Moral Hazard in Agricultural Insurance

– Evidence from A Non-Voluntary Sow Insurance Program in China

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Abstract:

Agricultural insurance has not yet lived up to its full potential despite its apparent benefits to agricultural producers. Moral hazard is suspected to be a major obstacle to the adoption of agricultural insurance, especially livestock insurance. In this study, we take advantage of a government-supported, non-voluntary sow insurance program in China and examine whether farmers being aware of having insurance coverage leads to their hazardous behaviors. We estimate these impacts by using an endogenous treatment effects model which controls for endogeneity in our treatment variable. Our results are robust and suggest that farmers' awareness of their insurance enrollment led to statistically and economically significant differences in their sow mortality rates. Therefore, our results demonstrate the presence of hazardous behavior.

1. Introduction

Insurance plays a vital role in agricultural production because of its apparent merits. By sharing risks among agricultural producers, insurance companies, and possibly governments, agricultural insurance can reduce the risks facing farmers and encourage them to pursue and expand risky production activities in exchange for higher economic returns (e.g., Karlan et al., 2014; Cai et al., 2015; Cole, Giné and Vickery, 2017; Hill et al., 2019). Moreover, insurance can serve as a close substitute for collateral such that farmers can access formal credit markets more easily to finance their production and long-term business growth (Hazell, 1992; Shee and Turvey, 2012). Notwithstanding the apparent merits, agricultural insurance worldwide has not yet lived up to its full potential. The total annual insurance premiums worldwide amounted to about 30 billion U.S. dollars in 2018 (Wang et al., 2020), representing a mere 1.3 percent of the total value of agricultural production globally. Geographically, agricultural insurance programs have concentrated in developed farming and forestry regions such as North America and Europe. Existing agricultural insurance programs are also unevenly distributed among commodity categories. Inferring from the data reported by USDA's Risk Management Agency, approximately 90 percent of U.S. crop acreage is insured under the federal crop insurance program, while only 0.13% of total cattle inventory was covered by federally provided livestock insurance between 2003-2019 and the coverage of other commodities is all likewise low.

The stagnant and uneven adoption of agricultural insurance can be explained by reasons such as the availability of alternative risk management strategies, lack of government support, and the complex production process of some agricultural commodities (e.g., livestock). Economists have believed the fundamental causes to be the adverse selection and moral hazard problems due to the asymmetric information in common insurance design (e.g., Nelson and Loehman, 1987; Chambers, 1989; Just, Calvin and Quiggin, 1999; Koontz et al. 2006). A persistent research interest has been to identify the presence and extent of hazardous behavior in agricultural insurance (e.g., Quiggin, Karagannis and Stanton, 1993; Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996; Coble et Al., 1997; Roberts, Key and O'Donoghue, 2006; Liang and Coble, 2009; Yu and Hendricks, 2020). For instance, Horowitz and Lichtenberg (1993) analyzed the Farm Costs and Returns Survey data from the National Agricultural Statistical Service and found that crop insurance participation had considerably increased corn farmers' use of risk-increasing inputs (i.e., fertilizer and pesticides), indicating the presence of moral hazard. Recently, Yu and Hendricks (2020) developed a stylized model and showed that farmers align their use of inputs with their moral hazard incentive in spite of the greater amount of information provided by precision agriculture technologies. Meanwhile, Roberts, Key, and O'Donoghue (2006) investigated the incidence of moral hazard for corn, soybeans and wheat in Iowa, Texas, and North Dakota and found little evidence of moral hazard affecting average yield or yield variability. Coble et al. (1997) examined the expected indemnities for a panel of Kansas wheat farms and suggested that hazardous behavior had occurred only in poor production years but not in years when growing conditions were favorable. Overall, the literature has reported mixed evidence on the presence of moral hazard in agricultural insurance, leaving it still largely debatable whether insurance participation will necessarily invite hazardous behavior of participants.

To complicate matters, the availability and quality of data from existing insurance programs has hampered the current research efforts in two significant ways. Firstly, the majority of studies have relied on data from voluntary insurance programs that will inevitably suffer from adverse selection (Zhang and Palma, 2021). Bias due to adverse selection will compound with moral hazard effects unless researchers can control for unobservable factors associated with insurance participants. Several studies (e.g., Gunnsteinsson 2020; He et al. 2019) have tried to remove the compounding effects by implementing an experimental insurance program that allowed farmers to enroll in a random or quasi-random fashion, although selection bias may still remain owing to unobservable factors and measurement errors.[1] Secondly, the current literature has predominantly focused on hazardous behavior in crop insurance programs (e.g., the U.S. federal crop insurance program), which have been the most prevalent among all agricultural insurance

[1] Gunnsteinsson (2020) conducted a three-stage random field experiment for the rice grower in the Philippines to separately quantify information asymmetries. This experiment elicited farmers' choices of which plots they would prefer to insure, and then randomly allocated insurance to farmers and plots, generating across- and within- farm variations in which plots were insured. The author found strong evidence for adverse selection and moral hazard in this experiment. However, the sample selection for this study is not completely random, so there is still a problem of selection bias (i.e. farmers who have insurance demand are more willing to participate in the experiment). He et al. (2019) also tried to solve the challenges of selection bias and mixed effects by asking that questions whether the farmer had a cost-of-production crop insurance and whether the farmer would have bought insurance if it was not required by lenders, which can divide farmers into three groups. Using the method of propensity score matching (PSM), they found ambiguous effects of moral hazard. Their study is still faced with the endogeneity from omitted variables and measurement errors.

programs. The implementation of crop insurance cannot be readily replicated for other commodities, such as livestock. The biological features of livestock production will likely affect livestock farmers' participation decisions and management practices differently than in the case of crop insurance. For example, Boyd et al. (2013) identified a few pronounced differences between livestock insurance and crop insurance and contended that it is thus more likely for livestock producers to adopt hazardous behaviors compared to crop producers.

Despite the challenges in data availability and quality, several recent studies (e.g., Cai et al., 2015; Zhang, Zhu, and Turvey, 2016; Rao and Zhang, 2020) have attempted to investigate the consequences of insurance participation in livestock production and producers' behavior. Cai et al. (2015) introduced exogenous variations in sow insurance coverage at the village level in 480 villages in China's Guizhou Province by randomly assigning performance incentives to village animal husbandry workers when they signed farmers up for the insurance. Their findings suggested that insurance participation had increased sow production at the village level. Using a natural experiment of pig insurance in a county in China, Zhang, Zhu, and Turvey (2016) detected no effect of insurance participation on mortality and vaccine use, implying no evidence of hazardous behavior. Their study provided insights into the unique situation where pig producers withdrew from the insurance market instead of purchasing insurance.

In this study, we will contribute to the ongoing debate on hazardous behavior associated with agricultural insurance and attempt to further our understanding of the role of insurance in the livestock sector, which generates significant economic value but remains vulnerable to risk and underinsured in both developed and developing countries. We take advantage of a government-supported, non-voluntary sow insurance program during 2008-2009 in Jiangshan County, China, and examine whether farmers' awareness of their insurance coverage leads to hazardous behavior. The negligent officials at local governments enrolled sow farmers in the insurance program on their behalf using funds from a concurrent national subsidy program for sow farmers. As a result, not all enrolled farmers were aware of their insurance coverage, hence creating a unique opportunity for us to observe potential hazardous behavior. We estimate the endogenous treatment effects using exogenous variables to control for endogeneity in the binary treatment variable. Our robust results suggest that farmers' awareness of their insurance enrollment led to statistically and economically significant differences in the sow mortality rates, thus confirming the presence of hazardous behavior.

