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Technical and environmental efficiency of livestock farms in China: A slacks-based DEA approach

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ABSTRACT

In the wake of economic development and raised living standards, Chinese pork consumption has risen significantly. As a response to the increased demand and active government support, the national hog sector, which was traditionally dominated by small backyard farms, is featuring a quick restructuring towards large-scale breeding enterprises. With the transformation of the hog sector, environmental externalities have become a very serious concern. Foremost non-point source pollution resulting from the leakage of pig waste into surface water and groundwater resources is seen as a serious threat. Via data envelopment analysis (DEA), we approach the question of efficiency gains from both technical and environmental perspective along a 2012 sample of 371 Chinese hog farms. Our results suggest that especially mid-size hog farms in transition face low environmental efficiency and high pollution abatement costs due to limited waste disposal options. Existent policies turn out to be yet hardly effective in decreasing environmental externalities. In some provinces, projects for rural biogas production could help to improve waste management. However, especially small farms require state support towards improving storage and transportations facilities.

1. Introduction

Over the past decades, fast population growth, rising incomes and changing nutrition patterns have led to a strong increase in China's meat consumption. Total annual meat consumption grew from about 6 million tons in 2000 to 8.6 million tons in 2015, with an annual growth rate of 2.8% (OECD & FAO, 2017). Pork consumption grew especially fast, from a per capita consumption of 10.5 kg/year (rural) and 18.9 kg/year (urban) in 1990, to 14.4 kg/year and 21 kg/year, respectively in 2012 (National Bureau of Statistics China, 2017). To meet the increased demand for pork meat, the production of domestic pork production expanded considerably, from 40 million tons of pig meat in 2000 to 55 million tons in 2015 (National Bureau of Statistics China, 2017).

To achieve this output expansion, China's hog sector had to undergo considerable structural changes. Under the traditional backyard farming system, producers raise hogs extensively as an addition to other farming activities, relying on household residues for feed and using pig waste as manure on their household plot. Nowadays, an increasing fraction of the total pork output is produced by landless, industrial enterprises purchasing nearly all feed from other farms and regions. In 2002, small farms with an annual

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output of <50 heads of hogs accounted for nearly 99% of all hog farms, but contributed 72.8% of the total slaughtered hogs. In 2010, small farms were still predominant in numbers (95.7%), but the few specialized farms accounted for about two thirds of the total hog production (Zhang et al., 2017).[1]

However, the quick transformation and intensification of the livestock sector comes with serious environmental externalities. In the case of hog farming, poor manure management causes considerable emissions of pollutants. Most farms are characterized by a high manure-land ratio, which leaves them with limited capacities to recycle manure back to cropland. Meanwhile, many enterprises neglected the development of manure management techniques during their quick expansion. In effect, manure management in China is underdeveloped, also in international comparison: only 1/3 of total manure nitrogen was utilized in China, while about 3/4 was utilized in the United States and 80% in the European Union (Bai et al., 2016).

The low level of manure management threatens air, water and land resources. For instance, animal manure has found to be an important source of heavy metal leakage in Northeast China (Zhang, Li, Yang, & Li, 2012). A study from Jiangsu Province in China shows that the concentration of copper and zinc in pig manure has been increasing by 770% and 410% from 1990 to 2008. Both heavy metals are used as food additive in industrial hog farming due to their antimicrobial and growth-stimulating effects (Wang, Dong, Yang, Toor, & Zhang, 2013). The leaching of organic nitrogen compounds contained in hog feces may also lead to a variety of environmental externalities in terms of greenhouse gas emission, acidification, eutrophication, photochemical ozone creation and human toxicity (see e.g. Nguyen, Hoang, & Seo, 2012).

In acknowledgment of the seriousness of agricultural non-point source pollution, the Chinese government has already taken action to regulate intensive livestock operations. The No.1 Central Document in 2014 (Ministry of Agriculture China, 2014) explicitly proposed encouraging large-scale farms to efficiently utilize livestock waste. Researchers and policy makers also suggested several specific measures, such as better monitoring of existing regulations, economic instruments like a cut of subsidies on chemical fertilizer, educational measures and technical improvements (Ju, Liu, Zhang, & Roelcke, 2004) or productivity increase through management and technological measures (Ministry of Agriculture China, 2016a). Generally, large-scale farms face stricter regulations than small enterprises, as for instance stipulated by Animal Law, Animal Epidemic Law, Livestock and Poultry Scale Pollution, Prevention, and Control regulations (DBS Bank, 2017).

Taking into account both the structural and the policy background of the hog sector transformation and the repeated claims of the severe environmental burden of industrial hog farming, several important questions need to be answered in order to efficiently target specific policy measures. How does waste management from commercial farms differ from backyard hog farms? How does farm size affect both production and waste management? Can commercial hog enterprises meet the increasing demand without inducing negative environmental externalities? Are the existing policy measures efficient in reducing the emission of pollutants? This paper is the first contribution estimating both environmental and technical efficiencies of hog farms and analyzing the effects of farm types and environmental policy on these efficiencies.

Both parametric and non-parametric methods have been used in the literature to measure environmental and technical efficiencies. A stochastic frontier translog production is commonly used in the parametric domain. Zhou et al. (2015) applied stochastic frontier production function to show that the environmental efficiency and technical efficiency of Chinese hog production at province level are highly correlated. However, several limitations of the stochastic method have been discussed in the literature. One is the requirement that the production technology is to be specified a priori (Monchuk, Chen, & Bonaparte, 2010). The idea of treating undesirable outputs as additional inputs has also been seriously challenged, as it deflects from physical laws and the materials balance principles (Dakpo, Jeanneaux, & Latruffe, 2016).

Data envelopment analysis (DEA) has been widely applied to estimate environmental efficiency, since it features less restrictive assumptions. Among others, Asmild and Hougaard (2006) applied DEA to derive the measures of environmental performance of Danish hog farms. This paper employs a slack-based DEA model (SBM) to estimate both technical and environmental efficiencies using farm level data. The SBM was proposed by Tone (2001) and extended to account for undesirable outputs (Cooper, Seiford, & Tone, 2007; Zhou, Poh, & Ang, 2016). The SBM is appealing in that it allows for a non-radial non-oriented movement towards the efficiency frontier, i.e. the input and output mixes can be altered without arbitrary choice of the direction of optimization. A SBM extended to accommodate the weak disposability approach has been applied by Chang, Park, Jeong, and Lee (2014) and Wang et al. (2015, 2017) for the analysis of water use efficiency, energy efficiency, but also other industries with strong negative externalities, for instance airlines. Application of the SBM in the weak disposability setting allows one deriving the shadow prices, which are based on the endogenized choice of the direction of optimization (i.e. movement towards the efficiency frontier).

