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1. Introduction

The livestock sector has experienced remarkable growth over the past century, largely driven by technological advancements in animal science and farm management. Innovations such as improved animal breeds, veterinary pharmaceuticals, and mechanized systems have significantly enhanced productivity. As a result, global meat production has nearly quintupled over the past 50 years (Ritchie, 2023), and livestock now accounts for approximately 40% of the total value of global agricultural output (FAO, 2021).

Among the most transformative technologies has been the use of antibiotics. Initially introduced in the 1940s by veterinarians and researchers to prevent, treat, and control bacterial infections in animals, antibiotics quickly became a cornerstone of modern livestock production. Shortly thereafter, scientists discovered that administering antibiotics at sub-therapeutic levels could promote animal growth by improving feed efficiency and accelerating weight gain (Cox, 2016; Key & McBride, 2014; MacDonald & Wang, 2011; Sneeringer et al., 2015). This dual functionality led to the widespread adoption of antibiotics across all major livestock-producing regions, including the United States, European Union, China, India, and Brazil. Global antibiotic use in food animal production is projected to increase by 67%, from 63,151 tons in 2010 to approximately 105,596 tons by 2030 (Van Boeckel et al., 2015), with further growth expected to reach 143,481 tons by 2040 (Acosta et al., 2025).

Despite the clear benefits of antibiotics in enhancing animal health and productivity, researchers have long warned of the adverse consequences associated with their excessive use. Overdosing antibiotics in livestock has been linked to a range of health issues, including organ damage, disruption of the gut microbiome, and increased susceptibility to disease (e.g., Looft et al., 2012; Looft et al., 2014). These effects not only compromise animal welfare but also undermine the long-term sustainability of livestock systems. More critically, the intensive and widespread use of antibiotics has accelerated the emergence and spread of antimicrobial-resistant (AMR) pathogens, as highlighted by the World Health Organization.[1] These drug-resistant bacteria can move between animals, wildlife, and humans, posing a serious threat to food safety and public health. The growing prevalence of AMR has led to more frequent disease outbreaks and reduced effectiveness of life-saving treatments (Hennessy & Marsh, 2021; Jia et al., 2024; Sneeringer et al., 2015).

In response to those concerns, the European Union banned the use of antibiotics for growth promotion in livestock in 2006. More recently, the U.S. Department of Agriculture implemented a regulation in 2023, requiring veterinary prescriptions for all antibiotic purchases by livestock producers. While such measures aim to curb misuse, ensuring their effectiveness and enforceability requires robust national surveillance systems capable of monitoring antibiotic use across various production stages. However, such systems can be both costly and time-intensive to establish (e.g., Van Boeckel et al. 2017; WHO 2018; Zhou et al. 2025). Despite these stringent regulatory efforts, antibiotics remain essential tools for livestock producers. They are not only effective and affordable for managing disease risks but also contribute to growth promotion—functions for

[1] Source: World Health Organization. “Antimicrobial Resistance”. November 2023. https://www.who.int/news-room/fact-sheets/detail/antimicrobial-resistance?

which few viable alternatives currently exist. A complete ban on antibiotic use could increase producers' vulnerability to disease outbreaks, reduce productivity, and negatively impact farm income. As a result, many countries have opted for partial regulations rather than outright bans. Given the multifaceted role of antibiotics in livestock production—ranging from disease prevention and treatment to growth enhancement, alongside the risks of overuse—this raises a critical question: What is the optimal balance between reducing risks of animal diseases and death, maintaining productivity, and safeguarding public health?

In this study, we aim to examine livestock producers' use of antibiotics within a conceptual framework of production economics, treating antibiotics as inputs in the production process. This approach enables us to analyze producers' decisions by considering the dual role of antibiotics in enhancing productivity and managing production risks, such as disease outbreaks. Antibiotics can reduce risk when used at therapeutic levels but may increase risk when used as growth promoters. Therefore, producers' choices reflect a tradeoff between these opposing risk effects, influenced by their individual risk preferences. To explore this dynamic further, we introduce agricultural insurance, a widely adopted risk management policy across many regions, as an external factor. By doing so, we aim to observe how access to insurance affects producers' antibiotic use. Given that most agricultural producers, particularly small-scale ones, tend to be risk-averse, we anticipate that participation in insurance programs will lead to increased antibiotic use. This behavior could heighten exposure to animal disease risk without necessarily increasing overall production risk.

To conduct our analysis, we leveraged a natural policy experiment in a Chinese county where a hog insurance program was introduced in two towns but not in others. We drew a random sample of hog farmers and conducted two rounds of household surveys covering their production activities during 2013–2014. In collaboration with local government officials and the participating insurance company, we obtained detailed information on each farmer's insurance participation status and, where applicable, their claims related to hog diseases. We employed difference-in-differences models under various specifications and obtained consistent estimates. The results indicate that participation in agricultural insurance significantly increased antibiotic use among Chinese hog farmers. This finding is consistent with observations and estimates reported in other studies and highlights a critical unintended consequence of agricultural insurance—its potential to exacerbate animal disease risks through increased reliance on antibiotics.

The remainder of the paper is organized as follows: Section 2 outlines the conceptual framework after a brief literature review; Section 3 describes the study context and experimental design; Section 4 details the data and the empirical methodology; Section 5 presents the model estimates along with interpretations; Section 6 concludes with a discussion of the findings and their policy implications.

2. Conceptual Framework

2.1 Literature Review

Most economics studies on antibiotic use in the food and agriculture sectors have approached the issue from the perspective of food safety and consumer behavior. These studies have investigated the credibility of "raised without antibiotics" labeling (Price et al., 2022) and sought to elicit consumer perceptions of antibiotic use, often quantifying their preferences through willingness-to-pay estimates for antibiotic-free food products (e.g., Barrett et al., 2021; Picardy et al., 2020; Tackie et al., 2017). Despite variations in context, study design, and valuation methods, a

consistent finding across these studies is the widespread negative perception of antibiotics among consumers. On the production side, earlier research primarily focused on the potential impacts of restricting or banning antibiotic use on farm-level or industry-wide productivity and output (e.g., Key & McBride, 2014; MacDonald & Wang, 2011; Miller et al., 2005; Salois et al., 2016).

