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Estimating effects of cooperative membership on farmers' safe production behaviors: Evidence from pig sector in China

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ABSTRACT

This research studies the determinants of pig farmers' participation in farmers' cooperatives and the effects of farmers' cooperatives on pig farmers' behaviors in adopting safe production practices using data from a household survey of 540 cooperative farmers and 270 non-cooperative farmers from four main pig production provinces in China. The propensity score matching (PSM) method was adopted to deal with possible self-selection bias associated with farmers' participation in farmers' cooperatives due to observables, which is further supplemented by a sensitivity analysis to assess the degree to which the PSM results are robust to the presence of unobservables. The PSM results show that the cooperative membership has significant and positive influence on farmers' propensity to adopt safe production practices and the effects are heterogeneous across a number of key cooperative, farm and household attributes. Specifically, the membership effects tend to be bigger for cooperatives led by Investor-owned firms (IOFs) and farms of small production scale. And the effects tend to be greater for households (1) of medium and high level of education, (2) of less than 10 years of pig production experience, (3) of no off-farm job experience, and (4) that are specialized in pig production. The sensitivity analysis further increases our confidence in the results for the feed use and the breed use, however, the results for vaccination, drug use and waste disposable are more sensitive to the influence of unobservables, therefore should be interpreted with caution.

1. Introduction

With the emergence of large-scale farms, agricultural conglomerates and modern marketing companies, smallholder farm production in developing countries has been increasingly challenged in terms of access to modern agricultural inputs, technologies, and markets (Dorward et al., 2004; Markelova et al., 2009). To address these challenges, governments of many developing countries have taken measures to facilitate smallholders to form collective action groups to improve their production and marketing performances (Fischer and Qaim, 2012; Abebaw and Haile, 2013). Agricultural cooperatives have widely been viewed as an effective means to help farm households access inputs at lower prices, enhance market linkage and bargaining power, improve production skills, raise agro-food safety and quality standards, and shield against risks (Barton, 1989; Fulton, 1995; Hellin et al., 2009; Nilsson 1998; Xu et al., 2013).

Correspondingly, there has been an explosion of research on the determinants and impacts of farmers' cooperatives in developing countries, especially in the past decade or so. The existing studies on impacts of farmers' cooperatives are mainly focused on impacts of farmers' cooperatives on farm income, productivity, price, household welfare (Ma and Abdulai, 2016; Chagwiza et al., 2016; Ma and Abdulai, 2017; Mojo et al., 2017; Verhofstadt and Maertens, 2015), and farmers' behaviors in adopting technologies (Abebaw and Haile, 2013; Wossen et al., 2017) and farm inputs (Ma et al., 2018). Despite the growing importance of food safety concerns in developing countries and the increasing discussions on the potential effects of farmers' cooperatives on food safety and quality (Moustier et al., 2010; Naziri et al., 2014; Liu et al, 2009; Ji et al., 2018), rigorous evidence-based research on the effects of farmers' cooperatives on food safety and quality is scant (though emerging in recent years).

Among the limited literature linking farmers' cooperatives and food safety issues, past research has focused on the role of: (1) farmers' cooperatives in farmers' adoption decisions of food safety standards (Kirezieva et al., 2016; Zhou et al., 2015), (2) production scale (Zhong et al., 2016; Wang et al., 2011), (3) farmers' socio-economic and demographic characteristics (Zhang and Fu, 2016a, 2016b; Tong et al.,

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2011), and (4) government's control policies (Huang et al., 2016; Li et al., 2015). However, the potential effects of cooperative membership on farmers' safe production behaviors are rarely studied. For the few studies that attempted to relate farmers' cooperatives to farmers' safe production behaviors (Wang, 2009; Moustier et al., 2010; Wang and Wang 2012; Yuan et al., 2018), they tend to suffer from methodological and data problems. These studies typically estimated simple logit/probit models, or linear OLS models without addressing the self-selection bias problems, and the sample sizes of these studies are small.

This paper aims to contribute to the scant literature on effects of farmers' cooperatives on individual farmers' safe production behaviors by rigorously examining the causal effects of farmers' cooperative membership on pig farmers' safe production behaviors using data from 810 pig farms (540 cooperative farmers and 270 non-cooperative farms). We attempt to fill in this knowledge gap by addressing a couple of related issues. First, we investigate whether and the extent to which pig farmers' participation in farmers' cooperatives affects their safe production behaviors. Second, we are also interested in exploring the potential heterogeneous effects of cooperatives on pig farmers' production behaviors across production scales, different types of cooperatives and other farm level characteristics (i.e., level of education, off-farm job experience, experience in pig production, degree of specialization in pig production).

To deal with the fact that pig farmers who are members of farmers' cooperatives are likely to be different from those who are not, we employ the propensity score matching (PSM) method, a commonly used matching method to address self-selection bias on observables. Our PSM analysis highlights a few important findings. (1) Our results indicate that cooperative membership has significant and positive effects on farmers' safe production behaviors. (2) Our results also show that the impacts of cooperative membership vary with production scale and a number of other attributes of individual farms. Specifically, the positive impacts of cooperatives on safe production behaviors are bigger for small farms, for farms with head of little production experience and for those with head of lower levels of education. (3) Agricultural cooperatives initiated by IOFs are more effective in influencing member farmers' behaviors in adopting safe production practices, and a higher level of member heterogeneity is generally associated with larger effects of farmers' cooperatives on farmer's safe production behaviors. (4) A sensitivity analysis confirms that the PSM results are not sensitive to the presence of unobserved factors in cases of feed use and breed use, but more sensitive in cases of vaccination, drug use and waste disposal, suggesting caution is warranted in the interpretation of the results for the latter three production practices.

The reminder of the paper is structured as follows. Section 2 presents the background of the study with focus on the literature review of studies on farmers' cooperatives and discussion of the possible channels through which farmers' cooperatives could affect farmers' production behaviors. Section 3 discusses PSM method. Section 4 presents study sample, data and descriptive analysis. Section 5 presents the empirical results, followed by a conclusion in Section 6.

2. Background

2.1. Pig production in China

Pig industry plays a dominant role in China's livestock sector. China is the largest pig producer in the world and pork production reached 52.99 million tons by the end of 2016 (China Livestock Yearbook, 2017). Meanwhile, Chinese resident consume more pork than any other types of meat, and its consumption accounts for more than 60% of total meat consumption (National Bureau of Statistics of China, 2015). Pork safety incidents (including several high profile scandals[1]) occurred frequently over the past 10 years and pork safety remains a major concern for Chinese consumers (Ortega et al., 2011). Pig production is a comprehensive process involving multiple production practices such as feed use, breed use, vaccination, drug use, and waste disposal, each of which can potentially introduce pork safety hazards. Despite a rapid increase in the number of large-scale pig producers, small pig producers still dominate pig production in China. How to ensure a myriad of small pig farms to produce high quality and safe pork is a top policy priority of Chinese government.

2.2. Farmers' cooperatives in China

Chinese government encouraged the development of farmers' cooperatives with its promulgation of the Law of Farmers' Professional Cooperatives in 2007, which led to a total of 1.3 million farmers' cooperatives in China by the end of 2014 (Industrial Operations and Management Yearbook of China Rural Area, 2015). The rapid growth of farmers' cooperatives in rural China has also generated great interests among scholars to study various aspects of this rapidly emerged rural organization. Based on two recent review articles on farmers' cooperatives in China (Xu et al., 2013; Dong, 2014), the number of papers published on Chinese farmers' cooperatives is large and growing. Despite the emerging literature on the determinants and impacts of the farmers' cooperatives in China, there is no rigorous study on the effects of farmers' cooperatives on farmers' safe production behaviors. Based on our knowledge, this is the first study that rigorously analyzes the effects of cooperative membership on pig farmers' safe production behaviors using PSM method and data from a large number of cooperative and non-cooperative pig farms from geographically representative provinces in China.

2.3. Cooperative membership and farmers' safe production behavior

It can be hypothesized that farmers' cooperative membership would influence farmers' safe production behaviors through a number of channels. *First*, it is argued that farmers' collective action plays an important role in promoting quality, primarily because it facilitates access to training resources (Moustier et al., 2010), which is shown to have effect on farmers' behaviors in producing pigs in a safe manner (Wang, 2009). Fischer and Qaim (2012) found that collective action taken by farmers' organizations in Kenya could improve farmers' access to agricultural assets as well as credit, improve farmers' income and technology adoption. Naziri et al. (2014) argued that collective action may facilitate the access of small farmers to demanding markets in terms of safety, primarily through increasing farmer capacity to undertake joint investments, providing farmers with information, technical assistance and proper inputs, making possible vertical integration or contract farming; and building favourable conditions for the establishment of public-private partnerships.

Second, Wu et al. (2015) found that the main reason why farmers are not willing to use feed of high quality from more reliable sources is the high price. Therefore, bulk purchasing by cooperative members would help farmers acquire feed products of high quality at a relatively lower price due to the economies of scale associated with the group purchasing (Fischer and Qaim, 2012). Similarly, bulk purchasing of breed piglets by members of the same cooperative would incentivize individual member farmers to purchase high quality breeds at a more affordable price.

