# Factors Affect Chinese Producers' Adoption of a New Production Technology: Survey Results from Chinese Fruits Producers

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**Abstract**

*This study develops an expected utility model to examine Chinese fruit farmers' adoption of a newly introduced production technology, the artisan fruit production technique. We analyzed a three-stage adoption process and examined factors influencing farmers' adoption decision in each stage. Survey data collected from 398 fruit farmers were used to quantify farmers' probability to understand, actually adopt, and determine the magnitude of adoption. We found that farmers' adoption varies with their education, plans to expand, and their risk concerns regarding the new technology. We also detected that adoption changes with farm accessibility to government supported agricultural assistances and the availability of privately funded fruit cooperatives. Overall the three-stage adoption framework performs well in adjusting potential sample selection bias problems.*

**Keywords:** *Agricultural production technology adoption; fruit production technology adoption; Chinese fruit farmers' adoption behavior; artisan fruit production technology; three-stage adoption in fruit production; Heckman Probit application in adoption*

## Introduction

As the world's third largest apple producer and a large producer of fruits in general, China has prioritized its fruit production by adding acres into production and improving unit yields. Planting areas reached 5 million acres in 2008 and per acre yield rose from 1.9 metric tons in 1995 to 4.6 metric tons in 2008 (Zhai et al. 2008). In addition, new fruit breeds and technologies have been widely adopted by farmers, leading to enhanced output. The resulting supply surplus in the domestic market has caused falling apple prices, which have dramatically reduced farm level profits. Under tremendous pressure from the market, Chinese fruit producers have started planting value-added fruits. Using new production technologies, namely the artisan fruit production technology, farmers have begun to grow premium fruits to be sold at a price seven to nine times higher than regular fruits (China Daily online, 2009). This innovative technology selects visually-appealing fruits at a late stage of maturity and manually glues onto them Chinese letters and figures to create pictures on the surface of the fruits. Exploiting the natural process of photosynthesis, these figures block sunlight from reaching the surface of the fruit,

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inhibiting natural color change, thus revealing the figure's pattern upon the surface of the fruit. Designing and carving the figures and letters is itself an art form, and it takes considerable effort to choose the ideal fruits, paste the figures, adjust the position of the fruits to collect sunlight, harvest the fruits with additional care, and pack the fruits into delicate gift boxes. Apples, peaches, pears, and persimmons are popular value-added artisan fruits. Figure 1 shows a sample of artisan apples packed in a gift box. The letters read "Happy Birthday", with pictures of a dragon and a heart printed on the fruits.

This value-added innovation was introduced in 1992 in the Yantain County of Shangdong province, China's largest apple production province. Apple producers developed the idea of "painting" on their fruits to specialize their products. Unexpectedly, the market demand for the artisan fruits sky-rocketed, generating considerable returns. The technology then quickly spreads to other fruit production regions in China, including Beijing's biggest fruit production counties of Fangshan, Changpin, Pinggu and Daxing, from which data for this study were collected. The production of artisan fruit requires the selection of large fruits with an even color and balanced shape. Thus, it is the variety a farm grows, not the size of the farm, that determines its involvement in this new technology. Smaller farms that produce big fruit are observed to be more likely to engage in this value-added technology. Uncertain output, changing consumer preferences, and intense competition from imported fruits are reasons that influence adoptions. To create a good image, producers have to dump imperfectly printed fruits, which could cause substantial income loss. Though the production of artisan fruits is costly and may involve remarkable risks, farmers believe that the successfully marketed fruits could bring lucrative returns. Rising exports to Hong Kong, Taiwan, Marco, Japan, and Korea have further pulled demand, making the production of artisan fruits more popular (China Daily Online, 2009).

Little attention has been paid to this newly available value-added production technology and no official statistics[footnote] have documented the production of artisan fruits in the past years. Little, if any, research has examined fruit producers' adoption of this new technology. However, discussions surrounding it are often heard among producers. Debates about pro and cons of adoption appear in popular local news and on fruit production websites. Empirically, understanding who has adopted this new technology (adopters' profile), why they adopt, and the intensity of adoption is critical to assist potential adopters in making adoption decisions, considering the remarkable impact of this new technology in the fruit industry. Agricultural policy makers seek academic evidence to plan policies to possibly aid the utilization and diffusion of this new technology. Given the growing interest among industry, government, and academia in production-related information diffusion in general and the adoption of this new technology specifically, the present study hopes to add useful information to the literature.

