EEPSEA

2016-RR11

An Estimation of the External Cost of Photovoltaic-Oriented Silicon Production in China

Zanxin Wang, Wei Wei, Shuangli Xu

WorldFish

Published by WorldFish (ICLARM)– Economy and Environment Program for Southeast Asia (EEPSEA)
SEARCA Bldg., College, Los Baños, Laguna 4031 Philippines; Tel: +63 49 536 2290 loc. 196; Fax: +63 49 501 7493; Email: admin@eepsea.net

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ISBN: 978-971-9680-72-7

Front cover photo: Workers are smashing quartzite stones at the field of a silicon plant in Nujiang, Yunnan province, China. The buildings behind are the workshop, where the big stacks are connected with furnaces for silicon purification.

Suggested Citation: Wang, Z.; W. Wei; and S. Xu. 2016. An estimation of the external cost of photovoltaic-oriented silicon production in China. EEPSEA Research Report No. 2016-RR11. Economy and Environment Program for Southeast Asia, Laguna, Philippines.

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July, 2016

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ACKNOWLEDGMENTS

The authors would like to thank the following individuals and institutions that provided support and/or assistance for the study:

The Economy and Environment Program for Southeast Asia (EEPSEA), especially the director, Dr. Herminia A. Francisco, the administrative staff Ms. Julienne Bariuan-Elca, Ms. Noor AiniZakaria, and Ms. Mia V. Mercado, for their invaluable support to the study.

Prof. David James, Faculty of Science, Health, Education and Engineering, University of the Sunshine Coast, Queensland, Australia for his valuable comments and suggestion for the implementation of the project.

Prof. Daigee Shaw, Research Fellow at the Institute of Economics, Academia Sinica; President of the Taiwan Association of Environmental and Resource Economists; and also Professor in National Cheng-Chi University and National Taipei University in Taiwan, and Xi'an Jiaotong University in China, for his valuable comments and suggestions for project proposal design.

Prof. Benoit Laplante, an independent consultant and Adjunct Professor at the School of Public Policy of Simon Fraser University, for his valuable comments and suggestions for project proposal design.

Ms. Lizhi Wang and Mr. Chan Zhou, postgraduate students, for their help in the data collection.

Mr. Jun Wang, an employee of Nujiang Silicon Industrial Zone, for his provision of secondary data associated with silicon production and his assistance in the field surveys.

Village managers of the surveyed villages for providing the basic data on agricultural situations and demographic information of villages, who were important in estimating the external cost of silicon production.

Finally, I appreciate those anonymous villager respondents who provided useful information for this study during the field surveys.

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EXECUTIVE SUMMARY

Global warming has become a driver for the exploitation of renewable energy, especially solar. The rapidly increasing demand for silicon panels has resulted in severe pollution from its manufacture in China. This study aims to estimate the external costs of silicon production so as to provide information for making policies on the sustainable exploitation of solar energy. In particular, the study first theoretically analyzed the impact of industrial pollution on crop production by integrating a damage function with the stochastic frontier analysis (SFA) model followed by an empirical study, and then estimated the external cost of health damage and agricultural loss resulting from industrial pollution from a silicon industry zone in Southwest China.

The theoretical results show that industrial pollution can reduce the marginal output and change the substitution or complementary elasticity of crop production factors. This finding is consistent with empirical results in the case of rice. The empirical results show that industrial pollution reduces the marginal outputs of rice production factors and changes the relationships between seed and labor as well as chemicals and capital while reducing the complementary elasticity value between seed and capital, seed and chemicals, and chemicals and labor.

The external costs are the resulting health damage and agricultural loss. The data in this report was collected from a silicon industry zone in Southwest China. The external cost of agricultural loss was estimated using a production function method, while the external cost of health damage was estimated using dose-response functions, in which the pollutant concentration in air is estimated based on a Gaussian dispersion model. The results show that the annual external cost of agricultural loss is CNY 1.5–4.8 million and that of health damage is CNY 26.5–44.6 million. That is, the total external cost is CNY 28.0–50.4 million. The average external cost is CNY 461.5 (CNY 329.9–593.1) per ton of metallurgical silicon, which is equivalent to the abatement cost of dust removal and wastewater treatment (approximately CNY 441.6 per ton). The internalization of the external cost would reduce the silicon plant's financial profit by 28%.

The results have important policy implications. First, although promoting the production and use of solar energy can contribute to sustainable development, attention should also be given to the external cost of producing its related products. Second, information on external costs can be taken into account in economic feasibility studies of silicon production projects in rural areas. Third, the negative externality can be internalized by installing and operating abatement equipment, as the external cost is approximately equal to the abatement cost. This gives local governments the justification to require silicon plants to install abatement equipment. Fourth, information on external costs can be used in making policies that would compensate affected local farmers and residents and in designing instruments to control pollution from metallurgical silicon production.

1.0 INTRODUCTION

1.1 Background

Along with increasing concern about environmental pollution and greenhouse gas (GHG) emissions from fossil fuels, a transition has occurred where development has moved toward green energy and power generation from renewable energy sources that are abundant and free (Mekhilef, Saidur, and Safari 2011). Governments and industries all around the world are increasingly exploring ways to reduce the GHG emissions from their operations, with a major focus on using and installing sustainable renewable energy systems (Abdelaziz, Saidur, and Mekhilef 2011). Solar energy is one of the most promising backup energy sources since it is naturally available and a clean energy source, and thus has many advantages over other resources (Saidur 2010). Many countries have made medium- and long-term plans for the development of their photovoltaic (PV) industries. The International Energy Agency (IEA) estimates that solar electricity will represent up to 20%–50% of global electricity by 2050.

Through time, the dramatic growth in demand has been matched by an expansion of the silicon industry. The world output of polysilicon has increased rapidly since 2007. At least 38.4 gigawatts (GW) of PV systems were installed globally in 2013, up from 30 GW in 2012 (EPIA 2014). Although declining political support for the PV industry in the European Union in 2011 caused a decline of polysilicon output in 2012, the implementation of new feed-in-tariff policies has led to a dramatic increase of the polysilicon markets in other countries, resulting in an increase in the world output in 2013.

The rapid expansion of the PV market in China has been due to the implementation of the Renewable Energy Law (enacted in 2006) and to the 10-year development program aiming for an increase in China's total primary energy consumption from around 10% in 2009 to 15% by 2020 from non-fossil and renewable sources. In 2013, China became the world's leading installer of photovoltaics, adding 11.3 GW to a cumulative total of 18.3 GW (IEA 2014). Moreover, solar water heating is also being extensively implemented in China.

The demand for silicon products drives more producers to increase their production capacity and explore silicon resources. Since 2011, China has become the biggest supplier of polysilicon, the primary material of solar cells, accounting for around one-third of the annual world output of polysilicon. However, as an important part of the industrial chain of PV systems, metallurgical silicon production is characterized by capital intensiveness, high-energy consumption, and high rate of waste emission. Coupled with China's rapid increase in PV-oriented metallurgical silicon output, the resulting pollution is becoming more and more of a concern.

In recent years, the number of reported cases of pollution from silicon production has continued to increase, mainly in rural and remote areas in central and western China. Silicon producers prefer these locations for their plants because of the availability of high-quality quartzite sand, and because the environmental pressure is not as stringent as in Eastern China. On the other hand, the local governments in these areas are eager for the income brought by the establishment of industrial production bases, but often at the expense of the environment and with unforeseen health costs due to the rapid expansion of silicon production bases.

With the aggravation of pollution from silicon production, conflicts between the government, silicon producers, and local residents have gradually intensified. The pollution has directly resulted in a sharp decline in agricultural outputs, including rice, corn, vegetable, as well as fruit such as walnut. Local farmers also reported that noise, smog, and foul-odor gases have become intolerable for them. Likewise, the local residents' health is seriously affected, with the observed cases silicosis and cough increasing. Thus, the local government has to make a trade-off between economic development and environmental protection.

The question then is, "How much is the external cost of pollution from silicon production?"

Local governments usually fail to make the acceptable trade-off due to the lack of this information. This information is also needed to determine the amount of penalties for pollution that should be implemented in the existing laws and to obtain a reference for compensating those who are adversely affected as a result. This study therefore aims to estimate the external costs of metallurgical silicon production in order to provide information for drafting policies for the sustainable exploitation of solar energy. Specifically, this study estimates the external cost of health damage and agricultural loss.

The results of this study are also useful for conducting cost-benefit analyses for introduced projects and for assessing the sustainability of solar electricity. Moreover, unlike the rapid increase in installed PV capacity, literature on the externalities of silicon production remains scarce, especially in China. Therefore, this study is expected to fill this gap in the literature and provide local authorities with the information required in policy making. At the local level, the authorities urgently need to find a solution to the pollution problem as more and more residents protest against the pollution due to silicon production, which makes the conflict between silicon firms and local residents to intensify. The local government plans to make a policy or mechanism to balance silicon industrial development and environmental protection; however, this requires understanding the economic losses from pollution. The information on external costs is not only for determining the appropriate fines for pollution in accordance with the laws on water and air pollution control, but is also needed for making new policies for pollution control and for the introduction of additional investment.

1.2 Literature Review

Although rapid industrialization and urbanization improve many of the citizens' standards of living, the ensuing unwelcome environmental effects inevitably lead to a legitimate public health and environmental concern (Tang et al. 2008). As environmental quality worsens, there have been frequent media coverage and increasing scholarly writings on China's pollution threats (e.g., Kan and Chen 2003; Kanet al. 2004; and Mead and Brajer 2006).

Industrial pollution usually affects human health, agricultural output, and ecosystem health. The impacts result in external costs. External costs are non-internalized economic cost imposed on society that are not accounted for in the producer's and consumer's economy; that is, external costs are not included in the market prices, and thus considered as a market failure (Fahlen and Ahlgren, 2010). Studies have shown that accounting for external costs may improve the competitiveness of certain renewable energy sources (El-Kordy et. al 2002; Roth and Ambs 2004) and provide information for the design of environmental policies, such as environmental fees and taxes to internalize the external cost (Fahlen and Ahlgren 2010).

1.2.1 The impacts of industrial pollution on human health

Researchers have demonstrated that there is a close relationship between human health and pollution. The World Health Organization (WHO) has identified ambient air pollution as a high priority in its global burden of disease initiative, estimating that air pollution is responsible for 1.4% of all deaths and 0.8% of disability-adjusted life years globally (WHO 2002). Several epidemiological studies have shown that chronic exposure to PM_{10} and $PM_{2.5}$ increases an individual's risk to cardiovascular and respiratory diseases and lung cancer (Raaschou-Nielsen et al. 2013). A link between respiratory disease and particulate air pollution and/or sulfur oxide pollution had been well established by the 1970s (Pope, Bates, and Raizenne 1995). After the work of Dockery et al (1993), researchers have placed more emphasis on fine particles, which are thought to pose a particularly great risk to health. In China, majority of the literature are about the health effects of total suspended particulates (TSP) and PM_{10}. For example, Chang, Hans, and Haakon (2001) found that along with an increase of 100 $\mu g/m^3$ in PM_{10} in Beijing, the incidence rates of lead respiratory disease-related deaths, cardiovascular and erebrovascular (CVD and CHD) deaths, coronary disease deaths, and chronic obstructive pulmonary disease (COPD) deaths increased by 4.08%, 4.98%, 3.77%, and 4.95% respectively. Furthermore, Dai et al. (2004) revealed that a 10 $\mu g/m^3$ increase in PM_{10} and $PM_{2.5}$ were associated with 0.53% and 0.85% increase in total daily mortality, respectively, in Shanghai.

To assess the impacts of industrial pollution on human health, the relationship between emission and pollutant concentrations need to be understood. Many dispersion models can be used for public health research, including the Gaussian plume, Lagrangian (trajectory), Eulerian, and regression mapping. Each model has its advantages and disadvantages (Holloway, Kinney, and Sauthoff 2005). It is recognized that for a scale of a few kilometers, the conventional Gaussian-type model is capable of adequately estimating the $PM_{2.5}$ and PM_{10} concentrations in certain open environments, especially for longer average periods (Holmes and Morawska 2006). The model takes into account elevation above ground level and the gravitational settling. However, the chemical formation or aerosol dynamics (nucleation, coagulation, condensation, etc.) to evaluate particle processes occurring within the plumes are not included in the model. The implemented model is adequate for particles with diameter between 0.1 mm and 20 mm, covering the submicrometer and micrometer size ranges, which have the same behavior of the gas that drags the particles. This is consistent with the practical interest in environmental air quality evaluations (the range of 2.5–10 mm). A further limitation is that Gaussian models have been shown to overestimate concentration levels under low-wind conditions (Holmes and Morawska 2006). Despite these limitations, the Gaussian model is well accepted for regulatory purposes and for environmental impact assessment of industrial power plants. More importantly, the model does not require extensive computer power or time (Lorber, Eschenroeder, and Robison 2003).

1.2.2 Impacts of industrial pollution on agriculture

The impact of pollution on agriculture is also well-recognized. Industrial pollution affects agricultural production mainly through air and water pollution. There are three main sources of air pollutants (Birley and Lock 1999):

1. sulfur oxides from the use of fossil fuels and solid particles;
2. photochemical oxidants and carbon monoxide from vehicle engines; and
3. various pollutants such as vulcanization hydrogen, lead, and cadmium from furnaces, refineries, processing plants, and vehicle emissions.

Air pollution affects agricultural productivity in two ways (Heck, Taylor, and Tingey 1988): (1) pollutants disrupt plants' biochemical and physiological reactions to a certain degree, while (2) acid rain resulting from air pollution causes soil degradation and lowers the concentration of nutrients that crops need. These effects are cumulative and permanent (Heck, Taylor, and Tingey, 1988).

