As indicated by Guo and Jolly (2008), oral contracts tend to be used by the cooperatives, as underwriting and enforcement may rely on the network and norms of smallholders. The cooperative variable has a negative and significant impact on no contracts, but no impact on written contracts. Farmers who are not liquidity constrained are more likely to choose written contracts and less likely to use oral contracts. The positive and significant marginal effect of the timely payment variable for written contracts indicates that farmers who prefer timely payment are more likely to choose written contracts, while the negative and significant effects for no contracts suggest that those who can accept delayed payment are more likely to use no contracts. This finding contrasts with the results reported by Abdulai and Birachi (2009) for fresh milk marketing in Nakuru district of Kenya. As noted by Schipmann and Qaim (2011) in their study on Thailand, delayed payment in contract schemes may deter smallholder farmers from using marketing contracts. In particular, timely payment can improve the situation of written contract users, especially resource-poor farmers, although delayed payment may be compensated by higher prices to some extent. Relative to their counterparts in Shandong province (reference division), apple farmers in Gansu and Shaanxi provinces appear to favor the use of written contracts, while they are less likely to use no contracts. The significance of location variables indicates the importance of spatial effects. The volumes of apple sold have a negative, but statistically insignificant effect on both oral and no contracts. However, a positive and statistically significant coefficient is observed for written contracts. The estimates also reveal that longer distance to reach buyers is positively and significantly associated with oral contracts, which is consistent with the finding by Abdulai and Birachi (2009). Finally, the variables such as age, education, orchard size, ownership of farming vehicle and computer, extension contact, access to information through neighbor, and the transacted prices did not appear to influence apple farmers' choice of marketing contracts.

As indicated earlier, another purpose of the MNL selection estimates of marketing contract choices is to account for the unobserved heterogeneity that could bias the results of the coefficients in the net returns equations. Thus, the MNL selection equations need to include one or more valid instruments for model identification, which should strongly influence farmer's choices of marketing contracts, but do not influence the net returns. In this study, we employed a variable representing farmer's perception of apple market demand as an instrument. As evident from the Table 6.9.A1 in the Appendix, the employed instrument is uncorrelated with net returns. However, it is highly significant in MNL selection equations, suggesting that it is a valid instrument. Besides, the significant marginal effects of market perception variable also indicate that farmers with perception of higher market demand for produced apples are less likely to use both written and oral contracts, but more likely to use no contracts, suggesting that marketing contracts are more likely to be used to deal with sluggish markets.

Table 6.3 Determinants of marketing contract choices: First-stage BFG estimation

	Written contract (N=179)		Oral contract (N=71)		No contract (N=172)	
Variable	Marginal effects	*z*-value	Marginal effects	*z*-value	Marginal effects	*z*-value
Age	-0.001 (0.004)	-0.22	-0.004 (0.003)	-1.04	0.004 (0.005)	0.88
Education	0.021 (0.014)	1.53	-0.018 (0.011)	-1.67*	-0.003 (0.017)	-0.18
Orchard size	-0.001 (0.017)	-0.09	0.024 (0.015)	1.61	-0.023 (0.023)	-0.97
Specialization	0.052 (0.208)	0.25	-0.444 (0.167)	-2.66***	0.392 (0.264)	1.48
Farming vehicle	0.014 (0.109)	0.13	0.058 (0.090)	0.64	-0.072 (0.141)	-0.51
Computer	0.001 (0.087)	0.00	-0.001 (0.074)	-0.02	0.001 (0.117)	0.01
Cooperative sales	-0.010 (0.098)	-0.10	0.404 (0.091)	4.43***	-0.394 (0.091)	-4.31***
Extension contact	0.063 (0.073)	0.87	0.064 (0.062)	1.03	-0.127 (0.087)	-1.46
Access to credit	0.175 (0.072)	2.44**	-0.135 (0.061)	-2.20**	-0.040 (0.090)	-0.45
Timely payment	0.171 (0.073)	2.36**	0.066 (0.073)	0.91	-0.237 (0.113)	-2.10**
Neighbor	-0.079 (0.076)	-1.03	-0.058 (0.061)	-0.96	0.137 (0.096)	1.43
Distance (log)	-0.008 (0.010)	-0.75	0.022 (0.009)	2.60***	-0.015 (0.013)	-1.10
Quantity (log)	0.194 (0.099)	1.96*	-0.015 (0.082)	-0.18	-0.179 (0.120)	-1.49
Price (log)	0.063 (0.179)	0.35	0.115 (0.154)	0.75	-0.178 (0.249)	-0.71
Market perception	-0.155 (0.044)	-3.55***	-0.087 (0.037)	-2.37**	0.241 (0.054)	4.47***
Gansu	0.662 (0.107)	6.16***	-0.087 (0.085)	-1.02	-0.575 (0.076)	-7.55***
Shaanxi	0.774 (0.060)	13.01***	0.073 (0.061)	1.21	-0.848 (0.050)	-17.04***

Notes: Base group is no contract sellers; *, **, *** denote significance at 10%, 5% and 1% levels, respectively.

6.5.2 Impact of Marketing Contract Choices on Net Returns: Second-stage BFG Estimation

The estimates of the impact of marketing contract choices on net returns are presented in Table 6.4. As indicated previously, the net returns equations are estimated using OLS, in which selection bias correction terms derived from the MNL model are automatically included. The three types of marketing contracts generate three selectivity correction terms, denoted in Mills 1-3, which are used to control for selectivity effects arising from unobserved factors. The estimator variances are all bootstrapped with 100 replications to deal with heteroskedasticity (Huesca and Camberos 2010).

The results reveal that the selectivity correction terms are significant in the choices of both written contracts and no contracts, indicating the presence of sample selectivity effects in these specifications. Hence, accounting for selectivity is essential to ensure unbiased and consistent estimates of the coefficients in the net returns equations. For the written contract specification, the estimated coefficient of the selectivity correction term related to no contracts is significantly negative, indicating lower than expected net returns (downward biased) for written contract users relative to a randomly chosen apple producer. Thus, for farmers who obtained net returns from using written contracts, switching from written contracts to no contracts leads to a negative and significant impact on their net returns. This finding also indicates that apple farmers with worse unobserved attributes are more likely to sell their products with written contracts rather than sell with no contracts. For instance, farmers who perceived lower competitiveness of their apple quality in spot markets may be more likely to choose written contracts in order to stabilize marketing channel and reduce marketing risks. In addition, the BFG estimation reveals that all selectivity correction terms are insignificant in the choice of oral contracts, indicating the absence of selectivity effects resulting from unobservable factors, and that OLS is appropriate for identifying factors influencing net returns in the oral contract specification.

With regards to the factors influencing selection towards net returns, both the age and education variables tend to have a negative and statistically significant impact on net returns of written contract users. Orchard size appears to have negative and statistically significant impact on net returns of marketing contract users, indicating larger orchard size obtained significantly lower net returns than smaller farms. The finding is consistent with earlier studies by Chen et al. (2011) and Abdulai and Huffman (2014). Interestingly, we found that the variables representing selling apples primarily through cooperative organizations have positive and statistically significant impacts on net returns of both written and no contract users, but positive and insignificant impact on that of oral contract users, indicating the growing importance of agricultural cooperatives in providing apple circulation service towards increasing net returns. Contact with extension agents tends to have a positive and significant effect on net returns for written contract users, but a negative and significant effect on net returns of no contract users. The extension contact variable has no significant impact on net returns for oral contract users. The finding indicates the important role of extension service in enhancing net returns for marketing contract users, especially written contract users. Transacted quantities and prices also seem to positively influence net returns through the choices of marketing contracts. In particular, a one percent increase in the quantity transacted entails a larger increase in net returns for oral contract users, while one percent increase in transacted price entails a larger increase in net returns for written contract users.

The estimates for the first-stage BFG approach are presented in Table 6.3, while the second-stage results are presented in Table 6.4. The results provide insights of the important factors that influence the choice of marketing contracts and the related net returns. However, in order to understand the change in net returns between a specific marketing contract and another contract type, some further estimations are required. In particular, given the evidence of significant selectivity correction term resulting from unobservable factors for written contract specification in Table 6.4, this study employs ESR model to estimate the related causal effects (Lokshin and Sajaia 2004). However, since we find no significant selectivity effects in the oral contract specification in Table 6.4, indicating the absence of selection bias arising from unobservable factors, we use PSM technique to estimate the related causal effects (Dehejia and Wahba 2002).