By measuring both the technical and environmental efficiency of the hog sector, this study aspires to close an existing research gap. Previous studies separately tackled the topics of manure management in the Chinese hog sector (e.g. Ju, Zhang, Bao, Römheld, & Roelcke, 2005; Qiao, Huang, Wang, Liu, & Lohmar, 2016), its environmental consequences (e.g. Bai et al., 2014; Bai et al., 2016; Wang et al., 2010; Zhang, Ni, & Xie, 2015) and mitigation strategies (e.g. Chadwick et al., 2015; Federolf, Westerschulte, Olfs, & Trautz, 2015; Jongbloed & Lenis, 1992; Nahm, 2002; Szogi, Vanotti, & Ro, 2015). Few studies however have measured the environmental efficiency of the Chinese farming sector via DEA models, among them one study on Chinese fish cultures (Sharma, Leung, Chen, & Peterson, 1999) and one work on land use efficiency for crop-farming (Kuo, Chen, & Tsou, 2014). There are only three studies on the environmental efficiency of the Chinese hog sector, however none of them using farm-level data but only aggregated province-level data (Zhang & Sun, 2015; Zhou et al., 2015; Zhou & Yu, 2005).

The paper is structured as follows: Section 2 describes the data, and Section 3 introduces the SBM model. The results are presented

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[1] For a detailed description of the transformation of the Chinese hog sector see a comprehensive overview by Qiao et al. (2016).

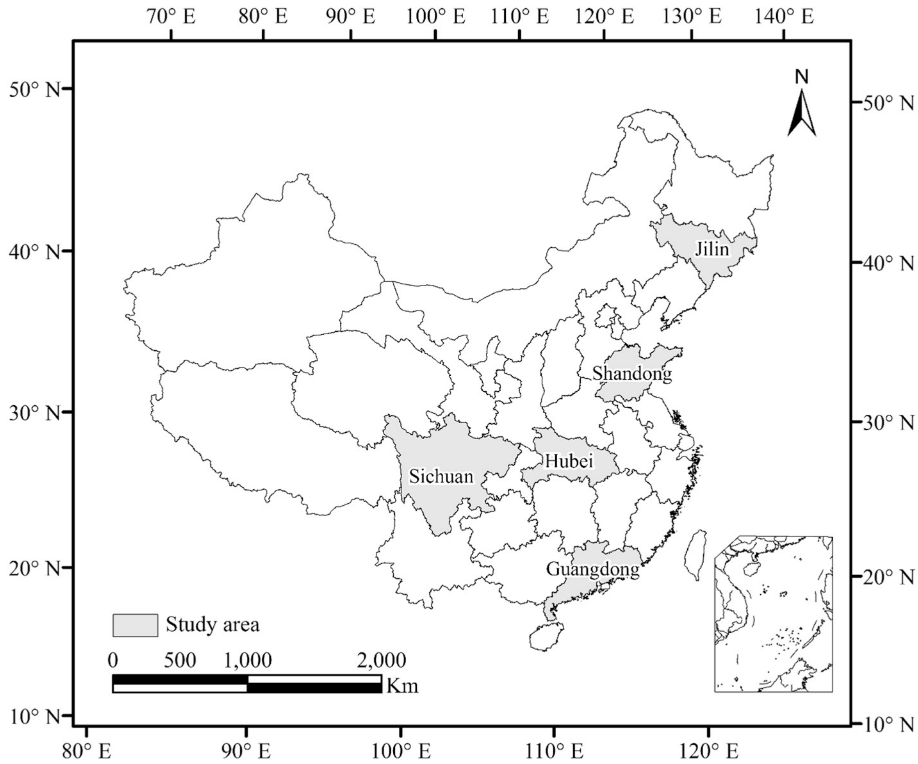

Fig. 1. Location of the study area.

in Section 4, while Section 5 delivers an outlook to possible mitigation strategies based on the insights produced by the previous sections.

2. Data

The data used in this study are from a unique 2013 farm survey in five Chinese provinces, which was conducted by the China Center for Agricultural Policy at Chinese Academy of Sciences in collaboration with the U.S. Grains Council and Asian Agribusiness Consulting. Following a random stratified sampling strategy, five major hog production provinces were selected to represent the main geographical and agricultural regions (Fig. 1). The five province together accounted for about 31% of the total Chinese output of slaughtered fattened pigs in 2015 (National Bureau of Statistics China, 2017). Jilin province stands for the Northeastern provinces dominated by large-scale agriculture. Shandong represents the North China Plain. Hubei represents the semi-humid central provinces. Sichuan represents the diverse southwestern regions dominated by hilly terrain and plateaus. The maritime south is represented by Guangdong.

From each of the five provinces, three counties were selected to represent areas of low, medium and high hog production intensity in the respective province. According to the same criteria, three townships from each county were selected. From each of these townships, three villages were randomly selected. From each village, three hog producers were selected to represent the low medium and high quantile in terms of the total inventory at the end of 2012. We finally surveyed 405 sample farms. One thing to note is that we oversampled the large farms for the purpose of this study as compared to the national sector structure as featured in Yuan and Song (2013). Because its deterministic nature makes the DEA method highly sensitive to outliers, we dropped some observations following the approach by Kapelko, Lansink, and Stefanou (2015).[2] Thus, the final sample was reduced to 371 valid observations.

The survey consists of face-to-face interviews with the heads of hog farms and village leaders. Farmers were asked detailed information on personal socioeconomic characteristics, general farm characteristics and hog production. Socioeconomic information includes age, education, livestock production experiences, and the ratio of family members with off-farm jobs. General farm information includes the distance between home and the feed shop, the value of consumption goods and the area of cultivated land. Specific questions on hog production included farm size (number of marketed hogs in 2012), information on the category of hog feed (complete feed, concentrate feed, premix feed and other feed), labor investment, other costs (including vaccine fee, electricity and water fee, etc.), and the average starting and selling weight of hogs. Waste management practices were assessed in terms of

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[2] A farm was treated as an outlier in case any of the input (or undesirable output) to desirable output ratio fell outside the region defined by the median plus/minus two standard deviations (Kapelko et al., 2015).

percentage of each of the following six types: direct disposal to river or pond, application as manure, use of biogas production, use as fish feed, sale, and others. Village leaders were asked whether their villages conducted any of the following clean village projects: *New Rural Construction Project*, the *Rural Cleaning Project*, the *Biogas Engineering Project* and the *Toilet Reconstruction Project*. Descriptive statistics of the key variables in the regression analysis are given in Table A1.

