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Costs of an environmental regulation in livestock farming: Evidence from pig production in rural China

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Abstract

We investigate the cost and benefit of one of the most stringent Chinese environmental regulations that led to a shutdown of a large number of livestock farms. The temporal and spatial variation in programme implementation allows us to employ a staggered difference-in-difference (DID) to identify the causal effects of the regulation. Our DID estimates show that while the regulation significantly reduced NH_3-N, it has no significant effect on the other three important livestock related pollutants (pH, DO and COD). In contrast, the regulation consistently reduced the number of pigs slaughtered, inventory of live pigs and pork production by 8.3%, 10.3% and 11.2%, which alone is equivalent to a 2.9 percentage point loss of China's entire agricultural output value in 2016. Further analyses reveal evidence of partial substitution between pig and other livestock animals and the possibility of relocation to other regions. The policy-induced reduction in export and increase in pork price is consistent with the reduction of pig and pork production. Overall, we find that the regulation achieved rather limited environmental benefit at a large economic cost.

KEYWORDS

China, environmental regulation, livestock, water pollution

JEL CLASSIFICATION

Q51; Q52; Q53

Chen, Ji and Jin contributed equally to this work.

1 | INTRODUCTION

China has achieved an average annual growth rate of nearly 10% in the past 40 years, lifting 800 million people out of poverty (Lin, 2018; Lin et al., 2016). Such a remarkable economic accomplishment, however, has been coupled with growing environmental degradation (Zheng & Kahn, 2017). It has been widely documented that China has been facing mounting air and water pollution problems (Gleick et al., 2009; Hao et al., 2018; Shi et al., 2016; Tao & Xin, 2014), not only causing various health problems ranging from minor respiratory discomforts to fatal diseases such as digestive and lung cancers (Ebenstein, 2012; Tanaka, 2015), but also posing a critical threat to the country's future economic growth (He et al., 2020; Liu et al., 2012; Zhang & Wen, 2008). Since the late 1990s and early 2000s, the Chinese government has implemented a series of environmental regulations to reduce pollution (Cai, Lu, et al., 2016; Liu et al., 2017; Zhang & Wen, 2008).

Despite the increasing regulatory efforts to reduce pollution, China's pollution condition remains at alarming levels (Cai, Chen, et al., 2016; Lai, 2017). Bai et al. (2018) pointed out that the livestock production transition in China has put pressure on resource use and environment, and the combination of the limited success of the early efforts and difficulty in measuring non-point pollution triggered Chinese governments to adopt some of the most stringent administrative regulations to improve air and water quality (Liu et al., 2017; Wang et al., 2018, 2019). Hundreds and thousands of factories and livestock farms closed down their businesses as the result of these harsh regulations (Bai et al., 2018; Kuhn et al., 2018; Pan et al., 2016; Qian et al., 2018). It is reported that in 2015, the Chinese government banned livestock production in some regions (called non-livestock production regions, NLPRs) to control surface water pollution near vulnerable water bodies. In total, 90,000 NLPRs had been established by 2017, covering a land area of 0.82 million km^2 and shutting down 0.26 million pig farms (Bai et al., 2019).

In this paper, we add to the literature by empirically evaluating one of these stringent environmental regulations that require livestock farms located next to major water sources to close down their operations regardless of the actual amount of pollution they produce. The regulation was initiated in Guangdong province in 2010, and quickly expanded to other provinces. In 2013, the State Council made this regulation a nation-wide environmental regulation (known as the 'Regulation on Water Pollution of Livestock and Poultry Sectors'—'the Regulation'). Identifying effects of the Regulation, however, is empirically challenging due to the non-random nature of the regulation adoption. In a review of the literature, this endogeneity problem is either ignored or poorly addressed in many of the studies (Lu & Wu, 2017; Wu et al., 2017). We took advantage of the fact that the adoption of the Regulation rolled out over time from one region to another, creating spatial and temporal variations in treatment status, which allows us to employ the difference-in-difference (DID) approach to identify the causal effects of the Regulation. We seek to answer two research questions: (1) has the Regulation reduced water pollution as intended; (2) what are the economic effects of the Regulation on the livestock sector?

Our study contributes to the limited but emerging literature that seeks to understand the effectiveness of environmental regulations in developing countries. Although examining effects of environmental regulations in developed countries has long been a subject of study in the economic literature (e.g., Longhurst et al. 2009; Walker, 2011; Shapiro & Walker, 2018), similar studies in developing countries have emerged only recently (e.gHao et al., 2018; Hou & Ma, 2017; Wu et al., 2017; Zhang, 2018). With few exceptions (e.gCai, Lu, et al., 2016; Greenstone & Hanna, 2014; Tanaka, 2015), rigorous empirical studies of environmental regulations in developing countries are rare. This knowledge gap is significant as findings from more established literature on environmental regulations in developed countries have little application to developing countries due to the vast institutional differences between developed and developing countries (Greenstone & Hanna, 2014). As governments in developing countries are keen to learn the lessons needed to guide the designs of future environmental regulations, rigorous evidence-based research on environmental regulations in developing countries is urgently warranted.

Our study also contributes to the sparse literature on the benefit and cost of environmental regulations that directly regulate the operations of agricultural/livestock farms. A review of relevant literature reveals that the vast majority of existing studies on environmental regulations tend to focus on the manufacturing sector (e.gCai, Lu, et al., 2016; Dechezleprêtre & Sato, 2017; Wu et al., 2017; Zhang, 2018; Zhao & Sun, 2016). And the wide range of issues explored includes the effects of pollution regulations on labour demand (Liu et al., 2017), location choice of new plants (List & Co, 2000; Wu et al., 2017), the barrier to small establishments (Dean et al., 2000), FDI investment (Cai, Lu, et al., 2016), innovation and competitiveness (Zhao & Sun, 2016), technology adoption (Perino & Requate, 2012), compliance behaviours of the firms (Zhang, 2018) and external trade (Wang et al., 2016).

Surprisingly, very little research has been devoted to investigating the environmental regulations that regulate agricultural or livestock operations. Among the few studies, Hou and Ma (2017) focus on the effect of regulation on livestock production scale; Zhou (2011) focuses on the industrial structural concentration, but the effects of these regulations on livestock production have been largely neglected. A few studies investigating the costs of environmental regulations in US dairy farming (Isik, 2004; Njuki & Bravo-Ureta, 2015; Zhang 2018) are more closely related to our research. Zhang (2018) showed that dairy farms adopted labour-intensive practices to comply with the regulations. Njuki and Bravo-Ureta (2015) found out that the gas emission regulation significantly increased the technical efficiency of an average farm. Isik (2004) found substantial spatial patterns of dairy operations, as the dairy inventory is negatively correlated with the levels of stringency of the environmental regulation across counties. The main difference between the US regulations and the regulations being investigated here is that the former is a more practice-based, market process while the latter is an administrative process of shutting down farms regardless of their performance in terms of production or pollution.

