The Impact of China's Place-based Environmental Regulations on its Hog Industry: A Synthetic Difference-in-differences Approach*

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Abstract: Agricultural water pollution from the livestock industry is a growing concern in China and globally. As opposed to size-based regulations targeting larger facilities as in the United States, China's regulations are place-based in nature. In 2014, China classified eight urban provinces in the southeast as a Development Control Zone, which prohibits new hog facilities construction and encourages hog farms to relocate to other regions. Leveraging a novel identification strategy, synthetic difference-in-differences, and the place-based nature of China's environmental regulations, we provide one of the first systematic analyses of the impacts of the regulations on county-level hog and sow inventory. By relying on synthetic controls constructed with both county and year weights, synthetic difference-in-differences yields a more accurate and doubly robust estimate of regulations' treatment effects. Our results show that, on average, the 2014 regulations led to a 6.4% and 7.4% reduction in hog and sow inventories, respectively, from 2014 to 2017 in the treated counties in Development Control Zone provinces, mainly resulting from extensive margin changes due to the closures of existing hog farms. We also find the treatment effects vary substantially both within and across Development Control Zone provinces: wealthier urban provinces such as Zhejiang experienced greater reduction in hog and sow inventories of over 40%; and counties upstream of big cities or those designated as main hog counties saw steeper declines as well.

Key words: China, Hog, Synthetic difference-in-differences, Difference-in-differences, Agricultural water pollution, Place-based policy

JEL Codes: Q13, Q18, Q53, C23

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1 Introduction

Agricultural water pollution, especially resulting from livestock production, is a growing concern in China and globally. China's expansive hog production produces considerable manure, which leads to severe downstream water quality problems including eutrophication of rivers and lakes. A 2013 newspaper article reporting dead pigs floating in the Huangpu River in Shanghai exemplifies the growing concerns about the water pollution from the livestock industry in China, especially in urban areas (Bu, Hu, and Li, 2013). In response, China initiated sweeping environmental regulations to restrict hog production to improve water quality. As opposed to size-based regulations targeting large facilities as in the United States, China's regulations are place-based in nature. China's 13th Five-Year-Plan for Agriculture in 2015 announced "moving hog production away from waterways and crowed urban populations" and shifting production to the west and northeast. Starting in late 2014, eight urban provinces in southeast China—Jiangsu, Zhejiang, Fujian, Guangdong, Hubei, Hunan, Anhui, and Jiangxi provinces—were designated as a Development Control Zone (DCZ) in which regulations mandate closures of hog farms located near environmentally sensitive areas, prohibit the construction of new hog facilities, and encourage large hog farms to move to western provinces with higher environmental capacity or northeast corn-producing provinces (Ministry of Agriculture, 2017). These policies are widely blamed for causing drastic hog inventory reductions during the African swine fever (ASF) outbreak; however, there lacks a systematic evaluation of the effectiveness of the regulations in curbing hog production and improving water quality.

China swiftly implemented environmental regulations targeting DCZ provinces, yet their impacts remain understudied. According to China's statistical yearbooks, total annual hog inventory reduced 20-–25 million hogs from 2015-–2017.(National Bureau of Statistics of China, 2010-2017), which suggests that these regulations could be consequential in curbing China's hog production, consistent with anecdotal reports after the enactment of the regulations. However, the causal estimates of these regulations remain scant except for some descriptive industry reports[1] and Ji, Chen, and Jin (2018) who applied canonical difference-in-differences with variation in treatment timing to study the impact of closing scaled farms and found no noticeable water quality improvement. Large-scale commercial production facilities replacing smaller-scale hog farms further complicates estimating the impact of regulations.[2] Furthermore, several studies question the effectiveness of thee regulations in improving environmental quality. For example, Bai et al. (2019) demonstrate unexpected consequences (e.g., additional air and/or water pollution) in relocation areas. Hu et al. (2019) also discuss the possibility of higher chemical fertilizer use due to lower

[1] For example, Zhaoshang Securities estimated around a 20 million head reduction in hogs in southern provinces by the end of 2016 (Dong and Lei, 2017).

[2] The top 10 hog firms in China produce less than 5% of pork. Backyard production represented 40% of China's hog inventory before the 2018 ASF outbreak (Essig, 2020).

hog manure availability and additional water demand from relocated hog farms.

We provide the causal estimates of the impacts of China's place-based environmental regulations on its hog industry. We hypothesize that these regulations could result in significant reductions in hog and sow inventories in DCZ provinces that might lead to decreased downstream ambient ammonia nitrogen (NH_3) levels, which closely relate to agricultural production, especially hog manure. Additionally, we expect the treatment effects vary within and across affected DCZ provinces, which may result from heterogeneity across counties and provinces in terms of hog production level, proximity to waterbodies, and regulation timing. We also quantify the economic costs of the regulations borne by individual hog producers and the aggregate economic impact for DCZ provinces and the agricultural sector.

We use a novel identification strategy, synthetic difference-in-differences (SDID) (Arkhangelsky et al., 2020). We label counties in the DCZ as treated units and non-DCZ counties as control units. Our main specification assumes uniform treatment time for 2014, which is when China implemented a suite of environmental regulations. By adjusting both county and year weights, SDID constructs a doubly robust synthetic counterfactual and thus, a more accurate estimate of the treatment effects. This estimator is doubly robust in that it is unbiased unless the constructed synthetic counterfactuals do not satisfy parallel pre-trends assumption and we concurrently misspecify our model. In contrast, a growing literature finds that parallel pre-trends assumption between the control and treatment groups are often violated in standard DID, and the synthetic control (SC) methods proposed by Abadie, Diamond, and Hainmueller (2010) often suffer misspecification problems. In addition, SDID allows us to uncover the separate treatment effect for each treated prefecture or province, allowing for different treatment timing. These heterogeneous treatment effects across and within provinces help identify the causal channels of how these place-based environmental regulations affected construction and relocation of hog facilities.

To quantify the treatment effects of the 2014 regulations, we combine multiple datasets with extensive information on the hog industry and environmental quality. In particular, we combine annual hog and sow inventory data from 112 province-level statistical yearbooks and 789 prefecture-level statistical yearbooks; thus, our dataset contains hog inventory in 726 counties and sow inventory in 107 prefectures from 2010 to 2017. Specifically, this dataset covers 436 counties and 75 prefectures in DCZ provinces. Due to SDID's computational demands, our main specification uses Least Absolute Shrinkage and Selection Operator (LASSO) to select four covariates—province-level pure chemical fertilizer consumption, prefecture-level sown area, cattle inventory, and pure chemical fertilizer consumption. Furthermore, we use weekly ambient water quality data from 60 of China's national surface-water-quality stations directly downstream of hog counties. To prevent the impact of chemical fertilizer, a large NH_3 contributor, we only average the last 8-week NH_3 which mostly lies in the post-harvest season, as the index of water quality. We quantify the economic costs of the regulations using back-of-the-envelope calculations and a Computable General Equilibrium (CGE) model of China's subnational economies calibrated to a 30

provinces by 30 sectors Multi-Regional Input-Output table (He et al., 2021).

Our main results reveal that, on average, the 2014 regulations led to significant reduction in hog and sow inventories in affected provinces and counties. On average, counties in DCZ provinces saw 6.4% and 7.4% reductions in hog and sow inventories, respectively, compared to non-DCZ provinces, mainly from extensive margin changes through closures, as opposed to relocation, of existing hog farms. In addition, SDID estimations of the treatment effects for each treated prefecture reveal substantial heterogeneity across and within treated provinces. Our results also show that counties located upstream of big cities in DCZ provinces and those with hog production as the pillar industry saw steeper declines in hog inventory numbers than other counties did.[3] Furthermore, our results show that the regulations caused huge direct monetary loss in treated provinces and indirect loss, including welfare and labor productivity losses, in all of China. Finally, our preliminary water quality results do not find statistically significant evidence that the regulations led to noticeable improvements in water quality.

Our research contributes to three strands of literature. First, we provide one of the first systematic evaluations of the consequences of China's recent environmental regulations on its livestock industry, in particular, hog and sow inventories, and the associated economic costs. As opposed to previous analyses (Bai et al., 2018, 2019; Hu et al., 2019), we provide spatially-explicit causal estimates of the regulation impacts. Our results provide empirical evidence that the 6%-7% reduction in hog and sow inventories in the DCZ, which translates to less than 5% reduction nationwide, were not large enough to trigger the dramatic hog and pork price hikes after 2018's ASF outbreak. Our focus on the livestock industry is important because previous literature tends to focus on China's industrial emissions regulations (Cai, Chen, and Gong, 2016; Wu et al., 2017; Chen et al., 2018; Shen, Jin, and Fang, 2017); however, agricultural nutrient runoff is often the major source of pollution in southern China's rivers and lakes (Luo et al., 2015; Li, Yungui, and Tianzhi, 2008; Wang et al., 2011; Du and Luo, 2013). Other literature studies the relationship between backyard hog production and market development in China (Qiao et al., 2011), the impacts of hog barns on nearby house values (Lawley, 2021), size-based environmental regulations on hog industry structure (Azzam, Nene, and Schoengold, 2015), and the effects of concentrated hog production on ambient air pollution (Sneeringer, 2010). Our paper stresses the hog industry's responses from China's environmental regulations targeting on water pollution. Although our results of inconclusive downstream water quality improvements are preliminary due to data limitations, we show that the regulations resulted in significant economic loss for affected counties in DCZ provinces.

Second, to the best of our knowledge, ours is the first article applying SDID to agricultural economics topics, and we demonstrate that SDID is beneficial for evaluating place-based regulations. SDID provides more accurate and robust estimates of regulation impacts because it can mitigate misspecification of both DID and SC with proper controls or counterfactuals, and it satisfies double robustness properties.

[3] We define a big city as a province capital or mega city with a population of 10 million or more permanent residents.

SDID's consistency relies on either the correct model specification or well-chosen weights, but not both (Arkhangelsky et al., 2020). Our application demonstrates that standard DID fails the critical parallel pre-trends assumption in our context, and could yield biased estimates. A difference in pre-treatment levels between the control and treatment groups also exists in our context, which could relate to the future trends, leading to more implausible context for DID application (Kahn-Lang and Lang, 2020). In contrast with Ji, Chen, and Jin (2018) which uses a canonical DID on a similar topic, our methodology improves on theirs on two fronts: 1) by constructing a synthetic counterfactual using both unit-specific and time-specific weights, SDID method relaxes the parallel pre-trends assumption embedded in DID; 2) it also facilitates estimation of unit-specific treatment effects for each treated province and prefecture. SDID is not without limitations—it is data-intensive, and requires a strongly balanced panel and a uniform treatment timing in each estimation. We bypass these restrictions by also estimating the SDID treatment effects separately for each province and prefecture, in which we use different treatment timing at the province level.

Third, this article contributes to a growing literature on the effects and effectiveness of place-based regulations. Most previous studies in urban and labor economics focus on place-based policies that provide jobs and public service assistance and subsidies to underperforming or distressed areas (Neumark and Simpson, 2015; Bartik, 2020; Koster and Van Ommeren, 2019). Other than Garg and Shenoy (2020), Wang, Wu, and Zhang (2018) and Chen et al. (2019), place-based policies related to environmental protection or resource allocation from resource-rich zones are understudied. Only a few studies, including Kolko and Neumark (2010), Fujishima, Hoshino, and Sugawara (2020), Briant, Lafourcade, and Schmutz (2015) and Lu, Wang, and Zhu (2019), explore heterogeneity in the treatment effects of place-based policies in terms of regional characteristics. Our research, which focuses on place-based regulations targeting hog facilities closure and downstream water quality improvements, can provide more evidence of the effectiveness of non-economic-growth-driven place-based regulations. Our results show that these place-based policies could have substantial variation in the distribution of treatment effects, which, in our case, leads to significantly higher hog inventory losses in regions with higher economic development and more stringent environmental regulations. This suggests the need to better understand the political economy in the implementation of these prevalent place-based policies and the resulting economic impact.

2 Institutional Background

2.1 Water Pollution Caused by China's Hog Production

Each year 750,000 people die prematurely as a result of air or water pollution (World Bank, 2007). In the past few years, most research attention focused on pollution from industrial activities; however, livestock pollution accounts for 45% of total chemical oxygen demand (COD) emissions, 95% of agricultural

COD emissions, 25% of total NH_3 emissions, and 79% of the agricultural NH_3 emissions (Ministry of Agriculture and of Environmental Protection, 2013).

In 2017, China's hog industry total production value was nearly 1.3 trillion RMB (U.S. $250 million), accounting for more than half of its livestock production (Bu, Hu, and Li, 2013), which could result in severe manure production and water pollution. Additionally, water used for daily cleaning of large hog facilities is shown to potentially yield 100–150 m^3 waste water with an average 1,500mg/L COD, 1,200-–1,300mg/L biological oxygen demand (BOD), 1,100mg/L nitrogen, and 440mg/L phosphorus(Liu and Sima, 2017).

2.2 Environmental Regulations

On January 1, 2014, China's central government published **Regulation on the Prevention and Control of Pollution from Large-scale Breeding of Livestock and Poultry**, which officially requires local governments to regulate livestock industry emissions by establishing livestock control zones and limiting hog breeding quantities and production scales for hogs and other livestock. In late-2014 and 2015, China rolled out more stringent regulations, including **Environmental Protection Law of the People's Republic of China (2014 Revision)** and the **Action Plan for Prevention and Control of Water Pollution**, which exerted more pressure on local governments to control livestock emissions in order to improve downstream water quality.

Figure D1 shows China's hog development zones. China's regulations divide all provinces into four hog development zones with differing regulations and policies that encourage or discourage livestock production. There are significant restrictions on new and existing hog production facilities within the DCZ.[4] The eight provinces in the DCZ accounted for 37% of pork production in 2014 and are currently dealing with rising environmental concerns due to their high population density and complex waterways (Ministry of Agriculture, 2017). China's regulations are more stringent in DCZ provinces located near environmentally sensitive or population-dense areas and encourage closing or relocating hog facilities to other provinces. The regulations explicitly required all livestock farms in environmentally sensitive areas to close or relocate by the end of 2017, though some places were required to do so by the end of 2016. Although the regulations initially focused on environmentally sensitive and population dense areas in DCZ provinces, in reality, many cities and provinces in the DCZ implemented expansive policies closing existing hog facilities.

[4]The DCZ includes mega cities such as Beijing, Tianjin and Shanghai, which collectively only accounted for 1.3% of pork production in 2014 (Ministry of Agriculture, 2017), and thus, we do not include them in our analysis.

2.3 Regulation Implementation

China published the first nationwide regulations in early 2014. Some counties, such as Wuyi (Zhu, Zhang, and Zhu, 2015), Lanxi (Soozhu Website, 2015), and Yiwu (Yiwu Bureau of Statistics, 2014) in Zhejiang province began setting up control zones in 2013; however, most counties in DCZ provinces implemented the regulations in 2014. While closure and relocation are both mechanisms of the regulations, closure has been the dominant implementation (see section 4). We find evidence of relocation; however, that option is limited due to associated financial and time costs.

In general, provinces with higher economic development and denser populations face greater environmental pressures, and thus, adopted stricter, and sometimes simpler, hog closure approaches. For example, all hog facilities in the city of Sihui in prosperous Guangdong Province are required to close regardless of production scale or location inside or outside environmentally sensitive areas (Yi, 2017). Similarly, Zhejiang Province expanded measures in 2017 to target smaller-scale and backyard hog farms (Free Trade Website, 2016). In contrast, poorer provinces such as Anhui and Jiangxi did not achieve hog reduction goals until late 2017. In 2017, other provinces outside the DCZ started developing and initiating policies restricting hog production in environmentally sensitive and population-dense areas. However, these policies quickly halted due to the 2018 ASF outbreak.

To ensure effective regulation implementation, China's Ministry of Environmental Protection and MOA conducted four rounds of environmental inspections from early 2016 to late 2017 (Zhang, 2017). Producers found to have broken environmental regulations were referred to the local government for further investigations and punishments.