To estimate the pollutants associated with hog production, we follow the method from the *First National Census of Pollution* (FNCP) *Manual of Discharge Coefficient of Livestock and Poultry Industry* (IEDA & NIES, 2009). Four pollutants common in the livestock industry are estimated: chemical oxygen demand (COD), total nitrogen (TN), total phosphorus (TP), and ammonia. In the first step, we transfer the default produced pollutant coefficients of hogs at different stages in different regions (as given in the FNCP manual) to the farm-specific ones. The pigs in different regions and with different weights produce different amount of waste. The following formula is given by the FNCP Manual to obtain the region-specific coefficient:

$$C_{i,s} = C_{i,d}\frac{W_s^{0.75}}{W_d^{0.75}} \tag{1}$$

where $C_{i,s}$ is the produced pollutant coefficient for the i*th* pollutant in the s*th* farm, $C_{i,d}$ is the default coefficient for the i*th* pollutant in the manual, W_s is the hog weight gain in kg for the s*th* farm (subtracting the starting weight from the selling weight), while W_d is the reference hog weight given in the manual. The default pollutant coefficient, which gives the amount of pollutant in grams that a standardized pig produced per day, is provided by the FNCP Manual. The produced pollutant coefficient refers to the amount of pollutant in grams produced by a specific hog per day.

The second step is to estimate the amount of the i*th* pollutant produced in the s*th* farm, $P_{i,s}$ as a function of the produced pollutant coefficient $C_{i,s}$, the average raising days for the s*th* farm D_s and the total number of hogs N_s:

$$P_{i,s} = C_{i,s} \bullet D_s \bullet N_s \tag{2}$$

Raising days are the number of days the hog is fattened until reaching slaughter weight.

In the third step, the total *discharged* pollutants for each specific farm is estimated. The amount of discharged pollutants $PD_{i,s}$ indicates leakage of pollutants into the ecosystem, depending on both the amount of produced pollutants and waste management practices. Algebraically, $PD_{i,s}$ is defined as

$$PD_{i,s} = P_{i,s} \bullet \sum_{j=1}^{n} k_j \bullet M_j \tag{3}$$

where $PD_{i,s}$ is the amount of the i-th discharged pollutant for the s-th farm, M_j is the percentage of pollutants dealt with the j-th waste management practice and k_j measures the degree to which the produced pollutants leak into the environment for the j-th waste management practice. Direct disposal to rivers and ponds leads to 100% discharge of pollutants, while k for application as manure, biogas production, fish feed, sales and others was fixed at 30%, 10%, 10%, 0% and 50% of discharged pollutants, respectively.

The pollution degrees k for different waste management practices where carefully chosen after extensive literature research: A comparison of existing studies revealed an average loss of organic matter during and after application in the field as manure of about 30% (e.g. Beckwith, Cooper, Smith, & Shepherd, 1998; Pain, Phillips, Clarkson, & Klarenbeek, 1989; Yang, Huffman, Drury, Yang, & Jong, 2011). For biogas production and fish feed, pollutant discharge is considered to mainly occur through leakage during transport and storage. Existent research reports a typical nitrogen loss of at least 10% during storage (Eghball, Power, Gilley, & Doran, 1997; Kirchmann, 1985; Petersen, Lind, & Sommer, 1998). For "other" uses, we chose a pollutant weight of 50%, since we assume that at least part of this matter is in fact illegally discharged (i.e. results in 100% pollutant discharge), while the remainder is subject to the usual storage discharge of 10%.

To model technical and environmental efficiency, we consider three inputs and three outputs for each farm. The inputs comprise labor days (including both family and hired labor), feed quantity in tons, and other cost in Chinese RMB. The desired output is the total hog weight gain (tons per farm) over the raising days. We keep only COD and ammonia as two undesired outputs since adding highly correlated variables to a DEA model implies assigning higher weight to a certain dimension of performance represented by those variables (in our case, that would correspond to excessively rewarding farms that show relatively low levels of pollution).[3] Since COD is, basically speaking, an indirect measure of TN and TP and highly correlated with both values, omitting TN and TP will not affect the estimation of environmental efficiency. The descriptive statistics of all key variables used in the SBM model are shown in Table A2.

3. Methodology

In this section, we firstly present the slacks-based DEA model for measuring the technical and environmental efficiency of hog farms and the derivation of shadow prices of pollutants. In the next step, the efficiency scores are regressed on a set of explanatory variables using a Tobit model to find explanations for the observed differences in technical and environmental efficiencies between farms.

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[3] COD, TP and TN are nearly perfectly correlated (correlation coefficients >0.9). The correlation between COD and ammonia is considerably lower (correlation coefficient = 0.65).

3.1. Slack-based DEA model (SBM)

The underlying idea is that DEA establishes a non-parametric (no functional form is assumed), deterministic (distance to the frontier is explained as inefficiency) and empirical (the frontier spans the actual data) best practice frontier. In such a setting, the frontier goes through the best practice observations, which are considered as fully efficient ones. In fact, DEA results in a piece-wise linear approximation of the underlying technology. The basic principles of the DEA have been outlined for instance by Charnes, Cooper, Lewin, and Seiford (2013).

We follow Wang et al. (2015; 2017) using an up-to-date weak disposability SBM model to measure technical and environmental performance of Chinese hog farms. The standard SBM proposed by Choi, Zhang, and Zhou (2012) and Wei, Ni, and Du (2012) outperforms traditional DEA or directional distance function approaches by allowing specific efficiencies for each input and output. Meanwhile, the standard SBM assumes strong disposability, which means that there is no connection between desired and undesired outputs. In contrast, weak disposability approaches, as applied for instance by Chang et al. (2014), assume that desired and undesired outputs are positively correlated and allow slack variables for all inputs and outputs.

Consider that there are K farms, each of which uses feed, labor, and other costs as inputs (denoted by x) to produce hog meat (denoted by y) along with two pollutants (denoted by u). We firstly assume a variable returns to scale (VRS) weak disposability approach (Färe, Grosskopf, & Kuosmanen, 2009):

$$T_{VRS} = \left\{ (x, y, u) \;\middle|\; \begin{array}{l} x \geq \sum_{k=1}^{K} \lambda^k x^k,\ y \leq \theta \sum_{k=1}^{K} \lambda^k y^k,\ u = \theta \sum_{k=1}^{K} \lambda^k u^k, \\ \sum_{k=1}^{K} \lambda^k = 1,\ \lambda^k \geq 0,\ 0 \leq \theta \leq 1,\ k = 1, 2, \ldots, K \end{array} \right\}, \tag{4}$$

where k is an index for farms, λ is a vector of intensity variables and θ is an abatement parameter or disposability factor. The linear combinations of inputs and outputs are constructed by treating the intensity variables as weights. Therefore, convex technology is assumed (e.g. combination of feasible production plans is also considered as a feasible production plan). In the multi-dimensional space, the efficient surface is formed.