Third, cooperatives' marketing service is critical for farmers to access the market (Hellin et al., 2009; Mojo et al., 2017), and it assists

[1] Some notorious pork safety scandals include: clenbuterol have been detected in branded pork products (Yurun 2009; Shineway 2011; Jinluo 2015); Pigs died of sickness found in the market selling to consumers (Shandong province, Hunan province); Pigs died of sickness have been directly discharged to rivers (Zhejiang Province, Shanghai, 2013).

(*footnote continued*)

farmers in achieving more stable sales and possibly at a better price. When selling their products via cooperatives by contracts, farmers not only reduce opportunistic behaviors in production (Staatz, 1987; Ji et al., 2012), they are also more willing to abide by the best practice codes required by the cooperative because they expect to generate better sales income. A study using data from Vietnam found that the vegetable cooperatives failed to help farmers correctly use pesticide, and the main reason is that the cooperatives did not help their members market their products through the market channels of high safety standard (Van Hoi et al., 2009). Therefore, whether marketing services are provided by a cooperative could influence on farmers' safe production behaviors because such services reduce their opportunistic behaviors and safer production practices would also guarantee better sales' revenue.

Different types of cooperatives may affect farmers' production behaviors through different channels. For example, the objectives of cooperatives led by farmers are primarily to reduce production cost by bulk purchase of feed and piglets and to sell pigs via more marketing channels (Ji et al., 2018). And for the cooperatives led by investor-owned firms (IOFs), their objectives are likely to be different from those of the cooperatives led by farmers. More specifically, IOF-led cooperatives have three specific objectives (Ji et al., 2017). The first objective is to ensure quality and safety of pork meat. To achieve this objective, IOFs strictly regulate farmers' production practices including feed use, vaccination, drug use, and waste disposal. The second objective of IOF-led cooperatives is to ensure a stable pig supply. The third objective of IOF-led cooperatives is to help lift poor pig farmers out of poverty. While safety production practices are implied in all three objectives, the first object is more directly related to the farmers' safe production behaviors.

While we would like to detect the existence (or lack thereof) of each mechanism in our analysis, our data does not allow us to do so. Nonetheless, the discussion on the possible mechanisms of the cooperative effects herein provides us a foundation to understand the expected direction of the effects of cooperative membership on pig farmers' adoption of safe production practices. Accordingly, we will interpret the estimated effects as the net outcome through all the possible mechanisms.

3. The evaluation problem and matching methods

3.1. The evaluation problem

Let Y_i^M be the safe production behaviors of pig farmer *i* if the farmer is a member of a farmers' cooperative ("treated"), and Y_i^{NM} the safe production behavior of the same farmer *i* if the farmer is not a member of a farmers' cooperative ("control"). According to Rosenbaum and Rubin (1983), the treatment effect of being a cooperative member can be simply defined as

$$T_i = Y_i^M - Y_i^{NM}. \tag{1}$$

In estimating Eq. (1), a problem arises because we can observe either Y_i^M or Y_i^{NM}, but not both of them for each individual farmer *i* at the same time. This is a classical impact evaluation problem, which is also known as a missing data (counterfactual) problem.

Various empirical impact evaluation methods including propensity score matching (PSM) were developed to address this missing data problem. In practice, one hopes to use the observed data from the treatment group (in our case, a group of cooperative members) and the control group (a group of non-cooperative members) to perform the evaluation. For example, having data from both cooperative farmers (D = 1) and non-cooperative farmers (D = 0) allows one to compute $\mathrm{E}(Y_i^M|D=1) - E(Y_i^{NM}|D=0)$, which can be easily decomposed into $E[(Y_i^M - Y_i^{NM})|D=1]$ and $[E(Y_i^{NM}|D=1) - E(Y_i^{NM}|D=0)]$ by adding and subtracting a same term, $\mathrm{E}(Y_i^{NM}|D=1)$. The term $E[(Y_i^M - Y_i^{NM})|D=1]$ is the average treatment effect on the treated (ATT), which is what we want. The other term, $[E(Y_i^{NM}|D=1) - E(Y_i^{NM}|D=0)]$, is the pre-existing difference between the member farmers and the non-member farmers, commonly known as selection bias. Except for the case where members and non-members are assigned randomly, the selection bias is unlikely to be zero. Different evaluation methods are developed to eliminate or minimize the selection bias.

3.2. Propensity score matching method

As one of the popular evaluation methods, the basic idea of matching is to find in a large group of nonmember farmers who are similar to the member farmers in all relevant pre-treatment characteristics X.[2] The problem is that matching member farmers to non-member farmers can be unmanageable when the number of characteristics in X is large. Rosenbaum and Rubin (1983) showed that PSM can overcome this matching problem under certain assumptions. Specifically, PSM method summarizes the pre-treatment characteristics of each subject into a single index variable, and then match members to nonmembers according to the estimated index (i.e., the propensity scores). The PSM, this is the probability of assignment to treatment conditional on pre-treatment variables, is given by:

$$\mathrm{p(X)} = \Pr[D=1|X], \tag{2}$$

where X is a vector of pre-treatment characteristics.

Once the propensity score is estimated, the ATT can then be estimated as follows:

$$\begin{aligned}\mathrm{ATT} &= E(Y_i^M|\mathrm{D}=1) - E(Y_i^{NM}|D=1)\\ &= E(Y_i^M|\mathrm{D}=1) - E\{E(Y_i^{NM}|D=0, P(D=1|X))|D=1\}\\ &= E\{[E(Y_i^M|D=1, P(D=1|X))\\ &\quad - E(Y_i^{NM}|D=0, P(D=1|X))]|D=1\}\end{aligned} \tag{3}$$

The key assumption underlying PSM is the conditional independence assumption (CIA), or the condition of un-confoundedness, which means that after conditioning on all the relevant covariates (X), participants would have the same potential outcome as non-participants if participants had not participated in the program. To make sure the CIA is not violated, we include as many control variables as we can. For some variables, both the linear and the square terms are included.[3]

There are several methods to match similar member farmers and nonmember farmers. The most commonly used approaches are the nearest neighbor matching (NNM) and kernel-based matching (KBM) methods. The nearest neighbor method consists of matching each treated individual with the control individual that has the closest propensity score(s). It is usually applied with replacement in the control units especially in the case when the number of observations in the control group is relatively smaller.

The differences of each pair of matched units is then calculated, and finally the ATT is obtained as the average of all these differences. In the kernel-based method, all treated subjects are matched with a weighted average of all controls, using weights that are inversely proportional to the distance between the propensity scores of treated and control groups. This study adopts these two methods to estimate the ATT

[2] Ideally, one would want to collect data on the pre-treatment variables through a baseline survey. Unfortunately, the baseline survey was not implemented so we had to rely on what we have. While this is not ideal, we are fortunate to have collected data for a set of household characteristics variables (head's age, head's gender, household size, production experience, level of education, production scale at the time of joining cooperatives) that are either time invariant or allow us to generate pre-treatment variables that could potentially affect farmers' participation in agricultural cooperatives and/or their production behaviors.

[3] The final specification of the logit model took into consideration of a number of metrics including the CIA assumption, the range of overlap in propensity scores across the treatment and control groups, and the balance of covariates between the treatment and comparison groups after matching.

effects. The reliability of the matching estimates is largely dependent on the quality of matching (e.g., the balance of the pre-treatment variables between the treatment and control groups after matching, overlapping region). Both criteria will be checked in our paper.

4. Data and descriptive statistics

4.1. Sample and data

The data used in our analysis were collected from pig farmers from 4 provinces (Zhejiang, Anhui, Sichuan, Shandong), each of which was randomly drawn from one of the four major pig production regions – coastal region, inner-middle region, southwestern region and the new emerging northwestern region (MOA, 2009). The four major pig production regions produce 90% of the total pig production in China (China Livestock Yearbook, 2017). From each of the four sample provinces, we randomly selected two pig production prefectures, and in each prefecture, 3–4 cooperatives were randomly selected. And 20 cooperative pig farmers were randomly chosen from each of the selected cooperatives.[4] As a result, a total of 540 cooperative farmers from 27 cooperatives were interviewed and they form the treatment group in the study sample. Based on the discussion in the method section, our analysis would also need data from non-cooperative farmers that will be the control group. Guided by the principal that the control households should be as comparable to treatment households as possible, we randomly chose 270 non-cooperative farmers from villages that have similar level of per capita income to the villages where the member farmers were drawn. We also restricted the villages where non-cooperative farmers were drawn to have no single cooperative of pig production and to be adjacent to villages where the cooperative farmers were drawn.

Data collection was implemented from September 2015 to June 2016 simultaneously by two research teams. The geographic distribution of the 27 cooperatives could be found in Fig. 1. Among the 27 pig cooperatives, 22 are led by pig farmers, two are led by vertically integrated pork feed companies, one is led by feed production company, another one by pig production company, and another one by pig slaughtering company.