Only recently have researchers begun to explore agricultural producers' perceptions, intentions, and incentives in their decision-making regarding antibiotic use. For example, Nthambi et al. (2023) conducted a choice experiment with 1,224 livestock and poultry farmers in Tanzania to examine their preferences for treatment methods, such as consulting professional veterinarians or sourcing antibiotics from various channels. Mao (2018) surveyed 399 livestock and poultry farmers in China and identified the determinants of antibiotic use based on the theory of planned behavior. Parkhi et al. (2023) investigated how antibiotic use varies by farm size and region in Nigerian poultry farming. In Denmark, Belay and Jensen (2020) used the public release of antibiotic use data among hog farms as a quasi-experiment and found that information disclosure significantly reduced antibiotic use. Similarly, Belay et al. (2020) introduced an adapted auction mechanism to regulate antibiotic use more efficiently in the Danish livestock sector. Zhou et al. (2025) conducted a randomized controlled trial among poultry farmers in China, examining how antibiotic use changed when farmers were offered monetary coupons for alternative production methods and exposed to role models and varying social norms. Collectively, these studies reveal the complex interplay between producers' antibiotic use decisions and a range of factors, including other input choices, individual characteristics (e.g., socio-economic status and risk preferences), and external incentives (e.g., subsidies, regulations, and social norms).

2.2 Conceptual Framework

For this study, we build on the theoretical framework developed by Ramaswami (1993) and adapt the method used by Parkhi et al. (2023) to formulate testable hypotheses. Ramaswami (1993) introduced a general model to analyze how agricultural insurance participation influences farmers' input choices, distinguishing between risk-increasing inputs (e.g., fertilizer, irrigation) and risk-decreasing inputs (e.g., pesticides, machinery). Under relatively non-restrictive assumptions, he demonstrated that participation in actuarially fair insurance encourages risk-averse farmers to reduce their use of risk-decreasing inputs while increasing their use of risk-increasing inputs. In this context, insurance serves as a substitute for other risk-mitigating inputs, while simultaneously incentivizing the use of riskier inputs that offer higher expected returns. This framework has since been widely adopted and extended in empirical studies examining the effects of agricultural insurance on input use (e.g., Horowitz & Lichtenberg, 1993; Goodwin & Smith, 2003; Weber et al., 2016; Roll, 2019). For a different line of inquiry, Parkhi et al. (2023) studied antibiotic use over farm size and regions in Nigerian poultry farming by incorporating the damage control function developed by Lichtenberg and Zilberman (1986). They explicitly modeled poultry farmers' antibiotic use as a function of variables reflecting the dual roles of antibiotics: growth promotion and disease control. Their findings confirmed that antibiotics were used for both purposes within their sample.

Building on these findings, we propose that the relationship between antibiotic use and animal disease risk follows a U-shaped curve (see Figure 1). When actual antibiotic use is below the optimal dosage level, denoted as $d*$, antibiotics serve as risk-reducing inputs. However, once usage exceeds $d*$, they begin to function as risk-increasing inputs. According to Ramaswami's (1993) propositions, insurance participation influences antibiotic use based on its risk effect. Specifically,

when antibiotic use is below $d*$, insurance is expected to reduce usage by substituting for the risk-mitigating role of antibiotics. Conversely, when antibiotic use exceeds $d*$, insurance may encourage greater use by amplifying the appeal of antibiotics, which are now risk-increasing but offer higher expected growth rates of animals. By estimating the change in antibiotic use due to insurance participation, we can infer whether farmers are currently using antibiotics at levels below or above the optimal threshold. In the empirical estimation below, we will estimate the causal effects of insurance participation on farmers' antibiotic use using a sample from China.

[Figure 1 Relationship between Use of Antibiotics and Risks of Animal Diseases]

3. Context and Experimental Design

3.1 Context

As one of the world's largest producers and consumers of antibiotics, China lacks timely and comprehensive surveillance systems for monitoring antibiotic production and usage. National-level statistics, particularly for earlier years, are scarce. A widely cited estimate by Zhang et al. (2015), based on a survey of major antibiotic manufacturers in China, reported that the country produced approximately 248,000 tons of antibiotics in 2013. Of this total, 52% was used in livestock and poultry production, while the remaining 48% was allocated for human use.

More disaggregated data on antibiotic use remain largely unavailable. However, by synthesizing available statistics and findings from various studies, researchers have concluded that antibiotic use in China's animal husbandry is both extensive and intensive. For instance, Zhang et al. (2015) estimated that the intensity of antibiotic use in Chinese livestock production was 2.8 times higher than in the United States. In 2013, China used 84,240 tons of antibiotics to produce 87.76 million tons of meat, compared to the United States, which used 14,600 tons for 42.62 million tons of meat in 2012. Further highlighting the environmental impact, Lyu et al. (2020) conducted a comprehensive survey and found antibiotic residues in 100% of soil samples, 98.0% of surface water samples, and 96.4% of coastal water samples across China.

At individual levels, Chinese livestock farmers, many of whom operate on a small scale and exhibit high levels of risk aversion, have been observed to frequently use antibiotics to prevent disease, treat sick animals, and promote animal growth (Tian et al., 2021). In the absence of accessible or affordable professional veterinary services, farmers often rely on their own judgment, frequently increasing or even doubling the recommended dosage. For convenience, antibiotics are typically mixed into feed or water rather than administered via the recommended injection method. This oral delivery approach not only reduces the efficiency of antibiotic absorption but also leads to significant waste, reinforcing the misconception that higher dosages are necessary for effectiveness.

Amid escalating concerns over antimicrobial resistance linked to excessive antibiotic use, the Chinese central government began implementing targeted measures to reduce antibiotic consumption in the agricultural sector. It launched the *National Action Plan for Combating Animal Antimicrobial Resistance* in 2017. Even prior to this initiative, the Ministry of Agriculture and Rural Affairs had already begun promoting reduced antibiotic use across more than 21,000 farms nationwide, covering 16 livestock and poultry species, including hogs and chickens. These efforts produced notable results: antibiotic use in agriculture declined by 57% between 2014 and 2018, reaching 32,776 tons in 2020. Following a brief plateau during the COVID-19 pandemic, total

consumption further decreased to 32,500 tons in 2022. However, this level remains substantially higher than in other major regions. For comparison, China's 2022 usage was approximately five times that of the United States (6,200 tons), 7.3 times that of the European Union (4,500 tons), and 15 times that of India (2,200 tons, based on 2020 data).

3.2 Experimental Design

The experiment was conducted in *Jiyuan* County, *Henan* Province, China—a major hub for hog production. In 2012, approximately 11,000 of the county's 135,000 rural households were engaged in hog farming, with around 30% of these households marketing more than 100 hogs annually. Recognizing hog production as a vital component of the local economy and a primary income source for many farmers, the county government launched a hog insurance program in 2012 in partnership with the *Jiyuan* branch of China United Insurance Holding Company (CUIH). This initiative was part of a broader national effort to support the hog industry, promoted by the central government.