Finally, our research also contributes to the hot debate on possible causes of the sharp increase in pork prices in China, in recent years. Outbreaks of epidemic diseases such as the African swine flu and the stringent environmental regulations are blamed as among the main causes of the pork price hike in recent years (Haley & Gale, 2020; Mason-D'Croz et al., 2020; Mo & Wen, 2019; Zhang et al., 2019). Although there are more studies on the effect of animal disease outbreaks on pork production and price (e.gLan & Wang, 2019; Pitts & Whitnall, 2019; Shao et al., 2018), there has been no rigorous evidence to substantiate the blame of environmental regulations for the increase in pork price. In fact, most of the discussions are limited to media outlets, newspapers and magazines.[1] Therefore, our study is among the first to rigorously investigate this issue.

The rest of the article is organised as follows. Section 2 provides the research background, which includes description of livestock pig production, water pollution in China and the detailed description of the Regulation. Sections 3 and 4 introduce the identification strategy and data sets used for the analysis, respectively. Section 5 presents the estimation results from various specifications and robustness checks, and Section 6 presents internal validity checks. Section 7 concludes and draws policy implications.

[1]https://www.reuters.com/article/idUSL3N10H1RC20150806; https://thepigsite.com/news/2017/12/the-pollution-regulations-affecting-chinas-pork-producers-1; https://www.ers.usda.gov/webdocs/publications/81948/ldpm-271-01.pdf?v=0

2 | BACKGROUND OF THE RESEARCH

2.1 | Livestock pig production in China

China ranks first in the world in terms of pork production and consumption, and more than half of the pork in the world is produced and consumed in China. The livestock sector accounts for nearly 30% of China's agricultural production value. The annual production volume of pork in China is around 55 million tons, with pork imports of around 1.8 million tons (Ministry of Agriculture in China, 2019; China Livestock Yearbook, 2019). Generally, the number of live pigs slaughtered and the inventory of live pigs have increased steadily since 1980, indicating the growing importance of pig production in China (Figure A1(a), online). Meanwhile, pork accounts for the largest share of the meat consumed by the Chinese. Pork consumption in China accounts for half of the world's pork consumption. The pork consumption per capita is 40 kg annually, which accounts for 60% of the meat consumption in 2016 (China Meat Association, 2018). In this sense, any policy or regulation concerning the Chinese pig industry has far-reaching implications on China's livestock sector, livestock farms' income and nutrition conditions of the Chinese consumers.

The four major pig production regions, Coastal region, Inner-middle region, Southwestern region and Northwestern region, produce 90% of pigs in China (Sun, 2015). A few other notable changes occurred in the past 10 years. First, although production in the Northeastern region has experienced marked growth, production in the Coastal region experienced a sharp drop since 2013. Second, the production scale of pig farms has also changed spatially during the same period. Although the number of scaled farms and commercial farms[2] has grown considerably in both the Northeastern and the Southwestern regions, the increase has been very marginal in Zhejiang and Fujian provinces.

2.2 | Water pollution in China

According to the World Health Organisation (WHO), contaminated water can transmit diseases such as diarrhoea, cholera, dysentery, typhoid and polio, and contaminated drinking water is estimated to cause 502,000 diarrhoeal deaths each year (WHO, 2018). The 2016 Chinese Environment Communique published by the Department of China's Environmental Protection indicated that among the main river resources in China, 15% of water in the Yellow River, the Liao River and the Hai River were polluted with V-water resource,[3] and the figure for the Haihe River was over 40%. Several indicators are commonly used to measure water pollution; they include water pH value, dissolved oxygen (DO), chemical oxygen demand (COD), biochemical oxygen demand (BOD), total organic carbon (TOC) and ammonia nitrogen (NH_3-N). Livestock production pollutes water mainly through its contribution to the DO, BOD, COD and NH_3-N of water resources (Department of China Environment and Ecology Protection, 2018). The COD index and NH_3-N index of water resources in China have declined from 2004 to 2016, but the pH value and DO value have remained largely constant (Figure A1(b), online). The overall improvement in water quality in China was not significant during the past decade.

[2]Scaled farms are those with over 500 heads of fattening pigs per year and commercialised farms are those with over 20,000 heads per year.

[3]Water resources in China are categorised into five levels based on the quality, from I, II, III, IV, V. V-water resource is the worst quality and it has no beneficial use.

2.3 | Livestock production and water pollution

Livestock production in general and pig production in particular has been the key contributor to China's water pollution.[4] According to the 'First Report on National Pollution Investigation' provided by the National Bureau of Statistics in 2010,[5] livestock production produced 243 million tons of faeces and 163 million tons of urine, releasing a total of 12.68 million tons of COD emission and 717,300 tons of NH_3-N emission. In other words, livestock production was responsible for 95.8% of the total COD emission from the agricultural sector or 41.9% of the overall COD emission from all sources. And the corresponding figures for NH_3-N emission are 78.1% and 41.5%, respectively. It is clearly evidenced that pollution from livestock production is the main source of water pollution in agricultural production and in all industries in China.

The existing academic research on the impact of Chinese livestock production on water pollution mainly concentrated in the fields of agronomy and chemistry. These studies revealed various water pollutants and heavy metals produced by livestock production from the view point of formation mechanisms and animal raising techniques (Cang et al., 2004; Huang et al., 2015; Wang et al., 2015). The aforementioned research tends to concentrate in some parts of China, specifically the north and northeastern areas (Wang et al., 2018; Yang et al., 2012; Zhang et al., 2014). Although several studies estimated the total amount of pollutants discharged from livestock production using input-output methods and data from certain regions or cities of China using input-output analysis (Okadera et al., 2006; Sun & Wu, 2013), rigorous economic analysis using nation-wide data is lacking. These existing studies suffer from two main limitations. First, as input-output analysis does not take into account the self-purification capacity of the watershed, the water pollution volume could be over-estimated, and the estimation results are sensitive to the parameters of the mathematical programming models. Second, the current research has not paid attention to specific regulatory policies; the policy relevance of the research results is, therefore, relatively limited.

2.4 | Pollution regulations

The Chinese government has implemented a series of environmental regulations to reduce pollution since the beginning of the 2000s (Li et al., 2019; Zhang & Wen, 2008). Despite these early regulatory efforts, there has been little improvement in China's pollution condition (Cai, Lu, et al., 2016). This has motivated central and local governments to take more stringent regulatory measures. A livestock regulation initiated in Guangdong province in 2010 that eventually became the national regulation in 2013 is one of these strict regulations. The regulation forces livestock farms located near water sources to shut down their operations completely. The regulation was soon adopted by Zhejiang province in March 2011, Hunan province in June 2011, and Fujian and Jiangxi provinces in 2012. On 8 October 2013, the State Council made it a national regulation called 'The Regulation on Water Pollution of Livestock and Poultry Sectors' (or simply 'the Regulation'). Since then, Hubei, Sichuan, Henan, Shandong provinces, Beijing city, and Shanghai city adopted the Regulation, and the Regulation has now been implemented in the entire country. Despite the fact that the Regulation is given slightly different names in different provinces, its content is the same.