In case of a single desirable output, the weak disposability VRS SBM renders an efficiency measure, which incorporates slacks of inputs s^x, desirable outputs s^y, and undesirable outputs s^u for the t-th decision making unit (DMU):

$$\begin{aligned} &\rho_t = \min_{\lambda_k, s_i^x, s^y, s_l^u} \frac{1 - \frac{1}{I} \sum\limits_{i=1}^{I} \frac{s_i^x}{x_i^t}}{1 + \frac{1}{1+L} \left(\frac{s^y}{y^t} + \sum\limits_{l=1}^{L} \frac{s_l^u}{u_l^t} \right)} \\ &\text{s. t.} \\ &\sum_{k=1}^{K} \lambda_k x_i^k + s_i^x = x_i^t, \quad i = 1, 2, \ldots, I; \\ &\sum_{k=1}^{K} \lambda_k y^k - s^y = y^t; \\ &\sum_{k=1}^{K} \lambda_k u_l^k + s_l^u = \left(1 + \frac{s^y}{y^t} \right) u_l^t, \quad l = 1, 2, \ldots, L; \\ &\sum_{k=1}^{K} \lambda_k = 1; \\ &\lambda_k \geq 0, \quad k = 1, 2, \ldots, K; \\ &s_i^x, s^y, s_l^u \geq 0, i = 1, 2, \ldots, I, l = 1, 2, \ldots, L, \end{aligned} \tag{5}$$

where t is the index for an arbitrary chosen farm, $t = 1, 2, \ldots, K$ and $0 < \rho_t \leq 1$, I and L are numbers of inputs and outputs in the model respectively, and the rest of notations come from Eq. (4). A fully efficient DMU is indicated by $\rho_t = 1$. Note that the constraints associated with undesirable outputs feature factor $\left(1 + \frac{s^y}{y^t}\right)$, which represents the abatement factor and thus ensures weak disposability among desirable and undesirable outputs. Let $s_i^{x^*}$, s^{y^*}, and $s_l^{u^*}$ be the optimal values of s_i^x, s^y, and s_l^u in Eq. (5), respectively. Then, the optimal production plan for the t-th DMU (farm) is defined as follows:

$$\left(x_i^t - s_i^{x*}, y^t + s^{y*}, u_l^t - \left(s_l^{t*} - \frac{s^{y*}}{y^t} u_l^t \right) \right), i = 1, 2, \ldots, I, l = 1, 2, \ldots L. , \tag{6}$$

As the SMB model given in Eq. (5) is a non-linear one, efficiency scores are actually obtained by employing the linearized model:

$$
\begin{aligned}
&\tau_t = \min_{\eta_k, h, S_i^x, S_j^y, S_l^u} h - \frac{1}{I}\sum_{i=1}^{I}\frac{S_i^x}{x_i^t}\\
&\text{s. t.}\\
&1 = h + \frac{1}{1+L}\left(\frac{S^y}{y^t} + \sum_{l=1}^{L}\frac{S_l^u}{u_l^t}\right)\\
&\sum_{k=1}^{K}\eta_k x_i^k + S_i^x = hx_i^t,\ \ i = 1, 2, ..., I;\\
&\sum_{k=1}^{K}\eta_k y^k - S^y = hy^t;\\
&\sum_{k=1}^{K}\eta_k u_l^k + S_l^u = \left(h + \frac{S^y}{y^t}\right)u_l^t,\ \ l = 1, 2, ..., L;\\
&\sum_{k=1}^{K}\eta_k = h,\\
&\eta_k \geq 0,\ \ k = 1, 2, ..., K;\\
&S_i^x,\ S^y,\ S_l^u \geq 0,\ i = 1, 2, ..., I,\ l = 1, 2, ..., L;\\
&h > 0.
\end{aligned}
\tag{7}
$$

The efficiency scores rendered by Eqs. 5 and 7 coincide and feature the same interpretation. After linearization, the solutions of Eqs. 5 and 7 are related as follows: $\eta_j{}^* = h^*\lambda_j{}^*$, $S_i^{x*} = h^* s_i^{x*}$, $S^{y*} = h^* s^{y*}$, and $S_l{}^{u*} = h^* s_l{}^{u*}$. In order to compare the performance of farms in regard to slacks for different variables, we consider the normalized slacks:

$$E_{i,t}^x = 1 - \frac{S_i^{x*}}{h^*}/x_i^t,\ i = 1,\ 2,\ ..., I, \tag{8}$$

$$E_t^y = 1 - \frac{S^{y*}}{h^*}/y^t, \tag{9}$$

$$E_{l,t}^u = 1 - \left(\frac{S_l^{u*}}{h^*} - \frac{u_l^t S^{y*}}{h^*}/y^t\right)/u_l^t,\ l = 1,\ 2,\ ..., L, \tag{10}$$

where unity indicates efficiency in the use of an input or production of an output.

To approximate the marginal abatement costs for undesirable outputs, we employ the dual problem for Eq. (7) as follows:

$$
\begin{aligned}
&\varepsilon_t = \max_{\varepsilon, \pi_i^x, \pi^y, \pi_l^u, \mu} \varepsilon\\
&\text{s. t.}\\
&\varepsilon + \textstyle\sum_{i=1}^{I} \pi_i^x x_i^t - \pi_j^y y_j^t + \sum_{l=1}^{L} \pi_l^u u_l^t + \mu = 1\\
&\pi_j^y y_j^k - \textstyle\sum_{l=1}^{L} \pi_l^u u_l^k - \sum_{i=1}^{I} \pi_i^x x_i^k - \mu \leq 0,\ k = 1,\ 2, ..., K;\\
&\pi_i^x \geq \frac{1}{I}(1/x_i^t),\ i = 1,\ 2, ..., I;\\
&\pi^y \geq \sum_{l=1}^{L}\frac{u_t^l}{y^t}\pi_l^u + \frac{1}{1+L}(\varepsilon/y_j^t);\\
&\pi_l^u \geq \frac{1}{1+L}(\varepsilon/u_l^t),\ l = 1,\ 2, ..., L;\\
&\mu \text{ unrestricted,}
\end{aligned}
\tag{11}
$$

where ε_t is the efficiency score, and π^x, π^y, and π^u stand for the virtual prices of inputs, outputs, and undesirable outputs, respectively; μ allows for variable returns to scale.

Indeed, the constraints in Eq. (11) imply that for the t-th observation, one seeks to maximize the virtual profit, given that no positive profits are found for any of the other observations. The virtual prices of inputs and outputs are set to meet the constraints, and the zero virtual profit equals zero in case of optimality with $\varepsilon_t = 1$. The virtual prices rendered by Eq. (11) then serve to obtain the absolute shadow prices of the undesirable outputs (Wei et al., 2012):

$$p_l = p\pi_l^u/\pi^y, \tag{12}$$

where p is the market price of the desirable output hog weight gain in tons per farm.