In the program's pilot phase, which began in 2013, two towns (*Chengliu* and *Sili*) were selected as pilot sites. All eligible hog farmers in these towns were offered the opportunity to insure their hogs weighing over ten kilograms (approximately 22 pounds). The annual premium was set at 30 *yuan* (about 4.5 USD) per hog, of which farmers paid only 20% (6 *yuan* or 0.85 USD), with the remaining 80% subsidized jointly by local and central governments. In the event of hog death due to major diseases, natural disasters, or accidents, the insurance provided compensation of five *yuan* per kilogram (approximately 0.64 USD per pound), up to a maximum of 500 *yuan* (about 75 USD) per hog. In practice, nearly all claims were approved, as determining the exact cause of death was often difficult and costly. To encourage participation, the insurance terms were intentionally kept simple and easy to understand.

During the pilot stage, the county's Agriculture and Animal Husbandry Bureau (AAHB) actively promoted the program in the two towns, offering technical support and assistance with dispute resolution. Farmers in *Chengliu* and *Sili* could voluntarily enroll under the described terms, while the insurance remained unavailable to farmers in non-pilot towns during this period.

The authors' research team was actively involved in all stages of the insurance program in *Jiyuan* and was granted access to individual-level data on hog farmers, thanks to long-standing collaborations with local government agencies and the China United Insurance Holding Company (CUIH). With formal authorization, we used these data to design economic experiments and surveys, and to evaluate the program's impact on behalf of the county government.

In December 2012, the Agriculture and Animal Husbandry Bureau (AAHB) conducted a county-wide census of all households raising at least one hog. Based on this census, we employed a stratified sampling strategy to select hog farmers from both the two pilot towns (*Chengliu* and *Sili*) and two comparable non-pilot towns (*Lilin* and *Wulongkou*) for comparison. The non-pilot towns were chosen in consultation with local livestock specialists due to their geographic proximity and similarity in hog production practices to the pilot towns.

As shown in Figure 2, the two non-pilot towns are located on the opposite side of the county's urban center, where hog farming was minimal. Within each of the four towns, all hog farmers were ranked by the total number of hogs they raised. Using computer-generated random numbers, we selected one farmer from every group of three, ensuring representation across different farm sizes.

This process yielded a sample of 681 hog farmers out of the 2,043 identified in the four towns, including 325 from the pilot towns and 356 from the non-pilot towns.

[Figure 2 Map of Jiyuan County]

In June and July 2013, just prior to the launch of the pilot insurance program, we conducted the first round of household surveys with the 681 randomly selected hog farmers. The survey collected detailed information on farming practices (e.g., expenditures on antibiotics and other medications), herd size, demographic characteristics, micro-financial conditions (e.g., access to insurance and credit), and farm-level biosecurity measures. To minimize misinterpretation and misreporting, most questions were designed in a multiple-choice format. Due to sanitation concerns, many farmers were reluctant to allow strangers into their hog barns. To address this, we recruited veterinarian specialists from local AAHB offices as enumerators. These individuals received training from the research team to ensure consistent and accurate data collection.

A follow-up survey was conducted in June and July 2014, near the end of the pilot insurance period, using the same questionnaire. However, during the second half of 2013, *Jiyuan* County began implementing the *Building a New Countryside* initiative, which designated certain areas as protected zones that prohibited hog farming and other high-pollution activities. This policy led to the forced closure of many hog farms across the county. As a result, only 366 farmers of the original 681 farmers continued raising hogs by the time of the second survey, including 135 from the two pilot towns and 231 from the non-pilot towns.

Despite the availability of insurance and active promotion by local authorities, not all farmers in the pilot towns chose to participate. Of the 135 farmers surveyed in the pilot towns, 113 (83.7%) purchased insurance, while 22 (16.3%) did not. In contrast, none of the 231 farmers in the non-pilot towns purchased insurance, as it was not available outside the pilot areas.

4. Data and Empirical Strategy

4.1 Data and Descriptive Statistics

For the purposes of this study, we further restricted the sample to farmers who answered all the questions regarding their expenses on antibiotics, dosages of antibiotic used, and expenses on drugs other than antibiotics. This resulted in a total sample of 207 farmers who completed the survey in both years, comprising 75 insurance participants from the two pilot towns and 132 non-participants from the two non-pilot towns. The flow chart in Figure 3 illustrates the steps we took to derive the sample for this study and the associated changes in the sample sizes over the two survey periods.

[Figure 3 Experiment Design and Sampling Procedure]

Table 1 presents the descriptive statistics for the variables collected from the survey, including the socio-demographic characteristics in July 2013 as the baseline. On average, hog farmers in the sample were about 52 years old, ranging from a minimum age of 28 to a maximum of 86 and with a standard deviation (S.D.) of nine years. These farmers, 59% of whom were smokers, had completed an average of eight years of education with a S.D. of two years. Some of these farmers received no formal education, while the most educated ones finished high school (i.e., 13 years of education). The experience in hog farming ranged from three years to 28 years, with an average of nine years and a standard deviation of 3.57 years. Hog farming provided a significant source of

income for many of these farmers, with an average of 64.71% of their total income coming from hog farming, although this value varied widely from 8% to 100%. Overall, this sample of hog farmers closely represented farmers residing in *Jiyuan* county in the aspects above, according to our other surveys conducted in this region during the same period.

[Table 1 Descriptive Statistics of Farmers in the Sample (N=207)]

During the baseline period of July 2013, farmers owned as few as zero hogs and as many as 450 hogs,[2] with an average of 82 and a S.D. of 61. The hog mortality rate in the same period averaged 13.19% (S.D. = 11.33%), with a minimum of 0.40% and a maximum of 100%, indicating high variability in farmers' success in managing hog health. Regarding drug expenses, the average expenditure on antibiotics per hog in July 2013 was 7.17 *yuan* (i.e., about one dollar), although some farmers spent as much as 166.67 *yuan* (i.e., 23.41 dollars), while others relied exclusively on free samples handed out by government veterinarian specialists and did not purchase any on their own. By July 2014, the antibiotics expenditure decreased significantly to an average of 1.81 *yuan* (i.e., 0.25 dollars), with a maximum expense of 55.56 *yuan* (i.e., 7.8 dollars). This trend was similar for non-antibiotics drugs as well, for which the average expenditure was 9.11 *yuan* (i.e., 1.28 dollars) in July 2013 and quickly dropped to 1.71 *yuan* (i.e., 0.24 dollars) by July 2014. Despite the decreased expenses on antibiotics, the average dosage of antibiotics used per hog remained relatively stable between July 2013 (i.e., 1.20 times of the recommended dosage in the instructions) and July 2014 (i.e., 1.21 times). The range of dosage also remained constant, with a minimum of 0.5 units and a maximum of six units in both periods.