Water pollution, on the other hand, is mainly due to wastewater emissions from industrial plants. When crops are irrigated by wastewater, the development of root and seedling crops can be adversely affected, including a decrease in crop height, leaf area, and dry weight. It can also cause decline in leaf area, which results in a reduction in photosynthesis, and consequently, of crop yields (World Bank 2007).

Many studies show that industrial pollution has a significant impact on crop growth and yield. Crop yield depends largely on the ambient conditions, especially air quality; air pollution can result in a reduction in crop yield. In the United States, economic losses due to air pollution were USD 40–50 billion in 1997 (Lee 1999). In Pakistan, when the seasonal average concentration of O_3, NO_2 and SO_2were 70, 28, and 15 parts per billion, the yields of three rice varieties decreased by 43%, 39%, and 18%, respectively, during the 2003–2004 season (Wahid 2006).

The impact of water pollution is also significant. Wastewater irrigation can reduce the quality and quantity of agricultural products. The degradation of quality is associated with two factors:

1. The product which contains pollutants (such as heavy metals and other toxic substances from the wastewater) is not suitable for consumption.
2. The nutritional quality can also deteriorate, such as the value of protein, amino acids, Vitamin C, and other nutrients (World Bank 2007).

In China, in comparison to clean irrigation water, wastewater irrigation caused a total loss of CNY 360/mu[1] in 2003, and the economic loss of reduction in yield quantity and quality was estimated to be CNY 285/mu and CNY 75/mu, respectively (Lindhjem 2007). As far as wheat, corn, rice, and vegetables were concerned, wastewater irrigation has resulted in a total economic loss of CNY 7 billion per year in China (World Bank 2007).

The existing literature on the impacts of industrial pollution on agriculture can be divided into three categories in terms of methods:

1. the use of existing dose-response functions to calculate the yield loss based on the concentration of pollutants (e.g., World Bank 2007);
2. the comparison of field experiment results e.g., Rai and Agrawal [2008] used the open-top chamber to study the changes in rice yields as the concentration of SO_2, NO_2 and O_3 change; and
3. the comparison of the crop yields in polluted and non-polluted areas, such as Khai andYabe (2012) and Lindhjem (2007).

These studies analyzed the relationship between pollution and health or yield of crops. Despite this, there is still scant literature that focuses on the use of economic methods to assess the impacts of industrial pollution on agricultural production (Aragon and Rud 2015). Although Aragon and Rud (2015) recently

[1] 1 ha = 60 mu

studied the problem using an economic method, few studies have focused on how industrial pollution reduces crop yield by affecting the relationship between production factors; these studies need to establish the relationship between the factors and the output, which is usually assessed using production efficiency measures.

Production efficiency is mainly quantified using the data envelop analysis (DEA) method and the stochastic frontier analysis method (SFA). Although the directional distance function (DDF) is also widely used in production efficiency analysis, DDF has the same idea as that of DEA, and thus is considered only one part of DEA (Pang and Deng 2014). DEA, first proposed by Farrell (1957) and then further developed and promoted by Charnes, Copper, and Rhodes (1978), is a nonparametric method that measures the efficiency of a decision-making unit (Yan and Shi 2014). Despite its wide uses, DEA is usually considered a deterministic approach. The SFA method, on the other hand, was first proposed by Aigner, Lovell, and Schmidt (1977). It is different from the DEA method such that the stochastic frontier production function divides production inefficiency into technical inefficiency and random error. Thus, a relationship between factor and production efficiency can be built based on the SFA method.

Owing to the methodological advantage, SFA has been widely used to study production efficiency in the agriculture sector (Battese 1992; Wahid 2006); industrial sector (Kopp and Smith 1980; Henningsen 2014); and service sector (Zhu, Ellinger, and Shumway 1995). Furthermore, it has been used to analyze the factors affecting productivity (Coelli and Battese 1996); the impact of policies (Serra, Zilberman, and Gil 2008); and the impact of resource management projects (Solis, Bravo-Ureta, and Quiroga 2009) among others.

Although the SFA method can be used to estimate production efficiency, it has two critical shortcomings. First, there exists an obvious difference in the production efficiency estimated using different production functions (Giannakas et al. 2003). Second, the factor has the same effects on both the deterministic and frontier parts in the production function (Serra, Zilberman, and Gil 2008). However, as the external environment changes, the deterministic part may be changed while the frontier part remains constant. In such a case, the traditional SFA is no longer suitable for production efficiency analysis.

The first shortcoming, as addressed by many scholars, can be solved by choosing a suitable production function. Very few studies have delved on addressing the second shortcoming, although there are common cases that recommend efficiency to be estimated in the presence of production environmental change, such as the adjustment of the national strategy, implementation of new industrial policy, and incidence of environmental pollution, and so on. The application of the traditional SFA is limited because efficiency cannot directly be estimated when the production technology is heterogeneous (Just and Pope 1978). On one hand, changes in the external environment may affect the technical inefficiency; on the other hand, the traditional frontier production function cannot be directly used to analyze the impact of industrial pollution on production efficiency. In the agriculture sector, production is usually affected by environmental pollution and changes in government programs. If these two shortcomings are not addressed, then the result obtained by using the traditional frontier production function is biased and invalid (Serra, Zilberman, and Gil 2008).

Pollution control usually involves two phases. The first phase involves applying traditional legal remedies, such as emissions standards. However, it has become clear that these traditional regulatory approaches to pollution control are incapable of achieving their stipulated goals (Tietenberg 1995). Failures have been common in developing countries, where legal and regulatory institutions are often weak (Afsahand Laplante1996). In response to these deficiencies, the second phase of pollution control focused on market-based approaches, such as tradable permits, emission charges, deposit-refunds, and performance bonds (Hahn1989; Tietenberg1990). In theory, market-based instruments minimize the aggregate cost of achieving a given level of environmental protection (Baumol and Oates 1988), and provide dynamic incentives for the adoption and diffusion of cheaper and better control technologies (Jaffe and Stavins 1995). As stated in the work plan of the Ministry of Environmental Protection in 2013, the Chinese government is putting greater emphasis on market-based instruments for pollution control, although the active ones are mainly mandates. Thus, the information on the external cost of pollution and the abatement cost of technology is important when selecting a certain technology and instrument.

1.3 Objectives of the Study

This study generally aims to estimate the external costs of silicon production and analyze their policy implications for the sustainable development of solar energy in China. The specific objectives of the study are the following:

1. To estimate the external cost of health damage,
2. To analyze the impact of industrial pollution on agricultural production and estimate the economic cost of agricultural loss,
3. To estimate the abatement cost of silicon production, and
4. To provide policy implications of these external costs for the sustainable use of solar energy.

1.4 Scope of the Study

1.4.1 Study site

Because of the high electricity consumption in silicon production, silicon producers usually locate their production bases in areas where high-quality quartzite sand is abundant and where the price of electricity is low. High-quality quartzite sand is mainly found in Western China, especially in Yunnan province. Within this province, high-quality quartzite sand is particularly abundant in the Nujiang, Dali, and Baoshan prefectures. Water resource is also rich in these prefectures, and thus the price of hydropower is relatively low. Moreover, the environmental regulation is not as stringent as those in eastern and coastal regions. Thus, these areas are ideal for silicon producers to establish their production bases. According to the China Metal Association, there were 68 silicon plants in Yunnan with a production capacity of 1.25 million tons in 2011, accounting for 35% of the national total, and an annual output of 0.7 million tons of silicon products, accounting for more than 45% of the national total.

The study area is Nujiang prefecture, which is located in the southwest of Yunnan province, China. It has a land area of 14,703 km^2 and a total population of 0.54 million. Besides silicon quartzite resource, this region is also endowed with rich natural resources including water and minerals such as zinc, lead, copper, tin, gold, and others. Despite this, Nujiang prefecture is still poverty-stricken. Its GDP was only CNY 7.5 billion in 2012. It is the third poorest area in Yunnan, after Zhaotong prefecture, and the 12th poorest in China in terms of annual GDP per capita. According to the Nujiang Statistic Bureau, annual income per capita of Nujiang is very low, especially for rural population, although its rate of increase is more than 10%. About 0.14 million people, or 46% of the total population in this region, has a yearly income per capita of CNY 935[2] (~USD 148) in 2013, which is far below the national poverty line of CNY 2,300 per year per capita. In particular, this region has a large percentage of minority people, for whom the poverty problem is more common. In this prefecture, about 96% of Dulong people, 90% of Nu people, 90% of Lisu people, and 89% of Pumi people were poverty-stricken in 2013.

To promote regional economic development, the Nujiang government puts great effort into introducing investments to explore its natural resources, including minerals, hydropower, and biological resources. The quantity of investment introduced from other provinces was CNY 3.2 billion in 2012. In the past several decades, Nujiang, as an underdeveloped area, had been free of environmental pollution because there were only few industrial production activities. The introduction of industries into this prefecture significantly changed the environmental quality in the industrial zones as compared to the undeveloped areas. According to the *Monthly Report of Environmental Quality* of Nujiang in December 2013 (announced in January 2014), the air quality is at Level I or II (almost no pollution), and the water is at Level II (drinkable with simple treatment) in most of those areas where there is no silicon production, such as Liuku township. However, the environmental quality is lower in areas where industry is located. For example, water quality is at Level IV in Laowo township, which is worse than in other areas. As more investments were introduced into this region, environmental pollution has become more and more of a concern in recent years. In particular, silicon producers become the major targets of environmental protesters. Complaints about the effects of pollution on health and agricultural yields have increased.

[2] USD 1 = CNY 6.3

The survey was conducted in Laowo township, the silicon production base in Nujiang, where transportation is convenient and water resource is rich. There are around 10,000 households in this township, where approximately 1,000 households are near the silicon production areas. The product is the metallurgical grade silicon, which is further processed into solar grade silicon to make the final product PV cell elsewhere. At the beginning of 2008, only one silicon plant was in this township; now there are eight. Each plant covers an area of almost 2,500 m^2 with around 300 employees.

1.4.2 Production chain of PV electricity

Figure 1 shows that the production chain of photovoltaics involve (1) the production of raw materials, (2) their processing and purification, (3) the manufacture of modules and balance-of-plant components, and (4) the installation and use of the system (Fthenakis et al. 2011). The production chain starts from mining quartz sand, followed by their processing and purification. The silica in the quartz sand is reduced into metallurgical grade silicon in an arc furnace, and then further purified into solar-grade silicon, to finally be formed into PV cells. The study focused on the initial stage of the production lifecycle, that is, the production of metallurgical silicon from silica (as shown by the dotted box in Figure 1).

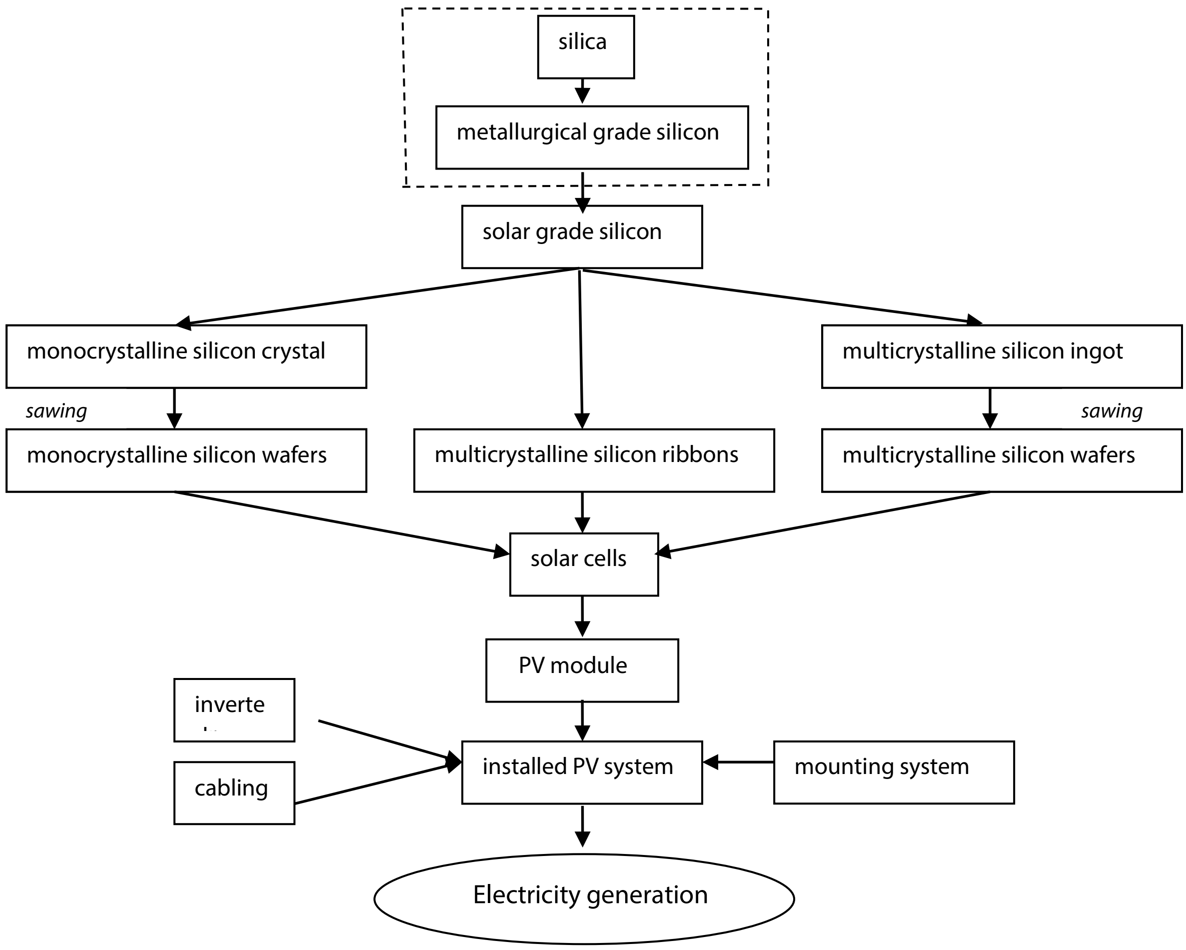

Figure 1. Production chain of PV electricity

The production of metallurgical silicon involves reducing SiO_2 and transforming it into Si through the reduction reaction of quartzite and charcoal in an electrical thermal stove. The reactions are as follows:

$$SiO_2 + C = Si + 2CO$$
$$SiO_2 + C = SiO + CO$$
$$SiO + O_2 = SiO_2$$

In the reactions, Si flows to the bottom of the stove and is then released outside. Meanwhile, the incompletely reduced product, SiO, is oxidized into SiO_2 when it reacts with oxygen near the inlet of the stove where it is then partially released along the flume (Zhang and Jin 1994). To produce one ton of silicon, the required inputs and their specification are as shown in Table 1.

