Does industrial water pollution impede agriculture? Evidence from rice farming in China

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Abstract

In the process of industrialization, relocation of manufacturing industries from urban to rural areas may have important implications for the rural environment and agricultural production. As a demonstration, the aim of this paper is to estimate the impact of wastewater from industrial firms on agricultural yields in rice farming of Jiangsu province, China. Using 2011-2015 panel data from both the China Rural Fixed Point Survey and the China Environmental Statistics Database between 2011 and 2015, we find that industrial wastewater significantly reduces rice yields. The econometric strategy implemented allows us to assume that this result reflects a causal and detrimental biological effect of wastewater on the growing process of the rice. These results highlight the need to better understand the conflicts between industry and agriculture at the local level in a context of rapid industrialization.

Keywords

Industrial water pollution, Rice farming, Rural environment, China.

JEL Codes

D24, O12, Q12, Q15, Q53.

1 Introduction

In the process of industrialization, relocation of manufacturing industries from urban to rural areas may have important implications for the rural environment and agricultural production. As a demonstration, the aim of this paper is to estimate the impact of wastewater from industrial firms on the Chinese rice production of about 600 rural households located in six villages in Jiangsu province. This province is situated in the heart of the Yangtze Delta region, on China's east coast. With a population of about 78 million and an average GDP per capita of 62,173 yuan (about 9,000 US dollars) in 2011, Jiangsu was ranked the second largest economy of the country, just behind Guangdong province (NBS, 2012). However, its rapid industrialization and economic growth was accompanied by the development of polluting industries such as the chemical, paper, textile and dyeing industries, which generated severe water pollution in the province. According to the Ministry of Environmental Protection, in 2011, 11,291 polluting manufacturing firms in Jiangsu discharged 2.46 billion tons of industrial wastewater, 0.24 million tons of Chemical Oxygen Demand (hereafter COD) and 17 thousand tons of ammonia nitrogen (hereafter NH3-N) (MEP, 2012). The tremendous amount of water pollution stimulated the abnormal growth of algal in water reserves, which resulted in the eutrophication of rivers and lakes. This problem was particularly acute in the Jiangsu's Tai Lake watershed. In 2007, a severe algal bloom caused the emergency shutdown of the Wuxi City water supply system. Similar problems in tributaries and canals also caused frequent disruptions to irrigation and water supply systems in Jiangs's towns and rural areas. The severe water eutrophication therefore created a scarcity of adequate quality water for residential and agricultural needs in the region. As a result, farmers and water plants reverted to using groundwater sources, which in turn caused the over-extraction and quality deterioration of groundwater, as well as saltwater intrusion in coastal areas. At the time, the severe industrial pollution and water eutrophication were recognized to be one of the most critical challenge for the sustainability of the environment and future development in the province.

Beyond the significance of industrial wastewater issues for farming in Jiangsu province, this study aims to contribute to the literature on the industrial pollution-agriculture nexus. In fact, while most of the studies in this literature rely on the analysis of the consequences of air pollution on agricultural activities, the water pollution issue is very rarely investigated[1].

We focus on different measures of industrial wastewater derived from the large administrative database of Chinese Environmental Statistics (CES), i.e., total industrial wastewater, untreated industrial wastewater, industrial COD pollution and industrial NH3-N pollution[2]. For each of these four types of water pollution, we construct a measure of water pollution encountered by each farmer in a given village[3].

We then link these pollution measures to the rice production of farmers using data derived from the China Rural Fixed Point Survey between 2011 and 2015. More precisely, we investigate the impact of wastewater on rice yields (measured in terms of produced quantity per unit area).

The aim of the study is to test the presence of a negative and direct biological link between wastewater and the growth of the rice. In fact, industrial wastewater can weaken the growth of roots, seedlings and tillers in crops resulting in lower produced quantities (World Bank, 2007). We use a translog production function that accommodates non-neutral technical change in order to isolate this direct and negative biological effect of wastewater from other potential interaction effects of waster with the production process (through input uses and technical change)[4].

Two results are worth noting. First, we find a significant, negative and strong direct biological effect of total wastewater, untreated wastewater and COD. These results are robust to the use of external instruments to control for potential endogeneity of wastewater[5]. The effect of a one percent increase of wastewater leads to a 0.06 to 17.41 percent reduction of rice yields with regards to the model specification (i.e., the types of interactions included) and water pollution measures (i.e., total wastewater, untreated wastewater and COD). Regarding NH3-N, we find a strong and negative direct biological effect once we use external instruments. Second, we do not find robust interaction effects of wastewater with the production process (input uses or technical change)[6]. Taking together, our results confirm that wastewater weakens rice production through a causal, direct and detrimental biological effect.

The remaining of the paper is organized as follows. Section 2 presents the literature related to the impact of industrial pollution on agriculture and highlights the theoretical links between wastewater and rice farming expected in this study. Section 3 gives the econometric framework. Section 4 shows the data and descriptive statistics. Section 5 presents the econometric results and Section 6 provides concluding remarks.

2 Background

2.1 Literature reviews

Most of the studies on the industrial pollution-agriculture nexus rely on the analysis of the consequences of air pollution (related to industry or not) on agricultural activities. The water pollution issue is very rarely investigated. We first present the literature on air pollution before highlighting the literature on water pollution.

2.1.1 Air pollution and agriculture

The investigation of the link between air pollution and agriculture relies on two main approaches: natural science methods using dose-response functions with data from field experiments and social science methods based on econometric models and empirical analysis.

There are many studies on the impact of total (not directly related to industrial pollution) air pollution (e.g., fine particulate matter (PM), surface ozone (O3), sulfur dioxide (SO2)) and agriculture. First, several papers conclude that air pollution, mainly surface O3 and SO2, lead to a reduction of crop yields in China. For instance, an earlier paper by Cao (1989) looks at the relationship between SO2 and its effects on plants and finds that ambient concentrations of SO2 reduce growth and crops and plants yields by 5-25 percent. On surface O3 pollution, more recent studies find a negative impact of O3 on crop yields. Aunan et al. (2000) use exposure-response functions to show that surface O3 leads to substantial but different crop yields losses according to the concurrence of peak levels of O3 and the growth season of crops. Also, Feng et al. (2003) use open-top chambers to show that an increase of O3 concentrations leads to stronger decreases of winter wheat and rice. In the same vein, Wang and Mauzerall (2004), Feng et al. (2015), Zhu et al. (2015) and Miao et al. (2017) also conclude that O3 pollution induces a reduction of crop yields. Moreover, while Yi et al. (2016) also find a significant and negative impact of surface O3 pollution on the productivity of winter wheat, they differ from others studies by using an econometric approach rather than natural science methods.

Other studies focused outside China reach the same conclusion of a negative impact of air pollution on crop yields (for instance, Avnery et al. (2011) at the global level, Emberson et al. (2001) in several developing countries, Wahid et al. (1995); Maggs et al. (1995) in Pakistan, Tai and Martin (2017) in the US and Europe, and Benton et al. (2000) in Europe).

While previous studies focus on biological effects of air pollution on crops, some papers investigate the impact of air pollution on crops through labor productivity. Using an econometric model with daily data on labor and ozone pollution, Graff Zivin and Neidell (2012) conclude that a 10 parts per billion change in O3 concentration leads to a significant and robust 5.5 percent change in agricultural worker productivity in the Central Valley of California in the US. In the same vein, Hanna and Oliva (2015) use an econometric model and exploit exogenous variations in SO2 pollution resulting from the closure of a large oil refinery in Mexico City. They find that neighborhoods located near the refinery experienced on average an eight percent reduction in SO2 and about a five percent increase in hours worked relative to other neighborhoods.

However, few studies have explored the specific impact of industrial pollution on agriculture, although many pollutants such as SO2, O3 or PM are related to industry. In China, Wei et al. (2014) look at 2,069 state-monitored enterprises and find negative effect of industrial SO2 pollution on agricultural yields in the 899 Chinese counties where these firms are located. Finally, Aragón and Rud (2016) examine how mining, a highly polluting industry, can affect agricultural productivity in Ghana. Using a consumer-producer household framework and an econometric model, they find that expansion of mining activities is associated with an economically significant reduction in agricultural productivity.

2.1.2 Water pollution and agriculture

There are very few papers that investigate the impact of water pollution on agricultural activities.

From a comparison between two villages (a pollution-affected village and a non-affected control village) located in South India, Reddy and Behera (2006) find that industrial water pollution has substantial negative monetary impacts on agricultural yields, land under cultivation, livestock (through contaminated water), rural employment and human health of inhabitants of the affected village compared to inhabitants living in the non-affected village. In the same vein, Khai and Yabe (2012) find that wastewater irrigation is associated with yields losses, cost increases and profit loss in rice farming in Vietnam.

In China, Lindhjem et al. (2007) use the same methodology (comparison between wastewater-irrigated and clean water-irrigated areas) to quantify the value of reduced crop quantity and quality due to wastewater irrigation in four villages in Shijiazhuang district in Hebei Province. A World Bank (2007) report shows that wastewater irrigation areas in China began increasing in the 1980s to represent about 4.05 million hectares in 2003. From dose-response functions, the report also estimates that the economic costs of wastewater irrigation on yields and produce quality (rice, wheat, vegetables and corn) amount to 7 billion yuan. This report also points out that the increase of wastewater irrigation in China is mainly the consequence of water scarcity. Yongguan et al. (2001) provide a global estimation of the cost of industrial water pollution in Chongqing. This city, located in Sichuan basin, is one of the most heavily polluted mega cities in China. From a resource cost analysis (resources spent to mitigate the impact of pollution and the potential loss of GDP because of pollution), they find that damages in monetary value due to water pollution on crops (grain and vegetables) production (quantity and quality) are greater than damages to industry (water shortages), human health (medical costs, premature death or water treatment measures) and animals (livestock, poultry and fish).

2.2 Theoretical links between industrial water pollution and rice farming

The link between industry and rice farming relies on the assumption that industrial activities influence rice farming activities through their effects on the farmer's environment. In this scenario, industry releases wastewater into the environment shared with farmers. In this study, we assume that industrial wastewater will influence rice yields, measured in terms of produced quantities per unit area, through both a direct effect and through interaction effects with technical change (TC) and input uses.

First, wastewater can reduce rice yields through a direct biological effect[7]. The underlying idea is that industrial wastewater can weaken the growth of roots and rice seedlings as well as the development of the rice's tillers. A World Bank (2007) report explains that the height, leaf area, and dry matter of the crop can be reduced because of water pollution.

Second, we assume that wastewater may influence rice yields through TC. Here, wastewater can be viewed as a technology "shifter". The theoretical effect of wastewater on TC is not easy to predict and depends on the composition of TC. More precisely, the rate of TC can be broken down into effects due to pure technical change (the effect of technology accumulation) and biased technical change (through the use of inputs over time). We do not hypothesize any sign of the effect of wastewater and leave our data and estimation model to do this.

Third, we assume that wastewater can modify rice yields through input uses (labor, capital, fertilizers, irrigation and other running costs). The underlying idea is to investigate whether rice yields can be plagued by wastewater through a reduction of input productivity. For instance, wastewater can damage workers' health (through water they consume as well as through their consumption of food and water "polluted" through industrial wastewater) that can be transmitted to a reduction of worker productivity and, in turn, crop yields losses. In order to isolate the direct negative biological effect from interaction effects, we propose an econometric framework, presented in Section 3.

3 Econometric framework

The aim of the econometric analysis is to estimate the impact of industrial water pollution on rice farming. To do so, our approach relies on two strategies. First, we study the link between water pollution and rice yields by testing a direct negative biological effect of wastewater as well as interaction effects of wastewater through TC and input uses. Second, we investigate the effect of water pollution on technical efficiency in order to study an overuse of inputs to overcome the direct negative biological effect.

3.1 The production function model

We start by assuming the following rice production function with a translog form that accommodates non-neutral technical change (TC hereafter) as follows:

$$\begin{aligned} ln(y_{i,v,t}) = \beta_0 + \sum_{j=1}^{5} \beta_j ln(x_{ji,v,t}) + 0.5 \sum_{j=1}^{5} \sum_{k=1}^{5} \beta_{jk} ln(x_{ji,v,t}).ln(x_{ki,v,t}) \\ + \beta_t t + 0.5\beta_{tt} t^2 + \sum_{j=1}^{5} \beta_{jt} ln(x_{ji,v,t}) t + \mu_i + \nu_{i,v,t}, \end{aligned} \tag{A}$$

where $i = 1, \ldots, N$ are the farmer unit observations at time t ($t = 1, \ldots, 5$) in village v ($v = 1, 2, \ldots, 6$) ; $ln(y_{i,t})$ is the logarithm of rice output (in kg) of farmer i at time t ; $x_{j,k} = 1, \ldots, 5$ are the five following inputs: labor (l: number of working days (both family labor and hired labor)), the value of fixed assets (c), fertilizer costs (f), irrigation costs (ir) and other running costs (insecticides, seed, etc.) (rc) and $ln(x_{ji,v,t})$ is the logarithm of the jth input ; t (time trend), t^2 and $ln(x_{i,v,t})t$ are used to take into account non-neutral TC where the measure of TC is the elasticity of output with respect to time that is both time and farm specific and varies with inputs ; μ_i are time-invariant farmer-specific effects and $\nu_{i,v,t}$ is idiosyncratic factors uncorrelated with input decisions. β_0, β_j, β_{jk}, β_t, β_{tt} and β_{jt} are parameters to be estimated.