[4]See http://www.stats.gov.cn/tjsj/tjgb/qttjgb/qgqttjgb/201002/t20100211_30641.html for details.

[5]See http://www.stats.gov.cn/tjsj/tjgb/qttjgb/qgqttjgb/201002/t20100211_30641.html for details.

By the end of 2017, 10 out of 33 provinces adopted the Regulation. At the county-level, a total of 1036 counties (40% of the total counties in China) had adopted the Regulation by the end of 2017. The Regulation has already caused unprecedented closure of livestock farms in many areas. For example, in Jiangshan county of Zhejiang Province, more than 90% of the pig farms were shut down, which has caused huge economic loss to pig farmers (Lu & Wu, 2017).

3 | EMPIRICAL STRATEGY

The main objective of this study is to estimate the causal effect of the Regulation on water pollution and pig production. In the absence of a random control trial, the implementation time may be correlated with many confounding factors (e.g., the initial condition or future potential of pollution or pig production, livestock farm location, etc.). Therefore, failing to control for those confounding factors would lead to inconsistent estimates of the regulation effects on pollution and pig production. We employ a difference-in-differences (DID) approach to identify the causal effect of water pollution regulations on water pollution and pig production. Our basic DID specification is given as follows,

$$\log(Y_{it}) = \beta_0 + \beta_1 Treat_{it} + W_{it}\gamma + E_{it}\theta + D_t + \varphi_i + \varepsilon_{it} \tag{1}$$

where log(Yit) is the log-transformed outcome variable (either water pollution or pig production) of county i in year t;[6] $Treat_{it}$ is county $i's$ treatment status equal to one for the year that county i implemented the *Regulation* and for the years after, and zero otherwise; φ_i are county fixed effects capturing time-invariant unobservables that could confound the estimated regulation effects; D_t is the time fixed effects capturing time trend common across all counties; W_{it} is a vector of time-varying weather condition variables, and E_{it} is a vector of time-varying social-economic factors. We include W_{it} and E_{it} as additional controls to further address the fact that weather and socio-economic conditions could be potentially correlated with the implementation time of the regulation and the outcome variables. Failing to control for these variables would cause the omitted variable bias problem.[7] The key parameter of interest, β_1, measures the causal effects (percentage change) of the Regulation on water pollution or pig production.

In addition, the most important assumption underlying the validity of DID specification is that both the treatment group ($Treat_i$ = 1) and the control group ($Treat_i$ = 0) follow the same time trend of water pollution or pig production in the absence of the Regulation, which is known as the parallel trend assumption. We test this assumption graphically and econometrically. Finally, we also conduct a battery of robustness checks to further examine the sensitivity of our results to differential controls, different model specifications, and allow the treatment to be implemented at the prefectural city level instead of the county level.[8]

[6]The dependent variables in all the regressions are defined in logarithmic form. The advantage of using the log-transformed dependent variables is that the coefficients of $treat_{it}$ in Equation (1) are interpreted as percentage changes, and the percentage change interpretation would avoid the potential interpretation problem associated with the structural differences across counties. However, in the descriptive table (Table 1), the pollution indices and pig production outcomes are reported by levels (the number of pig farms, and number of pigs slaughtered, the level of pollution, etc.) for ease of interpretation.

[7]Subsequent tests confirmed that when weather conditions and socio-economic factors are controlled, neither whether or not the Regulation is carried out in a certain region nor the time length of the implementation of the Regulation is dependent on Y_{it}.

[8]In China, prefecture is a higher administrative level than county where one prefecture supervises several counties.

4 | DATA AND DESCRIPTIVE STATISTICS

4.1 | Data sources

We use a total of six data sets in this study. First, we compiled information about the exact time of adoption of the Regulation by each of the 1281 counties in 154 prefectures from 12 provinces in China, based on the data published on official web pages of prefectural or county livestock bureaus. We define the adoption time of the Regulation in a given county (or prefecture) based on the following consistent criterion. If a county livestock bureau announced in their 'red-title' documents the commencement time to implement an environmental regulation, the key elements of which are consistent with those of the Regulation, then we define that time as the adoption time of the Regulation of that county. A sample web page on how the Regulation was introduced in the government's 'red-title' document can be found in Table A11 in Appendix 2 (online).

Figure A2 (online) provides more detailed information on how the Regulation was implemented in a staggered fashion. Few counties each year adopted the Regulation between 2010 and 2013. The number of counties adopting the Regulation really started to increase considerably each year from 2013, the year it was officially announced by the State Council. In our DID analysis, the implementation time is a critical information for us to define the treatment variable ($Treat_{it}$). More specifically, for the year when county i started implementation of the Regulation and for the years after, county i is in the treatment group (or $Treat_{it} = 1$). It is worth noting that there exist a large number of counties that had not implemented the Regulation by 2016 and remained as control during the entire sample period. For each given year, we define treatment group as counties that have ever implemented the water regulation till that year, and we define control group as counties that have never implemented the water regulation till that year.

The second data set is the water pollution data obtained from two statistical sources, which is a weekly report on automatic water quality monitoring data from the Chinese National Environmental Monitor Center (CNEMC). The report provides weekly water quality data of all the main rivers in China for all the major pollutants such as DO, COD, PH and NH_3-N. Names and locations of the monitoring stations and the specific locations for the sections of the rivers are also indicated.[9] To merge with the yearly data in the other datasets, we first collapsed the week-section data into the yearly average value of the water pollutants across different monitoring stations. Then the water pollution data was merged with the data set on the implementation times by the county code.

Third, the livestock data set used in our analysis is from two sources. The county-level livestock production data from 1990 to 2016 in 12 provinces are from the provincial statistical yearbooks. The county-level socio-economic data are from the China County Statistical Yearbook. The yearbooks were downloaded from the China socio-economic databases from the '*Zhiwang*' website.[10] The county-level livestock production data and socio-economic data are merged by the county code, which can then be merged with the other three datasets (see Online Appendix 2, Table A10).

Figure A3 (online) displays the spatial distribution of the number of live pigs slaughtered in our sample. It is shown that large-scale farms, with an average annual number of pigs slaughtered between 401 and 2823 heads, are predominantly located in south China, with a small portion located in the north-eastern part of China. Since the unit of our analysis

[9]See the official website of CNEMC, http://www.cnemc.cn and http://123.127.175.45:8082/.

[10]See http://tongji.cnki.net/kns55/index.aspx for details.

is county and pig production is the main focus of our study, we define the overall sample of our study as all the counties for which data on livestock production are reported in provincial and/or county statistical yearbooks. By this definition, our sample is composed of 1281 counties from 12 provinces (as shown by the coloured areas in Figure A3, online). And this sample was applied for estimation of pig production outcomes (Panel A: Livestock pig [2000–2016] in Table 1). Then, a subsample of the 1281 counties (i.e., 88 counties) was applied for estimation of water pollution outcomes as water pollution data are only available for the first-order and second-order rivers in China (since 2004), and only 88 counties of the 1281 counties have the first-order or second-order rivers crossed (Panel B: Water pollutant [2004–2016] in Table 1). Therefore, the sample for water pollution analysis covers much fewer counties (88 of the 1281 counties) and a shorter time span (2004–2016) than that for the pig production analysis.