Table 6.4 Impact of marketing contract choices on net returns: Second-stage BFG estimation

	Written contract (N=179)		Oral contract (N=71)		No contract (N=172)	
Variable	Coefficients	*z*-value	Coefficients	*z*-value	Coefficients	*z*-value
Constant	2.286 (1.178)	1.94*	1.093 (1.868)	0.59	3.447 (1.106)	3.12***
Age	-0.012 (0.004)	-2.68***	-0.008 (0.013)	-0.59	0.001 (0.005)	0.21
Education	-0.033 (0.016)	-2.13**	-0.045 (0.052)	-0.86	-0.014 (0.013)	-1.07
Orchard size	-0.102 (0.017)	-5.86***	-0.167 (0.046)	-3.67***	-0.174 (0.059)	-2.94***
Specialization	-0.026 (0.342)	-0.07	-0.030 (0.757)	-0.04	0.002 (0.190)	0.01
Farming vehicle	0.021 (0.098)	0.21	-0.192 (0.356)	-0.54	0.039 (0.107)	0.37
Computer	0.107 (0.082)	1.29	0.184 (0.201)	0.92	0.054 (0.091)	0.59
Cooperative sales	0.528 (0.211)	2.50**	0.677 (0.646)	1.05	0.503 (0.122)	4.12***
Extension contact	0.203 (0.0712)	2.84***	0.047 (0.186)	0.25	-0.192 (0.126)	-1.52
Access to credit	-0.157(0.123)	-1.27	-0.052 (0.367)	-0.14	-0.135 (0.086)	-1.57
Timely payment	-0.098 (0.097)	-1.01	-0.250 (0.200)	-1.25	-0.041 (0.124)	-0.33
Neighbor	-0.052 (0.092)	-0.57	-0.076 (0.175)	-0.43	0.016 (0.064)	0.25
Distance (log)	0.009 (0.014)	0.68	0.018 (0.035)	0.52	0.371 (0.138)	2.69***
Quantity (log)	0.762 (0.100)	7.63***	0.952 (0.261)	3.65***	0.021 (0.009)	2.25**
Price (log)	0.793 (0.127)	6.24***	0.353 (0.577)	0.61	0.612 (0.120)	5.11***
Mills 1	-0.368 (0.262)	-1.40	0.493 (1.186)	0.42	0.551 (0.211)	2.61***
Mills 2	0.979 (0.668)	1.47	0.682 (0.610)	1.12	-0.380 (0.560)	-0.68
Mills 3	-0.797 (0.402)	-1.99**	0.541 (0.688)	0.79	1.201 (0.424)	2.83***

Notes: *, **, *** denote significance at 10%, 5% and 1% levels, respectively;

The dependent variables is the logarithm of net returns of apple production;

Location fixed effects includes in the estimation, but not reported here.

6.5.3 Impact of Written Contract Choice on Net Returns: ESR Estimation

The estimates of the impact of written contract choice (treatment group) on net returns are presented in Tables 6.5 and 6.6, where the control groups are no contract users and oral contract users, respectively. As indicated previously, the FIML approach estimates both the selection and the outcome equations jointly. Considering the primary purpose of ESR estimation in this study is to estimate the causal effect of written contract choice on net returns, the interpretation of detailed results in Tables 6.5 and 6.6 is not put forward. It is worthy to note here that the coefficients of variables in the written contract choice equations in Tables 6.5 and 6.6 usually have the similar sign and significance with the variables estimated from MNL model in Table 6.3.

An interesting finding in Tables 6.5 and 6.6 is the sign and significance of the correlation coefficients ($\rho_{\eta 1}$ and $\rho_{\eta 0}$) of covariance terms between the error terms in the selection and outcome equations. In particular, the results show that the correlation coefficients ($\rho_{\eta 1}$) for the written contract users in both Tables 6.5 and 6.6 are statistically significant, indicating the presence of selection bias resulting from unobservable factors. Hence, taking into account both observable and unobservable factors is essential to obtain unbiased treatment effects (ATT). Moreover, the positive sign for $\rho_{\mu 1}$ indicates a negative selection bias, suggesting that farmers with lower than average net returns have a higher probability to choose written contracts. The negative selection bias here is consistent with the interpretation of negative and significant selectivity term in the net return equation for written contract specification in Table 6.4, confirming that BFG selectivity model proposed by Bourguignon et al. (2007) is appropriate for the analysis of different types of marketing contract choices

Table 6.5 The impact of written contract choice on net returns (relative to no contract users): ESR estimation

Variable	Selection	Net returns	
		Written contract users (N=179)	No contract users (N=172)
Constant	-8.912 (3.114)***	-0.057 (0.800)	2.484 (0.750)***
Age	0.005 (0.014)	-0.007 (0.003)***	0.004 (0.004)
Education	0.073 (0.045)	-0.005 (0.010)	0.004 (0.011)
Orchard size	-0.085 (0.073)	-0.136 (0.012)***	-0.157 (0.017)***
Specialization	-0.337 (0.716)	0.354 (0.153)**	0.252 (0.127)**
Farming Vehicle	0.260 (0.341)	-0.017 (0.084)	-0.020 (0.104)
Computer	0.146 (0.278)	0.118 (0.055)**	0.094 (0.081)
Cooperative sales	0.373 (0.420)	0.212 (0.087)**	0.302 (0.072)***
Extension contact	0.112 (0.236)	0.145 (0.052)***	-0.181 (0.074)**
Access to credit	0.660 (0.261)**	0.060 (0.051)	0.037 (0.063)
Timely payment	0.387 (0.276)	-0.016 (0.066)	0.056 (0.106)
Neighbor	-0.228 (0.286)	-0.026 (0.063)	0.008 (0.059)
Distance (log)	-0.005 (0.034)	-0.008 (0.008)	0.004 (0.007)
Quantity (log)	0.706 (0.353)**	0.878 (0.079)***	0.642 (0.070)***
Price (log)	0.119 (0.569)	0.766 (0.109)***	0.592 (0.167)***
Gansu	2.733 (0.493)***	0.634 (0.236)***	0.493 (0.210)**
Shaanxi	3.718 (0.508)***	0.402 (0.243)*	0.367 (0.373)
Market perception	-0.409 (0.141)***		
$Ln\sigma_1$		-1.140 (0.069)***	
$\rho_{\eta 1}$		0.704 (0.348)**	
$Ln\sigma_0$			-1.108 (0.071)***
$\rho_{\eta 0}$			0.368 (0.775)
Log likelihood	-172.70		
Likelihood ratio test for independent equations $x^2(1)$		2.79*	
Observations	351	351	351

Notes: The dependent variable is the log form of apple net returns measured in yuan/mu (1$=6.14 yuan);
In selection equation, it takes the value of one if farmers used written contract, 0 otherwise;
*, **, *** denote significance at 10%, 5% and 1% levels, respectively.

Table 6.6 The impact of written contract choice on net returns (relative to oral contract users): ESR estimation

Variable	Selection	Net returns	
		Written contract users (N=179)	Oral contract users (N=71)
Constant	-3.379 (2.926)	0.371 (0.733)	0.590 (1.024)
Age	-0.003 (0.011)	-0.007 (0.002)***	-0.002 (0.005)
Education	0.036 (0.040)	-0.007(0.010)	-0.0221 (0.015)
Orchard size	-0.006 (0.05)	-0.133 (0.012)***	-0.178 (0.020)***
Specialization	1.095 (0.610)*	0.436 (0.154)***	0.246 (0.244)
Farming Vehicle	-0.229 (0.351)	-0.032 (0.084)	-0.116 (0.157)
Computer	0.061 (0.244)	0.105 (0.054)*	0.155 (0.110)
Cooperative sales	-0.526 (0.316)*	0.144 (0.090)	0.299 (0.136)**
Extension contact	0.033 (0.210)	0.143 (0.051)***	0.0236 (0.077)
Access to credit	0.691 (0.212)***	0.0704(0.052)	0.096 (0.108)
Timely payment	0.341 (0.254)	-0.024 (0.066)	-0.183 (0.104)*
Neighbor	0.117 (0.239)	0.008 (0.060)	-0.077 (0.092)
Distance (log)	-0.074 (0.030)**	-0.011 (0.008)	0.002 (0.013)
Quantity (log)	0.291 (0.328)	0.852 (0.076)***	0.977 (0.122)***
Price (log)	0.368 (0.520)	0.750 (0.108)***	0.229 (0.275)
Gansu	0.611 (0.563)	0.436 (0.213)**	0.281 (0.183)
Shaanxi	1.025 (0.507)**	0.152 (0.206)	-0.069 (0.170)
Market perception	-0.677 (0.158)***		
$Ln\sigma_1$		-1.152 (0.066)***	
$\rho_{\eta 1}$		0.523 (0.273)*	
$Ln\sigma_0$			-1.220 (0.118)***
$\rho_{\eta 0}$			-0.401 (0.410)
Log likelihood	-154.99		
Likelihood ratio test for independent equations $x^2(1)$		3.65*	
Observations	250	250	250

Notes: The dependent variable is the log form of apple net returns measured in yuan/mu (1$=6.14 yuan);
In selection equation, it takes the value of one if farmers used written contract, 0 otherwise;
*, **, *** denote significance at 10%, 5% and 1% levels, respectively.

