Investigating the Impact of Agricultural Subsidy on Chemical Fertilizer Use in China

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Abstract

Understanding the overuse of chemical fertilizer is critical for global food security and environmental protection. We use a nationally representative rural household survey from China, the difference-in-difference, three-step approach, and Seemingly Unrelated Regression methods to assess the impacts of China's new agricultural subsidy on chemical fertilizer use, heterogeneity effect, and mechanism. The results show that, first, the new agriculture subsidy reduces the use of chemical fertilizer by about 7.2 percent. A series of robustness tests confirms the finding. Second, the heterogeneity analysis shows that the subsidy's negative impact on fertilizer use is substantially greater among younger farmers than among older farmers. The negative effect also is significantly more in the main grain-producing areas than in non-grain-producing areas of China. Third, the mediating effect analysis shows that farmland scale mediates 8.3 percent of fertilizer use, and adoption of agricultural machinery mediates 48.6 percent of fertilizer use. Thus, China's new agricultural subsidy reduces fertilizer use by helping farmers expand their farmland scale and adopt farm machinery. Our findings underscore the positive role that reforming the agrarian subsidy policy plays in sustainable development.

Keywords: agricultural subsidy, chemical fertilizer use, difference-in-difference, mediating effect, China

JEL classifications: C21, C33, H22, L86, Q12, Q18

1. Introduction

In developing and transition economies, finding an optimal balance between chemical fertilizer use and food production is vital for food production, productivity, and a nation's food security (Yuan et al., 2022; Tang et al., 2019). Since its inception, chemical fertilizer has been key in increasing crop yields, food security, and farmers' incomes (Guo et al., 2022; Pan et al., 2017). However, the overuse of chemical fertilizer has occurred in many developing countries such as China (Tang et al., 2020; Tang, 2022) and has caused and still is causing a range of environmental problems, including greenhouse gas emissions, the degradation of soil and water quality, and the loss of biodiversity and ecosystem services (Kanter, 2018; Pan et al., 2017; Tang et al., 2016; Tang et al., 2019).

Reducing the excessive use of chemical fertilizer is crucial for global food security, sustainable food production, resource conservation, and achieving net zero emissions in the agricultural sector (Duan et al., 2021; Zhang et al., 2015; Zuo et al., 2018). Countries have introduced different strategies, including information services, knowledge training, and policy incentives, to achieve the reduction targets for chemical fertilizer. For example, in 2015, India's government launched a large-scale soil health information program. About 24 million soil samples were tested, and 93 million soil health cards, test results, and fertilizer recommendations were delivered to farmers (Kishore et al., 2021). A series of farmer field schools have been built in China to improve farmers' soil nutrient management through the participatory training approach using local farmer-trainers (Cui et al., 2018). In Europe, agricultural support policies have long been coupled with environmental protection, known as cross-compliance conditions, to reduce chemical inputs, e.g., fertilizers and pesticides (Baráth et al., 2020; Gocht et al., 2017; Mamun et al., 2021).

Prior evidence shows that the agricultural subsidy, an incentive strategy, has become an effective policy tool in promoting global green and sustainable agricultural development (Zhang et al., 2021a). For example, in the opinion of many European and American scholars, combining an agricultural subsidy with environmental standards or subsidizing fertilizer-saving crops could make environmentally friendly management practices more attractive for farmers and reduce the excessive input of chemical fertilizer (Schmid and Sinabell, 2007; Sun et al., 2016). Similarly, some Chinese scholars, Liang et al. (2019) and Luo et al. (2014), also found that an agricultural subsidy can encourage farmers to reduce their overuse of chemical fertilizer and bring environmental benefits to agricultural production.

However, some scholars held a contrary opinion. The results of Repetto (1987) argued that an agricultural subsidy promoted farmers' incremental investment in chemical fertilizer by distorting the price of agricultural materials. Scholz and Geissler (2018) found that any fertilizer subsidy provides an economic incentive for farmers to increase fertilizer use and further suggest that policies such as taxes or fines be used to regulate fertilization practices in countries with excessive fertilizer use, like China and Vietnam. Li (2016) argued that China's agricultural subsidies prompted farmers to increase chemical fertilizer use, which in turn deteriorated soil fertility and triggered farmers to spend more of their subsidies on fertilizer inputs and increasing fertilizer use.