3 Empirical Design

3.1 Benchmark: Difference-in-differences

Our main objective is measuring the treatment effect of livestock regulations on hog and sow inventories and NH_3. We designate counties in DCZ provinces as treatment counties and use DID as our benchmark, a common econometric approach to identify the causal relationship between two variables and address omitted variable bias with parallel pre-trends assumption satisfied (Currie et al., 2015; Haninger, Ma, and Timmins, 2017; Zabel and Guignet, 2012). A growing literature employs this method to identify the average treatment effect on the treated (ATT) (Tang, Heintzelman, and Holsen, 2018; Abadie, Diamond, and Hainmueller, 2010; Dobkin et al., 2018). DID enables us to identify the within-variation in dependent variables over time due to regulation implementation during the study period and the between-variation in dependent variables at a given time across space from the differences in regulation implementation between DCZ provinces and non-DCZ provinces.

Empirically, we specify the corresponding regression model for DID as follows, where equation (1)

uses county-level hog inventory or NH_3 level from the nearest monitoring station as dependent variables, and equation (2) uses sow inventory at prefecture level:

$$Y_{crpt} = \alpha_0 + \alpha_1 Regulation_{crp} + \alpha_2 Post_{crpt} + \tau Regulation_{crp} \times Post_{crpt} + \epsilon_{crpt} \tag{1}$$

$$Y_{rpt} = \alpha_0 + \alpha_1 Regulation_{rp} + \alpha_2 Post_{rpt} + \tau Regulation_{rp} \times Post_{rpt} + \epsilon_{rpt} \tag{2}$$

where Y_{crpt} is the log of hog inventory and NH_3 level in county c prefecture r province p at time t; Y_{rpt} is the log of sow inventory in prefecture r province p at time t; dummy variable $Regulation_{crp}$ equals 1 if in county c prefecture r province p where province p is in the DCZ treatment region and 0 if not implementing the policy (in the control group); and, $Post_{crpt}$ indicates post-treatment periods and equals 1 if county c prefecture r province p implemented the regulations at time t. Similarly, equation (2) shares the same regression settings, except the independent variables are at prefecture level, where τ represents the expected change in log of hog inventory (or log of sow inventory, NH_3 level) for the treated group, less the expected change for the control group. For brevity, we use equation (1) (county-level) to illustrate the treatment effects estimation:

$$\begin{aligned} \tau =& (E[Y^1_{crp1}|Regulation_{crp} = 1] - E[Y^1_{crp0}|Regulation_{crp} = 1]) \\ &- (E[Y^0_{crp1}|Regulation_{crp} = 0] - E[Y^0_{crp0}|Regulation_{crp} = 0]) \end{aligned} \tag{3}$$

where the superscripts on Y denote the counterfactual regulation status (1 if implemented, 0 otherwise) regardless of actual implementation status.[5] The main identifying assumption underlying the model above is parallel pre-trends:

$$\begin{aligned} &E[Y^0_{crp1}|Regulation_{crp} = 1] - E[Y^0_{crp0}|Regulation_{crp} = 1] \\ &= E[Y^0_{crp1}|Regulation_{crp} = 0] - E[Y^0_{crp0}|Regulation_{crp} = 0] \end{aligned} \tag{4}$$

This assumption implies that, in the absence of regulation implementation, the potential hog inventory (sow inventory, NH_3 level) in the treated group would follow the same trend as that in the control group.[6] Under this assumption, τ measures the ATT. In our case, the parallel pre-trends assumption could be difficult to satisfy because the DCZ and non-DCZ provinces could have very different characteristics. Failing to control for these observable covariate differences (X_{crpt} or X_{rpt}) may invalidate the parallel pre-trends assumption. Following Aronow and Samii (2016) and Solon, Haider, and Wooldridge (2015), we also incorporate the county- and year-fixed effects to control for time-invariant unobservables and

[5] For sow inventory, the corresponding equation is $\tau = (E[Y^1_{rp1}|Regulation_{rp} = 1] - E[Y^1_{rp0}|Regulation_{rp} = 1]) - (E[Y^0_{rp1}|Regulation_{rp} = 0] - E[Y^0_{rp0}|Regulation_{rp} = 0])$

[6] Similarly, the identification assumption for sow inventory is $E[Y^0_{rp1}|Regulation_{rp} = 1] - E[Y^0_{rp0}|Regulation_{rp} = 1] = E[Y^0_{rp1}|Regulation_{rp} = 0] - E[Y^0_{rp0}|Regulation_{rp} = 0]$

macroeconomic trends, respectively, which results in the following familiar two-way fixed effects model:

$$Y_{crpt} = \alpha_0 + \lambda_c + \sigma_t + \tau Regulation_{crp} \times Post_{crpt} + \gamma_1 X_{1,rpt} + \gamma_2 X_{2,pt} + \epsilon_{crpt} \tag{5}$$

where λ_c and σ_t are county- and year-fixed effect, respectively. X_{rpt} and X_{pt} are vectors that represent characteristics of prefecture r province p at time t, and characteristics of province p at time t. For sow inventory, we also add the covariates X_{rpt} and X_{pt}.

We add province-level and prefecture-level covariates as well as their one-year lag variables because, even though we incorporate county-fixed effect and time-fixed effect, the changes over time across provinces or prefectures or counties might be different; thus, there could be some unobservables we cannot capture at prefecture or province level. Due to the high computational demands of SDID, we cannot incorporate all relevant covariates. Instead, we use LASSO to select variables with non-zero coefficients as covariates—province-level pure chemical fertilizer consumption, prefecture-level sown area, cattle inventory, and pure chemical fertilizer consumption. Omitting these covariates could lead to endogenous problems. Local chemical fertilizer is generally considered as a substitute to organic fertilizer like hog manure; however, prefecture- or province-level chemical fertilizer could be complimentary to county-level hog manure as the central government is also trying to limit the chemical fertilizer consumption in treated provinces to curb water pollution. County fixed effects may only capture the local relation and not region-level changes. Similarly, hog and cattle are locally substitutes; however, county-level hog and prefecture-level cattle could be complimentary as the prefecture-level livestock industry is restricted to producing in a treated province. Missing the prefecture-level cattle inventory would lead to estimation bias.

Empirically, we can test the parallel pre-trends assumption by interacting the regulation status dummy variables with year dummy variables, as follows.

$$Y_{crpt} = \lambda_c + \sigma_t + \gamma_1 X_{1,rpt} + \gamma_2 X_{2,pt} + \sum_{\tau=2010, \tau \neq 2014}^{2017} \alpha_\tau [1(t = \tau) \times Regulation_{crp}] + u_{crpt} \tag{6}$$

where λ_c is the county-fixed effect; σ_t is the year-fixed effect; and, X_{crpt} and $Regulation_{crp}$ are as previously defined. The parameter of interest is α_τ for $\tau = 2010, 2011, 2012, 2013, 2015, 2016, 2017$. We omit the treatment year 2014 for a dummy variable trap. α indicates the difference between the control and treatment groups in each year after holding the covariates. If α_{2010} to α_{2013} are statistically insignificant and α_{2015} to α_{2017} are statistically significant, the parallel pre-trends assumption holds. This means that there is no significant difference in hog inventory (sow inventory, NH_3) between treatment and control groups in the pre-treatment periods, while the difference is quite significant in the post-treatment periods.

3.2 Identification Problems of Difference-in-differences

The DID estimator is unbiased if and only if the parallel pre-trends condition specified in equation (4) is satisfied. However, as discussed, the treatment and control provinces differ significantly in their economic development level, livestock feed stock, and environmental capacity. Furthermore, Kahn-Lang and Lang (2020) point out that DID is generally more plausible if the treatment and control groups are similar in levels to begin with, not just in trends, even when the parallel pre-trends assumption is satisfied. Figure D2 provides the descriptive evidence that the treatment and control groups share neither similar trends nor similar levels in the pre-treatment periods; thus, if the empirical parallel pre-trends test passes, we still cannot be sure of unbiased DID estimates.

We can rewrite the misspecification of DID on both levels and trends in econometrics language. Following Arkhangelsky et al. (2020) we write DID counterfactuals as the simple average outcomes across all control units and pre-treatment periods plus two bias-adjusting items (see Appendix A). The bias-adjusting items map to the difference in levels between the treatment and control groups (α_1) and the difference in trend in the control (α_2) group. However, these two items do not perfectly adjust bias, which is why we use SDID in our article.

3.3 Synthetic Difference-in-differences

The SDID method can significantly alleviate DID's identification problems by constructing a new synthetic counterfactual using unit-specific and time-specific weights. SDID assigns higher weights to control units that are more similar to the treated units and to time periods that correlate more with post periods, making it more reliable.

SDID is suitable for either a large number of treatment units or a large number of post-treatments periods, which is where our context meets this assumption.

SDID adjusts the bias of DID estimator in two dimensions. By generating unit weights denoted as ω_n and a new SC, the time trends among the SC and the treated units can match (see figure 1b). However, the generated SC may not perfectly match the trend of treatment group. Figure 1b also shows an example of mismatched pre-treatment periods—the green and red lines in the pre-treatment periods do not overlap, especially the last pre-treatment period, which could lead to the overall generated counterfactual bias. For the second adjustment, SDID introduces time-specific weights. By assigning higher weights to the most recent periods, we can further narrow the bias of the two trends near the implementation timing. Figure 1c provides an example of the SDID SC overlapping with the trend of the treatment group in the last two pre-treatment periods, thus reducing the bias of the SC method. To distribute more uniform weights to more units, we introduce ridge regression penalty and intercept terms, thus adding extra flexibility to generating $\hat{\omega}_n$ (see equation (26)). Similarly, we generate $\hat{\lambda}_t$ by minimizing the gap between the pre- and post-treatment periods for the control units (see equation (27)).

Other than $\hat{\omega}_n$, we do not add ridge regression terms for $\hat{\lambda}_t$ because we want the weights to concentrate on the most recent pre-treatment periods as these periods are more related to the post-treatment periods. See Appendix A for details about how we generate $\hat{\omega}_n$ and $\hat{\lambda}_t$.

Similar to the two-way fixed effects DID, we incorporate the unit fixed effect and time fixed effect in our estimation, as follows:

$$(\hat{\tau}^{SDID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = argmin \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{nt} - \mu - \alpha_n - \beta_t - W_{nt}\tau)^2 \hat{\omega}_n^{SDID} \hat{\lambda}_t^{SDID} \right\} \tag{7}$$

where Y_{nt} is the outcomes; $W_{nt} \in \{0, 1\}$ denotes exposure to the binary treatment; α_n and β_t are unit fixed effect and time fixed effect, respectively; and, τ is the parameter of interest.

SDID can generate covariates-adjusted outcomes, which can help to eliminate the time-varying variation of Y_{nt} from covariates. The corresponding adjustments are:

$$(\hat{\tau}_{\gamma}^{SDID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}, \hat{\gamma}) = argmin \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{nt} - \mu - \alpha_n - \beta_t - X_{nt}\gamma - W_{nt}\tau)^2 \hat{\omega}_n^{SDID} \hat{\lambda}_t^{SDID} \right\} \tag{8}$$

As mentioned in section 2, each province may have their own implementation timing. One implementation timing may not accurately measure the ATT of the regulations; thus, we separately estimate the ATT for each province regarding their own implementation timing:

$$(\hat{\tau}_{\gamma}^{SDID,i}, \hat{\mu}^i, \hat{\alpha}^i, \hat{\beta}^i, \hat{\gamma}^i) = argmin \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{nt} - \mu - \alpha_n^i - \beta_t^i - X_{nt}\gamma^i - W_{nt}\tau^i)^2 \hat{\omega}_n^{SDID,i} \hat{\lambda}_t^{SDID,i} \right\} \tag{9}$$

where superscript i indicates different treated provinces.

In the same way, we can express DID and SC estimation as:

$$(\hat{\tau}^{DID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}, \hat{\gamma}) = argmin \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{nt} - \mu - \alpha_n - \beta_t - X_{nt}\gamma - W_{nt}\tau)^2 \right\} \tag{10}$$

$$(\hat{\tau}^{SC}, \hat{\mu}, \hat{\beta}, \hat{\gamma}) = argmin \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{nt} - \mu - \beta_t - X_{nt}\gamma - W_{nt}\tau)^2 \hat{\omega}_n^{SC} \right\} \tag{11}$$

DID estimation uses equal county weights $1/N_0$ and year weights $1/T_0$, respectively, where N_0 is the number of control counties and T_0 is the number of pre-trend periods. For SC estimation, DID only uses unit-specific weights $\hat{\omega}_n^{SC}$ and equal year weights $1/T_0$ and does not contain a unit fixed effect α_n. Omitting fixed effects or incorporating invariant weights could increase the possibility of misspecification, thus leading to biased estimates.

However, note that the SDID application has several limitations. First, we must assume uniform

treatment timing across treated units, as treatment with variation in timing is not suitable for this method. Moreover, SDID requires strongly balanced panel data; thus we must eliminate samples with missing values. Lastly, SDID is computationally demanding and time-consuming; thus, we use LASSO to perform variable selection[7]. We choose four variables with non-zero coefficients,[8] which can increase efficiency and retain accuracy.

4 Data

4.1 Data Sources and Variables

Our data contains hog inventory of 726 counties from 14 provinces (Zhejiang, Jiangsu, Fujian, Guangdong, Anhui, Hunan, Hubei, Sichuan, Hainan, Yunnan, Gansu, Shandong, Henan, and Hebei) and sow inventory of 107 prefectures from 10 provinces (Zhejiang, Fujian, Guangdong, Anhui, Hunan, Hubei, Sichuan, Shandong, Henan, and Hebei). All hog and sow inventories are annual year-end data with unit head. We collect data from 112 provincial statistical yearbooks and 789 prefecture statistical yearbooks from 2010 to 2017 (see Table C7 for access details). We make efforts to verify hog inventory data from statistical yearbooks, as some counties based their data on the Third National Agricultural Census.[9] We transpose the data into log form for easier explanation.

Our second dataset is weekly national station-level NH_3 in unit milligram per liter (mg/L) from 2010 to 2017 obtained from China National Environmental Monitoring Center (2010-2017), which reports four indicators—NH_3, COD, pH, and dissolved oxygen (DO). Figure D5 shows the water station locations in our sample. We choose NH_3 as our measure for water quality as it mainly comes from agricultural activities rather than industrial activities. We exclude COD because it's hard to distinguish if a change came from regulations related to hog manure or industrial activities, and we exclude pH and DO due to their high single-day variation rates, which leads to identification difficulty. We construct the water quality dependent variable as an average of the last 8-week NH_3 data, as that is when almost all crop production is finished, thus there is less chemical fertilizer consumption and lower river water volume, enabling more accurate NH_3. Moreover, the whole-year variation is quite large for NH_3, and averaging it across the year could generate a variable with low variation conditional to precipitation.

The first regulation came in early 2014, thus we define the pre-treatment period as 2010–2013 and the post-treatment period as 2014–2017. We perform a robustness check on the county-level implementation timing in section 5. In addition, we give each county the same implementation timing as there may be a spatial spillover effect; that is, one county may follow the behavior of another nearby county as

[7] First, we use cross validation to choose tuning parameter lambda, which minimizes mean square predicted error, then we use this lambda to select variables.

[8] LASSO can help to do variable selection by assigning unimportant variables zero coefficient.

[9] Some statistical yearbooks report all previous years' hog inventory, thus we can compare if all the hog inventory data is the same using statistical yearbooks from subsequent years.

there is promotion competition among same-level local officials, implying an incentive to mimic others' behaviors.

