Hog Insurance Adoption and Suppliers' Discrimination:

A Bivariate Probit Model with Partial Observability

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Abstract:

This paper explores the factors that impact insurance choices. Specially designed survey questions allow one to fully observe the demand tendency by the farmers and partially observe the supply tendency by the insurance company. A joint estimation of insurance decision by both supply and demand sides suggested that factors performing different roles in affecting insurance participation game. Farmer's age and education have positive impact on insurance demand, but are indifference to the insurance providers. Insurance suppliers care more about farmers' experience in the field, but this experience occasionally results in overconfidence for the farmers and hence, impedes insurance purchasing. Production scales, proxy by sow inventory, is put more weight by the farmers than the suppliers when making decisions. Production efficiency measures, which performs as incentives for farmers to purchase insurance, acts as some disadvantages in the suppliers' point of view. While the suppliers prefer customers who use vaccine, the hog producers tend to treat vaccine as a substitute for insurance so as to prevent disease risk. The study also generates discussion on the topics such as short-run vs. long-run factor impact by comparing past insurance choices and current choices. Information on choices regarding different types of insurance (hog and breeding sow) is also discussed. Results from bivairate probit model offers deeper understanding about livestock insurance choices and further insights to improve policy design and promote participation.

Key Words:

Livestock Insurance Choices, Bivariate Probit, Partial Observability

JEL Code:

C35, D13, Q12

1. Introduction

China is one of the biggest hog exporters in the world. Its annual finished hog production takes about one half of the global market. However, most hog operations in China are of small scale and lack of effective risk reduction mechanism. Meanwhile, research has shown about 70% of the hog operation owners claim livestock disease to be the most deadly shock to their annual income and hog production (Patrick et al, 2000). In 2007, hog insurance became widely available in China and government also began to offer subsidy to purchase insurance. By the end of June 2009, there were around 153 million hogs under insured and insurance had been proved to be the most effective way for production risk management in hog industry (China Insurance Regulatory Commission, CIRC, 2009). Despite all these, hog insurance participation rate is still quite low in China (i.e. only around 20% for hog insurance in Zhejiang). This paper explores the factors that might impact insurance choices. Using specially designed survey questions, this study differentiates the participation tendencies for both supply (insurance companies) and demand (farm households) sides. Results from bivairate probit model offers deeper understanding about hog insurance choices and further insights to improve policy design and promote participation.

Agricultural insurance research started as early as 19th century. Generally speaking, in either theory or practice, most studies are for crop insurance (for example, Knight and Coble, 1997) and very few for livestock. Of those which concentrated on livestock insurance, most research addressed questions for product design and market reaction in a supplier's perspective (for example Gramig et al, 2007 and Turvey, 2007) and relatively less study paid attention to the demand side. In China, research on livestock insurance started even later. Recently, there exist some studies regarding the market demand for hog insurance, such as Cai et al. (2009). But research based on micro level data is still very rare.

Our study contributes the livestock insurance literature in the following ways: First, this is one of the very few studies that are based on information and behavior about micro level farm households. Second, the specially designed survey allows us to differentiate the participation tendency for both farm households and insurance companies and thus, be able to investigate the insurance choice as a joint result from both demand and supply sides. Third, the estimation method, bivariate probit model with partial observability, which was previously widely used in labor and health economics (Poirier, 1980; Berinsky, 2004), is introduced to livestock insurance research.

The data comes from two sources. One is a survey for 531 hog raisers with annual finished hog of 100 or more in Deqing County conducted by the Deqing Bureau of Animal Husbandry in Zhejiang province, China in 2009. The other part is the claim and settlement information about these 531 households which comes from the insurance company. The survey consists of information on demographics, farm management, farm bio-security and micro financial situation (such as insurance choices, debt and loan, etc). Data from insurance company consists of information about policy coverage, premium, subsidy, reported livestock death and final payment, etc.

By using information on insurance choices and self-reported reasons, this data allows us to fully observe the farmers' demand tendency and partially observe the supply tendency by the insurance company. Treating the insurance choice as a joint result of both demand and supply sides and estimating a biprobit model, results showed that factors performing different roles in affecting insurance participation game. Farmer's age and education have positive impact on insurance demand, but are indifference to the insurance providers. Instead, insurance suppliers care more about farmers' experience in the field, but for the farmers this experience results in overconfidence occasionally and hence, impedes insurance purchasing. Production scales, proxy by sow inventory, is put more weight by the farmers than the suppliers when making decisions. Production efficiency measures, which performs as incentives for farmers to purchase insurance, acts as some disadvantages in the suppliers' point of view. While the suppliers prefer customers who use vaccine, the hog producers tend to treat vaccine as a substitute for insurance so as to prevent disease risk.

The study also generates discussion on the topics like: short-run vs. long-run factor impacts, by comparing past insurance choice history and current insurance choices; information on choices regarding different types of insurance, hog and breeding sow; and endogenous relationship between insurance choice and production security behavior.

In summary, this study provides explanations for the low participation rate of the livestock insurance in China in particular and offers further understanding on how specific factors impact insurance choice on both demand and supply sides in general. Better understanding about the insurance choice behavior can help to promote insurance participation so as to reduce risk, smooth income flow, stabilize market supply and increase food security. The insurance suppliers will also benefit for marketing development strategies.

The remaining parts of this paper are organized as follows: Section 2 reviews previous research on agricultural insurance and livestock insurance. Section 3 outlines the empirical models. Section 4 describes the data and section 5 presents the results. Section 6 provides discussion and at last, section 7 concludes the paper.

2. Literature Review

Studies on agricultural insurance dated back to as early as 19^{th} century. Given the very few successful cases of insurance operation by private parties, researchers have begun to widely use economic theory to explain the insurance market failure since 1970s (For example, Knight and Coble (1999); Just, Calvin and Quiggin (1999); Wright and Hewitt (1990); and Serra and Goodwin (2003)).

In developed countries, there exists literature that examined the effect of federal crop insurance on farmers' decisions. For instance, Horowitz and Lichtenberg (1993) examined how crop insurance affects corn farmers' fertilizer and pesticide use in the US Midwest and found that on average, farmers who purchased insurance applied more nitrogen, spent more on pesticides and treated more acreage with both herbicides and insecticides than those without insurance. Goodwin, Vandeveer and Deal (2004) examined the extent to which crop insurance programs have resulted in additional land being brought into production and found that increased participation in insurance programs led to statistically significant, but very modest, acreage responses. O'Donoghue, Key and Roberts (2007) used a large increase in Federal crop insurance subsidies as a natural experiment to examine how harvested acreage and diversification changed in response to the policy-induced change in insurance coverage. They found that changes in the risk environment do not seem to have large overall effects.

