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IMPACT OF MARKET PRICE SUPPORT MEASURES ON CHEMICAL FERTILIZER USE IN CHINA

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Abstract:

This paper evaluates the impact of a market price support measure (TPSP) on the chemical fertilizer use in China. This policy was implemented by the government to support farmers' income and grain production in four provinces in Northeast China. This paper collected data of 390 counties before and after the policy implementation, then applied difference-in-differences (DID) and DID-matching approaches to evaluate the treatment effects and find evidence that supports this identification strategy. The results show that an average of approximately 8.7% of chemical fertilizer was overused by each county that implemented the policy compared to the counterfactual scenario with no policy. Our findings suggest that the impact of market price support measures on the environment needs to be considered.
Keywords: *Chemical fertilizer, overuse, market price support measure, subsidy, treatment effect*
JEL Codes: *Q18, Q52, Q56*

1. Introduction

Chemical fertilizer plays an important role in crop yields worldwide and therefore is essential to global food security (Chen et al., 2014; Li & Zhang, 2013). However, crop plants cannot assimilate all the nutrients, and the overuse of chemical fertilizer can lead to multiple environmental problems (Lehnert, Dong, Harland, Hunt, & White, 2018; Reay et al., 2012). Accordingly, the negative environmental externalities of chemical fertilizer use need to be considered, although the global demand for chemical fertilizer in agriculture has consistently increased to meet the growing needs of food.

Overuse of chemical fertilizer and a high proportion of loss of nitrogen are commonly found in China when farmers attempt to increase yields, leading to serious local, regional, and global pollution (Abler, 2015; Chen et al., 2014; Liu et al., 2013; Reay et al., 2012; Zhang et al., 2015). China is the world's largest consumer of chemical fertilizer, uses approximately 28% of global chemical fertilizer on only 8.64% of global cropland (FAOSTAT, 2017). The average rate of chemical fertilizer application is 389.79 kg ha^{-1} in China compared to 97.90 kg ha^{-1} worldwide excluding China (FAOSTAT, 2017); and the nitrogen use efficiency (NUE), which is the fraction of nitrogen input harvested as product, is only 0.25 in China compared to 0.42 worldwide (Zhang et al., 2015). In 2010, China released its 1st National Pollution Source Survey which showed the total nitrogen loss from crop cultivation was 1,597,800 tons, and the total phosphorus loss was 108,700 tons, accounting for 33.79% and 25.69% of the total emissions, respectively (MEE, NBS, & MOA, 2010). In recent years, the adverse environmental and health impact from chemical fertilizer overuse is starting to gain attention of central and local authorities. The Chinese government has exerted effort to reduce pollution from chemical fertilizer overuse, including the removal of subsidies to chemical fertilizers manufacturers, the implementation of soil testing, and engaging millions of smallholder farmers to adopt enhanced management practices (Cui et al., 2018; Zhang et al., 2016). However, the effects of these measures have been limited (Wu et al., 2018). To promote the sustainable development of agriculture in China, it is critical to understand the reasons for which Chinese farmers on average overuse chemical fertilizer.

According to Heisey and Norton (2007), both the decision to adopt chemical fertilizer and the application rate are determined by the interaction between agronomic response and the prices of chemical fertilizer and crop, suggesting both technical and price factors are important in explaining chemical fertilizer demand. A variety of explanatory factors can be important influences on the basic price and technology determinants of fertilizer use, such as subsidies (Khataza, Hailu, Kragt, & Doole, 2017; Koppmair, Kassie, & Qaim, 2017; Mason, Jayne, & van de Walle, 2017; Scholz & Geissler, 2018), training (Jia et al., 2013; Pan & Zhang, 2018), improved management practices (Chen et al., 2019), farm scale (Hu, Zhang, & Zhou, 2019; Ju, Gu, Wu, & Galloway, 2016; Wu et al., 2018; Zhang, Chen, & Vitousek, 2013), input market and trade liberalization (Morello et al., 2018; Qiao, Lohmar, Huang, Rozelle, & Zhang, 2003; Williams & Shumway, 2000). Other inputs, such as labor (Lamb, 2003), organic fertilizers (Li et al., 2017; Ning et al., 2017), conservation tillage (Tessema, Asafu-Adjaye, & Shiferaw, 2018), and irrigation (Fan et al., 2014), may be related to chemical fertilizer use.