The mixed findings of the above studies can be partially attributed to their ignoring the changes of other agrarian factor inputs simultaneously affected by the agricultural subsidies. Agricultural production requires multiple inputs, such as fertilizer, irrigation, labor, and machinery (Coomes et al., 2019; Mueller et al., 2012). These differences in agricultural inputs are the main driver of differences in environmental impact across farms (Ren et al., 2021; Zuo et al., 2018). Some recent studies no longer restrict themselves to the direct impact of an agricultural subsidy but begin to explore its indirect effects. For example, Guo et al. (2021) found that doubling an agricultural subsidy decreases chemical fertilizer use by about 3.4%, with agricultural machinery mediating its use by 5.3% and farmland scale mediating it by 41%. However, Wu et al. (2019) conclude that an agricultural subsidy increased chemical fertilizer use by encouraging farmers to increase their farmland scale. He et al. (2022) suggest that an agricultural subsidy acted to reduce the intensity of chemical fertilizer application by encouraging farmers to expand the scale of operation, but the subsidy increased the intensity of chemical fertilizer application by incentivizing farmers to purchase farm machinery and adopt mechanical farming. Even though these studies contribute to our understanding of the relationship between agricultural subsidies and fertilizer use, academics still do not agree about this issue. In addition, a nationwide reform of agricultural subsidy policy[1] began in China in 2016 by distributing part of a subsidy to the actual producers, encouraging them to enlarge their operations and use the advanced technical means to achieve a high grain yield in green methods (MOF-MOA, 2016). Although this subsidy policy has been implemented in China for several years, its impact is still poorly understood. This study not only can bridge the research gap but also enlighten those countries dominated by smallholder and intensive farming, like China, to achieve green and sustainable agricultural development by reforming their agricultural subsidy systems.

This study's objective is to empirically examine the effects of China's new agricultural subsidy on the use of chemical fertilizer. Specifically, we aim to answer two questions. First, does the agricultural subsidy reduce farmers' use of chemical fertilizers? We further examine what differences in the above may exist between different regions and types of farmers? Second, how does the agricultural subsidy reduce the use of chemical fertilizers? This paper contributes to the growing literature on the impact evaluation of agricultural subsidies in at least two ways. The first contribution is to be the first study to look at the environmental impact of China's new agricultural subsidy policy. It could provide a reference

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[1] After the reform, China's agricultural subsidies consist of the "*farmland quality subsidy*" and the "*moderate-scale operation subsidy*." The allocation of the "*farmland quality subsidy*" still is based mainly on farmers' contractual rights. However, the "*moderate-scale operation subsidy*" is granted to the actual cultivated area by the operator. This paper regards the "*moderate-scale operation subsidy*" as the evaluation target because it is the main force of transformation in this round of China's agricultural subsidy reform. We also call it the new agricultural subsidy for short.

to formulate a “green” and“decouple” agricultural subsidy policy for developing and transition economies like China’s. The second contribution is that the robustness and reliability of the model estimates have been enhanced by using seemingly unrelated regression (SUR) combined with bootstrapping to estimate the multiple mediating effects in one step. It provides the assumption of non-independence of equations missing from earlier studies to assess multiple mediating effects.

2. China’s fertilizer use and the evolution of the agricultural subsidy policy

China already has become the world’s largest fertilizer producer and consumer, employing more than 30% of the world’s fertilizer on less than 9% of the global cropland (www.fao.org/faostat). According to the National Bureau of Statistics of China (https://data.stats.gov.cn/), China’s fertilizer use increased from about 463 hundred thousand tons in 2004 to 602 hundred thousand tons in 2015, an average annual increase of 2.41% (Figure 1). This is nearly equivalent to the total fertilizer used in the United States and India. The intensity of chemical fertilizer use has likewise increased by an average of 1.03% yearly, rising from about 456 kg per ha in 2004 to 510 kg per ha in 2015 (Figure 1). The average intensity of fertilizer use in China was about 2.6 times higher than the global average in 2016 (https://data.worldbank.org). The overuse of chemical fertilizer has caused various environmental problems in China, including eutrophication of surface waters in the Yangtze River basin, nitrate pollution of groundwater in the north, severe soil acidification in the south, and growing emissions of greenhouse gases (Cui et al., 2018; Zhang et al., 2020; Tang and Ma, 2022).

In 2004, China’s agricultural sector entered a new era when the government began subsidizing rather than taxing agriculture (Figure 2). The subsidy program comprised the "*direct grain subsidy*" and the "*quality seed subsidy.*" Then in 2007, the "*aggregate input subsidy*" was added when the global food crisis of 2006-2008 increased the price of fertilizer and other agricultural inputs. However, most surveys show that China's grain subsidy program does not impact agricultural production, since the subsidy payment is not based on farmers' current-year grain inputs or outputs but on contracted land areas or taxable grain-sown areas (Huang et al., 2011; Tian and Meng, 2010). The land contractors still receive agricultural subsidies even if they have rented out their land, while the actual operators who rent land do not receive grants associated with the rental land (MOF-MOA, 2015).

In 2016, the Chinese government began to reform agricultural subsidies by distributing part of them to the actual producers (Figure 2). The above three subsidies have been merged into one and renamed the "*agricultural support and protection subsidy.*" One part of the "*agricultural support and protection subsidy*," known as the "*farmland quality subsidy,*" still is based mainly on the farmer's contractual rights. However, the other part is the "*moderate-scale operation subsidy,*" granted according to the actual area cultivated, and encourages the operators to enlarge their operations and use the advanced technical means to achieve a high grain yield in green agricultural subsidy policy (MOF-MOA, 2015, 2016).