**Literature review**

A small amount of research analyzing China's fruit production has focused primarily on output levels in various production regions (Zhai, et al. 2008), trends in development and government supported fruit industry (Jiang and Yu 2008), and the recently emerged fruit grower cooperatives (Sun and Collins, 2006). For example, Sun and Collins noted that China's fruit farming is based on a farmer decision-making system which ensures sufficient freedom for farmers to choose which crop to grow. Over the past two decades during which this farming system has been in place, China's fruit production was not systematic. Various quality standards were applied across geographic regions leading to inconsistent fruit quality. The resulting over-supply of low quality fruits, frequently rejected by the domestic and the international market, led to huge post-harvest losses (Zhang et al. 1994; Chen et al. 2001). A government supported agricultural cooperative system was recently established to achieve quality standardization, specialization and economies of scale in fruit production (Kong at al. 2007; Sun and Collins, 2008). Though the impact of this new system has been unclear, Sun and Collins have documented that fruit producers' cooperatives have helped unify production quality, reduced the odds of sending low quality fruits to the market, improved farmers' market access, and helped farmers obtain farm loans.

In the Western literature, theoretical research on farm-level technology adoption in general is abundant (Kislev and Shchori-Bachrach, 1973; Perrin and Winkelmann, 1976; Feder and O'Mara, 1982; Just and Zilberman 1983; Feder and Slade, 1984; Feder et al., 1985; Feder and Umali, 1993; Huang et al. 2008; Perdew and Shively, 2009; Useche, Barham, and Foltz, 2009). Among recent published works, Perdew and Shively examined Sulawesi Indonesian farmers' adoption of production strategies aimed to increase the size of cocoa pods and reduce hosts of pest transmission. They concluded that the average increases in private returns arising from more intensive cocoa management and that the increases appears sufficient to compensate for higher production costs. Useche, Barham, and Foltz (2009) applied an integrated adoption model of technology traits and producer heterogeneity to analyze Minnesota and Wisconsin farmers' demand for four corn varieties of Ht, Bt, Ht/Bt, or non-GM) and found that farmers in higher farm-revenue groups are willing to pay more in terms of seed price differential for specific traits than their low-revenue counterparts. In addition, they found that traits related to environmental and marketability concerns are important in explaining farmers' choice of non-GM varieties. Though studies on farm adoption behaviors are plentiful in the western literature, rigorous analyses on Chinese farmers' technology adoption remain few. The earliest study was conducted by Lin (1991a) who analyzed how farm adoption decisions are formed during China's switching from a collective farming system to a household responsibility system. The collective system, a primary farming institution set forward in China, features team leaders who dominate adoption decision-makings. This collective system was perceived to be effective for promoting new technologies because of its economies of scale in obtaining information, farm inputs, and credits (Perkins and Yusuf, 1984; as cited by Lin, 1991 a). The household responsibility system, in which farmers bear the full risk of their own decisions and also receive the full benefit of their effort, began to replace the collective system in 1979. Lin showed that the adoption of hybrid rice in a collective system was determined by farmers' past experiences rather than the expected profitability of the new technology. This finding reflects the impact of government intervention and how this intervention change farmers' experiences with the hybrid rice technology. However, under the household responsibility system, profitability was found to be the major factor driving adoption behavior. Using a cross-sectional survey of 500 households in China's main rice production provinces, Lin further explored the role of education in the adoption of hybrid rice under the household responsibility regime (Lin 1991, b). He detected a positive impact of a household head's education on the probability of adoption and on adoption intensity. In addition, acres cultivated were found to positively correlate with adoption, due to the economies of scale of acquiring information, credit, and hybrid seeds (Lin, 1991 b).

The methodology of the previously reviewed analyses involves the expected utility maximization framework in which farmers adopt pieces of the package and adoption occurs in a step-wise manner (Byerlee and Polanco, 1986; Lin, 1991 a,b; Leathers, and Smale, 1991). For example, Khanna, Epouhe, and Hornbaker (1999) examined farm adoption of a site-specific crop management system and found that only a small percentage of farmers that adopted soil testing also adopted VRT, a site specific input application technology that uses soil maps to decide input application levels. In terms of estimation methods, a substantial portion of applied adoption research employed probability analyses using survey data to identify factors changing adoption behavior (Jamison and Lau 1982; Lesser, Magrath, and Kalter 1986; Zepeda 1990; Lin 1991, b).

Saha, Love and Schwart (1994) proposed a multilevel probability model to adjust the potential sample selection bias problem inherent in probability analysis using survey data. This estimation added to the adoption equation a separate step to address the "learned" versus "have not learned" the technology before estimating the "whether or not to adopt", in order to correct the sample selection bias problem. In this paper, we derive a Chinese fruit producers' adoption framework based on the structure developed by Saha, Love and Schwart (1994).