Considering an annual output of 10,000 tons of silicon, the main pollutants from each stove and their emission rates are shown in Table 2. Without control, these pollutants can severely affect the local residents and agricultural production. In particular, the impacts tend to increase as more pollutants are released as a function of increases in output of metallurgical silicon.

In general, producing 1 ton of silicon will generate 120–200 kg plume. According to Zhu (2005), the dust content of a plume is 2.4–4.4 g/m^3 from a 16,500 kVA silicon furnace, and 1.9 g/m^3 from a 5,500 kVA silicon furnace. As measured by the local silicon production institute, about 85% of the particulate mass in the emitted plume has a diameter of 0.3 µm on average, with a minimum of 0.01µm. This fine particulate matter (PM) can easily enter the lungs, resulting in lung diseases with long-term exposure. The basic chemical contents of the plume sampled from the outlet of the stack outlet are SO_2, Al_2O_3, Fe_2O_3, MgO, CaO, SO_2, and CO. According to Liang (2013), about 90% of PM from metallurgical silicon plant is PM_{10}, and only 10% is ≥ 10 µm. By assuming that $PM_{2.5}$ accounts for 70% of PM_{10}, the content of $PM_{2.5}$ would be 63% of the total PM. Aside from PM from the stack, there are also other sources. As measured, the PM content is 1.4 g/m^3 in an area 2 m away from the stone smasher, and 12.98 g/m^3 at an area 2 m away from the wood charcoal smasher.

Table 1. Inputs of metallurgical production and their content

Item	Main Content	Quantity
Sand (SiO_2) or quartzite	SiO_2 = 99.2%, Al_2O_3 = 0.15%, Fe_2O_3 = 0.28%, CaO = 0.14%	2.5
Petrol coke	C = 95.5%, Fe_2O_3 = 2.5%, Dust = 0.16%, S, P, and others = 1.84%	0.72
Refined coal	C = 85.5%, Dust = 10%, Fe_2O_3 = 1.5%, Al_2O_3 = 1.8%, S, P, and others = 1.2%	0.56
Oxygen		0.08
Wood and charcoal		0.5
Electricity		12,000 Kva

Table 2. Pollutants and their emission rates

Item / Type	Source	Pollutant	Emission Rate	Treatment
Atmospheric pollution	Furnace	Plume	110,000 Nm^3/h	–
		Dust	3.5g/Nm^3	–
Water pollution	Washing	Waste water	17 t/h	Discharged to stream
		SS	3.4 t/a	
		COD	7.8 t/a	
Solid waste	Furnace	Residual	250 t/a	Sold to steel refinery
	Waste of supplementary inputs and sediment dust	Sand and dust	600 t/a	Dumping

1.5 Study Framework

To achieve the objective and answer the questions mentioned above, the study was conducted according to the following framework (Figure 2).

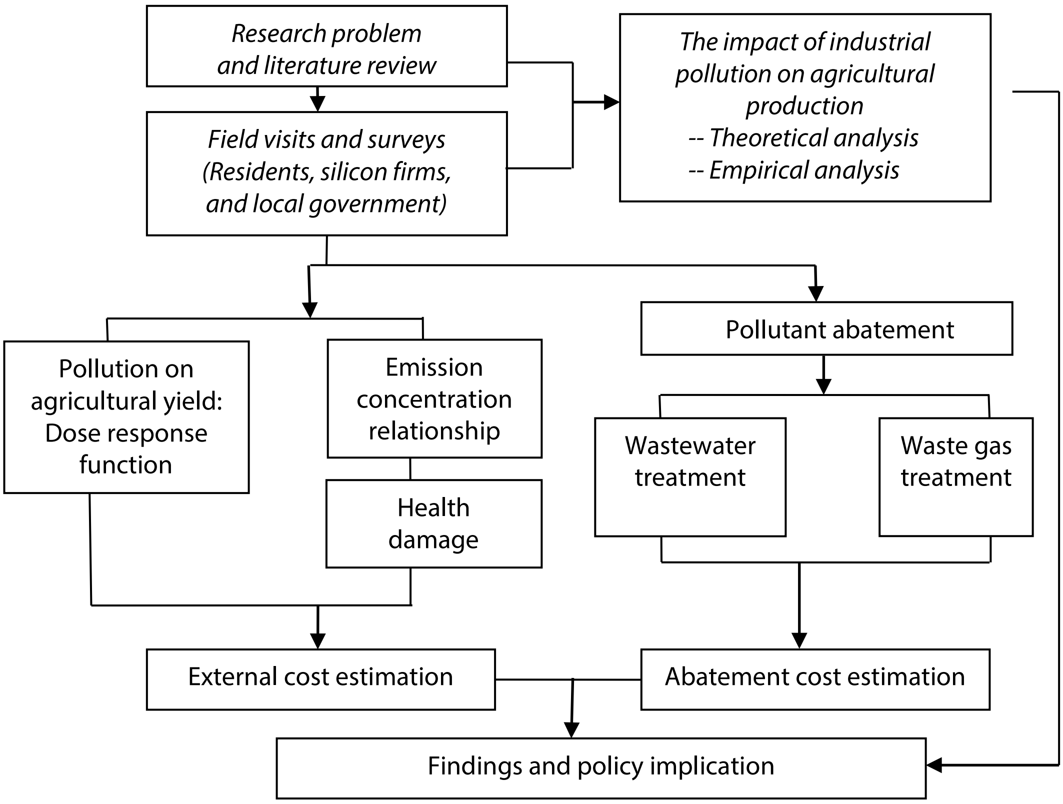

Figure 2. Flowchart of research framework

2.0 THEORETICAL ANALYSIS OF THE IMPACT OF INDUSTRIALPOLLUTION ON AGRICULTURAL PRODUCTION

The report argues that the impact of industrial pollution on crop yield is a result of the impact on the production function. To prove this argument, the analysis is carried out as follows.

The traditional frontier production function (TFPF) is a better expression of production as defined in economics than an ordinary deterministic production function, and is thus more appropriate for empirical analysis (Wan and Battese 1992). However, this method cannot be directly used for efficiency analysis when the production environment is changed; otherwise, the result is biased (Serra, Zilberman, and Gil 2008). This paper aims to study how industrial pollution affects the production efficiency of crops using a modified frontier production function (MFPF).

The output of pollution-affected crops is determined by two components. The first is a common production function, indicating the relationship between output and the factors in an unpolluted production environment, while the second is a damage function, representing the impact of industrial pollution on factors and crop yield. The MFPF is thus expressed as (Jondrowet al. 1982):

$$Y = \left[f(X, \alpha) + g\left(P^* \hat{X}, \beta\right)\right]^* exp(v - u) \qquad \text{Equation (1)}$$

where:

Y	=	output of crops;
X	=	set of production factors;
$\hat{X}, \hat{X} \subseteq X$	=	set of factors which are affected by industrial pollution;
P	=	severity of industrial pollution;
$f(X, \alpha)$	=	deterministic production function;
$g(P^*X, \beta)$	=	damage function, in which P is the level of industrial pollution;
α, β	=	parameters in related functions;
$v(\sim N(0, \sigma_v^2))$	=	system error of a normal distribution; and
$u(\sim N(\mu > 0, \sigma_u^2))$	=	gap between the maximum potential output and the actual yield, representing the inefficiency of production.

According to the traditional frontier production function, the production efficiency is quantified as follows, after Battese (1992):

$$PE^a = \frac{f(X, \ \alpha) * exp(v-u)}{f(X, \alpha) * exp(v)} = exp(-u). \qquad \text{Equation (2)}$$

The measure is not appropriate or is biased in the presence of industrial pollution. The reasons are as proved in the lemmas discussed in the succeeding subsections.

2.1 Lemma 1: Marginal Product of Factor as Affected by Industrial Pollution

In the process of agricultural production, some factors may be affected by industrial pollution, while others are not. The marginal output of the factors is shown in Equation (3). Let X represent the set of total factors and $\hat{X}$ the set of factors affected by industrial pollution ($\hat{X}$ is a subset of X). The marginal output of x_i is

$$MP_i = \frac{dY}{dx_i} = \begin{cases} f_{x_i}(X) x_i \in X, x_i \notin \hat{X} \\ f_{x_i}(X) + g_{x_i}(P * \hat{X}) x_i \in \hat{X} \end{cases} \qquad \text{Equation (3)}$$

When $x_i \in X$ and $x_i \notin \hat{X}$ the marginal output of the i^{th} factor (x_i) is not affected by industrial pollution. If $x_i \in \hat{X}$ then there exists $g_{xi}(P * X) \leq 0$ as industrial pollution has a negative effect on output. Thus, the relation of $f_{xi}(X) + g_{xi}(P^*\hat{X}) \leq f_{xi}(X)$ holds. That is, industrial pollution can reduce the marginal product of some factors.

2.2 Lemma 2: Industrial Pollution can Change the Relationship between Production Factors

In a production function, there exists a substitution or complementary relationship between factors. This relationship can be expressed in the following equations (Henningsen 2014):

$$\varepsilon_{ij} = \frac{d(x_i/x_j)}{x_i/x_j} * \frac{\frac{MP_j}{MP_i}}{d\left(\frac{MP_j}{MP_i}\right)} \qquad \text{Equation (4)}$$

where:

x_i, x_j	=	i^{th} and the j^{th} factors
MP_i, MP_j	=	marginal output of the two factors, respectively

Case 1: $\varepsilon_{ij}^0 = dln\left(\frac{x_i}{x_j}\right) / dln(\frac{f_{x_j}(X)}{f_{x_i}(X)})$, if $x_i, x_j \notin \hat{X}$ Equation (5.1)

Case 2: $\varepsilon_{ij}^1 = dln(\frac{x_i}{x_j})/dln(\frac{f_{x_j}(X) + g_{x_j}(P * X)}{f_{x_i}(X)})$, if $x_i \notin \hat{X}, x_j \in \hat{X}$ Equation (5.2)

Case 3: $\varepsilon_{ij}^2 = dln(\frac{x_i}{x_j})/dln(\frac{f_{x_j}(X) + g_{x_j}(P * X)}{f_{x_i}(X) + g_{x_i}(P * X)})$, if $x_i, x_j \in \hat{X}$ Equation (5.3)

Case 1 represents the substitution or complementary elasticity when both factors x_i and x_j are not affected by industrial pollution. Case 2 is the elasticity when one factor is affected by industrial pollution while the other is not. Case 3 is the elasticity when both factors are affected by the impact of industrial pollution.

To prove Lemma 2, we compare Case 1 and Case 2, namely,

$$\frac{\varepsilon_{ij}^1}{\varepsilon_{ij}^0} = dln(\frac{f_{x_j}(X) + g_{x_j}(P*X)}{f_{x_i}(X)})/dln(\frac{f_{x_j}(X)}{f_{x_i}(X)}) \quad \text{Equation (6)}$$

In agricultural practice, if $f_{x_j}(X) = g_{x_j}(P*X)$, then industrial pollution reduces crop yield to zero. It makes no sense to make the comparison. However, if farmers do harvest some grains, no matter how much it is, then we can deduce that there exists the relation of $f_{x_j}(X) + g_{x_j}(P*X) > 0$.

Obviously, if $\frac{f_{x_j}(X)}{f_{x_i}(X)} > \frac{f_{x_j}(X)+g_{x_j}(P*X)}{f_{x_i}(X)} > 1$, then $\frac{\varepsilon_{ij}^1}{\varepsilon_{ij}^0} > 0$, i.e., industrial pollution changes the strength of the relationship between factor x_i and x_j.

If $\frac{f_{x_j}(X)}{f_{x_i}(X)} > 1 > \frac{f_{x_j}(X)+g_{x_j}(P*X)}{f_{x_i}(X)} > 0$, then $\frac{\varepsilon_{ij}^1}{\varepsilon_{ij}^0} < 0$, then the relationship between the factors is changed by industrial pollution. In detail, it is possible that the relationship between factors is changed from substitution to complementary, and vice versa.

When both x_i and x_j are affected by industrial pollution, the same reasoning can be made by comparing Case 1 and Case 3.

Thus, Lemma 2 is proven.