In developing world, insurance studies were more concentrated on the use of insurance as income smoothing, loss prevention and poverty alleviation strategies. Townsend (1994) suggested that community-based informal insurance effectively shields villagers from their idiosyncratic shocks, thus policymakers should only provide insurance against more aggregate shocks. Udry (1994) found that credit contracts with state-contingent repayments plays an important role in pooling risks across households in northern Nigeria, even though a fully efficient risk-pooling equilibrium is not achieved.

There also exist studies on insurance take-up rate. Some recent research includes Gine et al. (2008) and Cole et al. (2008). Gine et al. (2008) studied the determinants of purchasing an innovative rainfall insurance policy offered to small farmers in rural India. They found that insurance take-up is decreasing in the basis risk between insurance payouts and income fluctuations, increasing in household wealth and decreasing in the extent to which credit constraints bind. These results match the predictions of a simple neoclassical model augmented with borrowing constraints. However, they also found that risk-averse household are less likely to purchase insurance, and participation in village networks and familiarity with the insurance vendor are strongly correlated with insurance take-up decisions. Cole et al. (2008) documented low levels of rainfall insurance take-up, and then conducted field experiments to understand why adoption is so low. Results demonstrated that high price of the insurance and credit constraints of the farmers are important determinants of insurance adoption, but also showed evidence that endorsement from a trusted third party about the insurance policy significantly increase the insurance take-up.

Comparing to the studies on crop insurance mentioned above, relatively less research was focused on livestock insurance. Among those existing research, most of them addressed questions for product design and market response in a supplier's perspective, rather than the demand side. Patrick et al. (2000) found 70% hog farmers reported livestock disease as the most influential factor for income shock and most farmers adopted risk-reducing production practice to cope with risk, such as use of antibiotics and/or vaccine (90%), all-in/all-out production system (78%) and segregated early weaning (53%), etc. Gramig et al. (2007) emphasized the importance to take into account the farmers' purchase intention when designing new insurance product and suggested failure of doing so would potentially make the government face huge payment burden. Shaik et al. (2005) proposed a matrix to compare risk management tools and the insurability conditions and explored the challenges and opportunities of disease risk management tools. Turvey (2007) used a general model to illustrate the complexity of the risks at the farm level and discussed several possibilities for insuring all risks in a qualitative way. A more specific class of net revenue insurance models were presented and evaluated empirically, as well. Green, Driscoll and Bruch (2007) analyzed the data requirement in the design of livestock disease risk. Meuwissen (2007) dealt with designing livestock insurance so as to encourage farmers to behave in the interest of the collective and using risk-financing model to address systematic risk with a diminishing role for government over time. Grannis, Green and Bruch (2007) reported on producer interest in livestock disease insurance in the US and argued that since different challenges are faced by producers of each species, segment and operation size, a single insurance product will not fit the needs of every livestock producer.

Recently, Cai et al. (2009) conducted a randomized natural field experiment in China in the context of sow insurance and found that providing access to formal insurance significantly increases farmers' tendency to raise sows. Evidence also suggested that trust, or lack of government-sponsored insurance products is a significant barrier for farmers' willingness to participate in the formal insurance program, despite partial premium subsidy from the government.

Our study contributes the literature in the sense that both demand and supply tendencies were investigated so as to further understanding the low take-up rate in hog insurance. Using micro level household production data and jointly considering both sides in the market interaction offered more accurate and reliable suggests and strategies to promote insurance participation.

3. Empirical Model

Bivariate probit model was used in a range of fields in the applied research, but mainly in labor and health economics. Depending on the level of observability of dependent variables, the model had 3 different types, full observability of both dependent variables, as in Zellner and Lee (1965) and Ashford and Sowden (1970); partial observability in the sense of Poirier (1980); and the intermediate case, called partial partial observability, such as Farber (1982). Meng and Schmidt (1985) reviewed these three cases, gave discussion on the cost of partial observability (defined as the loss of asymptotic efficiency) relative to the full obervability case and suggested that due to the high cost, some extra observability information may be worth collecting when possible.

In the bivariate model which underlies all of the above cases, there are 2 binary dependent variables, Y_j, j=1, 2, each of which is generated by a probit equation and the two error terms in the equations are correlated. The two dependent variables could represent either two related decisions made by the same agent or decisions made by two different economic agents.

In general, the model looks like

$$(1)\begin{cases} Y_1^* = X_1\beta_1 + \varepsilon_1 \\ Y_2^* = X_2\beta_2 + \varepsilon_2 \end{cases},$$

where Y_j^* are unobservable and are related to the binary dependent variables Y_j by the rule

$$(2)\, Y_j = \begin{cases} 1 & if \quad Y_j^* > 0 \\ 0 & if \quad Y_j^* \le 0 \end{cases} \quad j = 1{,}2\,.$$

The error terms $(\varepsilon_1, \varepsilon_2)$ will be assumed to be iid as standard bivariate normal with correlation ρ . The cases considered above differ in the assumptions about how much information about Y_1 and Y_2 one could observe.

3.1 Bivariate probit with Full Observability

The bivariate probit model with full observability dates back to Zellner and Lee (1965).They analysed durable goods purchase decisions (buy or not buy) and use of credit decisions (use or not use installment credit).They suggested that a joint estimation approach for such relationships provided asymptotically more efficient estimators than single equation estimators if the correlations existed among the variables analyzed. They also concluded that the joint estimation procedure was flexible in the sense that it could readily be adopted to incorporate exact and stochastic restrictions on the parameters of the relationships.

Ashford and Sowden (1970) estimated parameters for a bivariate probit model for two endogenous variables, breathlessness and wheeze of a coal miner with full observability, taking age as the exogenous variable. A coal miner might have a positive response to neither, to one or the other, or to both of the symptoms. There were four possible outcomes, all of which were distinguishable, since number of individuals within each age group could be found with each combination of symptoms.