**The conceptual model**

A conceptual model is designed to describe fruit producers' technology adoption process (Figure 1). This model describes a three stage adoption framework which includes: 1) an information gathering stage; 2) a decision-making stage of adopt of not to adopt stage; and 3) a further decision-making stage of adoption share (% of adoption). Selected factors affecting adoption in each stage is presented below.


**Figure 1:** A Picture of Artisan Apples in a Delicate Gift Box.

*Stage 1: Information gathering stage*

In this stage, a fruit producer's acquired information level determines whether or not he understands the artisan fruit production technology. When the information obtained reaches a threshold level, the producer understands the technology and thus, become potential adoption of this technology. Information has been noted as an important factor affect adoption (Marra, Hubbell, and Carlson, 2001; Xu, et al. 2009). Lin (1991 a, b) and Zhou et al. (2008) concluded that the level of exposure to information relevant to the new technology could significantly change Chinese producers' adoption decisions. Thus we assume information could be significant in determining the adoption of artisan fruit technology. Dynamic adoption models (Fernandez-Cornejo, Alexander, and Goodhue 2002) and farmer adoption choice models (Marra, Hubbel, and Carlson 2001; Gouse, Pray, and Schimmelpfennig 2004; Marra, Piggot, and Carlson 2004; and Qaim et al. 2006) have identified age, education, farm size, as key explanatory factors of farm adoption. In addition, information could be obtained through talking to experienced peers (Xu et al. 2009). For example, being a member of a fruit cooperative could influence information gathering. The availability of agricultural technology assistance programs could affect information dissemination which could expedite the diffusion of the new technology (Rogers, 2003). All above discussed factors are listed under "phrase 1: factors affection information gathering" in the conceptual model. We posit that a producer collects an optimal level of information that maximizes his expected utility of random wealth.

$$i^* \equiv i(d) \qquad (1)$$

Where $i^*$ represents the optimal level of information and d is the vector containing producers' economic and demographic characteristics. When information level exceeds a threshold level, $i^0$, the producer understands the new technology, which we posit as a condition for adoption.

*Stage 2: Whether or not to adopt*

In this stage, farmers' characteristics, farm traits as well as factors relevant to producers' attitude toward risk, their current farm efficiency in return, and their expansion plan may all affect the adopt or not to adopt decision. This second stage equation must be dependent on acquired information level, thus the first stage of the equation.

Specifically, in this second stage of decision-making, a producer maximizes his expected utility of random wealth $\widetilde{W}$ through randomly choosing the number of fruit trees in traditional production and the number of fruit trees applying the artisan fruit technology. A maximize expected utility framework is:

$$\max_{t,a} H \equiv \underset{i^*}{E}[U(\widetilde{W})]$$
$$\equiv \underset{i^*}{E}[U\{p_t \cdot f(t) + p_a \cdot g(a)\widetilde{e} - w \cdot (t+a) - r \cdot a\}] \qquad (2)$$

Subject to: t + a= x

Where $\widetilde{Q} \equiv f(t) + g(a)\widetilde{e}$ denotes the producers' stochastic fruit production function, t is the number of fruit trees using traditional production technology, and a is the number exposed to artisan fruit technology, with total number of trees as x, and $\widetilde{e}$ is a random variable denoting the uncertain yields from the new technology. The variable cost per tree is denoted by w, and r is the additional cost incurred only for trees treated with artisan fruit technology (assume r is not random). Finally, $p_t$ denotes price for traditional fruits; $p_a$ denotes price for artisan fruits.

Assume the function is increasing and concave, we derive the first order condition of (2) under the situation that the inequality constraints are not binding:

$$\underset{i^*}{E}[U'(\cdot)\{p_t f_t(\cdot) - w\}] = 0 \qquad (3a)$$

$$\underset{i^*}{E}[U'(\cdot)\{p_a g_a(\cdot)\widetilde{e} - (w + r)\}] = 0 \qquad (3b)$$

Assume separability between t and a, and that (3a) can be solved independently from (3b) for $t^* = t(p_t, w)$. Thus, optimal production of traditional fruits is determined only by prices of traditional fruits and costs associated with this technology and it is unaffected by risks associated with the new technology ($\widetilde{e}$).

We can prove that adoption (a>0) is an optimal choice when expected net marginal benefit of adoption exceeds its marginal costs: $p_a g_a(a = 0)\overline{e}(i^*) > (w + r)(\cdot)$. Producers' perceived net marginal dollar increases change with the optimal of information obtained $i^*$.