2.3 Lemma 3: Traditional Frontier Production Function is not Appropriate for the Estimation of Agricultural Production Efficiency in the Presence of Industrial Pollution

In the presence of industrial pollution, the agricultural production efficiency is measured as:

$$PE^b = \frac{[f(X,\ \alpha) + g(P*X,\ \beta)] * exp(v-u)}{f(X,\alpha)*exp(v)} = PE^a + \frac{g(P*X,\beta)}{f(X,\alpha)} * exp(-u) \quad \text{Equation (7)}$$

Since $g(P*X, \beta) < 0$ and $f(X, \alpha) > 0$ always hold, it is concluded that the relationship of $PE^b < PE^a$ holds. That is, the use of PE^a to estimate the production efficiency in the presence of industrial pollution is biased.

Thus, Lemma 3 is proven.

3.0 EMPIRICAL RESEARCH METHODOLOGY

3.1 Data Collection

Both primary and secondary data were used in the study. Primary data was collected through field surveys and discussion with silicon producers and related government officials and with the affected residents. Secondary data was obtained from literature and data recording agencies, such as the Bureau of Environmental Protection, the Commission of Development and Reform, and the Bureau of Commerce, among others.

The primary data included input and output variables of farmers' agricultural production activities and their socioeconomic characteristics, variables to be used in estimating economic cost of damage to health, parameters for the costing of solid waste treatment, and data on the cost of abatement equipment. Primary data was collected through questionnaire-based surveys, through interviews with the local residents, businessmen, silicon firms, and local authorities regarding pollution control.

The secondary data included the technical economic data of silicon production, including outputs, production and abatement inputs, emissions of wastes, and the data of variables to be measured in estimating the economic cost of agricultural production and health effects, such as the dose-response relation between pollutant and health. These data were collected from silicon plants, databases, and related administration and research agencies. Secondary data was collected from the statistical documents at the village administration office, the Bureau of Environmental Protection, and silicon firms, as well as from related databases and literature.

To estimate agricultural loss, two groups of households were surveyed and included in the sample: treatment group (polluted) and control group (not polluted). The selection of the polluted and non-polluted area was based on their distance from industrial zones; otherwise, they have similar characteristics of agricultural practices.

The total number of affected households (n) included in the survey was determined using the formula

$$n = \frac{N}{\left(1 + Ne^2\right)} \qquad \text{Equation (8)}$$

where:

n = sample size;
N = total number of households in the area (1,000 in the study); and
e = desired margin of error

The surveyed villages were selected according to their distance from the silicon firms. In each village, households were randomly selected for the survey.

As shown in Table 3, the total number of households in the treatment group is 1,016. With a desired margin of error of 7.5%, a total of 151 affected households were included in the survey. Similarly, the sample size for the treatment is 145. Assuming 20% invalid completed questionnaires, the total numbers of sample households for the two groups were 180 and 175, respectively. The samples were proportionately allocated to selected villages, using the total number of households per village as the basis of allocation. In each village, respondent households were randomly selected.

The primary data were collected through focus group discussions (FGDs) and a household survey. FGDs were mainly used to get the information about the agricultural practice and the environmental situation in the villages surrounding the silicon production zone, so as to choose survey villages. Three FGDs were organized in November 2014. Two were from the polluted villages and one was from a non-polluted village. The three FGDs were conducted in the meeting rooms of the village councils. Each FGD consisted of 5–7 persons, including village managers and farmers. Basic information was collected regarding the social and natural conditions in the area, crops, agricultural practices, environmental situation, and pathways of pollution. This information was used to revise the questionnaire.

The household surveys were conducted from November 2014 to January 2015. A total of 180 farmers were interviewed. The numbers of valid completed questionnaires for the two groups were 167 and 163, respectively.

Table 3. Sample distribution

Group	Village	Distance to IZ	HH size	Population	HH Sample
Treatment group	Yi ethnic village, Caojian	2–3 km	98	298	17
	Ronghua village, Laowo	Surrounding the IZ	705	2,741	125
	Zhongyuan village, Laowo	5–9 km	213	912	38
Control group	Congren village, Laowo	30 km	806	3,289	175

Note: HH = household; IZ = industrial zone

3.2 Impact of Industrial Pollution on Agricultural Production

The empirical study of the impacts of industrial pollution on agricultural production was carried out as follows. First, two regions with similar natural and socioeconomic characteristics were selected for data collection. One was considered as the polluted area and the other as the non-polluted area. Data sets from the two areas were classified as the experimental group and the control group, respectively. Second, three translog production functions were estimated using the *R* statistical software package. Based on the estimated production functions, the impacts of industrial pollution on agricultural production were further analyzed. Lemma 1 was empirically proven by analyzing the impact of industrial pollution on the marginal output of factors using numerical simulation method in the MATLAB package. Lemma 2 was proven by numerically comparing the elasticity of substitution or complementarity between factors. Lemma 3 was tested by comparing the difference in production efficiencies estimated using PE^a and PE^b.

3.2.1 Formulation of econometric model

In the presence of industrial pollution, the production function of crops is expressed as Equation (9.1). Further, $f(X)$ is set to be a translog production function, which is generally expressed as follows (Aigner, Lovell, and Schmidt 1977):

$$lny=\alpha_0+\sum_{i=1}^{n}\alpha_i lnx_i+\frac{1}{2}\sum_{i=1}^{n}\alpha_{ii}ln^2x_i+\sum_{i,j=1;i\neq j}^{n}\alpha_{ij}lnx_i lnx_j+\sum_{k=1}^{m}\gamma_k z_k \qquad \text{Equation (9.1)}$$

Industrial pollution (P) would affect crop yield (y). Generally, the relationship between P and y can be expressed in a form of Cobb-Douglas function (Hritonenko and Yatsenko 2013). To include the quadratic form of the impact of industrial pollution on production, the damage function in this study is extended as

$$g(P{*}X)=\theta_0 lnP+\sum_{i=1}^{n}\beta_i lnx_i+\frac{1}{2}\theta_1 ln^2P+\sum_{i=1}^{n}\beta_{ii}ln^2x_i+\sum_{i=1}^{n}\beta_{pi}lnPlnx_i+\sum_{i,j=1;i\neq j}^{n}\beta_{ij}lnx_i lnx_j \qquad \text{Equation (9.2)}$$

where:

y	=	crop yields;
x_i	=	input of the i^{th} factor;
$lnx_i{*}\,lnx_j$	=	interaction of the logarithm of the i^{th} and the j^{th} factors;
Z_k	=	socioeconomic characteristics of the k^{th} households, including household respondent's gender, educational attainment, and number of family members;
P	=	variable representing the severity of industrial pollution;
$lnP{*}\,lnx_i$	=	interaction of the logarithm of industrial pollution and the i^{th} factor;
α	=	impact of the factors and their interaction term on crops; and
β	=	impact of industrial pollution on crop output.

The impact of industrial pollution on crop output include two effects: the direct impact of industrial pollution on output via factors and the indirect impact of industrial pollution on the relationship among factors and on the output. Obviously, if the i^{th} factor is not affected by industrial pollution, then both β_i and β_{ii} are equal to zero. When both the i^{th} and/or the j^{th} factors are affected by industrial pollution, then β_{ij} is not zero. The factors considered in this study include labor (L), capital (K), seeds (S), and chemicals (C), which include fertilizers, pesticides, and herbicides. The variable of the severity of industrial pollution is represented using a proxy variable, which is the reciprocal linear distance between farmland and the pollution source (i.e., the industrial silicon zone), based on the justification that the shorter the distance is, the stronger the industrial pollution would be, and vice versa.

This paper analyzes the impact of industrial pollution on agricultural production by affecting the factors of seeds and chemicals. Since industrial pollution has little impact on capital, the impact on the labor force would lead to the heterogeneity of the labor factor, which would make it impossible for the following regression to proceed. Thus, the impact of industrial pollution on capital is ignored, labor input is assumed to be homogeneous, and the corresponding interaction of these two variables with the industrial pollution variable is not included in the model.

To sum up, the agricultural production function in the presence of industrial pollution is formulated as follows:

$$\begin{aligned}
\ln y = {} & \alpha_0 + \alpha_1 \ln L + \alpha_2 \ln K + (\alpha_3 - \beta_3) \ln S + (\alpha_4 - \beta_4) \ln C + \frac{1}{2}\alpha_{11} \ln^2 L + \frac{1}{2}\alpha_{22} \ln^2 K \\
& + \frac{1}{2}(\alpha_{33} - \beta_{33}) \ln^2 S + \frac{1}{2}(\alpha_{44} - \beta_{44}) \ln^2 C + \alpha_{12} \ln L * \ln K + (\alpha_{13} - \beta_{13}) \ln L * \ln S \\
& + (\alpha_{14} - \beta_{14}) \ln L * \ln C + (\alpha_{23} - \beta_{23}) \ln K * \ln S + (\alpha_{24} - \beta_{24}) \ln K * \ln C \\
& + (\alpha_{34} - \beta_{34}) \ln S * \ln C + \sum_{K=1}^{3} \gamma_k Z_k - \beta_0 \ln P - \frac{1}{2}\beta_1 \ln^2 P \\
& - \beta_{p3} \ln S \ln P - \beta_{p4} \ln C \ln P + \mu
\end{aligned} \qquad \text{Equation (10)}$$

where:

Lny	=	logarithm of output;
L	=	labor;
K	=	capital;
S	=	seeds;
C	=	chemicals (i.e., fertilizers, pesticides, and herbicides)
α, β	=	coefficients to be estimated
P	=	variable representing the level of industrial pollution;
Z	=	socioeconomic characteristics of respondents, including gender, educational attainment, and number of family members;
k	=	number of socioeconomic variables; and
μ	=	error term.

As shown by Equation (11), some restrictions are used to test the constant return to scale.

$$\begin{cases}
\alpha_1 + \alpha_2 + (\alpha_3 - \beta_3) + (\alpha_4 - \beta_4) - \beta_0 = 1 \\
\alpha_{11} + \alpha_{22} + (\alpha_{33} - \beta_{33}) + (\alpha_{44} - \beta_{44}) - \beta_1 = 0 \\
\alpha_{11} + \alpha_{12} + (\alpha_{13} - \beta_{13}) + (\alpha_{14} - \beta_{14}) = 0 \\
\alpha_{22} + \alpha_{21} + (\alpha_{23} - \beta_{23}) + (\alpha_{24} - \beta_{24}) = 0 \\
(\alpha_{33} - \beta_{33}) + (\alpha_{13} - \beta_{13}) + (\alpha_{23} - \beta_{23}) + (\alpha_{34} - \beta_{34}) - \beta_{p3} = 0 \\
(\alpha_{44} - \beta_{44}) + (\alpha_{14} - \beta_{14}) + (\alpha_{24} - \beta_{24}) + (\alpha_{34} - \beta_{34}) - \beta_{p4} = 0 \\
\beta_{p3} + \beta_{p4} = 0
\end{cases} \qquad \text{Equation (11)}$$

3.2.2 The elasticity of substitution or complementary

The substitution or complementary elasticity between factors can be estimated using Equation (4). The i^{th} and the j^{th} factors has a relationship of substitution if $\varepsilon_{ij} > 0$, and a complementary relationship if $\varepsilon_{ij} > 0$ (Henningsen 2014).

3.2.3 Efficiency measure and its improvement

Production efficiency is defined as the ratio of real output (*y*) and the potential output (maximum output which can be achieved, *y**) for a given set of factors (Battese and Coelli 1988).

In SFA, let $\mu = v - u$; and define $\sigma_\mu^2 = \sigma_v^2 + \sigma_u^2$, $u_* = -\frac{\sigma_u^2 * \mu}{\sigma_\mu^2}$, $\sigma_* = \frac{\sigma_u^2 * \sigma_v^2}{\sigma_\mu^2}$. Since *u* is a truncated distribution of $N(u_*, \sigma_*^2)$ at given values of μ, its expectation is as follows (Jondrow et al. 1982):

$$E(u/\mu) = \mu_* + \sigma_* \frac{f(-\mu_*/\sigma_*)}{1 - F(-\mu_*/\sigma_*)} \qquad \text{Equation (12)}$$

where *f* and *F* represent the standard normal density (SND) and cumulative distribution function (CDF).

To obtain the value of u, Equation (12) can be rewritten as (Materov 1981):

$$E(u|\mu) = -\mu\left(\frac{\sigma_u^2}{\sigma_\mu^2}\right) \text{ if } \mu \leq 0 \qquad \text{Equation (13)}$$
$$= 0 \text{ if } \mu > 0.$$

Equation (13) is thus further specified as:

$$PE^a = exp(-u) = exp\,(\mu^* \frac{\sigma_u^2}{\sigma_\mu^2}). \qquad \text{Equation (14)}$$

Since the deterministic function [$f(X, \alpha)$] in the presence of industrial pollution is different from that in a non-polluted production environment, it is impossible to obtain $exp(-u)$ as shown in Equation (2). Moreover, to study the current industrial pollution on agricultural production efficiency, it is usually difficult to collect data on agricultural production before the farmland is polluted. That is, it is difficult to estimate the maximum potential production efficiency of the farmland before it became polluted. To deal with this issue, the corresponding data from the control group is used as a reference. Based on the measure shown in Equation (12), a modified measure is proposed to estimate the agricultural production efficiency in the presence of industrial pollution. It is mathematically expressed as follows:

$$PE^b = \frac{\frac{1}{N}\sum_{n=1}^{N}[f(X,\alpha) - g\ \ (P^*\hat{X}, \beta)]_n}{\frac{1}{M}\sum_{m=1}^{M} f(X, \alpha)_m} exp(\mu^* \frac{\sigma_u^2}{\sigma_\mu^2}) \qquad \text{Equation (15)}$$

where:

$[f(X, \alpha) - g(X, \beta)]_n$	=	amount of output in the experimental group of the n^{th} household,
N	=	total number of households in the experimental group,
$F(X, \alpha)_m$	=	output of the m^{th} household in the control group, and
M	=	total number of farmers in the control group.