Full observability means Y_1 and Y_2 are fully observed with all the 4 combinations (Y_1=1, Y_2=1), (Y_1=1, Y_2=0), (Y_1=0, Y_2=1) and (Y_1=0, Y_2=0). This is the case that has the most complete information and naturally leads to the most efficient estimates. One can always estimate the two probit equations separately. But when ρ is not equal to zero, it is more efficient to estimate the two equations simultaneously. The log-likelihood function is

(3)

$$\ln L(\beta_1, \beta_2, \rho) = \sum_i^n \begin{Bmatrix} Y_{i1}Y_{i2} \ln F(X_1\beta_1, X_2\beta_2; \rho) + Y_{i1}(1 - Y_{i2}) \ln(\Phi(X_1\beta_1) - F(X_1\beta_1, X_2\beta_2; \rho)) \\ + (1 - Y_{i1})Y_{i2} \ln(\Phi(X_2\beta_2) - F(X_1\beta_1, X_2\beta_2; \rho)) \\ + (1 - Y_{i1})(1 - Y_{i2}) \ln(1 - \Phi(X_1\beta_1) - \Phi(X_2\beta_2) + F(X_1\beta_1, X_2\beta_2; \rho)) \end{Bmatrix}$$

Here $F(X_1\beta_1, X_2\beta_2; \rho)$ represents the bivariate standard normal distribution function with correlation ρ , while $\Phi(\cdot)$ is the univariate standard normal distribution function. I=1, 2, …, N are the indexes of the observations.

Predicted probabilities and marginal effects for all outcomes could then be calculated accordingly. To test the hypothesis that the bivariate probit model fits the data better than the separate probits, likelihood ratio test could be used. For the separate probits, the joint likelihood is just the product of the two separate (marginal) likelihoods. This means that the joint log-likelihood is just the sum of the two log-likelihoods. One can compare this joint log-likelihood of the separate models to that for the bivariate probit model using a standard LR test.

3.2 Bivariate probit with Partial Observability

For many cases in the real world, two decisions will be made to jointly determine an economic outcome, but as an outsider, one cannot observe the specific responses of the two decisions, but can only observe the joint outcome. That is, instead of observing Y_{i1} and Y_{i2} for all i=1, 2, …, n, one could only observe $Z_i = Y_{i1} \cdot Y_{i2}$. Of all the 4 combinations (Y_{i1}=1, Y_{i2}=1), (Y_{i1}=1, Y_{i2}=0), (Y_{i1}=0, Y_{i2}1) and (Y_{i1}=0, Y_{i2}=0), the last 3 are now indistinguishable.

An example was given by Poirier (1980). Following from the problem posed by Gunderson (1974), Poirier discussed alternative statistical models for estimating the probability that an on-the-job trainee will be retained by the sponsoring company after training. In this situation, the employer must decide whether or not to make a job offer, and the trainee must decide whether or not he would accept the job offer. Each individual's (either employer's or trainee's) decision is not observed; only whether the trainee continues working after training is known. Poirier (1980) suggested using a partial observability bivariate probit model because random utility models in which the observed binary outcome does not reflect the binary choice of a single decision maker, but the joint unobserved binary choices of two decision makers. This model was also used in Connolly (1983) to analyse the decision to arbitrate or negotiate the contracts between public employees' unions and municipalities in Michigan.

Given the available information, two equations must be jointly estimated and the log-likelihood function is

$$(4)\ln L(\beta_1,\beta_2,\rho)=\sum_{i}^{n}\{Z_i \ln F(X_1\beta_1, X_2\beta_2;\rho)+(1-Z_i)\ln(1-F(X_1\beta_1, X_2\beta_2;\rho))\}.$$

3.3 Bivariate Probit with Demand Identified

In some cases, one could observe more than in Poirier's model, but less than in the full observability case. Farber (1982) proposed a model for this case to study the demand for unionism. Let Y_{i1} = 1 if individual i wishes to be in a union, and Y_{i1} = 0 otherwise; let Y_{i2} =1 if a union employer is willing to hire individual i, and Y_{i2} = 0 otherwise. Individual i is a union member (Z_i = Y_{il} Y_{i2} = 1) if both Y_{i1}= 1 and Y_{i2} = 1, and is not a union member (Z_i = 0) otherwise; Z_i is observed for all i. If nothing more were known, this model would be Poirier's model. However, non-union workers in Farber's sample were asked if they desired union representation, so that Y_{i1} is also observed for all i.

On the other hand, Y_{i2} is observed only if $Y_{i1} = 1$. This is so because if $Y_{i1} = 1$, then $Y_{i2} = Z_i$, and Z_i is observed. However, if $Y_{i1} = 0$ we have no information about Y_{i2}. Thus, the first probit equation is completely observed, but for the second we have a censored (or selected) sample. Note that in terms of the four possible outcomes, two ($Y_{i1} = 0$, $Y_{i2} = 1$) and ($Y_{i1} = 0$, $Y_{i2} = 0$) are indistinguishable. This is an improvement in observability relative to Poirier's case, where three outcomes were indistinguishable.

Since the first probit equation is fully observed, it can always be estimated separately. However, this will be inefficient unless $\rho = 0$. Furthermore, there will be selectivity bias in separate estimation of the second equation, unless $\rho = 0$. The likelihood function for the joint estimation of both equations is

(5)

$$\ln L(\beta_1, \beta_2, \rho) = \sum_i^n \left\{ \begin{array}{l} Y_{i1}Y_{i2} \ln F(X_1\beta_1, X_2\beta_2; \rho) + Y_{i1}(1 - Y_{i2}) \ln(\Phi(X_1\beta_1) - F(X_1\beta_1, X_2\beta_2; \rho)) \\ + (1 - Y_{i1}) \ln(\Phi(-X_1\beta_1)) \end{array} \right\}$$

Some recently application included but not limit to Devaney and Chien (2000), which used a bivariate probit model to analyze the decision of employment status and retirement plan participation; Newman and Canagarajah (2000), which used a bivariate probit model to compare trends in rural poverty by gender for Ghana and Uganda; and Berinsky (2004), which provided an example of this model when he examined the attitudes towards race issues. There were also studies in labor economics, such as Orellano and Picchetti (2001), Mohanty (2002) and Wetzels and Zorlu (2003).

4. Data

4.1 Resource

The data used in this study consists of two parts. One is a survey for 531 hog raisers with annual finished hog of 100 or more in Deqing County conducted by the Deqing Bureau of Animal Husbandry in Zhejiang province, China in 2009. The other part is the claim and settlement information about these 531 households which comes from the insurance company. The survey consists of information on demographics, farm management, farm bio-security and micro financial situation (such as insurance choices, debt and loan, etc). Data from insurance company consists of information about policy coverage, premium, subsidy, reported livestock death and final payment, etc.

4.2 Past and Current Insurance Choices

4 different insurance statuses are investigated here. *Insurance* represents the general hog/sow insurance participation, which takes value 1 if the farmer either had the insurance before or is currently insured or both and 0 if the farmer has never participated in any hog insurance. *Ins_now* represents the current insurance status, which takes value 1 if the farmer is currently

insured, either for hog or sow or both and 0 if he/she is not insured in the survey year. *Ins_hog* indicates whether the farmer purchased insurance for hogs in the current year and *ins_sow* indicates whether the farmer purchased insurance for sows.