4.2. Variables description

Based on review of relevant literature and interviews with experts in the animal science field, we use five indicators to measure farmers' safe production behaviors that include farmers' behaviors in feed use, in breed use, in vaccination, in drug use, and in production waste disposal (Plumed-Ferrer and Von Wright, 2009; Missotten et al., 2015; Nicholsen et al., 2007; Prapaspongsa et al., 2010; McGlone, 2001; Liu et al.,2009). For each indicator, the safety level can be affected by two aspects: (1) whether or not the input sourcing channel meets the safety and quality standards, and (2) whether or not a pig farmer strictly follows the recommended method of production practices. However, for a given indicator, one aspect may be more important than the other or the information on one aspect may be easier to collect than on the other. Therefore, what specific information is collected in the field survey depends on which one of the two aspects could better reflect farmers' safe production behaviors. Our final decision on what information to collect in our survey based on opinions of experts in the animal science field and what we learned from pre-survey interviews with a group of pig farmers. In cases of feed use and breed use, we focus on collecting information on the reputation of input sourcing channels. And in cases of vaccination use, drug use and disposal of production wastes, we focus on gathering information on application methods. Column 2 of Table 1 provides the exact definition for all the key variables including the five behavioral variables.[5]

4.3. Descriptive evidence

Table 1 presents the basic statistics of the key variables used in our analysis by membership status. The descriptive evidence shows that the household head of an average pig farm in our sample is a middle-aged male with an average level of education around 8–9 years. An average pig farm in the study sample is endowed with a little more than three laborers and has more than 11 years of pig production experience. The production scale of an average pig farmer in the sample is between 300 and 400 heads per year, which is a medium-scale pig producer in China. Overall, more than 45% of the pig farmers are also engaged in crop (i.e. corn, wheat, rice, etc.) production.

A simple cross-tabulation of the key variables by the cooperative membership status allows us to compare the household characteristics and the behavioral outcomes between the cooperative farmers and non-cooperative farmers. A few interesting findings are worth highlighting here. First, we note that the head's level of education is significantly higher for cooperative farmers than for non-cooperative farmers (9.16 vs 8.53 years), though the magnitude of difference is still small. Second, the cooperative farmers (vs. non-cooperative farmers) are endowed with more family laborers. Third, the cooperative farmers (vs. non-cooperative farmers) are more likely to be engaged in off-farm job and have higher likelihood to be village leaders. The finding of significant difference in a subset of household characteristics variables between cooperative and non-cooperative farmers tends to support the fact that participation in farmers' cooperative is a voluntary and self-selection process, which further suggests the need to use a method that accounts for selection in evaluating the impact of cooperative membership on safety production behaviors.

Concerning the five production behavioral variables, our descriptive analysis shows that the share of farmers engaged in safe production behaviors is just a little over half (ranging from 50% in cases of breed use and waste disposal to 58% in the case of drug use), pointing toward a considerable potential for improvement. Meanwhile, our data indicates statistically significant and large difference in proportion of farmers adopting safe production practices between the cooperative farmers and non-cooperative farmers across all five behavioral variables. For example, while 62% of cooperative farmers used feed of nationally and locally renowned brands, only 32% of the non-cooperative farmers did the same. Similarly, for feed use, share of farmers used feed from reliable sources was 56% among the cooperative farmers as compared to 36% among the non-cooperative farmers. The

[4] We contacted the local livestock bureaus of these prefectures and got the checklists of registered pig cooperatives, and cooperatives that do not have any functions were ticked out. Although our data are not representative at the national level, the cooperative households are representative of all the cooperative households of the four important pig production regions due to the randomly selection process. The non-cooperative households, however, are not drawn randomly. Instead, they were drawn to minimize the differences between the cooperative and the non-cooperative households. There is some tradeoff between internal validity versus external validity in the sample selection, which is common in any impact evaluation (Duflo et al., 2007).

[5] Unfortunately, the information on profitability, weight gains, unexpected disease outbreak, and prices of inputs and output was not collected in the survey. This additional information is necessary to show whether adopting safe production practices would lead to better economic outcome for farmers? Or whether adopting these behaviors is because the cooperatives are successful in bargaining prices for output and inputs, which allows members to invest more into safe production practices. While it is impossible to identify the exact channels underlying the differences in safe production behaviors between members and non-members without the additional data, we posit that at least one than one channels (lower input prices, better credit accessibility, standards required by IOFs, collective actions, etc.) reviewed in Section 2.3. In future research, we hope to collect this additional information to allow us to better identify the channels.

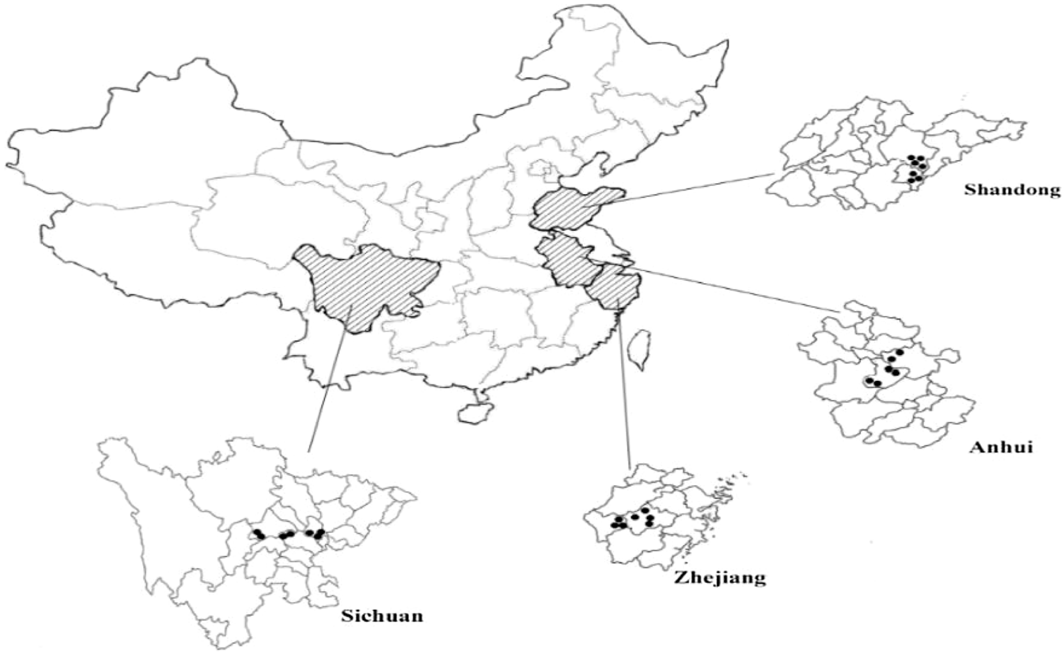

Fig. 1. Regions of the 27 sample pig cooperatives. Note: Sample cooperatives are from Hefei (4), Chu'zhou (2), Qu'zhou (3), Jinhua (4), Weifang (4), Rizhao (3), Chengdu (4), Suining (3).

Table 1
Descriptive statistics of key variables.

Variables	Description	All (1)	Members (2)	Non-members (3)	Difference (2) − (3) (4)	Test for Diff. = 0 (5)
Gender	1 if the household head is male, 0 otherwise	0.89	0.90	0.88	0.02	
Age	Age of household head (years)	47.32	47.58	46.79	0.79	
Education	Maximum education level of household members (years)	8.95	9.16	8.53	0.63	***
Household labor	Number of household members who are able to work on farm	2.59	2.74	2.29	0.45	***
Off-farm job experience	1 if a farmer has off-farm job experience, 0 otherwise	0.16	0.20	0.09	0.11	***
Village cadre	1 if the head is a village cadre, 0 otherwise	0.28	0.34	0.15	0.19	***
Production experience	# of years a farmer has been engaged in producing pigs	11.96	12.07	11.72	0.35	
Crop production	1 if a farmer has crop production, 0 otherwise	0.48	0.48	0.47	0.01	
Production scale	Pigs fattened by the end of the production year	382.35	381.70	383.63	−2.07	
Feed use	1 if feed was from nationally/locally renowned brands, 0 otherwise	0.52	0.62	0.32	0.30	***
Breed use	1 if the breeds are either from breeding companies with industrial and commercial registration or from its own farm. 0 otherwise	0.50	0.57	0.37	0.20	***
Vaccination use	1 if farmer uses vaccination according to the epidemic disease environment of his farm, 0 otherwise	0.56	0.61	0.46	0.15	***
Drug use	1 if farmer uses drug strictly according to the instruction of the prescription, 0 otherwise	0.58	0.63	0.47	0.15	***
Wastes disposal	1 if farmer disposes production wastes into methane/organic fertilizer, 0 otherwise	0.50	0.56	0.39	0.17	***

Data source: Authors' own computation based on own survey data.
***, **, * denote significance at 1% level, 5% level, and 10% level, respectively.

share of households engaged in safety production behaviors are also much larger among member farmers (vs. non-cooperative farmers) in terms of vaccination use (61% versus 46%), drug use (63% versus 47%), and disposal of production wastes (56% versus 39%). The co-existence of similar farm characteristics but consistent and huge gaps (from 17 to 29 percentage points) in all the production behaviors between the member farmers and non-member farmers points toward possible large effects of cooperative membership on farmers production behaviors. To rigorously verify this possible causal relationship, we will rely on the matching analysis the results of which are presented in the following section.