In Table A4, we further report year-by-year the number of treatment counties and the number of control counties for the pig production regression subsample (Panel A) and the water pollution regression subsample (Panel B). As defined above, for each year, the treatment group includes counties that have ever implemented the water. Our definition for treatment and control groups is exactly the same for both the pig production regression subsample (panel A) and the water pollution regression subsample (panel B).

We also assembled meteorological data from the China Meteorological Data Service Center (CMDC).[11] The CMDC records daily maximum, minimum and average temperature, precipitation, relative humidity, wind speed, and sunshine duration for 820 weather stations in China. We match meteorological conditions to Chinese counties using the inverse-distance weighting (IDW) (Currie & Neidell, 2005; Deschênes & Greenstone, 2011; Schlenker & Walker, 2016). The basic algorithm is to take the weighted average of all monitoring stations within the circle with certain radius for the centroid of each county. Towards this end, a radius of 100 km is used and our results are robust to different radius distance (see Table A1).

The fifth data set is a socio-economic data set containing information on county-level population, added value of different industries, financial revenue and expenditure, savings and loan of residents, investment, agricultural machinery and output, and factory numbers and factory output. These variables are also from different yearbooks. For detailed description of the socio-economic control variables, see Appendix Table A2.

Finally, we compiled data on pork price and import/export volumes of pork and meat products. These data allow us to explore the response of the livestock sector to the effects of the Regulation on pig production. The data of pork prices were retrieved from a web page of the Ministry of Agriculture in China. The website reports the daily pork prices at the county level.[12] In our analysis, the daily data were aggregated into the annual price data from 2000–2016 (see Appendix Table A2). To analyse the influence of the Regulation on meat import and export, the meat trade dataset was obtained from the international trade and decision system.[13] Since the trade data are only available at the provincial level, we analyse the effect of the Regulation on meat import and export using a provincial panel data. The trade data are import and export volumes for main meat products (i.e., beef, pork, mutton, poultry and total meat) between 26 Chinese provinces and the rest of the world during 2002 to 2016 (see Table A3 online).

[11]http://data.cma.cn/.

[12]See http://www.caaa.cn/.

[13]http://trade.drcnet.com.cn/web/login.aspx.

TABLE 1 Summary statistics and comparisons between treatment group and control group

Total sample			**Control group**		**Treatment group**		**Control-treatment**	
Variable	**Definition (Unit)**	**Mean (SD)**	**Variable**	**Mean (SD)**	**Variable**	**Mean (SD)**	**Dif. (SE)**	**Con.-Dif. (SE)**
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Panel A: *Livestock pig* (2000–2016)		(*# of counties* = 1281)			(*# of counties* = 851)	(*# of counties* = 430)		
Slaughter	Number	420.41	Slaughter	408.93	Slaughter	440.77	−31.83***	−5.28**
[*N* = 19,220]	(thousand)	(432.66)	[*N* = 12,292]	(402.09)	[*N* = 6,928]	(481.52)	(6.49)	(2.22)
Stock	Number	282.16	Stock	279.49	Stock	286.89	−7.41***	−0.09
[*N* = 19,191]	(thousand)	(272.61)	[*N* = 12,277]	(252.51)	[*N* = 6,914]	(305.01)	(4.09)	(1.57)
Pork	Ton	33.24	Pork	34.45	Pork	31.53	2.92***	−0.24
[*N* = 16,885]	(thousand)	(3496)	[*N* = 9,875]	(35.13)	[*N* = 7,010]	(34.65)	(0.55)	(0.20)
Total meat	Ton	50.65	Total meat	54.22	Total meat	46.16	8.05***	−0.13
[*N* = 15,147]	(thousand)	(190.92)	[*N* = 8,438]	(210.92)	[*N* = 6,709]	(162.18)	(3.12)	(0.26)
Panel B: *Water pollutant* (2004–2016)		(*# of counties* = 88)			(*# of counties* = 66)	(*# of counties* = 22)		
pH	pH*	7.70	pH*	7.75	pH*	7.58	0.17***	−0.00
[*N* = 1092]	(mg/L)	(0.45)	[*N* = 812]	(0.44)	[*N* = 280]	(0.43)	(0.03)	(0.02)
DO	DO	7.61	DO	7.70	DO	7.33	0.38***	−0.01
[*N* = 1092]	(mg/L)	(1.91)	[*N* = 812]	(1.80)	[*N* = 280]	(2.17)	(0.13)	(0.07)
COD	CODMn	5.41	CODMn	5.71	CODMn	4.51	1.20*	0.07
[*N* = 1,092]	(mg/L)	(9.61)	[*N* = 812]	(9.97)	[*N* = 280]	(8.41)	(0.67)	(0.42)
NH_3-N	NH_3-N	0.95	NH_3-N	0.97	NH_3-N	0.90	0.07	0.01
[*N* = 1092]	(mg/L)	(2.10)	[*N* = 812]	(2.29)	[*N* = 280]	(1.43)	(0.15)	(0.07)

Notes: This study uses two data sets: the livestock pig data set includes 1281 counties during 2000–2016, as described in Panel A; and the water pollutant data covers 88 counties during 2004–2016, as summarised in Panel B. Columns 1–3 provide descriptive statistics based on total county sample. Columns 4–5 provide summary statistics based on control group that is defined as counties without water pollution regulation during our study period, and the treat group summarised in Columns 6–7 is defined as counties that have once experienced water regulation during our study period. Column 8 reports the direct difference and relative *t*-test between control group and treatment group. We also provide the magnitude and significance of variable difference after removing county fixed difference, which are listed in Column 9.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.2 | Summary statistics

Summary statistics of pig production and water pollution are shown in Table 1. Panel A reports the pig production data for 1281 counties during 2000–2016, and panel B reports the summary descriptive on water pollution data for 88 counties during 2004–2016 as the water pollution data are not available before 2004. The descriptive statistics for the entire sample, the treatment group (counties where the Regulation was implemented during 2010–2016), and the control group (counties where the Regulation was not yet implemented during 2010–2016),[14] are reported in Columns 1–2, 3–4 and 6–7, respectively.

Our data show that an average county of our sample slaughtered 420,400 heads of pig and produced an inventory of 282,200 heads every year during the study period. The average annual pork and total meat production of an average sample county is 33,200 and 50,700 tons, respectively. The comparison between the treatment and permanent control groups further reveals that the treatment counties produce slightly more pigs, pork and meat when the county fixed effect is controlled (Column 9). Except for the number of pigs slaughtered, the difference is not statistically significant (Panel A and Panel B in Table 1). Although the counties in the control group experienced higher pollution according to the sample mean (Column 8), none of the differences is statistically significant after the county fixed effect is removed (Column 9).