Comparing the estimated results between the first two insurance statuses enable us to understand how the factors are different in determining long-term and short-term insurance choices. While comparing the estimation between the last two insurance choices could let one know how farm owners evaluate each factor when choosing different types of insurance in the same given period.

Table-1 gives the distributions for the 4 insurance choices. Of the whole sample, 48% (N=252) farmers indicated they had experience in participating hog/sow insurance (now or past). 35% (N=187) farmers were insured (hog or sow) in 2009. That is around 13% farmers who were previously insured but not in the year 2009. Of the 35% who were currently insured, nearly all of them purchased sow insurance (N=185), and only 119 farmers purchased hog insurance, which takes about 22% of the whole sample.

4.3 Insurance Demand and Supply Identification

Each of the above 4 insurance choice variables is a joint outcome variable Z as discussed in the model in section 3.2. As mentioned, the joint outcome is actually determined by two terms, insurance demand intention of the farmer $Y_1 = D$ and insurance supply intention of the insurance company $Y_2 = S$, and each can take values of 0 or 1. Hence, Z could be considered as the product of the two terms and takes value 1 only when D=1 and S=1, and 0 otherwise (i.e. D=1, S=0; D=0, S=1; D=0, S=0).

A specially designed survey question can help to further identify the demand intention of the farmers. The question asked is “For which of the following reasons did you choose Not to participate/Quit any insurance?” 7 reasons were given in the question and the farmers were told to choose all reasons that apply.

Of the 7 reasons, reason A “The premium is too high.” was considered to indicate D=0, no demand intention, while all other reasons, B to G, such as “Product pool is too narrow”, “Coverage is too low”, “Claim is not fair” and “The procedure is too complicated”, etc were all considered as D=1 (positive demand intention). These reason designs and determination rules followed literature in farm credit demand, such as Feder et al. (1990), Jappelli (1990), Kochar (1997), Mushinski (1999) and Boucher (2002, 2005). So far we do not see any study using this method in the insurance participation literature. Table-2 gives a list of the reasons, description of the identification cases and the distribution statistics for each reason.

When demand was identified as 1, supply was merely equal to the joint outcome, i.e. S=Z. The supply remained inconclusive when D=0. The sample could be then divided into 3 groups, (D=1, S=1), (D=1, S=0) and (D=0), where the last group had two indistinguishable sub cases

(D=0, S=1) and (D=0, S=0). Table-3 gives the number and the proportion of farmers that fall into each group.

4.4 Explanatory variables

The explanatory variables used to predict insurance choices are divided into 3 groups, the household demographic group, production group and the security group. Household demographics include the farm owner's *age*, *education*, *experience* (years) working in hog operation and whether the household has any *loan* (formal or informal) or not. Production variables include two sub categories, measures for production scale and measures for production efficiency. The former has variables like income percentage of hog operation (*inc_pctg*), hog inventory (*hoginv*) and sow inventory (*sowinv*). The later has two variables indicate the average number of breeds per sow per year (*sowbreed*) and the annual breed frequency (*breedfrq*). In the security group, there are total cost on quarantine (*quarcost*), total cost on medicine (*medcost*), average cost of vaccine per hog (*hogvac*), average cost of vaccine per sow (*sowvac*), purchase extra vaccine other than required or not (*buy_vac*) and a score ranging from 0-22, which indicates the security level in the production procedure. This score is calculated based on 20 questions regarding the production process. Table-4 gives the summary statistics for each variable under different insurance cases.

5. Results

For each of the 4 insurance statuses, 3 models were estimated, univariate probit model (Model 1), bivairate probit model with partial observability (Model 2) and bivariate probit model with demand being observed (Model 3). Explanatory variables in demand and supply function include demographics, and variables in production scale, efficiency and security as discussed above. The only difference between demand and supply function is that demand function has loan as one explanatory variable but supply function does not. It is assumed that whether a household has loan debt would have an impact on the farmer's insurance demand intention, but not on the insurance company's supply intention. There are several reasons for this assumption. For one thing, loan debt could be used to infer the credit constraint and/or accessibility to credit of one household, which was proved to have positive impact on insurance demand (Udry, 1994). For another, research also showed that there might exist some substitution effect between loan credit and insurance participation in some poor areas, due to the potential possibility to default and the extra high premium for insurance (Gine and Yang, 2009). But for insurance provider, the loan status should not have any impact.

5.1 Past Insurance Choices

Table-5a showed the regression results for insurance choice. Since the positive response in the choice variable included both currently insured farmers and previously insured farmers, long-term choice behaviors were discussed here. There are three panels in the table, each represents one model. Marginal effects were evaluated at mean level for positive insurance participation, i.e. (D=1, S=1) or Z=1. The log pseudo-likelihood, Wald Chi-squared and the percentage of correct predictions were listed on the bottom part of each panel.

Age was shown to have a positive impact on insurance demand, when the demand and supply intention were jointly estimated. Under partial observation of insurance choice (i.e. only observe Z=1), the marginal effect at mean age 46.2 for positive insurance participation was about 0.1%. With demand identified case in the right panel, the marginal effect was even enlarged to 0.6%, which means one year increase from the mean age would lead to 0.6% increase in the possibility to participate in insurance. *Education* seemed to have no significant impact on either demand or supply. *Years* working in hog operation had a significant positive association with supply intention. The marginal effect showed for 1 more year experience in hog operation, there was about 1.5% increase in the possibility that the insurance company was willing to offer insurance service. Within those who had intention to purchase insurance, more experienced farmers had a slightly better chance to be offered the service by the company.

Loan only had significant impact on demand intention in the bivariate partially observed model (Model 2). Compared with the demand equation in Model 3, one could infer that a larger proportion of farmers who were actually insured had access to credit than those who had positive demand intention but were not insured. Or one can say the accessibility to insurance and credit are highly correlated.

Income percentage (*inc_pctg*) had a positive impact on supply intention. 1% increase in the household income percentage from hog operation yielded a 0.3% increase in the possibility to be insured. From the insurance provider's perspective, the company intended to offer service to the households whose income came mainly from hog operation, since these household would be more likely to take the production procedure seriously than those whose income was more diversified. This could be seen as some screening strategy for the insurance company to control the risk.