Output and inputs are normalized to land devoted to rice farming[8].

We then assume that the rice production of each farmer may be influenced by time-varying local conditions such as the presence of industrial water pollution ($p_{i,v,t}$). More precisely, we investigate the effect of four types of $p_{i,v,t}$ which are successively studied: total wastewater (treated and untreated), only untreated wastewater, COD wastewater and NH3-N wastewater[9]. We assume that $p_{i,v,t}$ modifies rice production through three different channels as highlighted in Section 2.2: a direct biological effect, interaction effects with input uses and interactions effect with TC. We present four models to test these effects.

First, $p_{i,v,t}$ is added to Model A that becomes[10]:

$$\begin{aligned} ln(y) = \beta_0 + \sum_{j=1}^{5} \beta_j ln(x_j) + 0.5 \sum_{j=1}^{5}\sum_{k=1}^{5} \beta_{jk} ln(x_j).ln(x_k) \\ + \beta_t t + 0.5\beta_{tt} t^2 + \sum_{j=1}^{5} \beta_{jt} ln(x_j).t + \beta_p ln(p) + \mu_i + \nu, \end{aligned} \tag{B}$$

where β_p is the effect of water pollution that has to be estimated. This model does not allow us to disentangle all potential transmission channels of p on y. Thus, in order to isolate the direct biological effect of p, we add interaction effects of p with input uses. Model B becomes:

$$\begin{aligned} ln(y) = \beta_0 + \sum_{j=1}^{5} \beta_j ln(x_j) + 0.5 \sum_{j=1}^{5}\sum_{k=1}^{5} \beta_{jk} ln(x_j).ln(x_k) + \beta_t t + 0.5\beta_{tt} t^2 + \sum_{j=1}^{5} \beta_{jt} ln(x_j).t \\ + \beta_p ln(p) + \sum_{j=1}^{5} \beta_{pj} ln(p).ln(x_j) + \beta_{pjk} ln(p).0.5(\sum_{j=1}^{5}\sum_{k=1}^{5} ln(x_j).ln(x_k)) + \mu_i + \nu, \end{aligned} \tag{C}$$

where β_{pj} and β_{pjk} are the effect of water pollution associated to input uses that have to be estimated. We study the interaction effects of p with each input j as: $\beta_{pj} + \sum_{j=1}^{5}\sum_{k=1}^{5} \beta_{pjk}$. The overall effect of water pollution is $\beta_p + \sum_{j=1}^{5} \beta_{pj} + \sum_{j=1}^{5}\sum_{k=1}^{5} \beta_{pjk}$.

Third, p is assumed to modify rice yields as a "technology shifter" by modifying TC. Model B becomes:

$$\begin{aligned} ln(y) = \beta_0 + \sum_{j=1}^{5} \beta_j ln(x_j) + 0.5 \sum_{j=1}^{5}\sum_{k=1}^{5} \beta_{jk} ln(x_j).ln(x_k) + \beta_t t + 0.5\beta_{tt} t^2 + \sum_{j=1}^{5} \beta_{jt} ln(x_j) t \\ + \beta_p ln(p) + \beta_{pt} ln(p).t + \beta_{ptt} ln(p) t^2 + \sum_{j=1}^{5} \beta_{pjt} ln(p).ln(x_j).t + \mu_i + \nu, \end{aligned} \tag{D}$$

where β_{pt}, β_{ptt}, β_{pjt} are the effects of water pollution associated to TC that have to be estimated. We investigate three types of interactions with TC. First, we compute the interaction effects of p with total TC as: $\beta_{pt} + \beta_{ptt} + \sum_{j=1}^{5} \beta_{pjt}$. Second, we calculate the interaction effects of p with pure technical change as: $\beta_{pt} + \beta_{ptt}$. Third, we focus on the interaction effects of p with biased technical change as: $\sum_{j=1}^{5} \beta_{pjt}$. The overall effect of water pollution is $\beta_p + \beta_{pt} + \beta_{ptt} + \sum_{j=1}^{5} \beta_{pjt}$.

The last model, which is the general model in which all the previous models are nested, is as follows:

$$\begin{aligned} ln(y) = \beta_0 + \sum_{j=1}^{5} \beta_j ln(x_j) + 0.5 \sum_{j=1}^{5} \sum_{k=1}^{5} \beta_{jk} ln(x_j).ln(x_k) + \beta_t t + 0.5\beta_{tt} t^2 + \sum_{j=1}^{5} \beta_{jt} ln(x_j).t \\ + \beta_p ln(p) + \sum_{j=1}^{5} \beta_{pj} ln(p).ln(x_j) + \beta_{pjk} ln(p).0.5(\sum_{j=1}^{5} \sum_{k=1}^{5} ln(x_j).ln(x_k)) \\ + \beta_{pt} ln(p) t + \beta_{ptt} ln(p) t^2 + \sum_{j=1}^{5} \beta_{pjt} ln(p).ln(x_j).t + \mu_i + \nu, \end{aligned} \tag{E}$$

where β_p is the direct biological effect of p since all other interaction effects of p with the production process are controlled for.

Finally, Models B, C, D and E are estimated with the *within* estimator that allows us to control for μ_i. Moreover, a potential problem arises if farmers operating within a geographic region experience similar unobservable market or agro-climatic shocks, causing the random error to be spatially correlated. We address this issue by clustering the random errors at the village level.

3.2 The endogeneity of wastewater

The estimation of the effect of p can be challenged by its endogeneity. p is also a measure of industrial activities surrounding rice farming. Therefore, p can catch both a negative competition effect between industry and agriculture to attract inputs and consumers or a positive agglomeration effect resulting in the presence of industry (e.g., more industry implies more consumers or more infrastructure which benefits agriculture). We deal with this bias of omitted variables by introducing two variables of industrial production (in value (I_1) and in hour (I_2)) in Models B, C, D and E[11]. These two variables should capture all effects of industry on rice farming except for the pollution effect (e.g., a competition channel effect between agriculture and industry or agglomeration effects).

Moreover, we use three external instruments (hereafter Z) for p. Specifically, we use the quantity of water intake by industrial production ($z1$; in tons) and the quantity of both COD ($z2$; in tons) and NH3-N ($z3$; in kg) generated by industrial production[12]. These three variables are used for the four types of p studied (total wastewater, untreated wastewater, COD and NH3-N). These three variables are calculated as follows. First, $z1$, $z2$ and $z3$ of each industrial firm are weighted by the distance between the firm and the center of the village where the firm is located[13]. Second, we aggregate Z at the village level to link Z to rice farmers as instrumental variables of p.

We assume that these three external instruments are valid[14]. Each of the four types of wastewater released by an industrial firm seem obviously related to the quantity of water consumed for its production ($z1$) as well as the quantity of COD and NH3-N generated by its production ($z2$ and $Z3$). Consequently, it is plausible to assume a causal link between Z and p. Moreover, regarding the effect of Z on rice production (y), it is reasonable to assume that COD and NH3-N generated by industrial firms ($z2$ and $z3$) can play on y only through the part of wastewater released into the environment (so p). However, the quantity of water intake by industry ($z1$) can influence y beyond the quantity of wastewater released by industrial firms (p). For instance, more water intake by industry can imply less water to rice production. Independently of p, $z1$ can reduce rice production because of a competition channel between industry and rice farming to capture water. However, we assume that this effect is not present in Jiangsu province. Water is abundant there, so a water-related conflict between industry and rice farming is unlikely.

Finally, the set of instrumental variables used is different according to the model estimated. Table 1 gives the list of endogeneous variables and their instrumental variables for each model.

Table 1: List of endogeneous and instrumental variables

	Model B	Model C
List of endogenous variables	p	p $p.\sum_{j=1}^{5} x_j$ $p.(0.5\sum_{j=1}^{5}\sum_{k=1}^{5} x_j x_k)$
List of instrumental variables	$\sum_{z=1}^{3} Z_z$	$\sum_{z=1}^{3} Z_z$ $\sum_{z=1}^{3}\sum_{j=1}^{5} Z_z.x_j$ $\sum_{z=1}^{3} Z_z.0.5(\sum_{j,k=1}^{5} x_j x_k)$
	Model D	**Model E**
List of endogenous variables	p t $p.t^2$ $p.t.\sum_{j=1}^{5} x_j$	p $p.\sum_{j=1}^{5} x_j$ $p.(0.5\sum_{j=1}^{5}\sum_{k=1}^{5} x_j x_k)$ $p.t$ $p.t^2$ $p.t.\sum_{j=1}^{5} x_j$
List of instrumental variables	$\sum_{z=1}^{3} Z_z$ $\sum_{z=1}^{3} Z_z.t$ $\sum_{z=1}^{3} Z_z.t^2$ $\sum_{z=1}^{3}\sum_{j=1}^{5} Z_z.x_j.t$	$\sum_{z=1}^{3} Z_z$ $\sum_{z=1}^{3}\sum_{j=1}^{5} Z_z.x_j$ $\sum_{z=1}^{3} Z_z.0.5(\sum_{j,k=1}^{5} x_j x_k)$ $\sum_{z=1}^{3} Z_z.t$ $\sum_{z=1}^{3} Z_z.t^2$ $\sum_{z=1}^{3}\sum_{j=1}^{5} Z_z.x_j.t$

Note: p: alternatively total wastewater, untreated wastewater, COD and NH3. $z1$: industrial water intake, $z2$: COD generated by industrial production and $z3$: NH3 generated by industrial production. x: the five inputs of rice production (l: labor, c: capital, rc: running costs, fe: fertilizer and ir: irrigation), t: time trend.

In Model B, only p is endogenous so that we use only $z1$, $z2$ and $z3$ as instruments. In Model C, all interaction terms of p with inputs are also assumed to be endogenous so that we use $z1$, $z2$, $z3$ and their interactions with inputs as instruments. In Model D, all interaction terms of p with TC terms are assumed to be endogenous. The set of instruments is $z1$, $z2$, $z3$ and their interactions with TC terms. In the general model (Model E), the set of instruments is all instruments used in Models B, C and D.

4 Data and descriptive statistics

The data used in this study are derived from crop and industry data.

4.1 Rice farming data

Rice farming data come from the China Rural Fixed Point Survey. The survey questionnaire is administered at the household level to collect data on agricultural production (inputs and outputs), non-agricultural activities and sociodemographic characteristics of individuals within a household. In our analysis, we retain only households that were surveyed at least twice over the period 2011-2015 (five waves) and that were involved in rice farming. We have in total 1,514 observations for 366 households located in 6 villages.

Table A1 gives descriptive statistics of the variables related to rice farming used in this study. All input and output variables are normalized by the area allocated to rice production. It is worth noting that the average rice farming area is very small (3.74 mu or 0.25 hectares, where mu is the unit of area used in China and 1 mu = 1/15 ha). This is not surprising in the context of Chinese agriculture. Regarding the output used in this study, we focus on the quantity of rice production in a year. The average production of rice is 580.26 kilograms per mu with a standard deviation of 81.70.

We use five inputs: 1) labor (number of working days of hired labor and family members), 2) capital costs (value of fixed production assets (large and medium sized farm tools, agriculture machinery, etc.) possessed at the end of the year), 3) expenditures related to fertilizers, 4) irrigation costs, and (5) all other running costs (expenditures related to pesticides, seeds, etc.). Labor and all running costs are specifically related to the farm's rice production but this is not the case for capital costs. In fact, in the questionnaire, there is no question related to the possession of fixed assets specifically related to rice production. Thus if the farmer is engaged in another farming activity (e.g., other grain production (soybean, wheat, ...), cash crops (cotton, oil plants, ...), garden crops (fruits, ...) or animal husbandry), capital costs may be overestimated. In our sample, rice farming is the most largest production activity. It represents 48.34 percent at mean (the median is 51.40) of all the farmer's farming revenues (rice production, other grain production, cash and garden production, and animal production) far ahead of other grain production (30.72 percent), animal production (11.13 percent) and cash and garden crops (9.81 percent). On average, there are 12.70 working days (hired labor and family members) per mu with a standard deviation of 3.77. Specifically, rice farming is mainly a family business because hired hands work less than one day (in total so not per mu) while family members work about 48 days (in total so not per mu). Also, these figures suggest that rice farming is not the main activity of households. In fact, in our sample, only 189 of 366 household heads declared that farming is their main activity. Moreover, some farms diversify their production with other grain production (about 48 working days for family members on average), animal husbandry production (about 30 working days for family members on average), and cash and garden crop production (about 33 working days for family members on average). On average, fixed assets (capital) are estimated at 3,629 yuan per mu with a high dispersion (standard deviation of 15,104 yuan per mu). In our sample, rice farmers spent about 213 yuan, 38 yuan and 309 yuan per mu, respectively, for fertilizers, irrigation and all other running costs (standard deviation of 40 yuan, 24 yuan and 65 yuan per mu for fertilizers, irrigation and all other running costs). Also, it is worth noting that all farmers spent money to irrigate (the minimum of irrigation costs is 1.46 yuan per mu). Variables in monetary value (capital costs and all running costs) are calculated based on the 2011 Consumer Price Index.