Table 2 compares the proportion of farmers who are engaged in safe production behaviors between the cooperative farmers and non-cooperative farmers, and across each of the three production scale categories. We divide the production scale into small scale (≤100 heads), medium scale (101–500 heads) and large scale (> 500 heads). Overall, the proportion of farmers who are engaged in safe production behaviors is bigger among cooperative farmers than non-cooperative farmers across all scale categories and for all the five behavioral variables. There also exist considerable variations in terms of the magnitude of differences across the production scales. For example, it is clearly evidenced that the difference is most prominent among farmers of small production scale and least noticeable for large scale farmers across all five behaviors. In fact, while the difference is significant at 1% among the small farmers for all five indicators, feed use is the only production behavior for which the difference is significant among large scale farmers.

In Table 3, we further divide farmers' cooperatives into three categories by ways how they are organized. Specifically, we define cooperatives that are composed of farmers of the same production scale as

Table 2
Safe production behavioral differences between cooperative member farmers and nonmember farmers by different production scale groups.

Production behaviors	Size category[a]	Members (1)	Non-members (2)	Difference (1) − (2) (3)	Test for Diff. = 0 (4)
Feed use	Small (≤100 heads)	0.55	0.15	0.40	***
	Medium (101–500 heads)	0.60	0.27	0.33	***
	Large (> 500 heads)	0.73	0.53	0.20	***
Breed use	Small (≤100 heads)	0.45	0.18	0.27	***
	Medium (101–500 heads)	0.52	0.33	0.19	***
	Large (> 500 heads)	0.75	0.61	0.14	
Vaccination use	Small (≤100 heads)	0.53	0.29	0.24	***
	Medium (101–500 heads)	0.53	0.41	0.12	
	Large (> 500 heads)	0.79	0.68	0.11	
Drug use	Small (≤100 heads)	0.58	0.29	0.29	***
	Medium (101–500 heads)	0.53	0.40	0.13	
	Large (> 500 heads)	0.80	0.72	0.08	
Wastes disposal	Small (≤100 heads)	0.41	0.10	0.31	***
	Medium (101–500 heads)	0.52	0.32	0.20	***
	Large (> 500 heads)	0.78	0.74	0.04	

***, **, * denote significance at 1% level, 5% level, and 10% level, respectively.
[a] The number of member farmers belonging to the small scale, medium scale and large scale farmers are, respectively 193, 176, and 171; and the corresponding numbers for non-member farmers are 94, 82, and 94.

Table 3
Farmers' safe production behavior differences among different types of cooperatives.

Safe production behaviors	Cooperative category (I)	Cooperative category (II)	Cooperative (III)
Feed use behavior	0.56	0.64	0.78
Breed use behavior	0.57	0.50	0.68
Vaccination use behavior	0.61	0.57	0.69
Drug use behavior	0.63	0.51	0.82
Production wastes disposal behavior	0.54	0.55	0.66

Data source: Authors' own computation based on own survey data.

Category I.[6] We define cooperatives that are composed of farmers of mixed production scales as Category II. And we define cooperatives that are organized by Investor-Owned-Firms (IOF) as Category III cooperatives. The cooperative farmers of this last category are small or medium sized pig producers organized by IOFs. Among the 27 study cooperatives, 14 belong to Category I cooperatives with six being organized by small-scale farmers and eight by large-scale farmers, 8 belong to the Category II cooperatives and 5 belong to the Category III cooperatives. It is evident in Table 3 that safe pig production behaviors are different across different categories of cooperatives with Category III cooperatives performing better than cooperatives of the other two categories.

5. PSM results and discussions

5.1. Logit model on determinants of participation in farmers' cooperative

To derive the propensity scores (PS) to be used to match cooperative farmers with non-cooperative farmers, we estimate a logit model. The dependent variable of the logit model takes value one for famers who have participated in farmers' cooperatives and zero for the others. The explanatory variables include a set of predetermined household and farm characteristics that could influence farmers' participation in cooperatives or the outcome variables (i.e., the five behavior variables related to food safety). While the main purpose of the logit model estimation is to obtain propensity scores, the estimated results are also worth of discussion as identifying factors affecting participation in farmers' cooperatives is important from both the practical and policy perspectives.

The logit model results are reported in Table 4. The regression results largely reconfirm the descriptive findings that education, household labor endowment, the household head's off-farm job experience, the head's political status, and the scale of pig production are the key determinants of farmers' participation in farmers' cooperatives. To facilitate the interpretation of the effects of variables that are statistically significant on participation in farmers' cooperatives, we also present the associated marginal effects. A few important results are worth more discussions.

First, an additional year of education would increase the likelihood of an average pig farmer to participate in a farmer's cooperative by 4%. This result is not too surprising as it is documented in the literature that a certain level of education is needed in order for farmers to benefit from farmers' cooperatives (Chagwiza et al., 2016; Ma and Abdulai, 2016).

Second, having off-farm job experience and being a village leader would increase an average farmer's likelihood to participate in agricultural cooperative by 20% and 25%, respectively. These findings may be explained by the fact that famers with off-farm job experience may be more open to accept new organizations and that the information about and benefit from agricultural cooperatives tend to vary across farmers with different social and political backgrounds (Abebaw and Haile, 2013; Mojo et al., 2017).

Third, the likelihood for an average small-scale (100 pigs or less) and medium-scale (100–500 pigs) farms to participate in agricultural

[6] The production scale was defined earlier in the descriptive analysis section. The production scale is divided into three categories – small scale, medium-scale and large-scale. So for each of the type I category cooperative is composed by pig farmers of the same production scale (either small, or medium or big).

Table 4
Logit model results of factors determining cooperative membership.

Variable	Cooperative		
	Coefficient	Clustered Standard Error	Marginal effect
Gender	0.020	0.242	0.004
Age	0.104*	0.055	0.022*
Age squared	−0.001	0.001	0.000
Education	0.188***	0.028	0.040***
Household labor	0.971***	0.294	0.205***
Household labor squared	−0.079**	0.042	−0.017**
Off-farm job experience	0.979***	0.126	0.207***
Village cadre	1.169***	0.156	0.247***
Small scale	0.601***	0.186	0.127***
Medium scale	0.372***	0.140	0.079***
Production experience	−0.030**	0.014	−0.006**
Production experience squared	0.001***	0.000	0.000***
Crop production	0.090	0.127	0.019
Anhui	0.129	0.094	0.027
Zhejiang	0.499***	0.173	0.105***
Shandong	0.362***	0.100	0.077***
Constant	−6.746	1.343	−1.426
Observations	810		
Pseudo-R^2	0.12		

The standard errors have been corrected for the clustering effects at the village level.
***, **, * denote significance at 1% level, 5% level, and 10% level, respectively.

cooperatives is respectively, 13 and 8%, higher than that of an average large scale farm (more than 500 pigs). This is also expected as a small scale farm is more likely to benefit from the collective action than a big scale farm which has better ability to access credit, inputs and market information due to its scale economy (Ito et al., 2012; Ma et al, 2018).

Fourth, the quadratic relationship between number of laborers and participation in agricultural cooperatives suggests that the probability of participation initially increases as the number of laborers increases, but the probability decreases as the number of laborers further increases. The relationship between farmers' participation in agricultural cooperative and farmer's production experience is also quadratic but it is in the opposite direction. For example, for households with production experience below 15 years, its likelihood to participate in cooperative is negatively correlated with the experience in pig production. It makes sense that the farmers with more experience in production are less interested in getting help from cooperatives.

5.2. Matching quality

Before we present the matching estimates on the effect of participation in farmer's cooperative on farmers' production behaviors, it's important to check the quality of the matching. Following the relevant literature, we measure the matching quality by evaluating the following three metrics: (1) how well the key pre-treatment variables are balanced between member and non-member farmers before and after matching; (2) the degree to which the overall bias is reduced due to matching; and (3) how well the predicted scores are overlapped between the member and non-member farmers. All the three criteria point toward high quality of the matching.

First of all, while five characteristics variables (education, household labor, household squared, off-farm job experience, and village cadre dummy) are significantly different at 1% between the member and non-member farms before the matching, all of them are insignificant after matching (Table 5).

Second, the results from the overall joint test for all the key characteristics variables to be the same between the member and non-member farmers change from very significant (with p-value = 0.00) prior to matching to very insignificant after matching (with p-value = 0.789 in the case of NNM matching method and 0.989 in the KBM matching method) (Table 6).

Finally, the distribution of predicted propensity scores for the members and non-member farmers shows a large common support of propensity scores between the member and non-member farmers. As a result, only 7 observations off support in control group and 36 observations off support in treatment group, and all the 49 observations not in the common support region are excluded from the analysis (Fig. 2). The high quality matching increases our confidence in the matching estimates.

Table 5
PSM quality indicators before and after matching.