Bhattacharyya and Kumbhakar (2003) shows that in many cases in developing countries fertilizer demand is more responsive to price changes or policy shifts. In China, the government has utilized some market price support measures to support farmers' incomes and increase agricultural products, including wheat, Indica rice, Japonica rice, and corn. When the support price is higher than the market clearing price, this policy will influence farmers' production decisions. Affected by price signals, farmers will take actions to increase production, such as increasing chemical fertilizer use intensity, expanding planting area, and substituting other crops with the target crop. These actions would affect the total amount of chemical fertilizer used. Although numerous studies have been carried out on the possible explanatory factors of chemical fertilizer overuse in China, impact evaluations of market price support measure are still scarce.

In this article, we evaluate the impact of a market price support measure on the chemical fertilizer use in China. In 2008-2016, the Chinese government implemented its market price support measure, called Temporary Purchase and Storage Policy (TPSP), for domestic corn producers in four provinces in Northeast China, including Liaoning, Jilin, Heilongjiang and Inner Mongolia (LJHI). The corn production of the four provinces accounts for approximately 40% of the country's total production. According to TPSP, the grain depots belong to China Grain Reserves Group LTD. Company (SINOGRAIN) and the grain depots rent by SINOGRAIN purchased the corn delivered by farmers at the support price set by the government, which was higher than the market clearing price. TPSP was launched in November 2008, and abolished in November 2016. Thus, this policy influenced farmers' production decision from 2009 to 2016.

An important research question is: to what extent can TPSP contribute to chemical fertilizer overuse? This study aims to address this question. Intervention provinces were not randomly selected, and to deal with this issue, we use the difference-in-differences (DID) and DID with propensity score matching (PSM) approaches. Although there are differences in crop structure, cropping seasons, labor inputs, and machinery inputs between the treated group in Northern China and the comparison group in other regions, our test can provide evidence supporting the parallel trend assumption that both groups follow the same trend during the pretreatment period. Therefore, the DID and DID-matching approach can be applied to capture the impact of TPSP on chemical fertilizer use based on the data from a sample of 70 counties in treated group (LJHI) and 320 counties in control group (where TPSP was not offered) in 2005-2016.

2. Materials and Methods

2.1. Data

Our main data sources are the statistical yearbooks for each province. We collected data of 390 counties in 2005-2016, with a total of 4,376 observations. Of these, 70 counties were surveyed in the intervention group and 320 counties in the comparison group. Our database includes variables related to chemical fertilizer use in two periods considering that TPSP was launched in 2008 and ended in 2016. Descriptive statistics is presented in Table 1. Since the data of chemical fertilizer use and planting area for each crop in each county are not available, we can only indirectly examine the impact of TPSP on chemical fertilizer use by total fertilizer use, average application intensity, grain area and total crop area of each county. Our identification strategy, DID and DID-matching approaches, can identify the treatment effects of the policy. The total chemical fertilizer use, chemical fertilizer use intensity, and grain area all increased in both groups before and after the TPSP. Our goal is to assess the extent to which such changes can be attributed to the policy implementation.

Table 1. Descriptive Statistics

Variable	**Treatment group (70 counties)**			**Comparison group (320 counties)**		
	Obs.	**Mean**	**Std. dev.**	**Obs.**	**Mean**	**Std. dev.**
Pre-treatment (2005-2008)						
Total chemical fertilizer use (ton)	280	32371.69	30147.76	1180	26655.42	23585.55
Chemical fertilizer use intensity (kg ha^{-1})	280	288.94	125.22	1180	340.97	122.46
Grain area (ha)	280	91438.09	76860.46	1180	51551.31	34934.28
Crop area (ha)	280	109443.50	86742.54	1180	73541.65	55321.07
Post-treatment (2009-2016)						
Total chemical fertilizer use (ton)	560	42968.45	39233.42	2356	30117.23	27683.96
Chemical fertilizer use intensity (kg ha^{-1})	560	314.49	136.31	2356	372.33	139.19
Grain area (ha)	560	116366.50	96216.73	2356	54773.27	37937.13
Crop area (ha)	560	133664.90	104693.60	2356	75121.94	55342.41