The rest of this paper is structured as below. Section 2 provides the context of hog production in China and its various hog insurance programs including the one in Jiangshan County, our study area. In Section 3, we discuss the empirical strategies to derive consistent estimates of moral hazard effects. Section 4 ensues with a discussion of the survey, data, and estimation results, followed by the conclusions in Section 5.

2. The Context

China runs the largest hog and pork business in the world by raising about half of the global hog population and contributing almost half of the global pork production in 2022. Despite the significant volume in aggregate, a salient feature of China's hog production is its large number of spatially scattered, small-sized hog farms that rely on an intensive use of labor and outdated technologies (Zhang et al. 2017). According to national statistics, as high as 98.7 percent of hog producers are small-sized farmers who raise fewer than 100 hogs, jointly contributing to about 51.6 percent of the national pork output in 2009 (China Animal Husbandry Statistical Yearbook, 2010). Among those individual hog farmers, approximately 38.8 percent are still backyard-style producers who raise fewer than five hogs annually and keep the hogs in a barn in their backyard or let hogs run freely in the village yard (Schneider, 2011).

To promote hog production, stabilize pork prices, and reduce the risks facing hog farmers, China's central government initiated its national support programs for hog production in 2007, starting by directly subsidizing sow farmers. Hog farmers in China can either buy sows from the market (e.g., from professional breeders or other farmers) or breed their own sows from female piglets. On many occasions, however, farmers choose to breed their own sows because of the limited supplies for sale and the high prices of sows and piglets. Hog farmers usually decide whether to keep a female piglet for breeding about one month after its birth. Female piglets not for breeding will be spayed for faster growth and better taste. Those to be used for breeding will be raised for an additional eight months before they mature and start to breed. A mature sow can breed multiple litters of piglets, with each pregnancy lasting for about four months. The litter size increases with more pregnancies and peaks at the 4^{th}-6^{th} pregnancy. Piglets from each litter can be sold to other farmers, raised into fattening pigs, or raised for breeding into sows. After the litter size peaks, farmers may keep the sow for another 4-6 years before it was culled out.

During this prolonged lifecycle of a sow, farmers have to keep spending on feed, vaccines, and other veterinary medicines until the sow starts to generate economic returns for its owner. A farmer may decide to keep more than one sow at various stages of growth depending on management capacities, cash flows, and market prices among other factors. Any adverse changes in these factors may make it less profitable, if at all, for the farmer to keep some or all his sows. Whenever farmers deem the risks of unfavorable prices and imminent hog diseases to exceed the expected payoffs, they usually react by slaughtering their sows and selling them for meat to prevent further losses. When a large number of hog farmers concurrently reduce their sow stocks in this manner, it is often an indicator of imminent market downturns, which can escalate into larger market disruptions. Therefore, policy makers have been vigilant to these signals and actively implement measures to stabilize sow supply to counterbalance the so-called "hog cycles."

As a national strategy, China's central government started promoting sow insurance nationwide since 2007, in collaboration with People's Insurance Company of China (PICC) as the main insurance underwriter.[2] The goal is to provide insurance coverage for as many hog farms as possible regardless of their size. In principle, hog farmers can opt to insure each of their eligible sows (e.g., aged between eight months and four years) for a premium of 60 yuan (approximately 8.5 dollars), with the central and local governments jointly subsidizing 50 to 80 percent of that amount. When sow death occurs due to common diseases, natural disasters or accidents,[3] farmers will receive an indemnity payment of 1,000 yuan (i.e., 142.3 dollars) for each insured sow. In practice, most local governments have retained the voluntary nature of the sow insurance program, while some, such as those with an abundant budget, have required all eligible hog farmers to participate. Since the exact cause of sow death is difficult and costly to identify, the insurance company has almost always accepted farmers' claims and made indemnity payments for the insured sow deaths (Rao and Zhang, 2020). Thus, it is possible for hog farmers to receive compensations for sow death due to causes that are originally uncovered by the sow insurance.

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[2] Data from PICC show that PICC underwrote a total number of 115 million sows in 2010, accounting for over 85 percent of the total number of insured sows nationwide.

[3] Major diseases include septicemia, blue tongue, scrapie, hyopneumoniae, swine erysipelas, porcine reproductive and respiratory syndrome virus, porcine epidemic diarrhea, streptococcus suis, and foot and mouth disease. Natural disasters covered by the insurance are typhoon, tornado, rainstorm, lightning stroke, earthquake, flooding, hailstorm/snowstorm, debris-flow and mountain landslide. Accidents include fire, explosion, building collapse, and falling parts or articles from aircraft and other flying objects.

The sow insurance program investigated in this study took place in Jiangshan County, Zhejiang Province. Jiangshan is located in a major hog-producing region in China and raised about 1.84 million hogs in 2010, out of which 95.2 thousand were sows. In the same year, the county sold 1.23 million hogs generating a total revenue of 1.1 billion yuan (i.e., 156.5 million dollars). Most of its hogs were sold for pork to nearby metropolises such as Shanghai and Hangzhou. In response to the central government's initiative in 2007, the Jiangshan government started its non-voluntary sow insurance program from September 2008 till August 2009. Working closely with the County's Bureau of Agriculture and Animal Husbandry, the local branch of PICC underwrote the sow insurance for all sows that aged between eight months and four years. In accordance with the nationally-uniform premium rate of 60 yuan per sow, the central and local governments subsidized 80 percent of the premium, with the remaining 20 percent (i.e., 12 yuan or 1.7 dollars) paid by sow farmers.

It is worth noting that in the same year, China's central government was implementing a direct subsidy program by paying all hog farmers nationwide 100 yuan (i.e., 14.2 dollars) for each sow they raise. The funds for this direct subsidy program were administered and paid out to hog farmers by the Bureau of Agriculture and Animal Husbandry at county governments, the same office that was administering the concurrent subsidized sow insurance program. In Jiangshan, the Bureau and its field offices at townships had been understaffed for a large number of spatially dispersed hog farmers.[4] Not all Bureau officials were able to conduct the usual home visits to all hog farmers in their township and sign them up for the non-voluntary insurance program during the open enrollment period. As a shortcut approach, some of the Bureau officials at the

[4] The predominant topographical features of Jiangshan, characterized by undulating hills and mountains, can be identified as a primary factor contributing to the scattered distribution of hog farms in the area.

townships skipped the home visits. Instead, they deducted 12 yuan from the 100-yuan direct subsidy for farmers and paid the 12 yuan as the premium to the insurance company on farmers' behalf. Eventually each farmer received a net of 88 yuan from the central government and was enrolled in Jiangshan's sow insurance program without necessarily knowing their insurance enrollment.[5] According to the Bureau's own statistics, the PICC branch in Jiangshan underwrote insurance for 91,843 sows and collected the total premium payments of 5.51 million yuan during the 2008-2009 policy period.[6] Our survey suggests that as many as 21.9 percent of farmers in the survey sample were not aware of their insurance enrollment.