Figure 1 shows that the new agriculture subsidy may reduce China's total use of chemical fertilizer. For instance, the use of chemical fertilizer fell 10.3% from its historic peak of 602 hundred thousand tons in 2015 to 540 hundred thousand tons in 2019. The intensity of fertilizer use also declined, from 510 kg per ha in 2015 to 465 kg per ha in 2019, with a decline over fours years of 8.81%. Conducting a rigorous causality analysis is essential, although the impact of China's new agricultural subsidy on the use of chemical fertilizer seems obvious.

3. Theoretical analysis and research hypothesis

Agricultural production requires multiple inputs, such as fertilizer, labor, machinery, and irrigation (Coomes et al., 2019; Mueller et al., 2012). According to Heisey and Norton (2007), the relative scarcity of agricultural land has been the main reason behind the expanded demand for chemical fertilizers in developing countries. Other causes include input factors that substitute for or complement fertilizer use, such as agricultural machinery and farm labor (Mazid Miah et al., 2016; Rychel et al., 2020; Zhang et al., 2021b). Theoretically, if farmers received the agricultural subsidy, farmers would adjust their farming production methods and change the production inputs, thus affecting fertilizer use (Guo et al., 2021; He et al., 2022; Mamun et al., 2021; Wu et al., 2019), mainly in three ways:

First, the use of chemical fertilizer will decrease with an increase in farmland scale by farmers getting the agricultural subsidy. Small-scale farms and smallholder management have been considered critical constraints in reducing the overuse of fertilizer in China, while large-scale farming has been regarded as a viable pathway to achieve food production and sustainable development (Duan et al., 2021; Ren et al., 2019; Wu et al., 2018). Farmers on small-scale farms prefer using more chemical fertilizers to reduce their labor and technology inputs (Hu et al., 2021; Ju et al., 2016; Zhang et al., 2020). One of the benefits of China's new agricultural subsidy is the consolidation of land resources, concentrating scattered and abandoned farmland into the hands of farmers who actually cultivate the land, thereby promoting the scale and specialization of agricultural production (Fan and Mishra, 2022).

Due to economies of scale, farms that have achieved scale and specialization tend to be more efficient than small-scale farms in their fertilizer use (Cao et al., 2022; Duffy, 2009; Su et al., 2022). For example, small-scale farms often apply fertilizer based on personal experience rather than the needed amounts, while large-scale farms prefer to apply fertilizer precisely for cost reduction (Ren et al., 2021; Wu et al., 2018). In addition, larger-scale farming helps reduce average (transaction) costs, including the cost of learning new fertilization techniques and the cost of purchasing fertilizer (Duan et al., 2021; Guo et al., 2021; Ju et al., 2016).

Second, farmers receiving the agricultural subsidy may choose to increase inputs of farm labor and thus reduce their use of chemical fertilizer. Agri-chemical inputs increase with off-farm employment, as farmers tend to replace labor with chemical fertilizer, reducing the risk of agricultural production (Zhang et al., 2021b). A typical example is that farmers prefer to save labor costs by reducing the frequency of fertilization and increasing the fertilizer dosage per application (in the Chinese proverb–*Yipao hong*), which often leads to the overapplication of chemical fertilizer (Zhu et al., 2021). Conversely, the agricultural subsidy attracting farmers to hire more labor can dilute the above effect. In addition, using organic fertilizer instead of chemical fertilizer could improve soil quality and reduce greenhouse gas emissions, which also has been regarded as a viable pathway to achieve sustained agriculture development in China (Wang et al., 2018). But farmers are not enthusiastic about applying organic fertilizer in China since it often requires more laborers and time than chemical fertilizer requires (Li and Shen, 2021). However, by reducing the outflow of farm households' labor from agriculture and increasing hired labor (Garrone et al., 2019), the agricultural subsidy could encourage farmers to adopt organic fertilizer to replace chemical fertilizer, thus reducing the use of chemical fertilizer.

Third, the agricultural subsidy will reduce chemical fertilizer use by incentivizing farmers to increase machine use. Farming households in China usually face liquidity constraints that often make them reluctant or unable to purchase agricultural machinery (Yi et al., 2015). Hand broadcasting is the most cost-effective approach to applying fertilizer for farmers, which generally results in a higher loss ratio than fertilization through machinery (Ren et al., 2021). Moreover, to cover the lack of agricultural machinery inputs and ensure farm productivity, farmers tend to overuse fertilizer, which further exacerbates fertilizer losses (Erisman et al., 2013). By contrast, China's new agricultural subsidy can encourage farmers to increase machine use by loosening their liquidity constraints (Guo et al., 2021; He et al., 2022). The mechanical fertilizer application eliminates or reduces the problems of uneven or nonstandard artificial fertilization, and precise fertilization and deep-plowing techniques improve the efficiency of chemical fertilizer application and thus reduce the use of chemical fertilizer (Mazid Miah et al., 2016; Rychel et al., 2020). For example, using stratified fertilization machinery can place fertilizers in different depths in the soil, allowing a higher proportion of it for crops across the whole growing season (Zhu et al., 2018). And using agricultural machinery to plow and loosen the soil can improve nutritional conditions and strengthen soil fertility (Baumhardt et al., 2008), then reduce chemical fertilizer use (Rychel et al., 2020; Mazid Miah et al., 2016).