Variables	Unmatched	% |bias| reduction		*t*-Test (P > |t|)	
	Matched	NNM	KBM	NNM	KBM
Gender	U			0.421	0.421
	M	46.4	−32.9	0.607	0.215
Age	U			0.236	0.236
	M	82.6	97.1	0.810	0.967
Age squared	U			0.224	0.224
	M	76.7	98.1	0.743	0.978
Education	U			0.000	0.000
	M	85.7	84.0	0.529	0.474
Household labor	U			0.000	0.000
	M	85.9	87.3	0.363	0.392
Household labor squared	U			0.000	0.000
	M	78.3	86.7	0.243	0.461
Off-farm job experience	U			0.000	0.000
	M	89.5	79.2	0.614	0.314
Village cadre	U			0.000	0.000
	M	95.9	95.2	0.785	0.751
Small scaled	U			0.795	0.795
	M	−28.6	69.3	0.691	0.925
Medium scaled	U			0.523	0.523
	M	−60.7	79.9	0.233	0.880
Production years	U			0.596	0.596
	M	−177.4	71.0	0.107	0.858
Production years squared	U			0.268	0.268
	M	−47.6	92.5	0.085	0.923
Crop production	U			0.843	0.843
	M	−516.1	28.3	0.146	0.866
Anhui	U			1.000	1.000
	M			0.652	0.946
Zhejiang	U			1.000	1.000
	M			0.272	0.868
Shandong	U			1.000	1.000
	M			0.566	0.489

Matching algorithm: nearest neighbor matching (NNM) and kernel-based matching (KBM).

5.3. Overall effects and heterogeneous effects across propensity scores.

The PSM estimates on the effects of cooperative membership on farmer's safe production behaviors using both NNM and KBM matching methods are reported on Table 7. The analysis based on the entire sample (cols. 1 and 2, Table 7) shows that cooperatives' membership significantly increases a pig farmer's likelihood to adopt safe production behaviors in all respects. The estimated effects for all five production practices regardless of which matching method is used are statistically significant at 1% level of significance except for one case where the level of significance is 5%. To address the fact that multiple outcome variables are tested and all are related, we also report the modified P-

Table 6
PSM quality indicators before and after matching.

All sample	Pseudo R^2 before matching	Pseudo R^2 after matching	$P > x^2$ before matching	$P > x^2$ after matching	Mean standardized bias before matching	Mean standardized bias after matching
NNM	0.120	0.008	0.000	0.789	14.1	5.4
KBM	0.120	0.004	0.000	0.989	14.1	2.6

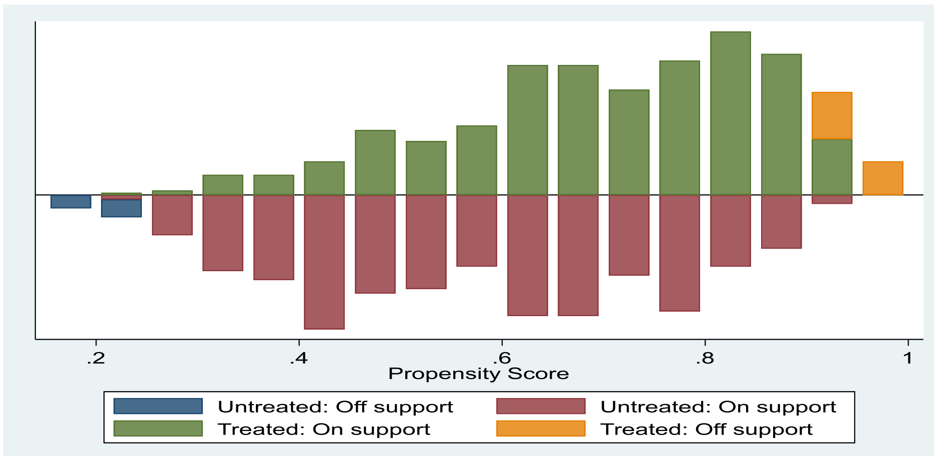

Fig. 2. Propensity score distribution and common support for propensity score estimation.

Table 7
PSM Regression results of behavioral difference between member and nonmembers (NNM estimation and KBM estimation).

Dep. Variable	All sample		Small scale (1-100heads)		Medium scale (> 100–500 heads)		Large scale (> 500 heads)	
	NNM	KBM	NNM	KBM	NNM	KBM	NNM	KBM
Feed use	0.267*** (0.038)	0.241*** (0.041)	0.397*** (0.058)	0.382*** (0.063)	0.318*** (0.068)	0.302*** (0.093)	0.100 (0.068)	0.034 (0.064)
Breed use	0.197*** (0.038)	0.199*** (0.040)	0.266*** (0.060)	0.313*** (0.049)	0.159** (0.079)	0.204** (0.083)	0.151** (0.068)	0.135 (0.088)
Vaccination use	0.150*** (0.040)	0.129*** (0.042)	0.233*** (0.067)	0.280*** (0.077)	0.128 (0.079)	0.099 (0.086)	0.096 (0.064)	0.048 (0.070)
Drug use	0.161*** (0.039)	0.093** (0.039)	0.327*** (0.066)	0.243*** (0.090)	0.105 (0.078)	0.089 (0.102)	0.049 (0.057)	−0.029 (0.050)
Production wastes disposal	0.176*** (0.036)	0.138*** (0.038)	0.299*** (0.051)	0.255*** (0.068)	0.202*** (0.072)	0.229*** (0.076)	0.019 (0.061)	0.001 (0.064)
Balancing property satisfied	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	810	810	287	287	258	258	265	265
Number of treated	540	540	167	193	160	176	157	171
Number of control	270	263	79	80	82	82	94	94

Note: Standard errors in parentheses.
***, **, * denote significance at 1% level, 5% level, and 10% level, respectively.

values that are adjusted for multiple hypotheses (Appendix Table A1). We followed the literature and adopted the Bonferroni and Holm methods, two commonly used adjustment methods (List et al., 2016).[7] While as expected, the adjusted P-values are much bigger than the original P-values, hypothesis testing based on the adjusted P-values does not change the level of significance for any outcome variables (Appendix Table A1) regardless of which adjustment method is used.

With regard to the magnitude of the estimated effects, participation in an agricultural cooperative would increase the likelihood of an average pig farmer to adopt safe production behaviors in feed use, breed use, drug use, production waste disposal and vaccination use by 26.7, 19.7, 15.0, 16.1, and 17.6 percentage points, respectively. Except for drug use behavior where the KBM-based estimate is somewhat smaller than the NNM-based estimate, the estimated cooperative effects for all other four behavioral variables are highly consistent between the two matching methods.

Next, we examine whether and the extent to which the treatment effects vary by the propensity scores (PS). To explore this heterogeneity is important because whether those who have higher likelihood to

[7] Bonferronican multiplicity-adjusted P-values are calculated by multiplying the unadjusted p-values by the total number of hypotheses, which is five in our case. Similarly, the Holm multiplicity-adjusted P-values are obtained by multiplying the smallest unadjusted P-value by the total number of hypotheses (5), multiplying the second smallest unadjusted P-value by one less than the total number of hypotheses (4), and continuing in this fashion until multiplying the largest unadjusted P-value by one.