In summary, the descriptive statistics in Table 1 provide an overview of the key characteristics of the pooled sample of 207 hog farmers in this study and highlight changes in management practices before and after the pilot insurance program. An overall downward trend in expenses on antibiotics and other drugs from 2013 to 2014 was observed for the pooled sample, suggesting potential improvements in farming efficiency or reduced costs. However, since these descriptive statistics consider both insurance participants and non-participants, the downward trend could be driven by factors in addition to insurance intervention. The likely presence of confounding factors necessitates using the control group (i.e., non-participating farmers) as the counterfactual through a difference-in-differences approach to derive the causal impact of the insurance program. Such an approach can help isolate the true effect of the insurance program on farming practices by comparing the changes between the participating and non-participating farmers.

Before comparing the outcomes between these two groups of farmers, we first examined whether the socio-demographic factors were balanced between them in the baseline period. Table 2 presents the means and standard errors for these key characteristics, along with the *p*-values for testing the differences between participants and non-participants. Overall, the two groups are well balanced regarding most socio-demographic factors, with no statistically significant differences reported. The only exception is smoking status, which shows that, on average, non-participating farmers had a higher proportion of smokers than their counterparts in the pilot towns, and the difference is statistically significant at the 5% level. This overall balance between the two groups of farmers

[2] It is possible for hog farmers to report owning zero hogs during a specific period, for instance, after selling all mature pigs and before raising or purchasing new piglets.

suggests that any post-pilot differences in outcomes are likely attributable to the insurance program rather than pre-existing differences between the groups.

[Table 2 Participants versus Non-participants in the Baseline Period]

4.2 Empirical Methodology

4.2.1 Unconditional Difference-in-Difference Estimates

Given the satisfactory balance between the two groups of farmers prior to the insurance program, Table 3 presents the summary statistics of the three outcome variables of interest for participants and non-participants of the hog insurance program before and after the intervention and the *unconditional* difference-in-differences (DID) estimates in the last columns following Equation (1), where $\overline{Y}_{treat,\ post}$ represents the average outcome for farmers in the pilot towns (the treatment group) after the implementation of the hog insurance program, while $\overline{Y}_{treat,\ pre}$ denotes the average outcome for the same group before the intervention. Similarly, $\overline{Y}_{control,\ post}$ is the average outcome for farmers in the non-pilot towns (the control group) after the intervention, and $\overline{Y}_{control,\ pre}$ is the average for the control group before the intervention.

$$\text{DID} = \left(\overline{Y}_{\text{treat, post}} - \overline{Y}_{\text{treat, pre}}\right) - \left(\overline{Y}_{\text{control, post}} - \overline{Y}_{\text{control, pre}}\right) \quad (1)$$

Panel A of Table 3 shows that the average expenses on antibiotics per hog for participants decreased from 4.39 *yuan* (0.62 dollars) before the intervention to 2.45 *yuan* (0.34 dollars) afterwards, reflecting a reduction of 1.94 *yuan* (0.27 dollars). In contrast, non-participants experienced a much larger drop, from 8.75 *yuan* (1.23 dollars) to 1.44 *yuan* (0.20 dollars), resulting in a reduction of 7.31 *yuan* (i.e., 1.03 dollars). The DID estimate shows that participants experienced a smaller expense decrease by the magnitude of 5.38 *yuan* (0.76 dollars) relative to non-participants, and this estimated difference is statistically significant given a standard error (S.E.) of 2.20. This result suggests that while both groups reduced their antibiotic expenses, non-participants experienced a more pronounced reduction.

[Table 3 Unconditional Difference-in-Differences Estimates]

Panel B of Table 3 shows that the average dosage of antibiotic per hog used by participants increased from 1.09 units to 1.32 units post-intervention, a rise of 0.23 units (S.E. = 0.07). On the other hand, non-participants saw a slight reduction in dosage, from 1.27 units to 1.14 units, representing a decrease of 0.12 units (S.E. = 0.06). The DID estimate of 0.36 units (S.E. = 0.10) indicates that participants increased their use of antibiotics more than non-participants.

Panel C of Table 3 shows that participants reduced their expenses on non-antibiotics drugs significantly from 11.12 *yuan* (1.56 dollars) to 2.56 *yuan* (0.36 dollars) per hog, representing a decrease of 8.56 *yuan* (i.e., 1.20 dollars). Non-participants also saw a decline from 7.96 *yuan* (1.12 dollars) to 1.23 *yuan* (0.17 dollars), with a reduction of 6.73 *yuan* (0.94 dollars). The DID estimate of -1.83 *yuan* (0.26 dollars) indicates that participants' reduced spending on other drugs was slightly larger than that of non-participants, though this difference is not statistically significant.

Thus, the DID estimates reveal different patterns in the use of antibiotics and other drugs between insured and uninsured farmers. Non-participants experienced larger reductions in both antibiotic and non-antibiotic expenses, while insured farmers increased their dosage of antibiotics. These findings suggest that the insurance program may have influenced participants' decision-making, possibly reducing their need to cut costs as aggressively as uninsured farmers, especially regarding antibiotics usage. However, the program had little effect on expenses related to other drugs.

4.2.2 Doubly-Robust Difference-in-Differences Estimator

The unconditional DID estimates reported above, however, do not account for factors that influence farmers' management strategies, such as age, education, and farm size. These factors are crucial even in a natural experiment setting. Additionally, unobserved characteristics may compromise the reliability of causal inferences drawn from the data presented. To address these limitations, we deployed a more robust empirical estimator that can report unbiased estimates of the impact of participation in the hog insurance program on farmers' drug usage behaviors.

We deployed the doubly-robust DID estimator (DRDID) proposed by Sant'Anna and Zhao (2020). This estimator re-weights observations in the control group (i.e., non-participants) according to their propensity score and adjusts the counterfactual outcome using a regression model by leveraging the covariates in the baseline period (i.e., before the implementation of the insurance pilot). The estimator is specified as follows:

$$ATT = E\left[\left(\frac{D}{E(D)} - \frac{\pi(\boldsymbol{X})(1-D)}{1-\pi(\boldsymbol{X})} \times \frac{1}{E\left(\frac{\pi(\boldsymbol{X})(1-D)}{1-\pi(\boldsymbol{X})}\right)}\right)\left(\Delta Y - f_{\{0,\Delta Y\}(\boldsymbol{X})}\right)\right] \quad (2)$$

