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Assessing the impact of feed technology adoption by smallholders in sweet potato-pig systems in Sichuan, China

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Abstract

We employ propensity score matching (PSM) to examine the impact of sweet potato-based feed technology adoption on household-based pig production in Sichuan, China. An ex post survey in six villages was conducted in 2009, of which five villages were in project intervention sites (exposed area) and one village in the same township but not exposed to project intervention (non-exposed area). We randomly selected 111 households in the exposed areas from the list of households previously interviewed in a baseline survey and 53 households from non-exposed area. Average treatment effects were estimated using matching estimators such as nearest neighbor matching (NNM), radius matching (RM) and kernel matching (KM). Results indicate positive net benefit from adoption of sweet potato-based feeding technology, i.e., gross margin estimates of silage adopters are on average higher by 2-4 RMB per kg liveweight of output than non-adopters of similar characteristics. Silage adopters are also likely to produce 3-7 more slaughter pigs per year than non-adopters having similar characteristics, on average. Analysis of factors driving adoption indicates that sweet potato-based feed technology is not suitable in all smallholder context in Sichuan. Overall, the results show that sweet potato-based feed technology plays an important role in helping household-based pig producers become resilient, by having options in feeding strategies that help them cope with volatility in output prices (e.g., prices of live pigs as a function of retail prices of pork) and input prices (e.g., price of corn vis-à-vis price of pork, price of industrial feed). Exposure to the technology and its benefits through actual demonstration also appears to be more effective in engendering uptake and sustaining adoption.

Introduction

Among millions of rural households in Sichuan, sweet potato-pig system is a major economic activity. Sichuan is the largest producer of pigs in China, and sweet-potato pig systems plays a significant role in smallholders' strategy to intensify their agricultural production in order to alleviate poverty that is endemic in this region. One of the key constraints being addressed by the sweet-potato pig systems is the seasonal crop shortages that result in fluctuating availability of feed supply to sustain the requirements of their pig herd. It is estimated that about 6.77 million households are in sweet-potato pig systems in Sichuan, of which some 1.46 million are poor, i.e., live on less than $1 per day (Huang et al. 2003). These are the potential direct beneficiaries of this feed technology.

Sweet potato is widely cultivated in Sichuan, especially in hilly or mountain regions. Estimated planted area is over 13 million Chinese mu (1mu=666.7m2); about 4 million tons of roots are produced every year, in which about 70% is used as pig feed. Sweet potato (SP) has been one of the four most important crops grown in China. The annual total root production reaches about 21 billion tons, second only to rice, wheat and maize, the three major food and feed crops (Kuang, 1996). Vines and roots are the two forms of SP used for feeding pigs. Overall, more than 95 percent of vine and 60-70 percent of roots of provincial total production go to pig ration.

As sweet potatoes are produced once a year, and vines and tubers are easily perishable, the conservation of both components as silages was identified as one of the technology options to be tested, applying the research results obtained from the Crop-animal systems research network (CASREN) Project implemented by the International Livestock Research Institute (ILRI) with national partners over the period 2002-2005. In 2008, more than 90 million fattening pigs were sold to market (Table 1), of which about 70% percent were from rural households. Sweet-potato pig systems thus play an important role in smallholders' livelihood strategy in Sichuan.

Table 1: Sweet potato tuber production and pigs sold to market in Sichuan province, 2001-2008.

Year	Sweet potato tubers produced (million ton)	Fattening pigs sold (million heads)
2000	18.8	65.9
2001	16.6	67.8
2002	17.4	70.9
2003	17.1	74.9
2004	17.7	81.0
2005	18.1	88.1
2006	17.1	94.0
2007	17.0	99.1
2008	17.0	90.2

Source of data: Sichuan Animal Husbandry Bureau (various years).

Through collaborative work of ILRI, International Potato Center (CIP) and national partners in Sichuan, innovations in sweet-potato based feed technology were developed and tested among pig producers in the CASREN Project. These include the utilization of new high-yielding sweet potato varieties that had been developed and tested by CIP and coupled with ILRI's contribution to improve post-harvest crop storability through ensiling of the roots and vines, thereby extending their shelf life and stabilizing the availability of sweet-potato based feed supply. As a result, by the end of the CASREN project, noticeable impacts had been observed that need to be properly documented for appropriate validation and assessed for lessons learned in how ILRI and other research partners can better implement similar projects.

This study is aimed at providing empirical basis for the effectiveness (or not) of the technology and the processes that facilitated its uptake. The main output from this study is solid evidence of impact of the intervention and the role of ILRI and its collaborators in making this happen. The results could also provide learning to future conduct of similar research and identify areas where things may be improved for better impacts and effective implementation.

Data Sources and Methodology

To assess the impact of the adoption of sweet potato-based feed technology, an ex post survey over six villages was conducted in 2009, about five years after the completion of the project. Five of the six villages were from intervention sites where the CASREN project had implemented field activities (exposed area) and one village was from the same township but was not visited nor exposed to project intervention (non-exposed area). For each household interviewed, several information was collected, including household demography, pig production characteristics (feed, breed, inventory, marketing, animal health, cost and assets for pig production) including current and pre-project practices, crop production, adoption of improved feeding technologies, assets and income from various sources other than pig production.

Survey site selection

Renhe township was the CASREN project implementation site. Five villages in Renhe township were chosen as survey sites in exposed area namely, Aiguo village, Baiguo village, Guanlong village, Tianle village and Xinming village. Tianle village was the benchmark site (BMS) of the CASREN Project. The other four villages were expansion sites where CASREN project activities were subsequently expanded. Renhe township is located at 105°21’ E and 31 °30' N, about 50 km far from the capital of Zitong County, and its elevation is 509 meters above sea level.

Ziqiang township and Baoshi township were chosen as potential candidates for non-exposed area; both are sweet potato-pig production system areas. Baoshi township was eventually not chosen because of its proximity to Renhe township. Ziqiang township lies in southeast of Zitong county, located at 105°16’ E and 31 °35' N, about 11 km far from the capital of Zitong County, and its elevation is 545 meters above sea level. Ziqiang village was selected as the non-exposed area in Ziqiang township; it is 11km from Renhe township. Figures 1 and 2 show the location of project study site and survey sites in Sichuan province.