*Stage 3: Adoption intensity*

In this stage, we explore the adoption intensity in response to perceive risk of the new technology. All factors that affect adoption or not could also affect the adoption share. The adoption intensity decision must be dependent on the acquired information level determined in phrase 1, and the adoption versus nonadoption decision in phrase 2. Assume the more information a producer obtained regarding the new technology, the more he knows about the yield associated with the new technology. Thus: $\frac{\partial \gamma(i^*)}{\partial i^*} < 0$, $\gamma$ denotes the mean preserving spread about the distribution of yield uncertainty ($\widetilde{e}$). And the more the information acquired, the higher the adoption intensity: $\frac{\partial t^*}{\partial i^*} > 0$.

## Econometric model

According to the above framework, we can specify the three phases in the following econometric models

$$Y^{H*} \equiv X^H \beta^H + \varepsilon^H \qquad (4)$$

$$Y^{A*} \equiv X^A \cdot \beta^A + \varepsilon^A \qquad (5)$$

$$Y^{p*} \equiv X^p \cdot \beta^p + \varepsilon^p \qquad (6)$$

The dependent variables $Y^{H*}$ (understand the technology or not); $Y^{A*}$ (adopt the technology or not) are binary indicator variables which equals 1 if it is greater than zero, and zero otherwise. $Y^{p^*}$ is adoption intensity. Given the information about the percentage of trees treated with artisan fruit production was not available, we use the percentage of artisan fruit income over total income to represent adoption share. $X^H$ represents a vector of explanatory variables relevant to personal characteristics and farm characteristics listed in Figure 2 under phrase 1. $X^A$ and $X^P$ represent personal characteristics and farm characteristics variables as well as the three added variables of farm operation status and managers' risk attitude, listed in Figure 1 under phrase 2 and 3.

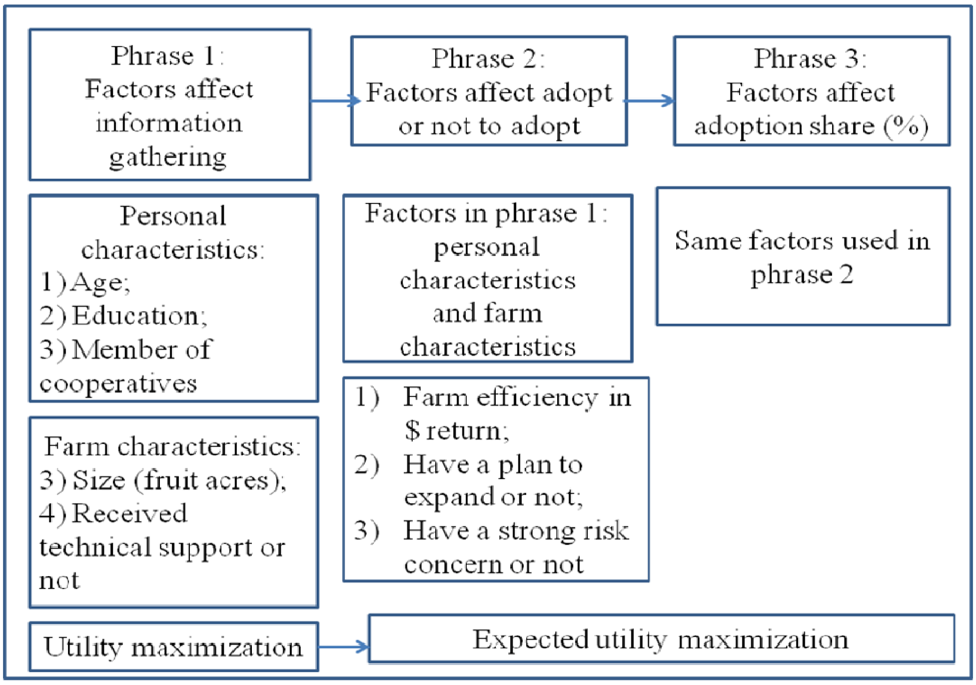


**Figure 2:** A Conceptual Framework to Describe Chinese Fruit Producers' Adoption of the Artisan Fruit Technology

We first estimate the following log-likelihood function on conditional probabilities to obtain $\beta^H$, $\beta^A$ and $\rho = corr(\varepsilon^A, \varepsilon^H)$, correlation between $\varepsilon^A, \varepsilon^H$.

$$\begin{aligned} \ln L = & \sum_{Y^A=1, Y^H=1} \ln \Phi_2[X^H \beta^H, X^A \beta^A, \rho] \\ & + \sum_{Y^A=0, Y^H=1} \ln \Phi_2[X^H \beta^H, -X^A \beta^A, -\rho] \\ & + \sum_{Y^H=0} \ln \Phi\ [-X^H \beta^H,] \end{aligned} \tag{7}$$