Apart from these indirect effects, the agricultural subsidy also may directly affect the use of chemical fertilizer. Several previous studies argue that agrarian subsidies can promote chemical fertilizer use by distorting the price of agricultural materials (Repetto, 1987; Wu et al., 2019). However, many Chinese scholars have recently found that farmers who receive subsidies are more likely than farmers who did not receive subsidies to buy higher-efficiency fertilizer or use more organic fertilizer, which reduces the use of chemical fertilizer (Guo et al., 2021; Wang et al., 2018). In particular, China's supplies of chemical fertilizer are abundant, and farmers' budget constraints exist mainly in buying higher-price organic fertilizer or high-quality fertilizer rather than the usual chemical fertilizer (Guo et al., 2021). Thus, the new agricultural subsidy may directly reduce the use of chemical fertilizer.

Based on the above analysis, two hypotheses are formulated:

Hypothesis 1 (H1): The new agricultural subsidy can reduce chemical fertilizer use.

Hypothesis 2 (H2): The new agricultural subsidy reduces chemical fertilizer use by helping farmers expand farmland scale, hire more farm labor, and increase machine use.

4. Data and empirical framework

4.1. Data source

The data used in this study are from the 2015 and 2017 China Rural Household Panel Survey (CRHPS), a nationwide survey of households in China conducted by Zhejiang University. The survey used a stratified, three-stage, and population-scale-proportional (PPS) sampling method (Fan and Mishra, 2022; Wu et al., 2018). At three levels — community, household, and individual — the survey covers the level of community economic development, the basic structure of the household, agricultural production, land use, land transfer, etc. Among them, agricultural production includes information about agricultural subsidies, chemical fertilizer, labor, machinery inputs, farm output, etc. The detailed dataset offers a unique opportunity to explore the impact of China's new agricultural subsidy policy on the environment. So far, four rounds of the CRHPS survey (2011, 2013, 2015, and 2017) are publicly available. This study uses only 2015 and 2017 data because only these two rounds include detailed production information, and China's new agricultural subsidy policy was fully implemented nationwide in 2016. In addition, this paper focuses only on the grain crops samples since the grain crops and cash crops have significant differences in fertilizer use, inputs of farm machines, and hired labor (Heisey and Norton, 2007). The data above allow us to explore agricultural subsidies' effect on the use of chemical fertilizer.

4.2. Model specification

To examine the effects of China's new agricultural subsidy policy, implemented nationally in 2016, on chemical fertilizer use, we employed the difference-in-difference (DID) model. The DID technique is a key identification strategy in applied economics and usually is used to estimate the effect of a specific intervention or treatment (e.g., enactment of a policy) by comparing the change in outcomes over time between those who participated in a program (the intervention group) and those who did not (the control group) (Heckman et al., 1999; Meyer, 1995). The following model was estimated.

$$Y_{it} = \beta_0 + cD_i * time_t + \sum_j \theta_j X_{it}^j + f_i + f_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the outcome variable, indicating chemical fertilizer use by the farmer. D_i indicates a dummy variable for the treated group (whether the farmer was granted the new agricultural subsidy). $time_t$ is used to distinguish the data before and after experiments, with $time_t$=1 indicating 2017 and $time_t$=0 indicating 2015. $D_i * time_t$ is the interaction term, the core explanatory variable measuring whether the agricultural subsidy policy was implemented. X_{it}^j is the covariance variable that affects the explained variables, including the information on householder, household, and village. β_0 is the constant term, and i and t represent the sample individual and time, respectively. c shows the total effect of the agricultural subsidy on the outcome variable Y_{it}. Given that omitting the individual change or time-variant factors may trigger an endogeneity problem, this paper has separately controlled the individual effects f_i and time effects f_t. ε_{it} is an error term.