Furthermore, we collect four groups of time-varying covariates from the statistical yearbooks: (a) year-end provincial-level economic variables including GDP, population, and sex ratio; (b) year-end province-level agricultural variables including pure consumption of chemical fertilizer, sown area, corn yield, soybean yield, grain crops yield, cattle inventory, goat inventory, large livestock inventory and one-year lag pure consumption of chemical fertilizer; (c) year-end prefecture-level economic variables including urban-rural income ratio, GDP, and population; and, (d) year-end prefecture-level agricultural variables including sown area, grain crops yield, cattle inventory, goat inventory, pure consumption of chemical fertilizer as long as one-year lag sown area, cattle inventory and pure consumption of chemical fertilizer. We do not collect county-level covariates as that could lead to missing values. SDID requires balanced panel data, thus, using county-level covariates would shrink our sample size. Furthermore, SDID is computationally demanding; thus, we choose four covariates—provincial pure fertilizer consumption, prefecture-level sown area, cattle inventory, and pure fertilizer consumption—with non-zero coefficients in LASSO regression, which can eliminate computational work and provide reliable estimates.[10]

Finally, precipitation data comes from Famine Early Warning Systems Network Land Data Assimilation System (McNally, 2018). The data are in 0.10-degree resolution and range from January 1982 to present. We match the location of water station to the nearest recording location based on longitude and latitude and average the data across months.

4.2 Summary Statistics

Table 1 presents descriptive statistics of the dependent variables and covariates. We replace the direct difference between the treatment and control groups with a standardized difference. As table 1 shows, the difference between the control and treatment groups in pre-treatment periods is greater than 0.1,[11] indicating an imbalance. The positive difference of hog inventory indicates that the treated units have higher hog production scale at the county level when compared to control units. Note that the sow inventory seems to provide opposing evidence that the control group raises more hogs than the treatment group. This is because we aggregate sow inventory at the prefecture level and aggregate hog inventory at the county level due to data availability; furthermore, both the number and the area of counties in control province prefectures exceeds those in treatment provinces. The control provinces are larger than DCZ provinces by area, which results in more sow inventory. NH_3 also has positive difference, implying that it could exacerbate water quality problems in DCZ provinces, as they contain dense waterways and

[10] Note that these covariates may be endogenous—either excluding them or keeping them could lead to bias of the estimation on the parameter of interest. The advantage of SDID in this case is its double robustness, which provides stable and reliable estimates despite possible misspecification. We also provide an robustness check using a genetic matching covariate that encompasses 20 characteristics.

[11] An absolute standardized difference of 0.10 or more may indicate that covariates are imbalanced between groups (see Austin (2009))

most major hog-producing counties.

For the covariates, the control and treatment groups do not share similarity in many dimensions—the huge difference in levels shows in both demographic and agricultural features, implying that the parallel pre-trends assumption is quite hard to satisfy. In our context, all the treated units are in southeastern China and the control units are in western China. Even though the western provinces are not similar to the southeastern provinces in many ways, DID still works as long as we can hold their difference, though it is quite hard to find enough covariates, another reason we use SDID in our regression—it can relax this assumption. Significant difference in precipitation estimates makes sense as a covariate, as the treated units are in a coastal area with high precipitation while the control units are the intra-continental areas with low precipitation levels.

Typically, the treatment group shows larger variation in most variables, which means that there is larger difference in each treated province as compared to a control province. Providing average treatment effect for all the treated units may cover the diversity of regulation effects across provinces or counties. SDID can uncover the heterogeneous effect of each province or prefecture.

We first provide preliminary evidence that hog facility relocation is not a major concern. We compare the total number of hog facilities in all non-DCZs provinces and the mean number of hog facilities across all non-DCZ provinces as well as the percentage of total hog inventory in non-DCZ provinces in nine different production scales before and after regulation implementation. Table C1 in Appendix C shows that the number of hog facilities decreases in the four smallest production scales and increases in the five largest production scales. However, the difference-in-mean is not statistically significant except for the largest production scale. Furthermore, the percentage of total hog inventory in all production scales do not change much, especially the large production scale group.[12] Moreover, even though the largest production scale presents significant change, the hog inventory in that group only accounts for 0.8% of total inventory in non-DCZ provinces where a significant increase in the number of hog facilities would not be a big problem, which implies that the 2014 regulations do not cause an obvious relocation phenomenon. As the regulations began in 2014 and it may take two-to-three years to build new hog facilities, production would not have begun at new facilities until the beginning of 2018, which is out of our estimation window.

[12] In some groups, the number of hog facilities decreases while the percentage of total hog inventory increases because the total post-regulation inventory also decreases, thus the facility's corresponding percentage increases.

5 Results

5.1 Results on Hog and Sow Inventories

5.1.1 Difference-in-differences

Our first set of results is the ATT of the regulation impacts on hog and sow inventories from the standard DID method.

Table C2 shows the DID results of hog and sow inventories as dependent variables without and with covariates. In models (3) and (6), we add all covariates, which give the positive coefficients. We can classify all the specifications as variants of the popular two-way fixed effects DID regressions (Goodman-Bacon, Forthcoming). For hog inventory regressions, the coefficients are all negative and statistically significant at the 10% level. However, conditioning on covariates gives a different estimate. Using all covariates with both year and county fixed effects, table C2 column (3) shows that the 2014 regulations led to roughly a 4.4% decline in hog inventory in DCZ provinces compared to control counties. The variability between columns (2) and (3) also suggests that missing important covariates would lead to very biased estimates. However, there is little difference between columns (1) and (2), implying that the time-invariant factors do not contribute much to adjusting the estimate bias. Compared to columns (1) and (2), column (3) gives a more accurate estimate.

For sow inventory, we build a dataset with post-treatment periods from 2014 to 2015.[13] We drop 2016–2017 from the post-treatment periods as the control provinces began clearing sow inventories, which could be a bad control for our analysis and cause overestimation of ATT on sow inventory. All sow inventory sector coefficients are negative and significant at the 10% level. Adding either fixed effects or covariates mitigates the underestimation.[14] Comparing columns (5) and column (6), the coefficients do not vary much, which demonstrates the the insignificance of covariates for sow inventory data. Column (6) still shows the most accurate coefficient, representing around a 7.4% reduction in sow inventory in DCZ provinces compared to non-DCZ provinces.

Before we commit to this estimate, we need to check the parallel pre-trends test following equation (6). Figure D3 in Appendix D shows the parallel pre-trends assumptions without and with covariates. If the assumption is satisfied, the coefficients of pre-treatment variables should not reject the null hypothesis: that is, the confidence interval should include zero. Figure D3 shows that for two-way fixed effects specification without (with) covariates, the test rejects (satisfies) parallel pre-trends assumption. Note our discussion in section 3.2—even if the parallel pre-trends assumption holds, we cannot assure our estimates are unbiased and accurate as the difference in levels and potential future trends in pre-treatment

[13] We also construct a dataset with all post-treatment periods from 2014 to 2017. The coefficients in the 2014–2017 dataset show positive but insignificant coefficients, implying an overall unchanged sow inventory overall after regulations (see table C3).

[14] Only adding fixed effect still changes the coefficient for sow inventory instead of hog inventory. This is possibly because we aggregate sow inventory at the prefecture level, which could lead to more differences in many dimensions when compared to county-level aggregate data.

periods are also concerns. As shown in section 4, our treatment and control groups have large differences in many covariates. The large variation and instability of the DID estimates also raises further concerns about the presence and severity of the omitted variable bias. As a result, it is worthwhile to use the SDID approach which has been shown to be doubly robust and more accurate (Arkhangelsky et al., 2020).

Figure D3 confirms the importance of controlling for agricultural conditions on province- and prefecture-level hog inventory and sow inventory. Omitting the covariates leads to a downward bias and overestimation of the magnitude of regulations' impacts. The agglomerative economies effect could make China's agricultural sector more inter-linked; however, the 2014 regulations impact all agricultural sectors. Including these in our model could mitigate the bias.

5.1.2 Synthetic Difference-in-differences

We estimate our SDID models based on Arkhangelsky et al. (2020), though that study does not use covariates. As a result, we also first present our SDID estimates without including covariates.

Table 2 columns (1) and (4) of replicate the two-way fixed effects DID results shown in table C2 with only county and year fixed effects and contrast them with the SC and SDID model estimates, neither of which incorporate covariates. Column (3) shows an SDID estimate of -0.0550, which is statistically significant at the 10% level. Sow inventory in column (6) shows an SDID estimate of -0.0732, statistically significant at the 10% level, which means that the average treatment effect of the hog and sow inventory treatment groups is around 5.5% and 7.3%, respectively; that is, the regulations helped reduce hog and sow inventories in DCZ provinces by 5.6% and 7.32%, respectively, compared to non-DCZ provinces. Compared to DID, SDID adjusts the overestimation of the magnitude of the DID estimate because it uses better counterfactuals and implicitly controls for province- and county-specific time trends. Similarly, the SC estimate has been adjusted upward in columns (2) and (5).

We use the *synthdid* package to construct and plot the SDID counterfactual and its comparison to the SC and DID counterfactual (see figure 2). Figure 2b indicates that, when only applying county weights, the SC pre-treatment periods are parallel until 2012. SC only uses unit weights; thus to deal with the dissimilarity between the treatment and the counterfactual from 2012 to 2013 we use SDID to incorporate year weights. Tables C5 and C6 in Appendix C show the sum of county-by-province-specific and time-specific weights. As figure 2b shows, incorporating year weights shifts the SC counterfactual down and makes 2012–2013 converge to the treatment line, which subtracts the SC overestimation. Moreover, figure 2c shows the comparison of SDID counterfactual and DID counterfactual—DID has the largest estimate and most nonparallel pre-trends, and SDID significantly mitigates the bias from both DID and SC.[15]

[15] The straight green line connects the pre- and post-trends average log of hog inventory in the control group that shifts along the black dotted line to estimate the DID ATT. The green area down the figure 2c represents the equal year weights for DID method.

The SDID model shown in table 2 does not include any covariates. Currently, it remains challenging to add many covariate variables in the *synthdid* R package; thus, we only add LASSO-selected covariates. Table 3 provides further robustness checks for the SDID estimates with different covariates that account for salient covariate controls for the time-varying variation of dependent variables from the covariates at first, then uses residuals to construct a synthetic counterfactual. Panel A shows SDID estimates for hog inventory, and column (5), which includes all covariates, indicates that the coefficient is around 6.4%. Similarly, panel B demonstrates the coefficients with and without covariates for sow inventory, which, in DCZ provinces, shows a significant 7.35% reduction. The coefficients rarely change across columns. Across all models with robustness checks shown in table 3, we find that the SDID estimates incorporating different covariate(s) are remarkably stable. This is, in fact, rooted in the SDID methodology and estimation procedure—when SDID estimates a regression that incorporates a new set of covariates, both the coefficients of covariates and the county weights and year weights are re-estimated to balance the pre-trends between the control and treatment groups. Through the adjustments of the county- and year-weights to balance pre-treatment outcomes, SDID adequately addresses the substantial variability shown in DID estimates due to covariates. Comparing the SDID estimates from tables 2 and 3 reveals that the SDID treatment effect estimates are also very robust and similar, even without covariates, providing more confidence and credence as to the true impacts of the policies.[16]

5.1.3 Heterogeneous Treatment Effects

We relax SDID's assumption of uniform treatment timing for all treated units for one particular regression by running a separate SDID regression using the treated counties or prefectures in one DCZ province only. Thus, we can uncover the heterogeneous province-specific or prefecture-specific treatment effects for each treated province or prefecture. We determine the province-specific implementation time as the time when more than 3 counties in a province report implementing the regulation. Column 1 in table 4 indicates the province-specific implementation timing and columns (2)–(3) show the effects of regulations on hog and sow inventories, which vary significantly across provinces. However, only Zhejiang, Fujian, Hunan and Hubei Provinces saw hog inventory declines that are statistically significant at the 10% level. Zhejiang Province reduced more than 50% of its hog inventory, followed by Fujian Province, which declined 25% hog inventory. Hubei and Hunan Provinces saw less than 10% hog inventory declines. For sow inventory, Zhejiang Province also reduced around half of its sow inventory and Fujian Province reduced around 20% sow inventory.[17] As an economically vibrant urban province, it is not surprising to see a larger treatment effect for Zhejiang Province. Numerous news sources demonstrate Zheijang Province's sweeping measures to close and regulate hog facilities—several "zero hog" counties bragged

[16] We also choose subsamples and use the genetic matching method to construct a new covariate using all 20 covariates. The SDID results are quite similar compared to those using LASSO-selected variables and genetic matching covariate.

[17] There is no sow inventory data available for Jiangsu Province.

they no longer have hog farms due to the drastic measures (Deng and Blue, 2014). However, the insignificant estimate for Guangdong Province, another key urban province, is surprising. Guangdong Province is home to many major hog production facilities and has several main hog-producing counties, and thus, we expect to see noticeable impacts of the regulations. One possible reason for the insignificant coefficient might be that Guangdong saw internal relocation of hog facilities. Figure 3 shows the SDID estimates for each prefecture in Guangdong Province—hog inventories in prefectures labeled in yellow rose as inventories in other regions fell, resulting in insignificant overall inventory changes. Another possible reason is that Guangdong Province began implementing closures of small-scale hog farms much earlier.

Figure 3 shows the extent of hog inventory changes in each prefecture in DCZ provinces. We find huge heterogeneity across provinces and among prefectures—Zhejiang Province saw the most severe hog inventory reduction and Anhui Province experienced a hog inventory increase. Note that the prefectures upstream of Shanghai in Zhejiang Province saw the steepest cut in hog inventory numbers. The map colors are based on coefficient values regardless of statistical significance, thus the prefectures experiencing increases may seem counter-intuitive. In particular, figure 3 shows that there was intra-province relocation of hog production across prefectures in Guangdong Province—border prefectures saw inventory increases and urban prefectures saw declines. Hunan used subsidies to encourage facility relocation to the south and saw a similar outcome with more stringent closures near urban cities along the Xiangjiang River (Zhang, Wu, and Li, 2017). In contrast, the positive growth in Anhui Province, although only modestly significant for hog inventory and insignificant for sow inventory, is likely due to relocation across provinces. The per-capita income level of Anhui Province is somewhat smaller than most other DCZ provinces, and the strict enforcement of hog farm closures in neighboring Zhejiang Province might encourage some hog farms to move to Anhui Province. However, as explained, relocation is not a major channel of the 2014 regulations and its effects remain modest.

In a two-way fixed effects DID framework, recent methodological advances, such as the decomposition approach proposed by Goodman-Bacon (Forthcoming), allow for different treatment timing at the province level using DID. Figure D4 shows the coefficients for each pair and its corresponding weight. The coefficients for *Timing* groups indicates the potential dynamic treatment effects, which means treating post-periods of early treated units as control units for later treated units. The small weights for *Timing* groups shows that the variation in treatment timing only contributes a little to the overall estimate, suggesting that this might not be a serious concern. *Guangdong*, *Jiangsu* and *Rest of Treatment Provinces* represent the groups that have different implementation timing but share the same control group. *Rest of Treatment Provinces* with 2014 as implementation timing has the largest weight.

In the previous analysis, we assumed uniform timing implementation for all treated units in one province, we now further examines the impact of variation in treatment timing at prefecture level within

provinces. Because of the difficulties collecting accurate timing for all treated counties, we use Zhejiang Province as an example to generate ATT for each prefecture with their own implementation timing using SDID. Table C9 shows the change of estimates is not significant for prefectures with one-year-early implementation timing. Thus, the variation in treatment timing does not seem to be a major concern.

5.1.4 Threats to Identification and Robustness Checks

Our estimates could be underestimated if provinces or prefectures anticipate these regulations and implemented closure or relocation measures beforehand. To explore how anticipation affect our regulation impact estimates, we use 2012 and 2013, rather than 2014, as the regulation implementation years across DCZ provinces. If there was anticipation, counties in the DCZ would have reduced hog inventory before the nationwide regulation was announced, leading to a decline in inventory before 2014, and thus, a lower magnitude for our ATT estimate using 2014 as the implementation year. Table 5 shows the coefficients with implementation years 2012 and 2013. We treat the implementation year as a post-treatment period. The higher coefficients for 2012 and 2013 in the hog inventory group seem to suggest that there might be evidence of anticipation. Table C4 in Appendix C shows that Fujian Province has the largest anticipation effect on hog inventory. With the existence of the anticipation effect, our estimates are conservative and the lower bound of the true estimates.