Then based on the bivariate probit model with sample selection, we used the estimated $\hat{\beta}^A$ $\hat{\beta}^h$ $\hat{\rho}$ to form the regressers in the adoption intensity equation:

$$Y^P = X^P \beta^P + \hat{\lambda}^H \theta^H + \hat{\lambda}^A \theta^A + \eta \tag{8}$$

Where $\hat{\lambda}^H \equiv \phi(-X^H\beta^H)\cdot\Phi[(-X^A\beta^A-\hat{\rho}Y^H)/(1-\hat{\rho}^2)^{1/2}]/\Phi_2$,

$\hat{\lambda}^A \equiv \phi(-X^A\beta^A)\cdot\Phi[(-X^H\beta^H-\hat{\rho}Y^A)/(1-\hat{\rho}^2)^{1/2}]/\Phi_2$, $\Phi_2$ is the bivariate normal cdf $\Phi(-X^H\hat{\beta}^H, -X^A\hat{\beta}^A, \hat{\rho})$ whose pdf is denoted by $\phi_2$. $\eta$ is the error term. We estimate the coefficient using the maximum likelihood method under the assumption that: $N[0, \sigma_\eta^2(Z^P)]$, where $Z^P$ denotes a subset regressors of (8), which affects the disturbance variance. The repressor, $\hat{\lambda}^H$ and $\hat{\lambda}^A$ are included to ensure that the estimation are not suffered from the omitted variable bias (Saha, Love and Schwart, 1994).

**Data**

Survey information was used to estimate the models. To collect the survey information, we interviewed fruit farmers in October 2009. Researchers from Fruit Industry Development Team of the Beijing Forestry Bureau and the Renmin University of China administrated the interviews in four fruit production countries of Daxing, Pinggu, Fangshan, and Changping. First, we selected the four fruit production counties based on their production output level and their different location (Daxing and Changping are located in a flat region, and Fangshan and Pinggu are located in a mountainous region). Selection of farmers from the two different landscapes ensures the samples are representative of fruit growers from both flat regions and the mountainous regions. Second, with the assistance of county fruit associations and using a snowball sampling method we successfully delivered 1,100 questionnaires to fruit farmers. We obtained 152 observations from Daxing; 436 from Pinggu; 151 from Fangshan, and 191 from Changping, with a total of 930 observations collected. Within these 930 observations, 116 have missing information about the dependent variable, resulting in a total of 814 observations. When independent variables were picked to fill the probability analysis, another 416 observations were omitted because of missing information of the selected explanatory variables. A total of 398 observations are used in this analysis.

Questions were designed based on previous discussions with fruit farmers. A three-page questionnaire containing 49 questions was used which include: 1) farmers' perceived risks of adopting a new technology and their level of risk concerns regarding the new technology; 2) information sources of where farmers first heard the new technology; 3) farmers' general tendency of adoption, i.e. early adopters or followers; 4) farmers' participation in new technology training and local farm cooperatives; 5) farmers' plan to expand the farm; 6) farm profile and farm household members' demographic information.

Summary statistics about fruit farmers' demographic information and statistics about selected independent variables appear in Table 1. We computed the mean age of the first male and female household members and used this information as the age information for the household operators. Statistics for subsamples of: 1) those who understood the new technology; 2) those who adopted; and 3) those provided the adoption intensity. On average, our respondents are around 46 years old and this information stays similar across the three groups. The surveyed fruit farm operators' education level was found to be low. We found 71% of respondents completed a middle school education; 26% completed high school and 3% technical school. Total acres owned are small with an average of 1.5 acres for the understood and the adopted or not group; and a slightly lower average acre of 1.4 for the how much adopted group. Limited by land, few respondents in the adopted group plan to expand the farm (35%), in contrast to the understood group in which more producers plan to expand (39%). Production efficiency of average dollar return per acre was computed and it shows that those who have adopted the new technology reported a slightly higher dollar return (0.48) than respondents in the other two groups (0.44 and 0.45). The adopted more group reported a higher availability of technical support provided by the agricultural assistance programs (0.90 vs. 0.87), and respondents in this group were less worried about production risks related to new technologies (0.67 vs. 0.68). Respondents who are more likely to adopt new technologies seems also more likely to be a member of local fruit cooperatives (47%) compared to the understand group (44%). However, the aforementioned statistics are not significantly different across groups and the information is only based on descriptive statistics.