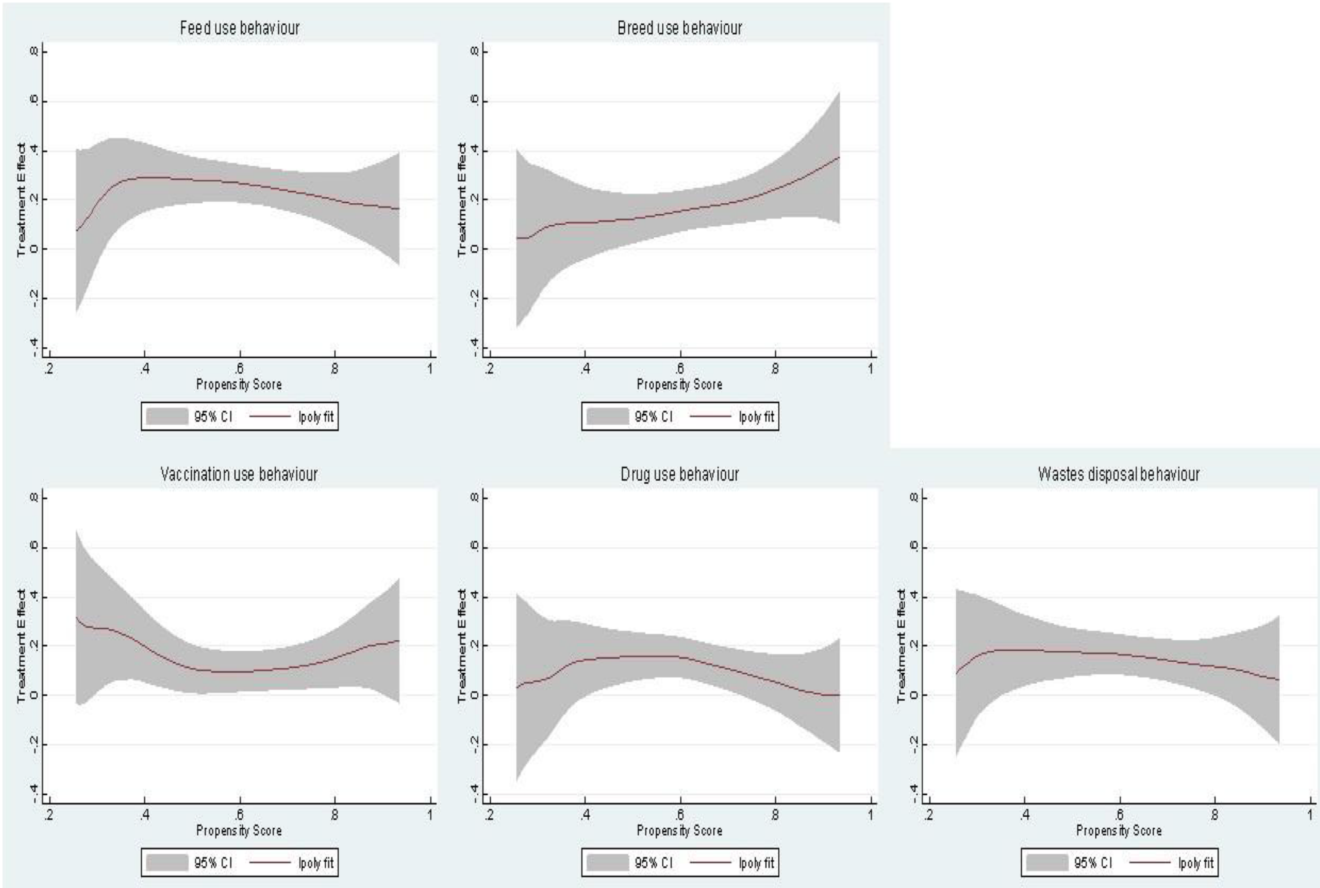

Fig. 3. Heterogeneous treatment effect over p-score.

participate in agricultural cooperatives tend to benefit more (versus less) from the program have different policy implications. Following the advice of Xie et al. (2012), we choose the smoothing-differencing (SD) nonparametric method, which is the most preferred method among all the three methods proposed in their article.[8]

The results based on SD method reveal a number of interesting insight (Fig. 3). First, there is considerable heterogeneity of cooperative effects across PS for all the safety behavior indicators. Second, Fig. 3 shows three distinct patterns across the five behavioral outcomes. The heterogeneity effects for the feed use, the drug use and the waste disposal behaviors share the same pattern where the cooperative effects are bigger and more significant for the mid-range propensity scores with the effects but smaller and less significant toward the two tails. The heterogeneity effects on vaccination use behavior has exactly the opposite pattern as the cooperative effects are bigger and more significant for the mid-range propensity scores than for the scores in the two tails. The case of the breed use behavior markedly differs from the rest in the sense that the cooperative effects increase almost linearly with the propensity scores. Fig. 3 also tends to suggest that the effects on breed use behavior is not only bigger in general, it tends to cover a much bigger range of propensity scores than the other outcome variables. While the heterogeneity effects across propensity scores are insightful, examining the heterogeneous effects across different farm and household characteristics is more intuitive and practical from a policy perspective, which will be the focus next.

5.4. Heterogeneous effects across production scale

To explore the heterogeneous effects across production scales, the PSM results are estimated separately for small-, medium-, and large-scale production groups (cols. 3–5). Analysis using subsamples of different production scales reveals that the cooperative effects on farmers' likelihood to adopt safe production behaviors vary considerably across production scales. In particular, the effects are found to decay with the production scale. For example, while the estimated effects of cooperative membership on farmers' probability to adopt safe production practices in all the five aspects are all highly significant at 1% level of significances for the small-scale farmers, the estimated effects are mostly insignificant for the large-scale farmers except in the case of breed use where the NNM-based result is significant at 5%. The level of significance for the medium-scale farmers falls between the small- and the large- scale farm groups. The results are also consistent across the two matching methods.

Using the adjusted P-values does not alter the story on the existence of heterogeneity effects across production scales in any significant way (Appendix Table A2). While the adjusted P-values do not have any influence on the statistical significance of the estimated cooperative effects among farmers of small scale production, it causes cooperative effects to change from significant to insignificant for 2–3 outcomes for the middle- and large-scale production farmers. In terms of the magnitude of effects, the effects are also bigger for small-scale farmers (the gain in probability of adopting safe production practices due to cooperative membership ranging from 0.23 in the case of vaccination use to 0.40 in the case of feed use according to NNM-based estimates) than the medium scale farmers (from 0.16 to 0.32) and the effects are the smallest for the large-scale farmers (0.019–0.151).

[8] SD method not only avoid the assumption of constant marginal effect within a strata, but also is a much simpler and requires fewer modeling decision (Xie et al., 2012).

Table 8
PSM Regression results of behavioral difference between different types of cooperative member and nonmembers (NNM estimation).

	Cooperative category (I) VS. non-cooperative farmers	Cooperative category (II) VS. non-cooperative farmers	Cooperative category (III) VS. non-cooperative farmers
Dep. Variable			
Feed use	0.137***	0.271***	0.660***
	(0.050)	(0.073)	(0.068)
Breed use	0.144***	0.154**	0.433***
	(0.046)	(0.077)	(0.085)
Vaccination use	0.153***	0.163**	0.300***
	(0.051)	(0.075)	(0.097)
Drug use	0.123***	0.146**	0.340***
	(0.045)	(0.076)	(0.093)
Production wastes disposal	0.0718*	0.213***	0.440***
	(0.042)	(0.071)	(0.081)
Balancing property satisfied	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes
No. of total observation	420	240	150
Number of treated	261	149	75
Number of control	135	80	45

Note: the results are based on matching between cooperative members and non-member farmers surrounded the cooperative. We have also run the tests using matching between cooperative member and all non-member farmers, and the results are basically the same.

5.5. Heterogeneous effects across cooperative categories

As discussed earlier, cooperatives can also be distinguished by their member compositions. Examining how the effects of agricultural cooperatives on farmers' safe production behaviors vary by cooperative's member composition reveals considerable heterogeneous effects across cooperative categories (Table 8). First, while cooperative membership has positive effects on safe production behaviors for all the five outcome variables for cooperatives of all categories, the effects are more significant and larger in magnitude for Category III cooperatives (IOFs) than for the other two categories. For example, while the cooperative effects are statistically significant at 1% for all the outcome variables in the case of Category III, the effects are statistically significant at 1% in four (or two) out of the five outcome variables in cases of category I (or category II).

Using the multiple-hypothesis adjusted P-values reconfirm the vast difference in cooperative effects between category III and the other two categories (Appendix Table A3). Based on the adjusted P-values, the cooperative effects remain statistically significant at 1% throughout all the five outcomes in the case of Category III cooperatives, both the number of significance or the level of significance reduced in cases of either Category I or Category II cooperatives. The magnitude of effects in cases of feed use and breed use is more than twice as bigger for Category III than for the other two categories. Second, while the difference in cooperative effects between Category I and Category II cooperatives is not as pronounced between Category III and the other two categories, the magnitude of effects is a little bigger for Category II than for Category I.

The results in this part of analysis confirms that (1) agricultural cooperatives initiated by IOFs are more effective in influencing member farmers' behaviors in adopting safe production practices, and (2) a higher level of member heterogeneity is generally associated with larger effects of farmers' cooperatives on farmer's safe production behaviors. These findings may be explained as the following. When IOFs started a cooperative of pig producers, one of the main aims is to ensure pig producers to supply IOFs with safer and high quality products through collective action. Meanwhile, the IOFs are capable of providing resources and services to help individual farmers improve their safe production behaviors. Similarly, pig producers of larger scales may also help smaller pig producers in the same cooperative to improve their safe production behaviors, which may be the reason why category II cooperatives perform better than category I cooperatives.

5.6. Heterogeneous effects along the other use indicators

To gain more insights on whether and the extent to which the effects of cooperative membership on farmers' production behaviors vary with farmers' characteristics, we conducted more analysis using data from different subsamples. We focus on four key variables which include head's education, whether or not a farmer was engaged in crop production, head's experience in off-farm wage employment, head's past experience in pig production. The results suggest the presence of considerable heterogeneity of the cooperative effects on farmers' safety production behaviors across farmers' characteristics (Table 9).

First, we note from Table 9 that the cooperative membership has more significant and bigger effects on safe production practices for farmers with more education than those with less education. For example, the effects are significant at 1% level for all the five production practices (or 1% level for four and 5% for the other one) for farmers with more than 9 years (or with 7–9 years) of education, which is in stark contrast to the fact that the cooperative effect is significant at 1% only in the case of feed use, and at 5% in cases of breed use and drug use, and insignificant in the remaining two cases. While the size of effects for all the five behavioral variables is clearly the smallest for the farmers with 0–6 years of education than the other two groups of higher level of education, the difference between the two higher education groups is less pronounced. Meanwhile, we note that the effects of cooperatives on adopting safe production practices is all significant for medium and high education group at 1% or at 5% level, the magnitude for medium education group (i.e. education between 7 and 9 years) is generally bigger (except for drug use) than for the high education group (more than 9 years).

Across the five production practices, the effect on the feed use is the most robust as it is significant at 1% level across all education levels with the size of effects being 0.19, 0.39 and 0.23, for farmers with 0–6 years of education, 7–9 years of education, and more than 9 years of education, respectively. The finding that the cooperative effects are least significant and also smallest in magnitude for farmers with low level of education (vs. those with medium- or high- level of education) may be explained by an argument that farmers of lower level of education may not be able to understand the importance of safe production behavior or have limited capacity to understand the training provided by cooperatives on food safety issues. And a possible reason why the effects slightly fall as the level of education further increases from medium to high is that farmers who are highly educated are able to gain knowledge and technologies associated with safe production practices

Table 9
PSM Regression results of behavioral difference between member and nonmembers for different groups (NNM-based results).