In this study, we apply the market price of pig meat in order to construct the absolute shadow prices of COD and ammonia emissions. Thus, the marginal abatement cost depends on the marginal rate of transformation between an undesirable output and the desirable one. In other words, the shadow price reflects the trade-off between the desirable and undesirable outputs. We use the General Algebraic Modelling System (GAMS) to solve the above SBM models.

Table 1

Waste management practices by farm size, village types and provinces (%).

	Manure	Biogas	Direct disposal	Sale	Fish Feed	other
All sample	44.6	23.3	15.4	4.5	8.9	3.3
Farm size (marketed hogs per year)						
Backyard (1–9)	67.3	28.7	3.8	0.0	0.1	0.0
Small (10–49)	59.6	22.4	13.6	1.4	2.4	0.6
Specialized (50–499)	38.2	21.3	18.0	5.3	12.4	4.8
Commercial (> =500)	19.7	28.3	18.5	11.5	16.0	6.0
Province						
Jilin	64.0	2.2	29.2	1.4	0.0	3.2
Shandong	63.0	4.8	20.5	10.9	0.0	0.9
Hubei	44.0	34.1	7.4	4.8	5.6	4.2
Sichuan	20.6	67.0	3.4	0.6	1.0	7.4
Guangdong	26.2	13.1	14.5	3.6	41.2	1.4
Whether a village has an environmental project						
1 = yes	38.9	34.4	13.2	3.5	6.7	3.3
0 = no	52.7	7.7	18.4	5.9	11.9	3.4

Source: authors' survey.

3.2. Tobit model

After obtaining technical and environmental efficiency from the SBM model, we separate the multiple effects of different determinants of technical and environmental efficiency using a Tobit model. We use ES_i to denote the efficiency score for the ith farm from the SBM model; ES_i^* is the unobservable latent variable. When ES_i^* is <0, we assign 0 to ES_i; when ES_i^* is >1, we assign 1 to ES_i. For ES_i^* is between 0 and 1, the Tobit model is specified as

$$ES_i = \beta_0 + \beta_1 EP_v + \beta_2 FS_i + \beta_3 X_i + e_i \qquad if\, \mathrm{ES}_i^* \in (0, 1] \tag{13}$$

where EP_v represents whether a village has an environmental project (1 = yes, 0 = no), FS_i denotes a set of dummy variables representing farm size, X_i stands for a vector of farm characteristics and farmers' socio-economic information (see Table A2, appendix), e_i is the error term and all β_s are the coefficients to be estimated.

4. Results

4.1. Waste management practices and pollutant emissions

On average, about 45% of pig waste was applied as manure, which makes it the most common utilization method (Table 1). Producing biogas (23.3%) is the second most popular option. Feeding fish and for sale account for 9% and 4.5%, respectively. However, still 15.4% of the manure was disposed directly to rivers or ponds, leading to full leakage of pollutants to the ecosystem. This finding coincides with previous estimations on manure management in China. For instance Bai et al. (2016) find high nutrient losses through direct discharge of manure, 24% for N, 41% of P losses and 31% of K. Strokal et al. (2016) report 30%–70% of direct discharge already in the 2000s as opposed to 5% discharge before the onset of transition in the 1970s. This supports the general validity of our farm level observations, taking into consideration that large farms are oversampled, thus leading to a lower rate of direct discharge on average in the sample.

As Table 1 reveals, waste management practices varied significantly across farm types. The percentage of application as manure on crop fields drops significantly as the hog farm size increases. We follow previous publications and differentiate between backyard farms (annual output of 1–9 heads of hogs), small farms (10–49 hogs), specialized farms (50–499 hogs) and commercial farms (> =500 hogs). Backyard farms utilize about 67% of waste as organic fertilizer, whereas the corresponding figures drop to about 60% for small farms, 38% for specialized farms and even lower for commercial farms (20%). Reversely, the share of discharged waste increases with farm size. Backyard farms only discarded about 4% of the waste, while small farms discharged about 14%. This number is even higher for specialized and commercial farms (18% and 19%, respectively). There was also a positive relationship between farms size and sale or utilization as fish feed. Only the use of residue for production of biogas did not significantly vary across farm types. These findings indicate that larger farms can exploit more channels for manure management than smaller farms, likely due to transaction costs (e.g. transport and storage) or market access.

Moreover, we also observe significant regional differences in terms of manure management. As Table 1 illustrates, Jilin and Shandong show the highest shares of manure used for application on fields (64% and 63%, respectively) and discarding (29% and 21%, respectively). Guangdong province exhibits a significantly higher share of utilization as fish feed (41%), while Sichuan has the highest share of residue used for biogas (67%).

We also observe that the rates of application as fertilizer and usage for biogas production differ significantly across villages with and without environmental projects. Villages with an environmental project have a lower percentage of application as manure (39%), 14 percentage points lower than those without any environmental project. About 34% was used to produce biogas in villages with an environmental project, while it's only <8% in those without any environmental project. Although direct disposal in villages with an

Table 2

Pollutant emissions in hog production by farm size, village types and provinces (kg per head of pig).

	COD	TN	TP	Ammonia
All sample	31.1	3.0	0.43	0.49
Farm size (marketed hogs per year)				
Backyard (1–9)	29.5	2.4	0.39	0.36
Small (10–49)	31.9	3.3	0.43	0.45
Specialized (50–499)	32.2	3.1	0.45	0.52
Commercial (> = 500)	26.8	2.6	0.38	0.57
Whether a village has an environmental project				
1 = yes	28.1	2.6	0.37	0.37
0 = no	35.4	3.7	0.51	0.51
Province				
Jilin	51.7	4.1	0.75	0.55
Shandong	36.9	4.9	0.54	0.41
Hubei	22.6	1.7	0.21	0.26
Sichuan	18.6	0.9	0.22	0.33
Guangdong	22.9	2.9	0.38	0.92

Source: authors' estimation.

environmental project (13%) is slightly lower than those without (18%), the differences are statistically insignificant.

Judging from our sample data, about 31 kg COD, 3 kg TN, 0.43 kg TP and 0.49 kg ammonia were emitted per head of pig. Extrapolating these values to the national level, the whole Chinese hog sector emitted about 207 million tons COD, 20 million tons TN, 2.9 million tons TP and 3.3 million tons ammonia in 2014. However, pollutant emissions in hog production showed to vary across farm types, village types and provinces (Table 2). Small and specialized farms emitted more pollutants for raising a head of hog than backyard and commercial farms. Taking COD as an example, the COD emission in small and specialized farms is about 32 kg per head of hog, while it's < 30 kg per head of hog in both backyard and commercial. Farms in the villages with an environmental project emitted slightly less pollutants (28 kg vs. 35 kg of COD). Stronger variation of pollutant emissions was observed across provinces. Jilin ranks the top with 51.7 kg COD per head of hog followed by Shandong (about 37 kg per head). Farms in Hubei and Shandong emitted 56% fewer pollutants than farms in Jilin, Sichuan ranking even lower (18.6 kg per head of hog).