which calculates the weighted average treatment effects on the treated (ATT) for each of the three outcome variables (i.e., expense on antibiotics, dosage of antibiotic used, and expense on other drugs). Specifically, the ATT measures the difference in outcomes between participants and non-participants. $\frac{D}{E(D)}$ is a normalizing factor using the participation status indicator D with $D=1$ for participants and $D=0$ for non-participants. The normalizing factor reweighs participation by its average $E(D)$, thereby adjusting for uneven participation assignment in the sample. The term $\frac{\pi(\boldsymbol{X})(1-D)}{1-\pi(\boldsymbol{X})}$ is a weighting factor using the propensity score $\pi(\boldsymbol{X})$, which is the probability of being a participant conditional on observed covariates $\boldsymbol{X}$ and is derived from a logistic regression, where $\boldsymbol{X}$ consists of all demographic and farm operation characteristics discussed in Table 1. This weighting adjustment is effectively applied only to the control group (non-participants) since ($1-D$) indicates the status of non-participants (for participants, $1-D=0$). The term $\frac{1}{E\left(\frac{\pi(X)(1-D)}{1-\pi(X)}\right)}$ normalizes the weighting factor to ensure that all the observation-specific weights sum to one. The term $\Delta Y - f_{\{0,\Delta Y\}(X)}$ represents the adjusted difference in outcomes Y, where ΔY is the observed difference and $f_{\{0,\Delta Y\}(X)}$ is a linear projection conditional on $\boldsymbol{X}$ (namely, the outcome regression), representing the expected difference if the farmers are not enrolled in the insurance. Because the distributions of these outcomes are not normally distributed, we log-transformed all outcome variables prior to estimation to help improve estimation efficiency. In addition, the log transformation normalizes the impact across farms of baseline expenditure levels, making the estimated treatment effects more representative and comparable across heterogeneous units. After

a bias-correcting procedure proposed by Kennedy (1981), the estimated ATTs are interpreted as percentage changes.

In summary, Equation (2) measures the expected difference in outcomes due to participation in the hog insurance, accounting for the probability of being enrolled, measured by a propensity score, and reweighing these differences based on both observed and expected distributions of characteristics of participants and non-participants. Each component of the formula works to adjust and reweigh the unconditional differences in outcomes between the two groups of farmers to account for potential biases in self-selection and covariate distributions. This estimation procedure relaxes the functional-form assumption of the evolution of potential outcomes: either the propensity score model or the outcome regression model is correctly specified, the treatment effect on the treated (*ATT*) of the insurance policy can be unbiasedly and consistently identified.

Since only two periods of data were observed, we were unable to detect the presence of parallel trends using event-study analysis. Additionally, given the small sample size, the standard errors associated with the estimates might be unreliable. Thus, we performed permutation tests to evaluate the statistical validity of the observed effects (Conley and Taber, 2011). A permutation test is a non-parametric method that does not rely on specific distributional assumptions about the data. It repeatedly shuffles the treatment assignment (i.e., insurance participation status) among the subjects (i.e., farmers) in the dataset to create a distribution of the estimator under the null hypothesis of no treatment effect. In this way, this method ensures that the observed differences are indeed due to the treatment and not merely due to random chance in the data structure. To implement the test, the actual participation status was randomly permuted 500 times. For each permutation, the DRDID estimate was recalculated, forming a reference distribution of the estimates under the null hypothesis. The p-value was derived from the proportion of permuted datasets where the estimated effect was at least as extreme as the effect observed in the actual data.

5. Estimation Results

The results from the analysis using the DRDID estimator reveal the pronounced impacts of participation in a hog insurance program on antibiotics expenditures and usage, but not on other drug expenses. Specifically, we found a substantial 152.44% (S.E. = 49.45) increase in expenses on antibiotics among participants, an effect that is statistically significant at the 1% level. Notably, overall antibiotic spending decreased for all farmers during the study year, but insured farmers reduced spending significantly less than they would have without insurance. Our estimate of a 152.44% increase should be understood as a relative effect. Essentially, insurance dampened or reversed the reduction in antibiotic use that uninsured farmers experienced. This finding indicates that the insurance program has led to increased expenditure on antibiotics among participating hog farmers. In terms of antibiotic usage, there was also a notable increase of 18.26% (S.E. = 6.04) in the dosage of antibiotic used, which is statistically significant at the 5% level. This significant increase in antibiotics dosage suggests that farmers were likely operating beyond the optimal threshold, $d*$, consistent with our conceptual framework. Thus, insurance participation appears to further amplify this excessive antibiotic use, reflecting a shift deeper into the risk-increasing region of the U-shaped curve presented earlier. Notably, the increase in antibiotic expenditures, disproportionately greater than the dosage increase, may reflect insured farmers shifting toward higher-quality or more expensive antibiotic formulations. Farmers under insurance may opt for premium antibiotic products perceived as more effective or convenient, a behavioral shift enabled by their reduced financial vulnerability. However, the impact on expenses for other drugs is not

446 statistically significant, with an estimate of 13.81% (S.E. = 20.16). This result suggests that the
447 insurance program does not significantly affect expenditures on drugs other than antibiotics, and
448 its impact might be more narrowly focused on antibiotics rather than a broader range of
449 pharmaceutical treatments.

450 Moreover, the permutation test results are illustrated in Figure 4. The histograms show the
451 distributions of the estimates from the permuted samples with blue kernel density curves. The
452 vertical dashed lines indicate the estimated effect of the actual assignment. The p-values associated
453 with expenses on antibiotics and dosage of antibiotic used were both smaller than 0.01, and the p-
454 value associated with expenses on other drugs equaled 0.37. These results confirm that the effects
455 observed for expenses on antibiotics and the dosage of antibiotic used were statistically significant
456 and attributable to the insurance program, whereas the increase in expenses on other drugs did not
457 differ significantly from what could occur by chance. In summary, the findings in this study
458 underscore the impact of the hog insurance program on antibiotic-related expenses and usage,
459 while its influence on other drug expenses appears to be minimal or indistinguishable from random
460 variations.

461 Overall, our findings provide empirical support for the theoretical proposition. Insurance
462 participation alters risk perceptions and incentives, causing farmers to substitute antibiotics for
463 other risk mitigation strategies. As antibiotics beyond d^* serve as risk-increasing inputs, insured
464 farmers, now financially shielded from production losses, appear more willing to accept the
465 increased risks associated with antibiotic overuse in exchange for higher expected productivity.

466 ***[Figure 4 Permutation Test – Distributions of Estimates for 500 Repetitions]***

467 **6. Conclusion and Discussion**

468 The use of antibiotics in livestock production has significant global implications, balancing the
469 benefits of improved animal health and productivity against concerns over antimicrobial resistance.
470 In this study, we explored the impact of livestock insurance on the use of antibiotics and other
471 drugs among hog farmers through a randomly selected sample of hog farmers in China. The
472 conceptual framework treated antibiotics as risk-increasing inputs to manage production risks,
473 considering the prevalent overuse of antibiotics by Chinese hog farmers. In this way, we estimated
474 how agricultural insurance, a commonly used risk management tool, influences farmers' decisions
475 regarding antibiotic use. Prior research has not explored the direct relationship between
476 agricultural insurance and antibiotic use, making this investigation particularly novel.