3.3 Estimation of External Cost

The production of silicon products has three major types of pollution and associated costs, including (1) water pollution-associated damage on agriculture, (2) air pollution-associated health damages, and (3) occupational risks for workers' health. The shadow price of silicon products will include both the cost of marketed inputs and the external costs. Since the cost associated with pollution is a gross term, which represents an accumulated effect, the external cost per unit of silicon product was allocated according to the emission-product relation.

3.3.1 Economic loss of agriculture

The assessment of the impacts of industrial pollution on agricultural production is carried out as follows. First, translog production functions were estimated using data from the control and the experimental groups, based on the *R* statistical software package. Second, the impacts of industrial pollution on agricultural production were quantified by comparing the output difference between the control group and the experimental group. The studied crops were rice and corn, which are the major crops cultivated in the study areas.

The estimation of production function. This study used the translog production function instead of the Cobb-Douglas (CD) production function because of its flexibility in analyzing the relationship between different variables in the production function. That is, the relationship can be analyzed by including the quadratic form of factors and the interaction between factors (Coelli et al. 2005).

The translog function is formulated as follows:

$$
\begin{aligned}
lny = {} & a_0 + a_1 lnL + a_2 lnK + a_3 lnS + a_4 lnC + \frac{1}{2}a_{11}(lnL)^2 + \frac{1}{2}a_{22}(lnK)^2 \\
& + \frac{1}{2}a_{33}(lnS)^2 + \frac{1}{2}a_{44}(lnC)^2 + a_{12}lnL * lnK + a_{13}logL * lnS + a_{14}lnL * lnC \\
& + a_{23}lnK * lnS + a_{24}lnK * lnC + a_{34}lnS * lnC + \beta_0 D + \beta_1 lnL * D + \beta_2 lnK * D \\
& + \beta_3 lnS * D + \beta_4 lnC * D + \sum_{i=1}^{3} \gamma_i z_i + \mu
\end{aligned}
\qquad \text{Equation (16)}
$$

Some restrictions are used to test the constant return to scale (Chiang and Cheng 2014):

$$
\begin{cases}
\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1 \\
\alpha_{11} + \alpha_{12} + \alpha_{13} + \alpha_{14} = 0 \\
\alpha_{22} + \alpha_{12} + \alpha_{23} + \alpha_{24} = 0 \\
\alpha_{33} + \alpha_{13} + \alpha_{23} + \alpha_{34} = 0 \\
\alpha_{44} + \alpha_{14} + \alpha_{24} + \alpha_{34} = 0 \\
\beta_1 + \beta_2 + \beta_3 + \beta_4 = 0
\end{cases}
\qquad \text{Equation (17)}
$$

The restriction in Equation (17) was used to test the existence of the CD production function. That is, the production function is in the form of CD if Equation (18) is satisfied.

$$\alpha_{ij}(\forall i,\ j \in [1, 4]) = 0 \qquad \text{Equation (18)}$$

The estimation of economic losses. Whether it affects agricultural production via air or water, industrial pollution will reduce crop yields or reduce the quality of agricultural products (Spash, 1997). The former can be measured by changes in crop yields, while the latter can be reflected through crop market prices. Therefore, the economic losses of a certain crop can be estimated by using the following formula:

$$EL = P \times (Y^C - Y^T) + \Delta P \times Y^C \qquad \text{Equation (19)}$$

where:

P	=	market price of quality product;
Y^C, Y^T	=	average outputs in the non-polluted and polluted areas, respectively;
ΔP	=	price difference between quality and low-quality products; and
y	=	normal output of crop.

To estimate the economic loss from industrial pollution, quantifying the output loss is essential. Since the crop output is affected by many factors, including cultivation practice and the socioeconomic characteristics of the farm household, the difference of output is thus to be quantified based on the same set of inputs. Except for the variable of industrial pollution, the value of all other inputs for the agricultural production should be the same. Thus, the difference of output can be quantified using the estimated production functions for the control group and the experimental group.

3.3.2 The relationship between emission and concentration

The relationship between emission and pollutant concentration in the air is fundamental when estimating the economic cost of pollution and when evaluating pollution regulation. Many dispersion models can be used for public health research, including the Gaussian plume, Lagrangian (trajectory), Eulerian, and regression mapping; each has its own advantages and disadvantages (Holloway, Kinney, and Sauthoff 2005). For a scale of a few kilometers, the conventional Gaussian-type model is capable of adequately estimating the $PM_{2.5}$ and PM_{10} concentration in certain open environments, especially for longer average periods (Holmes and Morawska 2006).

The Gaussian dispersion model is suitable for this study because, primarily, all silicon plants are concentrated in a small industrial zone in the study site, such that the pollution can be considered as a point source. Secondly, its computational cost is low. The relationship is established according to de Nevers (2000):

$$c = c_0 + \frac{Qe^{-0.5(\frac{y}{\sigma_y})^2}}{2\pi u \sigma_y \sigma_z}[e^{-0.5(\frac{Z-H}{\sigma_z})^2} + e^{-0.5(\frac{Z+H}{\sigma_z})^2}] \qquad \text{Equation (20)}$$

where:

c	=	concentration of pollutant in air (annual average);
c_0	=	background concentration (annual average);
Q	=	emission of pollutant from silicon firms;
U	=	mean wind speed, in meters per second (in m/s);
σ_y	=	standard deviation of horizontal plume concentration, evaluated in terms of downwind distance x (in m);
σ_z	=	standard deviation of vertical plume concentration, evaluated in terms of downwind distance x (in m);
Y	=	crosswind distance from the centerline of the plume (in m); and
Z	=	height of the point (at which the ambient concentration is estimated) above ground surface (in m).

The Gaussian dispersion model was estimated using the parameter values in Table 4, which were collected from the silicon plant, local meteorology agency, and references. The values of the dispersion parameters, σ_y and σ_z, are determined according to the Pasquil and Gifford dispersion curves.

Table 4. Plume and atmosphere parameters

Parameter	Value	Parameter	Value
Stack height (m)	40.0	CO in plume (mg/Nm^3)	120.0
Stack diameter (m)	2.2	TSP in plume (mg/Nm^3)	3,400.0
Ave. wind velocity at stack exist (m/s)	6.0	Air pressure (H Pa)	1,000.0
Plume emission (m^3/s)	22.2	Land-level wind velocity (m/s)	3.4–7.9
Plume temperature (°C)	145.0	Average air temperature (°C)	18.0
Plume flow rate (Nm^3/h)	115,000.0	Atmospheric condition category	Neutral
SO_2 in plume (mg/Nm^3)	300.0	Average wind velocity (m/s)	3.4–7.9

The relationship between short-term (e.g., 1hour) concentration and long-term (e.g., 24 hours or 1 year) concentration is established using an atmospheric stability dependent formula (Al Smadiet al. 2009):

$$c_2 = c_1 \left(\frac{t_1}{t_2}\right)^n \qquad \text{Equation (21)}$$

where:

t_1	=	shorter averaging time, in hour/s
t_2	=	longer averaging time, in hour/s
n	=	stability dependent exponent
c_1	=	concentration at the shorter averaging time, in ug/m^3 or ppm
c_2	=	concentration at the longer averaging time, in ug/m^3 or ppm

For converting from a 24-hr timeframe to timeframes of up to 1 year, the stability dependent exponent is 0.53 (Al Smadi et al. 2009).

The Gaussian dispersion model is consistent with the practical interest in environmental air quality evaluations (the range of 2.5–10.0 mm). Although the Gaussian model has been shown to overestimate concentrations in low-wind conditions (Holmes and Morawska 2006), it is well accepted for regulatory purposes and for environmental impact assessment of industrial power plants; more importantly, the model does not require extensive computing power or time (Lorber 2003).

3.3.3 Economic loss of air pollution-associated health damages

Local residents and workers at silicon firms are facing threats to their health from pollution. Based on the analyzed contents of emitted dust and gas, the studied pollutants are PM_{10}, SO_2, CO, and TSP. The first three pollutants are used as indicators in estimating the health effects on local residents, while TSP is mainly used to assess health effects on workers.

The economic cost of health damage is estimated in this study using the benefit-transfer method. First, the exposure-response relationships are established according to related literature; second, the costs of related cases of disease (as reported in literature) was adjusted to reflect the local situation; third, the total cost was estimated according to the total number of workers and costs of treatment for diseases.

Occupational exposure to breathable crystalline silica is also associated with lung cancer, bronchitis, chronic obstructive pulmonary disease (COPD), and emphysema. Some exposure-response relationships have been reported in studies of miners, diatomaceous earth workers, granite workers, and others. Several epidemiological studies have reported statistically significant numbers of excess deaths or cases of immunologic disorders and auto-immune diseases in silica-exposed workers. Crystalline silica may affect the immune system, leading to mycobacterial (tuberculous and non-tuberculous) or fungal infections, especially in workers with silicosis.

Based on the relative risk model estimated using Poisson regression, Murray and Lopez (1997) established the relationship between health effects and pollutant concentrations. That is,

$$H = exp\left(\beta x \left(C - C_0\right)\right) * H_0 \qquad \text{Equation (22)}$$

where:

ΔH	=	health effects of air quality change due to silicon production;
C, C_0	=	C and C_0 are the pollutant (i.e., PM_{10} or TSP) concentration at the current state (i.e., high pollution from silicon production) and the threshold concentration;
H, H_0	=	corresponding health status or the incidence rate, i.e., mobility or mortality at the states of C and C_0; and
β	=	concentration-response coefficient.

According to the WHO (2002), the threshold concentration of pollutants is 15 ug/m^3 for different endpoints of health effects. However, many studies also show that there is no threshold concentration for pollutants such as ambient PM (Morgan et al. 2003; Pope 2000).

The health effects (ΔH) of air quality change due to silicon industry can be estimated using the following equation:

$$\Delta H = H - H_0 = H_0 \times [\exp(\beta \times (C - C_0)) - 1] \qquad \text{Equation (23)}$$

The health effects of air quality change due to the shift to a silicon-based industry include three components: mortality, outpatient and hospital admission, and years lost due to disability. The composition of air pollution differs significantly between China and most Western states; however, although the exposure-response coefficients found in the Western studies cannot simply be transferred to a Chinese context (Aunan and Pan 2004), the study mainly uses the exposure-response coefficients for a Chinese context.

The exposure-response relationships between some pollutants and their health effects are listed in Table 5. The endpoints of the chronic respiratory illness ranges from milder symptoms, such as cough, phlegm, and wheezing, to more severe conditions, such as asthma, general COPD and bronchitis, and pneumonia (Aunan and Pan 2004).

Table 5. Exposure-response relationship between pollutant and health endpoint

Health Endpoints	Pollutant	β value	References
All-cause mortality	PM_{10}	0.038%	Xie, Liu, and Liu (2009)
	SO_2	0.04%	Aunan and Pan (2004)
	CO	0.37%	Shang et al. (2013)
Respiratory mortality	PM_{10}	PM_{10}	Xie, Liu, and Liu (2009)
Cardiovascular disease mortality	SO_2	0.1%	Aunan and Pan (2004)
	PM_{10}	0.066%	Xie, Liu, and Liu (2009)
	SO_2	0.04%	Aunan and Pan (2004)
	CO	0.477%	Shang et al. (2013)
Morbidity-outpatient			
Internal medicine	TSP	0.022%	Kanand Chen (2002)
Chronic bronchitis	PM_{10}	0.48%	Aunanand Pan (2004)
Morbidity-inpatient	PM_{10}	0.124%	Xie, Liu, and Liu (2009)
Respiratory disease	SO_2	0.15%	Aunan and Pan (2004)
	PM_{10}	0.066%	Xie, Liu, and Liu (2009)
Cardiovascular diseases	SO_2	0.19%	Aunan and Pan (2004)
Chronic obstructive pulmonary disease	TSP	0.2%	Jing (2000)
Chronic respiratory illness in adult	PM_{10}	0.31%	Aunanand Pan (2004)
Chronic respiratory illness in child	PM_{10}	0.44%	Aunanand Pan (2004)

Air pollution is usually the result of a mix of pollutants, including PM, SO_2, NO_2, CO and others. However, it is usually impossible to attribute the health effects to a particular pollutant. Thus, the health effect of pollution is not the addition of the effect of each pollutant; otherwise, it is biased due to double counting (Zhang, Chen, and Chen 2006). Since $PM_{2.5}$ monitoring has been instituted only recently in China, most epidemiological studies have thus far focused on TSP and PM_{10}. To avoid double accounting, only the effect of TSP or PM_{10} was considered for a particular health endpoint. PM_{10} was used as the pollutant indicator in the study, which is appropriate because about 90% of the dust of the plume from silicon plants is PM_{10}. Thus, the study estimated the health effects of the solid pollutant PM_{10} and the gaseous pollutants SO_2 and CO.

Note that β is a change in the percentage (%) of health hazard as the pollutant concentration (µg/m^3) varies. For mortality and hospital admissions, the coefficients refer to percentage change in number of cases per person per ug/m^3 change in daily ambient concentration. For chronic respiratory illness, they refer to percentage in prevalence rate per ug/m^3 change in long-term concentration.

These effects are estimated as follows discussed in the next subsections.