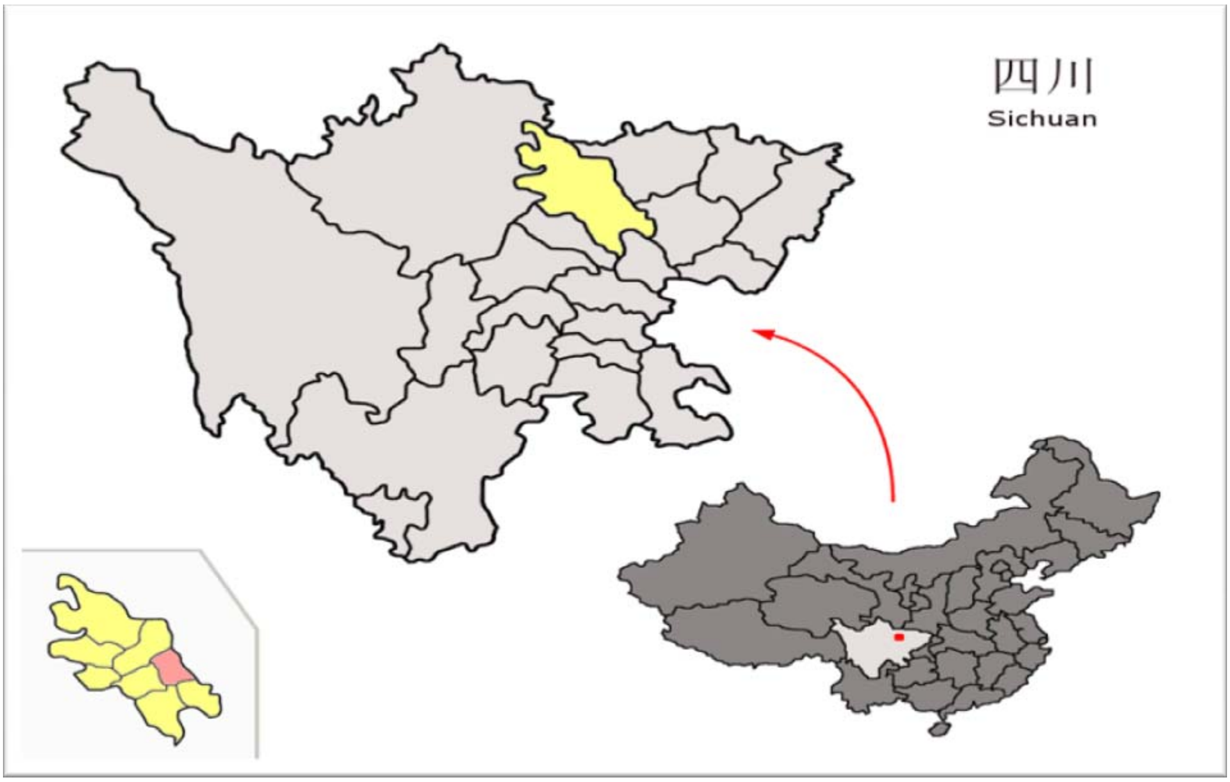

Figure 1: Location of the study sites in Sichuan.

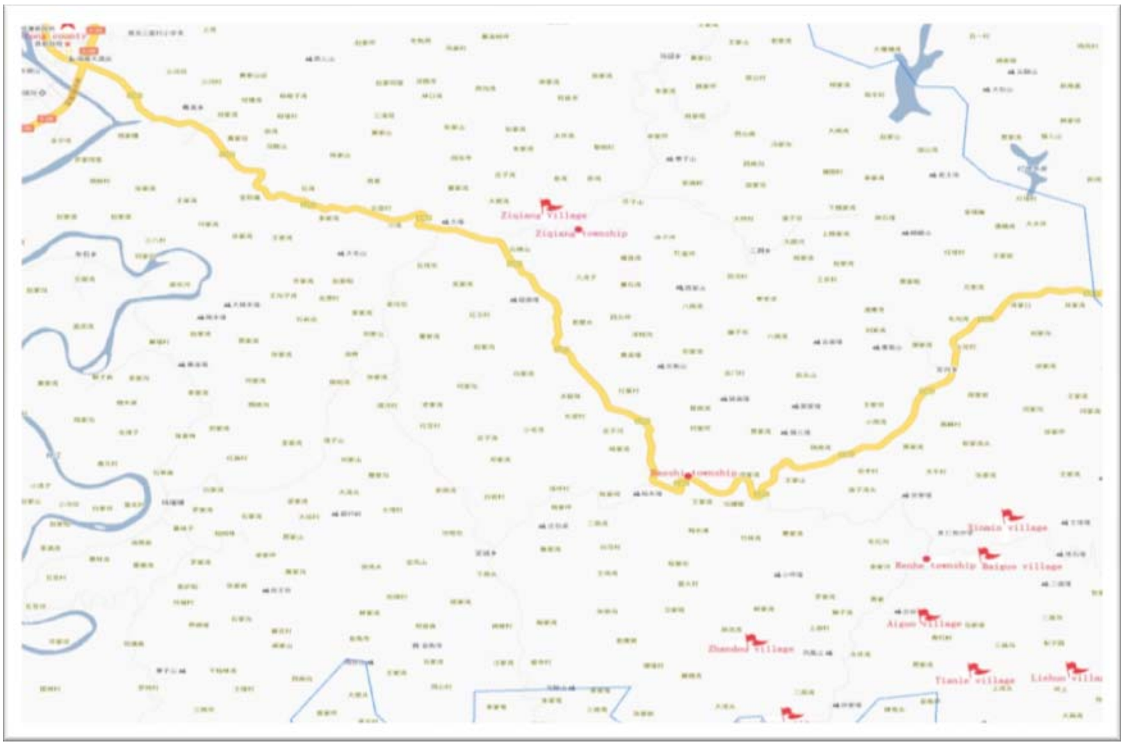

Figure 2: Survey sites in Renhe and Ziqiang townships in Sichuan province (marked in red).

Selection of sample respondents

We selected randomly 111 households from exposed area and 53 households from non-exposed area, including both households using sweet potato as pig feed and those that do not. Among households using sweet potato as feed, both ensiling technology adopters and non-adopters were classified ex post, as revealed from household questionnaire responses. In the exposed area, 71 of the 111 HHs selected were chosen from the baseline survey respondents in the CASREN project baseline survey. Among the 71 HHs chosen from the exposed areas, 11 were from the CASREN project BMS. On the other hand, 53 HHs were interviewed in Ziqiang village, the non-exposed area. The details of households and matched pre-project and post-project survey households by village are shown in Tables 2 and 3.

Table 2 : Distribution of survey households by villages

Village	Pre-project survey (2001)		Post-project survey (2009)	
	BMS HHs	Expanded HHs	Exposed HHs	Non-exposed HHs
Aiguo		35	20	
Baiguo		37	31	
Guanlong		22	17	
Liehuo		54		
Tianle	20		17	
Xinming		34	26	
Zhandou		36		
Ziqiang				53
Total	**20**	**218**	**111**	**53**

Table 3: Distribution of mached pre-project and post-project survey households by village

Village	Pre-project survey (2001)		Post-project survey (2009)	
	BMS HHs	Expanded HHs	Exposed HHs	Non-exposed HHs
Aiguo		16	16	
Baiguo		26	26	
Guanlong		8	8	
Liehuo				
Tianle	11		11	
Xinming		21	21	
Zhandou				
Ziqiang				
Total	**11**	**71**	**82**	**0**

A survey questionnaire was developed jointly by ILRI and collaborators from Sichuan Animal Science Academy (SASA) that was used as instrument for primary data collection. SASA staff member were trained by ILRI in using the survey instrument; SASA staff in turn trained the selected enumerators that included staff from SASA and Zitong County Animal Husbandry and

Food Bureau. Trained enumerators then conducted face to face interviews with selected respondents from the various survey sites. The survey was implemented and completed in September-December 2009. All completed questionnaires were checked and validated for accuracy with respondents before data processing and tabulation.