Log of *sow inventory* had positive signs for all the 3 models. It was also shown to be the one that had the highest marginal effect on the insurance decision. 1% increase in sow inventory leaded up to 27% increase in the chance of positive insurance choices. Sow inventory and hog inventory could be seen as measures for production scale (hog inventory was removed from the model due to its high correlation rate with sow inventory). On one hand, higher production scale performed as a good incentive for the farmers to participate into insurance program and a good signal to the insurance company that the farm under protection was a serious and promising business. One the other hand, the inventories, together with the household income percentage played a role as a proxy of the household total wealth. In this sense, the positive sign was also consistent with the previous findings that insurance choice was associated with the credit constraint. Farmers with higher wealth levels and lower (or non binding) credit constraints were more likely the take the insurance. Comparing demand and supply equations, the impact was higher on demand intention than supply. The gap could be attributed to the wealth effect.

Average *sow breeds* had a positive impact on the demand side but a slightly negative impact on the supply side. The combined marginal effect was about 0.2-0.3%. The different impact on demand and supply could be driven by two reasons. On the demand side, the farmers were more incentivized to purchase insurance for the sows when they could breed more hogs every year. The higher production efficiency made the farmer lose more when facing livestock disease risk. However, on the supply side, higher breeds implied more difficulty in monitoring and preventing "cheating" behaviors from the claims and hence, lowered the incentive to supply service. In 2009, the ear tag identification technology had not been introduced to hog industry. Insurance company could only use the farmers' self reported inventories to make inference and verify the claims. Since the average sow breeds per year was the major reason that could change the inventories, it turned to be a factor that could impede supply intention.

Buy vaccine more than required by the local government was proved to increase the chance to be offered insurance service from the supply side. Besides, for farmers, choosing to buy extra vaccine also differentiate those who were finally insured from the other two groups (those who wished to purchase insurance but didn't get the offer (D=1, S=0) and those who did not want insurance, D=0). The actual vaccine cost per hog had positive impact on demand and negative impact of supply, and in contrast, average sow vaccine cost seemed to have just the opposite impacts, positive on supply and negative on demand. But the overall marginal effects are all positive. The swinging effects among the 3 vaccine variable might be due to the correlation and common information contained in those variables. Scores that measured the production security did not have significant impact in any of the 3 models.

Based on the log likelihood, the likelihood ratio (LR) test statistics is about 36. This means the jointly estimated model was proved to be more efficient and accurate than univariate model. Since model 3 had a totally different structure of the likelihood functions, the likelihood was not comparable to the first two models. The estimated correlation between the demand and supply equations was shown to be significant in model 2, but not quite in model 3. One possible explanation was with limited information in the partial observation model (model 2) the two equations depended on each other for estimation. However, when the demand was identified with some extra information (model 3), the two equations no longer needed one another to be identified. The implication for this result was the supply decision made by the insurance companies was somehow independent to the farmers' demand intention. It was the farmers' background variables and production behaviors that determined the chance to get an insurance offer from the company. On the bottom of the panel, correctness of prediction was listed. On average, 80% of those with insurance (Z=1) were predicted correctly and model 3 had the highest prediction rate of 94.05%. More than 60% of all (farmer, company) joint choices (Z=1 or 0) were predicted correctly, with model 2 achieving the highest prediction rate (69.35%).

5.2 Current Insurance Choices

Regressions for the current insurance choice (*ins_now*) were presented in Table-5b. Different from section 5.1, positive insurance response here only included those who participated in insurance in the year 2009, but excluded those who took any insurance in the previous years. Comparing estimated results with Table-5a, one would find how economic agencies evaluate each factor differently between long-term and immediate decisions.

Within the background variables, *age* still had positive effect on demand and experience *years* had positive effect on supply with roughly the same magnitude as long-term choices in section 5.1. However, different from long-term case, age was also shown to have a positive impact on supply and *education* has a positive impact on demand. Compared with results for long-term choices in Table-5a, these effects here seemed only play roles at some certain period, but did not make any long-term differences. Interestingly, *years* working in hog operation now had a negative effect on demand. This suggested that for short-term and/or immediate decision, there existed some level of overconfidence. Even though this effect did not last very long, more experienced farmers were less likely to buy insurance at some certain point of time.

Household financial situation *loan*, production scale *lnsowinv* and production efficiency sowbreed had same impacts as for long-term case, except that the effect of *sowbreed* on supply turned to be positive now. One possible explanation for this difference could be for short-term case, insurance providers consider this production efficiency as positive signal for serious production and increase service tendency as the production becoming more efficient. But in the long-run, this term was still the main factor that made the real inventory hard to be observed by the insurance companies, that is, the higher the efficiency the more difficulty in getting the true inventory information from the farmer, and hence the less tendency to offer insurance service.

For production security, *hog vaccine* cost had a positive impact on demand, however, *sow vaccine* cost had a negative impact on demand. The different signs could be attributed to the constituents of the subject pool. Out of the 187 farmers who were insured in 2009 (and hence had ins_now=1), 185 took sow insurance but only 119 took hog insurance (117 took both). When farmers considered vaccine and insurance as two substitutive methods to prevent livestock disease risk, sow vaccine was expected to have negative sign on demand, since only those who did not have insurance would spend more on sow vaccine to prevent disease. Meanwhile, if the insurance choice behavior could reveal the risk preference or some precautionary habit as suggested by classic theory, those who took insurance (but mainly for sow insurance) would spend relatively more on hog vaccine as a complement for their risk prevention strategy. This latter interpretation was also supported by the significant positive effects of *sanitation cost* and production security *scores* on demand. These arguments were further verified in section 5.3 where the insurance choice behaviors were investigated for each single product.

Same as in the long-term case, the log pseudo-likelihood implied a 34.12 LR test statistics, suggesting the joint estimation being more efficient than single equation model. The percentage correct prediction achieved to about 65%. Comparing the single- and double-equation model, the percentage rates were also in favor of the latter.

5.3 Insurance Choices by Type – Hog and Sow

Table-5c and 5d listed the results for *hog insurance* choices and *sow insurance* choices respectively. Most results were consistent to those previous two tables. Slight changes in effects of vaccine costs in Table-5c further supported the substitution and complement interpretation between vaccine and insurance. Since most of the farmers who took hog insurance also took sow insurance, sow vaccine still had negative effects on demand (substitution effect remained). But since the target insurance type now was only hog, the hog vaccine effect became less significant (hog vaccine began to switch from a complementary strategy to substitutive).

6. Discussion

There are a few interesting points that need further discussion.