477 The experiment took place in selected towns within *Jiyuan* City, where the local government, in
478 collaboration with an insurance company, introduced a pilot insurance program for hog farmers.
479 This voluntary program was intended to shield farmers from hog losses due to major diseases or
480 natural disasters. Through stratified sampling, farmers from both insured (pilot) and uninsured
481 (control) towns were surveyed twice: before the program initiation in 2013 and after the
482 termination in 2014. The survey collected detailed data on farming practices, including usage and
483 expenses on antibiotics and other drugs, demographics, and farm biosecurity measures.

484 We employed a difference-in-differences (DID) estimation method to assess the causal impact of
485 insurance on antibiotic-related expenses and dosages. The DID approach allowed us to control for
486 time-invariant differences between the two groups and isolate the program's effect by comparing
487 the changes in outcomes over time. The findings suggest that insurance participation has led to an

increase in the dosage of antibiotics used and the associated expenses for farmers participating in the insurance program. Meanwhile, expenses on other non-antibiotic drugs were not significantly affected by insurance participation.

The findings of this study have significant implications for livestock insurance in China and similar contexts. We highlight that hog insurance, intended to protect farmers from losses due to hog diseases and deaths, may inadvertently encourage increased antibiotic use. This can lead to antimicrobial resistance if these results hold more broadly, threatening food security and public health. This unintended consequence is particularly concerning given that Chinese farmers already overuse antibiotics beyond recommended levels, potentially undermining government initiatives to reduce unnecessary antibiotic reliance in animal industries. An improved hog insurance program should include more restrictive terms on claim eligibility, such as excluding hog deaths caused by antibiotic overdose. While verifying such cases may be costly and difficult to implement consistently, a more feasible approach would involve conducting random checks or setting thresholds for antibiotic purchases—beyond which claims would trigger additional scrutiny or become ineligible. More effective strategies to combat the persistent and prevalent antibiotic overuse could include educational campaigns to raise farmers' awareness of proper antibiotic use and the associated risks if otherwise. Additionally, implementing prescription requirements for certain antibiotics, as seen in other countries, may be necessary given the wide availability and low costs of antibiotics.

Despite its contributions and policy implications, this study has some limitations that future investigations should address. Firstly, we did not differentiate between preventive and therapeutic antibiotics in the survey, which would have allowed for separate assessments of the effects of insurance participation. The net effects of the combined antibiotic use that were estimated in this study may provide limited insight into the targeted surveillance and management of each type of antibiotic. Future studies should include more specific questions about farmers' use of each type of antibiotic and evaluate the differential effects of insurance participation. Secondly, although we randomly selected farmers from both pilot and non-pilot towns before the launch of the pilot insurance program, an unanticipated government initiative (i.e., Building A New Countryside) led to different numbers of farm closures in the two groups. We could not fully evaluate its impact on sample representativeness and the subsequent comparisons between the two groups. This unforeseen attrition may limit the robustness of the key findings. Lastly, the pilot insurance program in this study lasted only one year, allowing us to collect data from only two periods. Longer-term studies could examine whether the increase in antibiotic use is temporary or grows over time, and whether it eventually leads to measurable differences in animal health outcomes. Despite these limitations, our field study provides important first evidence that agricultural insurance policies can have unintended effects on farm input use, specifically antibiotics, highlighting the need for integrated approaches to farm risk management and public health.

In summary, this study is the first, to our knowledge, to empirically investigate the causal relationship between livestock insurance and antibiotic use within a risk-management framework. Our findings highlight a critical yet previously unexplored unintended consequence: insurance participation significantly increases antibiotic usage, potentially exacerbating risks of antimicrobial resistance and animal disease. These results underline the importance of carefully designing agricultural insurance programs, incorporating safeguards against moral hazard and antibiotic misuse. Further research exploring longer-term effects, differentiating types of antibiotic

usage, and examining the heterogeneity of responses across diverse contexts is necessary to inform robust and targeted policy interventions.