Analytical framework

In order to estimate the effects of an intervention (or a treatment) on participants (or the treatment group), it is required to draw counterfactual outcomes that would have been observed for the treated (those received the intervention) in the absence of the treatment (Rubin, 1974; Rosenbaum & Rubin, 1983). Obviously, the challenge is that the counterfactual scenario is not directly observable. The simplest way to derive treatment effect of an intervention is to simply compare the treatment group before and after an intervention and attribute the difference as treatment effect. However, many other factors might come into play in the period of intervention that can affect the outcome. It might be seasonality or some other factors other than the intervention that might have influence on the treatment group. Comparison has, therefore, to be made with reference to a control group of non-participants, which are as similar as possible to the treatment group, except that they do not receive the intervention. There are a number of approaches to create such control group and estimate treatment effects, using either prospective or retrospective evaluation design. Prospective evaluation requires researchers' involvement from the beginning of the intervention, including the collection of ex ante (baseline) and ex post data from treatment and control groups. Retrospective evaluation, on the other hand, is carried out after the intervention based on ext post data.

A simple way to use a control group is to compute treatment effect as the difference in the mean outcomes ex post between the treatment and the control groups. This is, however, valid only when the treatment and control groups are selected randomly over a sufficiently large sample so that the treatment group and the control group are identical and had identical outcomes at baseline. It is rarely the case in practical impact assessment research. If the groups were different at baseline, the difference ex post might come from the inherent difference between the groups, not from the intervention. This selection bias might give misleading estimates. Ashenfelter & Card (1985) provides an example of this bias, showing that participants in subsidized training programs are observed to earn less than those in control groups. Bamberger & White (2007) discussed the limitations of this assumption in development interventions. A similar approach is using a treatment dummy as a regressor in a regression framework. The coefficient of the dummy, if statistically significant, can be used as an indicator of impact. But this too has the same selection bias problem with the simple ex ant and ex post comparison.

Difference in difference (DiD) method has emerged to deal with the above issue. The basis of DiD is to compare the treatment group after the treatment to itself before the treatment and to a control group. Under the assumption that factors other than the intervention have identical impact across the board, the DiD method uses a control group to “difference out” effects from these factors. This can be done in either simple mean-differencing form or regression form. Card and Krueger (1994) provides a good example of using DiD in impact assessment. DiD estimation is, however, only appropriate if the intervention is random. Bertrand et al (2004) also indicates that DiD studies often suffer from the problem of inconsistency of standard errors due to the use of serially correlated data.

While DiD appears as a popular method in impact evaluation, it is inapplicable in studies where baseline data is non-existent or incomparable with ex post data. Moreover, the influences of other factors on the groups might not be similar across the board due to the heterogeneity in their characteristics as a result of selection bias. In such a case, in order to have an unbiased comparison, one must identify a sub-control group, among non-participants, which is as similar in characteristics as possible to the treatment group (Caliendo & Kopeinig, 2005). This practically involves matching participants with non-participants using observable independent covariates.

The exercise is fairly simple if one or two characteristics are considered. When the number of characteristics grows large, matching based directly on them appears impractical. Rosenbaum & Rubin (1983) suggests matching participants and non-participants on the conditional probability of participation in the treatment, given their characteristics. This probability is termed propensity score. Instead of matching over a range of observable characteristics, matching is now reduced to a single indicator: the propensity score.

The propensity score of an individual conditional on a covariate vector X is defined as:

$$P(X) = \Pr(Z = 1 \mid X) \quad (1)$$

Where Z is a dummy variable indicating treatment status, which is equal to unity if the individual received the treatment and zero otherwise. Given that the treatment is random and independent of X conditional on P(X) or $Z \perp X \mid P(X)$, the propensity score is balanced such that individuals with the same propensity score must have the same distribution of the observables X regardless of treatment status. The difference between participants and non-participants with the same score is thus attributed only to the treatment. Rosenbaum & Rubin (1983) also proves that if outcomes $Y_1 (Y_0)$ are independent of treatment conditional on X or $Y_1, Y_0 \perp Z \mid X$, then they are also independent of treatment conditional on the propensity score P(X).

$$Y_1, Y_0 \perp Z \mid P(X) \quad (2)$$

The multi-dimensional matching exercise is then reduced to a single dimensional matching problem: matching on the propensity score.

A discrete choice framework such as logit model can be applied to estimate the propensity score in (1).

$$\Pr[Z=1|X]=\frac{e^{X'\beta}}{1+e^{X'\beta}}=\Lambda(X'\beta) \quad (3)$$

Based on propensity score matching obtained from the estimation of (3), the average treatment effect on the treated (ATT) can be computed as:

$$\begin{aligned} ATT &= E(Y_1 - Y_0 \mid Z=1) \\ ATT &= E[\{E(Y_1 \mid Z=1, P(X)) - E(\mid Y_0 \mid Z=0, P(X))\} \mid Z=1] \end{aligned} \quad (4)$$

The ATT shows the mean difference between the paired outcomes of the participants and non-participants once the pairs are identified. Dehejia & Wahba (1999) provides an illustration of the method. Further improvement in impact evaluation can be made by combining propensity score matching and DiD.

As finding identical individuals with the same value propensity score is impractical, several matching techniques have been proposed to match similar ones, each having its own pros and cons. Three most commonly used matching algorithms are nearest neighbor matching, radius matching and kernel matching.

The most straightforward method is for each participant, find a non-participant(s) with smallest distance in propensity score to that of the participant. This *nearest neighbor matching* (NNM) estimator usually results in a singleton or one-to-one matching. The case of multiple nearest neighbors is rare in practice. The nearest neighbor matching generates good pairs as long as the distribution of propensity scores of both groups is similar. However, in practice, nearest neighbors can sometimes be far away, resulting in poor matches. *Radius matching* (RM) avoids this drawback by imposing a maximum distance (radius) and match the participant not only with the nearest neighbor but all neighbors within a radius, allowing for usage of extra units when good nearest match is not available (Dehjia & Wahba, 2002; Smith & Todd, 2005). By having more neighbors, radius matching is less accurate as long as a good nearest match can be found. Another matching method, recommended by Heckman et al (1997, 1998) is the *kernel matching* estimator (KM). Whereas the NNM and RM methods select only one or some non-participant to draw counterfactual outcomes, kernel matching takes all individuals in the control group into account, using weighted averages that are based on the distances between the participant and the non-participants. Kernel function assigns higher weights to non-participants that are closer in propensity score to the participant in consideration and lower weights for those are far. This way, KM reduces variance by using more information. However, bad matches might come in (Caliendo & Kopeinig, 2005).