2.2. Parameters of Interest

First and foremost, we aim to measure the impact of TPSP on chemical fertilizer overuse among treated counties. This impact is measured as the average amount of chemical fertilizer overused by farmers in treatment counties as a result of the policy. We then also express our impact analysis in chemical fertilizer use intensity, in grain area, and in total crop area. To determine the average amount of chemical fertilizer overused among treated counties as a result of TPSP, we need to calculate the difference between the amount of chemical fertilizer observed on treated counties and the amount of chemical fertilizer that would have been observed in those counties in 2009-2016, had they not been involved in the policy. This is the so-called average treatment effect on the treated (ATT). It is defined as ATT=$E(y_{1i}\text{-}y_{0i}|D_i\text{=}1)$, where E means taking the expected value, y_{1i} denotes the amount of chemical fertilizer used by county i in the presence of the policy, y_{0i} denotes the amount of chemical fertilizer used by county i in the absence of the policy, and D_i is a dummy variable that takes on the value of one when the county i participated in the policy and zero otherwise (Simonet, Subervie, Ezzine-de-Blas, Cromberg, & Duchelle, 2019). We use DID and DID-matching methods to estimate the average treatment effect of the policy. The counties from the comparison group are used to construct valid control group, and the performance of the control group is assumed to be the counterfactual of the treatment group. Those estimators allow us to take into account possible group-specific effects and time-specific effects among counties in both the treatment group and the comparison group.

2.3. DID and DID-matching Approaches

We first regress the amount of chemical fertilizer on the DID treatment effect estimator. The DID estimator is commonly used in policy evaluation work, and measures the impact of the policy intervention by the difference in the before-after change in outcomes between treatment group and comparison group (Todd, 2007). Using DID method requires a parallel trend assumption, which says that both treatment and comparison groups follow the same trend during the pre-treatment period. The parallel trend assumption ensures that the two sets of samples are comparable before the policy is launched. In the present study, for multi-period panel data, this assumption can be tested by adding the interaction term between the time dummy variable and the policy variable in the regression (such as in this article, the year dummy variable is multiplied by the treatment group dummy variable). If the coefficient of the interaction term before the policy is launched is not significant, it indicates that there is a parallel trend between the two groups.

We then use three different PSM estimators, k-nearest neighbors matching (NNM), radius matching (RM), and kernel matching (KM) as a robustness test (Simonet et al., 2019). The PSM methods can adjust for pre-treatment observable differences between a group of treated and a group of untreated. The dependent variable in this paper is the amount of chemical fertilizer use and therefore we include the grain area and crop area in the set of observable factors.

2.4. DID Model

We estimate a Two-way Fixed Effects DID model of the following form:

$$Y_{it} = \alpha + \beta DID + u_i + \lambda_t + X'_{it}\gamma + \varepsilon_{it} \tag{1}$$

where Y_{it} refers to the log outcome in county i in year t. The variable of interest is *DID*, a dummy variable that equals one for the treatment counties in 2009-2016 and zero otherwise. In this DID model, we include county fixed effects (μ_i) to capture unobservable time-invariant characteristics of counties such as the geographic characteristics that can influence the chemical fertilizer use. This model also includes time fixed effects (λ_t) to capture covariate time-variant shocks such as the technical progress that may influence the chemical fertilizer application. Moreover, X_{it} is a set of time-varying county-level variables, and ε_{it} is the error term.

3. Results

3.1. Impacts on Total Chemical Fertilizer Use

To estimate ATT, we apply the aforementioned DID estimators to the group of treated counties using the comparison group to estimate the counterfactual level of chemical fertilizer use. Applying the DID-estimator only requires testing the parallel trend assumption, which has been tested and will be discussed later. Moreover, applying the DID-matching estimators requires examining whether the matching results balance the data well and whether most observations are within the common range of values.