To examine the mechanism of the agricultural subsidy on chemical fertilizer use, we also performed a causal mediation analysis in the last part of this paper. The mediated effects can be assessed either through the three-step procedure proposed by Baron and Kenny (1986) or estimated directly (Preacher and Hayes, 2008; Wang et al., 2021). Early studies have illustrated the causal step methods to test mediation (Baron and Kenny, 1986; Preacher and Hayes, 2008; Tang et al., 2021; Yuan et al, 2021). And the three-step approach is applicable for testing hypotheses regarding individual mediators in the context of multiple mediator models (Preacher and Hayes, 2008). Thus, following the existing studies (Hu et al., 2021; Wang et al., 2021; Yu and Tang, 2023), we used the three-step approach to estimate the mediated effect of farmland scale, hire of agricultural labor, and farm machinery inputs to assess the relationship between the agricultural subsidy and the use of chemical fertilizer. We constructed the following econometric approach:

$$Y_{it} = \beta_0 + cD_i * time_t + \sum_j \theta_j X_{it}^j + f_i + f_t + \varepsilon_{it} \tag{2}$$

$$M_{kit} = \alpha_0 + a_k D_i * time_t + \sum_j \theta_j^{'} X_{it}^j + f_i^{'} + f_t^{'} + \varepsilon_{kit}^{'} \quad \text{for } k = 1,2,3 \tag{3}$$

$$Y_{it} = \gamma_0 + c^{'} D_i * time_t + \sum b_k M_{kit} + \sum_j \theta_j^{''} X_{it}^j + f_i^{''} + f_t^{''} + \varepsilon_{it}^{''} \tag{4}$$

As mentioned above, Equation (2) indicates the total effect of the agricultural subsidy on the use of chemical fertilizer, which is fully compliant with Equation (1). Equations (3) and (4) represent the mediating mechanisms by which the agricultural subsidy affects the use of chemical fertilizer, where the coefficient a_k is the effect of the farm subsidy on the mediator and the coefficient b_k of M_{kit} represents the mediator's effect on the use of chemical fertilizer. The three mediation variables are farmland scale (M_1), hired agriculture labor (M_2), and agricultural machinery inputs (M_3). k is the mediator variable. The coefficients $a_1 * b_1$, $a_2 * b_2$, $a_3 * b_3$ are the estimated coefficients of agricultural subsidy that affect the use of fertilizer through three mediating mechanisms, respectively—mediation effects that we need to explore. The coefficient $c^{'}$ in Equation (4) measures the agricultural subsidy's direct effect on the use of chemical fertilizer after controlling for the mediators and other control variables.

5. Empirical results

5.1. Benchmark results

The results of the study are shown in Table 2. Moving from Column (1) to Column (4), adding other control variables gradually, the coefficients of agricultural subsidy are uniformly significant at the 1% level but progressively lower, which indicates that omitting variables may cause an overestimation of the agricultural subsidy's impact on reducing the use of chemical fertilizer. Thus, the results in the fourth column could be used for comparison with previous studies.

The results in Column (4) of Table 2 show that China's new agricultural subsidy policy has a significant negative impact on the use of chemical fertilizer, which is consistent with our expectations. This finding echoes many European and American scholars who regard the agricultural subsidy as an effective policy tool in promoting the sustainable development of agriculture (Schmid and Sinabell, 2007; Sun et al., 2016). In terms of marginal impact, implementing the new agricultural subsidy decreases expenditures on chemical fertilizer by 7.2%[2]. This finding is also consistent with some recent studies, which are no longer restricted to the direct impact of agricultural subsidies but have begun to explore their indirect effects. They argue that agricultural subsidies can reduce the overuse of chemical fertilizer by changing other agrarian factor inputs (Guo et al., 2021; He et al., 2022). However, our estimate is two times larger than Guo et al. (2021). An explanation is that the agricultural subsidies in Guo et al.'s (2021) study are still granted to landowners (the original contracted farm family), while the new agricultural subsidy in our paper focuses on the moderate-scale operation (subsidy granted to operators who cultivate) and has a stronger influence on changing traditional production practices. Recall that the new subsidy could encourage farmers to reduce their chemical fertilizer expenditures by adjusting their farmland scale and farming methods. The pathway for reducing the use of chemical fertilizer will be verified and presented in the mediating-effect analysis section below.

5.2. Robustness tests

In this section, we conduct a series of robustness tests to demonstrate the high level of reliability with our empirical results. First, we follow the methods that Baker (2008) and Eissa (1996) proposed to test the randomness of sample groupings. Table 3 shows that before the new agricultural subsidy policy was implemented, the relationship between fertilizer use and farmers' group affiliation was insignificant, suggesting that farmers' fertilizer use did not

[2] Here, we measure the dependent variable chemical fertilizer usage by its natural logarithm. Since some values are 0, 0.001 is added to all values before taking the logarithm to avoid the loss of observations. A similar approach has been taken in the following section.

determine the sample subgroups. Therefore, the DID model is valid under the random selection assumption. Second, we carry out a simplified test for the parallel trend assumption, a prerequisite to applying the DID method. Under the lack of data, we follow the method that Hu et al. (2021) proposed to use farmers' fertilizer usage in 2015 as the explained variable and whether the farmer belonged to the treatment group in 2017 (1 =Yes, 0 =No) as the key explanatory variable. The results are presented in Table 4. Before the new subsidy policy was implemented, the trends of fertilizer use between the treated and control groups were the same. The third robustness test concerns the influence of other policies during the sampling period, since other policies within this sample period might cause bias in our results (Tang et al., 2021). In 2016, China's National Development and Reform Commission (NDRC) announced a temporary corn storage policy reform in Heilongjiang, Jilin, Liaoning, and Inner Mongolia autonomous regions. We rerun the regression model after excluding these four pilot provinces to eliminate the potential interference with our results from the temporary corn storage policy reform. The results are presented in Table 5. The results are like the main findings in Table 2, with the agricultural subsidy significantly reducing chemical fertilizer use at the 1% level.