Propensity score matching has been widely used in impact evaluation of interventions, including those in research and development programs, where sufficiently large randomized sampling could not be attained. Pufahl *et al* (2007) considers the impact of farm programs in Germany using propensity score matching and found that participants in the programs increase cultivation area and reduce chemical purchase. Liebenehm *et al* (2009) applies propensity score matching to assess the impact of agricultural research on farmers' knowledge about African animal trypanosomosis and shows significant gain in farmers' know-how due to participation in livestock research activities. The method is also used frequently in assessing the impact of technology adoption decisions. For example, Mendola (2007) employs the method in evaluation the effect of agricultural technology adoption on poverty reduction in rural Bangladesh, showing a positive impact of the adoption on farmers' well-being.

In this paper, we employ the propensity score matching framework to examine the impact of sweet potato-based feed technology adoption on rural pig raising households in Sichuan province of China. The reason for not using DiD is that we do not have sufficient baseline data.

In evaluating treatment effect, we first want to compare outcomes between those that adopt ensiling technology and those that do not, among sweet potato users. The purpose is to examine whether or not ensiling does have positive impact on performance of pig farms from increased supply of sweet potato-based feed by extending its life and maximize its utilization. Secondly, we also would like to see whether using ensiled sweet potato as feed is a superior feeding strategy compared to not using sweet potato at all. Thus, two control groups are considered: the first one is non-silage sweet potato adopters; the second is non sweet-potato adopters. The treatment group includes households who apply ensiling technology to their sweet potato based pig feed. Accordingly, two treatment dummies are used as dependent variable in logit regression: treatment dummy 1 is unity if a household adopt ensiling technology in its sweet-potato based feeding and zero if the household uses sweet potato as feed but not adopt ensiling; and treatment dummy 2 is unity if a household adopt ensiling technology in its sweet-potato based feeding and zero if the household do not use sweet potato as feed. Estimation procedure is implemented for each choice of treatment dummy (see Table 4 below).

Table 4: Definition of treatment dummies in evaluating treatment effects.

Treatment Dummy 1	1	Ensiled sweet potato adopters
	0	Non-ensiled, sweet potato adopters
Treatment Dummy 2	1	Ensiled sweet potato adopters
	0	Sweet potato non-adopters

The empirical model is set up as follows:

The treatment dummy and explained covariates are estimated in logit model of (3) as follows:

$$\text{Model 1: Pr[Treatment dummy 1=1|X]}=\frac{e^{X'\beta}}{1+e^{X'\beta}}=\Lambda(X'\beta)$$

$$\text{Model 2: Pr[Treatment dummy 2=1|X]}=\frac{e^{X'\beta}}{1+e^{X'\beta}}=\Lambda(X'\beta)$$

with X as the vector of covariates used.

Adoption model

Descriptive analysis of household characteristics will give an overall picture of households surveyed and might suggest the inclusion of observable characteristics as covariates in logit models. The logit model is then estimated using survey data to generate propensity scores. The same set of covariates is used for logit regression with two treatment dummies as dependent variable. The logit estimates can provide empirical basis for evaluating factors of technology adoption. There are a number of factors that have been documented as influencing technology adoption in agriculture. Feder et al (1985) list several of these factors in a comprehensive literature survey. Cruz (1987), Lapar & Ehui (2004) and Jera & Ajayi (2008) also discuss factors affecting adoption of technologies in agriculture. These factors include household characteristics (e.g. age, education, gender of household head, household size, etc), characteristics of farm (e.g. location, resources, herd size, technologies adopted, etc), exposure to new technologies, characteristics of the new technologies, etc. In our study, the choice of covariates is guided by previous literature and the availability of data. Specifically, we consider four sets of characteristics to be used as covariates in the models: household demography, non-pig production and income, pig production characteristics and exposure to ensiling technology.

The first set of covariates might have influence on the decision whether or not to adopt ensiling technology as it affects household knowledge, their willingness to adopt new technologies and labor resource. For example, Adesehinwa et al (2003) shows that a number of household demographic characteristics, including age, gender, household size and education affect feeding patterns of pig farms. Lubwama (1999) discusses the relationship between gender and technology adoption in agriculture. Rangnekar (1999) observed that one of the reason for low adoption of silage technology in India is that ensiling is labor intensive. Adeoti (2009) indicates that household size and labor availability is the factor that increases the probability of adoption of irrigation technology in Ghana. Okoedo-Okojie & Onemolease (2009) show that age, farm size and interaction with extension agents had significant impact on farmers' adoption of improved yam storage techniques. Weir & Knight (2000), Feder et al (1985) and Rahm & Huffman (1984) prove that education has influence on the adoption of new technology.

The second set contains variables indicating household resources such as crop production area, income from activities other than pig production, value of livestock owned. Some of the resources might be used in pig production (e.g. crop products and by-products). Other resources might reduce household focus on pig production (e.g. income from other activities) and thus to the adoption of a new technology. Lubwama (1999) discusses the role of property ownership on technology adoption. Perz (2003) find households with more crop land are more likely to adopt new technologies. Suppadit (2006) show household income, among others, influences adoption of good cattle raising practices.

The third set consists of variables showing production characteristics, which might affect the adoption of ensiling technology. Obviously, any technology adopted must depend on the characteristics of the production system. For example, the choice of breed might influence the adoption of feed technology that can maximize the potential of the breed. Outlet for output can also be a factor, since each outlet has its own requirements, which then translate to requirements to technologies adopted. The choice of a new technology might also relate to the pre-adoption technology. These prior technologies can be used as proxies for farms' willingness to adopt new technologies and also can imply the cost of transition to new ones. If the change can be done easily with low cost, it is more likely to be adopted. Therefore, in the set, we include variables such as adoption of certain pig breed and feed, the choice of marketing outlet, dummy variable indicating reason for marketing, the pre-adoption of feed and parasite control.

The last set is comprised of variables indicating exposure to the technology. The more exposed the household, the more likely the adoption. Adeoti (2009) and Okoedo-Okojie & Onemolease (2009) report that frequent exposure to extension services increase adoption. In our study, we include variables such as the locational dummy showing whether a household is from exposed or non-exposed area, dummies showing household attendance in the technology training and household receipt of the technology supporting materials. These "exposure" variables might directly affect household decision to adopt the technology. Note that, in selecting specific variables in the sets, some variables potentially influence the technology adoption are excluded, e.g. farms' herd size, due to missing observations. Some other variables are not included to avoid potential endogeneity problem. The full list and definitions of the covariates used is reported in Table 5.