4.2. *Efficiency scores*

Table 3 shows the efficiency scores from the weak disposability SBM model. The average output- and feed-related efficiencies are 0.99 and 0.9, respectively. It means that possibilities for increasing the output and reducing feed input are rather limited in the surveyed farms at the given technology. However, COD and ammonia efficiency scores are only 0.53 and 0.48. Labor and other costs efficiencies are only 0.61 and 0.52, respectively. This indicates that there is a big potential (and need) to improve overall efficiency through reducing environmental pollution and reducing labor input and other costs. On average, Chinese hog farms could reduce COD and ammonia emission by 47% and 52%, respectively, if all farms operated on the efficient frontier associated with the observed productive technology. Labor use could be reduced by 39% and other costs by 48%.

As Table 3 illustrates, efficiency scores differ across farm types. All farms, except the backyard ones, showed full output efficiency. In the case of the backyard farms, the results indicate a potential to increase their output by 12% given current technology. However,

Table 3

Efficiency scores from SBM model across farm size, village type and province[a].

	Hog output	COD	Ammonia	Labor	Feed	Other costs	Overall
All sample	0.99	0.53	0.48	0.61	0.90	0.52	0.54
Farm size (marketed hogs per year)							
Backyard (1–9)	0.88	0.71	0.67	0.67	0.93	0.59	0.61
Small (10–49)	1.00	0.40	0.38	0.48	0.83	0.46	0.44
Specialized (50–499)	1.00	0.49	0.44	0.60	0.92	0.49	0.53
Commercial (> = 500)	1.00	0.76	0.71	0.85	0.96	0.73	0.76
Environmental project in village							
1 = yes	0.99	0.56	0.51	0.63	0.91	0.54	0.56
0 = no	0.98	0.48	0.44	0.58	0.89	0.50	0.51
Province							
Jilin	0.97	0.48	0.53	0.68	0.92	0.54	0.57
Shandong	1.00	0.34	0.38	0.51	0.85	0.47	0.45
Hubei	0.99	0.62	0.66	0.64	0.92	0.63	0.62
Sichuan	0.97	0.65	0.53	0.66	0.91	0.52	0.57
Guangdong	1.00	0.60	0.36	0.58	0.91	0.49	0.52

[a] 1 = full efficiency and 0 = the lower bound of efficiency scores.

in terms of environmental efficiency, backyard (0.71 for COD and 0.67 for ammonia) and commercial farms (0.76 for COD and 0.71 for ammonia) outperform small and specialized farms (around 0.4). The labor efficiency score is 0.85 for commercial farms, and only about 0.6–0.7 for backyard and specialized farms. Small farms have the lowest labor efficiency (0.48), indicating a large potential reduction (52%) in labor input with movement towards the production frontier.

Regarding the effects of the environmental policies, the differences in efficiency are less distinct: Farms in villages with an environmental project have higher environmental efficiency; however, the differences are not decisive. For obtaining a clearer idea on the effect of conducting environmental projects on environmental efficiencies, it is necessary to apply statistical inference (see Section 4.3).

Finally, the differences in efficiency can be observed across the provinces. With respect to input efficiencies, significant differences could only be found for Shandong, which featured low labor and feed efficiencies. In terms of environmental efficiency, again Shandong fared worst with COD and ammonia efficiency scores of 0.34 and 0.38, respectively. While Sichuan performed best in terms of COD output efficiency (efficiency score of 0.65), Hubei performed best in terms of ammonia output efficiency (efficiency score of 0.66). However, these province-level differences may to a certain degree reflect the differences in the farm structure prevailing in different provinces. For instance, in Shandong province, the sample (and production) was dominated by low-efficient small and specialized farms (85% of the sample farms in this province). Sichuan, meanwhile, had the largest share of backyard and commercial farms (together 33.3%), which fare comparatively well in terms of environmental efficiency (see Table 3).

The shadow price of a pollutant indicates the monetary value of the desired (hog) output reduction necessary to achieve a one-unit reduction of the pollutant given a specific production technology. This shadow price can also be compared with mitigation costs from adopting clean technology. If the shadow price is higher than the mitigation costs, it would be worth adopting new clean technology; otherwise, farms should rather attempt to mitigate pollutants by reducing the production in terms of desired outputs. As illustrated in Table 4, the shadow prices of both COD and ammonia vary across farm sizes, provinces and across villages with and without an environmental project.

In our example, the marginal cost of reducing 1 kg COD was 16.6 yuan/kg for small farms, which is well below that of commercial farms (24 yuan/kg). This indicates that the costs for pollution-saving adaptions are lower for small farms than for commercial ones. Similarly, villages with an environmental project had a mean shadow price of COD of 21.7 yuan/kg, compared to 18.5 yuan/kg for villages without an environmental project. Among the survey regions, Jilin province featured the lowest shadow prices of COD and ammonia, while Hubei had the highest ones. Given these results, the efforts for pollutant reduction should focus on small farms, villages with underdeveloped environmental projects, and provinces like Jilin, where shadow prices are significantly lower than in other regions. While low shadow prices in these regions (and farms) can be seen as an indicator for the monitoring effort required there for the enforcement of emission standards, they also reflect the lower marginal costs for emission restrictions under low environmental efficiency levels.

4.3. Determinants of efficiency

The estimation results suggest that all the models perform well (Table 5). The *F-stats* for all the six models are statistically significant at the 1% level, and the Pseudo R^2 range from 10.8% to 31.9%. The variance inflation factor for all variables is <10, indicating that multicollinearity is not a concern.

The regression results provide evidence for a significant correlation of farm size and technical and environmental efficiency. Small farms (the control) are least efficient in terms of not only overall efficiency but also environmental efficiency and input efficiency, while commercial farms are the most efficient both from environmental and production perspectives. For example, the overall efficiency of commercial farms is 0.405 higher than small farms. Backyard farms have a 0.139 higher overall efficiency than small farms. Specialized farms only have a 0.095 higher overall efficiency. The COD efficiency of commercial farms, backyard farms, and

Table 4
Estimated shadow prices of undesirable outputs.

	COD (yuan/kg)	Ammonia (yuan/kg)
All sample	20.4	1379
Farm size (marketed hogs per year)		
Backyard (1–9)	22.8	1695
Small (10–49)	16.6	1151
Specialized (50–499)	21.0	1395
Commercial (> =500)	24.0	1539
Whether a village has an environmental project		
1 = yes	21.7	1470
0 = no	18.5	1251
Province		
Jilin	6.6	622
Shandong	19.0	1657
Hubei	34.1	2817
Guangdong	20.7	528
Sichuan	23.0	1275
Average	20.4	1379

Table 5

Regression results of factors affecting technical and environmental efficiency.