3. Identification Strategy

3.1 Ordinary Least Square Regression

The implementation of the sow insurance program in Jiangshan during 2008-2009 provides us with a unique opportunity to detect the potential hazardous behavior of hog farmers. The non-voluntary nature of the program staves off possible adverse selection effects that complicate the analysis of voluntary insurance. The fact that some of Jiangshan's hog farmers were unknowingly enrolled in the insurance allows us to compare these farmers with those who were aware of their enrollment. The following linear-form function is deployed to test whether a farmer i's awareness of insurance enrollment affects his sow mortality rate:

[5] There were several reasons why farmers didn't show any concern about the deduction of 12 yuan. First, a majority of farmers only raised a limited number of sows, so the total reduction amount was not significant. Second, the subsidy was distributed to their bank accounts by the local government, and farmers didn't regularly check their accounts, so they might not have realized that the amount had changed.

[6] The statistic from the Bureau also shows that PICC made total claim payments of 6.11 million yuan to hog farmers during the same period, making the loss ratio as high as 110.9%, far exceeding the prevailing break-even loss ratio of 77%. Owing to the huge losses in 2008-2009, PICC decided to stop this sow insurance program in Jiangshan since 2009 until 2013.

$$mortality_i = \alpha_0 + \alpha_1 * awareness_i + \boldsymbol{\alpha_2} * \boldsymbol{X_i} + \varepsilon_i \qquad (1)$$

In the equation above, the dependent variable $mortality_i$ is calculated as the ratio of the number of dead sows and the number of sows raised by farmer i during the insurance period. This fractional variable has frequently been used in the relevant literature (e.g., Pai et al., 2015; Rao and Zhang, 2020) as a measure of the risk facing farmers, with a higher value representing a higher level of risk. Farmers in Jiangshan filed claims over deaths of sows and received compensations by the count, making $mortality_i$ a pertinent outcome variable for evaluating this insurance program.

For the interest of this study, this outcome variable is possibly affected by farmers' awareness of their insurance enrollment. The binary variable $awareness_i$, analogous to the treatment or intervention in a field experiment, takes the value of one when farmer i was aware of his insurance enrollment and the value of zero if otherwise. In addition, $mortality_i$ is likely determined by more factors, captured in the vector $\boldsymbol{X_i}$ with the associated parameter vector $\boldsymbol{\alpha_2}$, such as those related to biosecurity practices (e.g., vaccination and cleaning) against hog diseases, farm characteristics, and farmer socio-economics. Given the data available from our survey, we first include in $\boldsymbol{X_i}$ the following variables: farmers' age, education level, experience in hog raising (and its squared term), the ratio of income from hog raising to the annual family income, average vaccine expenditure per sow, average vaccine expenditure per hog, and a generated variable $biosecurity_i$ that counts the total number of different biosecurity practices (in addition to vaccination) adopted on the farm. Our survey included 27 yes-or-no questions that cover common biosecurity practices among hog farmers; such as, whether farmers have used enclosed barns, kept separate barns for sows and other hogs, kept vaccination records for each hog, changed on work uniforms before entering hog barns, installed sterilization equipment, and kept separate tools for different barns. The more such practices farmers have adopted, the lower the sow mortality rate is likely to be.

Moreover, the sow death ratio $mortality_i$ depends closely on farmers' abilities to manage their sows, although it is always challenging to accurately measure abilities using observable variables. We tapped into the literature on rural governance and social network in China and included three binary variables from our survey in the vector $\boldsymbol{X_i}$ as proxy variables for farmers' management abilities: farmers who are party members (i.e., $partymem_i$=1) or cadres in governments ($cadre_i$=1), and farmers whose registered primary residence is non-agricultural (i.e., $hukou_i$=1). According to the literature, Chinese farmers who are party members and more socially adept and connected are more likely to hold positions in the government (e.g., Morduch and Sicular 2000; Li et al. 2007; Jin et al. 2014; Gu and Zheng 2018). Farmers whose residence is registered as non-agricultural (e.g., living at township centers) are often better educated than their agricultural counterparts and have more access to knowledge on hog raising.

If we believe the vector $\boldsymbol{X_i}$ has included all the other explanatory variables for sow mortality so that ε_i captures only random noise, the coefficient α_1 for $awareness_i$ will measure the causal effects of farmer's awareness of insurance enrollment on the dependent variable. Then we can conduct a statistical significance test on the ordinary-least-squares (OLS) estimate for α_1 to detect the presence of hazardous behavior. However, this assumption is unlikely to hold because of unobservable factors, such as farmers' attitudes toward the risk from livestock diseases, that will affect both sow mortality and the chance they know their insurance enrollment.

Measurement errors associated with the proxy variables ($partymem_i$, $cadre_i$, and $hukou_i$) for farmers' management abilities may also violate this assumption. For instance, a conscientious and precautious hog farmer may raise sows to his best ability and actively seek any government policies that can support his business, hence lowering his sow mortality and increasing his chance to know the compulsory sow insurance program. In that case, the OLS estimate of α_1 will be biased and inconsistent. In other words, we need to address the plausible case where the treatment variable, $awareness_i$, is endogenous.

3.2 Endogenous Treatment Effects Model

Various techniques are available to address the issue of endogeneity arising from the selection of unobserved characteristics. One of these techniques is the class of functions referred to as "endogenous treatment effects". In Stata, this set of functions is called by the function "*eteffects*", which employs the control function approach (Wooldridge, 2010). The Stata implementation of the control function entails the estimation of simultaneous equations, diverging from the standard practice of employing a two-stage estimation technique in most instrumental variable (IV) approaches that may suffer from identification failure. Specifically, in the endogenous treatment effects estimation, treatment assignment is allowed to be correlated with the potential outcomes by estimating a treatment model and while subsequently incorporating the treatment model residuals in the potential outcome model.

The endogenous treatment effects model is based on the powerful potential outcomes framework (Morgan and Winship, 2015; Wooldridge, 2010). In this paper, we use three distinct treatment effects estimators that enable us to make causal links between the awareness of sow insurance program and sow mortality rates: average treatment effect on the treated (ATET), potential outcomes means (POMs) and average treatment effect (ATE).[7] Denoting $mortality_{1i}$ and $mortality_{0i}$ as the outcomes and $awareness_i$ as the treatment, the model can be written as:

$$mortality_{i0} = E(mortality_{i0}|\boldsymbol{X}_i) + \epsilon_{i0} \tag{2}$$

$$mortality_{i1} = E(mortality_{i1}|\boldsymbol{X}_i) + \epsilon_{i1} \tag{3}$$

$$awareness_i = E(awareness_i|\boldsymbol{Z}_i) + \nu_i \tag{4}$$

where $mortality_{i0}$ is the potential mortality rate of sows that farmer i has if farmers i has treatment 0 (i.e, a farmer is not informed of insurance), $mortality_{i1}$ is the potential mortality rate of sows that farmer i has if farmers i has treatment 1 (i.e., a farmer is informed of insurance), and $awareness_i$ is the observed treatment. It is impossible to observe both $mortality_{i0}$ and $mortality_{i1}$, only one or the other. For potential mortality outcomes we thus observe:

$$mortality_i = awareness_i * mortality_{i1} + (1 - awareness_i) * \ mortality_{i0} \tag{5}$$