Table 5: Definition of covariates used in the logit model

Variable	Definition
Hhsize	Total number of members in a household
Head_dummy	Dummy variable which is one if the household head is male and zero if the household head is female
Headage	Age of household head
Head_ schooling	Number of years schooling by household head
Head_havejob	Dummy variable which is one if the household head has salaried or waged job and zero otherwise
Total_crop_area_ha	Total areas for crop production in hectare
Nonpig_income	Income from sources other than pig production such as income from other livestock production, from wages, salary, remittances, small business, subsidy and others.
Otherlvst_val	Value of other livestock owned
Finisher_dummy	Dummy variable which is one if the household main output from pig production is finishers and zero if the main output is piglet.
Local_cur	Proportion of local breed pigs in total farm herd
Cross_cur	Proportion of cross breed pigs in total farm herd
T_cross_cur	Proportion of triple cross breed pigs in total farm herd
Spuse_pst	Dummy variable which is one if the household used sweet potato as pig feed in period before project
Concentrate_pst	Dummy variable which is one if the household used concentrate pig feed in period before project and zero if not use.
Premix_cur	Dummy variable which is one if the household uses premix feed and zero if not.
Sale_trader	Dummy variable which is one if the household main outlet for pigs is through pig traders and zero otherwise
Sale_for_expense	Dummy variable which is one if the reason for selling pigs is for household expense or input expense and zero otherwise.
Deworming_pst	Dummy variable which is one if the household dewormed its pigs in the period before the project and zero if not.
Exposure	Dummy variable which is one if the household is from exposed area and zero if from non-exposed area.
Sourcetech_extension	Dummy variable which is one if the household learnt about ensiling technology from Animal husbandry bureau officers or extension officers and zero if not.
Receive_bag	Dummy variable which is one if the household received bags for silage preparation and zero if not
Receive_material	Dummy variable which is one if the household receive sweet potato planting materials and zero if not
Assist_training	Dummy variable which is one if the household receive training and

	technical advice about sweet potato based feeding technologies and zero if not.

Impact assessment estimation

Three commonly used matching estimators described above namely, nearest neighbor matching, radius matching and kernel matching are used to identify matched controls. The purpose is to avoid bias that might come with a specific matching method, given our data. We use two performance indicators, namely, gross margin per live weight kilogram of pigs and volume of output (kg), as outcomes, of which treatment effects are measured. Both indicators are derived for each household in the dataset. For each matching method, the number of matched treated and controls are reported along with values of average outcomes and treatment effects on the treated. The estimation procedure is operationalized in STATA using functions written by Becker & Ichino (2002).

Results and Discussion

Profile of survey respondents

Details of the distribution and profile of households surveyed are described in the following sections. The information collected allows us to characterize households and their pig production performance.

As shown in Table 6, there are observed differences between households that were exposed to the sweet potato-based feed technology through the CASREN project, and those that were not exposed to the technology. For example, exposed households have older household heads than non-exposed households; on the other hand, non-exposed household heads have relatively more educated spouses than those in exposed households. While household size between the two groups are statistically significantly different, the difference in household size is small, i.e., 3.7 vis-à-vis 4.2.

Exposed households also have relatively more assets for pig production, and have slightly bigger land area for crop production in particular, and in total agricultural and non-agricultural land in general. Exposed households also generate higher volume of crop production, on average, per year, compared to non-exposed households. On the other hand, non-exposed households appear to have higher income from both agricultural employment and other non-agricultural sources, e.g., non-agricultural wages, remittances, trade, etc.

Table 6: Profile of households interviewed in exposed and non-exposed areas in 2009.

Variables	Exposed HHs	Non-exposed HHs
Number of HHs surveyed	111	53
Demographic characteristics		
Household size	3.7 (1.1)***	4.2 (1.2)***
Dependency ratio	0.3 (0.3)	0.3 (0.2)
Age of HH head	53 (11)**	49 (10)**
Age of HH spouse of head	51 (11)	49 (12)
Number of year attending school of HH head	7.4 (2.3)	7.0 (2.3)
Number of year attending school of HH spouse	6.6 (2.2)*	7.5 (4.8)*
Average number of year attending by HH head and spouse	6.9 (2.0)	7.1 (2.8)
Percentage of HH head unemployed	0.9	1.9
Assets for pig production		
Average pigpen area (m2)	44 (22)***	34 (16)***
No of electric fans for cooling pig pens	2.0 (1.2)*	1.5 (0.8)*
No of equipment for feed preparation	1(1)	1(1)
Crop production		
Area of crop production (ha)	0.9 (0.3)*	0.8 (0.4)*
Average production per year (kg)	5424 (2375)**	4636 (2296)**
Estimated value of crop production (Yuan)	9027 (3567)	8250 (3823)
Household assets		
Agricultural land (ha)	0.37 (0.19)**	0.31 (0.12)**
Non-agricultural land (m2)	1,187 (2599)*	610 (2832)*
House area (m2)	207 (118)**	173 (73)**
No of farm equipment	1.5 (0.8)*	1.3 (0.5)*
Financial asset (Yuan)	4,405 (11620)	5,560 (22,404)
Other income sources		
Wages from agriculture employment	654 (3202)*	2321 (11248)*
Income from other livestock (cattle, buffalo, poultry, goat, rabbit)	1463 (2169)	1144 (1147)
Non agricultural income (non-agricultural wage, remittance, trade, subsidy and others)	15263 (17144)***	24822 (24742)***
Total income from above sources	17380 (17944)***	28287 (26703)***

Notes: 1. Exposed households are those from villages in base line survey that adopt CASREN interventions whereas non-exposed households are those in the same township but not visited nor exposed to CASREN interventions. 2. The asterisk (*) denotes the level of significance in the difference of the mean between the variables: *** - significant at 1% level; ** - significant at 5% level; * - significant at 10% level. T-test is used for average figures, proportion test (z-test) is used for percentage numbers.

Source of data: ILRI-SASA survey, 2009.

A profile of sweet potato (SP) users and non-users is summarized in Table 7 below. The descriptive statistics comparing SP users and non-users show that SP users have slightly larger land for crop production, are generating relatively higher volume and value of crop production per year, on average; and have slightly larger total agricultural land size in. A higher proportion of SP users also have household heads that receive salaries or wages. No significant differences are observed in terms of other socio-demographic characteristics, assets for pig production and pig production output, and other income sources.

Table 7: Profile of sample respondents according to adoption status, 2009.

Variables	SP users			Non – SP users
	Silage adopter	Silage non-adopter	Overall	
Number of HHs surveyed	40	60	100	64
Demographic characteristics				
Household size	3.9 (1.1)	3.9 (1.1)	3.9 (1.1)	3.8 (1.3)
Dependency ratio	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)
Age of HH head	52 (15)	49 (14)	50 (14)	50 (13)
Age of HH spouse of head	49 (17)*	44 (19)*	46 (18)	45 (17)
Number of year attending school of HH head	7 (3)	7 (3)	7 (3)	7 (3)
Number of year attending school of HH spouse	5 (6)	5 (3)	5 (5)	5 (4)
Percentage of head of HH receiving salaries or wages	15	17	16**	5**
Assets for pig production				
Average pig pen area (m2)	40 (20)	39 (19)	39 (19)	43 (22)
No of electric fans for cooling pig pens	1.9 (1.1)	1.9 (1.1)	1.9 (1.1)	1.9 (1.1)
No of equipment for feed	1.0 (0.2)	1.0 (0.2)	1.0 (0.2)	1.0 (0.1)