**Table 1:** Summary Statistics on Selected Variables (Data, 2009)

| Variable | Description | Understood the new technology | Adopted or did not | Percentage adopted |
|---|---|---|---|---|
| | | Mean (minimum, maximum) | | |
| Age | The average age of the first male and female household members | 46.16<br>(24, 73.5) | 46.21<br>(25, 73.5) | 46.20<br>(25, 73.5) |
| Education | Average education of above. Education level:1)elementary school and below; 2)middle school; 3) high school; 4) technical school;5) college and above. | 1.95<br>(1, 4) | 1.95<br>(1, 4) | 1.94<br>(1, 4) |
| Fruit acres | Total acres of fruits | 1.56<br>(0.08, 32.94 | 1.53<br>(0.08, 32.94) | 1.40<br>(0.16, 23.88) |
| Efficiency | Average dollar returns per acre ($) | 0.44<br>(0, 1.42) | 0.45<br>(0, 1.55) | 0.48<br>(0, 1.42) |
| Expand | Dummy variable, equals 1 if producer expressed expansion plans, zero otherwise | 0.39<br>(0, 1) | 0.38<br>(0, 1) | 0.35<br>(0, 1) |
| Technical support | Dummy variable, equals 1 if received help from agricultural assistance programs, zero otherwise | 0.87<br>(0, 1) | 0.88<br>(0,1) | 0.90<br>(0, 1) |
| Risk concerns | Dummy variable, equals 1 if it is strongly worried about risk; zero otherwise | 0.68<br>(0, 1) | 0.68<br>(0, 1) | 0.67<br>(0, 1) |
| Member of Agricultural. Cooperatives | Dummy variable, equals 1 if a member of agricultural cooperative; zero otherwise | 0.44<br>(0, 1) | 0.45<br>(0, 1) | 0.47<br>(0, 1) |
| | Number of observations | 398 | 350 | 234 |
| | % of respondents heard about new technology | 88% | 100% | 100% |
| | % of respondents who will adopt | 59% | 67% | 100% |
| | % of income received from applying new technology | 3.85% | 3.53% | 4.52% |

**Results**

The probit, Heckman Probit and Heckman selection model results from STATA are reported in Table 2. Parameters estimates from the limited dependent variable models cannot be directly interpreted. Thus marginal effects on the probability of adoption were computed and were presented in Table 3. The coefficient estimates for $\lambda^H$ and $\lambda^A$ indicate that the conditional model specification is appropriate for the *adopted or did not* estimation (stage 2) and the *intensity adopted* (stage 3). This means that the null hypothesis that the coefficient of $\lambda^H$ and $\lambda^A$ is jointly equal to zero is rejected and that the stage one equation should be estimated jointly with the stage two adoption or not equation and that the stage two equation should then be jointly estimated with the stage three intensity equation. The Chi-square test was conducted to check the model performance and it shows that the fitted models are appropriate with high Chi-square values (Chi-square=21.59 or above) (Table 2).

**Table 2:** Three Stage Probability Estimation Results (Data, 2009)

| Estimation Results | Probit | Heckprob | Heckman | |
|---|---|---|---|---|
| Estimation Results | Phase 1: Whether understood the new technology | Phase 2: adopted or did not | Phase 3: % adopted (% income generated) | |
| Constant | -0.1942 (-0.32) | -2.8568*** (-4.06) | 75.0894* | (2.12) |
| Age | 0.0001 (0.01) | 0.0038 (0.39) | -2954 | (-0.63) |
| Education | 0.0227 (0.19) | 0.1963* (1.67) | -8.0311* | (-1.65) |
| Fruit acres | -0.0032 (-0.82) | 0.0026 (0.71) | -0.0533 | (-0.31) |
| Technical support | 0.7136*** (3.63) | 1.2684 *** (3.75) | 5.9594*** | (6.78) |
| Member of fruit Cooperatives | 0.5251 *** (3.58) | 0.6461*** (4.29) | 12.076 | (1.30) |
| Efficiency | -- | 0.4230 (1.38) | -0.0708 | (-0.20) |
| Expand | -- | -0.2978* (-1.71) | 0.4565** | (2.16) |
| Risk concerns | -- | 0.0689 (0.36) | -0.4472* | (-1.92) |
| $\hat{\lambda}^H$ | -- | -- | 0.4351*** | (-4.67) |
| $\hat{\lambda}^A$ | -- | -- | -25.49 * | (-1.84) |
| Number of observations | 398 | 350 | 234 | |
| Chi-square [a] | 26.26 (d.f.=5) | 33.48 (d.f.=8) | 21.59 (d.f.=8) | |
| % of correct prediction | 74.69% | 21.17% | -- | |
| Log likelihood | -216.52 | -318.64 | -- | |