Although Table 1 is informative about the production scale and pollution level of our sample, it does not show the change of pig production or water pollution over time or provide evidence on the effects of the Regulation on pig production and water pollution. Figure A4, online, shows the trend of county-level pig production from 2000 to 2016 and water pollution from 2004 to 2016 for the control counties and counties adopting the Regulation at different years.

Prior to 2011, the year when the first group of counties adopted the Regulation, all counties demonstrated a similar trend in pigs slaughtered. However, the trend starts to diverge after 2011. Whereas the same pre-2011 trend continued for the control counties until 2016, the pre-2011 trend for the treatment counties continued until the time of implementation of the Regulation. The number of pigs slaughtered declines immediately after implementation and remained at the declined level until 2016. The same observation can be seen in Appendix Figure A5(a) (online) for the inventory of live pigs.

Similar to the case of number of pigs slaughtered, all counties experienced the same trend of NH_3-N from 2004 to 2010, and this pre-2011 trend continued for the control group. Although treatment counties experienced some decline in NH_3-N after the implementation of the Regulation, the evidence is much less consistent compared to the pig production trends. For example, for the counties that adopted the Regulation in 2013, the level of NH_3-N initially increased and then decreased. This pattern is similar when the pollution is measured by pH (Appendix Table A2(b), online).

5 | RESULTS

5.1 | The baseline results

The results from the base DID model in Equation (1) are reported in Table 2. Columns 1–4 report the base DID results for the four water pollution indices. We find that the effects of the Regulation on water pollution indices are mixed. While the Regulation caused a significant reduction in NH (by 22.6%), it has no significant effects on the other three indices of

[14]Please note the control group is more accurately called the permanent control group. In our DID specification, counties adopting the Regulation in later years also served as control group for counties adopting the Regulation in earlier years.

TABLE 2 Baseline results of DID estimates

	Water pollutant				Livestock pig		
	Log(pH)	**Log(DO)**	**Log(COD)**	**Log(NH)**	**Log(Slaughter)**	**Log(Stock)**	**Log(Pork)**
Dependent Var.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Treat(*i*, *t*)	0.0022	0.1200	−0.0896	−0.2258**	−0.0832***	−0.1025***	−0.1118***
	(0.0118)	(0.0764)	(0.0765)	(0.1091)	(0.0276)	(0.0298)	(0.0266)
Observations	1092	1092	1092	1092	19,220	19,191	16,885
R-squared	0.1988	0.2201	0.2062	0.3795	0.2459	0.2845	0.2724
Number of counties	88	88	88	88	1281	1200	1058
County *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather condition	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-policy weight	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The sample for water pollution regression (88 counties) is a subsample of the total sample (1281) that is used for the pig production regression. The water pollutant dataset covers a shorter time span (2004–2016) than the pig production dataset (2000–2016). Weather condition includes every 3°C temperature bins, and 2nd order polynomials in rainfall, sunshine duration, relative humidity, and wind force, as described in Table A1. Economic controls include a set of county level socio-economic variables, which are the log form of population scale, value-added of primary industry and secondary industry respectively, fiscal revenue, fiscal expenditure, residents' deposit balance, loan balance, grain output, total power of agricultural machinery, capital investment, number of industrial enterprises above designated size, and total output value of large-scale industrial enterprises, as summarised in Table A2. Pre-policy weight is defined as the county-average annual slaughter prior to the implementation of water pollution regulation. Standard errors are clustered by county and are listed in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

water pollutant (i.e., PH, DO and COD). Unlike the case of water pollution, the results on pig production outcomes are much more significant and consistent (Columns 5–7). More specifically, the Regulation has significant and negative effects on all three pig production variables. In terms of the magnitude of the effects on pig production, implementation of the Regulation would cause an average county's number of pigs slaughtered, inventory of live pigs and pork production to drop by 8.3%, 10.3% and 11.2%, respectively. The estimation also controls the county fixed effect, year fixed effect, weather and socio-economic conditions. We also gradually control for the control variables, and the estimation results are robust (see Table A5, online).

5.2 | Robustness checks

Table 3 shows the results of four scenarios as robustness checks. First, in our base model, the results are clustered at county level because we consider the treatment variable (i.e., implementation time) to vary at the county level. As a robustness check, we cluster the standard errors at the prefectural level instead of county level to allow correlation between counties from the same prefecture. Although this specification is likely to inflate the standard errors of the estimated coefficients, we find that both the level of significance and the magnitude of coefficients are highly consistent with those from the base DID model (Scenario A).

Second, to show whether our results are sensitive to the sample size differences between the two sets of regressions, we conducted additional regressions for pig production outcomes by restricting the sample for the pig production regressions to be the same as that for the pollution regressions (88 counties covering the period 2004–2016) as a robustness check. The robustness results are reported in Scenario B in Table 3, and are largely consistent with the main results when the full sample (1281 counties for the periods from 2000–2016) is used (scenario B).

Third, in our base model, the implementation time of the Regulation is defined at the county level. As a robustness check, we define the implementation time of the Regulation at the prefectural level to allow the possibility that all counties in the same prefecture implemented the Regulation at the same time but reported different times by error. Again, we find that the results are robust with the base model (Scenario C).

Finally, in the base regressions, we use livestock production data from 2000–2015 and the water pollution data from 2004–2015. As a robustness check, we balance the time period of the two datasets, by dropping the livestock production data before 2004. The estimation results are still highly robust with our base model results (Scenario D).

5.3 | Other economic consequences

Having shown that the Regulation has significant and negative effects on pig production, an important policy question is how this regulation-induced reduction of pig production affects the overall structure of the pig industry and its relationship with other livestock. Our investigation focuses on three specific aspects. First, we investigate the possibility that other livestock may substitute for pigs. Second, we investigate the possibility that livestock farms may relocate their operations to different counties/prefectures/provinces that did not adopt the Regulation. And third, we investigate the implication of the Regulation for pork prices and trade.

Table 4 reports the results on substitution between pig production and sheep production within the same county. There is consistent evidence that the policy-induced decline in pig production was partially offset by the increase in sheep production. The adoption of the Regulation increased the number of sheep slaughtered, inventory of live sheep and mutton production by 7.7%, 12.1% and 8.7%, respectively. However, the increase in sheep and possibly other livestock