preparation				
Total value of assets for pig production (acquisition value)	5137 (4554)*	3923 (3319)*	4409 (3885)	4985 (4757)
Crop production				
Area of crop production (ha)	0.9 (0.3)	0.9 (0.4)	0.9 (0.4)***	0.8 (0.3)***
Average production per year (kg)	5845 (2452)	5556 (2554)	5672 (2505)***	4384 (1913)***
Estimated value of crop production (Yuan)	9163 (3385)	9198 (4049)	9184 (3379)**	8139 (3390)**
- ***Value of food crop***	*6363 (2389)*	*6313 (3184)*	*6333 (2879)**	*5651 (2474)**
- ***Value of cash crop***	*2800 (1646)*	*2885 (1687)*	*2851 (1663)**	*2488 (1386)**
Household assets				
Agricultural land (ha)	0.41 (0.2)**	0.33 (0.1)**	0.36 (0.18)*	0.33 (0.16)*
Non-agricultural land (m2)	1763 (3292)**	638 (2037)**	1088 (2655)	864 (2738)
House area (m2)	207 (88)	192 (105)	198 (98)	192 (119)
No of farm equipment	1.4 (0.8)	1.5 (0.8)	1.5 (0.8)	1.3 (0.6)
Financial asset (Yuan)	7650 (23384)	4862 (14666)	5977 (18587)	2989 (10127)
Other income sources (Yuan)				
Income from other livestock	1757 (3806)	1119 (1184)	1374 (2577)	1338 (1638)
Non agricultural income	16705 (2750)	21476 (25796)	19568 (22830)	16453 (15666)
Subsidy received	4088 (6427)***	9063 (10091)***	7525 (9213)	7963 (9335)
Total non-pig income	20736 (22570)	23429 (26131)	22351 (24685)	18645 (15888)
Pig production				
Total pig output (kg)	1803 (1633)*	1368 (1301)*	1642 (1451)	1813 (2466)

Notes: 1. Sweet potato (SP) users are households who indicated use of sweet potato as feed in pig production. The others are non sweet potato users. 2. The asterisk (*) denotes the level of significance in the difference of the mean between the variables: ******* - significant at 1% level; ****** - significant at 5% level; ***** - significant at 10% level. T-test is used to test differences in the means.

Source of data: ILRI-SASA survey, 2009.

Comparing users of SP silage and non-users among SP adopters (see Table 7), it is shown that silage users are older, have more assets for pig production, have larger agricultural land, and have higher output from pig production than non-users of silage. On the other hand, non-users of silage have received more subsidies from the government, in terms of cash rebates from purchases, among others.

Table 8 shows the cost and returns estimates from pig production based on information provided by survey respondents. Three types of pig production were observed: farrow-to-wean or piglet production, grow-to-finish or pig fattening, and farrow-to-finish or the full cycle pig raising from piglet to full slaughter/marketable weight. It is observed that the majority of respondents are engaged in either fattening or full cycle pig raising. The results show that adopters of silage feed technology earn slightly higher revenue from selling fattened pigs compared to non-adopters. Cost per unit of output is also relatively lower among adopters than non-adopters (except among those engaged in pig fattening), although these are not statistically significant. In terms of gross margin as an indicator of return or gains from pig production, adopters among those engaged in full cycle pig raising generate higher returns than non-adopters. It thus appears that adoption of SP silage for pig feed can lower cost per unit of output, thereby generating higher gains from pig raising.

Table 8: Cost and returns from pig production, by type of production system in the survey sites, 2009.

	Farrow to wean		Grow to finish		Farrow to finish	
	adopter	Non-adopter	adopter	Non-adopter	adopter	Non-adopter
Number of obs.	4	6	18	74	17	43
Revenue	27.6 (11)	30.7 (3.8)	11.7 (1.3)**	10.8 (1.4)**	11.9 (1.5)	11.2 (2.2)
Cost	6.5 (2.3)	8.9 (2.9)	10.9 (3.3)	10.7 (2.4)	6.9 (1.9)	7.6 (1.9)
Gross margin	21.1 (10.4)	21.8 (6.6)	0.8 (3.4)	0.03 (2.6)	5 (2.1)*	3.6 (2.7)*

Note: The asterisk (*) denotes the level of significance in the difference of the mean between adopter and non-adopter: *** - significant at 1% level; ** - significant at 5% level; * - significant at 10% level. T-test is used to test differences in the means.
Source of data: ILRI-SASA survey, 2009.

Results from econometric analysis

Determinants of adoption: logit model

Two types of adoption model were estimated using the logistic regression. The first model, using treatment dummy 1 as dependent variable evaluates the factors that determine adoption of SP silage technology among users of sweet potato-based feed technology. The estimated coefficients are shown in Table 9. The results show that aside from the dummy variable that captures the effect of being located in an exposed village, no other covariates are statistically significant. Thus, the results suggest that adoption ensiling of SP among users of SP-based feed technology is largely driven by exposure. That is, among those that are already using SP-based feed technologies, there is a 40% higher likelihood of using another form of SP-based feed technology in the form of ensiling when they are exposed to the technology through direct collaboration with a project, or through exposure to project activities such as workshops, extension activities, among other.

Table 9: Estimates of logit model: Dependent variable= Treatment dummy 1 (1 if silage adopters, 0 if non-silage, sp adopters)

Covariate	Odd ratio	Marginal effect
Household size	0.2 (0.2)	0.04 (0.05)
Male headed household (dummy)	1.4 (1.7)	0.2 (0.2)
Age of household head	0.02 (0.02)	0.006 (0.005)
Number of years schooling of household head	0.04 (0.1)	0.009 (0.02)
HH head having salaried or waged jobs (dummy)	0.5 (0.8)	0.1 (0.2)
Total crop planting area (ha)	-0.8 (0.8)	-0.2 (0.2)
Total income from non-pig sources (1000 Yuan)	-0.0 (0.01)	-0 (0.003)
Value of other livestock owned (10000 Yuan)	1.3 (1.3)	0.3 (0.3)
Producing finishers as output (dummy)	0.5 (1)	0.09 (0.2)
Proportion of local bred pigs raised	0.02 (0.03)	0.005 (.007)
Proportion of cross bred pigs raised	-0.003 (0.01)	-0.0006 (0.002)
Proportion of triple cross bred pigs raised	0.005 (0.01)	0.001 (0.003)
Use of sweet potato as feed before project (dummy)	0.3 (0.8)	0.07 (0.2)
Currently use of premix (dummy)	0.7 (0.6)	0.2 (0.1)
Use of high-protein concentrate before project (dummy)	0.4 (0.6)	0.09 (0.2)
Live pig trader as main sale outlet (dummy)	-0.2 (0.6)	-0.05 (0.1)
Selling pig when need cash (dummy)	0.2 (0.9)	0.05 (0.2)
Applying parasite control before project (dummy)	-1.1 (0.7)	-0.3 (0.2)
Locating in exposed villages (dummy)	2.1 (0.8)***	0.4 (0.1)***
Having learnt about silage technology from AHB/extension (dummy)	-0.2 (0.7)	-0.05 (0.2)
Having received bags for silage preparation (dummy)	-0.5 (0.8)	-0.1 (0.2)
Having received materials for sweet potato planting (dummy)	0.2 (0.8)	0.05 (0.2)
Having received training and technical advice on sweet potato based feeding technologies (dummy)	-0.7 (1.4)	-0.2 (0.4)

Constant	-4.3 (3.3)
Number of Observations	100
Log likelihood	-55.83
L2 chi2 (23)	22.9
Prob > chi2	0.46
Pseudo R2	0.17
P (Silage adoption=1)	0.36

Note: * denotes statistically significant at 10% level, ** denotes statistically significant at 5% level and *** denotes statistically significant at 1% level.