6. Further discussion

6.1. Heterogeneity analysis

We stratified the total sample by age group (young and older growers)[3]. Table 6 indicates that the new agricultural subsidy policy has a relatively lower impact on older growers' reduced

[3] Whether the age of the householder was more than 55 years was the classification criterion between the older and younger farmers in China's official statistics (Please see *third national agricultural census's main data bulletin*, http://www.stats.gov.cn/tjsj/tjgb/nypcgb/qgnypcgb/201712/t20171215_1563599.html).

use of chemical fertilizer than on younger growers. In contrast, the effect is higher among younger growers. A plausible explanation is that older farmers are more risk-averse and prudent in decision-making than younger farmers. Thus, older farmers are reluctant to change their traditional production practices (e.g., enlarging their farmland scale or using more agricultural machines) when they receive a farm subsidy (Zhou et al., 2010). By contrast, young farmers are willing to take risks, forward-looking, and ambitious to change their agricultural production practices after obtaining support (Hu et al., 2018).

We stratified the total sample by regions (grain-producing and non-grain-producing areas). Table 7 shows that the influence of the new agricultural subsidy policy on farmers' fertilizer use in grain-producing areas is relatively stronger than in non-grain-producing areas. One explanation for this finding is that it is easier to achieve economies of scale in grain-producing areas than in non-grain-producing areas, making the subsidies' impact on fertilizer reduction more obvious (Hua et al., 2022).

6.2. Mediation analysis

According to Baron and Kenny (1986) and Preacher and Hayes (2008), we used the three-step approach to test the effects of these mediating variables. However, we may encounter seemingly unrelated biases if we run single-equation models using ordinary least squares (OLS) for farmland scale, hire of agriculture labor, and machine use individually (Zellner, 1962). The assumption of independence for these equations would be invalid if one factor that affects the farmland scale also involves machine use or fertilizer inputs (Qiao, 2017; Su. et al., 2022). As a supplement, we also use seemingly unrelated regression (SUR) combined with bootstrapping methods to estimate the mediating effects above in one step. The SUR method accounts for the contemporaneous correlations. It estimates the parameters of all equations simultaneously so that the parameters of every single equation also consider the information provided by the other equations (Zellner, 1962). The bootstrapping method obtains correct standard errors for the mediating effects and reliable *z*-test and *p*-values for the indirect effects (Preacher and Hayes, 2008).

Table 8 shows that the coefficients of the effect of the implementation of the new agricultural subsidy on the use of chemical fertilizer are negative in Column (1) ($\beta = -0.072$, $p < 0.01$), Column (3) ($\beta = -0.058$, $p < 0.01$), Column (5) ($\beta = -0.070$, $p < 0.01$), and Column (7) ($\beta = -0.060$, $p < 0.01$). Thus, the results support the argument that China's new agricultural subsidy policy reduces the use of chemical fertilizer. Furthermore, in Column (2), the coefficient of the effect of the new agricultural subsidy on the farmland scale is positive and significant ($\beta = 0.061$, $p < 0.01$), while in Column (3), the coefficient of the effect of the farmland scale on the chemical fertilizer use is negative and significant ($\beta = -0.126$, $p < 0.01$). Large-scale farming can achieve economies of scale and thus reduce the use of chemical fertilizer (Guo et al., 2021; Ju et al., 2016; Wu et al., 2018). However, in Column (4), the effect of the new agricultural subsidy on hired agricultural labor is not significant ($p > 0.1$), while in Column (5), the coefficient of the impact of hired agricultural labor input on the use of chemical fertilizer is negatively significant. With increased migration from rural to urban areas, agricultural labor wages for hired workers have been rising recently in China, leading farmers to prefer farm machinery over hiring agricultural workers (Qiao, 2017).