TABLE 3 Robustness checks based on different scenarios

	Water pollutant				Livestock pig		
Dependent Var.	**Log(pH)**	**Log(DO)**	**Log(COD)**	**Log(NH)**	**Log(Slaughter)**	**Log(Stock)**	**Log(Pork)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Scenario A: *Clustering at prefecture level*							
Treat(i, t)	0.0022	0.1200	−0.0896	−0.2258**	−0.0832***	−0.1025**	−0.1118***
	(0.0121)	(0.0756)	(0.0687)	(0.1110)	(0.0313)	(0.0457)	(0.0300)
Observations	1092	1092	1092	1092	19,220	19,191	16,885
Scenario B: *Balanced sample with both water pollution record and pig production*							
Treat(i, t)	0.0022	0.1200	−0.0896	−0.2258**	−0.1227**	−0.1703***	−0.1597***
	(0.0118)	(0.0764)	(0.0765)	(0.1091)	(0.0482)	(0.0612)	(0.0522)
Observations	1092	1092	1092	1092	1092	1092	1092
Scenario C: *Policy definition at prefecture level*							
Treat(i, t)	−0.0024	0.0643	−0.0056	−0.2494**	−0.1351***	−0.0821***	−0.1375***
	(0.0105)	(0.0482)	(0.0744)	(0.1136)	(0.0277)	(0.0298)	(0.0282)
Observations	1092	1092	1092	1092	19,220	19,191	16,885
Scenario D: *Balanced period 2004–2015*							
Treat(i, t)	0.0022	0.1200	−0.0896	−0.2258**	−0.0650***	−0.0917***	−0.0788***
	(0.0118)	(0.0764)	(0.0765)	(0.1091)	(0.0242)	(0.0257)	(0.0228)
Observations	1092	1092	1092	1092	15,189	15,104	13,158

Notes: All model specifications, including weather condition, socio-economic controls, fixed effects, clustering, and pre-policy weight are strictly in line with our baseline, i.e., Table 2, unless specially pointed out in scenario instruction. Standard errors are listed in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 4 Livestock production structural changes within counties

	Slaughter		**Stock**		**Meat production**			**Pork price**
	Log(pig)	**Log(sheep)**	**Log(pig)**	**Log(sheep)**	**Log(pork)**	**Log(mutton)**	**Log(total meat)**	**Log(Price)**
Dependent Var.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Treat(i, t)	−0.0832***	0.0770**	−0.1025***	0.1212***	−0.1118***	0.0866**	−0.0624**	0.0519***
	(0.0276)	(0.0359)	(0.0298)	(0.0453)	(0.0266)	(0.0385)	(0.0288)	(0.0121)
Observations	19,220	18,804	19,191	12,399	16,885	13,508	15,147	6054
R-squared	0.2459	0.1680	0.0845	0.1294	0.2724	0.1721	0.2255	0.4222
Number of counties	1281	1266	1200	860	1058	904	974	1515

Notes: All model specifications, including weather condition, socio-economic controls, fixed effects, and pre-policy weight are strictly in line with our baseline, i.e., Table 2. Sample period for Columns (1)–(7) is 2000–2016, while sample period for Column (8) is 2009–2016. Standard errors are clustered by county and are listed in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

animals is not sufficient to fully offset the loss of pig production as the Regulation caused the overall meat supply to fall by 6.2%.

To investigate whether and to what degree farms relocated their operations to different counties, we re-estimate Equation (1) using different control groups according to their distances from the treatment counties. More specifically, we use counties outside the provinces of the treatment counties (A), counties outside the prefectures of the treatment counties in (B), and counties between the prefecture and province (C). The results are reported in Table A6, online. No matter which of the three control groups is used, the negative effects of the Regulation on pig production (i.e., number of pigs slaughtered, inventory of live pigs and pork production) are statistically significant (consistently at 1% levels, except for the case of the number of pigs slaughtered in C). In terms of the magnitudes of the impact, the policy-induced reduction effects are consistently the largest in A (13.1%, 17.8% and 13.3%), and the smallest in C (7.2%, 5.0% and 10.4%). These results suggest that farms are more likely to choose to move their operations to counties in another province than their own province. This is not too surprising because farms perceived that a control country located near its own county is more likely to adopt the same regulation. Another possibility is that farms in a control county close to another treatment county may indirectly be affected by the Regulation and decide to shut down and move to another location to avoid the loss. All these adaption behaviours are consistent with our results.

Finally, Table 5 presents the results on the effects of the Regulation on import and export volume of pork and other related meat (beef, mutton and poultry). Although the Regulation has no significant effect on the import volume of pork or any other kind of meat, it led to a significant reduction in pork export. For example, the adoption of the Regulation reduces pork export by 11% (the mean value of *Treat*(i,t) *ratio* is 0.0492). This is consistent with the fact that the Regulation caused a significant reduction in pork production. It is also interesting to note that poultry meat is the only other kind of meat that experienced a significant drop in the counties adopting the Regulation relative to those not adopting. This may be explained by the Chinese diet culture where poultry and pork are closer substitutes than pork and other meat. Therefore, a significant reduction in pork production resulted in an increase in domestic demand for poultry meat and decrease in poultry export. Finally, the reduction in production also caused a higher pork price (Column 8 of Table 5 showing a 5% increase in pork price).

TABLE 5 Influence on provincial level meat trade abroad

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Var.	**Log(Beef)**	**Log(Pork)**	**log(Mutton)**	**Log(Poultry)**	**Log(Meat)**
Panel A: *Export volume*					
Treat(i,t) ratio	−0.8118	−2.2631**	−1.2220	−2.3816***	−0.5642
	(0.9937)	(1.0816)	(1.3092)	(0.8479)	(0.8569)
Observations	292	314	293	321	427
Panel B: *Import volume*					
Treat(i,t) ratio	2.4067	−0.9122	−1.8843	−0.5336	0.2394
	(1.4837)	(1.3559)	(1.1971)	(0.6934)	(0.9523)
Observations	289	295	264	321	403

Notes: We define the continuous treatment variable, Treat(i,t), as the ratio of the number of treatment counties to total number of counties in a province, and the mean value of Treat(i,t) ratio is 0.0492 (see Table A3). All model specifications in Columns (1)–(5) include weather condition, socio-economic controls, province and year fixed effects, and regressions are weighted by pre-policy weight. Standard errors are clustered at province level and are listed in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

6 | INTERNAL VALIDITY CHECKS

We conducted several tests to support the validity of our identification assumptions.

6.1 | Pre-trend test of DID specification

To test for the pre-trend assumption econometrically, we slightly modify Equation (1) as the following:

$$Y_{it} = \beta_0 + \sum_{2000}^{2016} \beta_t \times Treat_i \times D_t + W_{it}\gamma + E_{it}\theta + D_t + \varphi_i + \varepsilon_{it} \quad (2)$$

Please note that $Treat_i$ in Equation (2) is different from $Treat_{it}$ in Equation (1) as the value of the former does not vary over time. More specifically, $Treat_i$ takes the value of one for any county that ever adopted the Regulation during 2010–2015 and zero for all the counties that never adopted the Regulation during the entire period. All the other variables in Equation (2) are defined the same way as in Equation (1). The interaction term between the treatment indicator and the time dummy variable ($Treat_i \times D_t$) allows us to estimate a series of β_t coefficients, each of which measures the conditional difference in Y_{it} between the treatment group and the control group in a given year t. For example, β_{2010} refers to the difference in water pollution or pig production between the treatment group and the control group in 2010. To avoid perfect multi-collinearity, we chose 2008 as the baseline year, so the estimated β_t will be the comparisons of the difference in water pollution or pig production between year t and 2008. The estimated $\beta_t s$ are plotted against years in Figure A6, online.