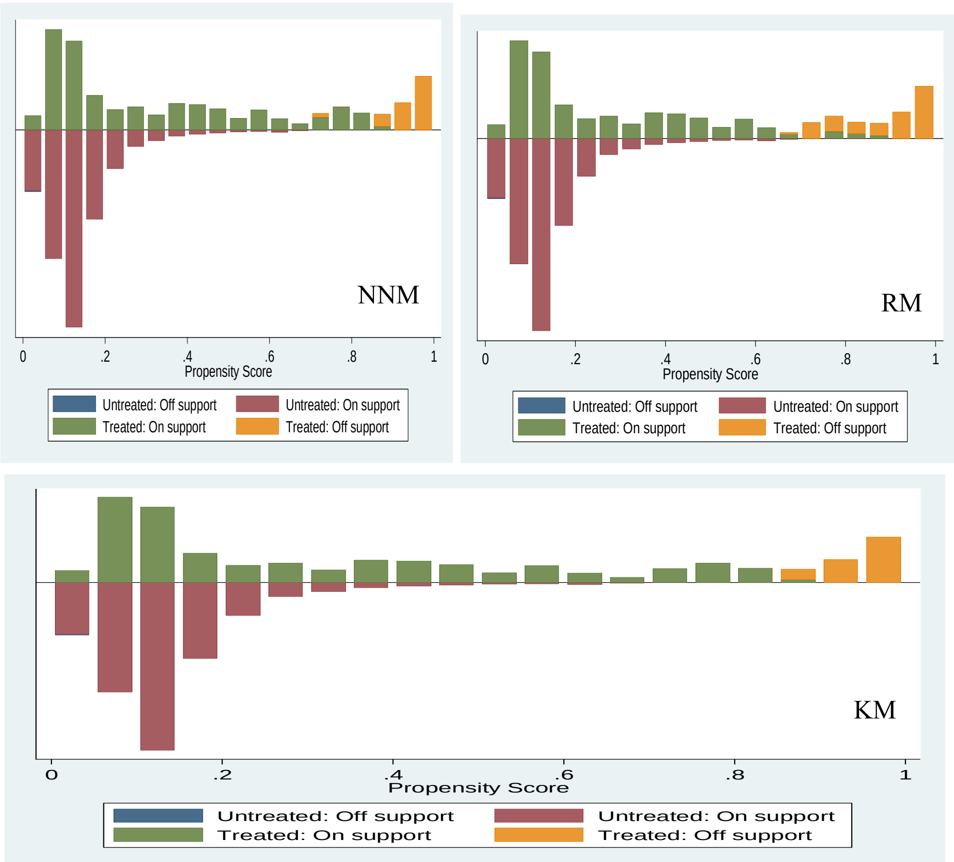


Figure 1. Common Range of Propensity Scores

Table 2. The Normalized Difference (%bias)

Variable	Unmatched	Matched		
		NNM	RM	KM

Total chemical fertilizer use (ton)	32.7	-7.1	-7.0	-5.1
Chemical fertilizer use intensity (kg ha^{-1})	-41.7	-7.6	-6.6	-5.3
Grain area (ha)	78.3	-5.6	-5.0	-3.3
Crop area (ha)	63.3	-6.6	-5.9	-4.5