4.2 Industrial wastewater data

Industry-related data focus on both industrial output and wastewater. These data are derived from the large administrative database of Chinese Environmental Statistics (CES), collected by China's Ministry of Environmental Protection (MEP).

First, industrial output is defined at the village level and measured by two variables: the production of industrial firms in yuan and in hours.

Second, we use detailed information on pollution discharged by industrial firms. More precisely, the database focuses on pollutants which account for approximately 85 percent of the total major pollutants (air + water): Chemical Oxygen Demand (COD), ammonia nitrogen (NH3-N), sulfur dioxide (SO2), industrial smoke and dust, and solid waste.

Based on the firm level pollution information, we construct a measure of industrial water pollution that influences a given farmer. First, we use the measure of the total wastewater released by all industrial firms in the farmer's village (in tons). Next, this measure is weighted by the distance between each firm and the center of the village. Note that we do not have the farmers' coordinates so we use the coordinates of the village center. This measure helps us to consider the importance of proximity between industry and farming in terms of water pollution. Next, this weighted measure of wastewater by distance is divided by the area of rice devoted to rice farming in the village. This gives us the quantity of wastewater per unit of rice area (tons per mu). Finally, we multiply this measure of wastewater per mu by the area of land devoted to rice on each farm unit. This final measure of wastewater varies over farm unit and is an approximation of the quantity of wastewater received by each farm given the size of their rice area.

This measure is applied to four types of wastewater. First, we use the total wastewater released by industrial firms as a global measure of water pollution. This water pollution is either received by water treatment plants or discharged directly into the water environment. Second, we focus only on the wastewater discharged directly into the water environment, without treatment by sewage plants. Third, we focus on two major water pollutants: COD and NH3-N. The COD and NH3-N are two commonly used indicators of surface water pollution in environmental chemistry and are monitored by the Chinese government as part of its water–environment regulation. The last three types of wastewater (i.e., untreated wastewater, COD and NH3-N) are nested into the first one (i.e., total wastewater).

Lastly, Maps A1, A2, A3 and A4 in the Appendix report the spatial distribution of the four types of wastewater over the six rural villages used in this study. The measure reported is the quantity of wastewater received by a village, weighted first by the distance of each industrial firm and the center of the village, and second, by the area devoted to rice farming in the village. The measure is thus the quantity per mu of wastewater in each village. It is worth noting a significant heterogeneity between villages helps us to estimate the effect of wastewater on rice yields. Finally, Table A1 gives descriptive statistics for all pollution variables.

5 Econometric results

5.1 Effects on rice yields

In this study, we assume that rice yields will be plagued by industrial wastewater. Figures 1 and 2 provide te first insight into this relationship. These figures give the resulting line, along with a confidence interval, of the prediction for rice yields (y) from a linear regression of y on each type of wastewater. More wastewater seems to be associated to lesser rice yields. While the relationships displayed in these graphs cannot be interpreted as a causal link between wastewater and rice yields, they confirm a negative pattern between industrial pollution and agricultural yields.

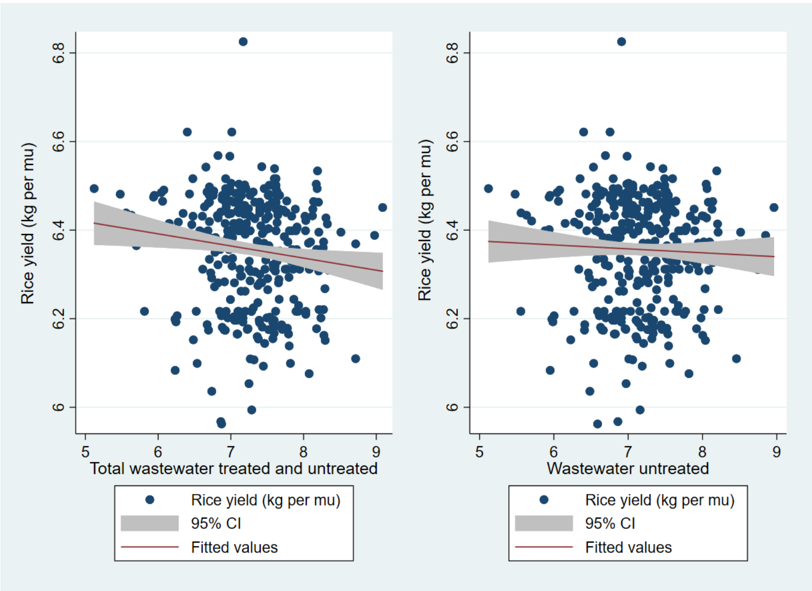

Figure 1: Total treated and untreated wastewater and rice yield

To more deeply investigate the study of the relationship between wastewater and rice yield, we run the production function models depicted in Section 3. Table 2 reports the results for total wastewater released by industrial firms (treated and untreated ; columns 1 to 4) and for only untreated wastewater (columns 5 to 8). Table 3 focuses on the results for COD (columns 1 to 4) and NH3-N (columns 5 to 8) released by industrial firms. In order to facilitate the reading, a short version of the results is presented in these tables (without interaction terms). The complete versions are in the Appendix (Tables A6 and A7).

For each type of pollution outlined in the two tables, we implement a step-by-step approach. Columns 1 and 5 present the estimation of Model B (only the additive effect of wastewater without controlling for interactions of wastewater with input uses or technical change (TC) terms). Columns 2 and 6 give the estimation of Model C (Model B + interaction effects between wastewater and inputs). We provide the total effect of wastewater through each input

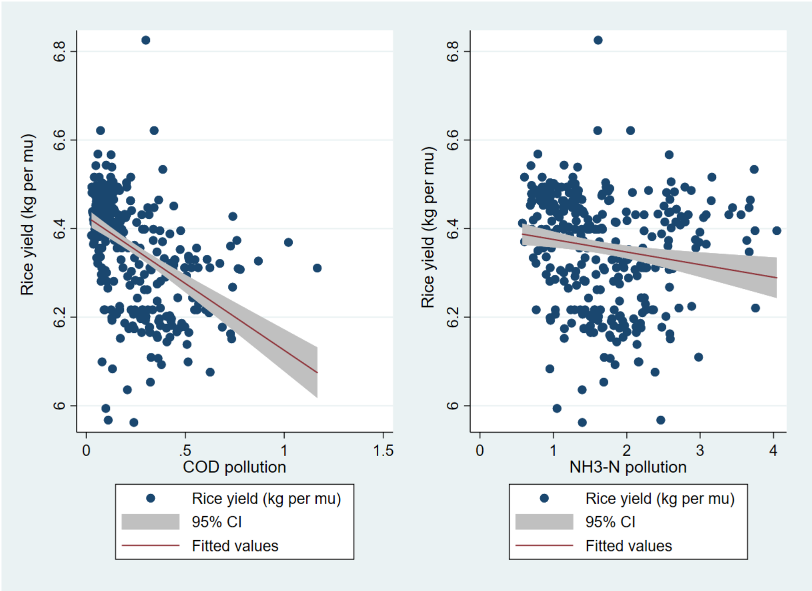

Figure 2: COD and NH3-N pollution and rice yield

as $\sum_{j=1}^{5} \beta_{pj} + \sum_{j=1}^{5} \sum_{k=1}^{5} \beta_{pjk}$[15]. Columns 3 and 7 concern the estimation of Model D (Model B + interaction effects between wastewater and technical change (TC) terms). We present the effect of wastewater through total TC as $\beta_{pt} + \beta_{ptt} + \sum_{j=1}^{5} \beta_{pjt}$, pure TC as $\beta_{pt} + \beta_{ptt}$ and biased TC as $\sum_{j=1}^{5} \beta_{pjt}$. Columns 4 and 8 provide the estimation of the general Model E (Model B + Model C + Model D).

In Table 2, our results suggest that wastewater alone (i.e., without interactions with inputs or TC terms - Model B) has a negative but non–significant effect (cols. 1 and 5). However, while taking into account interactions, the additive effect of wastewater becomes negatively significant[16]. We interpret this effect as the direct negative biological effect of wastewater on rice yields since all other effects of wastewater on rice yields through the production process are controlled for. Our results show that this direct biological effect can be quite significant. A one percent increase of total wastewater (untreated wastewater) decreases rice yields between 0.06 percent and 3.60 percent (0.06 percent and 3.53 percent) per mu.

With regards to the other effects of wastewater, two results can be highlighted. First, we do not find robust or significant interaction effects of wastewater with both inputs and TC. Second, the aggregated effect of wastewater (e.g., in Model C, the aggregated effect is the additive effect of p plus all interaction effects of p with inputs) is significantly and robustly negative in all regressions. More precisely, the effect is stronger in Model C (cols. 2 and 6) than in Model D (cols. 3 and 7). A one percent increase of total wastewaster and untreated wastewater reduces rice yields by 2.79 (col. 2) and 2.78 percent (col.6), respectively, in Model C while the reduction is 0.10 (col. 3) and 0.11 (col. 6) percent, respectively, in Model D.

Taken together, these two results suggest that wastewater weakens rice yields mainly through the direct biological effect highlighted previously rather than through the production process (input uses or TC).

Table 2: Industrial wastewater and rice yield

Type of p	Total wastewater (treated and untreated)				Untreated wastewater			
Estimated model	Model B	Model C	Model D	Model E	Model B	Model C	Model D	Model E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l	1.279**	8.559	0.856*	7.784	1.258**	8.648	0.838*	8.173
	(0.493)	(5.636)	(0.353)	(4.827)	(0.488)	(5.227)	(0.390)	(4.776)
c	-0.104	-0.0567	-0.0686	0.0363	-0.109	-0.317	-0.0880	-0.106
	(0.0811)	(1.198)	(0.0808)	(1.049)	(0.0820)	(1.380)	(0.0841)	(1.202)
rc	2.014***	-1.153	1.980***	-3.023	2.011***	-1.645	1.985***	-3.197
	(0.427)	(4.610)	(0.460)	(3.761)	(0.430)	(4.465)	(0.463)	(3.676)
fe	0.702	-10.11	0.731	-9.119	0.713	-8.853	0.697	-8.278
	(0.932)	(6.289)	(0.894)	(5.563)	(0.931)	(5.966)	(0.941)	(5.463)
ir	-0.0793	0.0566	-0.116	0.450	-0.0770	0.0696	-0.106	0.318
	(0.197)	(1.973)	(0.195)	(2.024)	(0.196)	(1.955)	(0.183)	(1.922)
t	0.144	0.0708	0.436	0.601	0.144	0.0638	0.526*	0.383
	(0.0756)	(0.0867)	(0.223)	(1.001)	(0.0741)	(0.0837)	(0.248)	(0.913)
t2	0.00305	0.00423	0.116*	0.131	0.00340	0.00399	0.0982*	0.104
	(0.00927)	(0.0108)	(0.0478)	(0.0883)	(0.00919)	(0.0106)	(0.0487)	(0.0840)
I_1 (yuan)	-0.00616	-0.00682	-0.00789	-0.00683	-0.00586	-0.00585	-0.00733	-0.00611
	(0.0118)	(0.0112)	(0.0117)	(0.0110)	(0.0118)	(0.0109)	(0.0116)	(0.0109)
I_2 (hours)	-0.181**	-0.182**	-0.175**	-0.185**	-0.182**	-0.187**	-0.173**	-0.184**
	(0.0625)	(0.0586)	(0.0601)	(0.0524)	(0.0622)	(0.0577)	(0.0618)	(0.0541)
p	-0.00873	-3.463*	-0.0583**	-3.583**	-0.0116	-3.388*	-0.0584**	-3.530**
	(0.00900)	(1.476)	(0.0169)	(1.008)	(0.00787)	(1.461)	(0.0194)	(1.032)
Constant	-0.779	28.71*	0.0484	30.04**	-0.739	27.78*	0.180	29.08**
	(1.145)	(12.43)	(1.362)	(9.681)	(1.157)	(12.03)	(1.439)	(9.584)
Effect of p through ...								
All inputs		0.670		0.757*		0.610		0.686
Labor (l)		-0.711		-0.652		-0.736		-0.703
Capital (c)		0.0831		-0.0256		0.0846		-0.0113
Running costs (rc)		0.455		0.642		0.516		0.666
Fertilizers (fe)		0.530		0.492		0.483		0.481
Irrigation (ir)		-0.0485		-0.0889		-0.0539		-0.0826
Technical change (TC)			-0.0368	-0.0630			-0.0469	-0.0379
Pure TC (t, t^2)			-0.0571	-0.0863			-0.0690	-0.0551
Biased TC ($t\times$inputs)			0.0203*	0.0233			0.0221*	0.0172
Aggregated effect of p		-2.792**	-0.0951**	-2.889***		-2.778**	-0.105**	-2.881***
Observations	1,514	1,514	1,514	1,514	1,514	1,514	1,514	1,514
R-squared	0.393	0.407	0.401	0.410	0.394	0.406	0.400	0.408
Number of ID	366	366	366	366	366	366	366	366
Translog terms	YES	YES	YES	YES	YES	YES	YES	YES
TC terms	YES	YES	YES	YES	YES	YES	YES	YES
Wastewater×inputs	NO	YES	NO	YES	NO	YES	NO	YES
Wastewater×TC	NO	NO	YES	YES	NO	YES	YES	YES

Estimation method: within regression estimator. The dependent variable is rice production (quantities) per mu. l: labor ; c: capital ; rc: running costs ; fe: fertilizers ; ir: irrigation ; I_1 and I_2 : industrial production in yuan and hours. All variables are in logarithm (except t and t2). Standard errors in parentheses are clustered at village level. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%. Translog terms not reported are: l^2, c^2, fe^2, ir^2, rc^2, l×c, l×fe, l×ir, l×rc, c×fe, c×ir, c×rc, fe×ir, fe×rc and ir×rc. Technical change (TC) terms not reported are: t×l, t×c, t×fe, t×ir and t×rc.