	Farmer's level of education			Crop production or not		Off-farm job experience		Past experience in pig prod	
Dep. Variable	1–6 years	7–9 years	> 9 years	Yes	No	Yes	No	0–10 years	> 10 years
Feed use	0.194***	0.386***	0.228***	0.233***	0.316***	0.195	0.269***	0.310***	0.270***
	(0.066)	(0.060)	(0.072)	(0.055)	(0.054)	(0.143)	(0.040)	(0.053)	(0.054)
Breed use	0.147**	0.258***	0.182***	0.122**	0.246***	0.128	0.198***	0.264***	0.095*
	(0.067)	(0.062)	(0.064)	(0.055)	(0.055)	(0.143)	(0.041)	(0.051)	(0.055)
Vaccination use	0.058	0.203***	0.167***	0.075	0.218***	−0.068	0.179***	0.202***	0.103*
	(0.072)	(0.068)	(0.063)	(0.056)	(0.057)	(0.101)	(0.043)	(0.057)	(0.055)
Drug use	0.126*	0.161**	0.182***	0.117**	0.199***	0.105	0.169***	0.257***	0.056
	(0.073)	(0.064)	(0.063)	(0.049)	(0.059)	(0.145)	(0.042)	(0.056)	(0.051)
Production wastes disposal	0.094	0.188***	0.174***	0.146***	0.195***	−0.068	0.207***	0.252***	0.075*
	(0.063)	(0.053)	(0.059)	(0.049)	(0.053)	(0.139)	(0.039)	(0.051)	(0.050)
Balancing property satisfied	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of total observation	191	340	279	388	422	133	677	397	413
Number of treated	105	205	154	244	260	90	397	230	264
Number of control	47	114	77	127	141	19	240	140	125

Note: PSM results are based on the NNM method. Standard errors in parentheses
***, **, * denote significance at 1% level, 5% level, and 10% level, respectively.

from more alternative sources

Second, results in Table 9 also show the cooperative effects on farmers' production behaviors tend to vary with a farmer's degree of specialization in pig production and a farmer's off-farm job experience. In general, the effects are more significant and larger for farmers who are more specialized in pig production, and for those who have no off-farm job experience. While all five production practices are significant at 1% for the farmers who are specialized in pig production, only two are significant 1% level (feed use) and two are significant at 5%, and one is not significant (vaccination use) for those working part time on pig production. In terms of the size of effect, the cooperative membership would increase the odd of a specialized pig farmer to use safer feed and breed by 32 and 25 percentage points, respectively, the effects are significantly less for a non-specialized pig farmer (25 on feed use and 12 on breed use to be more precise). The comparison between pig farmers with off-farm job experience and those without is even more striking. While cooperative membership would significantly increase the odd of farmers without off-farm job experience to adopt safe production practices for all the five practices, it has no significant effect on all five production practices for those with off-farm job experience; in fact, the PSM estimate is negative in one out of five practices for farmers without off-farm job experience. The result may be explained by the fact that that the farmers who specialized in pig production and who have little experience rely more on cooperatives in order to access market information and/or production skills and knowledge.

Finally, the PSM results also suggest that the effects of participation in farmers' cooperatives on farmers' production behaviors vary with farmers' experience in pig production. The effects are generally more pronounced for farmers with less pig production experience than those with more experience. While the effect is highly significant for all five production practices for farmers who have less than/equal to ten years of pig production, the effect is only significant for farmers who have more than 10 years on feed use (1% level), while at 10% barely significant for breed use, vaccination use, wastes disposal and insignificant for drug use. Regarding the size of the cooperative effect, it is twice (or three times) as large for farmers with less than/equal to 10 years of experience than that for those with more than 10 years of experience in breeds use (0.25 versus 0.10), vaccination (0.20 versus 0.10), drug use (0.26 vs. 0.06) and wastes disposal (0.25 versus 0.08). For feed use, the effect varies only slightly over the years of production experience (0.31 vs. 0.27). The result is in line with the fact that farmers who have less production experience would rely more on cooperatives to obtain trainings and skill instructions.

5.7. Sensitivity analysis (Rosenbaum bounds analysis)

The key underlying assumption of PSM method is that a farmer's decision to participate in a cooperative is solely dependent on observed factors. However, it is possible that the farmer's participation decision is also influenced by unobserved characteristics. For example, it may be the case that farmers who participate in cooperatives are also those who are more safety cautious farmers, then the estimated PSM results on effects of cooperative on safe production behaviors are overestimated. While it is impossible to test whether there are unobserved variables that influence selection into treatment with observed data (Rosenbaum, 2002), the Rosenbaum bound analysis was used to assess the sensitivity of the PSM results to the assumption of importance of unobserved factors relative to observed factors in affecting farmers' cooperative participation decision. In other words, the PSM results are more reliable if they are less sensitive to the increase in the importance of unobserved variables relative to the observed variables. The bound analysis has been popularly applied in empirical evaluation studies using PSM method after it was first introduced by Rosenbaum (2002).

The bound analysis results are presented in Table 10. It is worth a brief discussion on the interpretation of the result. The parameter Γ (≥ 1) is a measure of degree of departure from free of hidden bias with $\Gamma = 1$ being the benchmark scenario for no hidden bias (Rosenbaum, 2002). A bigger Γ means the presence of bigger hidden bias. We follow the literature and conduct the sensitivity analysis for a range of Γ from 1 to 2 (Dillon, 2011). For each value of Γ, the analysis reports the upper bound and lower bound level of significance. A significant upper (or lower) bound means the PSM estimated effect of cooperative membership is still significant even at a given degree of hidden bias. A positive (negative) hidden bias implies that the significance for the upper (lower) bound is the relevant statistics to evaluate (Becker and Caliendo, 2007). Since the PSM estimate of the effects are positive, our discussion of results to follow focuses on the significance levels of the upper bound (columns 2, 4, 6, and 8).

The sensitivity analysis yields a number of interesting results. First, at the benchmark scenario ($\Gamma = 1$), the results are significant at 1% level throughout the five production practices (except for drug use at 1.5% level), which is highly consistent with the results on the first and second columns of Table 7. In other words, when there is no selection bias due to unobserved factors, cooperative membership has significant and positive effects on adoption of safe production practices in all aspects. Second, we note that feed use is least sensitive to the presence of hidden bias as the result is significant at least at 1% level from $\Gamma = 1$ to

Table 10
Rosenbaum bounds sensitivity analysis for safe production behaviors (results for matching in covariates with one neighbor).

Γ	Feed use (1)		Breed use (2)		Vaccination use (3)		Drug use (4)		Wastes disposal (5)	
	Sig +	Sig −	Sig +	Sig −	Sig +	Sig −	Sig +	Sig −	Sig +	Sig −
1	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.015	0.000	0.000
1.1	0.000	0.000	0.000	0.000	0.003	0.000	0.006	0.002	0.001	0.000
1.2	0.000	0.000	0.000	0.000	0.018	0.000	0.032	0.000	0.008	0.000
1.3	0.000	0.000	0.000	0.000	0.070	0.000	0.108	0.000	0.039	0.000
1.4	0.000	0.000	0.001	0.000	0.185	0.000	0.254	0.000	0.120	0.000
1.5	0.000	0.000	0.003	0.000	0.361	0.000	0.449	0.000	0.267	0.000
1.6	0.001	0.000	0.014	0.000	0.559	0.000	0.644	0.000	0.458	0.000
1.7	0.003	0.000	0.040	0.000	0.733	0.000	0.799	0.000	0.647	0.000
1.8	0.011	0.000	0.094	0.000	0.858	0.000	0.900	0.000	0.798	0.000
1.9	0.031	0.000	0.181	0.000	0.932	0.000	0.956	0.000	0.897	0.000
2.0	0.071	0.000	0.299	0.000	0.971	0.000	0.982	0.000	0.953	0.000

Gamma: log odds of differential assignment due to unobserved factors.
Sig+: upper bound significance level.
Sig−: lower bound significance level.

Γ = 1.7, and even at Γ = 1.9 (when the hidden bias is doubled), the result is still significant at 5% level. The result for breed use is the second most robust as the result is significant at least at 1% until Γ = 1.5, at least at 5% until Γ = 1.7, and at 10% when Γ = 1.8, and it becomes insignificant only until Γ = 1.9, the case when the hidden bias is doubled. Third, the results for the rest three production practices are much less robust as the results become insignificant (bigger than 10%) when Γ = 1.4, 1.3 and 1.4 for vaccination use, drug use and waste disposal respectively, suggesting that the results for those three practices should be interpreted with cautions.

The sensitivity analysis suggests two distinct types of production behaviors – feed use and breed use as one type and the rest practices as another. The fact that the first type is not sensitive to hidden bias but the second type is may be explained by the following two reasons. First, while cooperatives have more leverage on farmer's feed use and breed use behaviors because there is price advantage for cooperative members to purchase qualified materials together, cooperatives have little influence on farmers' behaviors in vaccination, drug use and wastes disposal because the purchase and the use of these inputs are more individualized and need-based. Second, the data on farmers' behaviors in feed use and breed use are more objective whereas information on vaccination, drug use and wastes disposal is more subjective therefore is more difficult to measure accurately.