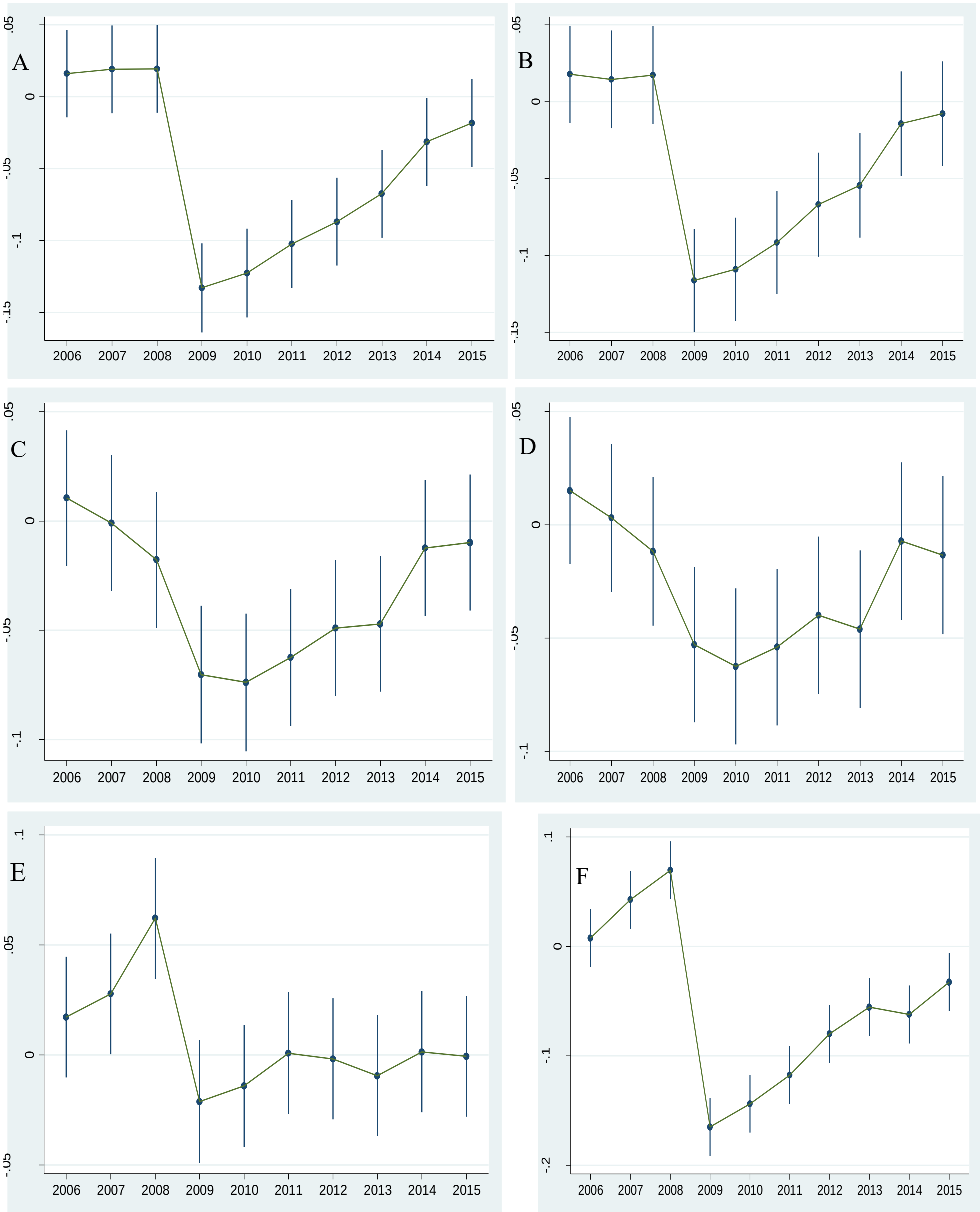
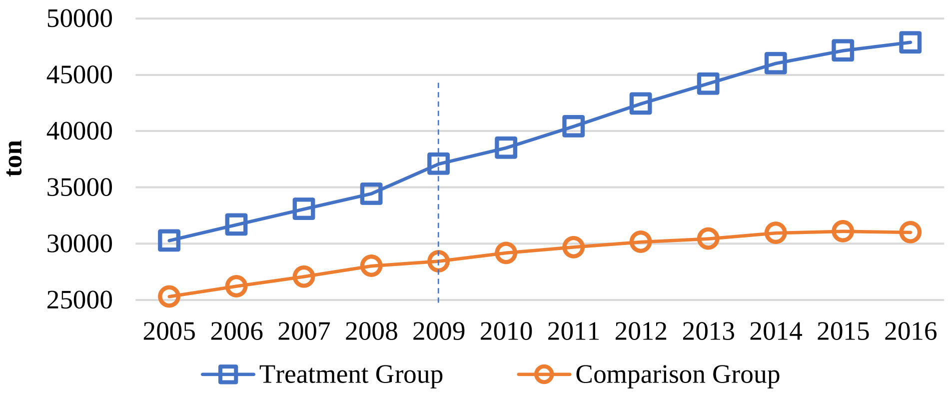