In Table 3, we find that COD has a stronger negative link with yields than does NH3-N. We notice three worthwhile results with regards to COD. First, COD is found to have a significant and negative direct biological effect when interactions are controlled for (columns 2, 3 and 4). The magnitude of the effect of COD is much higher than that of total wastewater or untreated wastewater. For instance, from Model C, a one percent increase of COD reduces rice yields by 11.08 percent (3.46 and 3.40 percent for total wastewater and untreated wastewater in Table 2, respectively). Moreover, COD has a significant and negative aggregated effect, which is also greater in magnitude than total that of wastewater and untreated wastewater (e.g., -9.33 for COD in Model C compared to -2.79 and -2.78 for total wastewater and untreated wastewater, respectively in Table 2). Third, COD significantly weakens rice yields through labor uses (by 2.39 percent in Model C and 2.18 percent in Model E). This effect suggests that COD reduces the productivity of labor. To our knowledge, no studies have been done on the link between this pollutant and labor productivity. Since COD is a measure of the quantity of organic compounds such as petroleum, solvents, lubricants, cleaning agents, etc. in water, we can assume that COD can damage workers' health, and in turn, reduce their productivity.

Regarding NH3-N, this pollutant is found to have a marginal impact on rice yields. In fact, while we also find a negative direct biological effect, this effect is insignificant. In the same vein, the aggregated effect of NH3-N is always insignificant (albeit negative). Similarly, two interesting results can be highlighted. NH3-N, unlike total wastewater, untreated water and COD, is found to weaken rice yields through irrigation (only in Model C) and increase rice yields through running costs (both in Model C and in Model E).

5.2 Robustness checks

We check the robustness of our results by dealing with the endogeneity of wastewater. Tables A3 and A4 replicate Tables 2 and 3, respectively, by using external instruments ($Z = z1$, $z2$ and $z3$ and the interactions of these variables with input uses and TC terms) for wastewater as well as for its interactions with input uses and TC terms. Table A5 in the Appendix gives the list of endogenous variables and instruments for each column of Tables A3 and A4. Also, in Table A5 we report the joint significance of all z variables on each of the measures of wastewater calculated from the instrumentation equation of each column of Tables A3 and A4[17]. In each model, instrumental variables are found to have joint significance on wastewater. Moreover, in Tables A3 and A4, a look at statistical tests of the validity of Z show that the Kleibergen-Paap underidentification test always rejects the null hypothesis that the excluded instruments are not correlated with the endogenous regressors. Also, the Hansen test accepts the null hypothesis that our set of instruments is valid in 10 of 16 regressions (except in Model D (interactions with TC terms) for the four types of wastewater and in Model E for COD and NH3-N).

Table 3: COD, NH3 and rice yield

Type of p	COD				NH3			
Estimated model	Model B	Model C	Model D	Model E	Model B	Model C	Model D	Model E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l	1.329*	1.251	1.215*	1.355	1.302*	2.358*	1.384*	1.994**
	(0.546)	(0.813)	(0.535)	(0.677)	(0.512)	(1.130)	(0.598)	(0.749)
c	-0.0928	-0.0739	-0.0604	-0.0614	-0.109	0.0411	-0.124	0.112
	(0.0742)	(0.127)	(0.0622)	(0.129)	(0.0772)	(0.195)	(0.0687)	(0.175)
rc	2.007***	0.499	1.724***	0.663	2.007***	-1.313	1.794***	-0.990
	(0.453)	(0.715)	(0.379)	(0.783)	(0.418)	(1.179)	(0.243)	(1.225)
fe	0.671	-1.436	0.382	-1.115	0.676	-0.112	0.530	0.410
	(0.926)	(1.137)	(1.044)	(1.258)	(0.929)	(1.223)	(0.885)	(1.188)
ir	-0.0767	0.112	-0.163	-0.00880	-0.0760	0.815*	-0.00357	0.304
	(0.200)	(0.199)	(0.223)	(0.239)	(0.187)	(0.347)	(0.121)	(0.320)
t	0.139	0.156	0.120	0.146**	0.146	0.104	0.184*	0.129
	(0.0803)	(0.0825)	(0.0792)	(0.0523)	(0.0779)	(0.102)	(0.0797)	(0.145)
t2	0.00260	0.00400	0.0140	0.0132	0.00321	0.00383	0.00135	0.00269
	(0.00956)	(0.00950)	(0.0129)	(0.0132)	(0.00925)	(0.0102)	(0.0124)	(0.00943)
I_1	-0.00665	-0.00807	-0.00938	-0.00839	-0.00627	-0.00701	-0.00269	-0.00326
	(0.0117)	(0.0127)	(0.0130)	(0.0132)	(0.0115)	(0.0118)	(0.0117)	(0.0119)
I_2	-0.180**	-0.181**	-0.182**	-0.181**	-0.169*	-0.164*	-0.175*	-0.182*
	(0.0637)	(0.0643)	(0.0610)	(0.0605)	(0.0663)	(0.0741)	(0.0680)	(0.0816)
p	-0.000659	-11.08***	-0.230**	-7.928**	-0.0155	-2.675	-0.0454	-1.658
	(0.0557)	(2.285)	(0.0846)	(2.105)	(0.0140)	(2.087)	(0.0273)	(1.974)
Constant	-0.859	8.970**	1.076	7.642**	-0.865	7.765	0.0970	6.506
	(1.031)	(2.419)	(2.021)	(2.965)	(1.154)	(5.145)	(1.445)	(5.187)
Effect of p through ...								
All inputs		1.744**		1.230		0.320		0.211
Labor (l)		-2.391*		-2.180**		-0.550		-0.401
Capital (c)		0.633		0.0504		-0.338		-0.346
Running costs (rc)		1.808*		2.249		1.667*		1.345*
Fertilizers (fe)		1.530		0.547		-0.358		-0.511
Irrigation (ir)		-0.535		-0.176		-0.305*		-0.101
Technical change (TC)			-0.0592	-0.277			-0.0221	-0.0224
Pure TC (t, t^2)			-0.120	-0.394			-0.0363	-0.0473
Biased TC ($t\times$inputs)			0.0604	0.117*			0.0142	0.0249
Aggregated of p		-9.334***	-0.289	-6.976***		-2.355	-0.0675	-1.469
Observations	1,514	1,514	1,514	1,514	1,514	1,514	1,514	1,514
R-squared	0.393	0.404	0.399	0.407	0.394	0.402	0.399	0.407
Number of ID	366	366	366	366	366	366	366	366
Translog terms	YES	YES	YES	YES	YES	YES	YES	YES
TC terms	YES	YES	YES	YES	YES	YES	YES	YES
Wastewater×inputs	NO	YES	NO	YES	NO	YES	NO	YES
Wastewater×TC	NO	NO	YES	YES	NO	YES	YES	YES

Estimation method: within regression estimator. The dependent variable is rice production (quantities) per mu. l: labor ; c: capital ; rc: running costs ; fe: fertilizers ; ir: irrigation ; I_1 and I_2 : industrial production in yuan and hours. All variables are in logarithm (except t and t2). Standard errors in parentheses are clustered at village level. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%. Translog terms not reported are: l^2, c^2, fe^2, ir^2, rc^2, l×c, l×fe, l×ir, l×rc, c×fe, c×ir, c×rc, fe×ir, fe×rc and ir×rc. Technical change (TC) terms not reported are: t×l, t×c, t×fe, t×ir and t×rc.

Three interesting results are found: (1) the negative direct biological effect as well as the aggregated effect of total wastewater, untreated wastewater and COD highlighted in Tables 2 and 3 are still found, while stronger (e.g., the direct effect of COD in Model E moves from 7.64 percent (col. 4 in Table 3) to 17.41 percent (col. 4 in Table A4)) ; (2) NH3-N now has a negative direct biological effect (only in Model C: a one percent increase of NH3-N leads to a

5.20 percent reduction of rice yields) and a negative aggregated effect (also only in Model C: a one percent increase of NH3-N leads to a 4.31 percent reduction of rice yields)[18] ; (3) we do not find robust interaction effects of wastewater through input uses or TC terms[19].

Taken together, our results suggest that wastewater impacts rice yields mainly through a strong negative biological effect. We assume that industrial wastewater can weaken the growth of roots, seedlings and tillers of the rice plant, resulting in lower produced quantities.

6 Conclusion

In recent decades, the rapid industrialization of the Chinese economy has been accompanied by the development of polluting industries such as the chemical, paper, textile and dyeing industries, which have generated severe water pollution. In this paper, we aim to estimate the impact of industrial wastewater on Chinese rice production in Jiangsu province, which is particularly impacted by severe industrial pollution. Using data from the Chinese Environmental Statistics (CES) and the China Rural Fixed Point Survey, we are able to link wastewater released by industrial firms to rice farming at the household level between 2011 and 2015 in six villages of Jiangsu province.

More precisely, we focus on four types of wastewater (total (treated and untreated) wastewater, untreated wastewater, COD and NH3-N) and we analyse the link between all these four types of industrial wastewater and rice yields, defined in terms of produced quantities per mu. We focus on this farming output in order to study the direct biological effect of wastewater on rice production. This effect reflects the negative influence of industrial wastewater on the growing process of rice. Our framework allows us to isolate a direct effect of wastewater on rice yields from other potential effects of wastewater through the production process.

Our results confirm the presence of a causal, direct and negative effect of wastewater on rice yields. We attribute this negative link to the detrimental biological effect of wastewater on the growing process of the rice. The damaging effect of COD, a major water pollutant in China, is particularly severe. A one percent increase of COD released by industrial firms in the surroundings of rice farmers is found to reduce rice yields by up to approximately 19 percents. The effect of NH3-N, another major water pollutant in China, is also negative but its statistical significance is less often robust. However, when this effect is robust, NH3-N is found to reduce rice yields by about 5 percents. With regards to the impact of total wastewater and untreated wastewater, we also find a direct and negative effect. For each of these two types of wastewater, a one percent increase can reduce rice yields by up to 7 percent.

Taken together, these results highlight the need to better understand the linkages between industry and agriculture at the local level. While there are (positive and negative) economic spillover effects of industry on agriculture, negative environmental spillovers such as water pollution should not be underestimated. Rapid industrialization in rural areas weakens agriculture as well as the livelihood of farmers.

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Notes

[1]See Section 2 for a discussion of the literature.

[2]These last two pollutants (COD and NH3-N) are commonly used indicators of surface water pollution in environmental chemistry and are monitored by the Chinese government as part of its water environment regulation.

[3]Our measure is weighted by the distance between each industrial firm and the center of the village where each farm is located because we do not have the farmer coordinates. See Section 4 for a complete explanation of our measure of wastewater.

[4]Section 2.2 goes back to theoretical links between wastewater and rice yield and Section 3 provides the econometric framework that allows us to disentangle the direct effect from the other effects.

[5]External instruments are the water intake for industrial production and the quantity generated of both COD and NH3-N by industrial production.

[6]For instance, wastewater is found to reduce rice yields through labor uses but while a negative effect is found in all specifications, it is rarely significant.

[7]Note that this biological effect can also impact crop quality. Lower crop prices reflect this reduction in quality. Also, farmers may want to compensate for possible productivity losses by implementing activities that can offset these losses but that are more costly to implement which implies an increase of input costs. These two factors (decrease of price and increase of production costs) are not investigated in this study, as we focus here only on yields (quantity).

[8]More information on all variables can be found in Section 4 and Table A2 in the Appendix.

[9]For the four types of $p_{i,v,t}$, we use a measure of water pollution which varies across farm units and takes into account the distance between the industrial firm and the village where the farm unit is located. Section 4 gives more information about $p_{i,v,t}$.

[10]We pull out subscripts i, v and t to facilitate the reading. Recall that all variables are defined at the household level (i), and each household level is located in a village v at time t.