The $awareness_i$ treatment is given by its expectation conditional on a set of regressors $\boldsymbol{Z}_i$ and an unobserved random component ν_i. Similarly, each one of the potential outcomes is determined by its expected value conditional on a set of regressors $\boldsymbol{X_i}$ as previously defined and an unobserved random component ϵ_{ij}, for $j \in \{0,1\}$. When $E\left(\epsilon_{ij}\middle|t\right) \neq 0$ for $j \in \{0,1\}$, we have an endogeneity issue in the empirical framework. While the treatment effect cannot be

[7] In the conventional instrumental variables approach, we interpret the results as local average treatment effects (LATE). There are two things that make LATE different from ATE, ATET, and POMs. First, LATE estimation is highly contingent upon the instrument, implying that the LATE estimate may change substantially when a different instrument is used (Card, 2001). In contrast, ATE, ATET and POMs are defined without reference to an IV, but with reference to a population, although IV approaches may be used when endogeneity is a concern (Wooldridge, 2010). Second, the LATE only captures a subset of treated (i.e., compliers), while the ATE averages over the entire population and ATET is the average for those who were actually treated (Wooldridge, 2010).

determined on an individual level, it can be deduced at the population level, provided that certain assumptions are met. The first assumption is that $E\left(\epsilon_{ij}\middle|\boldsymbol{X_i},\boldsymbol{Z}_i\right) = E\left(\epsilon_{ij}\middle|\boldsymbol{X_i}\right) = E\left(\epsilon_{ij}\middle|\ \boldsymbol{Z}_i\right) = 0$ for $j \in \{0,1\}$, which means the unobserved components in the potential outcome should be independent of $\boldsymbol{Z}_i$. The second assumption is that data are independently and identically distributed, which ensure that the outcome and treatment statuses of each individual are unrelated to the outcome and treatment statuses of all the other individuals in the population (Rubin, 1974). The third assumption is the overlap assumption, which states that each individual has a positive probability of receiving treatment (Wooldridge, 2010).[8]

The first assumption determines our choices of $\boldsymbol{Z}_i$, which entail a further explanation of how this government-backed sow insurance in Jiangshan was promoted among individual hog farmers. For such policy programs in China, county governments often divert funds and personnel to township governments, which then send their officials or technical staff to farm households for in-person visits and promotion. Such a top-down approach with home visits by government staff has played a preeminent role in how Chinese farmers become informed of government policies.

Before the sow insurance started, each township in Jiangshan was already staffed with a few "animal husbandry workers" who oversaw local livestock production such as disease prevention and monitoring, and handing out veterinary vaccines to farmers. County governments funded those staff positions based mostly on their annual budget and, if at all possible, the size of livestock production in each township. When the non-voluntary sow insurance program was launched, Bureau officials at the county level instructed the animal husbandry workers at the township level to promote this new program to farmers in addition to their routine work, while

[8] If only a subset of these assumptions is met, it may still be possible to calculate conditional average treatment effects such as the average treatment effect for the treated (ATET).

neither the county nor township governments provided any overtime compensations or job performance evaluations.[9] In some townships, the animal husbandry workers were proportionally far outnumbered by hog farmers, some of whom lived far apart and some even in remote mountain villages. In fact, the hog farmer to animal husbandry worker ratio varied notably from 1.7:1 to 20:1 among Jiangshan's 19 townships in the 2008-2009 cycle. Not all the animal husbandry workers had intentions to visit all the farm households within the short period of insurance enrollment. Instead, some workers took 12 yuan out of the 100 yuan from the subsidy payment made to farmers by the central government, and used the 12 yuan as the premium to enroll farmers in the insurance. Eventually, all hog farmers were enrolled in the non-voluntary program although not all of them necessarily had knowledge of their enrollment.

Given this, we first propose using the animal husbandry workers to hog farmers ratio ($ratio_i$) at each township as a key regressor for the likely endogenous variable $awareness_i$. As explained above, proportionally the more workers a township has staffed relative to its number of hog farmers, the more likely the workers in this township would have completed home visits and informed farmers of their insurance enrollment. Meanwhile, this ratio is unlikely to correlate with the unobservable variables (e.g., farmers' personal traits) contained in the error term ε_{ij} in potential outcome equations. Through this identification, $ratio_i$ may serve as a valid exogenous variable for the model. This county-level variable $ratio_i$, however, may turn out to be a poor

[9] The non-voluntary nature of the sow insurance program in Jiangshan generated at least two implications for how governments had operated in this case. First, it would be difficult for the government to supervise and evaluate whether the animal husbandry workers had worked diligently to promote the program since all farmers would anyhow enroll in the program in the end. Second, the Jiangshan government had to spend more on funds to subsidize the insurance premiums for a non-voluntary program than for a voluntary program and hence had fewer funds to compensate the animal husbandry workers for the extra workload. Therefore, the county officials acquiesced the animal husbandry workers taking the shortcut approach.

predictor for the individual-level variable $awareness_i$. We include $farmdistance_i$, as a second explanatory variable for $awareness_i$, which measures the distance (in meters) from each hog farm to its nearest hog farm. Farmers may learn of the insurance program from their neighboring hog farmers, although the actual dissemination of information among hog farmers may be complex enough to render $farmdistance_i$ inconsequential. Variables in $\boldsymbol{Z_i}$ also include those related to farmers' socio-economic indicators, such as age, education, experience, and social status. Table 1 reports the definitions of the major variables used in this study.

[Insert: *Table 1 Definitions and descriptive statistics of major variables*]

The second assumption is no spillovers across individuals. Given that we have conducted a rigorous random sampling at the household level throughout the entire Jiangshan County (see section 4) and given the scattered distribution of hog farms within Jiangshan, the potential impact of spillover effects is limited. With regard to the third assumption, it is expected that each hog farmer is cognizant of their enrollment in the non-voluntary sow insurance program, as mandated by policy, thereby ensuring that they all have a positive probability of receiving the "treatment".

To sum up, we confidently estimate the causal effect of the binary treatment variable $awareness_i$ on the outcome variable $mortality_i$ while taking into account of the possible endogenous nature of $awareness_i$. We identified two explanatory variables, $ratio_i$ and $farmdistance_i$, in order to explicitly characterize the probability of farmers' awareness of their insurance enrollment (i.e., $awareness_i$=1). Given the fractional nature of outcomes and the binary nature of $awareness_i$, we use a fractional probit for the potential outcomes and a probit model for treatment assignment.

The next section will first describe the data used for the empirical analysis and then report the estimation results with more discussions.

4. Data and Results

Survey and Data

To empirically estimate the effects of hog farmers' awareness of their insurance enrollment on their sow mortality rates, we conducted a field survey in Jiangshan, Zhejiang Province, in early 2011 using a stratified sampling approach. We obtained access to Jiangshan's hog production census data in 2009 and identified a total number of 10,003 hog farmers located in the 21 townships. Ranking those farmers by their numbers of sows from the largest to the smallest, we assigned all the hog farmers into 1,429 groups with each group having seven farmers indexed from one to seven. A computer-generated random number between one and seven was drawn for each group, and a farmer with the corresponding index was selected into our sample to represent that group. In this way, our sample contained hog farms of various sizes.