If the parallel pre-trend assumption is valid, we would observe that the estimated coefficients are not statistically significant before 2011, the year when very few counties started to implement the Regulation. And this is clearly supported by the evidence in Figure A6 (online) as the estimated β_t is not statistically significant from zero for almost all the years from 2000 to 2010. Intuitively, as 2008 is the omitted year, each estimated coefficient for year t should be interpreted as the comparison of the difference in the number of pigs slaughtered or the value of NH index between the treatment and control group, between year t and year 2008. Since both 2008 and any other year before 2011 were before the introduction of the Regulation in any of the counties, we should not observe any difference in pig production or water pollution after controlling for other variables. After the Regulation was implemented (2011 or later), both livestock production and water pollution of the treatment group are gradually and significantly reduced throughout 2012 to 2016 relative to the control group, which is consistent with the results in Table 3.

6.2 | Exogeneity of regulation implementation

In Equation (1), the time-invariant unobservables are controlled through county fixed effect. The remaining main threat to our identification is the correlation between the timing of adopting the Regulation and the time-path of pollution or pig production. Our estimated regulation effect on pollution or pig production would be biased if the Regulation was first adopted in counties experiencing faster growth in pollution or pig production. To check whether this is the case, we regress the timing of the implementation of the Regulation against the change in water pollutants and pig production from 2004 to the year prior to the Regulation implementation. The estimated results are reported in Table A7, online. The fact that the coefficient is insignificant for the changes in both water pollution variables and the pig production variables (except in one case) for the years prior to the regulation implementation allays the concern that the timing of regulation implementation is influenced by the change in pollution or pig production. We also replace the implementation time dummy by the regulation duration (i.e., the number of years since the regulation was implemented). We find the results to be consistent with our main results as none of the coefficients for the changes in pollution indices or pig production variable are statistically significant, which further increases our confidence with our identification.

6.3 | Possible anticipation effects

Another concern is that farmers/local governments may adjust their behaviours toward pollution and pig production in anticipation of the Regulation, though the biases associated with any anticipation effects are difficult to sign. On the one hand, if the local government or livestock farms started to take action to reduce pollution or pig production prior to the implementation of the Regulation, then the effects are likely to be underestimated. On the other hand, if the local government or livestock farms behave predatorily by increasing pig production activities and ensuing pollution prior to the implementation of the Regulation, then the effects are likely to be overestimated. To test for the anticipation effects, we estimate the following specification:

$$Y_{it} = \alpha_0 + \beta_0 \times T_{i,yr} + \sum\nolimits_1^5 \beta_j \times T_{i,jyrbf} + W_{it}\gamma + E_{it}\theta + D_t + \varphi_i + \varepsilon_t \tag{3}$$

where $T_{i,yr}$ is a dummy variable for the adoption year of the Regulation in county i, $T_{i,jyrbf}$ is a dummy variable for j years before the adoption of the Regulation in county i (where j ranges from 1 to 5). The vector of β_j coefficients measure whether the pollution or pig production were significantly different than average in the county during the years before the regulation adoption. The estimation results of Equation (3) are reported in Table A8, online.

The results show some evidence of anticipation effects in the year immediately before the implementation of the Regulation. The negative and statistically significant β_j coefficients for NH regression, the inventory of live pigs, and the pork production, suggest that local governments started to take action to shut down pig farms and/or the level of pig production in a year before the Regulation was officially launched in their counties. Except for the case of inventory of pigs, the β_j coefficients are negative but insignificant two years before the adoption and none of the β_j coefficients is significant for early years. Taken together, we find some evidence of negative anticipation effects in the year immediately before the adoption of the Regulation. Therefore, our estimated effects are lower bound estimates.

6.4 | Measurement errors of water pollution data

In the Introduction, we briefly mentioned the measurement error issue of the water pollution indices. Here we revisit this issue in more detail and formally demonstrate that the measurement error of the dependent variable is unlikely to be a real concern. There are two possible causes for the measurement errors. First, CNEMC only collect pollution information from the first-order river and the second-order river sections, but the rivers running across the counties are not necessarily all first-order of second-order rivers. Second, water pollutants could travel upstream to downstream, so the concentration of water pollutants for a given river section changes over time. However, we believe that the measurement error of the water pollution does not cause our estimates to be inconsistent. To illustrate this argument, we rewrite Equation (1) by accounting for measurement error of the dependent variable as follows:

$$Y_{it} + \rho\Delta_{it} = \beta_0 + \beta_1 Treat_{it} + W_{it}\gamma + E_{it}\theta + D_t + \varphi_i + \varepsilon_{it} \tag{4}$$

where Y_{it} denotes the true level of water pollution and Δ_{it} represents the measurement errors which vary by region and by time. Other variables were defined earlier. Moving the measurement error term to the right side of Equation (4) yields:

$$Y_{it} = \beta_0 + \beta_1 Treat_{it} + W_{it}\gamma + E_{it}\theta + D_t + \varphi_i - \rho\Delta_{it} + \varepsilon_{it} \tag{5}$$

Since Δ_{it} (the measurement error) is unobserved, it will be absorbed into the error term. It is clear from Equation (5) that the existence of Δ_{it} will lead to a biased and inconsistent estimator of β_1 only if Δ_{it} is correlated with both the Regulation implementation $Treat_{it}$ and the water pollution indices (Y_{it}). It is reasonable to assume that the measurement error of water pollution indices is not correlated with the implementation of the Regulation. Therefore, we argue that the measurement errors of water pollution indices are unlikely to cause inconsistent estimation of the coefficient β_1.

6.5 | Discussion on other possible biases of the estimates

The estimated effects of the regulation on environmental and economic indicators hold under the assumption of no indirect effects of the regulation on the treated or non-treated observations (counties). However, if indirect policy effects are present, the estimated results in our study may be biased.

First, the baseline results (Table 2) would be biased if there exist differentiated anticipation effects between the treatment group and the control group. Evidence from Figure A4 and Table A8 (online) helps us investigate this type of potential bias. The stable upward-trend of pig production and the stable downward-trend of pollution for the control group in Figure A4 suggest that the anticipation effect was absent in the control group. Meanwhile, the negative and statistically significant coefficient of *treat(i,t*-1) for some of the key outcome variables in Table A8 (online) (Columns 4, 6, 7) suggest that the treatment counties experienced a larger reduction in pig production than the control counties prior to the implementation of the programme. This finding, together with the fact that anticipation effects are absent in the control group, suggests that pig farms in the treatment counties anticipated the incoming regulation and started to reduce production the year prior to the implementation of the regulation. The existence of such negative anticipation effects in the treatment counties and the absence of anticipation effects in the control group imply that the DID estimates would be unambiguously biased downwards.