While there is an anticipation effect for hog inventory, we do not see evidence of such for sow inventory groups with 2014–2015 as post-treatment periods. This is understandable since the sows have longer production cycles, as a result producers would be unlikely to reduce sows especially during the early stage of the regulation implementation. Furthermore, the effects for hog inventory do not monotonically increase when we move from 2014 to 2012, and the ATT estimate using 2012 as the policy year accounting for anticipation yields a 5% decline in DCZ hog inventory, which is still on par with our key estimates. Furthermore, the SDID regressions using 2012 would have much less pre-treatment years, which potentially affects the validity of year weights and results in the higher magnitude.[18]

Another concern might be that some control counties also implemented environmental regulation. This works in our favor because it would mean that our SDID estimates would serve as lower-bound estimates. Nonetheless, we construct a new control group only using counties near rivers or located upstream of a big city in non-DCZ provinces. Table 6 column (8) reports the smaller magnitude of the estimate compared to the overall estimate in table 3 panel A column (5). The smaller magnitude is due to these counties beginning the process of clearing hog facilities located near waterways or densely populated cities earlier. This estimate provides more evidence for the conservativeness of our estimates.

[18] We perform another robustness check that treat 2010–2012 as the pre-treatment periods and 2013 as the post-treatment period. Results consistently indicate the possibility of anticipation, showing the conservativeness of our estimates.

5.1.5 Possible Mechanism of Regulation Impacts

To formally examine the mechanism of the regulation impacts, we first examine the impacts only using counties upstream and downstream of big cities as treatment units. Second, we choose counties with large water reservoirs as our treatment units to estimate the impact. Third, we estimate the impacts between main and non-main hog-producing counties. Fourth, we check for a border spillover effect between control provinces and treatment provinces.

Table 6 panel A column (1) shows if counties are located upstream of big cities. If so, they would see larger hog inventory reductions. The coefficient reports 15.9% reduction in hog inventory, higher than the overall impact of 6.4%. Interestingly, there is much smaller hog inventory reduction, though not statistically significant as panel A column (2) shows, when counties are located in the downstream of big cities. This is because putting pressure on upstream, as opposed to downstream, counties makes it easier for officials in big cities to achieve the environmental targets. These results are consistent with the literature that shows China's cadre evaluation system rewards local officials' green behaviors, which makes those officials care about the environment in addition to economic growth (Wu and Cao, 2021; He, Xie, and Zhang, 2020; Kahn, Li, and Zhao, 2015).

Panel A column (3) shows a 6.4% reduction in hog inventory in counties with large water reservoirs, which is not different from the overall impact. A possible reason is that contamination in reservoirs may not be as noticeable as they are often located in remote, rural areas with fewer surrounding residents.

Panel A columns (4)–(5) shows that main hog-producing counties saw more inventory reduction than non-main hog-producing counties-—14.0% and 5.8%, respectively. These estimates corroborate with news articles reporting greater efforts to close small-scale hog farms and consolidate and upgrade the production in main hog production counties (Chen, Xiong, and Zhang, 2019).

Panel A column (6)–(7) explores if a border spillover effect exists. First, we construct our treatment group using only county-level hog inventory data for border counties in treatment provinces that share a border with control provinces. Column (6) shows a similar estimate magnitude as the overall estimate, indicating no evidence of relocation to nearby control counties. We further use prefecture-level hog inventory data to check if the border prefectures in control groups experienced hog inventory increase. We do not use county-level hog inventory because our dataset does not include samples of border counties in control provinces that share a border with a treatment province. Column (7) shows the coefficient of our dataset without border prefectures in control groups is also similar to the overall estimate. This, together with table C1, shows evidence of no obvious relocation.[19]

To rationalize these possible mechanisms, we develop a partial equilibrium model of hog farmers' behaviors under closure regulations in Appendix B, which shows that farmers exceeding the critical

[19]The most ideal way to check the border spillover effect is to use treated and control counties that share the same border, which could lead to the upper bound of our estimates. Due to data availability, we revert to the methods in the main text.

production scale $\bar{q}$ are willing to relocate and those below $\bar{q}$ prefer closure. Moreover, we show that location factors relate to regulation stringency—where regulations are more stringent in economic-developed areas, a larger fraction of hog farms choose closure.

5.2 Economic Costs - Descriptive and CGE Estimates

To further quantify the economic cost of the 2014 environmental regulations, we use two approaches. First, we use back-of-the-envelope calculations and convert the provincial SDID estimates of hog inventory loss into number of hog farms or pigs affected and the corresponding monetary value. This captures the direct economic costs borne by the hog producers in DCZ provinces. Second, we use a CGE model calibrated to 30 provinces by 30 sectors of China's economy to assess the overall provincial-level welfare loss and implied labor productivity impacts due to the shocks induced by drastic hog sector losses.

Table 7 presents back-of-the-envelope estimates of the economic costs borne by hog producers for each treated province. To obtain these estimates, we first quantify the number of pigs affected by the regulations by multiplying the province-level average hog inventory from 2010 to 2013 as the base level with the provincial SDID estimates of hog inventory reduction percentage. Then we use average provincial hog prices from 2015 to 2017, average hog weight (110 kg), and the prevailing U.S.-China exchange rate to find the monetary value of economic costs measured in U.S. dollars.[20] Table 7 column (1)–(3) shows that, overall, the 2014 regulations resulted in an equivalent of almost 20,000 500-head hog farm closures or a US$2.95 billion dollar loss for the hog sectors across the eight DCZ provinces, almost equivalent to 4.2% of the 2013 total output value for these hog sectors in the DCZ. Zhejiang Province experienced a 3-million-head hog loss, equivalent to closure of over 6,000 500-head hog farms, or US$904.1 million in terms of monetary loss. Fujian and Hunan Provinces show similar loss of about $700 million. In contrast, Jiangsu and Guangdong Provinces experienced relatively smaller impacts.Note that the minus sign of Anhui Province represents a hog inventory gain equals to around $180 million. However, this gain is very small relative to the loss from other treated provinces, and the SDID estimate of sow inventory loss for Anhui Province is insignificant.

We also quantify the general-equilibrium welfare and labor productivity impacts across China due to the significant reductions in DCZ province hog sector output. To do so, we use a CGE modeling approach exploiting the input-output linkages across sectors and provinces, which accounts for extensive sectoral and provincial economic linkages in China, to quantify the provincial implied labor productivity shocks that best fit the observed changes in DCZ provinces and agricultural sector. For brevity, we refer readers to He et al. (2021) for technical details about this model. Simply, we construct the provincial all-sector shocks by multiplying the provincial SDID estimates of hog inventory loss with the share of hog sector's output relative to the overall provincial GDP.[21] We also compute a weighted average -0.325%

[20] We use the 2020 average RMB/U.S. dollar exchange rate.

[21] For example, the corresponding provincial all-sector value-added shock for Zhejiang Province is -0.13%, whereas the

national shock to the agricultural sector using province-level hog sector percentage change and the hog sector's share relative to a province's entire agriculture value-added for all DCZ provinces. Table 7 column (4)–(5) provides a set of hog-inventory-reduction welfare impacts for the DCZ provinces. We base our welfare calculations on equivalent variation and measure households' money-metric income loss (gain). Compared to pre-treatment period levels, Zhejiang and Hunan Provinces experienced welfare loss of around 0.2%, or around $1.14 billion and $679 million, respectively, while Jiangsu Province saw a much smaller 0.04% decline ($386 million) in welfare. Column (6)–(7) shows us the implied productivity reduction due to the hog inventory reduction. Zhejiang and Hunan Provinces experienced the most labor productivity loss, around 0.4% (166,664 jobs) and 0.42% (160,000 jobs), respectively, compared to before implementation of the 2014 regulations.

The descriptive and CGE estimates above show that the sweeping environmental regulations started in 2014 had imposed significant economic cost for DCZ provinces and beyond, with the agricultural sector bearing disproportionately large impacts.

5.3 Results on Ambient NH_3 Concentrations

5.3.1 Back-of-the-envelope NH_3 Emission Estimates

Before we empirically estimate the impact of the 2014 regulation on NH_3 emissions, we calculate the reduction in NH_3 resulting from less manure production due to our estimated treatment effect on the hog inventory.

Our results show heterogeneous hog and sow inventories reduction in DCZ provinces after implementing the regulations. We sum the number of hogs in inventory in DCZ provinces in each pre-trend period and average them across pre-trend periods. The average hog and sow inventories for all DCZ provinces are 101.4 million and 13.8 million head, respectively. Aggregating the losses for each province using province-specific SDID estimates, the total hog and sow inventory reductions are 9.58 million and 1.31 million head, respectively.

Following Wang et al. (2006), we calculate the amount of hog manure produced per year as:

$$Q = N \times T \times P \tag{12}$$

where Q is the amount of hog manure/urine per year (tons); N is the number of slaughtered hogs (head); T is the raising time length (days). Usually, T is 199 days per head, and P is discharge rate of 2 kg/day and 3.3 kg/day for manure and urine, respectively (Wang et al., 2006). Each ton of hog manure produces 3.08 kg of NH_3, and each ton of urine produces 1.43 kg of NH_3, respectively.

provincial shock for Jiangsu Province is only -0.016%. For simplicity, we assume no direct shocks for non-DCZ provinces beyond the input-output-sector linkages.

Utilizing the emission components, we find the hog inventory reduction in the DCZ provinces theoretically reduced NH_3 emissions by 20,739 tons. Meanwhile, the sow inventory reduction reduced NH_3 emission by 2,836 tons. The total 23,576 ton NH_3 emission reduction accounts for 2.43% of China's total NH_3 emissions in 2013. Due to limited data availability, we use the nationwide total NH_3 emissions instead of only from DCZ provinces (Ministry of Ecology & Environment, 2020), which means that 2.43% is a conservative estimation. As DCZ provinces accounted for around around 33% of nationwide total hog inventory in 2013, we can roughly estimate that the NH_3 emission reduction in DCZ provinces accounts for about 7.8% of total NH_3 emissions in DCZ provinces in 2017.

5.3.2 Preliminary Results on Ambient NH_3 Concentration

To gauge the direct impact of the regulations on downstream water quality, we first estimate a DID treatment effect of the regulations' impacts on NH_3 concentration. Table 8 columns (1)–(4) show the DID, SC, and SDID regressions without covariates, and SDID with all covariates including station-level precipitation. The DID and SC regression show counter-intuitively positive signs, suggesting these results might suffer from either omitted variable bias or insufficient samples. The estimates show that NH_3 emissions increased in DCZ provinces after regulation implementation. Figure D6 presents the parallel pre-trends figures for DID specifications with and without covariates—even though the assumption is satisfied, DID might not bring an unbiased estimate. By applying the SDID approach and incorporating all the covariates, the estimates shown in columns $SDID_1$ and $SDID_2$ adjust the negative bias of estimates from the DID and SC regressions. Estimates show that the regulations led to a 0.0667–0.0817 mg/L reduction in $NH3$ concentration, which is equivalent to around 10%–12.7% of the original ambient pollution level. However, neither estimate is statistically significant. Table 8 columns (5)–(6) further illustrate that even provinces with over 20% hog inventory loss, NH_3 concentration does not show noticeable, significant reduction.

To check if the heterogeneity masks a significant NH_3 reduction, we perform several robustness checks: (a) using water stations located in Zhejiang Province as the treated units; (b) only treating either 2017 or 2018 as the post-treatment period; and, (c) adding counties upstream of each water station. Zhejiang Province, which saw the most severe hog inventory reduction, may show evidence of water quality improvement. Moreover, the effect of hog reduction may not be obvious until 2017 or 2018 due to a delayed effect, thus we use 2017 (2018) as the post-treatment period. Lastly, we incorporate counties upstream of each water station—water stations record data for the county of location and the most nearby upstream counties. Table C8 yields estimates that are negative but still statistically insignificant at the 10% level. Zhejiang Province did not see more NH_3 concentration reduction, possibly because there are only three water stations. When only using 2017 as the post-treatment period, we see a large NH_3 reduction, though it is not statistically significant. Similarly, we found a smaller and

statistically insignificant estimate with 2018 as post-treatment period. Lastly, incorporating counties upstream of each water station gives a larger magnitude of coefficients.

Our results for hog and sow inventories are more robust than that for water quality, and the inconclusive effect of the 2014 regulations on downstream water quality needs further examination. First, the NH_3 level in our dataset represents the aggregate level of all upstream counties rather than any one county and the variation in NH_3 emissions might be too small for us to correctly capture. Thus, measurement errors and/or aggregation bias could influence the insignificant result. Second, there is a limited number of water monitoring stations, which may not be located in the counties that saw significant hog inventory reduction. Third, most of the available water monitoring stations in the DCZ are in Anhui Province, which experienced a hog inventory increase (see figure 3). Thus, using the subsample improperly could lead to the insignificant estimate. Fourth, the mechanism of hog manure contributing to NH_3 levels in rivers is not direct—even though the regulations have significant impact on hog inventory, the reduction of NH_3 in surface water from hog inventory decline may not be obvious. Nonetheless, our results seem to show that a clearly significant reduction in hog inventory did not lead to noticeable improvements in downstream water quality.

6 Conclusions

In early 2014, China initiated a series of place-based environmental regulations targeting its livestock industry in order to improve downstream water quality. Leveraging a novel identification strategy, SDID (Arkhangelsky et al., 2020), and the place-based nature of the environmental regulations, we provide one systematic analysis of the impacts of the regulations on county-level hog inventory, prefecture-level sow inventory, and monitoring-station-level NH_3. Our results show that regulations did lead to significant reduction in both hog and sow inventories——counties and prefectures in DCZ provinces show average hog and sow inventory reduction estimates of 6.4% and 7.4%, respectively, when compared to those in non-DCZ provinces. However, our preliminary results do not reveal noticeable and statistically significant improvements in ambient water quality as measured by NH_3 concentrations. Our results also show that most of the treatment effects come from hog facility closures, rather than relocations, in DCZ provinces; and, we find the effects are stronger for main hog-producing counties and counties upstream of big cities. By constructing the synthetic counterfactuals using the SDID approach, our estimates are more robust and accurate than the conventional DID estimates, which often fail the required parallel pre-trends assumption.

Changes in the hog sector have both significant welfare impacts for China's households and global trade implications (Carriquiry et al., 2020). Many blame the 2014 environmental regulations are a key factor in significant pork shortages and pork price hikes; however, since 2018, China has battled a severe

ASF outbreak, which eventually led to a 40% reduction in hog inventory (Li et al., 2019). The 6.4% hog inventory reduction we find led to, on average, around a 7.7% pork supply reduction, suggesting that the 2014 environmental regulations are not likely the main factor for the post-ASF price and supply issues.[22] Assuming pork's elasticity of demand is -0.23 (Chen et al. (2016)), the corresponding pork price increase is 33% or 20.9 CNY/kg, which is substantially lower than the actual price of 43 CNY/kg in 2019. Recent research shows that pork and hog prices did not substantially rise until after the 2019 Spring Festival when signals showed more than 15% inventory loss, which is more than twice our estimated effects for the 2014 environmental regulations (Carriquiry et al., 2020).

However, our results do reveal steep financial costs for the 2014 environmental regulations, especially for higher-income provinces. As mentioned, the typical hog-producing county in Zhejiang Province lost 3 million pigs due to the regulations, translating to around US$904 million in lost GDP, or 6,000 farms assuming a 500-head farm size. Furthermore, the financial costs are disproportionately borne by small-scale hog producers, especially those located in counties upstream of big cities. Without convincingly delivering water quality improvements, this naturally raises questions as to the overall benefits and costs of these environmental regulations and the necessity of these dramatic disruptions.

Our research has several key limitations that require future work. First, SDID requires strongly balanced panels for all units and all years, which means that we have to drop counties with missing covariates or dependent variables with only one year of data. Second, SDID assumes uniform treatment timing in one estimation, which is not true across provinces; thus, we bypass the uniform treatment timing by estimating separate SDID regressions to obtain heterogeneous treatment effects for each prefecture and province. Third, our lowest unit of observation is a county, thus we are unable to uncover the farm- or firm-level decisions underlying our results—an important micro-level analysis we leave for future research. Finally, our results on the null effects on water quality need more verification, and the current specifications based on the average last 8-week concentrations might still mask data variation. Future research will need more detailed province-level water station water quality data; however, these data are currently unavailable for researchers.