It is worth noting that the insignificant results associated with a relatively small value of Γ (1.4 for vaccination, 1.3 for drug use and 1.4 for waste disposal) does not guarantee the existence of the unobserved factors affecting farmers decision to join cooperatives. What it means is that a small influence of unobserved factors (relative to observed factors) on cooperative participation would cause the estimated cooperative effects to be zero (even if the PSM results are positive and significant). And in this sense, the significant PSM results are more likely to be association rather than causality. But in reality, it could be the case that the unobserved variables are non-existent and the significant PSM results are valid casual effects. Moreover, the results based on the sensitivity analysis do not imply whether the PSM estimates are over- or under- estimated.

6. Conclusion and policy implications

Despite a great deal of effort made to improve the food safety situation over the years, food safety incidents remain prevalent and food safety problem continues to be a wide spread concern for Chinese people and Chinese government. While fighting against food safety problems requires a comprehensive and multifaceted approach, this paper focus on the role of farmers' cooperatives on pig farmers' production behaviors which in turns has consequential impacts on the safety and quality of the final meat products. Our study contributes to the large literature on farmers' cooperatives in developing countries by focusing on the causal effects of cooperative membership on farmers' production behaviors affecting food safety and food quality. Taking advantage of unique data from both cooperative farmers (treatment group) and non-cooperative farmers (control group) from four main pig production provinces in China, we rigorously evaluate the causal impacts of cooperative membership on farmers' production practices affecting food quality and safety.

The PSM results show that farmers' cooperatives play positive and significant roles in improving farmers' safe production behaviors, suggesting that promoting farmers' cooperatives could be an effective means to ensure farmers to produce safer and better quality food. The magnitude of effects is also large. For example, participation in an agricultural cooperative would raise the probability of an average pig farmer to adopt safer feed and breed practices by 0.23 and 0.20, respectively, which is 40–45% of the mean probabilities of adopting these practices of the entire sample (0.50 and 0.53, respectively). Though the causal relationship between the cooperative membership and the safe practices in drug use and vaccination may be questionable if unobserved heterogeneity is present, the likelihood of adopting these safe practices in drug use and vaccination are higher than a non-cooperative member by 0.15 and 0.14, respectively. Again, these differences between cooperative farmers and non-cooperative farmers are also large because probabilities of adopting these three practices for the entire sample are 0.56, and 0.58, respectively.

We also find that the effects of farmers' cooperatives are heterogeneous across a number of household characteristics. More specifically, farmers who have no to little experience in pig production, have no off-farm job experience, are more specialized in pig production and are operating small- to medium-scale pig production tend to benefit more from cooperatives in terms of adopting safe production behaviors. The heterogeneous effects across groups may be explained by the fact that participation in the cooperatives may have alleviated the information or financial barriers for certain groups of farmers to adopt safe production behaviors. For example, the insignificant cooperative effect for large scale production (in Tables 2 and 3) is perhaps because farms operating large-scale are less subject to these barriers, and thus already use safe feed, drug, etc. before they were members of cooperative. A preferred policy to promote farmers' cooperatives is to target those who are likely to be subject to these barriers and are more constrained in participation in farmers' cooperatives.

We also find that cooperatives have heterogeneous effects on production behaviors across different categories of cooperatives.

Cooperatives initiated by IOFs and those with the mix of pig farmers of different production scales tend to have greater and more significant effects. These findings should be taken into account in future policy design to promote farmers' cooperatives as a means to address food safety issues and improve food standards. According to the Farmers' Professional Cooperative Law of China which was revised in 2017 (Huang, 2018), an IOF-cooperative has the same legal rights as any other types of farmers' cooperatives do as long as farmers account for 80% of the total number of its members and the participation of the company can improve the operations of the cooperative. However, based on the best of our knowledge, there is no special law or regulation that specifically targets at promoting the development of IOF-cooperatives, perhaps because of the co-existence of potential positive effects (Zhang, 2012) and negative effects (Deng and Qi, 2011) of IOFs. Our results have clearly shown that the effects of IOF-cooperatives are much bigger and statistically more significant than other types of cooperatives even in all the four main outcomes including drug use and vaccination, suggesting that the development of IOFs could help farmers (especially those of small production scales) to improve their behaviors in adopting safer practices.

There are some caveats of our study. First, PSM method has its shortcomings in evaluating cooperative's effect on pig farmers' safe production behavior because it matches farmers based on the observables, while the unobservable factors could not be included. We hope to have access to panel data or data generated from randomized control trial (RCT) so we can employ alternative methods such as DID and RCT to better address the unobservable issues in the future. Second, we focus on farmers' safe production behavior adoption in this paper. It would be useful if we can have data to directly measure the quality and safety of pork. Finally, as mentioned earlier, we hope to collect information on profitability, weight gains, unexpected disease outbreak, prices of inputs and output, etc., so we can more explicitly investigate channels through which cooperatives affect safe production behaviors.

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Appendix A

See Tables A1–A3.

Table A1
P values and adjusted p values for multiple outcomes of whole sample.

Outcomes	ATE	P values		
		Unadj.	Multiplicity adj.	
			Bonf.	Holm
Feed use behavior	0.2671	0.0000***	0.0000***	0.0000***
Breed use behavior	0.1973	0.0000***	0.0000***	0.0000***
Vaccination use behavior	0.1498	0.0002***	0.0010***	0.0002***
Drug use behavior	0.1609	0.0000***	0.0000***	0.0000***
Wastes disposal behavior	0.1756	0.0000***	0.0000***	0.0000***

ATE refers to average treatment effect based nearest neighbor matching results.
*, ** and *** indicates that the corresponding p-values less than 1%, 5% and 10% respectively.

Table A2
P values and adjusted p values for multiple outcomes of small scale, medium scale and large scale farmers.

	ATE	P values		
		Unadj.	Multiplicity adj.	
			Bonf.	Holm
Outcomes (small scaled farmers)				
Feed use behavior	0.3966	0.0000***	0.0000***	0.0000***
Breed use behavior	0.2660	0.0000***	0.0000***	0.0000***
Vaccination use behavior	0.2329	0.0005***	0.0025***	0.0005***
Drug use behavior	0.3269	0.0000***	0.0000***	0.0000***
Wastes disposal behavior	0.2988	0.0000***	0.0000***	0.0000***
Outcomes (medium scaled farmers)				
Feed use behavior	0.3178	0.0000***	0.0000***	0.0000***
Breed use behavior	0.1589	0.0446**	0.2230	0.1338
Vaccination use behavior	0.1279	0.1043	0.5215	0.2086
Drug use behavior	0.1047	0.1811	0.9055	0.1811
Wastes disposal behavior	0.2016	0.0054***	0.0270**	0.0216**
Outcomes (large scaled farmers)				
Feed use behavior	0.1000	0.1432	0.7160	0.4296
Breed use behavior	0.1509	0.0255**	0.1275	0.1275
Vaccination use behavior	0.0962	0.1368	0.6840	0.5472
Drug use behavior	0.0491	0.3924	1.9620	0.7848
Wastes disposal behavior	0.0189	0.7569	3.7845	0.7569

ATE refers to average treatment effect based nearest neighbor matching results.
*, ** and *** indicates that the corresponding p-values less than 1%, 5% and 10% respectively.

Table A3
P values and adjusted p values for multiple outcomes of cooperative type (I), type (II) and type (III).

	ATE	P values		
		Unadj.	Multiplicity adj.	
			Bonf.	Holm
Outcomes (cooperative type I)				
Feed use behavior	0.1365	0.0059***	0.0295**	0.0177**
Breed use behavior	0.1437	0.0017***	0.0085***	0.0085***
Vaccination use behavior	0.1532	0.0027***	0.0135**	0.0108**
Drug use behavior	0.1234	0.0059***	0.0295**	0.0177**
Wastes disposal behavior	0.0780	0.0650*	0.3250	0.0650*
Outcomes (cooperative type II)				
Feed use behavior	0.2708	0.0002***	0.0010**	0.0010***
Breed use behavior	0.1542	0.0461**	0.2305	0.0922*
Vaccination use behavior	0.1625	0.0300**	0.1500	0.0900*
Drug use behavior	0.1458	0.0545**	0.2725	0.0545*
Wastes disposal behavior	0.2125	0.0029***	0.0145**	0.0116**
Outcomes (cooperative type III)				
Feed use behavior	0.6600	0.0000***	0.0000***	0.0000***
Breed use behavior	0.4333	0.0000***	0.0000***	0.0000***
Vaccination use behavior	0.3000	0.0020***	0.0100***	0.0040***
Drug use behavior	0.3400	0.0003***	0.0015***	0.0003***
Wastes disposal behavior	0.4400	0.0000***	0.0000***	0.0000***

ATE refers to average treatment effect based nearest neighbor matching results.
*, ** and *** indicates that the corresponding p-values less than 1%, 5% and 10% respectively.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2019.01.007.

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