First, it has long been argued that the endogeneity problem between insurance decisions and production choices always makes the causal effect hard to be identified correctly. In this study, the insurance choices and production security behaviors (such as vaccine costs and sanitation costs) were jointly determined by some long-term unobservable risk preference and individual characteristics. There also existed some complicated short-term interactions resulting from potential adverse selection and moral hazard problems. To address endogeneity problem, we used some production behavior variables in the previous years, such as vaccine costs and sanitation costs in 2007 and 2008 as instruments for those of 2009. Two-stage regressions results (not presented in the paper due to space limit.) were consistent with previous results and Hausman test failed to reject the difference between the two methods. However, one should still admit that the method used here might be effective in controlling the short-term endogenous problem, but had limited power in controlling for the long-term unobervables.

Second, different proxies of the same underlying variables had different relative explanatory powers. Sow inventory and hog inventory were used as proxies for production scale directly and wealth level indirectly. But sow inventory, though smaller in absolute value, always represented higher prediction power than hog inventory. When each variable was used alone in the model, consistently positive sign was predicted, with sow inventory having more significant results. However, when both variables were used together in the model, the predicted sign for hog inventory turned to be either negative or insignificant. Moreover, when the two inventories together with income percentage were jointly used to proxy wealth level, even sow inventory was dominated by the newly generated wealth proxy, although by theory it should not make any difference in the reduced form model.

Third, estimated coefficients were a bit sensitive to the different combination of explanatory variables, suggesting some potential multicollinearity problems. To address this, similar variables within each category group were selected to be used in the model (i.e. to use sow inventory but not hog inventory, to use sanitation cost but not medicine cost, etc).

Fourth, compared to Model 3, it was hard to differentiate demand equation and supply equation from the Model 2 (bivariate probit model with partial observability). In model 3, one observed binary supply intentions only when demand was identified to be positive (i.e. D=1). In practical, model 3 was merely bivariate choices with sample selection and hence, it was easy to differentiate the demand and supply equations from one another. However, in model 2, since one could only observe positive insurance outcome (i.e. Z=1), two equations shared the same dependent variable Z. As a result, equations could only be differentiated from assuming different functional forms. For example, in section 5 we differentiated two equations by assuming that *loan* affected demand only. This assumption was partially verified by comparing regression results in model 2 and model 3 and observing roughly same patterns within two demand equations and two supply ones.

For future study, it would be interesting if one could further partition the sample pool for the long-term insurance choice into two groups (one for currently insured, the other for preciously insured) and make comparison to get more direct results between long-term and short-term differences. Multi-level discrete choice model and/or nested model could be used to investigate the relative preference between sow insurance and hog insurance. At last, with insurance choices in 2 consecutive years, panel regression could not only generate more accurate estimation, but also shed light on the changings in the decisions across years.

7. Conclusion

This paper aimed to offer some explanations for the low participation rate of the hog insurance in China. By partially observing insurance demand and jointly estimating demand and supply intentions, this study made clear how economic factors impact farmers' demand and insurance companies' supply differently. 4 insurance responses were studied. Comparisons were made between past (or ever) insurance choices and current insurance choices, and between different insurance products (hog and sow).

Results showed positive impact of credit accessibility and wealth level on insurance take-up rate, but also suggested demand side put more weights on these factors than supply side when making decisions on this interactive game. Farmers past experience in hog operation was proved to increase the chance of being offered insurance services, however, under certain circumstance, more experience impeded the farmers to take insurance, implying some evidence for overconfident behaviors. This study also tested the effects of production efficiency on both sides of the market. A more efficient and productive farm had higher tendency to take insurance, but due to asymmetric information and difficulty in monitoring, the higher efficiency might be considered as some disadvantages from the suppliers' prospective. Some production security behaviors were also shown to have substitution effect on insurance take-up decisions.

A better understanding about the insurance choice behaviors and how specific factors impact insurance choice on both demand and supply sides can help to promote insurance participation so as to reduce production risk, smooth income flow, stabilize market supply and increase food security. The insurance suppliers will also benefit for marketing development strategies.

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Table-1: Insurance Outcome Status

Z	Definition	Obs.	Mean	SD
Insurance	Have ever participated in any insurance or not, 1 or 0	528	0.48	0.50
ins_now2	Is currently insured or not, either hog or sow, 1 or 0	531	0.35	0.48
ins_hog	Currently have hog insurance or not, 1 or 0	531	0.22	0.42
ins_sow	Currently have sow insurance or not, 1 or 0	531	0.35	0.48

Table-2: Demand & Supply Identification Rule

ID	Why not insurance or quit?	Demand Intention (D)	Supply Intention (S)	Obs.[1]	Mean[2]	SD
A	Premium is too high.	0	in conclusive	414	0.55	0.50
B	Product pool is too narrow.	1	Z	414	0.14	0.35
C	Coverage is too low.	1	Z	414	0.13	0.34
D	Claim is not fair.	1	Z	414	0.12	0.32
E	Insurance company doesn't allow me to.	1	Z	414	0.08	0.27
F	I am not familiar with ag insurance.	1	Z	414	0.12	0.33
G	The procedure is too complicated.	1	Z	414	0.11	0.31

1: those who are currently insured or never quit do not response to this question.
2: Multiple choices allowed.

Table-3: Demand and Supply with Partial Identification

	Z=1	Z=0	Z=0	
	D=1, S=1	D=1, S=0	D=0	Total
Insurance	252	126	118	496
	50.81%	25.40%	23.79%	
ins_now2	187	132	155	474
	39.45%	27.85%	32.70%	
ins_hog	119	161	182	462
	25.76%	34.85%	39.39%	
ins_sow	185	133	155	473
	39.11%	28.12%	32.77%	

Table-4: Summary Statistics (Insurance)

					Insurance=1		Insurance=0		Insurance=0	
			All		D=1, S=1		D=1, S=0		D=0	
Group	Vars.	Definition	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
HH Demo.	*age*	age of household	46.20	7.68	46.47	7.32	45.76	7.86	45.03	8.00
	edu	education years	7.15	2.54	7.43	2.73	7.13	2.25	6.93	2.35
	year	years work in hog raising	8.65	4.91	9.17	4.93	8.03	4.60	7.66	4.41
	loan	Have loan or not, 1 or 0	0.34	0.47	0.40	0.49	0.31	0.46	0.27	0.45
Production	*inc_pctg*	% income from hog raising	74.89	21.03	78.60	19.01	70.16	25.99	74.41	18.63
Scale	*lnhog_inv*	log of hog inventory	5.76	0.93	6.11	0.95	5.42	0.84	5.63	0.60
	lnsow_inv	log of sow inventory	3.59	0.97	3.95	0.99	3.24	0.85	3.42	0.69
Efficiency	*sowbreed*	No. of breeds per sow per year	16.56	3.63	16.58	3.45	17.81	3.35	15.98	3.74
	breedfrq	annual breed frequency	2.13	0.16	2.12	0.14	2.15	0.18	2.11	0.15
Security	*buy_vac*	vaccine more than required, 1, 0	0.49	0.50	0.57	0.50	0.38	0.49	0.43	0.50
	vac_hog	vaccine cost per hog	5.72	6.11	5.89	6.17	6.74	6.89	5.14	5.50
	vac_sow	vaccine cost per sow	20.80	17.05	22.92	21.80	19.37	12.20	20.00	9.94
	lnquarcost	log of total sanitation cost	6.10	2.28	6.98	1.93	5.33	2.31	5.28	2.27
	lnmedcost	log of total medicine cost	7.39	2.37	8.25	1.92	6.48	2.63	6.72	2.34
	score	production security score, 0-22	15.20	4.06	15.74	4.08	14.94	3.92	15.45	2.92