[22] We find a 6.4% hog inventory loss for DCZ provinces; however, the national hog inventory loss should be less. Considering that our estimates are conservative, we use 6.4% to calculate the expected pork price rise.

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Main Tables

Table 1: Mean and Standard Deviation of Dependent Variables and Covariates for Control and Treatment Groups

	# of obvs.	Unit	Treatment Grp.	Control Grp.	Standardized Diff.
Hog Inventory	5808	10000 Head	29(25.7)	26.6(27.3)	0.20*
Sow Inventory	856	100000 Head	18.4(14.5)	109.5(158.9)	-0.81*
NH-3	480	mg/ L	0.53(0.87)	0.92(1.82)	-0.27*
Provincial Economic Vars.					
GDP	2352	$100 billion	41.4(22)	10.8(3.9)	1.93*
Population	2352	10000 persons	7468(2444)	4262(1254)	1.65*
Sex Ratio	2352	female=100	107.9(4.9)	105.6(2.1)	0.60*
Urban-Rural Population Ratio	2352	-	1.61(0.5)	0.74(0.2)	2.20*
Provincial Agricultural Vars.					
Pure Fertilizer Consumption	5808	10000 tons	260(84.6)	292(190)	-0.22*
Sown Area	2352	1000 hectare	5395(3010)	6076(1723)	-0.27*
Corn Yield	2352	10000 tons	221(247)	714(207)	-2.16*
Soybean Yield	2352	10000 tons	41.5(38.1)	33.3(12.6)	0.28*
Grain Crops Yield	2352	10000 tons	1935(1346)	1573(431)	0.36*
Cattle Inventory	2352	10000 head	138.6(87.6)	688.8(205.3)	-3.49*
Goat Inventory	2352	10000 head	268(254)	943(117)	-3.07*
Large Livestock Inventory	2352	10000 head	138(87)	826(250)	-3.66*
Prefecutural Economic Vars.					
Urban-rural Income Ratio	2352	-	2.3(0.4)	6.6(2.2)	-2.84*
GDP	2352	$1000 million	2057(1805)	940(970)	0.77*
Population	2352	10000 persons	449(195.4)	339(181.2)	0.59*
Prefectural Agricultural Vars.					
Sown Area	5808	1000 hectare	520(334)	547(307)	-0.08
Grain Crops Yield	2352	10000 tons	148.3(133.5)	129.5(67.6)	0.17*
Cattle Inventory	5808	10000 head	22(24)	55(34)	-1.08*
Goat Inventory	2352	10000 head	23.2(46.9)	103.7(68.7)	-1.37*
Pure Fertilizer Consumption	5808	10000 tons	23(19)	19(14)	0.21*
Weather					
Precipitation	480	mm	53(24)	34(17)	0.87*

Notes: Absolute standardized difference greater than 0.1 indicates an imbalance between groups.
$*$ represents imbalance between groups.
Standard deviations in parentheses.

Table 2: Results for Hog Inventory without Covariates for Three Methods

	Hog Inventory			Sow Inventory		
	(1-DID)	(2-SC)	(3-SDID)	(4-DID)	(5-SC)	(6-SDID)
Regulation$\times$*Post*	$-.1478^{***}$	$-.1170$	$-.0550^{*}$	$-.0805^{*}$	$-.1210$	$-.0732^{**}$
	(.0189)	(.0938)	(.0309)	(.0419)	(.3825)	(.0346)
County FE	Yes	No	Yes	No	No	No
Prefecture FE	No	No	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County Weights	No	Yes	Yes	No	No	Yes
Prefecture Weights	No	No	No	No	No	Yes
Year Weights	No	No	Yes	No	No	Yes
# of Obvs.	5808	5808	5808	642	642	642

Notes: Standard errors in parentheses.
$***$:statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table 3: SDID Results for Hog and Sow Inventories with Covariates

Panel A: Hog Inventory	(1)	(2)	(3)	(4)	(5)
Regulation×*Post*	$-.0779^{***}$	$-.0778^{***}$	$-.0698^{***}$	$-.0742^{***}$	$-.0639^{***}$
	(.0267)	(.0268)	(.0274)	(.0294)	(.0306)
Province-level chemical fertilizer amount	Yes	No	No	No	Yes
Prefecture-level sown area	No	Yes	No	No	Yes
Prefecture-level cattle inventory	No	No	Yes	No	Yes
Prefecture-level chemical fertilizer amount	No	No	No	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Year Weights	Yes	Yes	Yes	Yes	Yes
County Weights	Yes	Yes	Yes	Yes	Yes
# of Obvs.	5808	5808	5808	5808	5808
# of Groups	726	726	726	726	726
# of Treatment Groups	436	436	436	436	436
Panel B: Sow Inventory	(1)	(2)	(3)	(4)	(5)
Regulation×*Post*	$-.0733^{***}$	$-.0733^{***}$	$-.0731^{***}$	$-.0735^{***}$	$-.0735^{***}$
	(.0346)	(.0346)	(.0345)	(.0340)	(.0340)
Province-level chemical fertilizer amount	Yes	No	No	No	Yes
Prefecture-level sown area	No	Yes	No	No	Yes
Prefecture-level cattle inventory	No	No	Yes	No	Yes
Prefecture-level chemical fertilizer amount	No	No	No	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Prefecture Weights	Yes	Yes	Yes	Yes	Yes
Year Weights	Yes	Yes	Yes	Yes	Yes
# of Obvs.	642	642	642	642	642
# of Groups	107	107	107	107	107
# of Treatment Groups	75	75	75	75	75

Notes: Standard errors in parentheses.
$***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table 4: SDID Results for Hog and Sow Inventories using Each Province's Implementation Timing

Province	Time	Hog Inventory	Sow Inventory
Zhejiang	2013	$-.5261^{***}$	-0.4512^{*}
		(.0809)	(.2680)
Jiangsu	2015	$-.0435$	-
		(.0349)	-
Fujian	2013	$-.2496^{***}$	$-.1966^{***}$
		(.0959)	(.0772)
Guangdong	2012	-.0414	.0181
		(.0347)	(.1008)
Anhui	2014	$.0671^{*}$	.0380
		(.0399)	(.0253)
Hubei	2014	$-.0627^{***}$	-.0226
		(.0265)	(.0266)
Hunan	2014	$-.0858^{***}$	.0376
		(.0347)	(.0242)
Covariates	-	Yes	Yes
County FE	-	Yes	No
Prefecture FE	-	No	Yes
Year FE	-	Yes	Yes
County Weights	-	Yes	No
Prefecture Weights	-	No	Yes
Year Weights	-	Yes	Yes

Notes: Covariates include province-level chemical fertilizer amount, prefecture-level sown area, prefecture-level cattle inventory, and prefecture-level chemical fertilizer amount.
Standard errors in parentheses.
$***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table 5: SDID Results with Different Implementation Timing

Panel A: Hog Inventory	2013	2012
Regulation×*Post*	$-.1509^{***}$	$-.1223^{***}$
	(.0409)	(.0322)
Covariates	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	Yes
County Weights	Yes	Yes
Year Weights	Yes	Yes
# of Obvs.	5808	5808
Panel B: Sow Inventory	2013	2012
Regulation×*Post*	$-.0435$	$-.0410$
	(.0364)	(.0406)
Covariates	Yes	Yes
Prefecture FE	Yes	Yes
Year FE	Yes	Yes
Prefecture Weights	Yes	Yes
Year Weights	Yes	Yes
# of Obvs.	642	642

Notes: Covariates include province-level chemical fertilizer amount, prefecture-level sown area, prefecture-level cattle inventory, and prefecture-level chemical fertilizer amount.
Standard errors in parentheses.
$***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table 6: Mechanisms of the Impact of the 2014 Regulations on Hog Inventory

	Upstream Cities	Downstream Cites	Drinking Water Source	Main Hog	Non-main Hog	Only With Border Treated Counties	Without Border Control Counties	Control Counties (near Rivers or Big Cities)
Regulation$\times Post$	$-.1589^{**}$	-0.0820	$-.0634$	$-.1396^{*}$	$-.0576^{*}$	$-.0663^{***}$	$-.0620^{*}$	-.0275
	(.0765)	(.0984)	(.0394)	(.0823)	(.0305)	(.0271)	(.0337)	(.0431)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obvs.	2920	2240	3288	2696	5432	3328	5256	4456
# of Groups	365	280	411	337	679	416	657	557

Notes: Covariates include province-level chemical fertilizer amount, prefecture-level sown area, prefecture-level cattle inventory, and prefecture-level chemical fertilizer amount. Standard errors in parentheses.

$***$: statistically significant at 1% level.

$**$: statistically significant at 5% level.

$*$: statistically significant at 10% level.

Table 7: Economic Costs for Each Treated Province

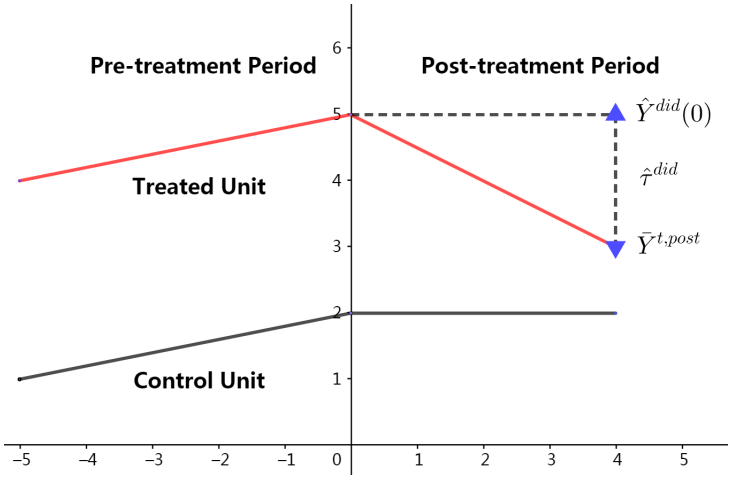
	Back-of-the-envelope Estimates			CGE Estimates			
	# of Hog Inventory Loss (1000 head)	# of 500-head Hog Farm Loss	Monetary Loss (U.S.$million)	Welfare Change (%)	Welfare Change (U.S.$million)	Implied Labor Productivity Change (%)	# of Job Loss
Zhejiang	3,228.3	6,456	904.1	-0.218	-1,142	-0.438	-166,664
Jiangsu	752	1,503	210.5	-0.045	-386	-0.137	-65,500
Fujian	2,575	5,150	721.3	-0.168	-567	-0.348	-68,656
Anhui	-1,007	-2,013	-183.3	0.104	309	0.149	65,303
Guangdong	875	1750	245.1	-0.034	-310	-0.118	-75,237
Hubei	1,577	3153	441.6	-0.134	-497	-0.301	-108,695
Hunan	2,535	5,070	710.0	-0.201	-679	-0.419	-159,954
Total	10,535	21,070	2,950.6	-0.091	-3,272	-0.217	579,403

Table 8: Ambient NH_3 Concentrations in Downstream Waterbodies

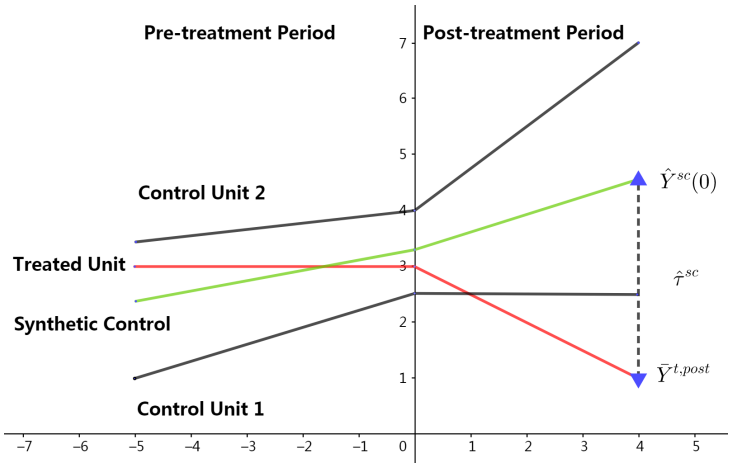
	DID	SC	SDID_1	SDID_2	SDID-Zhejiang	SDID-Hunan
Regulation$\times Post$	.2851*	.0139	$-.0667$	$-.0817$	-0.0560	.0062
	(.1508)	(.0999)	(.2008)	(.2408)	(.2220)	(.2629)
Covariates	No	No	No	Yes	Yes	Yes
County FE	Yes	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County Weight	No	Yes	Yes	Yes	Yes	Yes
Year Weight	No	No	Yes	Yes	Yes	Yes
# of Obvs.	480	480	480	480	304	288
# OF Groups	60	60	60	60	38	36

Notes: Covariates include province-level chemical fertilizer amount, prefecture-level sown area, prefecture-level cattle inventory, prefecture-level chemical fertilizer amount, and station-level precipitation.
Standard errors in parentheses.
$***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