For each sampled hog farmer, we obtained information from two sources: a non-anonymous household survey and farmer records at the insurance company. The animal husbandry workers working at each township were recruited and trained as enumerators for the household survey given their first-hand knowledge of local hog farmers. Survey topics included farmer socioeconomics, hog production (e.g., numbers of sows, mortality rates, use of feed), credit and insurance, livestock disease prevention (e.g., vaccines, veterinary medicines, and other preventive measures), and so on.[10] We used farmers' names to match the survey data with their

[10] After the enumerators completed the household survey, the management team of this study randomly selected more than five percent of the sampled farmers and conducted telephone interviews to verify the information their provided for the survey.

records at the insurance company, while the survey data were kept anonymous to the insurance company. Insurance records included information such as numbers of insured sows, dates, and amounts of claims and payments. In this way, we obtained a total number of 1,397 hog farmers out of the 1,429 initially selected, leading to a response rate of 97.76 percent.

Table 1 reports the definitions and descriptive statistics of variables used in the empirical analysis. It shows that the average number of sows each farmer raised increased from 17.9 in December 2008 to 19.2 in December 2009. Survey data also show that as high as 64.8 percent of hog farmers in 2009 raised fewer than five sows, suggesting that small-sized hog raising was still prevalent in this area. Table 1 also indicates that the average sow mortality rate for Jiangshan is 2.3 percent, slightly higher than the estimated national average.[11] Moreover, only 78.1 percent of sampled farmers were informed of their enrollment in Jiangshan's sow insurance despite its being a non-voluntary program. The animal husbandry workers to hog farmers ratio averaged 8.26 percent in 2009, meaning that each worker was responsible for about twelve hog farmers, and this ratio varied notably among townships.

We further compare hog farmers who were informed of their insurance enrollment with those who were not and report the comparisons in Table 2. The *t*-statistics suggest that the two groups report statistically significant differences in the mean values for a number of variables: education level, hukou, party membership, biosecurity practices, experience in hog raising, income ratio of hog raising, sow mortality rates, the ratio of animal husbandry works to number of sow farmers, and distance from the nearest hog farm. Meanwhile, age, cadre status, the number of sows in

[11] At the time of survey, there was no census data on national average sow mortality rate. The People's Insurance Company of China (PICC), which is the main insurance underwriter for China's livestock insurance including the one in Jiangshan, estimated the national average mortality rate of insured sows to be around two percent in 2009.

2009, and average vaccination costs per sow or hog seem to be close enough between the two groups.

[Insert: *Table 2 Comparing farmers by awareness status*]

Estimation Results

We use the command *eteffects* in $Stata^{©}$16 to estimate the endogenous treatment-effects models. Parameters and the ATE, ATET, and POMs are estimated using the generalized method of moments. Table 3 contains the estimates of the parameters associated with the potential outcome and treatment assignment equations. We first discuss these parameter estimates and compare them against economic theory and findings from the relevant literature (see Section 3) before giving credence to the estimated ATE and other related treatment effects.

[Insert: *Table 3 Parameter estimates of endogenous treatment effects model*]

Part 3 of Table 3 reports estimates for the treatment assignment equation , which uses a *probit* model to characterize the likelihood for farmer i to be informed of his insurance enrollment. As the primary explanatory variable, $ratio_i$ reports a positive coefficient estimate that is significant at the 10% level. This result indicates that the more animal husbandry workers are staffed in a township proportional to its total number of sow farmers, the more likely sow farmers in this township are to be aware of their insurance enrollment. In contrast, the coefficient for the distance variable, $farmdistance_i$, turns out to be statistically insignificant. This may be partly because nowadays physical distance is no longer a major obstacle to information dissemination and partly because farmers are unlikely to learn information from neighbors whom they may be competing with. The treatment model also includes a few explanatory variables from the outcome model, such as farmers' age, education, and experience. All of these variables, except

$cadre_i$, report coefficient estimates with the expected signs of direction and statistical significance. In particular, being registered with a non-agricultural residence (e.g., living in township centers, so $hukou_i = 1$) and being a party member (i.e., $partymem_i$=1) will increase farmers' chance to know this non-voluntary hog insurance. Being a cadre in the government is supposed to increase one's chance to know the insurance. The low occurrence of cadre farmers in our sample, 32 out of 800 observations, may account for the statistically insignificant result.

The residuals from the treatment assignment model are then used alongside other explanatory variables (i.e., the parameter vector $\boldsymbol{X_i}$) for the estimation of the potential outcome equations. The generic endogenous treatment model allows the parameter for the same explanatory variable to vary between the control and treatment groups. Part 4 and Part 5 of Table 5 report parameter estimates of the same set of variables for farmers who were unknowingly and knowingly enrolled in the sow insurance program, respectively. When farmers were unaware of their enrollment, their sow mortality rates would be negatively affected by their average vaccination costs per sow, experience in hog raising (beyond 22.5 years), and party membership. The number of different biosecurity practices that farmers adopted also seems to negatively affect their sow mortality rates, although the estimate is statistically insignificant (*t*-stat=-0.89). The only unanticipated estimate is for farmers who were cadres at local governments; their sow mortality rates are estimated to be higher than those of non-official farmers. It is a completely different story for farmers who were aware of their insurance enrollment (Table 3, Part 5). None of the explanatory variables reports a statistically significant parameter estimate, although they are jointly significant at the 10% level.

Given that the parameter estimates for the treatment effects model are satisfactorily consistent with what economic theory suggests, we are confident to answer our core research question using estimates from the current model. Part 1 of Table 3 reports the average treatment effect is 0.020 with a *p*-value of 0.000. This result implies that the average sow mortality rate would increase by about two percentage points had farmers become aware of their insurance enrollment. This model also reports in Part 2 a potential-outcome mean value of 0.004 with a *p*-value of 0.002, suggesting that the expected sow mortality rate would have been 0.004 if no farmers had been aware of their insurance enrollment. We also re-estimate the model using a variant of the command *eteffects* that report identical parameter estimates but with the average treatment effects on the treated. Part 1 of Table 3 shows the estimated ATET to be 0.03 with a *p*-value of 0.000. All these findings clearly indicate that farmers' awareness of their insurance enrollment leads to an increase in their sow mortality rates, corroborating the presence of hazardous behaviors. Considering the average sow mortality rate is 2.64% among all surveyed farmers (N=1,219) and 2.80% among those in the regression sample (N=800), an ATE around 2% is also economically significant.

Lastly, we conduct an endogeneity test against the null hypothesis of zero correlation between the unobservable factors that affect both the treatment (i.e., farmers becoming aware of insurance enrollment) and the outcome (i.e., farmers' sow mortality rates). This test reports a χ^2 of 10.78 and the associated *p*-value of 0.005. Therefore, we reject the null hypothesis of no endogeneity and believe our endogenous treatment model is justified to address the endogeneity problem.

Our main results can be put to further robustness tests by using alternative econometric models and estimation procedures. The endogenous treatment model elaborated above and estimated by the Stata command *eteffects* is based upon a potential-outcomes framework by viewing the binary variable *awareness* as the treatment or intervention in a field experiment setting. Alternatively, we can use the fractional *probit* model with an endogenous binary explanatory variable (Wooldridge, 2011; Lin and Wooldridge, 2017) to account for the fractional nature of our dependent variable; i.e., sow mortality rates. Instead, this model treats the endogeneity associated with the binary variable *awareness* as an omitted variable problem. Tables 4-7 report the estimates of the model parameters and marginal effects using the Stata commands *cmp* and *biprobit*. In spite of the differences in the magnitude, this new set of results once again finds the effect of farmers' awareness of their insurance participation on their sow mortality rates to be positive and statistically significant.