Source of data: ILRI-SASA survey, 2009.

Table 10 below shows the estimated coefficients of adoption model 2 in logit with treatment dummy 2 as dependent variable. This model evaluates the factors that drive adoption of silage among all respondents. The results suggest that adoption of silage is higher among those with household heads receiving salaries or with waged employment, are raising a higher proportion of triple cross pig breeds in their pig herd, were already using sweet potato as pig feed prior to the introduction of the project, and are located in exposed villages hence have been exposed to the technology through the project. It is interesting to note that application of parasite control prior to the project has a negative effect on adoption of silage; so does selling mainly to live pig traders. In the context of the survey sites in Sichuan, these two effects can be rationalized as follows. Use of parasite control and selling mainly to pig traders could capture the effect of scale; that is, relatively larger farms, i.e., those farms that have more pigs relative to the norm in the project site, may have less propensity to adopt ensiling and instead would opt to use more purchased feed such as industrial feed. With larger herd size and limitations of household labor, there is less incentive to adopt a labor-intensive feed technology such as ensiling. Also, parasite control is more likely to be used by bigger farms in order to minimize risks from animal diseases and the negative consequences to production.

Table 10: Estimates of logit model: Dependent variable= Treatment dummy 2 (1 if silage adopters, 0 if non- sweet potato adopters)

Covariate	Odds ratio	Marginal effect
Household size	0.3 (0.3)	0.06 (0.06)
Male headed household (dummy)	-0.07 (1.5)	-0.01 (0.3)

Age of household head	0.03 (0.02)	0.007 (0.005)
Number of years schooling of household head	-0.06 (0.1)	-0.01 (0.03)
HH head having salaried or waged jobs (dummy)	4.3 (1.6)***	0.7 (0.1)***
Total crop planting area (ha)	1.6 (1.2)	0.3 (0.3)
Total income from non-pig sources (1000 Yuan)	0.01 (0.02)	0.003 (0.004)
Value of other livestock owned (10000 Yuan)	0.07 (1.5)	0.01 (0.3)
Producing finishers as output (dummy)	0.3 (1.6)	0.05 (0.3)
Proportion of local bred pigs raised	0.07 (0.08)	0.02 (0.02)
Proportion of cross bred pigs raised	0.01 (0.01)	0.003 (0.003)
Proportion of triple cross bred pigs raised	0.04 (0.02)**	0.009 (0.004)**
Use of sweet potato as feed before project (dummy)	1.9 (0.8)**	0.3 (0.1)***
Currently use of premix (dummy)	1.2 (0.7)	0.3 (0.2)
Use of high-protein concentrate before project (dummy)	1 (.8)	0.2 (0.2)
Live pig trader as main sale outlet (dummy)	-2.3 (0.9)**	-0.5 (0.2)
Selling pig when need cash (dummy)	0.2 (0.9)	0.04 (0.2)
Applying parasite control before project (dummy)	-2.4 (1)**	-0.5 (0.2)***
Locating in exposed villages (dummy)	4.9 (1.5)***	0.6(0.1)***
Having learnt about silage technology from AHB/extension (dummy)	0.2 (1)	0.03 (0.2)
Having received bags for silage preparation (dummy)	-0.3 (0.9)	-0.06 (0.2)
Having received materials for sweet potato planting (dummy)	-0.5 (0.9)	-0.1 (0.2)
Having received training and technical advice on sweet potato based feeding technologies (dummy)	0.7 (1.4)	0.1 (0.2)
Constant	-9.1 (.7)**	
Number of Observations	104	
Log likelihood	-43.69	
L2 chi2 (23)	51.21	
Prob > chi2	0.00	
Pseudo R2	0.37	
P (Silage adoption=1)	0.32	

Note: * denotes statistically significant at 10% level, ** denotes statistically significant at 5% level and *** denotes statistically significant at 1% level.
Source of data: ILRI-SASA survey, 2009.

Treatment effects

Treatments effects were estimated using propensity scores from logit regression and applying three matching methods as discussed in the analytical framework section above. These estimates are shown in Tables 11 and 12. In general, the results suggest the following:

1. Silage technology does not generate significant treatment effects (or outcome) among users of sweet potato feed technology. That is, a household using sweet potato-based feed will not necessarily generate significant productivity gains by adding ensiling among its suite of sweet potato-based feed technology options, e.g., using fresh leaves, tubers or cooking.

2. Silage technology does generate significant positive treatment effects (or outcome) between those that use it and those that do not use sweet potato as pig feed. Thus, non-users of sweet potato-based feed technology could potentially obtain productivity gains from adoption of this feed technology option.

Using the estimated treatment effects from adoption of ensiling, it is seen that on average, a pig raising household is likely to gain at least 2 Yuan gross margin per kg liveweight pig sold when using silage technology. Alternatively, about 3-7 more heads of pigs (at 100 kg/head fattened pig sold) are likely to be produced per year on average by pig raising households when using silage technology. Given these estimates and the documented number of about 70 million pigs sold by rural households in 2008 from Sichuan Husbandry Bureau statistics, the technology could have potentially generated an additional 12.6 billion Yuan of income to pig raising households in the province (or approximately $ 1.8 billion at $1=7 Yuan in 2008).

Table 11: Treatment effects on the treated (silage adopter vs SP users, non silage adopter) by production systems and matching methods