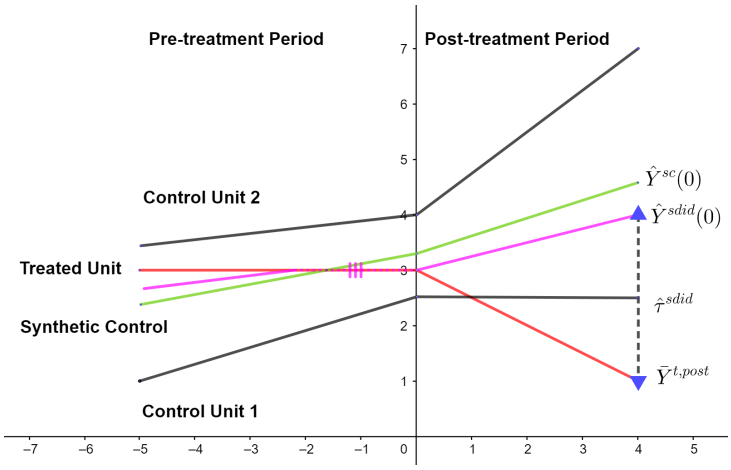
Main Figures



(a) Difference-in-differences

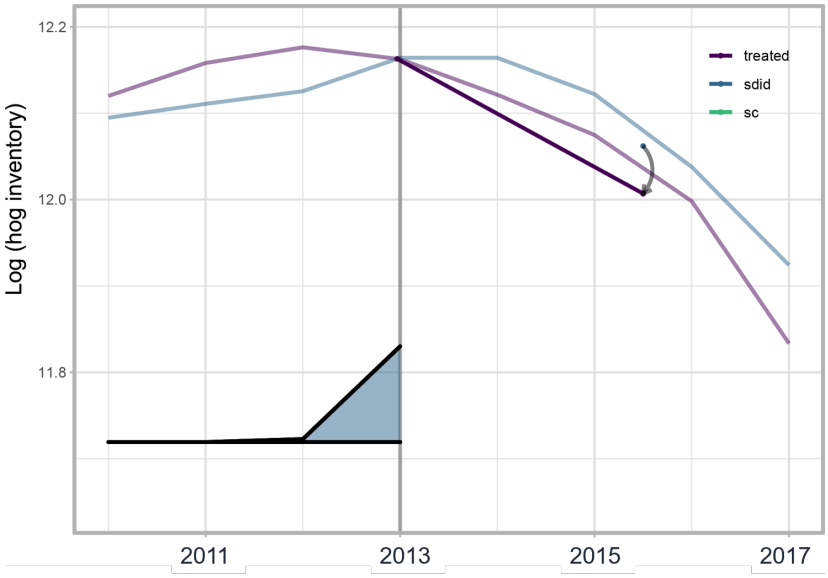


(b) Synthetic Control

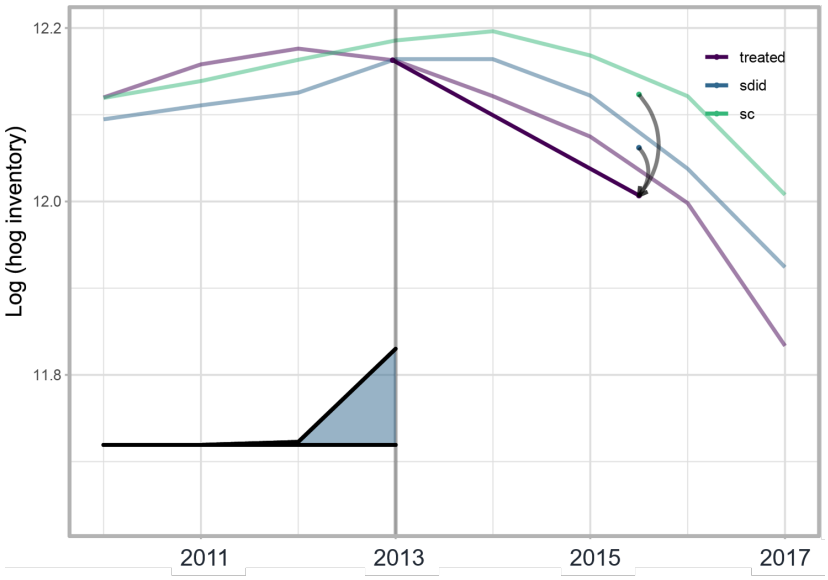


(c) Synthetic Difference-in-differences

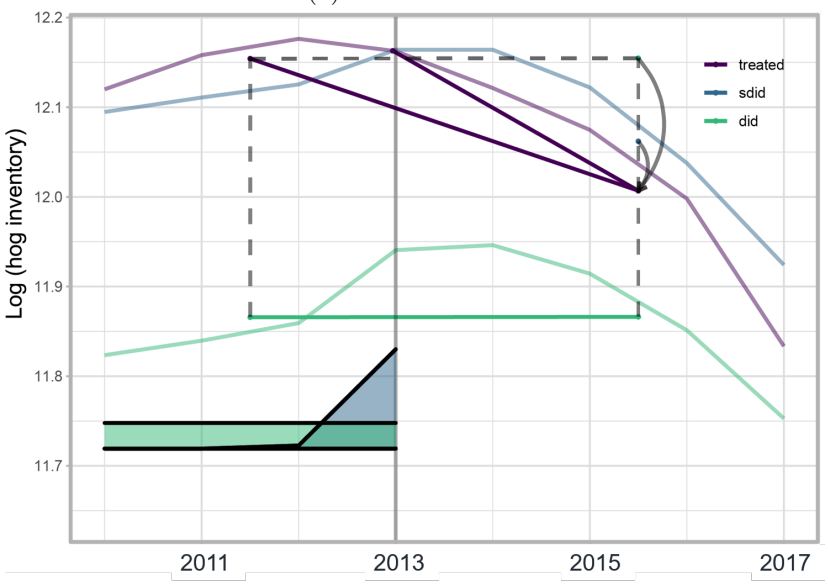
Figure 1: Intuition behind three methods



(a) SDID Counterfactual



(b) SDID versus SC



(c) SDID versus DID

Figure 2: SDID Counterfactual and the Comparisons with DID and SC

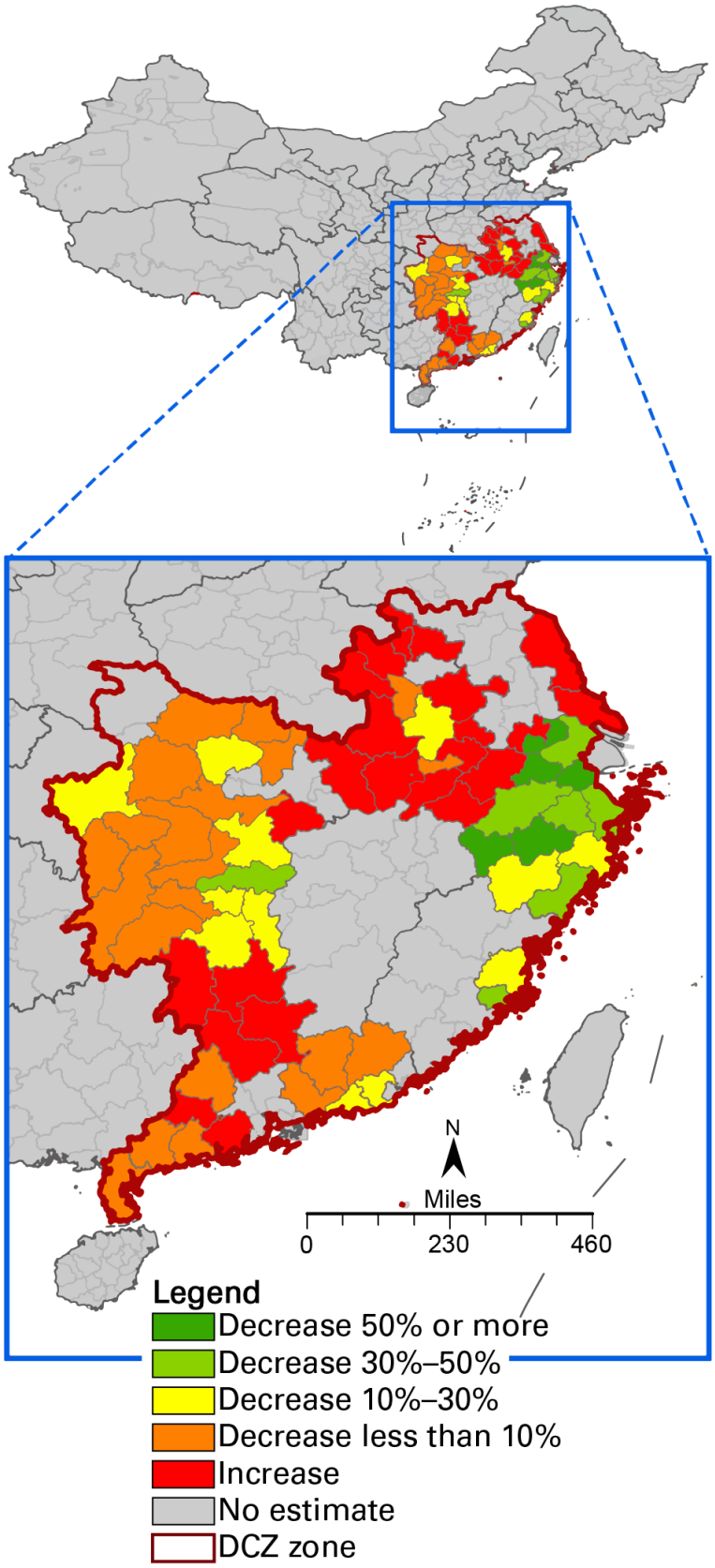


Figure 3: Map of Prefecture-level SDID ATT Results for Hog Inventory

Appendix A: Technical Details for Synthetic Difference-in-differences

Following (Arkhangelsky et al., 2020), we partition the $N \times T$ matrix of observed outcome Y by treatment/control group and pre/post-treatment period: $Y = \begin{pmatrix} Y_{N_0,T_0} & Y_{N_0,T_1} \\ Y_{N_1,T_0} & Y_{N_1,T_1} \end{pmatrix}$ where Y_{N_0,T_0}, Y_{N_0,T_1}, Y_{N_1,T_0} and Y_{N_1,T_1} are $N_0 \times T_0$, $N_0 \times T_1$, $N_1 \times T_0$ and $N_1 \times T_1$ matrices, respectively; N_0 is the number of control units; T_0 is the number of the pre-treatment periods; and, N_1 and T_1 are the number of treated units and post-treatment periods, respectively. In our dataset, N_0 is 290 and N_1 is 436. For the pre/post periods, T_0 equals 4 and T_1 equals 4.

To define the averages for the three sets of control outcomes and one set of treatment outcomes, we use:

$$\bar{Y}^{c,pre} = \frac{1}{N_0 \times T_0} \sum_{n=1}^{N_0} \sum_{t=1}^{T_0} Y_{nt} \tag{13}$$

$$\bar{Y}^{c,post} = \frac{1}{N_0 \times T_1} \sum_{n=1}^{N_0} \sum_{t=1}^{T_1} Y_{nt} \tag{14}$$

$$\bar{Y}^{t,pre} = \frac{1}{N_1 \times T_0} \sum_{n=1}^{N_1} \sum_{t=1}^{T_0} Y_{nt} \tag{15}$$

$$\bar{Y}^{t,post} = \frac{1}{N_1 \times T_1} \sum_{n=1}^{N_1} \sum_{t=1}^{T_1} Y_{nt} \tag{16}$$

$$\tag{17}$$

We can write the basic DID estimator as:

$$\hat{\tau}^{did} = \bar{Y}^{t,post} - \hat{Y}^{did}(0) = (\bar{Y}^{t,post} - \bar{Y}^{t,pre}) - (\bar{Y}^{c,post} - \bar{Y}^{c,pre}) \tag{18}$$

$$\begin{aligned} \hat{Y}^{did}(0) &= \bar{Y}^{t,pre} + (\bar{Y}^{c,post} - \bar{Y}^{c,pre}) \\ &= \bar{Y}^{c,pre} + (\bar{Y}^{t,pre} - \bar{Y}^{c,pre}) + (\bar{Y}^{c,post} - \bar{Y}^{c,pre}) \end{aligned} \tag{19}$$

We can treat the DID estimator as doubly bias-adjusting the simple average $\bar{Y}^{c,pre}$, with the first bias adjustment, $\bar{Y}^{t,pre} - \bar{Y}^{c,pre}$, accounting for difference stability between the treated and control units and the second bias adjustment, $\bar{Y}^{c,post} - \bar{Y}^{c,pre}$, accounting for difference stability over time for the control group. The intuition can be seen graphically from figure 1 in the DID subsection.

However, DID estimation is not accurate if both adjustments are not accurate. We find that the second bias adjustment is equivalent to equation (4), which is hard to hold. SDID can relax equation (4) by using unit-specific and time-specific weights to match the pre-treatment trend of treated units.

We can rewrite the control rows $n = 1, ...N_0$ of matrix Y with weights $\hat{\omega}_n^{sc}$ so as to make the time trends among the weighted controls and the treated unit track using an SC estimator(Abadie, Diamond,

and Hainmueller, 2010):

$$\hat{\tau}^{sc} = \bar{Y}^{t,post} - \hat{Y}^{sc}(0) \tag{20}$$

$$\hat{Y}^{sc}(0) = \frac{1}{T_0}\sum_{n=1}^{N_0}\sum_{t=1}^{T_0}\hat{\omega}_n^{sc}Y_{nt} + \sum_{n=1}^{N_0}\hat{\omega}_n^{sc}(\frac{1}{T_1}\sum_{t=1}^{T_1}Y_{nt} - \frac{1}{T_0}\sum_{t=1}^{T_0}Y_{nt}) \tag{21}$$

$$\hat{\omega}^{sc} = argmin\sum_{t=1}^{T_0}(\sum_{n=1}^{N_0}\omega_n Y_{nt} - \frac{1}{N_1}\sum_{n=1}^{N_1}Y_{nt})^2 \tag{22}$$

The SC estimator can improve DID estimation in its use of weights to address potential misspecification of the basic DID model. However, SC does not adjust the first bias term $\bar{Y}^{t,pre} - \bar{Y}^{c,pre}$ to $\frac{1}{T_0}\sum_{t=1}^{T_0}(\frac{1}{N_1}\sum_{n=1}^{N_1}Y_{nt} - \sum_{n=1}^{N_0}\hat{\omega}_n^{sc}Y_{nt})$. This adjustment seeks to correct for a potential systematic failure of the weights $\hat{\omega}_i^{sc}$ in order to achieve balance in the pre-treatment periods. Missing that term implies that $\hat{\omega}_i^{sc}$ can balance the pre-treatment periods perfectly, such that:

$$\frac{1}{N_1}\sum_{n=1}^{N_1}Y_{nt} - \sum_{n=1}^{N_0}\hat{\omega}_n^{sc}Y_{nt} = 0, \qquad \forall t = 1, ..., T_0 \tag{23}$$

This is also a very strong assumption that means for every pre-treatment period the weighted average of the control units in that period must match the treated unit. Since the weights are unit-specific rather than time-varying, it is quite hard to satisfy equation (23). Figure 1(b) also shows a simple example of mis-matched pre-treatment periods between SC and the treated unit. We can see that the green line and the red line in the pre-treatment periods do not overlap, especially in the last pre-treatment period, which could lead to the overall generated counterfactual bias.

SDID can adjust the first bias if equation (23) does not hold by adding other time-specific weights $\hat{\lambda}_t^{sc}$. Arkhangelsky et al. (2020) find that adding time-specific weights based on the SC method is doubly robust. If unit-specific weights cannot be correctly generated, which leads to misspecification, time-specific weights can adjust the bias.

$$\hat{\tau}^{sdid} = \bar{Y}^{t,post} - \hat{Y}^{sdid}(0) \tag{24}$$

$$\hat{Y}^{sdid}(0) = \sum_{n=1}^{N_0}\sum_{t=1}^{T_0}\hat{\omega}_n^{sdid}\hat{\lambda}_t^{sdid}Y_{nt} + \sum_{n=1}^{N_0}\hat{\omega}_n^{sdid}(\frac{1}{T_1}\sum_{t=1}^{T_1}Y_{nt} - \sum_{t=1}^{T_0}\hat{\lambda}_t^{sdid}Y_{nt}) + \sum_{t=1}^{T_0}\hat{\lambda}_t^{sdid}(\frac{1}{N_1}\sum_{n=1}^{N_1}Y_{nt} - \sum_{n=1}^{N_0}\hat{\omega}_n^{sdid}Y_{nt}) \tag{25}$$

Different from $\hat{\omega}^{sc}$, SDID adds two minor changes to generate $\hat{\omega}^{sdid}$. First, SDID adds the intercept term ω_0 to add extra flexibility when generating ω^{sdid}. By making unit fixed effects and time fixed effects incorporate, the intercept term can be absorbed. The second change is to add ridge regression to

distribute more weights to more units rather than concentrate on certain units.

$$(\hat{\omega}_0, \hat{\omega}^{sdid}) = argmin_{\omega_0 \in R, \omega \in \Omega} \sum_{t=1}^{T_0} (\omega_0 + \sum_{n=1}^{N_0} \omega_n Y_{nt} - \frac{1}{N_1} \sum_{n=1}^{N_1} Y_{nt})^2 + \zeta^2 T_0 ||\omega||^2 \tag{26}$$

$$\Omega = \left\{ \omega \in R_+^N : \sum_n = 1^{N_0} \omega_n = 1, \omega_n = N_1^{-1}, \forall n = N_0 + 1, ..., N_1 \right\}$$

$$\zeta^2 = \frac{1}{N_0 T_0} \sum_{n=1}^{N_0} \sum_{t=1}^{T_0} (\Delta_{nt} - \bar{})^2,$$

$$where \quad \Delta_{nt} = Y_{n(t+1)} - Y_{nt}, \quad \bar{\Delta} = \frac{1}{N_0(T_0 - 1)} \sum_{n=1}^{N_0} \sum_{t=1}^{T_0} \Delta_{nt}$$

where ζ is the regularization parameter that chooses to match the size of a typical one-period outcome change Δ_{it} for unexposed units in the pre-period.