Appendix A presents the statistical results from the seemingly unrelated regression (SUR) as a supplement. The mediating effect in Appendix A is consistent with the results of the three-step approach above, confirming that the new agricultural subsidy's effect on chemical fertilizer use is mediated by farmland scale and adoption of agricultural machinery. Table 9 shows the results of decomposing the effects of the new agricultural subsidy on the use of chemical fertilizer with the bootstrapping method applied. The direct effect is significantly negative at the 5% level, indicating that farmers' use of chemical fertilizer decreases by 3.1% after receiving the new agricultural subsidy, perhaps by buying more high-efficiency fertilizer or using more organic fertilizer (Guo et al., 2021). The total indirect effect is negatively significant at the 1% level. The finding shows that farmers' use of chemical fertilizer decreases by 4.1% after receiving the new agricultural subsidy, perhaps by changing traditional production practices, such as increasing their farmland scale (by renting land) and adopting agricultural machinery. Findings from this study imply that China's policymakers have partially realized their desire to reduce the overuse of agrochemicals by reforming the agricultural subsidy policy and changing traditional smallholder farming practices (Duan et al., 2021; MOF-MOA, 2016; Guo et al., 2021).

7. Conclusion and implications

In this study, we adopt the DID method, the three-step approach, and the SUR method to explore the effects of China's new agricultural subsidy on chemical fertilizer use and identify the internal mechanisms. The results show that, first, the new agriculture subsidy reduces the use of chemical fertilizer by about 7.2 percent. A series of robustness tests confirms the finding. Second, the heterogeneity analysis shows that the subsidy's negative impact on fertilizer use is substantially greater among younger farmers than among older farmers. The negative effect also is significantly more in the main grain-producing areas than in non-grain-producing areas of China. Third, the mediating effect analysis shows that farmland scale mediates 8.3 percent of fertilizer use, and adoption of agricultural machinery mediates 48.6 percent of fertilizer use. Thus, China's new agricultural subsidy reduces fertilizer use by helping farmers expand their farmland scale and adopt farm machinery. The findings underscore the importance of expansion in farmland scale (making farms larger by renting additional land) and increased adoption of farm machinery.

Although we have considered the non-independence of the mediating variables, we also demonstrated the consistency of the estimated results by using the seemingly unrelated regression (SUR) and three-step approach simultaneously. However, due to data limitations, the impact coefficients between the mediating variables could not be estimated in this study. Therefore, future research can be done by adding panel data and applying the modern causal mediation analysis method.

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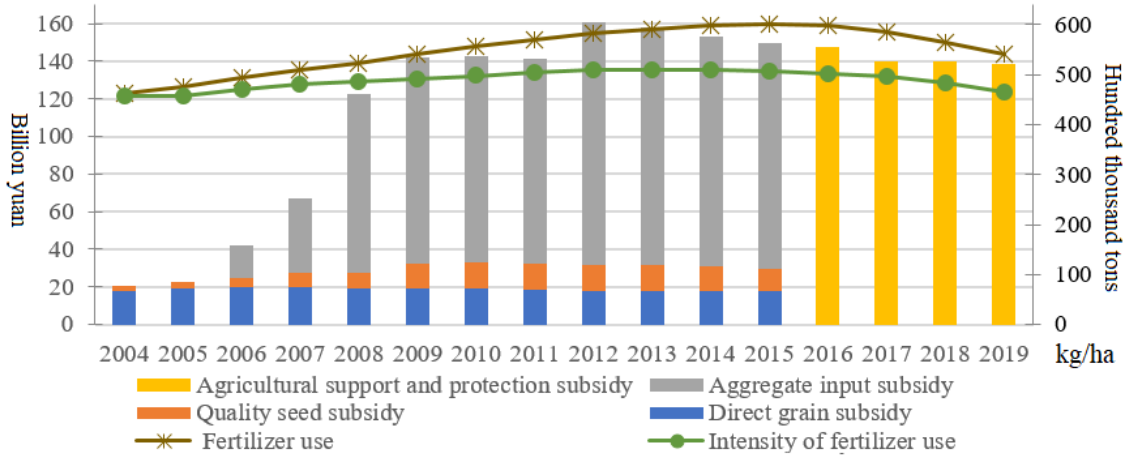
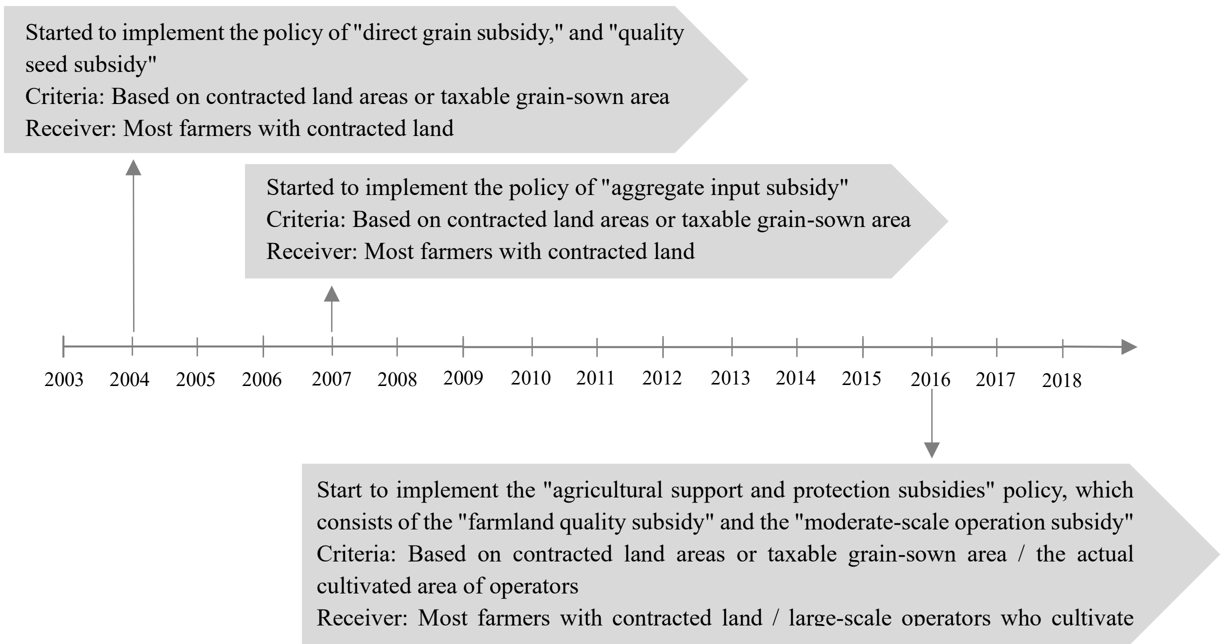
Figure 1. Chemical fertilizer consumption and the agricultural subsidies in China.