[11]More information on these two variables can be found in Section 4 and Table A2 in the Appendix.

[12]It is worth noting that COD and NH3-N, used as external instruments (respectively $z2$ and $z3$), are different from COD and NH3-N, used as water pollution (p). The former ($z2$ and $z3$) focus on the quantity of COD and NH3-N generated by industrial production while the latter (p) is the part of COD and NH3-N released into the environment.

[13]As mentioned in the introduction, we do not have the geographical coordinates of the farmers. We thus use the coordinates of the center of the village where the farmer lives. In other words, farmers located in the same village are the same Z.

[14]Beyond the economical validity of Z as instruments of p, the statistical validity of Z is measured by two tests. The Hansen test is used as a test of overidentifying restrictions (H0: instruments are valid instruments, i.e., uncorrelated with the error term). The Kleibergen-Paap test is used as an underidentification test (H0: the excluded instruments are not correlated with the endogenous regressors).

[15]For instance, the effect of wastewater associated to labor is the sum of the coefficients associated to variables $p.l$, $p.l^2$, $p.l.c$, $p.l.rc$, $p.l.fe$ and $p.l.ir$.

[16]This is the effect of the variable p in Table 2.

[17]Note that there are as many instrumentation equations as there are endogenous variables. For reading convenience, we present only the joint significance of Z variables on wastewater (for the other endogenous variables, i.e., wastewater and its interaction with input uses and TC terms, results are available upon request). Also, to save space, we do not report estimation results of the instrumentation equation. These are also available upon request.

[18] Note that the set of instruments is valid according to the Hansen test (i.e., the test accepts the null hypothesis) in Model C for NH3-N.

[19] The negative effect of COD through labor is no longer significant albeit still negative.

7 Appendix

7.1 Geographical maps

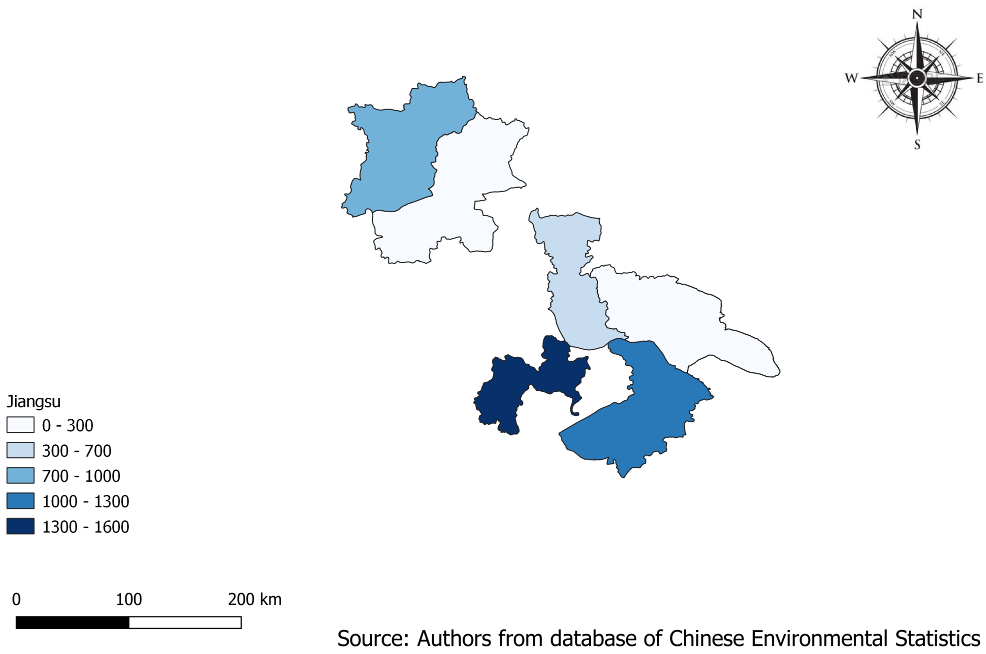


Figure A1: Quantity of total wastewater within the six villages (in ton per mu)

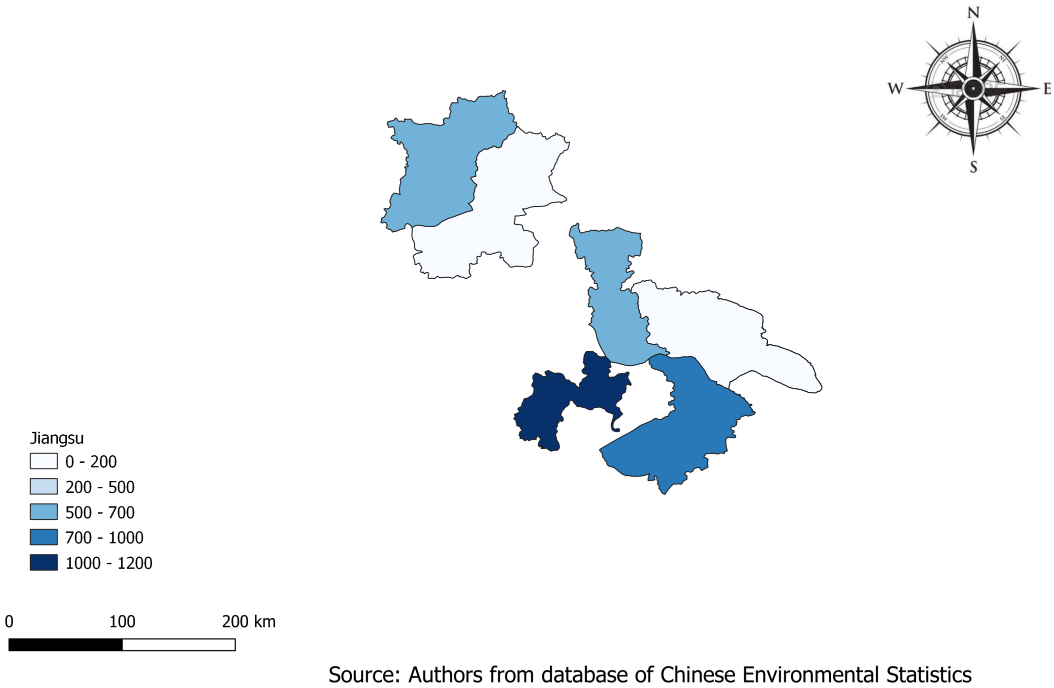
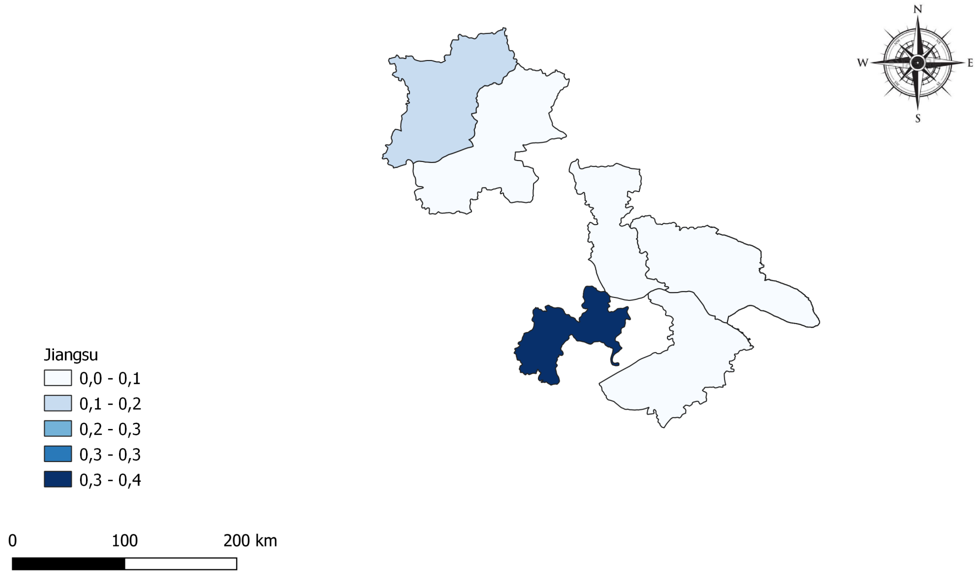
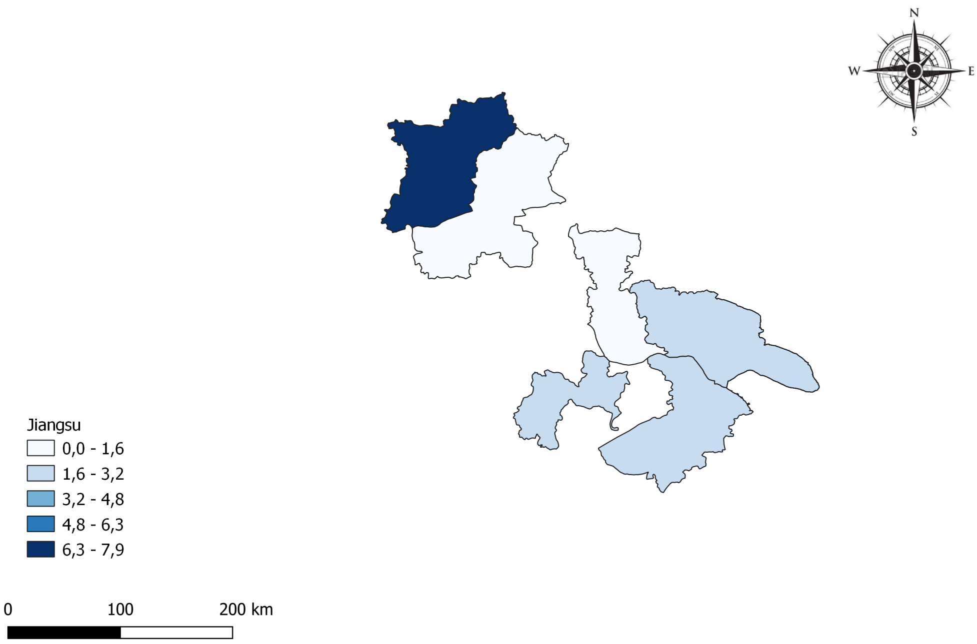


Figure A2: Quantity of untreated wastewater within the six villages (in ton per mu)



Source: Authors from database of Chinese Environmental Statistics

Figure A3: Quantity of COD within the six villages (in ton per mu)



Source: Authors from database of Chinese Environmental Statistics

Figure A4: Quantity of NH3-N within the six villages (in kg per mu)

7.2 Descriptive statistics and definition of variables

Table A1: Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max	Obs.
		Rice farming data			
Rice production (at household level)					
Rice yield (kg/mu)	580.25	81.7	51.66	920	1,514
Labor (in days per mu)	12.69	3.76	0.83	35	1,514
Capital costs (yuan per mu)	3,629.15	15,104.28	40.82	210,523.73	1,514
Fertilizer costs (yuan per mu)	213.70	40.149	19.977	653.178	1,514
Irrigation costs (yuan per mu)	38.29	24.12	1.46	192.881	1,514
Other running costs (yuan per mu)	309.26	64.98	21.11	900.644	1,514
Rice area (in mu, 1 mu = 1/15 ha)	3.73	3.31	0.3	30	1,514
		Industry data			
Industrial production (at the village level)					
Industrial production (yuan)	925,188.69	1,558,513.82	13,407	4,288,78	1,514
Industrial production (hours)	61346.41	23319.81	22,772	87,482	1,514
Wastewater variables (at the household level)					
Total wastewater (tons)	612.93	362.06	184.71	1,641.12	1,514
Untreated wastewater (tons)	527.93	307.7	184.71	1,246.47	1,514
COD pollution (tons)	0.08	0.07	0.02	0.43	1,514
NH3 pollution (in kg)	1.70	1.31	0.49	8.41	1,514

Authors' calculation. Rice farming data come from the China Household Living Standard Survey. Industry-related data come from the Chinese Environmental Statistics. See Table A1 for definitions of variables.

Table A2: Definition and description of variables

Variables	Definition and description
Rice production variables defined at the household level	
Rice yield (y)	Total rice production over the past 12 months (in kg per mu).
Labor (l)	Number of working days (family and hired labor).
Capital (c)	Original value of fixed assets owned for production (yuan per mu).
Fertilizers (fe)	Fertilizers costs for rice production (yuan per mu).
Irrigation (ir)	Irrigation costs for rice production (yuan per mu).
Running costs (rc)	All other running costs excepted fertilizers and irrigation (insecticide, seeds, etc) (yuan per mu).
Variables of industrial production defined at the village level	
Industrial production in yuan (I_1)	Production in yuan of all industrial firms located in one village.
Industrial production in hours (I_2)	Production in hours of all industrial firms located in one village.
Four measures of wastewater (p) defined at the household level	
Total wastewater	Wastewater released by industrial firms in the farmer's village, weighted by the distance between each firm and the center of the village and the area devoted to rice area per farm (in tons).
Untreated wastewater	Wastewater released in the farmer's village without passing through water treatment plant and weighted by the distance between each firm and the center of the village and the area devoted to rice area per farm (in tons).
COD pollutant	Chemical Oxygen Demand (COD) released in the farmer's village and weighted by the distance between each firm and the center of the village and the area devoted to rice area per farm (in tons).
NH3-N pollutant	Ammonia nitrogen (NH3-N) released in the farmer's village and weighted by the distance between each firm and the center of the village and the area devoted to rice area per farm (in kg).