	Overall	COD	Ammonia	Labor	Feed	Other
Village-level environmental programs (1 = yes, 0 = no)	0.063*	0.050	0.057	0.074*	0.030	0.079
	(0.033)	(0.041)	(0.040)	(−0.041)	(0.031)	(0.059)
Farm size (marketed hogs per year, baseline = small farms)						
Backyard (1–9)	0.139**	0.281***	0.241***	0.241***	0.184***	0.114
	(0.066)	(0.076)	(0.068)	(0.068)	(0.056)	(0.110)
Specialized (50–499)	0.095***	0.090**	0.095**	0.095**	0.136***	0.033
	(0.036)	(0.044)	(0.041)	(0.041)	(0.033)	(0.065)
Commercial (> =500)	0.405***	0.439***	0.504***	0.504***	0.255***	0.394***
	(0.070)	(0.082)	(0.085)	(0.085)	(0.062)	(0.113)
Distance to the feed shop (km)	−0.002	0.001	−0.000	−0.000	−0.010**	0.003
	(0.006)	(0.008)	(0.007)	(0.007)	(0.005)	(0.011)
Livestock production experience (yrs)	0.005**	0.006**	0.007***	0.007***	0.000	0.007*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
Education of the head (yrs)	0.008	0.009	0.008	0.008	0.002	0.015
	(0.006)	(0.008)	(0.008)	(0.008)	(0.006)	(0.012)
Age of the head	0.002	0.002	0.002	0.002	−0.001	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Whether a farm member has an off-farm job (1 = yes, 0 = no)	0.059*	0.047	0.043	0.043	0.017	0.098
	(0.035)	(0.043)	(0.041)	(0.041)	(0.031)	(0.067)
Consumable expenditure per capita (1000 RMB)	0.001	0.000	0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Cultivated land (ha)	−0.003	−0.003	−0.003	−0.003	−0.005	−0.008
	(0.008)	(0.010)	(0.009)	(0.009)	(0.005)	(0.013)
County dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.180	0.038	0.045	0.336**	0.950***	0.007
	(0.125)	(0.158)	(0.155)	(0.143)	(0.118)	(0.240)
Pseudo R2	0.319	0.249	0.295	0.257	0.280	0.108
F-stats	5.57***	7.89***	8.35***	7.17***	3.84***	3.20***
Observations	371	371	371	371	371	371

Robust standard errors in parentheses.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

specialized farms is 0.439, 0.281, and 0.090 higher than small farms, respectively. It is not surprising to see that commercial farms have the highest labor (0.504 higher than small farms) and feed efficiency (0.255 higher than small farms).

This U-shaped relationship between farm size and environmental efficiency is a unique finding. Of those few studies that tested environmental efficiency across farm size, all found positive relationships between farm size/farming intensity and environmental efficiency (Reinhard, Lovell, & Thijssen, 1999; Shortall & Barnes, 2013; van Passel, Nevens, Mathijs, & van Huylenbroeck, 2007). Other studies found no significant relationship with farm size (e.g. Karagiannēs, Tzouvelekas, & Xepapadeas, 2003). Therefore, the comparatively high environmental efficiency of backyard farms might be a special characteristic of the Chinese hog sector. The few contributions on the Chinese case do not provide opportunity for comparison. Zhang and Sun (2015) report only technical efficiency and find lower comprehensive technical efficiency for free-range hog breeding and medium-scale and higher efficiencies for small and large-scale enterprises. For pure technical efficiency, they find a positive correlation with the size of enterprises. Zhou et al. (2015) provide results on environmental efficiency, however only on regional level. They find highest environmental efficiency for pig farms in Southwest China and lowest efficiency levels for Northeast and the Northwest. Technical efficiency meanwhile is higher in East China than in Western and Central China.

The existence of environmental programs in the sample village did not significantly correlate with differences in environmental efficiency, only with overall production efficiency and labor efficiency. This indicates that the environmental programs may not come into effectiveness as expected, at least not in terms of reducing pollutants from the livestock sector.

The distance to feed shops is correlated only with feed efficiency. The more distant the respective feed shop, the lower the feed efficiency of the respective farm. The coefficient in the feed efficiency model is -0.01 and statistically significant at the 5% significance level. This indicates that with each additional kilometer of distance to the feed shop, feed efficiency decreases by 0.01. Improving the access to agricultural input markets therefore remains an important feature to improve input efficiency of the Chinese livestock sector.

Furthermore, also some socio-economic characteristics of the farmers may be connected with production efficiency. Farmers with higher livestock production experience feature both higher production efficiency and higher environmental efficiency. Each additional year of production experience increases COD efficiency and ammonia efficiency by 0.006 and 0.007, and labor efficiency by 0.007. Meanwhile, general school education of the farm head as well as his/her age has no effect on any efficiency scores. If a farm member has an off-farm job, the efficiency scores are slightly higher than those without any off-farm work. This result meanwhile is only significant in the overall model at 10% significance level. Neither wealth level nor cultivated land area has significant effect on any production or environmental efficiency.

5. Discussion and conclusion

Our empirical results underline the role of farm size for environmental efficiency. In backyard hog production, crop plots might be sufficient to absorb the small amount of manure produced by the few raised pigs. Therefore, application on the field was the most frequent management method among backyard farms and regions with a large rate of backyard farms. However, larger farms may lack sufficient crop land for manure application (e.g. Bai et al., 2014). With increasing size of hog farms, farmers have to resort to other forms of waste disposal, including methods with a high environmental impact like direct disposal of pig waste to rivers and ponds. Especially mid-size farms show significantly lower rates of environmental efficiency and thus increased non-point source pollution. Large commercial farms featured significantly increased environmental efficiency, very likely through the availability of financial and organizational means to maintain storage and transport capacities necessary for other methods of manure management. Large farms also face stronger environmental regulations than smaller farms and thus more powerful incentives towards sustainable manure management. For instance, several emission thresholds stipulated by national government and specified on province level apply only to farms with an annual hog output of 500 or more heads of pig (see e.g. Guangdong State Bureau for Environmental Protection & Guangdong State Bureau of Quality and Technical Supervision, 2009). Our results indicate that future emission regulations should also apply to small and medium sized farms, where environmental efficiency is lowest and abatement cost moderate.