Second, pig farms' adjusting behaviours (relocating farms from treatment counties to control counties) after the implementation of the regulation is another possible source of biases of the DID estimates. It is clear that if adaption behaviours exist, failing to account for such behaviours would lead to an upward bias of the baseline DID estimates no matter where the treatment farms were relocated. The fact that the estimated effects are the smallest when counties within own provinces or cities (C, Table A6, online) were chosen as the control group, and the largest when counties from outside of own provinces (A, Table A6, online) were chosen as the control group tends to suggest that pig farms are most likely to be relocated to control counties outside of provinces, which is consistent with the reality in China (National Plan of livestock pig production development plan [2016–2020][15]). Under this reasonable assumption that pig farms in treatment counties were relocated mostly to outside provinces, the results

[15]http://www.moa.gov.cn/nybgb/2016/diwuqi/201711/t20171127_5920859.htm. According to the website, the regional arrangements of livestock pig production in China is to move from eastern and middle areas to south-western and north-eastern areas.

using counties from outside provinces as the control group (Panel A) would give us most upwardly biased estimates of the regulation effects (upper bound estimates), and those using counties within own provinces/cities as the control group (Panel B) would likely give downward biased estimates (lower bound estimates) with the biases caused by the anticipation effects mentioned above. Taking the estimated policy effects on the number of pigs slaughtered as an example, the estimated regulation effect ranges between –0.131 (Panel A) and –0.072 (Panel C). The estimated effect in Table 2 is –0.083, comfortably falling in between these two estimates (–0.72. –1.31).

Overall, farmers' anticipation behaviours are likely to cause the underestimation of the baseline DID estimates, while farmers' relocation behaviours are more likely to cause overestimation of the baseline DID estimates. Although it is hard to determine the comprehensive influence of these two forces, the fact that farmers are more likely to relocate to counties in different provinces (which is further evidenced in our analysis) allow us to be more certain that the estimates using counties within own provinces as the control group gives us the lower bound estimates and the baseline DID estimates are also reasonable. Future research with more detailed information on adaptation behaviours at the farm level would help obtain more accurate quantification of the policy impacts.[16]

7 | DISCUSSION AND CONCLUSION

With an increasing body of literature evaluating the impact of government regulations to improve environmental conditions by interfering with agricultural or industrial production in China and elsewhere, few studies have rigorously analysed the causal effects of these regulations and even fewer have looked at both the environment impacts and the potential costs of these regulations. We take advantage of a unique policy regulation, where implementation was gradually phased in across regions, allowing us to rigorously evaluate the effects of the regulation on both the intended outcomes and the unintended consequences. Our research provides both empirical and policy insights.

Empirically, we find that while the regulation has led to a significant reduction of only one of the four livestock-related water pollutants, it has significantly reduced the number of livestock farms and the associated livestock production. More specifically, the regulation has caused 8% reduction in the number of pigs slaughtered, 10% reduction in inventory of pigs, and 11% reduction in pork production. These main results are consistent across a series of robustness checks and are unlikely to be driven by pre-selection biases or other confounding effects.

A back-of-the-envelope calculation reveals that the economic cost of the regulation overshadows the environmental benefits. Based on 2016 Chinese livestock production and price data, an 11% reduction in pig production is equivalent to a loss of $24 billion of pig production value. Such a loss accounts for nearly 2.9% of the total output value of China's entire agricultural sector. And this cost figure is a conservative estimate for two reasons. First, it only includes the direct costs of pig production. The potential negative consequences on trade, industry and consumers due to pork price changes are not considered in this estimate. Second, the cost estimate would be bigger had we used livestock data from years earlier than 2016 for our calculation (see Table A9 in Appendix S1, online). As far as benefits are concerned, the regulation only reduced the NH_3-N pollutant, but it had no significant effect on other types of water pollutants, suggesting that the original goal of pollution control was only achieved

[16]The price estimates in Column 8 of Table 4 are likely to be downward biased because through trade (and price arbitrage) pork price might increase across all (treated and non-treated) counties as a result of the pork production reduction caused by the introduction of the regulation. Therefore, we consider the estimated pork price effects (Column 8, Table 4) to be a conservative estimate. (We thank an anonymous reviewer for bringing this to our attention.).

partially and ineffectively. Another potential explanation for the mixed effect of the regulation obtained for environmental indicators might be caused by the fact that pork farms located further away from the rivers (which are not subject to the regulation) might be a source of the water pollution if, as seems likely, small rivers or canals stream into (and pollute) rivers targeted by the regulation. As only the pollution of the first-order and second-order rivers are captured in our sample, we are not able to detect the amount of water pollution of small streams, so the regulation effect on environmental indicators could not be fully captured. If we had data of these small streams, the pollution results might be more significant. Unfortunately, without detailed data, we are not able to make sure whether this is a reality. This is left for future research.[17]

On the policy front, striking the balance between environmental quality and economic development through regulatory changes is not a straightforward issue. Prior to the implementation of a regulatory policy, more careful pre-regulation research is needed to help understand the link between production and pollution and the potential negative consequences of implementing such a regulation. Although it is difficult to pinpoint the exact reason why closing down a large number of livestock operations did not lead to a noticeable environmental improvement, we could think of a number of possible explanations for such seemingly unexpected results. One possible explanation is that many livestock farms, especially those professional large-scale farms, may contribute little to the overall water pollution.

As early as 2003, the Chinese government implemented a discharge standard of pollutants for livestock and poultry production (GB18596-2001).[18] The discharge standard varies by the nature of livestock industry and is set according to their characteristics of pollution emissions. The prescribed control environmental items include biochemistry indicators, hygienic indicators, sensory indicators and environmental standard for harmless residuals. The Standard has been implemented in stages according to livestock farms' operational scales. In fact, the technology adoption, proper spatial distribution and pollution control of large-scale pig farms across China have already been achieved, which largely resulted from the implementation of the Standard. It is worth noting that the discharge standard is only aimed at intensive, large-scale livestock farms or zones of large-scale livestock farms, and does not apply to small-scale scattered livestock farms. With the implementation of the Standard, the number of large-scale farms (with more than 500 pigs slaughtered annually) increased from 22% in 2007 to 55% in 2016 (China livestock yearbook), a 1.5 times increase over a 10 year period. During the same time period, small-scale scattered farms decreased by more than half, from 82.2 million to 39.7 million. With the gradual tightening of the environmental protection policy, the livestock production structure is increasingly optimised. For example, the level of large-scale farming as well as the adoption of environmental protection technologies has both considerably increased. In this case, it is not surprising that the Regulation, which indiscriminately forces many large-scale pig farms to shut down their operations, has contributed very little to water pollution reduction.

Livestock production wastes is one of the main sources of water pollution, and the mechanism of water pollution with this waste and the magnitude of pollution caused by livestock wastes have been largely confirmed by studies in the fields of agronomists and chemists. Our research has shown that the Regulation achieved limited environmental benefits but has a high economic cost. If a large number of large-scale farms have already met the environmental protection standards, a regulation that indiscriminately shut down many livestock farms is likely to achieve little but could lead to a large cost. The more effective alternative

[17]We are grateful for this explanation, proposed by an anonymous reviewer, which helped us understand this result from a new perspective.

[18]https://m.dowater.com/Standards/2009-05-02/6599.html

policy regulation should be able to distinguish farms by their operational scale and adoption of environmental control technologies, instead of the 'one size fits all' regulation.

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