7.3 The IV strategy

Table A3: Industrial wastewater and rice yield: an IV strategy

Type of p	Total wastewater (treated and untreated)				Untreated wastewater			
Estimated model	Model B	Model C	Model D	Model E	Model B	Model C	Model D	Model E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l	1.286**	12.95	-0.409	15.44	1.269**	14.29	-0.363	15.96
	(0.542)	(14.88)	(0.763)	(14.47)	(0.543)	(13.84)	(0.778)	(12.91)
c	-0.103	-1.862	-0.0869	0.492	-0.107	-2.343	-0.194	0.312
	(0.105)	(2.662)	(0.150)	(2.826)	(0.103)	(2.666)	(0.158)	(2.582)
rc	2.013***	9.127	0.682	-0.372	2.011***	8.401	0.715	-5.799
	(0.353)	(10.13)	(0.667)	(10.68)	(0.354)	(9.140)	(0.653)	(8.373)
fe	0.697*	-35.91***	0.620	-19.96**	0.707*	-34.53***	-0.0630	-14.86
	(0.421)	(11.69)	(0.743)	(10.03)	(0.417)	(11.34)	(0.768)	(9.749)
ir	-0.0789	6.909	0.0379	3.154	-0.0770	5.969	0.103	4.564
	(0.216)	(6.884)	(0.275)	(7.338)	(0.216)	(5.979)	(0.290)	(6.644)
t	0.143*	0.0586	3.977**	0.0590	0.144*	0.0712	4.906***	-1.128
	(0.0835)	(0.0905)	(1.646)	(2.248)	(0.0809)	(0.0905)	(1.676)	(2.171)
t2	0.00299	0.00398	0.169*	0.157*	0.00329	0.00411	0.0796	0.0978
	(0.00434)	(0.00490)	(0.0909)	(0.0883)	(0.00436)	(0.00479)	(0.0911)	(0.0824)
I_1	-0.00623	-0.0109*	-0.00908	-0.00913	-0.00598	-0.00890	-0.00539	-0.00706
	(0.00564)	(0.00596)	(0.00717)	(0.00581)	(0.00558)	(0.00584)	(0.00739)	(0.00569)
I_2	-0.181***	-0.167***	-0.173***	-0.185***	-0.181***	-0.169***	-0.176***	-0.167***
	(0.0281)	(0.0322)	(0.0367)	(0.0310)	(0.0280)	(0.0318)	(0.0373)	(0.0314)
p	-0.00747	-7.282**	0.0222	-4.838*	-0.00990	-7.409***	0.0183	-5.091*
	(0.0304)	(2.844)	(0.0505)	(2.686)	(0.0250)	(2.690)	(0.0492)	(2.620)
Effect of p through ...								
All inputs		1.609*		0.749		1.599*		0.659
Labor (l)		-0.997		-1.206		-1.126		-1.302
Capital (c)		0.696		0.172		0.566		-0.0220
Running costs (rc)		0.623		0.360		0.322		1.070
Fertilizers (fe)		2.778**		1.578		2.676***		1.230
Irrigation (ir)		-0.528		-0.195		-0.472		-0.380
Technical change (TC)			-0.412**	-0.0113			-0.532***	0.131
Pure TC (t, t^2)			-0.528**	-0.00920			-0.665***	0.164
Biased TC (t×inputs)			0.116***	-0.00205			0.132***	-0.033
Aggregated effect of p		-5.672**	-0.390**	-4.100*		-5.810***	-0.514***	-4.303**
Observations	1,514	1,514	1,514	1,514	1,514	1,514	1,514	1,514
R-squared	0.393	0.360	0.293	0.344	0.394	0.360	0.310	0.357
Number of ID	366	366	366	366	366	366	366	366
Translog terms	YES	YES	YES	YES	YES	YES	YES	YES
TC terms	YES	YES	YES	YES	YES	YES	YES	YES
Wastewater×inputs	NO	YES	NO	YES	NO	YES	NO	YES
Wastewater×TC	NO	NO	YES	YES	NO	YES	YES	YES
Hansen test	0.574	35.81	32.34***	54.50	0.426	39.38	30.97**	60.69
Kleibergen-Paap test	108.6***	55.21*	31.04**	81.98**	150.0***	61.04**	33.60***	81.38**

Estimation method: within regression estimator. The dependent variable is rice production (quantities) per mu. l: labor ; c: capital ; rc: running costs ; fe: fertilizers ; ir: irrigation ; I_1 and I_2 : industrial production in yuan and hours. All variables are in logarithm (except t and t2). Robust standard errors in parentheses. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%. Translog terms not reported are: l^2, c^2, fe^2, ir^2, rc^2, l×c, l×fe, l×ir, l×rc, c×fe, c×ir, c×rc, fe×ir, fe×rc and ir×rc. Technical change (TC) terms not reported are: t×l, t×c, t×fe, t×ir and t×rc. Hansen test is a test of overidentifying restrictions (H0: instruments are valid instruments, i.e., uncorrelated with the error term). Kleibergen-Paap test is an underidentification test (H0: the excluded instruments are not correlated with the endogenous regressors).

Table A4: COD, NH3 and rice yield: an IV strategy

Type of p	COD				NH3			
Estimated model	Model B	Model C	Model D	Model E	Model B	Model C	Model D	Model E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l	1.260**	1.301	1.467***	1.681	1.328**	1.609	0.564	-1.186
	(0.612)	(1.695)	(0.538)	(1.643)	(0.535)	(1.797)	(0.677)	(1.914)
c	-0.107	-0.270	-0.0547	0.0574	-0.0941	-0.0635	-0.0434	0.321
	(0.129)	(0.165)	(0.0997)	(0.159)	(0.122)	(0.365)	(0.127)	(0.328)
rc	1.976***	-0.0697	1.687***	-1.229	2.008***	-2.032	1.553***	-2.289
	(0.418)	(1.048)	(0.590)	(1.156)	(0.356)	(1.581)	(0.573)	(1.957)
fe	0.672*	-2.941***	0.375	-2.297**	0.672*	-1.129	1.014*	2.593
	(0.404)	(1.106)	(0.555)	(1.058)	(0.405)	(2.070)	(0.537)	(2.593)
ir	-0.0707	0.572	-0.181	0.690	-0.0767	1.991*	0.0166	1.814
	(0.217)	(0.616)	(0.245)	(0.564)	(0.215)	(1.198)	(0.278)	(1.190)
t	0.149	0.180**	0.205**	0.344**	0.140	0.0951	0.275	0.438*
	(0.109)	(0.0773)	(0.0953)	(0.137)	(0.0865)	(0.0942)	(0.208)	(0.235)
t2	0.00248	0.00534	0.0161**	0.00970	0.00266	0.00371	-0.0473**	-0.0172
	(0.00394)	(0.00449)	(0.00704)	(0.00662)	(0.00505)	(0.00537)	(0.0202)	(0.0158)
I_1 (yuan)	-0.00632	-0.00927	-0.0113*	-0.00925	-0.00662	-0.00912	0.00822	0.00134
	(0.00580)	(0.00588)	(0.00619)	(0.00611)	(0.00563)	(0.00592)	(0.00635)	(0.00662)
I_2 (hours)	-0.180***	-0.190***	-0.246***	-0.231***	-0.179***	-0.177***	-0.178***	-0.199***
	(0.0281)	(0.0317)	(0.0356)	(0.0397)	(0.0509)	(0.0420)	(0.0553)	(0.0454)
p	-0.0418	-19.66***	-0.0477	-17.41***	-0.00148	-5.203**	0.000234	-1.506
	(0.234)	(5.604)	(0.243)	(5.411)	(0.0676)	(2.225)	(0.0736)	(2.241)
Effect of p through ...								
All inputs		3.154*		2.208		0.889		0.450
Labor (l)		-3.405		-4.242		-0.503		0.450
Capital (c)		2.243*		-0.706		-0.450		-0.581
Running costs (rc)		0.971		6.700		2.372**		1.983
Fertilizers (fe)		4.803*		2.018		0.459		-0.953
Irrigation (ir)		-1.676		1.198		-0.810*		-0.696
Technical change (TC)			-0.135	-0.0865*			-0.046	-0.147
Pure TC (t, t^2)			-0.184	-1.042*			-0.081	-0.212
Biased TC (t×inputs)			0.049	0.177			0.035	0.065*
Aggregated effect of p		-16.509***	-0.182	-16.063***		-4.314**	-0.046	-1.203
Observations	1,514	1,514	1,514	1,514	1,514	1,514	1,514	1,514
R-squared	0.393	0.392	0.384	0.384	0.393	0.378	0.332	0.376
Number of ID	366	366	366	366	366	366	366	366
Translog terms	YES	YES	YES	YES	YES	YES	YES	YES
TC terms	YES	YES	YES	YES	YES	YES	YES	YES
Wastewater×inputs	NO	YES	NO	YES	NO	YES	NO	YES
Wastewater×TC	NO	NO	YES	YES	NO	YES	YES	YES
Hansen test	0.642	53.87	42.48***	71.38*	0.681	53.21	31.47**	73.80*
Kleibergen-Paap test	31.55***	81.83***	68.26***	116.3***	45.38***	107.8***	71.17***	128.6***

Estimation method: within regression estimator. The dependent variable is rice production (quantities) per mu. l: labor ; c: capital ; rc: running costs ; fe: fertilizers ; ir: irrigation ; I_1 and I_2 : industrial production in yuan and hours. All variables are in logarithm (except t and t2). Robust standard errors in parentheses. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%. Translog terms not reported are: l^2, c^2, fe^2, ir^2, rc^2, l×c, l×fe, l×ir, l×rc, c×fe, c×ir, c×rc, fe×ir, fe×rc and ir×rc. Technical change (TC) terms not reported are: t×l, t×c, t×fe, t×ir and t×rc. Hansen test is a test of overidentifying restrictions (H0: instruments are valid instruments, i.e., uncorrelated with the error term). Kleibergen-Paap test is an underidentification test (H0: the excluded instruments are not correlated with the endogenous regressors).

Table A5: First stage (IV) regressions

Col. of Tables A3 and A4	(1) and (5)	(2) and (6)	(3) and (7)	(4) and (8)
List of endog. variables	p	p $p.\sum_{j=1}^{5} x_j$ $p.(0.5\sum_{j=1}^{5}\sum_{k=1}^{5} x_j x_k)$	p t $p.t^2$ $p.t.\sum_{j=1}^{5} x_j$	p $p.\sum_{j=1}^{5} x_j$ $p.(0.5\sum_{j=1}^{5}\sum_{k=1}^{5} x_j x_k)$ $p.t$ $p.t^2$ $p.t.\sum_{j=1}^{5} x_j$
List of Z variables	$\sum_{z=1}^{3} Z_z$	$\sum_{z=1}^{3} Z_z$ $\sum_{z=1}^{3}\sum_{j=1}^{5} Z_z.x_j$ $\sum_{z=1}^{3} Z_z.0.5(\sum_{j,k=1}^{5} x_j x_k)$	$\sum_{z=1}^{3} Z_z$ $\sum_{z=1}^{3} Z_z.t$ $\sum_{z=1}^{3} Z_z.t^2$ $\sum_{z=1}^{3}\sum_{j=1}^{5} Z_z.x_j.t$	$\sum_{z=1}^{3} Z_z$ $\sum_{z=1}^{3}\sum_{j=1}^{5} Z_z.x_j$ $\sum_{z=1}^{3} Z_z.0.5(\sum_{j,k=1}^{5} x_j x_k)$ $\sum_{z=1}^{3} Z_z.t$ $\sum_{z=1}^{3} Z_z.t^2$ $\sum_{z=1}^{3}\sum_{j=1}^{5} Z_z.x_j.t$
Col. No. of Table A3	(1)	(2)	(3)	(4)
Observations	1,514	1,514	1,514	1,514
R-squared	0.404	0.563	0.539	0.663
Number of ID	366	366	366	366
F-stat Z variables	14.96***	8.120***	7.720***	8.132***
Col. No. Table A3	(5)	(6)	(7)	(8)
Observations	1,514	1,514	1,514	1,514
R-squared	0.585	0.684	0.624	0.712
Number of ID	366	366	366	366
F-stat Z variables	22.89***	9.899***	11.99***	11.39***
Col. No. Table A4	(1)	(2)	(3)	(4)
Observations	1,514	1,514	1,514	1,514
R-squared	0.404	0.563	0.539	0.663
Number of ID	366	366	366	366
F-stat Z variables	14.96***	8.120***	7.720***	8.132***
Col. No. of Table A4	(5)	(6)	(7)	(8)
p is NH3 pollutant.				
Observations	1,514	1,514	1,514	1,514
R-squared	0.585	0.684	0.624	0.712
Number of ID	366	366	366	366
F-stat Z variables	22.89***	9.899***	11.99***	11.39***

p: alternatively total wastewater, untreated wastewater, COD and NH3. $z1$: industrial water intake, $z2$: industrial COD generation and $z3$: industrial NH3 generation. x: the five inputs of rice production (l, c, rc, fe and ir), t: time trend. Number of observations and ID, R-squared and F-stat come from the instrumentation equation (first stage) in which the dependent (endogeneous) variable is p. F-stat reports the joint significance of all Z variables on variables p (e.g. z are $z1$, $z2$ and $z3$, and p is total wastewater in col. (1) of Table A3). We do not report the results for all other endogeneous variables (p and its interactions with inputs and TC terms) but there are available upon request. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%.