Outcome	Production systems	Matching method	No of treated households	No of control households matched	Average outcome of the treated	Average outcome of the control	ATT
Gross margin per kg	Farrow to wean	Nearest neighbor matching	2	1	24.2 (6.3)	26.3	-2.1 (5)
		Kernel matching	2	2	24.2	26.3	-2.1 (4.9)
		Radius matching	2	1	24.2 (6.3)	26.3	-2.1 (5)
	Grow to finish	Nearest neighbor matching	17	7	2.1 (3.7)	1.1 (2.6)	1 (2.3)
		Kernel matching	17	24	2.1	1.3	0.8 (1.5)
		Radius matching	17	24	2.1 (3.7)	1.5 (3.1)	0.6 (1.1)
	Farrow to finish	Nearest neighbor matching	13	9	4.7 (2)	5.3 (4.3)	-0.6 (1.7)
		Kernel matching	13	16	4.7	4.1	0.6 (1.4)
		Radius matching	13	14	4.7 (2)	3.8 (4.3)	0.9 (1.3)
	Overall	Nearest neighbor matching	32	20	4.6 (6.2)	6.1 (8.7)	-1.5 (2.1)
		Kernel matching	32	42	4.6	4.6	0 (1.8
		Radius matching	32	42	4.6 (6.2)	4 (6.2)	0.6 (1.5)
Output weight (kg)	Farrow to wean	Nearest neighbor matching	3	2	1442 (1631)	1019 (674)	423 (1082)
		Kernel matching	3	4	1442	1091	351 (896)
		Radius matching	2	3	1869 (2056)	1070 (633)	799 (1499)
	Grow to finish	Nearest neighbor matching	20	10	1831 (1878)	1713 (1520)	118 (1040)
		Kernel matching	20	37	1831	1761	70 (629)
		Radius matching	17	37	1609 (1300)	1546 (1704)	63 (420)
	Farrow to finish	Nearest neighbor matching	17	10	2068 (1379)	1743 (660)	325 (442)
		Kernel matching	17	19	2068	1856	212 (370)
		Radius matching	17	17	2068 (1379)	1856 (966)	212 (406)
	Overall	Nearest neighbor matching	40	24	1903 (1633)	2061 (1377)	-158 (438)
		Kernel matching	40	60	1903	1819	84 (328)
		Radius matching	39	60	1750 (1331)	1742 (1297)	8 (299)

Note: The asterisk (*) denotes the level of significance of the estimated coefficient of the ATT: ******* - significant at 1% level; ****** - significant at 5% level; ***** - significant at 10% level.

Source of data: ILRI –SASA survey, 2009.

Table 12: Treatment effects on the treated (silage adopters vs. non SP adopters) by production systems and matching methods

Outcome	Production systems	Matching method	No of treated households	No of control households matched	Average outcome of the treated	Average outcome of the control	ATT
Gross margin per kg	Farrow to wean	Nearest neighbor matching	2	1	24.2 (6.3)	20.1	4.1 (2.9)
		Kernel matching	2	1	24.2	20.1	4.1 (3.5)
		Radius matching	Failed to match	Failed to match	Failed to match	Failed to match	Failed to match
	Grow to finish	Nearest neighbor matching	17	7	2.1 (3.7)	2.3 (1.7)	-0.2 (1.3)
		Kernel matching	17	31	2.1	2.1	0 (1.2)
		Radius matching	17	31	2.1 (3.7)	1.3 (2.3)	0.8 (1)
	Farrow to finish	Nearest neighbor matching	13	5	4.7 (2)	2.5 (1.6)	2.2 (1.2)**
		Kernel matching	13	19	4.7	2.6	2.1 (1.2)**
		Radius matching	8	14	5.2 (1.7)	3.2 (2.5)	2 (0.9)**
	Overall	Nearest neighbor matching	32	16	4.6 (6.2)	3.8 (5.7)	0.8 (2.4)
		Kernel matching	32	51	4.6	3.4	1.2 (2)
		Radius matching	22	40	5 (6)	3.2 (4.3)	1.8 (1.4)
Output weight (kg)	Farrow to wean	Nearest neighbor matching	3	2	1442 (1631)	786 (59)	655 (1029)
		Kernel matching	3	2	1442	786	655 (949)
		Radius matching	Failed to match	Failed to match	Failed to match	Failed to match	Failed to match
	Grow to finish	Nearest neighbor matching	20	8	1831 (1878)	2584 (4007)	-753 (3063)
		Kernel matching	20	37	1831	1767	64 (2882)
		Radius matching	13	25	1272 (424)	1922 (3010)	-650 (745)
	Farrow to finish	Nearest neighbor matching	17	8	2068 (1379)	976 (394)	1092 (456)**
		Kernel matching	17	24	2068	1356	712 (498)*
		Radius matching	10	24	1867 (1038)	1859 (1644)	8 (526)
	Overall	Nearest neighbor matching	40	17	1903 (1633)	1823 (3485)	80 (1741)
		Kernel matching	40	64	1903	1514	389 (1198)
		Radius matching	25	64	1508 (801)	1801 (2214)	-293 (392)

Note: The asterisk (*) denotes the level of significance of the estimated coefficient of the ATT: ******* - significant at 1% level; ****** - significant at 5% level; ***** - significant at 10% level.

Source of data: ILRI-SASA survey, 2009.

Conclusions and Implications

Adoption of sweet potato-based feed technology has potential to generate positive outcomes in terms of higher output and higher profits from pig production. Considering the likely recommendation domain of this technology in the context of Sichuan, technology adoption could have generated approximately 12.6 billion Yuan (or $1.8 billion) of additional income to pig raising households in rural areas. Thus, there is merit to promoting the scaling up of this technology among potential users in appropriate systems. Based on available statistics, this technology can potentially directly benefit some 1.46 poor households in sweet potato-pig systems in Sichuan. Sweet potato-based feed technologies are suitable only in certain agricultural systems, specifically, in less intensive systems where sweet potato is an important crop, areas with poor access to markets for inputs and outputs, where sweet potato and pigs are important contributors to household income and livelihood, in rainfed upland areas, and among households with relatively more land planted with SP. This suggests a targeted approach to scaling up in appropriate domains. Some constraints to scaling up include the labor intensive nature of feed technology preparation where availability of household labor in rural Sichuan is compromised by competition with other labor opportunities outside the farm. Technology modifications to suit conditions of potential users will also need to be explored to facilitate higher uptake, e.g., make it easier, more convenient for farmers to use the technology.

In addition to economic benefits that translate to better livelihood opportunities for pig raising households, sweet potato-based feed technology allows farmers to efficiently engage in full cycle pig production because of the availability of feed year-round. Ensiling can extend the shelf life of sweet potato leaves, vines and tubers, thereby minimizing wastage while ensuring supply of sweet potato for pig feed. This reduces cost of feeding, and specifically reduces cash cost of purchased feed by increasing supply of feed available on-farm. The technology also allows farmers to make use of less productive land in marginal areas. More importantly, there is a potential role for the technology to help poor farmers transition from subsistence pig production activities towards more market-oriented pig production, by helping them build assets from pig production in terms of increasing herd size and also improving efficiencies from cost-effective feeding. By having low cost feed options on-farm, pig raisers are enabled to be more resilient, in terms of being able to cope with external shocks from market, e.g., price volatility of inputs and outputs.

The project provides an example of inter-center collaboration between ILRI and CIP that actually worked, e.g., with CIP research generating appropriate breeding materials to Sichuan Academy of Agricultural Science (SAAS) to develop appropriate SP varieties which in turn resulted in collaboration between SASA and SAAS to develop and test appropriate SP varieties for feeding in collaboration with ILRI. The latter secured project funding to test the identified appropriate SP-based technologies in benchmark sites jointly selected with national partners, and introduced participatory approaches for field-based research and technology dissemination. Similar such partnerships will need to be explored and facilitated in order to generate successful outcomes from research for development initiatives.

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