Economic cost of change of premature mortality. As in most relevant epidemiological studies on the relationship between PM and mortality (Dockery et al. 1993; Pope, Bates, and Raizenne1995), the change in premature mortality focused on respiratory diseases and cardiovascular diseases. The monetary effect of mortality is to be estimated according to the following equation:

$$EH_a = \Delta H \times VSL \times YLL / LAP \qquad \text{Equation (24)}$$

where:

- EH_a = economic value of the effect of mortality,
- VSL = value of statistical life,
- YLL = year of lost life, and
- LAP = local average life span.

To estimate the economic cost of change of premature mortality, VSL is estimated by following Huang, Xu, and Zhang (2012). That is, VSL is estimated according to the following equality:

$$VSL_s = VSL_r \times (\frac{I_s}{I_r})^e \qquad \text{Equation (25)}$$

where:

- VSL_s = VSL of residents at the study site;
- VSL_r = VSL from the reference study;
- I_s = income per capita at the study site;
- I_r = income from the reference study; and
- e = income elasticity coefficient, which is normally set at 1.

The VSL in China varies a lot, although there are few studies that have estimated the VSL in China. Some of them are shown in Table 6. The study adopts the most recent reference, Tang et al. (2014), as the reference study. In 2010, the annual income per capita in Taiyuan was CNY 18,712 (Tang et al. 2014). In 2014, the annual income per capita in the study site was CNY 7367. According to the above equation, the VSL at the study site is estimated to be CNY 634 thousand.

The year of life lost (YLL) of all-cause mortality is around 18 years (Han, Guo, and Zhang 2006); the YLLs for chronic illness, cardiovascular disease, respiratory disease, and COPD are 7.68, 4.93, 2.75, and 2.52 years, respectively (Xu and Wei 2007). The local average life span is 67.6 years.

Table 6. Estimates of VSL in China

Study	VSL (in million CNY)
Wang and Mullahy (2006)	0.30–1.25
Zhang (2002)	0.20–1.70
Hammitt and Zhou (2005)	0.26–0.51
Krupnick et al. (2006)	1.40
Tang et al. (2014)	1.61 (for Taiyuan in 2010)

Economic cost of outpatient and inpatient hospitalization. The economic cost of morbidity was estimated using the cost of illness (COI) approach, which measures the total COI that is imposed on a society, including the sum of hospital admission costs, fees for service, and lost wages during days spent in hospital (Guo et al. 2010). Both outpatient and inpatient hospitalizations are considered here. The total cost of outpatient and inpatient care resulting for silicon production has been estimated as:

$$EH_b = EH_{b1} + EH_{b2} = \Delta H \times mc_1 + \Delta H \times mc_2 + \Delta H \times D \times GDP/365 \qquad \text{Equation (26)}$$

where:

- EH_b = economic cost of outpatient and inpatient care;
- EH_{b1} = economic cost of outpatient care;
- EH_{b2} = economic cost of inpatient care, including medical cost and economic loss for absence from work;
- mc_1 = medical cost per case of outpatient;
- mc_2 = medical cost per case of inpatient; and
- D = average days of stay in hospital.

The unit costs of inpatient and outpatient care were obtained from local data and reference. According to the report of the *3rd National Healthcare Survey*, the average lengths of inpatient care are 17 days for respiratory diseases and 25 days for circulatory diseases (Zhou and Ding 2012). The values of mc_1 and mc_2 include both direct and indirect medical costs. According to the *Chinese Health Statistical Yearbook 2006*, the medical costs per case of hospital admission are CNY 3,006 and CNY 6,627 for respiratory diseases and cardiovascular diseases, respectively. The values were referred from the Ministry of Public Health of China (MPH 1998) and MPH (2008), and were inferred using the benefit-transfer method.

As surveyed, the local medical cost for outpatient care is CNY 205, and for the inpatients of cardiovascular and respiratory illness are CNY 8,486 and CNY 3,406, respectively. According to the Nujiang Statistical Bureau, the GDP per capita was CNY 13,888.90 in 2013.

Years lost due to disability. Years lost due to disability (YLD) is a result of COPD because of long-term pain and even inability to work, whose cost is calculated according to the following formula:

$$EH_c = YLD \times GDP = \Delta H \times DW \times L \times GDP \qquad \text{Equation (27)}$$

where:

EH_c = economic cost of YLD
DW = disability weight in a range of 0–1
L = average years of the case until remission or death

According to Equation (27), the unit cost of mortality was estimated (Table 7). The total affected population was estimated according to the baseline incidence rates for different health endpoints, as shown in Table 8.

Table 7. Unit cost of mortality

Mortality	YLL (Years)	Unit Cost (in '000 CNY)
All-cause	18.00	168.70
Chronic disease	7.68	72.00
Cardiovascular disease	4.93	46.20
Respiratory disease	2.75	25.80
COPD	2.52	23.60

Table 8. Population baseline incidence rates for different health endpoints

Health Endpoint	Baseline Incidence Rate ($\times 10^{-3}$)	Reference
Premature mortality	4.98	MPH (2007)
Chronic bronchitis	1.48	World Bank (2007)
Outpatient visits to internal medicine	515.60	MPH(2007)
Cardiovascular illness	14.28	MPH (2003; 2008)
Respiratory illness	6.36	MPH (2003; 2008)
COPD	20.00	Kan and Chen (2002)

4.0 EMPIRICAL RESULTS AND DISCUSSION

4.1 Impact of Industrial Pollution on Agricultural Production

Using the SFA method, the production functions of rice in both the control and the experimental groups were estimated. The results are shown in Table 9. The robustness of the estimated models was checked. First, according to the correlation matrix, the correlation between the explanatory variables is less than 0.4, indicating a very weak correlation. Second, the homoscedasticity was checked using the White test. The $n*R^2$ are 1.475 and 16.558 for the control group and the experimental group, respectively, which are less than the corresponding critical values (i.e., 24.769 and 29.615, respectively) at 10% significance level. Thus, the homoscedasticity was accepted. Third, whether or not there are excessive variables in the production function was checked using the Wald chi-square value. As calculated, the Wald chi-square value of the two production functions were 581.7045 and 208.4611, respectively, and their p-values are 0.0000, i.e., there are no excessive variables in the estimated production functions.

Table 9. Estimated production function of rice

Variable	Control Group		Experimental Group	
	Coefficient	Z-value	Coefficient	Z-value
ln*L*	4.4506***	3.0954	–2.1183**	–2.2222
ln*K*	1.8704	0.7915	–15.4898***	–26.7967
Ln*S*	–0.5265*	–1.7854	–3.7802***	–4.0627
Ln*C*	–0.1446	–0.0936	1.4247**	2.2288
1/2(ln*L**ln*L*)	0.6420	1.0600	0.7647***	4.0832
1/2(ln*K**ln*K*)	1.3543***	4.4653	3.6123***	26.2558
1/2(ln*S**ln*S*)	–0.0225	0.0306	–0.0366	–0.5915
1/2(ln*C**ln*C*)	0.2963	0.7819	0.6511*	1.6921
ln*L**ln*K*	–1.7577***	–5.3794	–0.0561	0.2958
ln*L**ln*S*	–0.0674	–0.9515	0.2441***	3.9108
ln*L**ln*C*	0.7227**	2.0731	–0.0925	–0.6330
ln*K**ln*S*	0.1965*	1.8452	0.6249***	2.8864
ln*K**ln*C*	–0.6218**	–2.3952	–0.6928***	–5.3835
ln*S**ln*C*	–0.0692	–0.6914	–0.0651	–0.7739
Z_1	0.0058	0.3768	–0.0401*	–1.8747
Z_2	0.0001	0.0488	0.0061	1.4865
Z_3	0.0005	0.1162	0.0122*	1.6409
ln*P*	—	—	0.4865**	1.9791
1/2(ln*P**ln*P*)	—	—	–0.3867***	–9.9876
ln*P**ln*S*	—	—	–0.0013	–0.1403
ln*P**ln*C*	—	—	–0.2043***	–3.6157
Constant	–8.8418*	–1.6258	45.2594***	48.7409
Wald chi^2	581.7045 (p = 0.0000)		208.4611 (p = 0.0000)	
Log likelihood value	121.5738		93.5454	
Obs	86		93	

Note：*、**、***represents significance levels at 10%, 5%, and 1%.

Moreover, the sums of the coefficients of factor variables, as shown in the first equation in Equation (17), are 5.6499 and –19.885 for the control and the experimental group, respectively. That is, as the sum of the coefficients of factor variables are not equal to 1, the estimated production functions do not have the characteristics of constant return to scale.

The results revealed that the estimated coefficients of factor variable in the control group are significant. However, the coefficients of farmers' socioeconomic variables are not significant. In the experimental group, the coefficients of most of the factor variables are significant, and the coefficients of industrial pollution and the interaction term of industrial pollution and chemical input are also significant.

In the experimental group, the direct impact of industrial pollution on rice output is 0.4865 * ln*P* – ½ ln^2P, which is the dose-response function of rice to industrial pollution, characterized by an inverted U-shaped curve. That is, rice output has a positive correlation with industrial pollution before the "threshold" of crops' resistance is reached; otherwise, the relationship becomes negative. The reasons are that, on one hand, crops per se have a resistance to external stress, and a low level of industrial pollution can stimulate the metabolism of crops. On the other hand, industrial pollution becomes damaging to crops when the level of industrial pollution exceeds the maximum resistance threshold of crops. The estimated coefficients of the terms of ln*P* * ln*S* and ln*P* * ln*C* are negative, indicating that industrial pollution affects the crop output via its effects on factors, and that as the level of industrial pollution increases, the marginal products of seeds and chemical fall.

The coefficients of the gender of respondent (Z_1) and the number of household members (Z_3) are significant in the experimental group. There is no significant coefficient for socioeconomic variables in the control group.

When the control group is used as a reference for efficiency estimation, there should be no difference between the deterministic parts of the production function estimated from the control group and the experimental group. The significance of the difference is examined using a likelihood ratio (LR) test (Greene 2012) as expressed in Equation (28):

$$LR = -2\left(lnL_p - (lnL_C + lnL_T)\right) \sim \chi^2(k) \qquad \text{Equation (28)}$$

where:

L_P	=	likelihood value of the pooled data model,
L_C	=	likelihood value of the control group,
L_T	=	likelihood value of the experimental group, and
k	=	number of variable in $f(X)$.

The result shows that the value of LR is 3.715, which is less than the corresponding critical value of chi square, 24.769. The difference of estimated coefficients between the two models is not statistically significant.

4.2 Empirical Proof of Lemma

4.2.1 Impact of industrial pollution on the marginal output of factors

The impact of industrial pollution on the marginal output of factors was analyzed using the numerical simulation method in MATLAB package. To avoid overlapping, the paper only presents the results in the case of chemicals as a factor.The output elasticity of chemicals is expressed as follows:

Control group (E_c) = $-0.1446 + 0.2963lnC + 0.7227lnL - 0.6218\,lnK - 0.0692lnS$

Experimental group (E_e) = $1.4247 + 0.6511lnC - 0.0925lnL - 0.6928lnK - 0.0651lnS - 0.2043lnP$

Based on the definition of the output elasticity of factor, the elasticity equation is rewritten as: ${}^{dY}/_{dC} = e{*}^{Y}/_{C}$, which was used in the simulation. The values of other parameters refer to the survey data in Table 1. The weighted average of output and chemical inputs in the control group and the experimental group (y = 365.95, C = 1448.38) were used as the baseline in the simulation.

The simulation results are shown in Figure 3. In the control group, the marginal output of chemicals (*MPC*) increases as the inputs of chemicals and labor factor increases, with a maximum value of MPC of 2.5. In the experimental group, *MPC* becomes higher as the input of chemicals increases, but decreases as more labor is used, with a maximum value of 1.5. Similarly, *MPC* decreases as the inputs of capital and seeds increase in both groups, but the rate of change in the experimental group is greater.

Letting the values of all factors be their means, the numerical results show that there exists a negative correlation between industrial pollution and *MPC* (Figure 4). That is, as the level of industrial pollution increases, the simulated value of *MPC* decreases from 2.8 to 1.2.

In summary, industrial pollution reduces the marginal output factor. Lemma I is then empirically verified.