Unlike $\hat{\omega}^{sdid}$, we do not add a ridge regression term to generate $\hat{\lambda}^{sdid}$ as we want the weights to concentrate on the most recent pre-treatment periods, which are more related to the post-treatment periods. Thus, we generate $\hat{\lambda}^{sdid}$ as:

$$(\hat{\lambda}_0, \hat{\lambda}^{sdid}) = argmin \sum_{n=1}^{N_0} (\lambda_0 + \sum_{t=1}^{T_0} \lambda_t Y_{it} - \frac{1}{T_1} \sum_{t=1}^{T_1} Y_{nt})^2 \tag{27}$$

$$\Lambda = \left\{ \lambda \in R_+^T : \sum_t = 1^{T_0} \lambda_t = 1, \lambda_t = T_1^{-1}, \forall t = T_0 + 1, ..., T_1 \right\}$$

We can adjust the misspecification of the SC estimator by adding time-specific weights to better generate the counterfactual in the post-treatment periods. In figure 1(c), the purple line in the recent pre-treatment periods is more accurate than the green line, implying a more accurate counterfactual in post-treatment periods. In all, SDID generates two kinds of weights to pick units and periods that are similar to treated units and post-treatment periods, thus making the estimator more robust.

Following Arkhangelsky et al. (2020), we incorporate the unit fixed effect and time fixed effect to the estimation process as follows:

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = argmin \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{nt} - \mu - \alpha_n - \beta_t - W_{nt}\tau)^2 \hat{\omega}_n^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{28}$$

Furthermore, another advantage of SDID is that it can get covariate-adjusted outcomes, which can help to eliminate the time-varying variation of dependent variables from covariates. The corresponding adjustments are:

$$(\hat{\tau}_\gamma^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}, \hat{\gamma}) = argmin \left\{ \sum_{n=1}^{N} \sum_{t=1}^{T} (Y_{nt} - \mu - \alpha_n - \beta_t - X_{nt}\gamma - W_{nt}\tau)^2 \hat{\omega}_n^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{29}$$

Appendix B: Conceptual Framework

We model hog farmers' choices between closure and relocation as follows:

$$V_{close} = b(q) + \gamma \sum_{t=1}^{\infty} \alpha^t w \tag{30}$$

$$V_{relocation} = -(F + c(q)) + \sum_{t=1}^{\infty} \alpha^{t+3} E[p_{t+3}(q + \epsilon_{t+3})] \tag{31}$$

$$b_q > 0, \qquad b_{qq} < 0 \tag{32}$$

$$c_q > 0, \qquad c_{qq} < 0 \tag{33}$$

where V_{close} is the present value of choosing closure and $V_{relocation}$ is the present value of choosing relocation. Farmers choosing closure receive government subsidy $b(q)$ in the current period and the present value of an alternative job in the future (multiplying parameter γ). w is the constant wage rate, α is the discount rate, and γ measures regulation stringency, which could be related to the distance to nearby waterways or the distance to the nearest large city. The wage rate is higher in large cities and they are usually located near waterways and thus face more stringent regulations, which translates to a bigger γ if the location is near waterways or a large city. $b(q)$ is a concave function of production scale q, which means that as q increases, $b(q)$ increases, but the increasing rate decreases.

If a farmer chooses to relocate, F is the current period fixed cost of rebuilding the hog farm and $c(q)$ is the variable cost, which is a concave function of q, the production scale the farm will maintain. The rebuilding takes two periods and the farm will receive revenue starting in the fourth period. As the price of hogs and the hog production level is uncertain, we denote future revenue as expectation. Also, we assume that actual production is $q + \epsilon_{t+3}$, which is production scale q and a random variable ϵ_{t+3} with mean 0 and variance 1.

We can rewrite equations (30) and (31) as:

$$V_{close} = b(q) + \gamma \frac{\alpha}{1-\alpha} w \tag{34}$$

$$V_{relocation} = -(F + c(q)) + q \sum_{t=1}^{\infty} \alpha^{t+3} E(p_{t+3}) + A(p_4, p_5, ...; \epsilon_4, \epsilon_5, ...) \tag{35}$$

$$where \quad A(p_4, p_5, ...; \epsilon_4, \epsilon_5, ...) = \sum_{t=1}^{\infty} \alpha^{t+3} E(p_{t+3}\epsilon_{t+3}) \tag{36}$$

$V_{close} = V_{relocation}$ determines the threshold of $\bar{q}$; that is,

$$b(\bar{q}) + \gamma \frac{\alpha}{1-\alpha} w = -(F + c(\bar{q})) + \bar{q} \sum_{t=1}^{\infty} \alpha^{t+3} E(p_{t+3}) + A(p_4, p_5, ...; \epsilon_4, \epsilon_5, ...) \tag{37}$$

We then take first and second derivatives to get:

$$\frac{\partial V_{close}}{\partial q} = b'(q) > 0 \tag{38}$$

$$\frac{\partial^2 V_{close}}{\partial q^2} = b''(q) < 0 \tag{39}$$

$$\frac{\partial V_{relocation}}{\partial q} = -c'(q) + \sum_{t=1}^{\infty} \alpha^{t+3} E(p_{t+3}) \tag{40}$$

$$\frac{\partial^2 V_{relocation}}{\partial q^2} = -c''(q) > 0 \tag{41}$$

where V_{close} is a concave function of q and $V_{relocation}$ is a convex function of q. The sign of equation (40) is ambiguous, such that we make assumption 1:

$$\sum_{t=1}^{\infty} \alpha^{t+3} E(p_{t+3}) - c'(q) - b'(q) > 0 \tag{42}$$

Equation (42) indicates that the net future marginal payoff of relocation must be high enough; that is, it must exceed the net marginal payoff of closure, such that some farmers choose to relocate instead of closing. Under this assumption, equation (40) is greater than 0, thus $V_{relocation}$ is an upward convex function.

Furthermore, we need to compare $V_{close}|_{q \longrightarrow 0}$ and $V_{relocation}|_{q \longrightarrow 0}$.

$$V_{close}|_{q \longrightarrow 0} = \gamma \frac{\alpha}{1-\alpha} w \tag{43}$$

$$V_{relocation}|_{q \longrightarrow 0} = A(p_4, p_5, ...; \epsilon_4, \epsilon_5, ...) - F \tag{44}$$

Here we make assumption 2:

$$V_{close}|_{q \longrightarrow 0} > V_{relocation}|_{q \longrightarrow 0} \tag{45}$$

Assumption 2 makes sense because it is hard for small-scale farms to cover the cost of relocation, thus they are more willing to choose closure. Utilizing equations (34)—(45), there exists $\bar{q}$ such that

$$if \quad q < \bar{q}, \quad V_{close} > V_{relocation} \tag{46}$$

$$if \quad q > \bar{q}, \quad V_{close} < V_{relocation} \tag{47}$$

This conclusion is quite reasonable because small-scale producers prefer to close due to the fixed cost of relocation, which producers can only cover with a large enough production scale.

We want to see how the stringency of regulations impacts the threshold of q; that is, how γ impacts

$\bar{q}$. Taking the total derivative on both γ and $\bar{q}$, we get

$$\frac{\partial \bar{q}}{\partial \gamma} = \frac{\frac{\alpha}{1-\alpha} w}{\sum_{t=1}^{\infty} \alpha^{t+3} E(p_{t+3}) - c'(q) - b'(q)} > 0 \tag{48}$$

which means that if there is a distribution of farm production scale, a larger proportion of farms will choose to close with a larger γ. The threshold of q increases in a more stringent place, pushing more closure compared to a less stringent place.

Appendix C: Additional Tables

Table C1: Comparison of the Number of Hog Farms in Each Production Scale in non-DCZs Provinces Pre- and Post-regulations

	# Of Hog Farms		Mean		% Of Total Hog Inventory		Difference
	Before	After	Before	After	Before	After	
1–49	157058000	127826624	1963225	1597833	62%	56%	-365392.2
50–99	4886513	4212421	61081	52655	5.8%	5.7%	-8426
100–499	1922026	1834942	24025	22936	10.9%	11.6%	-1088
500–999	386100	378528	4826	4731	5.5%	6.5%	-94
1000–2999	132388	134841	1654	1685	5.5%	6.8%	30
3000–4999	28278	28882	353	361	2.3%	2.8%	7
5000–9999	13564	14792	169	184	2.2%	2.9%	15
10000–49999	7893	8425	98	105	5.6%	7%	6
50000+	280	621	3	7	0.4%	0.8%	4^{***}

Notes: $***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table C2: DID Estimate Results from 2014 Regulations

	Hog Inventory			Sow Inventory		
	(1)	(2)	(3)	(4)	(5)	(6)
Regulation$\times$*Post*	$-.1449^{***}$	$-.1478^{***}$	$-.0438^{*}$	$-.1152^{***}$	$-.0806^{*}$	$-.0739^{**}$
	(.0370)	(.0189)	(.0219)	(.0361)	(.0420)	(.0346)
Covariates	No	No	Yes	No	No	Yes
County FE	No	Yes	Yes	No	No	No
Prefecture FE	No	No	No	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
# of Obvs.	5808	5808	5808	642	642	642
# of Groups	726	726	726	107	107	107

Notes: Covariates include province-level chemical fertilizer amount, prefecture-level sown area, prefecture-level cattle inventory, and prefecture-level chemical fertilizer amount.
Standard errors in parentheses.
$***$:statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table C3: DID Results with Different Post-treatment Periods For Sow Inventory

	2014–2015	2014–2017	2016–2017
Regulation×*Post*	$-.0739^{**}$	.0628	$.1725^{**}$
	(.0346)	(.0469)	(.0683)
Covariates	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# of Obvs.	642	856	642
# of Groups	107	107	107

Notes: Covariates include province-level chemical fertilizer amount, prefecture-level sown area, prefecture-level cattle inventory, and prefecture-level chemical fertilizer amount.
Standard errors in parentheses.
$***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table C4: SDID Results for Each DCZ Province with Alternative Implementation Timing on Hog Inventory

	One Year Earlier	Two Years Earlier
Zhejiang	$-.4133^{***}$	$-.4214^{***}$
	(.0725)	(.0730)
Jiangsu	$-.1557^{**}$	$-.1536^{***}$
	(.0721)	(.0577)
Fujian	$-.5963^{**}$	$-.5126^{**}$
	(.3028)	(.2516)
Guangdong	-.0400	-
	(.0346)	-
Anhui	.0006	-.0028
	(.0561)	(.0415)
Hubei	$-.0671^{*}$	$-.0093$
	(.0379)	(.0369)
Hunan	$-.1450^{***}$	$-.1152^{***}$
	(.0323)	(.0315)
Covariates	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	Yes
County Weight	Yes	Yes
Year Weight	Yes	Yes

Notes: Standard errors in parentheses.
$***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table C5: Province Weights of SDID for Hog Inventory with and without Covariates

	With	Without
Yunnan	0.4352	0.4163
Sichuan	0.1045	0.1054
Ningxia	0.0589	0,0581
Shandong	0.0483	0.0503
Hebei	0.1283	0.1358
Henan	0.1609	0.1696
Hainan	0.0636	0.0643

Table C6: Year Weights of SDID for Hog Inventory with and without Covariates

	With	Without
2010	0	0
2011	0	0
2012	0.0342	0.0302
2013	0.9658	0.9698

Table C7: Hog and Sow Inventories Data Sources

	Hog and Sow Inventories	Link
Zhejiang	Zhejiang Statistical Yearbook	https://tjj.zj.gov.cn/col/col1525563/
Jiangsu	Jiangsu Agricultural Statistical Yearbook	https://www.cnki.net/
Fujian	Prefecture Statistical Yearbooks in Fujian Province	https://www.cnki.net/
Guangdong	Guangdong Agricultural Statistical Yearbook	https://www.cnki.net/
Anhui	Anhui Statistical Yearbook	http://tjj.ah.gov.cn/ssah/qwfbjd/tjnj/
Hubei	Hubei Agricultural Statistical Yearbook	https://www.cnki.net/
Hunan	Hunan Agricultural Statistical Yearbook	https://www.cnki.net/
Yunnan	Yunnan Statistical Yearbook	http://stats.yn.gov.cn/tjsj/tjnj/
Sichuan	Prefecture Statistical Yearbooks in Sichuan Province	https://www.cnki.net/
Henan	Henan Survey Yearbook	https://www.cnki.net/
Hebei	Hebei Agricultural Statistical Yearbook	https://www.cnki.net/
Shandong	Prefecture Statistical Yearbooks in Shandong Province	https://www.cnki.net/
Hainan	Hainan Statistical Yearbook	http://stats.hainan.gov.cn/tjj/tjsu/ndsj/
Ningxia	Ningxia Statistical Yearbook	http://nxdata.com.cn/publish.htm?cn=G01

Table C8: Robustness Check: Ambient NH_3 Concentrations in Downstream Waterbodies

	All	Only Zhejiang Province	Only 2017	Only 2018	All with Upstream Counties
Regulation$\times Post$	-.0817	-.056	-.1939	-.0491	-.101
	(.2408)	(.2220)	(.2116)	(.3565)	(.1367)
Covariates	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
County Weight	Yes	Yes	Yes	Yes	Yes
Year Weight	Yes	Yes	Yes	Yes	Yes
# of Obvs.	480	240	360	265	1216
# OF Groups	60	30	60	53	152

Notes: Covariates include province-level chemical fertilizer amount, prefecture-level sown area, prefecture-level cattle inventory, prefecture-level chemical fertilizer amount, and station-level precipitation.
Standard errors in parentheses.
$***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Table C9: Zhejiang Province SDID Results

	No Timing Variation		With Timing Variation	
	Timing	SDID	Timing	SDID
Lishui	2014	$-.1639^{***}$	2014	$-.1639^{***}$
		(.0487)		(.0487)
Jinhua	2014	$-.5449^{***}$	2013	$-.6148^{***}$
		(.1749)		(.1722)
Taizhou	2014	$-.2113^{**}$	2014	$-.2113^{**}$
		(.0936)		(.0936)
Ningbo	2014	$-.4204^{***}$	2014	$-.4204^{***}$
		(.0983)		(.0983)
Hangzhou	2014	$-.3116^{***}$	2014	$-.3116^{***}$
		(.105)		(.105)
Wenzhou	2014	$-.3373^{***}$	2013	$-.4157^{***}$
		(.145)		(.1099)
Huzhou	2014	$-.6918^{***}$	2014	$-.6918^{***}$
		(.2648)		(.2648)
Shaoxing	2014	$-.3886$	2013	$-.4164$
		(.4946)		(.3986)
Qvzhou	2014	$-.5536^{*}$	2013	$-.6500^{**}$
		(.3129)		(.3057)
Covariates	-	Yes	-	Yes
County FE	-	Yes	-	Yes
Year FE	-	Yes	-	Yes
County Weights	-	Yes	-	Yes
Year Weights	-	Yes	-	Yes

Notes: Covariates include province-level chemical fertilizer amount, prefecture-level sown area, prefecture-level cattle inventory, and prefecture-level chemical fertilizer amount.
Standard errors in parentheses.
$***$: statistically significant at 1% level.
$**$: statistically significant at 5% level.
$*$: statistically significant at 10% level.