Figure 2. Parallel Trends Test

We compute propensity scores by estimating a logit model, and then compare the extent of balancing by comparing the normalized difference between the treated and comparison groups before and after the matching procedure. The normalized difference (%bias), which is the difference in means divided by the square root of the sum of variances for both groups, is the most commonly accepted diagnostic used to assess covariate balance (Imbens, 2004; Stuart, 2010).

We then examine the validity of the parallel trends assumption by adding the interaction term between the year dummy variable and the treatment group variable in the regressions with and without PSM. For the total chemical fertilizer use, the results show that the coefficient of the interaction term before the policy was launched is not significant, applying DID and DID-matching method separately (Fig. 2A&B). For the chemical fertilizer use intensity, the results show that the coefficient of the interaction term before the policy was launched is not significant (Fig. 2C&D). These results indicate that the treatment group and comparison group had followed the same trend before the TPSP started, which supports our identification strategy, whether it is the DID or the DID-matching approach. We can also observe the parallel trends in Fig. 3. However, for the grain area and crop area, the coefficient of the interaction term before the policy was launched is significant, as shown in Figure 2E&F, that means the treatment group and comparison group had not followed the same trend before the TPSP started, so it is not appropriate to apply the aforementioned identification strategy.



Source: Authors' calculation from the statistical yearbooks for each province.

Figure 3. Total Chemical Fertilizer Use

The main results of our study, the effects of the policy among treated counties, are presented in Table 3. Row 1 gives the estimates of the DID estimator, which represents the impact of TPSP on chemical fertilizer use. We first apply Random Effect model (RE) and One-way Fixed Effect model (One-way FE) separately to our data to estimate the average effect of the TPSP (column 1 and 2). The p value of Hausman test is 0.0000, that suggests to apply One-way FE rather than RE. We then apply Two-way Fixed Effects model (Two-way FE) to our data to estimate the DID (column 3). The p value of F test is 0.0000, that means time effect should be included in the model, and suggests to apply Two-way FE rather than One-way FE.

We then use Two-way FE with three different PSM estimators as a robustness test (column 4, 5, and 6). In the majority of cases, the estimate of impact is accurate and robust, and there is little difference with and without PSM. Using the smallest significant impact estimator, which is the DID estimator with NNM, ATT equals 8.7 percentage points. ATT indicates that the treated counties applied, on average, about 8.7 percentage points more chemical fertilizer than that they would have applied had they not been involved in the policy. Given that the average chemical fertilizer use in participating counties equals 42,968.45 tons, an average of approximately 3,742.55 tons of chemical fertilizer was overused on each treated county compared to the counterfactual scenario of no policy. The total chemical fertilizer use of treatment and comparison groups is shown graphically in Figure 3. We observe that the total chemical fertilizer use continues to rise in both treatment and comparison groups in 2005-2016. However, we see a clear break in the trend among treated counties, which we can attribute to TPSP.

Table 3. Estimation Results of Impacts on Total Chemical Fertilizer Use

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	RE	**One-way FE**	**Two-way FE**	**NNM**	**RM**	**KM**
DID	0.13***	0.16***	0.094***	0.087***	0.090***	0.088***
Standard errors	0.0087	0.0085	0.0077	0.0082	0.0083	0.0082
95% Conf. Interval	(0.12, 0.15)	(0.14, 0.17)	(0.079, 0.11)	(0.071, 0.10)	(0.073, 0.11)	(0.072, 0.10)
County fixed effects	No	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
R^2	0.34	0.35	0.52	0.50	0.47	0.49
Observations	4376	4376	4376	4230	4166	4236

Note: ***, **, and * denote coefficients which are statistically significant at 1%, 5%, and 10% level, respectively.