Note: Numbers in parentheses are z-statistics [a]: *The Chi-square test statistics are for the null that all coefficients except the constant values are equal to zero.*

**Table 3:** Marginal Effects Estimates (Data, 2009)

| Variables | Phase 1 | Phase 2 | Phase 3 |
|---|---|---|---|
| Age | -0.0000<br>(-0.01) | 0.0008<br>(0.0029) | -0.0145<br>(-0.03) |
| Education | 0.0073<br>(0.19) | 0.0538<br>(1.53) | -3.0225<br>(-0.51) |
| Fruit acres | -0.0010<br>(-0.82) | 0.0007<br>(0.63) | 0.0485<br>(0.23) |
| Technical support | 0.2579 ***<br>(3.41) | 0.2337 ***<br>(6.81) | 140.6341***<br>(6.45) |
| Member of Fruit Cooperative | 0.1635 ***<br>(3.72) | 0.1987***<br>(4.28) | 26.06 **<br>(2.51) |
| Efficiency | -- | -0.0196<br>(-1.38) | -1.514<br>(-0.20) |
| Expand | -- | -0.0147<br>(1.6) | 9.6866 **<br>(2.17) |
| Risk concerns | -- | -0.0033<br>(-0.35) | -9.4733*<br>(-1.94) |

In the stage 1 estimation (understood the new technology or not), note that the coefficient of the variable technical support is significant and positive (TECHNICAL SUPPORT ($\alpha<0.001$) which indicates that individual farmers who have received technical support provided by agricultural assistance programs are more likely to understand the artisan fruit production technology. Marginal effects show that the availability of technical support increased farmers' probability to understand the new technology by 25.79% (more likely to understand). In addition, being a member of local fruit cooperative also substantially increases the likelihood of understanding the new technology ($\alpha<0.001$). The marginal possibility of understanding the technology is improved by 16.35% compared to a non-member. Surprisingly, education does not contribute to farmers' ability to understand the new technology, as we discovered in the first stage estimation.

It appears reasonable that the availability of technical support is a dominant factor influencing farmers' adopted or did not decision ($\alpha<0.001$). This result agrees with the findings of a previous study which examined factors affecting Chinese farmers' adoption of a water-saving technology (Zhou et al. 2008). The study revealed that being a member in an agricultural assistance service and receiving technical assistance could both remarkably increase the adoption of the water-saving technology. The authors relate this to the individual farmers' desire to enhance social status by joining a professional organization or actively seeking help from agricultural technology support programs in order to exceed other farms' in using new technologies and to set up an example in the farming community. In the Western adoption literature, Rogers (2003, pp. 283) explained this desire as an ideal characteristic of early adopters. Other farmers (potential adopters) look to early adopters for advices about the new technology and these early adopters serve as role models for many other members, earning esteem from colleagues and maintaining a central position in the farming community. Using our sample, we found that being a member of a fruit cooperative is significant and positive in affecting the adoption decisions (Table 2). Compared to a non-member, a member of a local fruit cooperative is about 20% more likely to adopt the new technology (Table 3). Our result suggests that the impact from agricultural cooperatives on the diffusion of the fruit technology innovation appear to be dramatic and profound. This result is consistence with another study, which examined the impact of forestry cooperatives on members' adoption of new technologies and found that holding a membership improves the adoption of the innovations (Kong et al., 2007). The authors relate this to a scale economy in which adoption of cost intensive technologies are only possible with cooperatives who are able to afford the cost. Though the artisan fruit production technology is less costly than large farming machinery, it is still pricey for small producers. Thus, joining a cooperative and sharing the costs of technical support could save production costs and thus improve the adopt intensity.

Education was found to contribute to the adoption of the fruit technology. Better educated farmers are more likely to use this new technology as compared to less educated farmers. The significance of the education coefficient in the stage 2 equation warrants comment. Recall that in the understood stage, estimation is based on the entire sample of respondents. The stage 2 estimation is only based on a subsample of respondent who understood the technology. The first stage estimation shows that education does not change respondents' probability of understanding the new technology. However, it does affect the respondents' conditional probability of adopting the fruit technology, as suggested by our sample. Interestingly, previous studies also found that Chinese farmers' education significantly contribute to the adoption of hybrid rice (Lin, 1991b), and the adoption of a new water saving technology (Zhou, et al. 2008).