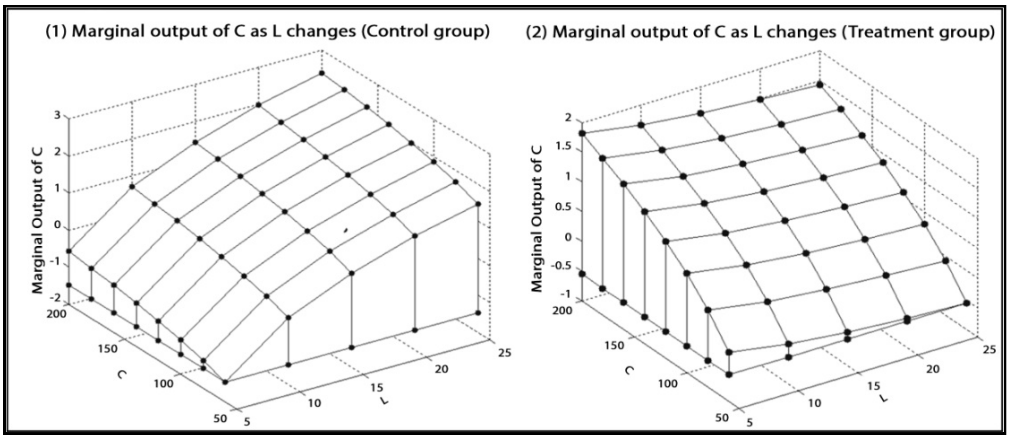

Figure 3. Marginal output of *C* as both *C* and *L* change

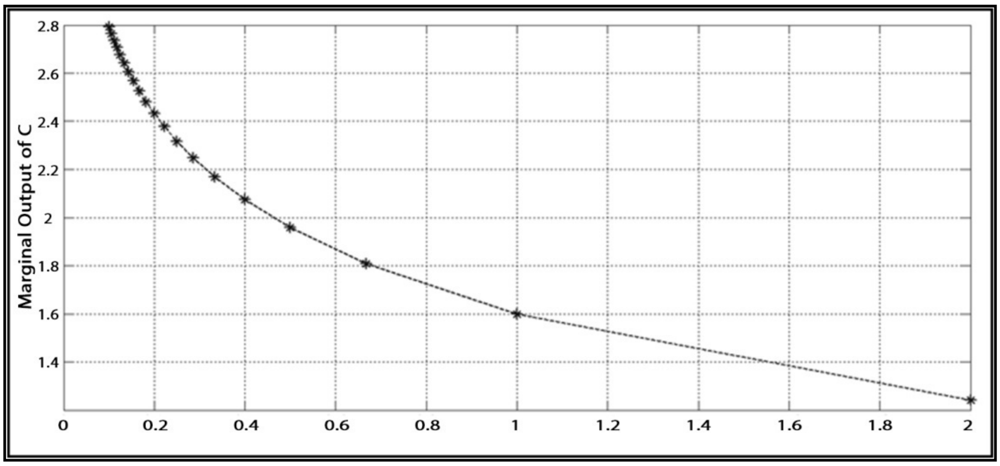

Figure 4. Marginal output of *C* as *P* changes

4.2.2 The impact of industrial pollution on the relationship between factors

As analyzed in the previous section, *C* and *L* have a positive correlation in the control group, but a negative correlation in the experimental group. The most plausible explanation is that industrial pollution alters the relationship.

As previously explained, this study assesses the impacts of industrial pollution on the inputs of chemicals and seeds, assuming that the input of capital is usually not affected by industrial pollution. Although labor is affected by industrial pollution, it is not analyzed because the estimation of the production function requires labor to be homogenous, but the impact of industrial pollution would result in heterogeneous labor. Since there are four factors, there were five relationships to be analyzed, namely, seed and labor (*S* and *L*), seed and capital (*S* and *K*), seed and chemicals (*S* and *C*), chemicals and labor (*C* and *L*), and chemicals and capital (*C* and *K*). Using the *R* statistical software, the elasticitiesof the five relationships was calculated for both the control and experimental groups. The frequency of elasticity of each of the factor combinations is shown in Figure 5.

The results reveal that industrial pollution changes the relationships between seed and labor, and chemicals and capital. Meanwhile, it reduces the complementary elasticity value between seed and capital, seed and chemicals, and chemicals and labor. Due to similar relationships, only the relationships between two pairs of factors (i.e., *C* and *K*, and *C* and *L*)are presented, while those of other pairs are not.

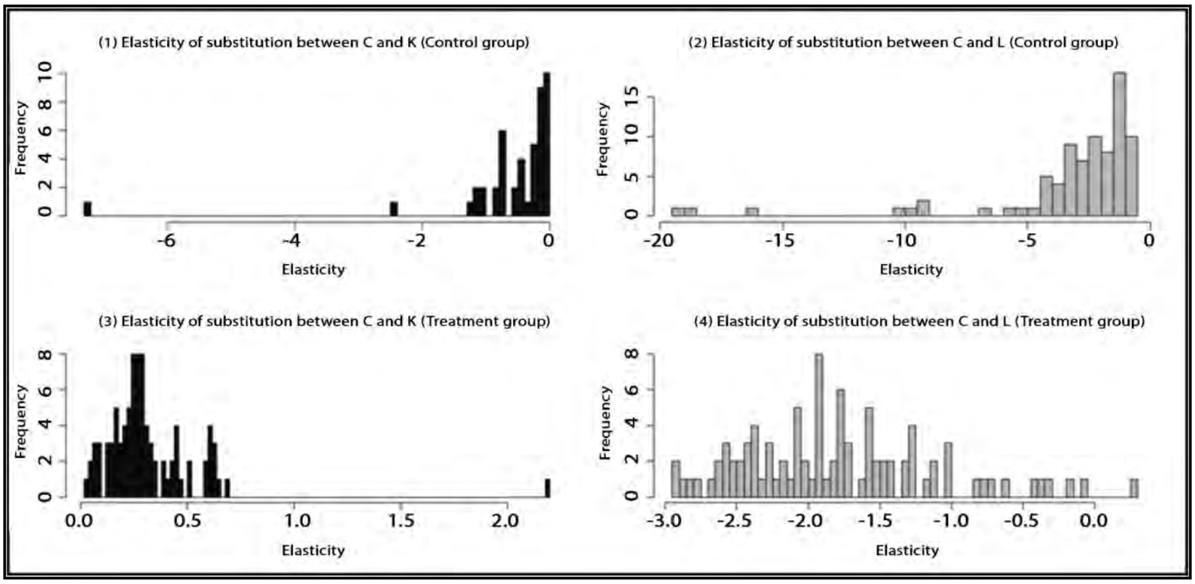

Figure 5. Elasticity of substitution/complementarity between factors

The results show that industrial pollution can affect factors in two aspects: by changing the relationship from substitution to complementary or vice versa, or by increasing or decreasing the values of substitution or complementary elasticity.The first aspect relates to the two relationship between seeds input (*S*) and labor input (*L*), and between chemical inputs (*C*) and capital input (*K*). Panels (1) and (3) in Figure 5 indicate the impact of industrial pollution on the relationship between chemicals and capital investment. In the control group, the range of elasticity is [–2, 0], with an average of –0.8, which shows a complementary relationship between chemical inputs and capital input. In the experimental group, the range of elasticity mainly is [0, 1] with a mean of 0.4, which indicates that the relationship between chemical input and capital input changed from complementary to weak substitution, as referred to that in the control group. In order to test whether the difference is statistically significant, a null hypothesis was made: there is no statistical difference in the mean elasticity between the two groups. The t-statistic value was –3.1007 ($p = 0.0026$), showing that the null hypothesis is rejected at 99% confidence level.

In other words, the two mean elasticity values of the two groups are statistically significant. The possible reason for this change is that industrial pollution disorders or hurts the crops' metabolism, and thus reduces their ability to absorb nutrients and resist diseases. Thus, more chemicals are required and the relationship between chemicals and capital changes.

The second aspect is associated with the relationship between chemical inputs (*C*) and labor input (*L*). Panels (2) and (4) in Figure 5 characterize the impact of industrial pollution on the relationship between chemicals and labor inputs. The range of elasticity is [–10, 0] in the control group with a mean of –4, and that of the experimental group is [–3, 0] with an average of –1.5. Obviously, chemicals and labor inputs have a complementary relationship in both groups but the value of elasticity is different. In order to test the significance of the difference, a null hypothesis was made: there is no statistical difference in the mean elasticity of the two groups. The value of t-statistic was –2.3899 ($p = 0.0185$), indicating that the null hypothesis is rejected at 95% confidence level. Obviously, industrial pollution changes the strength of the substitution or complementary relationship between factors.

To summarize, the empirical results are consistent with Lemma I.

4.2.3 The empirical comparison between method TFPF and MFPF

As theoretically proved, TFPF is not suitable for estimating efficiency in the presence of industrial pollution, as argued by the following empirical analysis. Instead of using Equation (2), the efficiency of polluted crops is estimated using the modified measure, as shown by Equation (13). Using the TFPF method, the interval of the production efficiency in the control group is [0.769, 0.988], and that in the experimental group is [0.628, 0.951] (Table 10).

However, the efficiency in the experimental group is [0.539, 0.692] as estimated using the MFPF, which is different from the values estimated using the TFPF. A null hypothesis was made to test the significance: the production efficiency estimated using the TFPF and the MFPF are not significantly different. The t-statistic value is –22.78 ($p = 0.0000$), indicating that the null hypothesis is rejected at 99.9% confidence level.

According to the empirical studies, the production efficiency in the presence of industrial pollution is overestimated if TFPF is used. That is, the TFPF method is not an appropriate measure of the production efficiency when crops are affected by industrial pollution.

The empirical results show that Lemma 3 holds.

Table 10. A comparison of production efficiencies estimated using different measures

Group		Efficiency			
		Min.	Max.	Mean	SD
Control group		0.7692	0.9877	0.9442	0.001069
Experimental group	TSFA	0.6279	0.9505	0.8776	0.007821
	MSFA	0.5387	0.6917	0.6613	0.000524

Note: SD = standard deviation

4.3 The Economic Value of Agricultural Loss

4.3.1 Descriptive statistical analysis

The descriptive statistical analysis of data is shown in Table 11. Village B is more than 30 km from the silicon industrial park, while the average distance of the surveyed households in Village A to the silicon industrial park is only 3.67 km. There were more male than female respondents in the experimental group, while the numbers of male and female respondents were nearly equal in the control group. Meanwhile, there was no obvious difference in the level of education, number of family members, and per capita household income among the interviewees. As a whole, the average area of farmland in the experimental group was a little higher than that of the control group, while the yield per hectare was slightly lower than that of the control group.

Table 11. Descriptive statistical analysis of respondents' socioeconomic characteristics

Variable	Sample	Mean	SD	Sample	Mean	SD
	Control Group			Experimental Group		
Respondent's sex (M = 1， F=0）	165	0.48	0.50	168	0.73	0.45
Respondent's age (year)	165	46.67	11.72	168	46.71	12.20
Respondent's education attainment (year)	165	5.78	2.87	168	5.67	2.61
No. of household members (person）	165	4.28	1.60	168	4.64	1.58
Ave. annual income (CNY）	165	7,393.33	3,584.03	168	7,362.02	3,927.79
Distance (farmland to silicon industrial zone, in km)				168	3.67	1.99

4.3.2 Estimated production function

The estimated results of the translogproduction function are shown in Table 12. Four models were estimated. Model 1 and Model 2 are the rice production functions, while Model 3 and Model 4 are the corn production functions. Models 1 and 3 are estimated from the control group data, whereas Models 2 and 4 are from the experimental group data. To achieve unbiased estimation, the robustness was checked.

1. We checked the multi-collinearity between explanatory variables according to the correlation matrix. The correlation between the explanatory variables is less than 25% (in the rice model) and 20% (in the corn model). That is, the multi-collinearity is very weak.
2. The homoscedasticity was checked using the White test. The Lagrange multipliers statistics are 8.611, 15.731, 12.154, and 23.031 for the four models, respectively. All of them are less than their critical chi-square values at the 99% confidence level, which are 27.685 (control group) and 29.141 (experimental group). Thus, the homoscedasticity is accepted.
3. Whether or not there are excessive variables in the production function was checked using the Wald chi-square value. As calculated, the Wald chi-square values of the four production functions were 1,792.44; 14,498.50; 586.73; and 679.29, respectively, whereas their p values were 0.0000. That is, there are no excessive variables in the estimated production functions.

According to estimated results, the coefficients of most of the input factors like labor and their interaction are statistically significant; the coefficients of the industrial pollution variable is also statistically significant. Not all the coefficients of the variable of family members are significant at the 95% confidence level in the four models.

Table 12. Estimated production functions for rice and corn

Variable	Rice		Corn	
	Model 1 (C)	Model 2 (E)	Model 3 (C)	Model 4 (E)
ln*L*	4.451000***	2.062000*	–2.90600***	–3.124000***
ln*K*	1.870000*	7.424000**	–1.45600***	2.373000*
Ln*S*	–0.526000*	–0.370000*	–0.95700*	–0.385000
Ln*C*	–0.145000*	1.916000*	2.35700**	3.465000***
1/2(lnL*ln*L*)	0.321000	0.207000**	0.17500	0.284000**
1/2(lnK*ln*K*)	0.677000***	–0.480000	0.10900*	–0.271000
1/2(lnS*ln*S*)	–0.011300	–0.005880*	0.09070***	0.000251
1/2(lnC*ln*C*)	0.148000	–0.078600	–0.27600***	–0.228000*
LnL*ln*K*	–1.758000***	–0.499000*	0.29100	0.438000*
lnL*ln*S*	–0.067400	–0.081100*	–0.19000**	–0.084400
lnL*ln*C*	0.723000**	–0.112000	0.25000	0.057200
lnK*ln*S*	0.196000*	0.122000*	0.11300	0.022200
lnK*ln*C*	–0.622000**	–0.126000	–0.01570	–0.240000*
lnS*ln*C*	–0.069200*	–0.001770*	0.18200***	0.101000*
Z_1	0.005810	0.013100*	0.04230*	–0.011100
Z_2	0.000125	–0.000260	–0.00892	0.001230*
Z_3	0.000522*	0.001200	0.01060	0.012500*
D	—	0.138000***	—	0.008490*
Constant	–8.84200	–23.590000***	–2.64200***	–5.520000
Wald chi^2	1,792.4400 (p = 0.0000)	14,498.5000 (p = 0.0000)	586.7300 (p = 0.0000)	679.2900 (p = 0.0000)
Log likelihood value	121.57	196.63	80.94	74.18
Obs	86	93	157	122

Note: *、**、***represents significance at 10%、5% and 1% level.

As shown in Table 12, the sum of α_i, i.e., the coefficients of factor variables, in each model is not equal to 1. That is, the estimated production functions do not have the characteristics of constant return to scale. The coefficients of the quadratic terms and the interaction terms are also significant. Since the restriction of Equation (4) is not satisfied, the estimated translog production function cannot be simplified into a CD production function. With non-constant elasticity of substitution between factors, the translog production function was more appropriate to describe the relationship between output and factors than the CD production function, whose elasticity of substitution is constant.