Table-5a: Probit Prediction (Insurance)

	Uni-Probit		Bi-Probit Partial Obs.			Bi-Probit Demand Identified		
VAR	ins	M.E.	ins_s	ins_d	M.E.[1]	ins_s	ins_d	M.E.[1]
age	0.0118	0.0047	0.0036	0.0308*	0.0012	-0.0041	0.027**	0.0063
	(0.01)	(0.00)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)
edu	0.0108	0.0043	0.0293	-0.0134	0.0091	-0.0172	0.0479	0.0083
	(0.04)	(0.01)	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)	(0.01)
year	0.0156	0.0062	0.048**	-0.0055	0.0148	0.0298	-0.0003	0.0086
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
loan	0.1640	0.0655		1.658***			0.2650	0.0717
	(0.16)	(0.06)		(0.49)			(0.19)	(0.05)
inc_pctg	0.0023	0.0009	0.0084*	-0.0066	0.0028	0.0046	-0.0032	0.0005
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
lnsowinv	0.578***	0.2306	0.384**	1.076***	0.1368	0.377**	0.59***	0.2738
	(0.14)	(0.06)	(0.18)	(0.23)	(0.07)	(0.18)	(0.16)	(0.05)
breedfrq	0.4710	0.1878	0.6070	-0.9010	0.2703	-0.1210	1.0920	0.2680
	(0.65)	(0.26)	(0.80)	(1.03)	(0.30)	(0.76)	(0.74)	(0.24)
sowbreed	0.0146	0.0058	-0.0645	0.104***	-0.025	-0.0557*	0.069**	0.0029
	(0.03)	(0.01)	(0.04)	(0.04)	(0.01)	(0.03)	(0.03)	(0.01)
buy_vac	0.446***	0.1767	0.360*	0.546**	0.1373	0.443**	0.0683	0.1465
	(0.17)	(0.07)	(0.19)	(0.22)	(0.07)	(0.20)	(0.18)	(0.06)
hogvac_09	-0.0029	-0.001	-0.049**	0.248***	-0.018	-0.033**	0.0345*	0.0000
	(0.02)	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.02)	(0.01)
sowvac_09	0.0011	0.0004	0.0119*	-0.028***	0.0047	0.0095*	-0.0078	0.0006
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
lnquarcost	0.166***	0.0664	0.19***	0.144**	0.0710	0.0804	0.12***	0.0554
	(0.04)	(0.02)	(0.04)	(0.06)	(0.02)	(0.06)	(0.04)	(0.02)
score	-0.0300	-0.012	-0.0335	-0.0193	-0.009	-0.0289	-0.0447	-0.021
	(0.03)	(0.01)	(0.03)	(0.04)	(0.01)	(0.03)	(0.03)	(0.01)
athrho			1205***			-0.959		
			(2.20)			(0.73)		
Pseudo lnL	-184.544		-166.86			-274.588		
Wald X^2(df)	80.09(13)		107.12(25)			32.94(12)		
% correct[2]	80.56		84.13			94.05		
% correct[3]	66.73		69.35			60.48		
Obs.	340		340			327		

Robust standard errors in parentheses

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

1: Marginal effect for positive outcomes (s=1, d=1)

2: % correct prediction for insured.

3: % correct prediction for all.

Table-5b: Probit Prediction (Ins_now)

	Uni-Probit		Bi-Probit Partial Obs.		Bi-Probit Demand Iden.	
VARIABLES	ins_now	M.E.	ins_now_s	ins_now_d	ins_now_s	ins_now_d
age	0.0241**	0.0091	0.0282**	0.0522	0.0189*	0.0231**
	(0.01)	(0.00)	(0.01)	(0.03)	(0.01)	(0.01)
edu	0.0399	0.0151	0.0294	0.1820	0.0372	0.0527**
	(0.03)	(0.01)	(0.04)	(0.12)	(0.03)	(0.03)
year	0.0042	0.0016	0.0372*	-0.168**	0.0033	0.0235
	(0.02)	(0.01)	(0.02)	(0.07)	(0.02)	(0.02)
loan	0.0228	0.0086		11.22*		0.0983
	(0.16)	(0.06)		(6.00)		(0.13)
inc_pctg	-0.0002	-0.0001	0.0020	-0.0246	-0.0011	-0.0015
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
lnsowinv	0.265**	0.0999	-0.0332	2.668***	0.359***	0.1590
	(0.13)	(0.05)	(0.14)	(0.81)	(0.11)	(0.10)
breedfrq	-0.1690	-0.0637	-0.3240		-0.7530	
	(0.64)	(0.24)	(0.63)		(0.49)	
sowbreed	0.0412	0.0155	0.0114	0.278***	0.0533**	0.0721***
	(0.03)	(0.01)	(0.03)	(0.08)	(0.02)	(0.02)
buy_vac	0.2330	0.0879	0.0325	0.801***	0.1920	-0.359***
	(0.16)	(0.06)	(0.17)	(0.29)	(0.12)	(0.11)
hogvac_09	0.0030	0.0011	-0.0273*	0.441***	0.0078	0.0316**
	(0.01)	(0.01)	(0.02)	(0.14)	(0.01)	(0.01)
sowvac_09	-0.0215***	-0.0081	-0.0041	-0.229***	-0.0236***	-0.0287***
	(0.01)	(0.00)	(0.01)	(0.07)	(0.01)	(0.01)
lnquarcost_09	0.162***	0.0609	0.149***	0.654***	0.170***	0.120***
	(0.04)	(0.01)	(0.04)	(0.17)	(0.04)	(0.03)
score	0.0375	0.0141	0.0546*	0.114***	0.0460**	0.0282
	(0.03)		(0.03)	(0.04)	(0.02)	(0.02)
athrho			1427***		11.85	
			(2.11)		(16.12)	
Pseudo lnL	-193.884		-176.831			
Wald X^2(df)	54.65(13)		2749.38(24)			
% correct[2]	55.61		65.24		65.24	
% correct[3]	64.77		66.88		66.46	
Observations	341		341		325	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

1: Marginal effect for positive outcomes (s=1, d=1)
2: % correct prediction for insured.
3: % correct prediction for all.