7.4 Complete table results

Table A6: Industrial wastewater and rice yield - complete results of Table 2

Type of p	Total wastewater (treated and untreated)				Untreated wastewater			
Estimated model	Model B	Model C	Model D	Model E	Model B	Model C	Model D	Model E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l	1.279**	8.559	0.856*	7.784	1.258**	8.648	0.838*	8.173
	(0.493)	(5.636)	(0.353)	(4.827)	(0.488)	(5.227)	(0.390)	(4.776)
c	-0.104	-0.0567	-0.0686	0.0363	-0.109	-0.317	-0.0880	-0.106
	(0.0811)	(1.198)	(0.0808)	(1.049)	(0.0820)	(1.380)	(0.0841)	(1.202)
rc	2.014***	-1.153	1.980***	-3.023	2.011***	-1.645	1.985***	-3.197
	(0.427)	(4.610)	(0.460)	(3.761)	(0.430)	(4.465)	(0.463)	(3.676)
fe	0.702	-10.11	0.731	-9.119	0.713	-8.853	0.697	-8.278
	(0.932)	(6.289)	(0.894)	(5.563)	(0.931)	(5.966)	(0.941)	(5.463)
ir	-0.0793	0.0566	-0.116	0.450	-0.0770	0.0696	-0.106	0.318
	(0.197)	(1.973)	(0.195)	(2.024)	(0.196)	(1.955)	(0.183)	(1.922)
lsq	-0.161*	-1.648*	-0.136**	-1.597	-0.160*	-1.435	-0.141*	-1.374
	(0.0633)	(0.813)	(0.0503)	(0.808)	(0.0629)	(0.727)	(0.0555)	(0.737)
rcsq	-0.151	-0.488	-0.172	0.231	-0.151	-0.301	-0.170	0.245
	(0.108)	(1.114)	(0.124)	(0.679)	(0.109)	(1.042)	(0.123)	(0.714)
csq	-0.00456	0.0421	-0.00454	0.0392	-0.00434	0.0469	-0.00430	0.0447
	(0.00281)	(0.0393)	(0.00297)	(0.0451)	(0.00285)	(0.0334)	(0.00308)	(0.0364)
fesq	0.0530	-1.178	0.0390	-1.082	0.0525	-1.103	0.0438	-1.021
	(0.0529)	(0.657)	(0.0599)	(0.669)	(0.0530)	(0.655)	(0.0620)	(0.655)
irsq	-0.0153	-0.500*	-0.0219	-0.433**	-0.0156	-0.479*	-0.0200	-0.428**
	(0.0116)	(0.208)	(0.0142)	(0.125)	(0.0126)	(0.188)	(0.0144)	(0.120)
l_rc	-0.314	-4.010*	-0.205	-3.225*	-0.308	-3.578*	-0.203	-2.938*
	(0.257)	(1.853)	(0.214)	(1.362)	(0.255)	(1.554)	(0.230)	(1.204)
l_c	0.0563*	-0.0682	0.0531*	-0.0684	0.0559*	-0.0753	0.0580*	-0.0883
	(0.0219)	(0.166)	(0.0237)	(0.221)	(0.0219)	(0.152)	(0.0249)	(0.196)
l_fe	-0.136	2.600*	-0.102	1.999	-0.136	1.897	-0.0987	1.349
	(0.165)	(1.148)	(0.162)	(1.088)	(0.165)	(1.234)	(0.169)	(1.097)
l_ir	0.0653	0.0339	0.0498	0.189	0.0670	0.0819	0.0423	0.205
	(0.0466)	(0.324)	(0.0479)	(0.172)	(0.0464)	(0.359)	(0.0490)	(0.177)
rc_c	0.0511	-0.0400	0.0462	-0.0396	0.0515	0.00852	0.0474	-0.0363
	(0.0279)	(0.509)	(0.0231)	(0.379)	(0.0280)	(0.458)	(0.0239)	(0.339)
rc_fe	-0.255	3.837**	-0.259	3.360**	-0.256	3.457**	-0.262	3.176**
	(0.199)	(1.296)	(0.191)	(1.116)	(0.199)	(1.182)	(0.196)	(1.117)
rc_ir	-0.0824	-0.697	-0.0547	-1.303**	-0.0816	-0.866	-0.0648	-1.315**
	(0.0771)	(0.601)	(0.0721)	(0.331)	(0.0772)	(0.525)	(0.0760)	(0.430)
c_fe	-0.0409	-0.0426	-0.0437	-0.110	-0.0400	-0.0165	-0.0422	-0.0787
	(0.0266)	(0.423)	(0.0293)	(0.401)	(0.0265)	(0.439)	(0.0296)	(0.433)
c_ir	0.0192**	0.0962	0.0140*	0.149	0.0190**	0.0952	0.0154**	0.148
	(0.00608)	(0.108)	(0.00637)	(0.109)	(0.00607)	(0.0948)	(0.00503)	(0.100)
fe_ir	0.0828	1.266	0.0895	1.534	0.0804	1.386	0.0958	1.592
	(0.0682)	(0.656)	(0.0625)	(0.864)	(0.0670)	(0.721)	(0.0651)	(0.909)
t	0.144	0.0708	0.436	0.601	0.144	0.0638	0.526*	0.383
	(0.0756)	(0.0867)	(0.223)	(1.001)	(0.0741)	(0.0837)	(0.248)	(0.913)
t2	0.00305	0.00423	0.116*	0.131	0.00340	0.00399	0.0982*	0.104
	(0.00927)	(0.0108)	(0.0478)	(0.0883)	(0.00919)	(0.0106)	(0.0487)	(0.0840)
l_t	0.0112	0.00895	-0.0709*	-0.0438	0.0112	0.00926	-0.0645*	-0.0320
	(0.00910)	(0.00506)	(0.0328)	(0.0668)	(0.00876)	(0.00501)	(0.0284)	(0.0547)
c_t	-0.00141	-0.00196	0.0160	3.64e-05	-0.00147	-0.00175	0.0125	0.00391
	(0.00251)	(0.00222)	(0.0129)	(0.0318)	(0.00254)	(0.00239)	(0.0117)	(0.0310)
rc_t	-0.0270	-0.0259	-0.137*	-0.307	-0.0270	-0.0260	-0.120**	-0.232
	(0.0222)	(0.0218)	(0.0539)	(0.352)	(0.0222)	(0.0224)	(0.0379)	(0.306)
fe_t	0.00105	0.0160	-0.00305	0.160	0.000517	0.0168	-0.0235	0.136
	(0.0123)	(0.0169)	(0.0498)	(0.208)	(0.0122)	(0.0175)	(0.0353)	(0.183)

ir_t	-0.000232	-0.00247	0.0319	0.01000	8.97e-05	-0.00223	0.0242	-0.00741
	(0.00479)	(0.00271)	(0.0193)	(0.0663)	(0.00479)	(0.00276)	(0.0156)	(0.0619)
industry (value)	-0.00616	-0.00682	-0.00789	-0.00683	-0.00586	-0.00585	-0.00733	-0.00611
	(0.0118)	(0.0112)	(0.0117)	(0.0110)	(0.0118)	(0.0109)	(0.0116)	(0.0109)
industry (hours)	-0.181**	-0.182**	-0.175**	-0.185**	-0.182**	-0.187**	-0.173**	-0.184**
	(0.0625)	(0.0586)	(0.0601)	(0.0524)	(0.0622)	(0.0577)	(0.0618)	(0.0541)
p	-0.00873	-3.463*	-0.0583**	-3.583**	-0.0116	-3.388*	-0.0584**	-3.530**
	(0.00900)	(1.476)	(0.0169)	(1.008)	(0.00787)	(1.461)	(0.0194)	(1.032)
p*l		-1.113		-0.997		-1.147		-1.076
		(0.725)		(0.596)		(0.682)		(0.604)
p*c		0.0139		0.00296		0.0473		0.0196
		(0.162)		(0.138)		(0.190)		(0.162)
p*rc		0.331		0.572		0.408		0.613
		(0.553)		(0.463)		(0.556)		(0.470)
p*fe		1.421		1.267		1.272		1.176
		(0.815)		(0.693)		(0.782)		(0.687)
p*ir		-0.0434		-0.0896		-0.0436		-0.0720
		(0.257)		(0.259)		(0.258)		(0.247)
p*lsq		0.202		0.195		0.177		0.168
		(0.102)		(0.102)		(0.0920)		(0.0942)
p*rcsq		0.0572		-0.0415		0.0332		-0.0435
		(0.142)		(0.0829)		(0.136)		(0.0904)
p*csq		-0.00643		-0.00605		-0.00715		-0.00686
		(0.00555)		(0.00647)		(0.00476)		(0.00527)
p*fesq		0.168		0.153		0.162		0.149
		(0.0931)		(0.0931)		(0.0949)		(0.0932)
p*irsq		0.0660*		0.0564**		0.0650**		0.0576**
		(0.0268)		(0.0152)		(0.0251)		(0.0153)
p*l_rc		0.523*		0.412*		0.473*		0.381*
		(0.238)		(0.166)		(0.202)		(0.148)
p*l_c		0.0174		0.0167		0.0190		0.0204
		(0.0235)		(0.0300)		(0.0222)		(0.0276)
p*l_fe		-0.351*		-0.267		-0.259		-0.180
		(0.153)		(0.144)		(0.172)		(0.152)
p*l_ir		0.00947		-0.0120		0.000715		-0.0171
		(0.0419)		(0.0219)		(0.0478)		(0.0235)
p*rc_c		0.0108		0.0109		0.00437		0.0109
		(0.0725)		(0.0524)		(0.0667)		(0.0478)
p*rc_fe		-0.550**		-0.475**		-0.511**		-0.463**
		(0.168)		(0.146)		(0.156)		(0.148)
p*rc_ir		0.0830		0.164***		0.108		0.168**
		(0.0857)		(0.0397)		(0.0759)		(0.0553)
p*c_fe		-0.00543		0.00340		-0.00848		-0.000407
		(0.0606)		(0.0564)		(0.0639)		(0.0620)
p*c_ir		-0.0108		-0.0181		-0.0109		-0.0183
		(0.0150)		(0.0151)		(0.0136)		(0.0142)
p*fe_ir		-0.153		-0.189		-0.173		-0.201
		(0.0836)		(0.111)		(0.0942)		(0.120)
p*t			-0.0415	-0.0689			-0.0557	-0.0411
			(0.0390)	(0.137)			(0.0437)	(0.129)
p*t2			-0.0155**	-0.0174			-0.0133*	-0.0140
			(0.00575)	(0.0111)			(0.00598)	(0.0107)
p*l_t			0.0111*	0.00733			0.0108*	0.00600
			(0.00487)	(0.00942)			(0.00440)	(0.00781)
p*c_t			-0.00242	-0.000253			-0.00196	-0.000770
			(0.00151)	(0.00415)			(0.00136)	(0.00410)
p*rc_t			0.0156**	0.0381			0.0135**	0.0284
			(0.00556)	(0.0463)			(0.00399)	(0.0409)
p*fe_t			0.000537	-0.0202			0.00334	-0.0171

			(0.00633)	(0.0280)			(0.00505)	(0.0249)
p*ir_t			-0.00454	-0.00160			-0.00361	0.000695
			(0.00262)	(0.00876)			(0.00221)	(0.00837)
Constant	-0.779	28.71*	0.0484	30.04**	-0.739	27.78*	0.180	29.08**
	(1.145)	(12.43)	(1.362)	(9.681)	(1.157)	(12.03)	(1.439)	(9.584)
Observations	1,514	1,514	1,514	1,514	1,514	1,514	1,514	1,514
R-squared	0.393	0.407	0.401	0.410	0.394	0.406	0.400	0.408
Number of ID	366	366	366	366	366	366	366	366
Translog terms	YES	YES	YES	YES	YES	YES	YES	YES
Time*inputs	YES	YES	YES	YES	YES	YES	YES	YES
Total effect of p		-2.792**	-0.0951**	-2.889***		-2.778**	-0.105**	-2.881***
p*inputs	NO	YES	NO	YES	NO	YES	NO	YES
p*TC	NO	NO	YES	YES	NO	YES	YES	YES

Estimation method: within regression estimator. The dependent variable is rice production (quantities) per mu. l: labor ; c: capital ; rc: running costs ; fe: fertilizers ; ir: irrigation ; I_1 and I_2 : industrial production in yuan and hours. All variables are in logarithm (except t and t2). Standard errors in parentheses are clustered at village level. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%. Translog term are: l^2, c^2, fe^2, ir^2, rc^2, l*c, l*fe, l*ir, l*rc, c*fe, c*ir, c*rc, fe*ir, fe*rc and ir*rc. Technical change (TC) terms are: t*l, t*c, t*fe, t*ir and t*rc.