The estimates for the average treatment effects on the treated (ATT), which shows the causal effects of written contract choice on net returns, are presented in Table 6.7. The ATT estimates account for selection bias arising from both observable and unobservable factors. The results reveal that the choice of written contracts tends to significantly increase net returns by 2.46%, when no contract users are treated as the control group. Moreover, the causal effect of written contract choice on net returns is much higher when it is against the use of oral contracts, with a 5.43% increase in net returns. These findings suggest that promoting the use of written contracts in fresh apply supply chain can be beneficial to farmers' welfare by contributing to higher net returns.

Table 6.7 Average treatment effects of written contract choice on net returns: ESR estimation

	Mean Outcome [a]				
	Written contract Users (N=179)	No contract Users (N=172)	ATT	*t*-value	Change (%)
Net Returns	8.74 (0.44)	8.53 (0.40)	0.21***	8.91	2.46
	Mean Outcome [a]				
	Written contract Users (N=179)	Oral contract Users (N=71)	ATT	*t*-value	Change (%)
Net Returns	8.74 (0.44)	8.29 (0.48)	0.45***	25.71	5.43

[a] As the dependent variable in the ESR outcome equation is the log form of net returns measured in yuan/mu, the predictions are also given in log forms;

*** denotes significance at 1% level.

6.5.4 Impact of Oral Contract Choice on Net Returns: PSM Estimation

Given the absence of selection bias resulting from unobservable factors for oral contract specification in BFG estimation in Table 6.4, we employ the PSM technique to assess the causal effect of oral contract choice on net returns. PSM includes two steps. In the first step, a probit model has been employed to predict propensity score (i.e. the probability) of choosing oral contracts. The estimated propensity score is given in Table 6.10.A2 in the Appendix, which shows that 83.65% of the sample observations are correctly predicted. The propensity score only serves as a device to balance the observable distribution of covariates across the oral contract users and non-users (Dehejia and Wahba 2002).

Table 6.8 presents the results estimated for the causal effects of oral contract choice (treatment group) on net returns, where the control groups are no contract users and written contract users, respectively. As indicated previously, the ATT is estimated with the nearest neighbor matching (NNM), Kernal-based matching (KBM) and Radius matching methods. The results generally indicate that the choice of oral contracts exerts a negative and statistically significant impact on net returns. The finding is surprising, because the use of oral contract is also expected to increase net returns. This is possibly due to the fact that oral contracts enable farmers to receive advance payments (i.e. deposit), which can help them overcome short-term capital constraints. However, advance payments normally result in lower product prices, resulting in lower net returns. Moreover, the choice of oral contracts also appears to negatively and significantly decrease net returns by 1.94-2.50% as well, when the control group is the written contract users. The result is in line with the finding by Munjaiton et al. (2014) for Thailand, who also used PSM method to control for selectivity bias and found that oral contract users received lower profitability than written contract users.

Table 6.8 Average treatment effects of oral contract choice on net returns: PSM estimation

	Mean Outcome [a]				
Matching algorithm	Oral contract users (N=71)	No contract users (N=172)	ATT	*t*-value	Change (%)
NNM	8.59	8.79	-0.20*	-1.72	-2.28
KBM (Bandwidth=0.4)	8.59	8.78	-0.19*	-1.78	-2.16
Radius (caliper=0.3)	8.59	8.79	-0.20*	-1.87	-2.28
	Mean Outcome				
Matching algorithm	Oral contract users (N=71)	written contract users (N=179)	ATT	*t*-value	Change (%)
NNM	8.59	8.81	-0.22**	-2.0	-2.50
KBM (Bandwidth=0.4)	8.59	8.76	-0.17*	-1.71	-1.94
Radius (caliper=0.3)	8.59	8.77	-0.18*	-1.78	-2.05

[a] As the outcomes used are the log form of net returns measured in yuan/mu, the predictions are also given in log forms;

*, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

6.6 Conclusions

This study examined the determinants of farmers' choices of marketing contracts, disaggregated by written contracts, oral contracts and no contracts, as well as the related impact on net returns, using data collected from apple farmers in Gansu, Shaanxi and Shandong provinces between September and December 2013 in China. Given the nature of multiple discrete choices of marketing contracts, a two-step BFG model based on the multinomial logit model was employed to address sample selectivity effects. The results did suggest the presence of selection bias, indicating that accounting for selection bias is a prerequisite for unbiased and consistent estimation.

The empirical findings of the multinomial logit model on determinants of marketing contract choices revealed that the choice of written contracts was positively and significantly influenced by access to credit, timely payment, and the transacted quantities. The choice of oral contract was positively associated with cooperative sales and distance to markets. With regards to the factors that influence selection towards net returns, we observed that written contracts were positively affected by cooperative sales, extension contact, as well as transacted quantities and prices, while oral contracts were positively influenced by the transacted quantity.

The results of BFG estimation showed significant and negative selectivity correction term in net return specification for written contract choice, suggesting that the expected net returns for written contract users was downward biased. This is because farmers who are better suited with written contracts switched from written contracts to no contracts, leading to a significant negative impact on their net returns. The result clearly suggests that unbiased and consistent evaluation of net returns due to certain marketing contract choices must take selectivity effects into account, which confirm the appropriateness of the BFG approach for the analysis.

On the basis of BFG estimation, we employed an endogenous switching regression model to estimate the causal effects of written contract choice on net returns, as well as a propensity score matching technique to assess the causal effects of oral contract choice on net returns. The results generally showed that the choice of written contracts was to increase net returns by about 2.46% and 5.43%, respectively, when the no contract users and oral contract users are treated as the control groups. However, the choice of oral contract tends to decrease net returns, no matter the control group is no contract users or written contract users. In particular, the causal effect of oral contract choice was to decrease net returns by 2.16-2.28% and 1.94-2.50%, respectively compared with no contract users and written contract users. Overall, the results indicate that marketing contracts functioned to enhance net returns increases only if written contract was chosen, and oral contract users tended to benefit more than no contract users from the use of marketing contracts.

Our results suggest that written contracts can be clearly welfare enhancing for its users. Therefore, its use should be further promoted in fresh apple supply chain in China. In particular, policies that enhance farmers’ access to credit and encourage timely payment from buyers would facilitate the use of written contracts. Given that cooperative sales and extension contact contribute to higher net returns for the written contract users, policy makers could promote effective measures to improve farmers’ access to extension agents, and continue to facilitate apple marketing through cooperative organizations.

Appendix

Table 6.9.A1 Correlation between instrument variable and outcome

Outcome	Instrumental variable	Correlation	*p*-value
Net returns	Market perception	0.0630	0.1967

Table 6.10.A2 Probit estimates of propensity score for the choice of oral contracts

Variable	Coefficient	Standard error	*z*-value
Constant	1.195	2.094	0.57
Age	-0.015	0.010	-1.55
Education	-0.067	(0.031	-2.18**
Orchard size	0.054	0.040	1.34
Specialization	-1.350	0.461	-2.93***
Farming vehicle	0.113	0.295	0.38
Computer	-0.016	0.207	-0.08
Cooperative sales	1.172	0.215	5.44***
Extension contact	0.169	0.173	0.98
Access to credit	-0.622	0.174	-3.58***
Timely payment	-0.039	(0.220	-0.17
Neighbor	-0.158	0.188	-0.84
Distance to markets (log)	0.057	0.023	2.49**
Quantity (log)	-0.111	0.228	-0.49
Price (log)	0.295	0.425	0.69
Gansu	0.707	0.333	2.12**
Shaanxi	0.745	0.303	2.46**
Pseudo-R2	0.181		
Log likelihood	-156.658		
Correctly classified	83.65%		
Observations		422	

Note: *, **, *** denote significance at 10%, 5% and 1% levels, respectively.