Conclusion and Discussion

Conceptually, agricultural insurance offers a safety net and optimistic returns for producers worldwide, particularly those in developing countries. However, insurance companies alone are often reluctant to offer such programs for various reasons, such as systemic risks, information asymmetry, and high costs of operation. This paper attempts to address the moral hazard problem which has long been deemed as a major obstacle to the adoption of livestock insurance. In this study, we examine a government-supported, non-voluntary sow insurance program in China in which some sow farmers were unknowingly enrolled by negligent officials at local governments. The implementation of this program created a unique opportunity for us to investigate whether farmers' awareness of their insurance coverage led to hazardous behavior. To this end, we estimate the endogenous treatment effects using unique exogenous variables to control for endogeneity in the treatment variable. Our robust results suggest that farmers' awareness of their insurance enrollment leads to statistically and economically significant differences in their sow mortality rates, thus confirming the presence of hazardous behavior.

The findings of this study may have strong implications for the role of livestock insurance in China's agricultural development. A well-functioning agricultural insurance program needs to appropriately control potential behavior changes in insurance participants. An effective agricultural insurance policy will include certain clauses (such as deductible amounts for farmers) to minimize the moral hazard effects. These clauses will not only reduce the undue costs incurred to insurance companies but also help increase insurance participation and coverage for more farmers, considering the limited governmental support of agricultural insurance programs of this kind. Furthermore, despite the gradual yet consistent growth in the production scale of the hog industry, the conventional practice of backyard hog production remains prevalent among rural farm households, wherein farmers raise a few hogs alongside their crops (China Animal Husbandry Statistical Yearbook, 2020). Thus, our study sample still represents the hog population, and our findings hold significance in emphasizing the need for a robust sow insurance program that entices the interests of farmers and insurers.

In spite of the contributions and policy implications, this study still faces some limitations to be overcome by future investigations. Firstly, we cannot completely rule out the effects of unobserved variables using cross-sectional data, thus making our estimated effects still subject to bias. Other sow insurance programs in China with observations available for multiple years were not implemented in the same way to allow us to use the same instrumental variable approach to control for the endogeneity in the treatment. Future studies should strive to select or even design insurance programs with implementations that are more amicable to causal identification. Secondly, we used sow mortality as the sole indicator for detecting hazardous behavior because of its popularity in the literature and availability in our survey data. This choice does not help us fully understand the more nuanced mechanism under which farmers adapt their production decisions with insurance coverage. More informative studies should examine the specific decisions of farmers (e.g., the use of various inputs and preventive measures) to be able to assist in better insurance design.

References

Boyd, M., Pai, J., & Porth, L. (2013). Livestock mortality insurance: development and challenges. *Agricultural Finance Review*, 73(2), 233-244.

Cai, H., Chen, Y., Fang, H., & Zhou, L. A. (2015). The effect of microinsurance on economic activities: evidence from a randomized field experiment. *Review of Economics and Statistics*, 97(2), 287-300.

Card, D. (2001). Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica*, 69(5), 1127–1160.

Chambers, R. G. (1989). Insurability and moral hazard in agricultural insurance markets. *American Journal of Agricultural Economics*, 71(3), 604-616.

Coble, K. H., Knight, T. O., Pope, R. D., & Williams, J. R. (1997). An expected-indemnity approach to the measurement of moral hazard in crop insurance. *American Journal of Agricultural Economics*, 79(1), 216-226.

Cole, S., Giné, X., & Vickery, J. (2017). How does risk management influence production decisions? Evidence from a field experiment. *The Review of Financial Studies*, 30(6), 1935-1970.

Gu, Y., & Zheng, B. (2018). Membership premium or self-selection? Communist party recruitment and social stratification in urban China. *Journal of Chinese Political Science*, 23(4), 499-518.

Gunnsteinsson, S. (2020). Experimental identification of asymmetric information: Evidence on crop insurance from the Philippines. *Journal of Development Economics* 144.

Hazell, P. B. (1992). The appropriate role of agricultural insurance in developing countries. *Journal of International Development*, 4(6), 567-581.

He, J., Zheng, X., Rejesus, R. M., & Yorobe Jr, J. M. (2019). Moral hazard and adverse selection effects of cost-of-production crop insurance: evidence from the Philippines. *Australian Journal of Agricultural and Resource Economics*, 63(1), 166-197.

Hill, R. V., Kumar, N., Magnan, N., Makhija, S., de Nicola, F., Spielman, D. J., & Ward, P. S. (2019). Ex ante and ex post effects of hybrid index insurance in Bangladesh. *Journal of Development Economics*, 136, 1-17.

Horowitz, J. K., & Lichtenberg, E. (1993). Insurance, moral hazard, and chemical use in agriculture. *American Journal of Agricultural Economics*, 75(4), 926-935.

Jin, Y., Fan, M., Cheng, M., & Shi, Q. (2014). The economic gains of cadre status in rural China: Investigating effects and mechanisms. *China Economic Review*, 31, 185-200.

Just, R. E., Calvin, L., & Quiggin, J. (1999). Adverse selection in crop insurance: Actuarial and asymmetric information incentives. *American Journal of Agricultural Economics*, 81(4), 834-849.

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, 129(2), 597-652.

Koontz, S. R., Hoag, D. L., Thilmany, D. D., Green, J. W., & Grannis, J. L. (Eds.). (2006). The economics of livestock disease insurance: concepts, issues and international case studies. CABI publishing.

Li, H., Liu, P. W., Zhang, J., & Ma, N. (2007). Economic returns to communist party membership: Evidence from urban Chinese twins. *The Economic Journal*, 117(523), 1504-1520.

Liang, Y., & Coble, K. H. (2009). A cost function analysis of crop insurance moral hazard and agricultural chemical use (No. 319-2016-9739).

Lin, W. & Wooldridge, J.M. (2017). Binary and fractional response models with continuous and binary endogenous explanatory variables. Working paper.

Morduch, J., & Sicular, T. (2000). Politics, growth, and inequality in rural China: does it pay to join the Party? *Journal of Public Economics*, 77(3), 331-356.

Morgan, S. L., & Winship, C. (2015). Counterfactuals and causal inference. Cambridge University Press.

Nelson, C. H., & Loehman, E. T. (1987). Further toward a theory of agricultural insurance. *American Journal of Agricultural Economics*, 69(3), 523-531.

Pai, J., Boyd, M., & Porth, L. (2015). Insurance premium calculation using credibility analysis: an example from livestock mortality insurance. *Journal of Risk and Insurance*, 82(2), 341-357.

Quiggin, J. C., Karagiannis, G., & Stanton, J. (1993). Crop insurance and crop production: an empirical study of moral hazard and adverse selection. *Australian Journal of Agricultural Economics*, 37(429-2016-29192), 95.

Rao, X., & Zhang, Y. (2020). Livestock insurance, moral hazard, and farmers' decisions: a field experiment among hog farms in China. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 45(1), 134-156.

Roberts, M. J., Key, N., & O'Donoghue, E. (2006). Estimating the extent of moral hazard in crop insurance using administrative data. *Review of Agricultural Economics*, 28(3), 381-390.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology*, 66(5), 688.