Table A7: COD, NH3 and rice yield - complete results of Table 3

Type of p	COD				NH3			
Estimated model	Model B	Model C	Model D	Model E	Model B	Model C	Model D	Model E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l	1.329*	1.251	1.215*	1.355	1.302*	2.358*	1.384*	1.994**
	(0.546)	(0.813)	(0.535)	(0.677)	(0.512)	(1.130)	(0.598)	(0.749)
c	-0.0928	-0.0739	-0.0604	-0.0614	-0.109	0.0411	-0.124	0.112
	(0.0742)	(0.127)	(0.0622)	(0.129)	(0.0772)	(0.195)	(0.0687)	(0.175)
rc	2.007***	0.499	1.724***	0.663	2.007***	-1.313	1.794***	-0.990
	(0.453)	(0.715)	(0.379)	(0.783)	(0.418)	(1.179)	(0.243)	(1.225)
fe	0.671	-1.436	0.382	-1.115	0.676	-0.112	0.530	0.410
	(0.926)	(1.137)	(1.044)	(1.258)	(0.929)	(1.223)	(0.885)	(1.188)
ir	-0.0767	0.112	-0.163	-0.00880	-0.0760	0.815*	-0.00357	0.304
	(0.200)	(0.199)	(0.223)	(0.239)	(0.187)	(0.347)	(0.121)	(0.320)
lsq	-0.162**	-0.239*	-0.157**	-0.256*	-0.162*	-0.204**	-0.178**	-0.138
	(0.0628)	(0.105)	(0.0552)	(0.110)	(0.0639)	(0.0756)	(0.0624)	(0.0855)
rcsq	-0.146	-0.0975	-0.130	-0.0641	-0.152	0.299	-0.0846	0.280
	(0.103)	(0.139)	(0.0976)	(0.153)	(0.107)	(0.322)	(0.0599)	(0.275)
csq	-0.00511	-0.00552	-0.00486	-0.00511	-0.00428	-0.00796	-0.00421	-0.00911
	(0.00288)	(0.00486)	(0.00315)	(0.00515)	(0.00286)	(0.00635)	(0.00350)	(0.00735)
fesq	0.0562	-0.0591	0.0478	-0.0118	0.0532	-0.172	0.0678	-0.114
	(0.0546)	(0.0763)	(0.0576)	(0.0421)	(0.0535)	(0.126)	(0.0676)	(0.118)
irsq	-0.0151	-0.0488	-0.0268*	-0.0562*	-0.0168	-0.117*	-0.0231	-0.117*
	(0.0111)	(0.0290)	(0.0132)	(0.0249)	(0.0131)	(0.0526)	(0.0130)	(0.0499)
l_rc	-0.330	-0.762	-0.351	-0.668	-0.319	-0.782	-0.337	-0.531
	(0.275)	(0.418)	(0.276)	(0.398)	(0.257)	(0.451)	(0.227)	(0.457)
l_c	0.0567**	0.0612	0.0580**	0.0661*	0.0565**	0.00853	0.0823**	-0.0136
	(0.0214)	(0.0364)	(0.0182)	(0.0317)	(0.0218)	(0.0497)	(0.0204)	(0.0333)
l_fe	-0.135	0.412	-0.0691	0.286	-0.136	0.0480	-0.139	-0.0771
	(0.159)	(0.257)	(0.178)	(0.282)	(0.163)	(0.245)	(0.115)	(0.266)
l_ir	0.0644	0.0713	0.0672	0.0876	0.0617	0.104	0.0218	0.114
	(0.0448)	(0.0769)	(0.0458)	(0.0784)	(0.0466)	(0.0856)	(0.0500)	(0.0973)
rc_c	0.0502	0.0551	0.0373	0.0503	0.0512	0.0906	0.0291	0.0463
	(0.0266)	(0.0404)	(0.0198)	(0.0415)	(0.0276)	(0.0687)	(0.0182)	(0.0751)
rc_fe	-0.251	0.452	-0.178	0.289	-0.247	0.357	-0.260	0.108
	(0.196)	(0.313)	(0.209)	(0.299)	(0.200)	(0.339)	(0.169)	(0.230)
rc_ir	-0.0854	-0.168**	-0.0552	-0.132	-0.0813	-0.345*	-0.103	-0.126
	(0.0770)	(0.0610)	(0.0629)	(0.0731)	(0.0770)	(0.134)	(0.0690)	(0.106)
c_fe	-0.0426	-0.0651	-0.0413	-0.0742	-0.0403	-0.111	-0.0260	-0.0990
	(0.0279)	(0.0323)	(0.0263)	(0.0450)	(0.0261)	(0.0652)	(0.0242)	(0.0642)
c_ir	0.0195**	0.0393**	0.0176*	0.0454*	0.0189**	0.0240	0.0208***	0.0509
	(0.00631)	(0.0147)	(0.00708)	(0.0179)	(0.00581)	(0.0219)	(0.00454)	(0.0279)
fe_ir	0.0855	0.122	0.0980	0.126	0.0838	0.148	0.103	0.0887
	(0.0715)	(0.100)	(0.0658)	(0.121)	(0.0680)	(0.206)	(0.0547)	(0.170)
t	0.139	0.156	0.120	0.146**	0.146	0.104	0.184*	0.129
	(0.0803)	(0.0825)	(0.0792)	(0.0523)	(0.0779)	(0.102)	(0.0797)	(0.145)
t2	0.00260	0.00400	0.0140	0.0132	0.00321	0.00383	0.00135	0.00269
	(0.00956)	(0.00950)	(0.0129)	(0.0132)	(0.00925)	(0.0102)	(0.0124)	(0.00943)
l_t	0.0103	0.00359	-0.00527	-0.00542	0.0106	0.00258	-0.00571	-0.0328*
	(0.00902)	(0.00802)	(0.00913)	(0.00905)	(0.00855)	(0.00627)	(0.00545)	(0.0140)
c_t	-0.00128	-0.000678	0.000309	-0.000168	-0.00140	-0.000985	0.00110	0.00421
	(0.00238)	(0.00241)	(0.00287)	(0.00425)	(0.00248)	(0.00235)	(0.00403)	(0.00492)
rc_t	-0.0270	-0.0269	-0.0266	-0.0454	-0.0270	-0.0246	-0.00532	-0.0322
	(0.0221)	(0.0205)	(0.0240)	(0.0261)	(0.0223)	(0.0220)	(0.0124)	(0.0410)
fe_t	0.00275	0.00137	0.00350	0.0228	0.000985	0.0121	-0.0237*	0.0364
	(0.0133)	(0.0124)	(0.0173)	(0.0231)	(0.0120)	(0.0129)	(0.0100)	(0.0267)
ir_t	-0.000553	-0.000398	0.000989	-0.00383	-0.000131	-0.00431	-0.00542	-0.0243*
	(0.00454)	(0.00317)	(0.00515)	(0.00761)	(0.00472)	(0.00428)	(0.00553)	(0.0101)

industry (yuan)	-0.00665	-0.00807	-0.00938	-0.00839	-0.00627	-0.00701	-0.00269	-0.00326
	(0.0117)	(0.0127)	(0.0130)	(0.0132)	(0.0115)	(0.0118)	(0.0117)	(0.0119)
industry (hours)	-0.180**	-0.181**	-0.182**	-0.181**	-0.169*	-0.164*	-0.175*	-0.182*
	(0.0637)	(0.0643)	(0.0610)	(0.0605)	(0.0663)	(0.0741)	(0.0680)	(0.0816)
p	-0.000659	-11.08***	-0.230**	-7.928**	-0.0155	-2.675	-0.0454	-1.658
	(0.0557)	(2.285)	(0.0846)	(2.105)	(0.0140)	(2.087)	(0.0273)	(1.974)
p*l		-3.804*		-3.367**		-0.815		-0.530
		(1.623)		(1.034)		(0.441)		(0.307)
p*c		0.729*		0.547		-0.105		-0.142
		(0.294)		(0.311)		(0.135)		(0.111)
p*rc		1.118		1.999		1.800**		1.582**
		(0.733)		(1.618)		(0.603)		(0.458)
p*fe		4.225*		1.937		-0.230		-0.625
		(2.044)		(2.341)		(0.852)		(0.657)
p*ir		-0.925		-0.200		-0.416		-0.0704
		(0.539)		(0.521)		(0.215)		(0.170)
p*lsq		0.484*		0.582*		0.0353		-0.00289
		(0.202)		(0.254)		(0.0415)		(0.0684)
p*rcsq		0.181		-0.248		-0.285		-0.271
		(0.323)		(0.342)		(0.254)		(0.161)
p*csq		-0.0160		-0.00756		0.00452		0.00546
		(0.0322)		(0.0368)		(0.00540)		(0.00671)
p*fesq		0.533		0.373		0.185		0.154
		(0.357)		(0.321)		(0.0988)		(0.104)
p*irsq		0.113		0.114		0.0609*		0.0610**
		(0.0583)		(0.0688)		(0.0250)		(0.0225)
p*l_rc		2.143*		1.559*		0.293		0.141
		(0.874)		(0.666)		(0.220)		(0.242)
p*l_c		0.0387		0.00593		0.0448*		0.0578**
		(0.133)		(0.116)		(0.0186)		(0.0214)
p*l_fe		-1.392**		-0.952		-0.0826		-0.0179
		(0.490)		(0.482)		(0.182)		(0.161)
p*l_ir		0.139		-0.00787		-0.0261		-0.0490
		(0.205)		(0.159)		(0.0383)		(0.0545)
p*rc_c		-0.163		-0.176		-0.0448		-0.0233
		(0.172)		(0.126)		(0.0394)		(0.0434)
p*rc_fe		-1.773*		-0.912		-0.233		-0.0662
		(0.830)		(0.550)		(0.296)		(0.151)
p*rc_ir		0.302		0.0276		0.137		-0.0182
		(0.336)		(0.345)		(0.0746)		(0.0595)
p*c_fe		-0.0255		0.0663		0.0580		0.0503
		(0.0936)		(0.0992)		(0.0404)		(0.0402)
p*c_ir		-0.128*		-0.145		-0.00552		-0.0181
		(0.0606)		(0.0742)		(0.0121)		(0.0150)
p*fe_ir		-0.0365		0.0349		-0.0551		-0.00648
		(0.261)		(0.296)		(0.0875)		(0.0657)
p*t			-0.0676	-0.349			-0.0375	-0.0459
			(0.143)	(0.255)			(0.0469)	(0.118)
p*t2			-0.0520*	-0.0450			0.00124	-0.00139
			(0.0257)	(0.0273)			(0.00478)	(0.00430)
p*l_t			0.0292	0.0334			0.00650	0.0175*
			(0.0170)	(0.0219)			(0.00583)	(0.00781)
p*c_t			-0.00641	0.000302			-0.000773	-0.00228
			(0.00552)	(0.0112)			(0.00182)	(0.00234)
p*rc_t			0.0242	0.122			-0.0170	0.00848
			(0.0340)	(0.0607)			(0.0127)	(0.0354)
p*fe_t			0.0127	-0.0683			0.0225	-0.0119
			(0.0151)	(0.0541)			(0.0112)	(0.0229)
p*ir_t			0.000679	0.0296			0.00293	0.0131**

			(0.0104)	(0.0184)			(0.00268)	(0.00455)
Constant	-0.859	8.970**	1.076	7.642**	-0.865	7.765	0.0970	6.506
	(1.031)	(2.419)	(2.021)	(2.965)	(1.154)	(5.145)	(1.445)	(5.187)
Observations	1,514	1,514	1,514	1,514	1,514	1,514	1,514	1,514
R-squared	0.393	0.404	0.399	0.407	0.394	0.402	0.399	0.407
Number of ID	366	366	366	366	366	366	366	366
Translog terms	YES	YES	YES	YES	YES	YES	YES	YES
Time*inputs	YES	YES	YES	YES	YES	YES	YES	YES
Total effect of p		-9.334***	-0.289	-6.976***		-2.355	-0.0675	-1.469
p*inputs	NO	YES	NO	YES	NO	YES	NO	YES
p*TC	NO	NO	YES	YES	NO	YES	YES	YES

Estimation method: within regression estimator. The dependent variable is rice production (quantities) per mu. l: labor ; c: capital ; rc: running costs ; fe: fertilizers ; ir: irrigation ; I_1 and I_2 : industrial production in yuan and hours. All variables are in logarithm (except t and t2). Standard errors in parentheses are clustered at village level. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%. Translog terms are: l^2, c^2, fe^2, ir^2, rc^2, l*c, l*fe, l*ir, l*rc, c*fe, c*ir, c*rc, fe*ir, fe*rc and ir*rc. Technical change (TC) terms are: t*l, t*c, t*fe, t*ir and t*rc.