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Chapter 7 General Conclusions and Policy Implications

The analyses conducted in this dissertation aimed at examining the impact of agricultural cooperatives on the adoption of technologies and farm performance of apple farmers in China, using the data collected between September and December 2013 from Gansu, Shaanxi and Shandong provinces of China. Given that agricultural cooperative membership is not randomly distributed among smallholder apple farmers, but farmers choose to join the cooperatives themselves, analyzing the true effects of membership in agricultural cooperatives on technology adoption and farm performance should address the issue of selection bias. Therefore, this study employed different econometric approaches to conduct the empirical analyses.

In sections below, the review of empirical analysis methods used in the dissertation is firstly presented. Next, the main results from the dissertation are summarized. Finally, policy recommendations to enhance apple production system and improve rural household income are suggested based on the main findings.

7.1 Review of Empirical Analysis Methods

The econometric methods used in this study include recursive bivariate probit (RBP) model, endogenous switching probit (ESP) model, endogenous switching regression (ESR) model, treatment effects model, BFG model, propensity score matching (PSM) model, and Ordinary Least Square (OLS) regression. Among them, RBP model, ESP model, ESR model, BFG model and treatment effects model address the issue of selection bias accounting for both observable and unobservable factors with inclusion of valid instrumental variables in application, while PSM method addresses the issue of selection bias accounting for only observable factors. In analyzing the impact of cooperative membership on the outcomes of interest by using OLS regression, cooperative membership was treated as an exogenous variable.

The RBP model was employed in chapter 2 to estimate the impact of cooperative membership on investment in organic fertilizer, farmyard manure, and chemical fertilizer. The RBP is appropriate to estimate the effect of a binary endogenous treatment variable (i.e. cooperative membership choice) on a binary outcome (i.e. whether or not to invest in organic fertilizer, farmyard manure and chemical fertilizer). The RBP model not only allowed us to analyze the marginal effects and average treatment effects of cooperative membership on investment in soil measures, but also estimated the marginal effects of other controlling factors on farmers' investment decisions.

In chapter 3, the ESP model was employed to examine the impact of cooperative membership on adoption of IPM technology. The model is also appropriate to examine the effect of a binary endogenous treatment variable on a binary outcome (i.e. whether or not to adopt IPM technology). Unlike RBP model that simultaneously estimated cooperative membership equation with one outcome equation, the ESP model analyzed the determinants of IPM adoption separately for cooperative members and nonmembers. Based on the estimated coefficients of variables in ESP model, the average treatment effects (ATT and ATU) of cooperative membership on adoption of IPM technology can be calculated. These ATT and ATU calculations accounted for the selection bias arising from both observable and unobservable factors, which reflected the true effects of cooperative membership on IPM adoption. Moreover, a treatment effects mode was employed in this chapter to examine the impact of IPM adoption on apple yields, net returns and agricultural income. Similar to ESR model, the treatment effect model is appropriate to estimate the impact of a binary endogenous treatment variable on a continuous outcome variable. However, treatment effects model estimates IPM adoption equation with one outcome equation simultaneously.

The study in chapter 4 employed the ESR model to analyze the impacts of cooperative membership on apple yields, net returns and household income. Unlike ESP model that aims at binary outcome variables, the ESR model is appropriate to estimate the impact of a binary endogenous treatment variable on a continuous outcome variable. The ESR model enabled us to understand the factors that influence apple yields, net returns and household income for cooperative members and nonmembers separately, and estimate average treatment effects of cooperative membership on apple yields, net returns and household income accounting for both observable and unobservable characteristics.

To evaluate the profitability of a number of different investments, the study in chapter 5 therefore employed a treatment effects model to analyze the impact of cooperative membership on return on investment (ROI). ROI was employed as a farm performance indicator since it not only concentrates on improving net returns from apple production, but also takes the profitability of different investments into account. A treatment effects mode was used to estimate the marginal effect and average treatment effect of cooperative membership on The ROI. Moreover, the effects of cooperative membership on the ROI estimated from the treatment effects model were respectively compared with the effects estimated from an OLS regression and a PSM method.

In chapter 6, a two-stage BFG method was employed to investigate the determinants of marketing contract choices including written contracts, oral contracts and no contracts, as well as to examine the impacts of marketing contracts on net returns from apple production in China. The model is appropriate to estimate the impacts of a large number of mutually exclusive choices (at least three) on a continuous outcome variable. The first-stage of BFG method applied an unordered multinomial logit (MNL) model to examine the factors that influence farmers' decisions to choose different types of marketing contracts, as well as creating selectivity terms for unbiased estimation of net returns equations. In the second stage, the net returns equations were estimated with inclusion of three selectivity correction terms. Given the finding of the presence of selection bias that arisen from unobserved factors for written contract specification in BFG estimation, the study in chapter 6 employed an ESR model to analyze the causal effect of written contract choice on net returns from apple production. Moreover, given the absence of selection bias resulting from unobservable factors for oral contract specification in BFG estimation, a PSM technique was used to assess the causal effect of oral contract choice on net returns.

7.2 Summary of Results

The results in chapter 2 showed that a number of factors tended to drive farmers' decisions to join contemporary agricultural cooperatives, including education, household size, farm size, asset ownership, and road condition. With respect to the investment decisions, the findings showed that cooperative membership had a positive and statistically significant impacts on investment in organic fertilizer and farmyard manure, but it had no statistically significant impact on investment in chemical fertilizer. Furthermore, the ownership of assets such as farming vehicle and rotary cultivator, access to credit were found to significantly increase the propensity to invest in soil quality measures such as organic fertilizer and farmyard manure.

The estimations in chapter 3 showed that cooperative members' decisions to adopt IPM technology were primarily influenced by education, farm size, household size, asset ownership, price knowledge, the establishment of refrigerated warehouse, and environmental and health perceptions, while IPM adoption decisions of nonmembers were influenced by education, off-farm work, price knowledge and environmental perception. With respect to the average treatment effects of cooperative membership, the results showed that the causal effect of cooperative membership was to increase the probability of IPM adoption by 30%, and farmers without cooperative membership would be 10% more likely to adopt IPM technology if joined cooperatives. Moreover, IPM adoption significantly increases apple yields, net returns and agricultural income.

The findings in chapter 4 showed cooperative membership positively increased apple yields by 5.36%, net returns by 6.06% and household income by 4.66%, and small-scale farms benefited more from cooperatives than medium and large farms. In this chapter, computer ownership was found to be an important factor that influenced farmers' decisions to join agricultural cooperatives and enhances household welfare. Extension contact and access to credit improved the welfare of cooperative members.

The results in chapter 5 showed that agricultural cooperative membership had a positive and statistically significant impact on the ROI. In particular, the causal effect of cooperative membership was to increase ROI by 14% on average for the population as a whole. The ROI was found to be positively and significantly influenced by income specialization, marketing contract and labor availability. The further estimations showed that OLS model underestimated the marginal effect of cooperative membership on the ROI, while PSM method underestimated the average treatment effect of cooperative membership, which was consistent with the finding of negative selection bias in treatment effects model estimation.

The empirical analysis in chapter 6 revealed that the choice of written contracts was positively and significantly influenced by access to credit, timely payment, and the transacted quantities, and the choice of oral contracts was positively associated with cooperative sales and distance to markets. With regards to the factors that influenced selection towards net returns, the results showed that cooperative sales, extension contact, as well as transacted quantities and prices were primary factors that influenced the net returns from choosing written contracts, and transacted quantity was a vital determinant of higher net returns from choosing oral contracts. The further estimations from ESR model and PSM model showed that the causal effect of written contract was to increase net returns by about 2.46% and 5.43%, respectively, when the no contract users and oral contract users were treated as control groups. However, the causal effect of oral contract choice was to decrease net returns by 2.16-2.28% and 1.94-2.50%, respectively compared with no contract users and written contract users.

7.3 Policy Implications

The findings from this study showed that contemporary agricultural cooperatives can facilitate the adoption of soil-improving measures such as organic fertilizer and farmyard manure and environmentally-friendly pest management technology such as IPM, as well as increase apple yields, net returns, household income and return on investment. Thus, the government in China should step up its efforts to encourage smallholder farmers to join agricultural cooperatives.