Schneider, M. M. (2011). Feeding China's pigs: implications for the environment, China's smallholder farmers and food security.

Shee, A., & Turvey, C. G. (2012). Collateral-free lending with risk-contingent credit for agricultural development: indemnifying loans against pulse crop price risk in India. *Agricultural Economics*, 43(5), 561-574.

Smith, V. H., & Goodwin, B. K. (1996). Crop insurance, moral hazard, and agricultural chemical use. *American Journal of Agricultural Economics*, 78(2), 428-438.

Wang, H.H., Tack, J.B., & Coble, (2020). K.H. Frontier studies in agricultural insurance. *Geneva Pap Risk Insurance Issues and Practice* 45, 1–4.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. 2nd Edition. MIT press.

Wooldridge, J.M. (2011). "Fractional response models with endogeneous explanatory variables and heterogeneity," CHI11 Stata Conference 12, Stata Users Group.

Yu, J., & Hendricks, N. P. (2020). Input Use Decisions with Greater Information on Crop Conditions: Implications for Insurance Moral Hazard and the Environment. *American Journal of Agricultural Economics*, 102(3), 826-845.

Zhang, X., Chu, F., Yu, X., Zhou, Y., Tian, X., Geng, X., & Yang, J. (2017). Changing structure and sustainable development for China's hog sector. *Sustainability*, 9(1), 69.

Zhang, Y., Liu, C. C. & Li, C. S. (2013). Hog insurance, information asymmetry and false reporting: A case study based on the problem of "insufficient insurance". *Journal of Agrotechnical Economics*, 1, 11-24. (Published in Chinese)

Zhang, P., & Palma, M. A. (2021). Compulsory versus voluntary insurance: An online experiment. *American Journal of Agricultural Economics*, 103(1), 106-125.

Zhang, Y., Zhu, X., & Turvey, C. G. (2016). On the impact of agricultural livestock microinsurance on death-loss, production and vaccine use: Observations from a quasi-natural experiment in China. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 41(2), 225-243.

Table 1 Definitions and descriptive statistics of major variables (Regression sample size is 800)

Variable	Definition	Mean	SD	Min	Max
numsow2009	Number of sows in December 2009	26.203	96.544	1	1,200
mortality	Fraction of total sows reported to be dead during the insurance period	0.028	0.081	0	0.5
awareness	A dummy variable that equals 1 if the farmer knew that he/she participated in insurance in 2008, and 0 otherwise	0.786	0.410	0	1
ratio	Ratio of the number of local husbandry veterinary workers to the number of sow farmers in each town	8.416	4.692	5.02	58.82
age	Age of pig farm owner	51.400	9.216	26	84
edu	Years of education of pig farm owner	6.629	2.708	0	15
hukou	A dummy variable that equals 1 if the farmer had a non-agricultural household registration, and 0 otherwise	0.106	0.308	0	1
partymem	A dummy variable that equals 1 if the farmer was a party member; and 0 otherwise	0.105	0.307	0	1
cadre	A dummy variable that equals 1 if the farmer was a village cadre; and 0 otherwise	0.040	0.196	0	1
experience	Pig farm owner’s experience in pig production, measured in years	13.651	9.149	0	50
incomeratio	Income from sow/total income	40.664	30.352	0	100
biosecurity	Number of different biosecurity practices used on farms	9.538	3.370	1	22
vac_cost_per_sow	Average vaccination costs (in yuan) per sow during the insurance period	1.482	2.677	0	35.24
vac_cost_per_hog	Average vaccination costs (in yuan) per hog during the insurance period	0.159	0.947	0	16.2
farmdistance	Distance (in meters) from the nearest hog farm	329.331	1,024.179	0	20,000

Table 2 Comparing farmers by awareness status

Variable	Not Aware (N=171)		Aware (N=629)		Difference	
	Mean	SE	Mean	SE	Diff	SE
age	52.245	0.713	51.170	0.366	1.076	0.794
edu	6.304	0.185	6.717	0.111	-0.413*	0.233
hukou	0.064	0.019	0.118	0.013	-0.053**	0.027
partymem	0.058	0.0180	0.0118	0.013	0.105**	0.026
cadre	0.035	0.014	0.041	0.008	0.040	0.007
biosecurity	7.678	0.245	10.043	0.129	-2.365***	0.278
experience	10.801	0.532	14.426	0.380	-3.625***	0.779
incomeratio	29.269	2.087	43.762	1.213	-14.492***	2.569
mortality	0.019	0.005	0.306	0.003	-0.012*	0.007
numsow2009	17.556	7.070	26.496	3.649	-8.940	7.910
vac_cost_per_sow	1.547	0.151	1.465	0.113	0.082	0.231
vac_cost_per_hog	0.168	0.099	0.156	0.033	0.012	0.082
ratio	6.859	0.419	8.839	0.174	-1.980***	0.399
farmdistance	203.222	43.631	363.615	44.417	-160.392*	88.201

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

Table 3 Parameter estimates of endogenous treatment effects model

mortality	Coefficient	Standard. Errors	z	P>z	[95% Conf. Interval]	
Part 1: Average treatment effects (ATE)						
awareness (1 vs 0)	0.020	0.003	6.510	0.000	0.014	0.026
Part 2: Potential outcomes means (POMs)						
awareness =0	0.004	0.001	3.040	0.002	0.001	0.007
Part 1’: Average treatment effects on treated (ATET)						
awareness (1 vs 0)	0.030	0.003	8.910	0.000	0.024	0.037
Part 3: Treatment model estimates (TME1)						
ratio	0.057	0.030	1.890	0.058	-0.002	0.116
farmdistance	0.000	0.000	0.930	0.351	0.000	0.000
age	-0.015	0.007	-2.190	0.028	-0.029	-0.002
edu	0.042	0.021	1.970	0.048	0.000	0.084
experience	0.041	0.008	4.950	0.000	0.025	0.058
hukou	0.376	0.186	2.020	0.043	0.011	0.741
partymem	0.367	0.184	2.000	0.046	0.007	0.727
cadre	-0.239	0.276	-0.860	0.387	-0.780	0.303
constant	0.257	0.465	0.550	0.580	-0.654	1.168
Part 4: Outcome model estimates for the untreated (OME0)						
vac_cost_per_sow	-0.151	0.085	-1.780	0.075	-0.317	0.015
vac_cost_per_hog	0.051	0.034	1.500	0.135	-0.016	0.119
incomeratio	-0.003	0.004	-0.700	0.486	-0.012	0.006
age	0.000	0.012	-0.030	0.975	-0.025	0.024
edu	-0.084	0.052	-1.610	0.108	-0.186	0.018
experience	-0.090	0.034	-2.630	0.009	-0.157	-0.023
experience_sq	0.002	0.001	2.100	0.036	0.000	0.004
biosecurity	-0.030	0.034	-0.890	0.375	-0.095	0.036
hukou	-0.497	0.385	-1.290	0.197	-1.252	0.258
partymem	-1.177	0.290	-4.070	0.000	-1.745	-0.610
cadre	0.754	0.394	1.910	0.056	-0.018	1.527
constant	-2.350	1.134	-2.070	0.038	-4.572	-0.128