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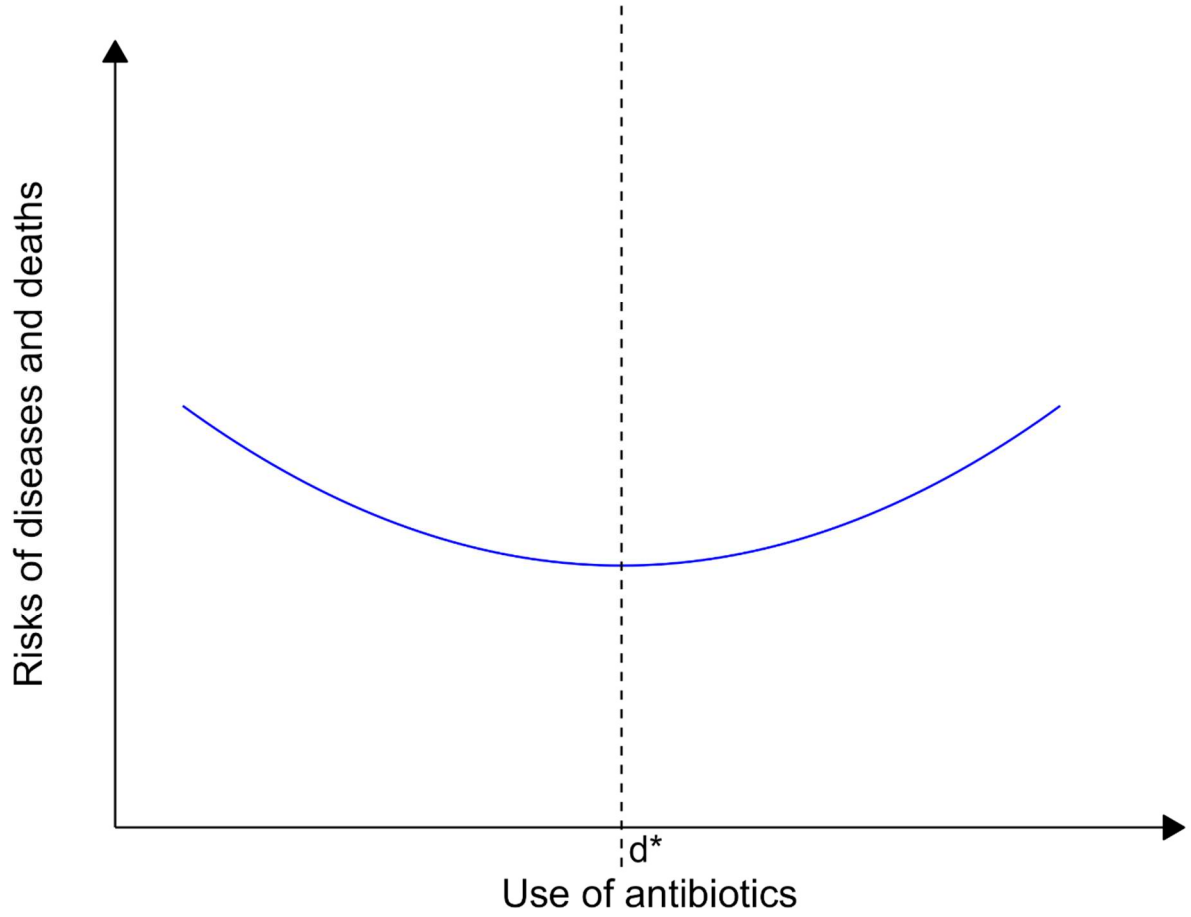
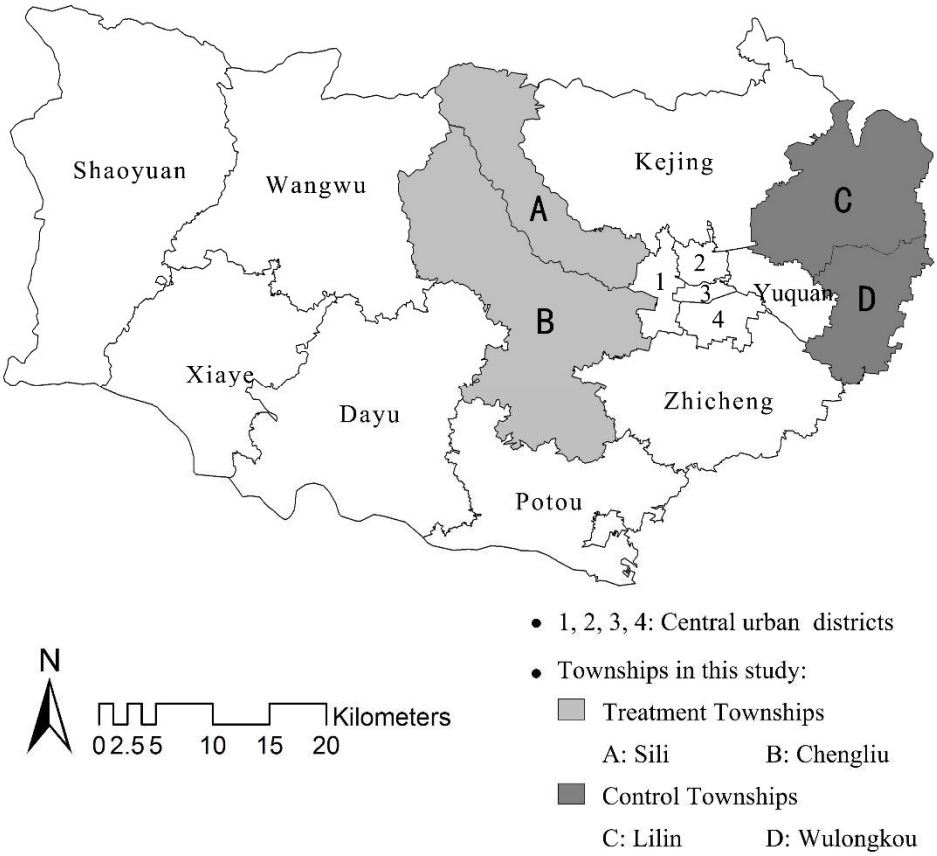


Figure 1 Relationship between Use of Antibiotics and Risks of Animal Diseases

Note: Relationship between antibiotic use and risks of animal diseases, illustrating a theoretical U-shaped risk profile. The optimal dosage level d* is depicted as the threshold at which antibiotic inputs transition from risk-decreasing to risk-increasing effects.



644

645 **Figure 2 Map of *Jiyuan* County in 2013**

646 *Note:* Map of Jiyuan County in 2013, Henan Province, China. This map identifies the pilot towns (Chengliu
647 and Sili) and the comparison towns (Lilin and Wulongkou), providing geographical context for the
648 insurance intervention experiment.

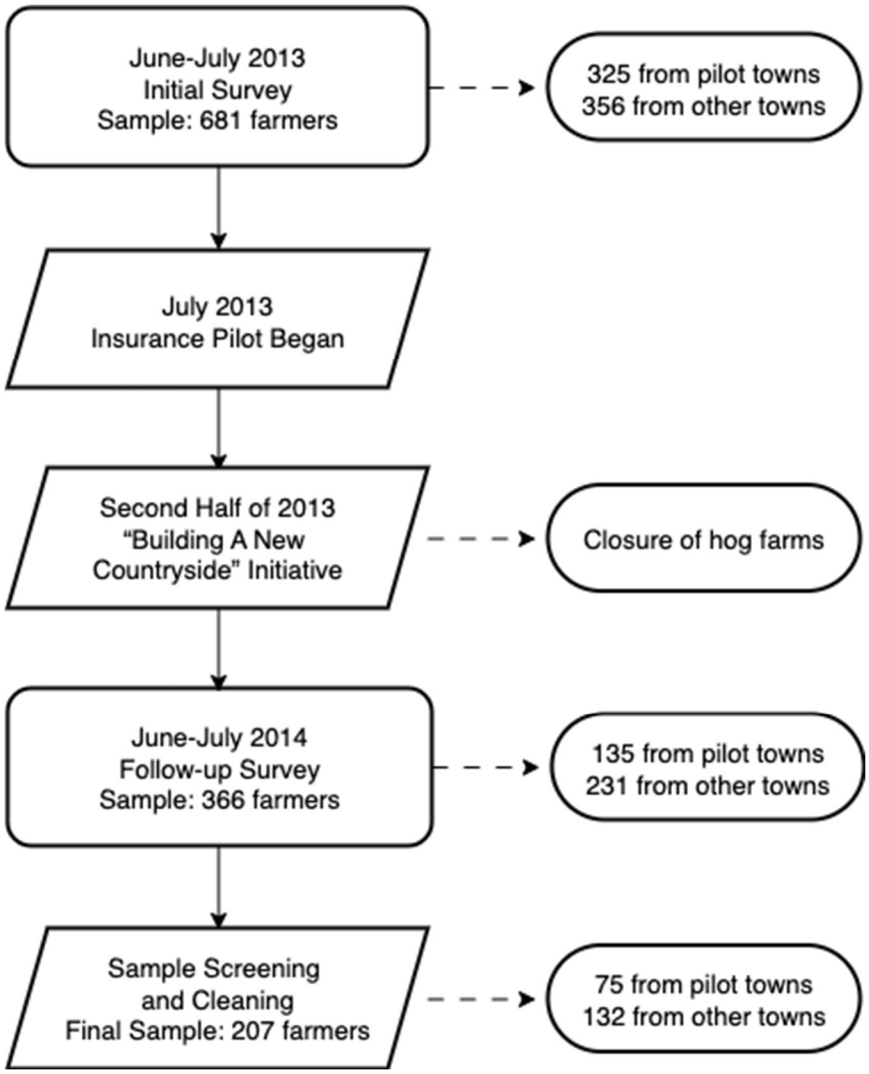


Figure 3 Experiment Design and Sampling Procedure

Note: This flowchart outlines the experimental design, sampling procedure, and sample size at different study stages, from initial participant selection to final analysis.