Since the access to credit and irrigation facilities appeared to be important factors facilitating farmers' investment in soil quality measure, policies focusing on improving farmers' access to credit and accelerating the development of rural infrastructure such as irrigation system would enhance investment in soil-improving measures. The finding of the positive relationship between agricultural cooperative membership and IPM adoption suggests that agricultural cooperatives can be a transmission route in the efforts to facilitate IPM technology. Given that price knowledge and environmental perception positively influence farmers' decisions to adopt IPM technology, enhancing farmers' knowledge with respect to organic food, green food and pollution-free food production standards, and negative environmental effects of continuous use of chemical pesticides, would help increase farmers' adoption of IPM technology. This could be achieved through cooperatives' collective activities.

Access to computers appeared to positively influence farmers' decisions to join agricultural cooperatives and affected household welfare. Thus, government policy should help improve rural internet routing infrastructure. The positive and significant impacts of extension contact and access to credit suggest that promoting effective measures to improve farmers' access to extension service and credit would help improve farm household welfare. The positive and significant impacts of written contract on net returns and ROI of apple production suggest that government should take effective measures to promote the use of marketing contracts in fresh apple supply chain. Given that cooperative sales and extension contact contribute to higher net returns for the written contract users, policy makers could promote effective measures to improve farmers' access to extension agents, and continue to facilitate apple marketing through cooperative organizations.

Appendix A: Questionnaire

Number: __________________

Date: __________________

Survey Questionnaire for Apple Production and Marketing in China

（2012-2013）

Enumerator: __________________

Province: __________________

City: __________________

County __________________

Town __________________

Village: __________________

Reviewer: __________________

Instructions：

- Before interview, please say to the respondent: “Thank you very much for your cooperation. The information that is going to collect is only used for academic purpose and will be kept strictly confidential”.
- During interview, please emphasize to the respondent that we are collecting apple production information in 2012 as well as apple marketing information for the produce. Besides, please also repeat to the respondent when it is necessary that targeted information is for apple variety of Fuji.
- During interview, please specify units clearly whenever you write quantities and prices and try to complete as accurately as possible
- Please write the right answer(s) on corresponding place or use “√” to cross the correct answer. For some questions with multiple choices, if there is no prepared answers, please choose the answer “Others” and specify.
- After finishing the interview, please check the questionnaire again before say to the respondent: “Thank you again for your collaboration about this survey”.
- The partner reviewer should examine the questionnaire in order to ensure the written information clear and easily identified.

1. General Information

1-1 Age (years)____; 1-2 Gender____(1=male; 0=female); 1-3 Education (years)____;

1-4 Village cadre or not____(1=Yes; 0=No); 1-5 Farming experiences (years)____;

1-6 Household size____; 1-7 Do you have family members above 60 years__ (1=Yes; 0=No);

1-7-1 Family members above 64 years (numbers)____;

1-8 Labors for apple production (numbers)____; 1-9 Children in school (numbers)____;

1-9-1 Family members below 15 years (numbers)____;

1-10 Off-farm work participants of household members (numbers)__;

1-11 Total land areas cultivated (mu)____; 1-12 Land rented-in (mu)____;

1-13 Land rented out (mu)____; 1-14 Total land plots (numbers)____;

1-15 Irrigated land areas (mu)____; 1-16 Hillside land (mu)____;

1-17 What is your total family living expenditures (yuan/month)______;

1-18 Did you grow any other commercial crops except apples?_____(1=Yes; 0=No)

If yes: 1-18-1 Please specify which crop(s)_________;

1-19 Did you raise livestock?____(1=Yes; 0=No)

If yes: 1-19-1 Please specify which livestock(s)______________;

1-20 What is your total family income in 2012? (yuan)______________;

1-21 what is your total income from agriculture in 2012? (yuan)_______;

1-22 Did you participate in off-farm work (local or outside) in 2012?_____(1=Yes; 0=No)

If yes:

- 1-22-1 How many months in all?_____;
- 1-22-2 What is the salary (yuan/month)?_____;

1-23 Is the off-farm work available in the surrounding areas of your village?____(1=Yes; 0=No)

1-24 How do you think the role of income diversification through off-farm work in agricultural production?____(1=less important; 2=neutral attitudes; 3=very important)

1-25 In addition to apples, what is the income from other crop(s) on a commercial basis?(yuan)______;

1-26 Do you have a computer?____(1=Yes; 0=No);

1-27 Do you have a rotary cultivator?____(1=Yes; 0=No)

1-28 Do you own a farming vehicle?____(1=Yes; 0=No)

1-29 Do you have hand sprayers?____(1=Yes; 0=No); **If yes:** 1-29-1 How many hand sprayers do you have?____;

1-30 Do you have power sprayer?___(1=Yes; 0=No); **If yes:** 1-30-1 How many power sprayers do you have?____;

2. Agricultural Cooperatives

2-1 Is there an agricultural cooperative in your residing village?____(1=Yes; 0=No)

2-2-1 Does any of your neighbors have cooperative membership?____(1=Yes; 0=No)

2-2.2 Does any of your friends have cooperative membership?____(1=Yes; 0=No)

2-2-3 Does any of your relatives have cooperative membership?____(1=Yes; 0=No)

2-3 Are you a member in an agricultural cooperative?____(1=Yes; 0=No)

If yes:

- 2-3-1 Where is the cooperative?____(1=In the local or neighboring village; 0=In other place (e.g., the county or township))
- 2-3-2 How many years have you been a cooperative member? (years)____;
- 2-3-3 How much do you have to pay for the annual membership fee? (yuan/year)____;
- 2-3-4 Does the cooperative have a brand that is used to promote the products?___(1=Yes; 0=No); If yes: 2-3-4-1 What is the brand name?_______________;
- 2-3-5 In which aspect do you think that the cooperative can play the most important role to your benefits in apple production and marketing____(1=Technical guidance; 2=Providing marketing information; 3=Providing services for produce circulation and transportation; 4=Divvying up returns; 5=Other_______)
- 2-3-7 Does the cooperative provide you with production inputs?____(1=Yes; 0=No)
- 2-3-8 Does the cooperative control your production behaviors?____(1=Yes; 0=No)
- 2-3-9 Does the cooperative collectively purchase the inputs for the members?______; (1=Yes; 0=No）

If no:

- 2-3-10 What is the reason for not choosing the cooperative membership?____(1=Local cooperative is not available; 2=The expected profit is not optimistic; 3=Self-farming condition is lower than requirement of farmer organization; 4=I am used to the traditional farming; 5=Others_________)

2-4 Do you think that the services provided by agricultural cooperatives are useful?_____; (1=Yes; 0=No)

2-5 Do you think that contemporary agricultural cooperative is more effective than people's commune system (PCS)?____(1=Yes; 0=No)

2-6 Can you acquire sufficient information to understand the functions of contemporary cooperatives?____ (1=Yes; 0=No)

3. Apple Orchard Information

Information of Sapling Orchards

	3-1-1	3-1-2	3-1-3	3-1-4	3-1-5
Variety	Size (mu)	Plot (Number)	Land rented-in (mu)	Rental fee (yuan/year/mu)	Irrigated Land (mu)
Fuji[1]					

Information of Fruiting Orchards

	3-2-1	3-2-2	3-2-3	3-2-4	3-2-5
Variety	Size (mu)	Plot (Number)	Land rented-in (mu)	Rental fee (yuan/year/mu)	Irrigated Land (mu)
Fuji					

3-3 Growing density (trees/mu)____;

3-3-1 Average tree costs (yuan/sapling)____;

3-3-2 The oldest fruiting apple tree age (years)____;

3-3-3 The youngest fruiting apple tree age (years)____; 3-3-4 Average tree age (years)____;

3-4 When you plant apple trees, how do you decide space between trees?___________________;

3-5 Apple growing experience (years)____;

3-6 Soil type____(1=Loan; 2=Sand; 3=Clay)

3-7 Where did you primarily purchase saplings?____(1=Fellow farmers; 2=Market dealers (or nursery garden); 3= Government; 4=Village community; 5=Agricultural cooperatives; 6=other________)

3-8 What are the reasons for you to choose to grow Fuji variety?___(1=Higher yield; 2=Higher price; 3=Easy to store; 4=Good quality; 5=It is grown widely by other farmers; 6=Recommended by village community; 7=Recommended by government; 8=Pest resistant; 9=High market demand; 10=other_____________)

3-9 Except the Fuji variety, what other apple varieties do you grow?____(1=Gala; 2=Jonagold; 3=Sparking; 4=Red Delicious; 5= Golden Delicious; 6= Qinguan delicious； 7=Other____)

3-9-1 How much land are you used for other apple varieties (mu)?____;

3-10 What is the distance from orchard to closest sales markets? (km)_____; 3.10.1 How long does it take for transportation? (Minutes)_____ (Note: use 0 if sales at orchard gate)

[1] After preliminary test for the questionnaire, we learnt that Fuji variety is the main variable grown by each apple producing household.