Table-5c: Probit Prediction (Ins_hog)

	Uni-Probit		Bi-Probit Partial Obs.			Bi-Probit Demand Iden.		
VARIABLES	ins_hog	M.E.	ins_hog_s	ins_hog_d	M.E.[1]	ins_hog_s	ins_hog_d	M.E.[1]
age	0.0023	0.0007	-0.116***	0.0359**	0.0123	-0.0035	0.0249**	-0.0011
	(0.01)	(0.00)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
edu	0.0434	0.0129	0.110*	0.0334	0.0115	0.0648*	0.0767**	0.0209
	(0.04)	(0.01)	(0.06)	(0.04)	(0.01)	(0.04)	(0.04)	(0.01)
year	0.0206	0.0061	0.209***	-0.0101	-0.0035	0.0212	0.0193	0.0068
	(0.02)	(0.00)	(0.06)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
loan	0.2420	0.0735		0.510***	0.1801		0.327**	
	(0.17)	(0.05)		(0.19)	(0.07)		(0.14)	
inc_pctg	0.0009	0.0003	0.0324***	-0.0084	-0.0029	-0.0012	-0.0028	-0.0004
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
lnhoginv	-0.0224	-0.0066	0.2150	-0.1000	-0.0344	0.1800	0.0910	0.0583
	(0.13)	(0.04)	(0.18)	(0.14)	(0.05)	(0.12)	(0.12)	(0.04)
breedfrq	-0.7790	-0.2312	-2.888**	-0.7640	-0.2626	-0.5880	0.9910	-0.1898
	(0.70)	(0.21)	(1.17)	(0.76)	(0.26)	(0.61)	(0.64)	(0.20)
sowbreed	0.0108	0.0032	-0.0536	0.0360	0.0124	0.0098	0.0272	0.0032
	(0.03)	(0.01)	(0.05)	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)
buy_vac	0.322*	0.0960	-1.346***	0.672***	0.2301	0.1810	-0.439***	0.0583
	(0.17)	(0.05)	(0.45)	(0.19)	(0.07)	(0.15)	(0.15)	(0.05)
hogvac_09	-0.0014	-0.0004	0.0412	-0.0078	-0.0027	0.0008	0.0337**	0.0002
	(0.02)	(0.00)	(0.04)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
sowvac_09	-0.0157**	-0.0047	-0.0190	-0.0210**	-0.0072	-0.0136*	-0.0268***	-0.0044
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
lnquarcost_09	0.125***	0.0370	0.180**	0.141***	0.0485	0.141***	0.0987***	0.0454
	(0.04)	(0.01)	(0.07)	(0.05)	(0.02)	(0.05)	(0.04)	(0.02)
score	0.0889***	0.0264	0.140**	0.0961***	0.0330	0.0785***	0.0566**	0.0254
	(0.03)	(0.01)	(0.06)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)
athrho			140.1***			16.91		
			(1.34)			(38.49)		
Pseudo lnL	-164.7075		-150.9582			-279.6576		
Wald X^2(df)	46.89(13)		74.98(25)			196819.22(12)		
% correct[2]	52.94		56.30			58.82		
% correct[3]	66.67		67.32			68.40		
Observations	342		342			303		

Robust standard errors in parentheses

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

1: Marginal effect for positive outcomes (s=1, d=1)

2: % correct prediction for insured.

3: % correct prediction for all.

Table-5d: Probit Prediction (Ins_sow)

	Uni-Probit		Bi-Probit Partial Obs.			Bi-Probit Demand Iden.		
VARIABLES	ins_sow	M.E.	ins_sow_s	ins_sow_d	M.E.[1]	ins_sow_s	ins_sow_d	M.E.[1]
age	0.0198*	0.0075	0.0191	0.0255**	0.0101	0.0191*	0.0317***	0.0075
	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
edu	0.0415	0.0158	0.445***	-0.0541	-0.0215	0.0475	0.0533	0.0187
	(0.03)	(0.01)	(0.12)	(0.04)	(0.02)	(0.04)	(0.04)	(0.01)
year	0.0085	0.0032	0.0179	0.0213	0.0085	0.0022	0.0184	0.0009
	(0.02)	(0.01)	(0.04)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
loan	0.0150	0.0057		0.1870	0.0744		0.245*	
	(0.16)	(0.06)		(0.16)	(0.06)		(0.14)	
inc_pctg	0.0014	0.0005	0.0176**	-0.0064	-0.0026	0.0005	-0.0017	0.0002
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnsowinv	0.1480	0.0564	0.528**	0.1310	0.0523	0.302**	0.1320	0.1189
	(0.12)	(0.05)	(0.23)	(0.15)	(0.06)	(0.12)	(0.12)	(0.05)
breedfrq	0.2880	0.1100	1.3130	-0.2480	-0.0987	0.3690	1.426**	0.1453
	(0.60)	(0.23)	(1.07)	(0.70)	(0.28)	(0.58)	(0.62)	(0.24)
sowbreed	0.0409*	0.0156	-0.0255	0.0586**	0.0233	0.0419**	0.0543***	0.0165
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
buy_vac	0.1000	0.0382	-0.745***	0.368**	0.1459	0.1150	-0.379**	0.0452
	(0.15)	(0.06)	(0.28)	(0.17)	(0.06)	(0.16)	(0.16)	(0.07)
lnquarcost_09	0.161***	0.0614	0.434***	0.0740	0.0295	0.159***	0.0998***	0.0626
	(0.04)	(0.01)	(0.08)	(0.05)	(0.02)	(0.04)	(0.04)	(0.02)
score	0.0371	0.0141	-0.0209	0.0528**	0.0210	0.0299	0.0119	0.0118
	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)
athrho			111.7***			33.606***		
			(1.00)			(7.19)		
Pseudo lnL	-208.5556		-197.1048			-297.4707		
Wald X^2(df)	50.13(11)		72.80(21)			53.13(10)		
% correct[2]	57.84		61.62			61.08		
% correct[3]	60.04		61.10			60.04		
Obs.	353		353			320		

Robust standard errors in parentheses

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

1: Marginal effect for positive outcomes (s=1, d=1)

2: % correct prediction for insured.

3: % correct prediction for all.