Appendix D: Additional Figures

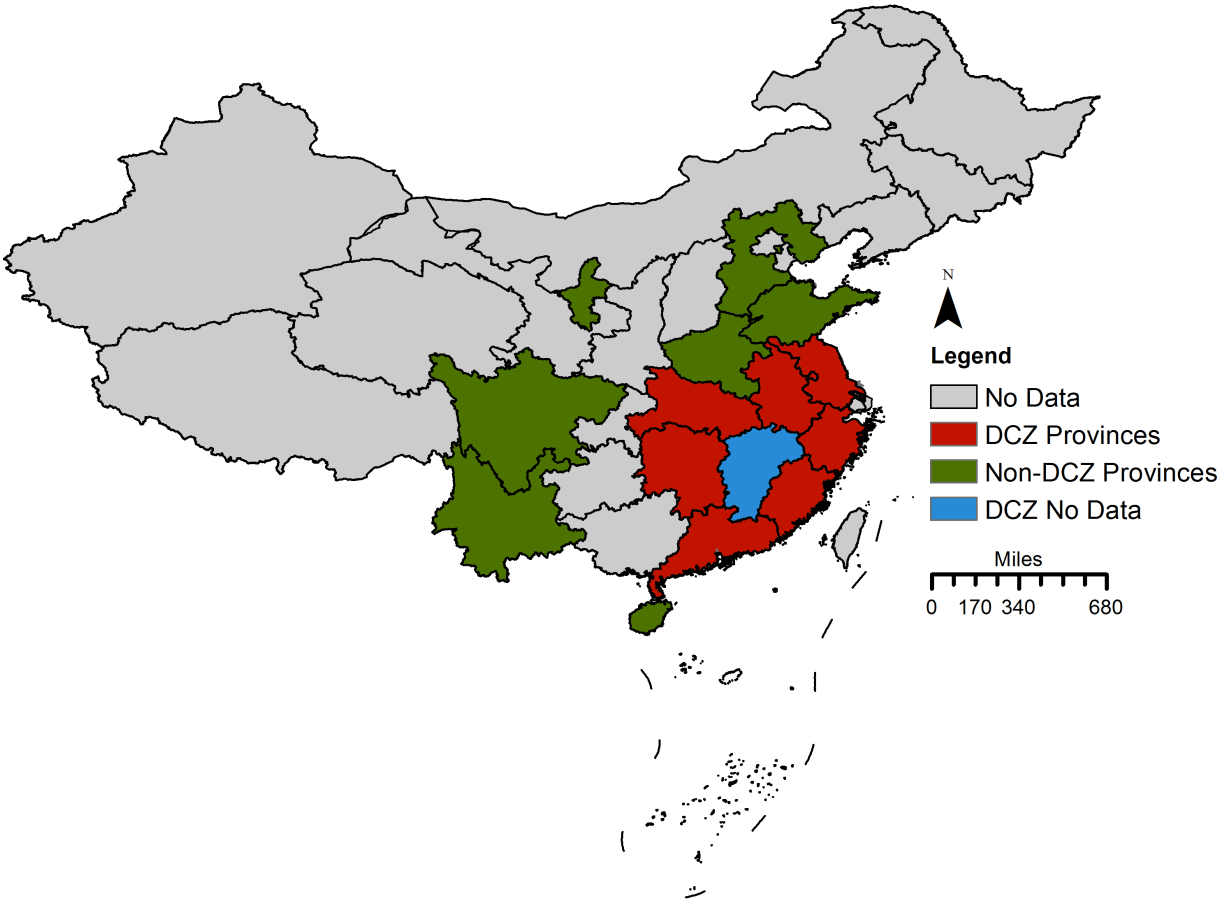


Figure D1: China's hog development control zones

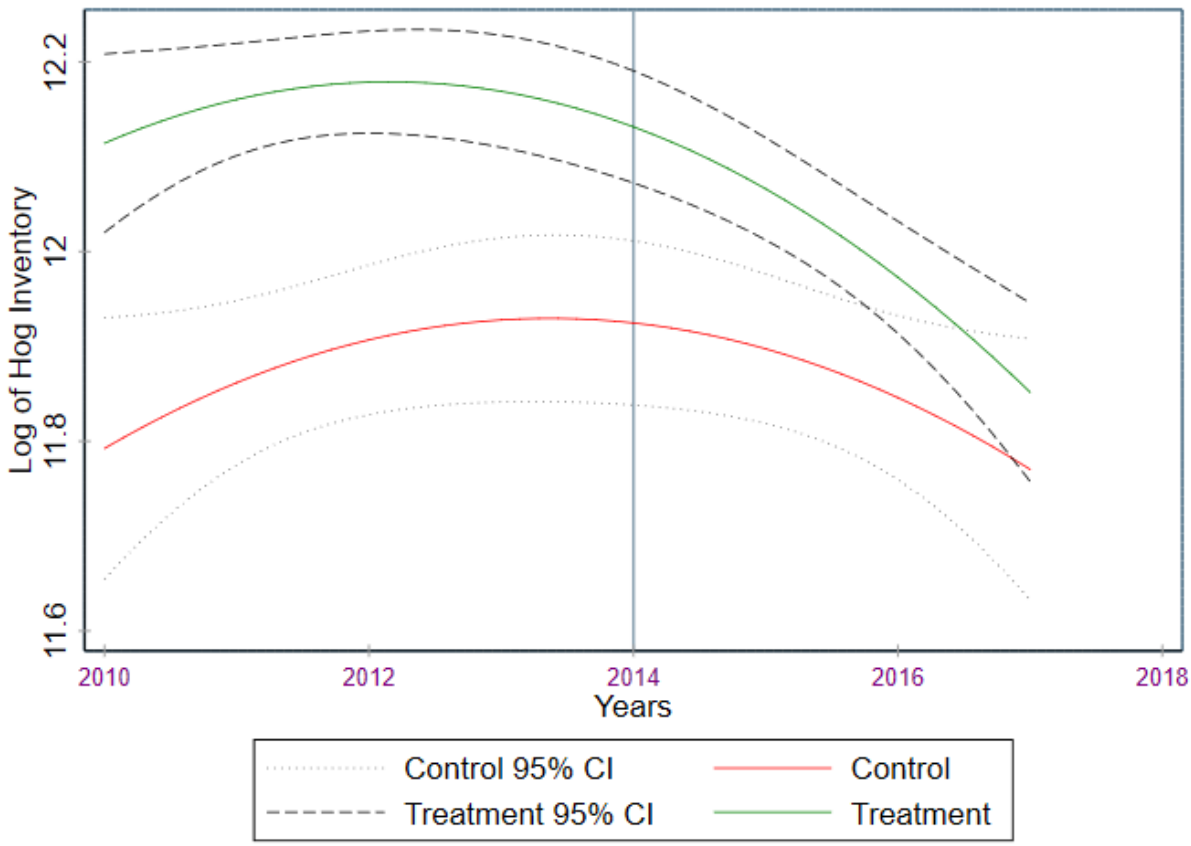


Figure D2: Trend of log of hog inventory between treatment and control groups.

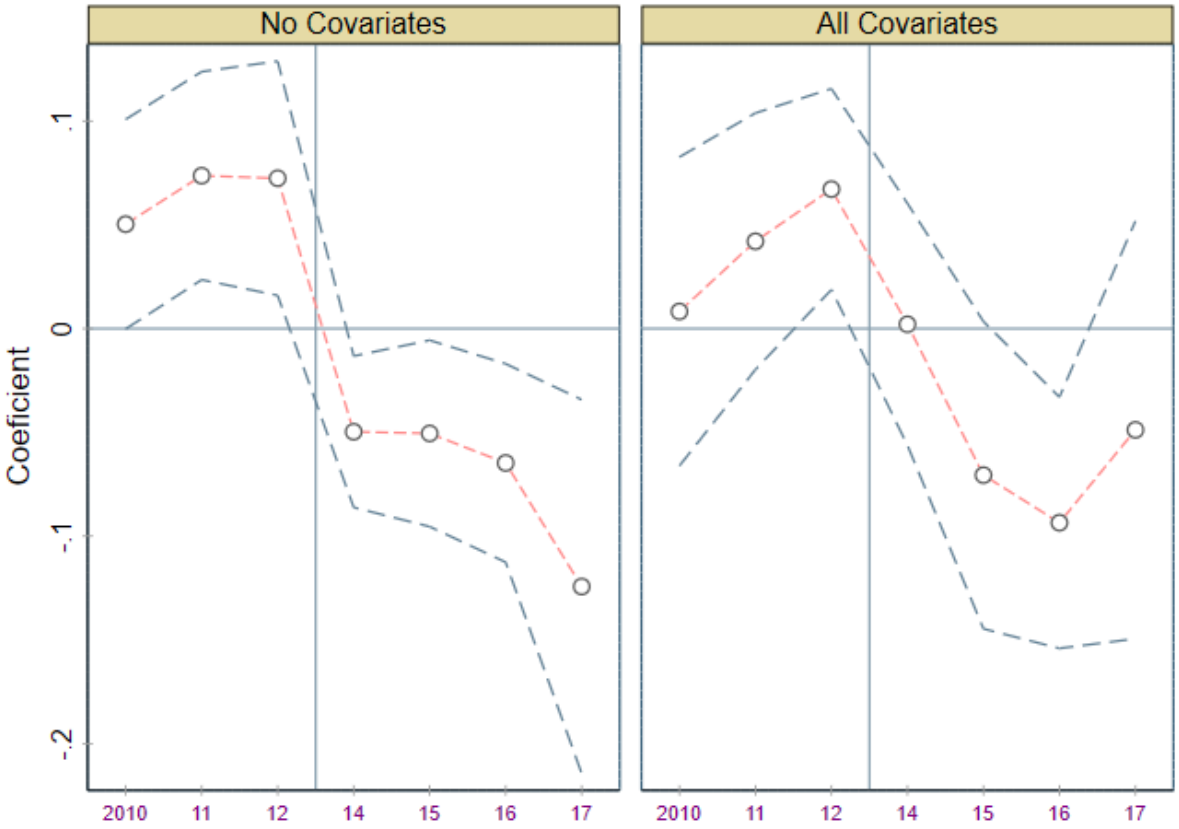


Figure D3: Prediction for pre-treatment periods for hog inventory using DID

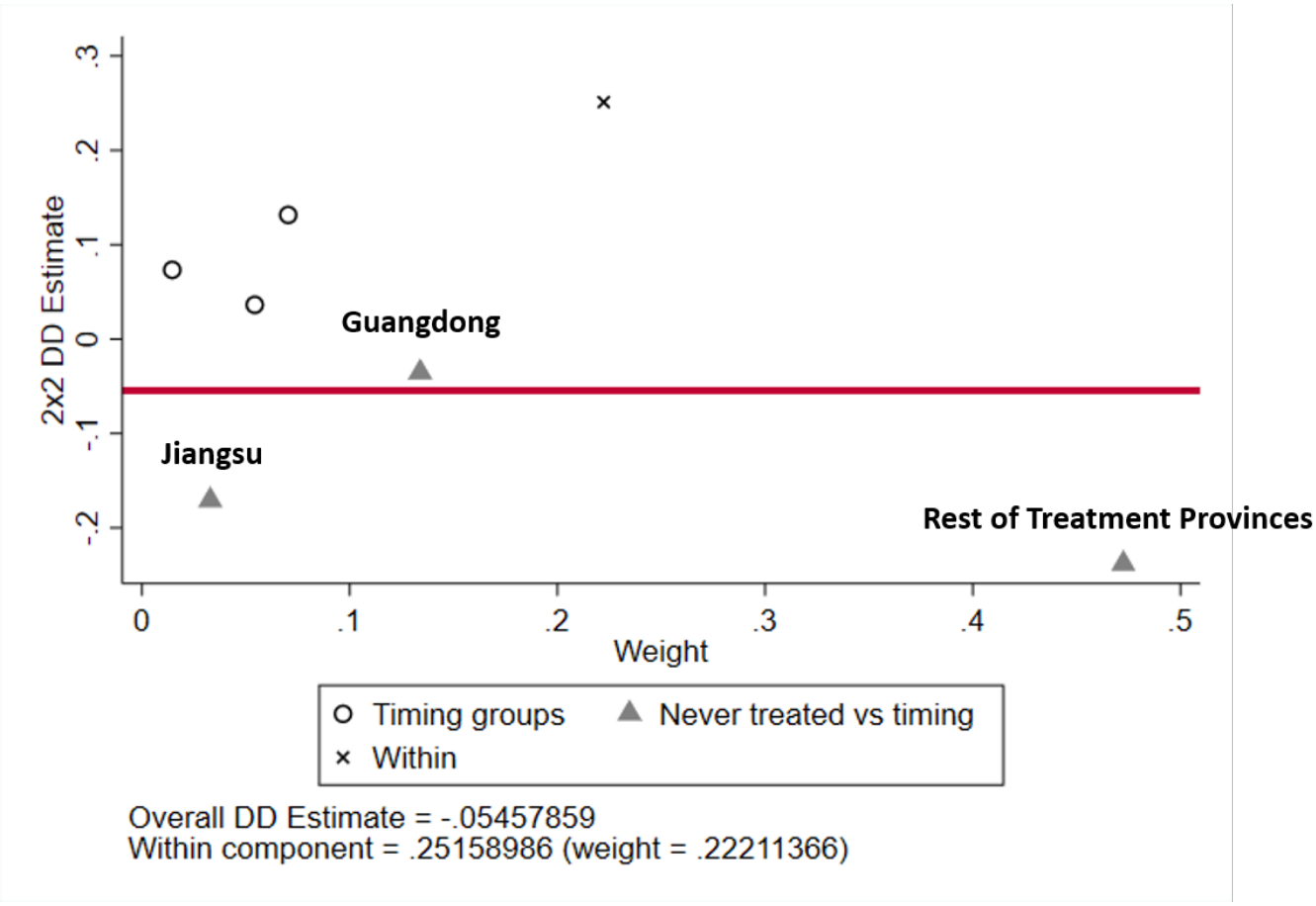


Figure D4: Goodman-Bacon decomposition method for two-way fixed effects difference-in-differences

Figure D5: Water station locations in our sample

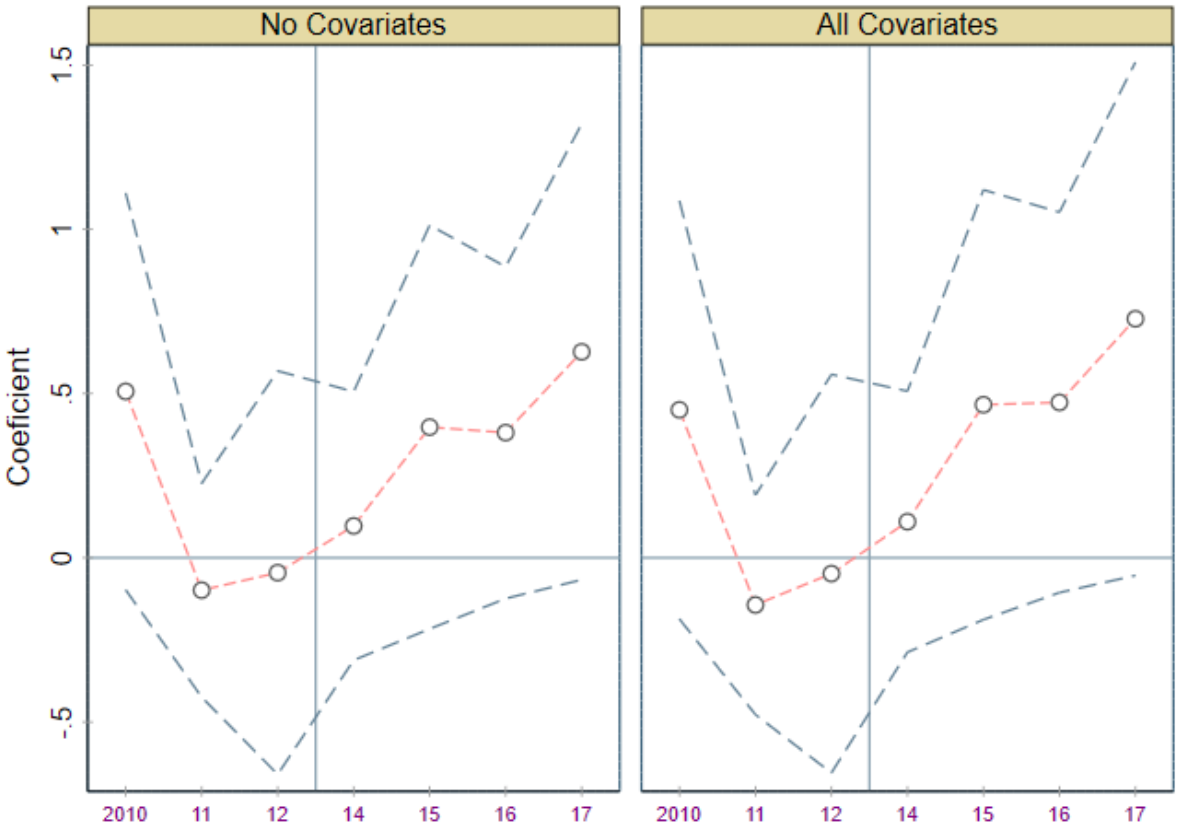


Figure D6: Parallel pre-trends test for NH_3 using DID