In the third stage of estimation, we found that the availability of technical support contributed significantly to the magnitude of adoption ($\alpha<0.001$). We detected that being able to access technical support is the only explanatory variable that significantly influenced respondents' probability to understand, adopt, and decide how much to adopt. However, the accessibility to agricultural assistance service programs is an exogenous factor which is not controlled by farmers. The agricultural assistance programs are primarily funded by the government and which, according to a previous study, are made available in limited agricultural communities and this support is less likely to be available in isolated regions (Dai and Xue, 2000). Our results suggest that not being able to get technical support has constrained farm adoption of the fruit technology.

Farmers' expansion plans also affect their adoption decisions. Our results from stage two suggest that those farmers who plan to expand are less likely to adopt the new technology ($\alpha<0.1$). However, once an adoption decision has been made, farmers who tend to expand would obtain a bigger share of income from the new fruit technology, as indicated from the stage three result ($\alpha<0.01$). Interestingly, though education was found to be positively related to an improved adoption possibility, once the adoption decision is made, farmers with higher education would receive a smaller share of income from the technology. In addition, farmers' risk concern was shown to negatively affect *adoption intensity.*

## Conclusion

In this paper, we developed a theoretical framework to examine Chinese fruit farmers' adoption relevant to a newly introduced technology, the artisan fruit production technique. We established an expected utility framework to analyze a three-stage adoption process by examining factors determining farmers' adoption decision in each stage. An econometric model was then set up and survey data were used to quantify farmers' probability to understand and adopt the new technology and their intensity to adopt. The model developed in this paper emphasizes sample selection errors which probit model cannot correct. Previous studies have shown that considering sample selection in model specification could show substantially different results and inference compare to traditional dichotomous model specification, such as probit specification (Heckman, 1979; Saha, Love, and Schwart, 1994). This study presents an effective framework which adjusts sample selection bias and it effectively applies the framework to measure fruit producers' adoption of a new production technology. Although the model and its empirical application are presented using the adoption of a fruit production technology, the framework could be used to measure farm adoption of other emerging production technologies in order to effectively adjust existing sample selection bias of popular discrete choice specification.

We found that farmers' adoption behavior varies with their education, plans to expand, and their risk concerns regarding the new technology and that the effect of these factors differs depend on the stage of adoption decision-making. Similar to another study on farm adoption in Western agricultural literature, education was found to positively impact Chinese fruit farmers' *adopt or not to adopt* and negatively impact *adoption intensity* (Saha, Love, and Schwart, 1994). Also, Chinese farmers with stronger risk concerns were found to be less likely to adopt a big share of the new technology, similar to conclusions drawn from Western adoption studies (Greiner, Patterson, Miller, and Jacquet, 2010). In addition, we detected that adoption changes with Chinese farm accessibility to government supported agricultural assistances and the availability of privately funded fruit cooperatives. Thus, the effort of government aided agricultural assistance in the form of agricultural technical assistances is proved to effectively help Chinese fruit farmers understand, adopt, and adopt more of a new technology. Therefore, improving farmers' accessibility to fruit production assistance programs should be considered by the government to aid fruit farm adoption. This linkage between agricultural assistance and farm adoption is again established long ago in the Western agriculture. Fifty years ago, Rogers (1962) in his diffusion theory argued that agricultural assistance services in the U.S. were most successful in helping farmers adopt agricultural innovations. Since then, numerous empirical studies have demonstrated the critical contributions of agricultural assistance programs in helping U.S. farmers adopt new technologies. Our sample shows that this linkage exists in the Chinese fruit production industry and that Chinese fruit farmers need technical support to help them understand and use the new technology.

This current study contributes especially to international agriculture and farm adoption literature in the way that we found Chinese fruit farmers' adoption behavior is not significantly different from Western farmers' adoption behavior. For instance, we found education, a critical factor affects Western farm adoption, is already an important factor differentiates Chinese fruit farmers' adoption decision. A decade ago, the effect of this factor could be trivia given Chinese farmers' limited access to education. From our random sample, we found 2/3 of our respondents completed a middle school and 1/3 a high school and their received education determined their adoption behavior toward a new technology. The similar adoption behavior between the Chinese and U.S. farmers deserve close examination by international agricultural researchers and food policy planners. After all, China, as a large fruit producer and the third largest apple producer worldwide, is importing much of its production technology from the Western world (Gao, 2010). Understanding farm adoption behavior is a key to plan successful diffusion strategies to Chinese farmers. An efficient diffusion strategy could bring significant gain to the Western agricultural technology industry.

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**Footnote:**

The only statistics available are from ShanXi Xian Jiaotong University. A group of students conducted an internship with 67 fruit farms to help with artisan apple production and marketing. They found a $441 potential income increase/per hectare by using artisan production technology (2009). http://xiangcun.baidu.com/view_project.php?pid=2117&rtn_url=%2Findex.php