3.2. Impacts on Chemical Fertilizer Use Intensity

We then apply aforementioned identification strategy to the chemical fertilizer use intensity to check whether any change should be detected and attributed to the TPSP. We did this because one might expect that farmers in the treated counties have increased the amount of total chemical fertilizer into the same crop area to increase corn production.

Table 4. Estimation Results of Impacts on Chemical Fertilizer Use Intensity

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	RE	**One-way FE**	**Two-way FE**	**NNM**	**RM**	**KM**
DID	0.079***	0.096***	0.045***	0.042***	0.043***	0.043***
Standard errors	0.0081	0.0082	0.0077	0.0084	0.0085	0.0084
95% Conf. Interval	(0.063, 0.095)	(0.080, 0.11)	(0.030, 0.061)	(0.025, 0.058)	(0.026, 0.060)	(0.027, 0.060)
County fixed effects	No	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
R^2	0.12	0.12	0.30	0.29	0.29	0.29
Observations	4376	4376	4376	4230	4166	4236

Note: ***, **, and * denote coefficients which are statistically significant at 1%, 5%, and 10% level, respectively.

Table 4 presents the effects of the policy on the chemical fertilizer use intensity among treated counties. In the majority of cases, the estimate of impact is accurate and robust. Using the smallest significant impact estimator, which is the DID estimator with RM, the ATT equals 4.2 percentage points. The ATT represents that the treated counties' chemical fertilizer use intensity is, on average, 4.2 percentage points more than that had they not been involved in the policy. Given that the average chemical fertilizer use intensity in treated counties equals 314.49 kg ha^{-1}, an average of approximately 13.15 kg ha^{-1} of chemical fertilizer was overused on each treated county compared to the counterfactual scenario of no policy.

3.3. Impacts on Reactive Nitrogen Losses and GHG Emissions

We apply our main estimate of the impact of TPSP on chemical fertilizer to calculate the reactive nitrogen losses and GHG emissions generated by the policy. According to Cui et al. (2018), the average ratio of reactive nitrogen losses (N_2O emission, NH_3 volatilization, NO_3-leaching and nitrogen runoff losses) to nitrogen(N) fertilizer use is 22.41%, and the average coefficient of GHG emission (CO_2, CH_4 and N_2O) is 1.526. Our findings show that an average of approximately 8.7% of chemical fertilizer was overused by each treated county compared to the counterfactual scenario. Given that the total N fertilizer use in LJHI in 2009-2016 equals 24,633,954 tons, an average of approximately 2.15 million tons of N fertilizer was overused, which lead to around 0.48 million tons of reactive nitrogen losses and 3.28 million tons CO2-equivalent emission. Therefore, TPSP had brought significant negative environmental externalities while supporting farmers' income and grain production.

4. Conclusion

Chinese agricultural system relies heavily on high-to-excessive inputs, and chemical fertilizer overuse has resulted in enormous damages to environmental quality. This paper applies DID and DID-matching approaches to estimate the impact of a market price support measure (TPSP) on chemical fertilizer overuse in four provinces in Northeast China. Our identification strategy can identify the treatment effects of the policy by using a Two-way Fixed Effects DID model. The results show that an average of approximately 8.7% of chemical fertilizer was overused by each county that implemented the policy compared to the counterfactual scenario with no TPSP. The treated counties' chemical fertilizer use intensity is, on average, 4.2% more than that had they not been involved. These results indicate that TPSP significantly increased the amount of chemical fertilizer used in the treatment group. Moreover, our calculation suggests that massive reactive nitrogen losses and GHG emissions were generated as a result of TPSP during 2009-2016. These results indicate that market price support measures, which set the support price higher than the market clearing price, had caused price distortions and brought significant negative environmental externalities. Although TPSP for corn producers had expired since 2017, the market price support measures for agricultural producers of wheat, Indica rice, and Japonica rice are still in use in China. The impact of these policies on the overuse of agricultural chemicals needs to be considered, since China is the world's largest consumer of agricultural chemicals. It is necessary to evaluate the impact of agricultural policies on the environment, especially in developing countries.

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