Table 3 Parameter estimates of endogenous treatment effects model (Continued)

mortality	Coefficient	Standard. Errors	z	P>z	[95% Conf. Interval]	
Part 5: Outcome model estimates for the treated (OME1)						
vac_cost_per_sow	-0.040	0.033	-1.220	0.223	-0.103	0.024
vac_cost_per_hog	0.002	0.042	0.050	0.963	-0.080	0.084
incomeratio	0.000	0.002	-0.160	0.873	-0.003	0.003
age	-0.008	0.007	-1.090	0.275	-0.022	0.006
edu	0.015	0.024	0.640	0.522	-0.032	0.062
experience	0.038	0.022	1.700	0.090	-0.006	0.082
experience_sq	-0.001	0.000	-1.370	0.170	-0.001	0.000
biosecurity	0.006	0.016	0.370	0.708	-0.026	0.038
hukou	0.104	0.184	0.570	0.571	-0.257	0.466
partymem	0.169	0.166	1.020	0.310	-0.157	0.494
cadre	-0.142	0.294	-0.480	0.629	-0.717	0.433
constant	-2.225	0.530	-4.200	0.000	-3.264	-1.187
Part 6: Treatment residuals for outcome model for the untreated (TEOM0)						
constant	-2.612	0.898	-2.910	0.004	-4.372	-0.853
Part 7: Treatment residuals for outcome model for the treated (TEOM1)						
constant	1.301	1.007	1.290	0.196	-0.673	3.274

Table 4 Parameter estimates of a fractional *probit* model with an endogenous binary explanatory variable

mortality	Coefficient	Standard. Errors	z	P>z	[95% Conf. Interval]	
Second stage: mortality						
awareness	0.865	0.245	3.540	0.000	0.386	1.345
vac_cost_per_sow	-0.048	0.033	-1.470	0.143	-0.111	0.016
vac_cost_per_hog	0.006	0.029	0.190	0.846	-0.051	0.062
incomeratio	-0.000	0.001	-0.200	0.840	-0.003	0.002
age	-0.001	0.005	-0.100	0.921	-0.011	0.010
edu	-0.018	0.019	-0.950	0.343	-0.055	0.019
experience	0.000	0.016	0.000	0.998	-0.032	0.032
experience_sq	-0.000	0.000	-0.550	0.582	-0.001	0.001
biosecurity	0.002	0.014	0.110	0.912	-0.026	0.029
hukou	-0.095	0.146	-0.650	0.513	-0.381	0.190
partymem	0.001	0.141	0.010	0.995	-0.275	0.276
cadre	-0.096	0.259	-0.370	0.711	-0.603	0.411
constant	-2.270	0.374	-6.070	0.000	-3.003	-1.536
First stage: awareness						
ratio	0.063	0.028	2.270	0.023	0.009	0.117
farmdistance	0.000	0.000	1.740	0.081	-0.000	0.000
age	-0.015	0.006	-2.570	0.010	-0.026	-0.004
edu	0.035	0.018	1.900	0.058	-0.001	0.071
experience	0.039	0.007	6.020	0.000	0.027	0.052
hukou	0.386	0.179	2.160	0.031	0.035	0.736
partymem	0.358	0.170	2.110	0.035	0.025	0.690
cadre	-0.284	0.255	-1.110	0.266	-0.783	0.216
constant	0.307	0.414	0.740	0.459	0.505	1.118

Note: The reported standard errors are robust standard errors.

Table 5 Marginal effects of fractional *probit* with an endogenous binary explanatory variable

mortality	dy/dx	Standard. Errors	z	P>z	[95% Conf. Interval]	
awareness	0.070	0.032	2.180	0.029	0.007	0.133
vac_cost_per_sow	-0.004	0.003	-1.480	0.138	-0.009	0.001
vac_cost_per_hog	0.000	0.002	0.190	0.848	-0.004	0.005
incomeratio	-0.000	0.000	-0.200	0.841	-0.000	0.000
age	-0.000	0.000	-0.100	0.921	-0.001	0.001
edu	-0.001	0.002	-0.890	0.375	-0.005	0.002
experience	0.000	0.001	0.000	0.998	-0.003	0.003
experience_sq	-0.000	0.000	-0.550	0.583	-0.000	0.000
biosecurity	0.000	0.001	0.110	0.912	-0.002	0.002
hukou	-0.008	0.012	-0.630	0.527	-0.032	0.016
partymem	0.000	0.011	0.010	0.995	-0.022	0.022
cadre	-0.008	0.021	-0.370	0.708	-0.048	0.033

Table 6 Parameter estimates of a *biprobit* model with an endogenous binary explanatory variable

mortality	Coefficient	Standard. Errors	z	P>z	[95% Conf. Interval]	
Second stage: mortality						
awareness	1.081	0.310	3.480	0.000	0.473	1.689
vac_cost_per_sow	-0.147	0.046	-3.210	0.001	-0.236	-0.057
vac_cost_per_hog	-0.018	0.036	0.500	0.619	-0.089	0.053
incomeratio	0.010	0.002	4.940	0.000	0.006	0.014
age	-0.006	0.007	-0.850	0.397	-0.020	0.008
edu	0.025	0.026	0.980	0.327	-0.025	0.075
experience	0.008	0.021	0.410	0.685	-0.032	0.049
experience_sq	-0.001	0.000	-1.10	0.272	-0.002	0.000
biosecurity	0.061	0.018	3.390	0.001	0.026	0.096
hukou	-0.012	0.154	-0.080	0.937	-0.313	0.289
partymem	0.216	0.167	1.300	0.195	-0.110	0.542
cadre	-0.279	0.276	-1.010	0.312	-0.821	0.262
constant	-2.333	0.469	-4.970	0.000	-3.252	-1.414
First stage: awareness						
ratio	0.065	0.026	2.560	0.011	0.015	0.115
farmdistance	0.000	0.000	1.000	0.391	-0.000	0.000
age	-0.015	0.007	-2.160	0.031	-0.029	-0.001
edu	0.038	0.021	1.800	0.073	-0.004	0.080
experience	0.041	0.008	5.030	0.000	0.025	0.058
hukou	0.319	0.181	1.770	0.077	-0.034	0.673
partymem	0.359	0.187	1.920	0.055	-0.008	0.726
cadre	-0.241	0.273	-0.880	0.377	-0.776	0.294
constant	0.219	0.455	0.480	0.631	-0.673	1.110

Table 7 Marginal effects of a *biprobit* model with an endogenous binary explanatory variable

mortality	dy/dx	Standard. Errors	z	P>z	[95% Conf. Interval]	
awareness	0.273	0.093	2.940	0.003	0.091	0.454
vac_cost_per_sow	-0.037	0.010	-3.530	0.000	-0.058	-0.016
vac_cost_per_hog	-0.005	0.009	-0.500	0.617	-0.022	0.013
incomeratio	0.003	0.000	5.810	0.000	0.002	0.003
age	-0.002	0.002	-0.860	0.392	-0.005	0.002
edu	0.006	0.006	1.010	0.314	-0.006	0.019
experience	0.002	0.005	0.410	0.683	-0.008	0.012
experience_sq	-0.000	0.000	-1.110	0.265	-0.000	0.000
biosecurity	0.015	0.004	3.620	0.000	0.007	0.024
hukou	-0.003	0.039	-0.080	0.937	-0.079	0.073
partymem	0.054	0.041	1.330	0.184	-0.026	0.135
cadre	-0.071	0.069	-1.020	0.307	-0.206	0.065