4. Apple Production Information

4-14 How do you evaluate your apple yields in 2012, compared to the yields in previous year?____;(1=lower; 2=average; 3=higher)

4-15 Did you make records for input use during apple production?___(1=Yes; 0=No)

4-16 What is the distance from your dwelling to the furthest apple orchard? (kms)____; 1-20 How long does it take by walking? (Minutes)____;

4-17 Do you have sufficient capital for apple production?____(1=Yes; 0=No)

If no:

- 4-17-1 Did you borrow money?____(1=Yes; 0=No)
- 4-17-2 Is it easier for you to get money (e.g., from friends, relatives, and banks), when you have to borrow money for apple production____(1=Yes; 0=No)

4-18 The distance between your home and available capital sources (e.g., banks, friends or relatives) (km)____;

4-19 From which source do you usually acquire apple production information?____________;

4-20 Did you receive pesticide residue test?____(1=Yes; 0=No)

- 4-20-1 From which department do you get the service?____;

  (1=Government；2=Produce dealer；3=Cooperatives；4=Others_________)

- 4-20-2 Do you have to pay?_____(1=Yes; 0=No); 4-20-3 **If yes**, how much did you pay?(yuan/time)____;

4-21 How do you evaluate the average level of natural disasters (e.g., drought, frost damage, hail or pest damage) happened in 2012?____(1=severe; 2=moderate; 3=mild)

4-22 Did you buy the crop insurance for apple production in 2012?____(1=Yes; 0=No)

If yes:

- 4-22-1 What kind of insurance?_(1=Policy-based insurance; 2=Commercial insurance)
- 4-22-2 What is the insurance rate? (%)____;
- 4-22-3 What is the total insurance premium?(yuan/mu)____; 4-22-4 How much is paid by you ?(yuan)______, and 4-22-5 how much is paid by the government?(yuan)_____;

If no:

- 4-22-6 Are you willing to buy the insurance in the future?____(1=Yes; 0=No)

4-23 Is the road condition from orchards to village/market good?____(1=Yes; 0=No)

4-24 Have you established apple storage?____(1=Yes; 0=No)

4-25 Is there any apple refrigerated warehouse in local areas?____(1=Yes; 0=No)

If yes:

- 4-25-1 What is the distance from your home to the warehouse?(minutes)

4-26 Did you use anti-hail net for the fruiting apple orchards?____(1=Yes; 0=No)

If yes:

- 4-26-1 Who built it?__1=Self-construction (____yuan); 2=By fruit center for free; 3=By fruit company for free; 4=Other___________)
- 4-26-2 Do you have to pay?____(1=Yes; 0=No): If yes, 4-26-3 How much do you have to pay? (yuan)_____;

4-27 Do you have sugar meter?____(1=Yes; 0=No)

4-28 Did you adopt soil and water conservation measures?____(1=Yes; 0=No);

If yes:

- 4-28-1 What kind of measures?_____(1=Growing grass or legumes; 2=Put sand; 3=Put crop straw; 4=use agricultural mulch; 5=Others_________)

4-29 Where do you usually buy agricultural materials (e.g., fertilizer and pesticide)?______; (1=dealers in home village; 2=dealers in other village; 3=agricultural cooperatives; 4=dealers in township; 5=fruit service center; 6=fruit company; 7=other_________)

4-30 How do you usually pay for the purchased production materials?____(1=By cash; 2=On credit; 3=Part of cash and part of credit)

4.31 How far is it from your home to input shops? (km)______; 4.31.1 How long does it take?(minutes)___; 4.31.2 Which kind of transports do you use?_____(1=Motor vehicles; 2=Non-motor vehicles）

4-32 Which way did you use for picking?____(1=According to apple maturity; 2=Picking all at one time)

4-33 Labor use (days/mu)____;

4-34 Did you attend any extension service programs provided by the government?____(1=Yes; 0=No)

If yes:

- 4-34-1 How many times have you attended?____;
- 4-34-2 Which contents are included in the extension service?____(1=pruning branches; 2=fertilizer use; 3=pesticide use; 4=irrigation technology; 5= pesticide residue control; 6=other________)

If no:

- 4-34-3 What is the main reason for non-participation?___(1=No time; 2=No use; 3=No such service; 4=Other_________)

4-35 Do you think that the extension service provided by the government is useful?____; (1=Yes; 0=No)

4-36 Did you get subsidy for apple production?____(1=Yes; 0=No)

If yes:

- 4-36-1 If subsidized in cash:____yuan/mu；
- 4-36-2 if subsidized in material, including:_____; 4-36-3 Evaluated in_______yuan

4-37 Where do you usually acquire information associated with apple production technology?__________________;

4-38 Did you use soil testing and fertilizer recommendation technology in 2012?___; (1=Yes; 0=No)

If yes:

- 4-38-1 Service provider____(1=Agricultural extension department; 2=Farmer organization; 3=The village committee; 4=Other(s)_____)
- 4-38-2 How much do you have to pay each time? (yuan)____(0 if no payment)

If no:

- 4-38-3 What is the main reason?____;

5. Fertilizer Use

5.1 Organic Fertilizer Use

5-1 Did you apply organic fertilizer?____(1=Yes; 0=No)

If yes:

- 5-1-1 Total bags used____; 5-1-2 Price (yuan/bag)____; 5-1-3 Application frequency (times/year)____; 5-1-4 Applied areas (mu)____; 5-1-5 Total expenditures (yuan)_____;

5-2 What did you consider in mind when you buy organic fertilizer?___(1=the price; 2=apple quality improving effect; 3=yield-enhancing effect; 4= environment effect; 5=others________)

5.2 Farmyard Manure Use

5-2 Did you apply farmyard manure?____(1=Yes; 0=No)

If yes:

- 5-2-1 Where did you get it?_____(1=From family yard; 2=Purchased from livestock raising farms; 3=from 1 and 2; 4=others____)
- 5-2-2 Which kind of manure it is?_____________;
- 5-2-3 If you purchased it, how much does it cost?_________;

5.3 Chemical Fertilizer Use

5-3 Did you apply chemical fertilizer?__(1=Yes; 0=No)

If yes:

- If you applied Pure Nitrogen (N):

  5-3-1 Total bags used____; 5-3-2 Weight (kg/bag)____; 5-3-3 Price (yuan/bag)____;

  5-3-4 Application frequency (times/year)_____; 5-3-5 Applied areas (mu)_____;

- If you applied Pure Phosphate (P):

  5-3-6 Total bags used___; 5-3-7 Weight (kg/bag)____; 5-3-8 Price (yuan/bag)____;

  5-3-9 Application frequency (times/year)____; 5-3-10 Applied areas (mu)____;

- If you applied Pure Potash(K):

  5-3-11 Total bags used____; 5-3-12 Weight (kg/bag)___; 5-3-13 Price (yuan/bag)____;

  5-3-14 Application frequency (times/year)____; 5-3-15 Applied areas (mu)____;

- If you applied compound fertilizer (NPK):

  5-3-16 Total bags used____; 5-3-17 Weight (kg/bag)____; 5-3-18 Price (yuan/bag)____;

  5-3-19 Application frequency (times/year)____; 5-3-20 Applied areas (mu)____;

5-4 The total expenditures of all kinds of chemical fertilizers (yuan)_______;

5.4 Fertilizer Use Behaviors

5-4-1 How do you decide the amounts of fertilizer use?____(1=following packing instructions; 2=following suggestions of technical persons; 3=following previous experiences; 4=others______)

5-4-2 Do you thank that continuous use of chemical pesticides is a threat to environmental performance?_____(1=Yes; 0=No)

5-4-3 Do you think that continuous use of chemical pesticides is a threat to human health?_____;(1=Yes; 0=No)

5-4-4 Previously, agricultural pollution is a serious problem because of excessive fertilization, which has caused negative environment impacts (e.g., reducing quality of soil, water and air, increasing cost of fertilizer use, food safety issues). Therefore, are you willing to reduce the amounts of fertilizer use on the base of original level in the future?_____(1=Yes; 0=No)

If yes:

- 5-4-4-1 What is the main reason?____(1=Reduce fertilizer cost; 2=Improve soil quality; 3=Protect environment; 4=Improve apple quality； 5=Other________)
- 5-4-4-2 How much do you want to reduce on the original base? (%/tree)____;

If no:

- 5-4-4-3 What is the main reason?___________________________________;

5-4-5 Compared with fertilizer use amounts recommended by specifications or technical person, how do you usually decide the amount of fertilizer use?_______(1=higher than the recommended level; 2=the same as the recommended level; 3=Lower than the recommended level)

- 5-4-5-1 If you used higher than recommended level, what is the main reason?_________;
- 5-4-5-2 If you used lower than recommended level, what is the main reason?__________;

6. Pesticide Use and Pest Management

6.1 Chemical Pesticide Use

6-1 Did you use chemical pesticides in apple production?____(1=Yes; 0=No)

If yes:

- 6-1-1 Did you apply herbicide?____(1=Yes; 0=No)

If yes: 6-1-2 Application frequency (times/year)____; 6-1-3 Total costs (yuan)____; 6-1-4 Applied areas (mu)____;

- 6-1-5 Did you apply insecticide?____(1=Yes; 0=No)

If yes: 6-1-6 Application frequency (times/year)__; 6-1-7 Total costs (yuan)____; 6-1-8 Applied areas (mu)____;

- 6-1-9 Did you apply fungicide?____(1=Yes; 0=No)

If yes: 6-1-10 Application frequency (times/year)____; 6-1-11 Total costs (yuan)____; 6-1-12 Applied areas (mu)____;

6.2 Biological/Green Pesticide Use

6-2 Did you use biological/green pesticides in apple production?_____(1=Yes; 0=No)

If yes:

- 6-2-1 Application frequency (times/year)________; 6-2-2 Total costs (yuan)_________; 6-2-3 Applied areas (mu)______;

If no:

- Are you willing to use biological pesticide within five years?____ (1=Yes; 0= No)

6-2-4 Have you ever used fake pesticides?____ (1=Yes; 0= No)

6.3 Pesticide Use Behaviors

6-3-1 How did you decide the quantity of pesticide use?____(1=following packing instructions; 2=suggested by technical persons; 3=following previous experiences; 4=others_________)

6-3-2 What do you care mostly when you purchase pesticide?_______(1=price; 2=effects; 3=pesticide residue level; 4=environment impact; 5=human and livestock impact; 6=other_______)

6-3-3 Do you use self-protection measure (such as mask) when you spray the chemical pesticides?______;(1=Never; 2=Sometimes; 3=Always)

6-3-4 How many interval days does it take between your last pesticide spraying and apple harvest? (days)______;

6-3-5 Do you know the chemical safety interval period for apple production?____;

(1=Yes; 0= No)

6-3-6 Compared with pesticide use quantity suggested by technical persons or instruction books, how do you usually decide the amount of pesticide use?________(1=higher than the recommended level; 2=the same as the recommended level; 3=Lower than the recommended level)

- 6-3-6-1 If you used higher than recommended level, what is the main reason?__________;
- 6-3-6-2 If you used lower than recommended level, what is the main reason?__________;

6-3-7 At present, pesticide residue is the main factor that influences food safety and environmental performance, which not only causes a series poisoning incidents and influences food export, but damages the eco-environment. Therefore, are you willing to reduce level of pesticide use?____(1=Yes; 0=No).

If yes:

- 6-3-7-1 What is the main purpose?____;
- 6-3-7-2 How much would you like to reduce per tree? (%)______;

If no:

- 6-3-7-3 What is the reason?____;

6-3-8 Are you willing to replace chemical pesticide with bio-pesticide in the future?____;

(1=Yes; 0= No)

6-3-9 Do you consider the environmental effect associated with pesticides when you purchase pesticides?____ (1=Yes; 0= No)

6-3-10 Do you consider the health effect associated with pesticides when you purchase pesticides?____ (1=Yes; 0= No)

6.4 Integrated Pest Management Technology

6-4-1 Did you use both scouting for pests and economic thresholds in making pest treatment decisions?____(1=Yes; 0=No)

6-4-2 Did you adjust application rates, time, and frequency of pesticide use?___(1=Yes; 0=No)

6-4-3 Did you use yellow sticky mobile, fixed traps, insect-trap light, trap band, cardboard traps for pest management?____(1=Yes; 0=No)

If yes:

- 6-4-3-1 Where did you get those stuff?_____(1=Self-purchasing (___Yuan); 2=Free distribution from government fruit office; 3=Free distribution from agricultural cooperatives; 4=Other__________)
- 6-4-3-2 In addition to the methods mentioned above, what other methods have you used for pest management?_____(1=Yes; 0=No)

6-4-4 Did you purchase beneficial insects that prey on insects damaging to the crop for pest management?_____(1=Yes; 0=No)

7. Labor Use and Other Production Costs

Bagging	7-1-1 Hired labors (persons)_____; 7-1-2 Working days_____;
Bagging off	7-1-3 Hired labors (persons)_____; 7-1-4 Working days_____;
Picking	7-1-5 Hired labors (persons)_____; 7-1-6 Working days_____;
Others (e.g. fertilizer application)	7-1-7 Hired labors (persons)_____; 7-1-8 Working days_____;
7-1-9 average wage for hired labors (yuan/day)_____;	

7-2 Do you usually have sufficient labors during apple production and marketing period?_____;

(1=Yes; 0=No)

If no:

- 7-2-1 Is it easier for you to hire labors?____(1=Yes; 0=No)

7-3 How many bags did you buy for apple bagging?______; 7-3-1 Price (yuan/bag)______;

7-4 The total labor days used for apple production (days)_____;

Other production costs

7-5-1	Rope for branch pulling (yuan)_____;
7-5-2	Input and output transportation (yuan)_____;
7-5-3	The costs for repairing production tools (e.g., tractor and sprayer)_____;
7-5-4	Reflection film for apple coloring (yuan)_____;
7-5-5	Film for water and soil conservation (yuan)______;

8. Irrigation

8-1 What is the main water source for your orchard irrigation?___;

(1=Canals; 2=Own well; 3=Commercial well; 4=Rain)

- 8-1-1 If you used canals, what are the total costs?(yuan)________;
- 8-1-2 If you used commercial well, what are the total costs? (yuan)________;

8-2 During the apple production season in 2012, is there scarcity of water?_____(1=Yes; 0=No)

If yes:

- 8-2-1 How do you manage water scarcity?___(1=Ignore it; 2= transporting water for irrigation; 3=Purchasing from commercial well)
- 8-2-2 What percentage yield is lost due to water scarcity? (%)____;

8-3 Are the local irrigation facilities available?____(1=Yes; 0=No)

8-4 In your opinion, does water quality (e.g., alkalinity or acidity) affect apple quality?____; (1=Yes; 0=No)

9. Apple Marketing Information

9-1 Did you sell apples primarily through agricultural cooperatives?____(1=Yes; 0=No)

9-2 How do you evaluate apple market demand situation?____(1=Bad; 2=Fair; 3=Good)

9-3 How do you evaluate the apple market fluctuation?_____; (1=No fluctuation; 2=Average; 3=Big fluctuation)

9-4 Can you get the timely payment after sales?____(1=Yes; 0=No)

If no:

- 9-4-1 How many days do you have to wait?______;

9-5 How often do you care about apple price information?____; (1=Seldom; 2=Sometimes; 3=Always)

9-6 How do you evaluate apple price fluctuation weekly in the sales season?_____; (1=Smaller; 2=Average; 3=Bigger)

9-7 As a whole, how do you evaluate the average sales price of apples?_____; (1=Lower; 2=Acceptable; 3=Higher)

Sales Information by Apple Size

Big size (>=80 mm)	9-8-1	Quantity		Small size (<=65 mm)	9-8-7	Quantity	
	9-8-2	Price			9-8-8	Price	
	9-8-3	Income			9-8-9	Income	
Medium size (75-70 mm)	9-8-4	Quantity		Inferior products	9-8-10	Quantity	
	9-8-5	Price			9-8-11	Price	
	9-8-6	Income			9-8-12	Income	
Note: Unit of measurement: Quantity: kg; Price: yuan/kg; Income: yuan;							

Sales Information by Marketing Channels

Cooperatives	9-9-1	Quantity		Fruit market	10-9-10	Quantity	
	9-9-2	Price			10-9-11	Price	
	9-9-3	Income			10-9-12	Income	