Our results also point to the necessity of regionally adapted measures, as differences in terms of environmental efficiency and waste management across the sample provinces were distinct. Primarily, the observed differences could be due to structural differences of the sample provinces concerning the development of manure markets, which impacts transaction costs and thus manure management. Among all Chinese provinces, Guangdong produced the highest output of aquaculture products in 2014, which constitutes a considerable market for manure as fish feed. Sichuan, on the other hand, was the third-biggest producer of biogas, the province with by far the largest biogas consumption across all Chinese provinces, and second largest consumer of biogas in proportion to overall consumed energy (National Bureau of Statistics China, 2017). Thus, it does not come as a surprise that the usage of manure for fuel gas was predominant in Sichuan and Hubei provinces. Guangdong with its large fish industry featured very high rates of use for feed. In summary, farmers in regions with either an appropriate infrastructure or respective markets were more likely to use other forms of manure management than direct disposal to rivers and ponds. Surprisingly, Jilin featured the highest rate of direct disposal to river or ponds. As the province with the third-largest per capita plot size of the whole country (as of area of cultivated land managed per rural household in mu/person), one would have assumed the emergence of a market for selling manure as natural fertilizer to large-scale crop farmers. This last finding highlights the need to further develop manure markets in Jilin, but also adds additional momentum to the debate over the sustainability of direct and indirect subsidies for chemical fertilizer.

Generally, not only structural characteristics but also the policy setting in the sample provinces may offer an explanation for the distinct differences between provinces. Manure management in Chinese agriculture is regulated through a set of national polices, among them the “Environmental Protection Law of the People's Republic of China” (National People's Congress, 2014), the “Regulation on the Prevention and Control of Pollution from Large-scale Breeding of Livestock and Poultry” (National People's Congress, 2014), the “Regulation on Breeding Livestock and Poultry” (State Council of the People's Republic of China, 2011), the “Law of the People's Republic of China on Prevention and Control of Environmental Pollution by Solid Waste” (Standing Committee of the National People's Congress, 2004), the “Animal Husbandry Law of the People's Republic of China” (Standing Committee of the National People's Congress, 2005), and the “Law of the People's Republic of China on Prevention and Control of Water Pollution” (National People's Congress, 2008).

Central Government regulations, however, grant considerable leeway to province or even county-level governments to specify or tighten existing regulations. In effect, environmental policies may vary considerably between sample regions. Guangdong province 2009 emission standards for instance referred to two groups of farms: Group I are farms with 500 heads of pigs or more, group II are pig farms with an output of 200–499 heads of pigs. The emission standards are binding for both groups, with the only difference that mid-size farms were granted an additional year for implementation (Guangdong State Bureau for Environmental Protection & Guangdong State Bureau of Quality and Technical Supervision, 2009). For Jilin province, meanwhile, only national regulations seem to be applying, which set the size thresholds at ≥ 3000 heads of pigs for group I and 500–2999 heads of pigs for group II (National Bureau For Environmental Protection, 2003). In our sample, this meant that only 10% of the sample farms were actually bound to these emission standards at all. While this is only a very narrow perspective on the whole regulatory body, this might still mean that laxer regulations may the one reason for the low environmental efficiency in Jilin province.

All in all, an efficient pig sector does not only require intensified, large-scale farms with high technical efficiency, but dedicated measures to solve the decreasing manure-land ratio. The education of farmers towards advanced manure management practices may improve environmental efficiency, as regression analysis indicates. Where abatement cost for manure pollutants is high, raising the awareness of farmers may not be sufficient though. In our study, the impact of existent environmental programs on environmental efficiency is rather doubtful. Monitoring measures are certainly one option, however may prove expensive and hardly sustainable as long as shadow prices for improved waste management remain high.

Our evidence rather points towards the necessity of government support when it comes to improving the participation of small- to medium farm size in existent manure markets, especially over the subsidization of transport and storage facilities. Manure sales or use as feed, for instance in aquacultures, are certainly to be preferred before disposal to rivers and ponds. At the same time, also these management methods entail problems like deposit of nitrogen, phosphorus, heavy metal and antibiotics in soil, ground- and surface water due to excess application of manure. The use of manure for biogas, on the other hand, requires few additional land resources and entails less pollution of soils and water than disposal or application on the field. While the absorbing capacity of cultivated land is limited, it could be observed that a market for biogas can absorb large ratios of produces pig waste, for instance in Sichuan province. The rural biogas project, which was firstly proposed in 2007 and now recently seized again by the Ministry of Agriculture's rural waste treatment pilot (Ministry of Agriculture China, 2016b) may therefore be one way to solve the challenge of managing the transition between backyard and large scale commercial hog-farming.

The cross-sectional character of the dataset entails certain limitations with regards to the interpretation of the results. First of all, no development trends of the hog sector in general and residue management in particular can be inferred. Also, cross-sectional data limits the interpretation of our results in terms of causality. Another limitation is the relatively small sample size. While existing research confirms the general traits of the observed problem of poor manure management, there are no national statistics or previous studies for comparison of farm size effects and regional effects of residue management. Therefore, further studies regarding livestock residue management and environmental efficiencies are called for.

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Table A1
Descriptive statistics of the key variables in the regression analysis.

Variable	Mean	Std. dev.	Min	Max
Whether a village has environmental project related with livestock production (1 = yes, 0 = no)	0.59	0.49	0	1
Farm size (marketed hogs per year)				
Backyard (1 = yes, 0 = no)	0.11	0.31	0	1
Small (1 = yes, 0 = no)	0.26	0.44	0	1
Specialized (1 = yes, 0 = no)	0.48	0.50	0	1
Commercial (1 = yes, 0 = no)	0.15	0.36	0	1
Distance to the feed shop (km)	3.35	3.04	0	17
Livestock production experiences of the household head (yrs)	12.01	7.36	0	42
Education of the household head (yrs)	7.29	2.53	0	15
Age of the household head	47.41	9.28	21	71
Whether a farm member has an off-farm job (1 = yes, 0 = no)	0.25	0.43	0	1
Consumption expenditure per capita (1000 RMB)	19.92	35.97	1.2	300
Cultivated land (ha)	1.29	3.39	0	50

Table A2
Descriptive statistics of the key variables in SBM model.

Variable	Type of variable	Mean	Std. dev.	Min	Max
Weight gain (tons per farm)	Good output	25.8	52.7	0.1	452.0
COD (tons per farm)	Bad output 1	6.4	12.9	0.0	124.9
Ammonia (kg per farm)	Bad output 2	124.6	347.5	0.2	4998.8
Labor (including both family and hired labor, days per farm)	Input 1	249.6	671.4	2.3	8376.0
Feed (including complete, concentrate, premix feed and other feed, tons per farm)	Input 2	79.7	162.2	0.23	1596.8
Other cost (including vaccine fee, electricity and water fees, etc.) (1000 yuan per farm)	Input 3	86.4	235.1	0.0	2096.9

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