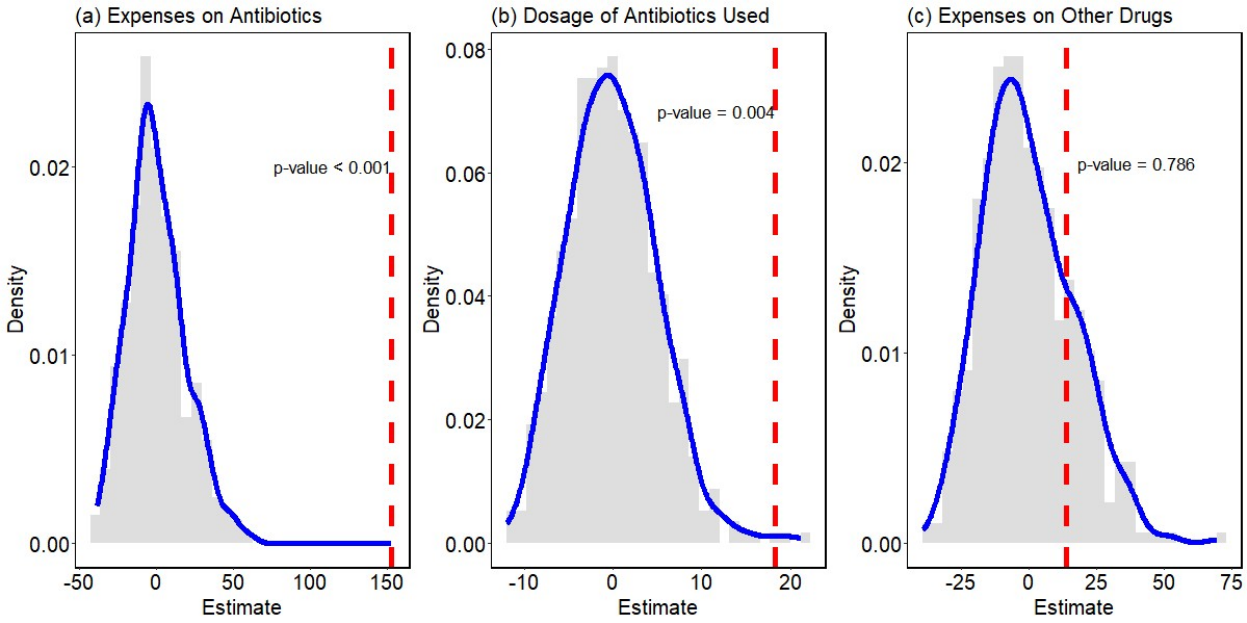


Figure 4 Permutation Test – Distributions of Estimates for 500 Repetitions

Note: This figure presents permutation test results displaying distributions of estimated effects from 500 randomized permutations. Vertical dashed lines indicate the actual observed estimates. Statistical significance is determined by comparing observed estimates against these empirical distributions.

Table 1 Descriptive Statistics of Farmers in the Sample (N=207)

Variable	Mean	SD	Min	Max
Age	51.53	8.96	28	86
Years of Education	7.95	2.08	0	13
Smoke (Binary)	0.59	0.49	0	1
Years of Experience in Hog Farming	9.16	3.57	3	28
Percentage of Income from Hog Farming	64.71	24.89	8	100
Number of Hogs as of July, 2013	81.87	60.95	0	450
Hog Mortality Rate as of July, 2013	13.19	11.33	0.4	100
Expenses on Antibiotics as of July, 2013	7.17	14.6	0	166.67
Expenses on Antibiotics as of July, 2014	1.81	4.82	0	55.56
Dosage of Antibiotics Used as of July, 2013	1.2	0.53	0.5	6
Dosage of Antibiotics Used as of July, 2014	1.13	0.44	0.5	3
Expenses on Other Drugs as of July, 2013	9.11	8.64	0	47.62
Expenses on Other Drugs as of July, 2014	1.71	2.54	0	23.81

Note: This table presents descriptive statistics of the sampled hog farmers at baseline (July 2013). Variables include farmer demographics, farm characteristics, antibiotic expenditures, dosages, and other drug expenditures, providing a baseline overview of sample heterogeneity.

663 **Table 2 Participants versus Non-participants in the Baseline Period**

Variable	Non-Participants	Participants	p-value
Age	50.871	51.761	0.435
	(0.682)	(0.911)	
Education	7.882	8.120	0.382
	(0.160)	(0.218)	
Smoke	0.653	0.533	0.061
	(0.037)	(0.052)	
Experience	9.018	9.391	0.405
	(0.298)	(0.334)	
Income Ratio	63.153	60.435	0.397
	(2.046)	(2.465)	
Number of Hogs in July, 2013	81.871	77.75	0.634
	(5.850)	(6.373)	
N	170	92	

664 *Note:* This table reports the comparison of baseline characteristics (July 2013) between insurance
665 participants and non-participants, including statistical tests (p-values) indicating balance across the two
666 groups.

Table 3 Unconditional Difference-in-Difference Estimates

Expenses on Antibiotics (N = 524, Two Periods)	N	Before	After	Difference
Participants				
		(0.636)	(0.489)	(0.803)
Non-Participants	170	7.807	1.320	-6.487
		(1.222)	(0.336)	(1.267)
Difference in Differences (DID)				4.309
				(1.810)

Dosage of Antibiotics Used (N = 502, Two Periods)	N	Before	After	Difference
Participants	87	1.149	1.305	0.155
		(0.066)	(0.062)	(0.091)
Non-Participants	164	1.247	1.131	-0.116
		(0.046)	(0.027)	(0.053)
Difference in Differences (DID)				0.271

Expenses on Other Drugs (N = 516, Two Periods)	N	Before	After	Difference
Participants	92	11.218	2.254	-8.965
		(1.137)	(0.354)	(1.191)
Non-Participants	166	7.733	1.233	-6.500
		0.618	(0.112)	(0.628)
Difference in Differences (DID)				-2.465
				(1.217)

Note: This table reports unconditional difference-in-differences (DID) estimates of antibiotic expenses (yuan per hog) (Panel A), dosage (Panel B), and expenses on other non-antibiotic drugs (yuan per hog) (Panel C), comparing insurance participants and non-participants before and after the insurance intervention. Standard errors (S.E.), reported in parentheses, indicate statistical significance of observed differences.