Agro-enterprises	9-9-4	Quantity		Others	10-9-13	Quantity	
	10-9-5	Price			10-9-14	Price	
	10-9-6	Income			10-9-15	Income	
Rural purchaser	10-9-7	Quantity		Quantity: kg; Price: yuan/kg; Income: yuan;			
	10-9-8	Price					
	10-9-9	Income					

10-11 Which aspects are paid more attention by apple vendors?____(1=Acidity level; 2=Rigidity level; 3=Color; 4=Sugar content level; 5=Shape; 6=Fruit diameter; 7=Surface defects; 8=Pesticide residue; 9= other___)

10-12 To whom do you usually sell the apples?____;

(1=Local traders; 2=Traders from other provinces; 3=Exporters）

10-13 From which channel do you acquire market transaction information (such as sales price)?_____;(1=government; 2=internet; 3=neighbor or friends; 4=dealers; 5=media such as TV and magazines; 6=Others___________)

10-14 How do you evaluate apple sales in last harvest year?____;

(1=Dull of sale; 2=Average; 3=Sell well)

10-15 Did you acquire apple marketing information from neighbors?____(1=Yes; 0=No)

10-16 Did you use production contract[2]?____(1=Yes, 0=No)

10-17 Which kind of marketing contract did you use for apple sales?____;

(1=written contract; 2=oral contract; 3=no contract)

If you used written contract or oral contract:

- 10-17-1 what was the purpose(s) for you to use written or oral contract?_____________;
- 10-17-2 What provisions or terms are included in the contract?_______(1=Quantity; 2=Quality required; 3=Price; 4=Delivery date; 5=Package requirements; 6=Delivery place; 7=Fertilization; 8=Pesticide application; 9=Irrigation; 10=Bagging; 11=New technology adoption; 12=Harvest time; 13=Agro-inputs supply; 14=Other___)
- 10-17-3 Will the contracted price change?_____(1=Yes, 0=No); **If yes:** 10-17-3-1 What is the reason?__(1=Fluctuating along with market changes; 2=Other___)
- 10-17-4 How does the buyer give you the payment?____(1=Cash on delivery; 2=Deposit first, then rest money on delivery; 3=Delivery first, then wait__days for final payments)
- 10-17-5 Have you ever experienced contract breach in your side?_____(1=Yes, 0=No);

[2] Production contract involves the provision of production inputs, and farmers' production behaviors are partly or fully controlled by the contractors. Marketing contract refers to the contract made after apple production.

If yes: 10-17-6 What is the main reason?______(1=Contract price is lower than market price; 2=Un-satisfaction with produce grading; 3= Payment in arrears; 4=Other___)

- 10-17-7 Have you ever experienced contract breach in buyer side?____(1=Yes; 0=No); If yes: 10-17-7-1 what is the reason?__(1=Contract price is higher than market price; 2=Bad sales; 3=Other______)

If you did not use written or oral contract:

10-17-8 What is the main reason?___________________________;

Transaction information with marketing contracts

Written contract	10-18-1	Transacted quantity (kg)	
	10-18-2	Average price (yuan/kg)	
	10-18-3	Total income (yuan)	
Oral contract	10-18-4	Transacted quantity (kg)	
	10-18-5	Average price (yuan/kg)	
	10-18-6	Total income (yuan)	
No contract	10-18-7	Transacted quantity (kg)	
	10-18-8	Average price (yuan/kg)	
	10-18-9	Total income (yuan)	

10. Organic Farming

10-1 Are you aware of food safety issues associated with conventional agricultural production?____;(1=Yes; 0=No)

10-2 Are you aware of environmental issues associated with conventional agricultural production?____(1=Yes; 0=No)

My understanding of the organic farming:

10-3-1	Organic farming is environmentally friendly	(1=Yes; 2=No; 3=I don't know)
10-3-2	Organic farming produces safer food that sells at premium prices	(1=Yes; 2=No; 3=I don't know)
10-3-3	Organic farming avoids the use of artificial fertilizers and pesticides	(1=Yes; 2=No; 3=I don't know)
10-3-4	Organic farming requires a two or three year conversion period	(1=Yes; 2=No; 3=I don't know)
10-3-5	Organic farming enhances soil fertility with sustainable means	(1=Yes; 2=No; 3=I don't know)
10-3-6	Organic farming wins the market via improved product quality and safety	(1=Yes; 2=No; 3=I don't know)

10-4 Did you acquire information to understand the essence of organic farming?____;

(1=Yes; 0=No)

10-5 Do you think that sufficient channels (e.g., newspapers, television and radio, internet, farmer organizations such as agricultural cooperatives, neighbors and friends, and agricultural extension agents) are available for you, if you want to acquire specific information about organic farming?____(1=Yes; 0=No)

Perceptions of organic apple production:

10-6-1	Compared with conventional apple production, how do you think the costs of organic apple production?___(1=Lower,__%; 2=Almost the same; 3=Higher,_%)
10-6-2	Compared with conventional apple production, how do you think the market price of organic apple?____(1=Lower,___%; 2=Almost the same; 3=Higher,___%)
10-6-3	Compared with conventional apple production, how do you think the revenue of organic apple?___(1=Lower,___%; 2=Almost the same; 3=Higher,___%)
10-6-4	Compared with conventional apple production, how do you think the yields of organic apple?____(1=Lower,___%; 2=Almost the same; 3=Higher,___%)

10-7 Are you willing to adopt organic farming in the future?____(1=Yes; 0=No)

If yes:

- 10-7-1 What benefits do you think that the organic farming may bring?____(1=Higher price/profitable; 2=Improving food quality and safety; 3=Access to international markets; 4=Environment-friendly practice; 5=Other______)

If no:

- 10-7-2 What is the main reason?___(1=Lower yields; 2=No guarantee of sales price; 3=No obvious advantage in sales; 4=technology scarcity; 5=Other___)

11. Food Safety Awareness

11-1 Among three types of safer foods (pollution-free food; green food and organic food) produced under food safety standards proposed by the Chinese government, which one do you think has the highest safety standards?__(1=No idea; 2=Pollution-free food; 3=Green food; 4=Organic food); and 11-1-2 Which one do you think may obtain the highest market price?__(1=No idea; 2=Pollution-free food; 3=Green food; 4=Organic food)

11-2 Do you think that the price of food produced under food safety standards (i.e. organic food standard, green food standard or pollution-free food standard) and the price of conventionally produced food?____(1=Food produced under food safety standards may be sold at a higher price than conventional food; 0=others)

11-3 Have you been encouraged by the government to produce apples under food safety standards?____(1=Yes; 0=No)

11-4 In order to produce apples under food safety standards, in which aspects do you think the government should provide help?____________________________;

11-5 Do you think that the current pesticide residue level in apple will affect consumer' health?____;(1=Yes; 0=No)

11-6 Is there any food safety inspection center in the local area?____(1=Yes; 0=No)

11-7 Whether agricultural cooperatives you participated can provide food safety inspection service?____(1=Yes; 0=No)

11-8 Whether the government carried out the test or inspection activities in apple production season?____(1=Yes; 0=No)

The End

Many Thanks for Your Cooperation

Appendix B: Curriculum Vitae

CURRICULUM VITAE

Name: Wanglin Ma

Place of Birth: China (Gansu province)

Nationality: Chinese

Education background

2012 - 2016	Ph.D. student at the Department of Food Economics and Consumption Studies, University of Kiel, Kiel, Germany
2009 - 2012	M.Sc (with honours) at Sichuan Agricultural University, Chengdu, China
2005 - 2009	B.Sc at Yunnan University of Finance and Economics, Kunming, China

Publications:

Wanglin Ma and A. Abdulai (2016). Does Cooperative Membership Improve Household Welfare? Evidence from Apple Farmers in China. ***Food Policy.*** Vol. 58, pp. 94-102

Wanglin Ma and A. Abdulai (2016). Linking Apple Farmers to Markets: Determinants and Impacts of Marketing Contracts in China. ***China Agricultural Economic Review,*** Vol. 8 (1), pp.1-21

Cai, R. **Wanglin Ma** and S. Ye (2016). Effects of member size and selective incentives of agricultural cooperatives on product quality. ***British Food Journal***, Vol. 118 No. 4, pp.858-870

Cai, R. and **Wanglin Ma** (2015). Trust, Transaction Costs, and Contract Enforcement: Evidence from Apple Farmers in China. ***British Food Journal***, Vol. 117 (10), pp.2598 – 2608