Intuitively, the stronger industrial pollution is, the greater the agricultural loss becomes. There are two reasons for this relationship:

1. As the distance between the industrial pollution and the cornfield decreases, the concentrations of pollutants increases, resulting in greater inhibition ofcrop growth.
2. More severe industrial pollution would more likely reduce the output elasticity of production factor, and thus indirectly affect the output of crops.

Table 12 shows that the coefficients of industrial pollution (*D*) are positive and significant in Model 2and Model 4 at a significance level above 10%. That is, industrial pollution has negative impacts on crop yield, and the impact increases as the pollutant concentration becomes higher.

4.3.3 Economic cost of agricultural loss

Based on the set of inputs, the researchers estimated the agricultural economic loss using three steps. First, the set of inputs was identified and quantified. Second, the outputs were estimated by entering the values of all explanatory variables into the production functions (Table 13). Third, the economic loss was calculated by multiplying the output loss and the market price of quality products.

As surveyed, the data on corn output refer to the quantity of quality product. The quantity of low-quality corn was either small or not measured by farmers. Thus, it is impossible to estimate the economic loss of quality reduction in the study. Since there are various combinations of inputs for production, it is impossible to present all the results. As shown in Table 14, the study presents three basic combinations of inputs, including the set of minimum input value, the set of mean value of input, and the set of maximum input value. Note that because the distance from farmland to the pollution source is a proxy of pollution, the shortest distance represents the maximum pollution that crops receive.

Table 13. Values of variables for crop yield estimation

Variables		L	K	S	C	Z_2	Z_3	Distance	Price
Corn	Minimum	5.0	10.0	0.4	48.0	0.0	1.0	0.5	1.6
	Median	17.1	67.6	3.8	120.2	5.7	4.5	3.9	2.5
	Maximum	37.0	106.0	43.8	600.0	16.0	12.0	9.0	3.6
Rice	Minimum	9.0	147.5	1.0	40.0	0.0	1.0	0.5	2.1
	Median	23.4	257.0	5.3	144.4	5.7	4.4	4.0	5.1
	Maximum	35.0	415.0	25.0	250.0	11.0	9.0	8.0	7.0

Note: L = labor; K = capital; S = seeds; C = chemicals; Z = socioeconomic characteristics

Table14. Estimated agricultural loss

Output		Control Group (kg/mu)	Treatment Group (kg/mu)	Unit Loss (CNY/mu)	Total Loss (million CNY)
Corn	Minimum	130.07	104.78	63.22	0.28
	Mean	321.23	235.63	213.99	0.94
	Maximum	745.05	582.89	405.41	1.79
Rice	Minimum	203.16	109.62	477.05	1.23
	Mean	387.51	273.18	583.08	1.51
	Maximum	644.99	418.11	1,157.07	2.99

Note: 1 mu = 0.067 ha; 1 ha = 15 mu

The crop outputs were thus estimated by entering the values of each of the three sets into the production functions. According to the statistical data collected from the surveyed areas, the cultivation areas for corn and rice are 4,403 mu (294 ha) and 2,584 mu (172 ha), respectively. The prices of rice and corn are CNY 5.1/kg and CNY 2.5/kg, respectively. That is, the average losses of corn and rice are 85.6 kg/mu (1,284 kg/ha) in outputs, or CNY 214.0/mu (CNY 3,210/ha) and CNY 583.1/mu (CNY 8,745/ha) in economic value, respectively, with a distance of 0.5–9 km from the pollution source.

4.3.4 The economic cost of health damage

The economic loss of health damage was estimated in three steps. First, the atmospheric pollutant concentration was estimated using the Gaussian dispersion model. Second, the health effects of pollution were quantified according to the exposure-response relationships between different health endpoints and pollutants. Third, the health effects were monetized according to the medical costs and VSL. The exposed population was categorized into two groups: the local residents and employees at silicon production zone.

The estimated ground-level pollutant concentration is shown in Table 15. The results show that atmospheric pollutant concentration tends to decrease as the distance from the silicon industrial zone increases. The population exposed to different levels of pollution was estimated according to the distance between local residents' houses and the silicon industrial zone. As there is no other industry in this region, the silicon industrial zone is the only source of pollutants. Thus, the data in Table 15 can be used to quantify the health effect of pollution from silicon production.

The results of the economic loss of health effects on local residents are shown in Table 16. Based on the results, the total economic loss of mortality is CNY 3.4983–5.9732 million, and that of morbidity is CNY 22.9021–37.4359 million.

The major economic costs are associated with PM_{10} and TSP, although the costs resulting from CO cannot be neglected. Comparatively speaking, the cost of SO_2 pollution is relatively small. In terms of health endpoints, the major economic costs are associated with all-cause mortality, inpatient visits of respiratory and cardiovascular diseases, and COPD, among which the cost of COPD morbidity cost is the highest.

In the study, the cost of damage to workers' health associated with pollution at silicon firms was estimated using the benefit-transfer method. The health endpoints include outpatient visits of internal medicine, hospital admission of respiratory and cardiovascular diseases, and COPD. The major pollutants are TSP and PM_{10}.

Approximately 2,000 employees work in seven silicon plants, and they are the ones considered as the exposed population. According to Yan et al. (1991), the average TSP concentration is 10.6 mg/m^3 in the workshop and 0.92 mg/m^3 in the plant outside the workshop, which translates to 9.9 mg/m^3 on average. The threshold value of TSP referred to the Grade I quality of the national air quality standard, i.e., 120 ug/m^3. Assuming that the plant areas is a circle with a diameter of 2 km centered on the workshop, the concentration of PM_{10} is estimated to range from 54–1,893 ug/m^3.

The results are shown in Table 17. Based on the results, the total cost of health damage to employees is CNY 0.1271–2.2215 million.

Table 15. Distribution of daily pollutant concentration, distance, and exposed population

Wind Velocities (m/s) and Exposed Population		Estimated Concentration of Ground-Level Pollution (ug/m^3) on Plume Centerline at Selected Distances (km) from Source				
		2	5	10	20	35
TSP	3.4	2,305	2,171	1,220	611	343
	7.9	3,263	1,400	635	288	155
PM_{10}	3.4	2,075	1,954	1,098	549	308
	7.9	2,937	1,260	572	259	140
CO	3.4	112	105	59	30	17
	7.9	158	68	31	14	8
SO_2	3.4	280	264	148	74	42
	7.9	396	170	77	35	19
Exposed Population		3,039	2,635	5,243	34,311	47,186

Table 16. Economic costs of pollution on local residents' health

Health Endpoints	Pollutant	Economic Cost (million CNY)
Mortality		
All cause	PM_{10}	1.7500–2.8000
	SO_2	0.0520–0.1100
	CO	0.5200–0.9200
Respiratory mortality	PM_{10}	0.4800–0.7700
	SO_2	0.0140–0.0300
	CO	0.1400–0.2500
Cardiovascular disease mortality	PM_{10}	0.2700–0.4300
	SO_2	0.0080–0.0017
	CO	0.0800–0.1400
	PM_{10}	0.2500–0.3900
	SO_2	0.0070–0.0015
	CO	0.0073–0.1300
Morbidity-outpatient		
Internal medicine	TSP	0.2102–0.3318
Chronic bronchitis	PM_{10}	0.6600–1.2087
Morbidity-inpatient		
Respiratory disease	PM_{10}	3.3486–3.7997
	SO_2	0.0189–0.1349
Cardiovascular diseases	PM_{10}	4.0726–5.5347
	SO_2	0.4918–0.8261
COPD	TSP	14.1000–25.6000

Table 17. Economic loss of pollution to employees' health

Health Endpoint	Pollutant	Economic Cost (million CNY)
Morbidity-outpatient		
Internal medicine	TSP	0.1159–0.2107
Morbidity-inpatient		
Respiratory disease	PM_{10}	0.0053–0.9965
Cardiovascular diseases	PM_{10}	0.0059–0.5926
COPD	TSP	0.4217

4.4 Total External Cost and the Abatement Cost

As estimated above, the total annual external cost of metallurgical silicon production is CNY 28.038–50.411 million. The total output of metallurgical silicon was 85 thousand tons in 2014. That is, the average external cost is CNY 461.46 (CNY 329.85–593.07) per ton of metallurgical silicon.

The external cost is equivalent to the abatement cost of dust removal and waste water treatment, which is CNY 441.6/ton (Table 18). Specifically, the abatement cost includes CNY 40.4/ton of allocated fixed cost of equipment and CNY 401.2/ton of variable cost. That is, the external cost can be internalized by installing abatement equipment.

How will the installation and operation of abatement affect the silicon plants' financial profit? For a silicon plant with a production capacity of 0.5 million tons of metallurgical silicon per year, the financial profit is CNY 1,579/ton, as the local price of metallurgical silicon is CNY 12,500/ton metallurgical silicon. The total cost is CNY 8,063.7/ton of metallurgical silicon, including CNY 244.16/ton of fixed cost and CNY 7,819.5/ton of variable cost. The value-added tax is CNY 2,295/ton or 17% of revenue, and the income tax is CNY 897/ton or 16.5% of pre-tax profit. Since the abatement cost is CNY 441.6/ton of metallurgical silicon, installing and operating abatement equipment will reduce the plant's profit by 28%. This is the reason that there is no abatement equipment in many silicon plants or why the abatement equipment is usually closed, to be opened only before an environmental monitoring will be conducted by the environmental protection authority.

Table 18. Abatement costs of dust removal and wastewater treatment

Item	Fixed Cost	Variable Cost	Unit Cost (CNY/ton of Silicon)
Dust removal equipment	2 million per unit, depreciated by 10% for 10 years or equals to CNY 40/ton	Electricity, filtering sacks, and workers' salary, which is equal to CNY 400/ton	440.0
Waste water treatment	0.2 million depreciated by 10% for 10 years or equals to CNY 0.4/ton	Water treatment agent, workers' salary; CNY 1.2/ton	1.6
Total			**441.6**

Table 19. Financial analysis of metallurgical silicon production

Item	Specification	Annual Cost (million CNY)	Unit Value (CNY/ton of Silicon)
Fixed cost			244.16
Electrical mechanics	Depreciation rate of 10% for 10 years	6.40	128.00
Infrastructure	Depreciation rate of 5% for 20 years	0.96	19.20
Financial cost	Interest rate of 6%	4.85	96.96
Variable cost			7,819.50
Sand or quartzite	3 tons and CNY 190/ton		570.00
Charcoal	1 ton and CNY 1,150/ton		1,150.00
Electrical node	0.1 ton and CNY 5,540/ton		554.00
Petro coke	0.66 ton and CNY 1,200/ton		792.00
Electricity	12,000 kVa and CNY 0.403/kVa		4,836.00
Supplementary	Oxygen, water, bricks and others		80.00
Equipment maintenance	Check and repair		84.00
Transport			150.00
Packaging			100.00
Insurance and salary			195.50
Total production cost			8,063.70
Total revenue			12,500.00
VAT	17%		2,295.00
Income tax	16.5% of pre-tax profit		897.00
Profit	revenue – total production cost – tax		1,579.30

5.0 CONCLUSION AND POLICY IMPLICATION

Rapid increase in silicon production has resulted in severe pollution in China. This study aims to estimate the external costs of silicon production so as to provide information for policy making on the sustainable exploitation of solar energy.

First, the study analyzed how industrial pollution affects agricultural production. Theoretical results show that industrial pollution affects agricultural productivity in two ways: (1) by changing the relationship between factors from substitution to complementarity, and vice versa; and (2) by changing the elasticity of substitution or complementarity. Accordingly, the empirical results show that

1. the relationship of the two pairs of factors—seed and labor, and chemical and capital— changed from complementary substitute to weak substitute;
2. industrial pollution lowers the elasticity of the three pairs of factors—seeds and capital, seeds and chemicals, and chemicals and labor; and
3. the marginal products of some production factors are reduced.

Obviously, the empirical findings are consistent with the theoretical results.

Second, the study estimated the external cost of health damage and agricultural loss using field survey data. The data was collected from a silicon industry zone in Southwest China. The external cost of agricultural loss was estimated using a production function method. Meanwhile, the external cost of the health damage was estimated using dose-response functions, in which the pollutant concentration in air is estimated based on a Gaussian dispersion model.

The results show that the annual external cost of agricultural loss is CNY 1.51–4.78 million and that of health damage is CNY 26.528–44.63 million. That is, the total external cost is CNY 28.038–50.411 million. The average external cost is CNY 461.46/ton of metallurgical silicon, which is equivalent to the abatement cost of dust removal and waste water treatment of CNY 441.6/ton. The internalization of the external cost would reduce the silicon plant's financial profit by approximately 28%.

The results have important policy implications as follows:

First, promoting the production and use of solar energy can contribute to sustainable development, but more attention should be attached to the external cost of production of related products. As the initial stage of industrial chain of photovoltaic cell, metallurgical silicon is mainly produced in developing countries. Thus, information on the external cost of its production is an important evidence for understanding the international industrial chain of PV cells.

Second, the information on external cost can serve as reference for economic feasibility studies undertaken for silicon production projects in rural areas.

Third, the negative externality can be internalized by installing and operating abatement equipment, as the external cost is approximately equal to the abatement cost. This gives local governments the justification to require silicon plants to install and operate abatement equipment.

Lastly, the information on the external costs can be used for making policies to compensate the local affected farmers and residents, and for designing instruments that would control the pollution from metallurgical silicon production.

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