Source: National Bureau of Statistics of China (https://data.stats.gov.cn/)

Figure 2. Changes in China's agricultural subsidy policy



Source: Authors' own summary.

Notes: Despite the agricultural tax has been abolished since 2003, localities still have records of each household's 'pay tax.'

Table 2. Impact of agricultural subsidy on chemical fertilizer use (DID model).

	Dependent variable: fertilizer use (yuan/mu)			
	(1)	(2)	(3)	(4)
$D_i \times Time_t$	-0.127*** (0.048)	-0.095*** (0.031)	-0.083*** (0.024)	-0.072*** (0.027)
Gender		-0.015 (0.075)	-0.012 (0.096)	-0.011 (0.088)
Age		-0.005 (0.023)	-0.006 (0.015)	-0.007 (0.012)
Age squared		0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Education		-0.014** (0.006)	-0.013* (0.007)	-0.014* (0.008)
Health		-0.001 (0.014)	-0.006 (0.061)	-0.005 (0.031)
Family size		0.008 (0.012)	0.014 (0.015)	0.013 (0.014)
Agricultural laborer		-0.026* (0.014)	-0.051 (0.053)	-0.047 (0.049)
Grain revenue			-0.003 (0.004)	-0.001 (0.005)
Training			-0.035** (0.015)	-0.030** (0.014)
Land titling			-0.074*** (0.020)	-0.082** (0.040)
Off-farm employment				-0.023** (0.010)
Personal income				-0.004 (0.011)
Internet use				-0.031** (0.015)
Individual fixed effect	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Constant	6.177*** (0.265)	7.512*** (0.570)	6.319*** (0.602)	5.785*** (0.579)
Observations	7,114	6,986	6,624	6,624
within_R^2	0.430	0.379	0.421	0.418

Notes: The dependent variable is natural logarithm form. Standard errors are reported in parentheses.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 3. Results of testing on random selection assumption (Logit model).

	Dependent variable: farmer in the treatment group (1 = Y, 0 = N) (year=2015)
Ln fertilizer	-0.012 (0.034)
Other controls	YES
Constant	0.857 (0.779)
Observations	3,312
R^2	0.011

Notes: Standard errors are reported in parentheses.
Other controls are the same as column (4) of table 2.

Table 4. Results of testing of common trend assumption (OLS model).

	Dependent variable: fertilizer use (year=2015)
Treatment group	-0.032 (0.042)
Other controls	YES
Constant	4.258^{***} (0.647)
Observations	3,312
R^2	0.121

Notes: The dependent variable is natural logarithm form. Standard errors are reported in parentheses.
Other controls are the same as column (4) of table 2.

Table 5. Results after the elimination of other government policies (DID model)

	Dependent variable: fertilizer use (yuan/mu)
$Di \times Time_t$	-0.065^{***} (0.022)
Other controls	YES
Individual fixed effect	YES
Time fixed effect	YES
Constant	7.390^{***} (0.646)
Observations	5,682
within_R^2	0.558

Notes: The dependent variable is natural logarithm form. Standard errors are reported in parentheses
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 6. Heterogeneity: Older growers and young growers. (DID model)

	Dependent variable: fertilizer use (yuan/mu)	
	(1) Older growers	(2) Young growers
$D_i \times Time_t$	-0.057**	-0.083**
	(0.028)	(0.041)
Other controls	YES	YES
Individual fixed effect	YES	YES
Time fixed effect	YES	YES
Constant	8.219**	3.458
	(4.026)	(5.425)
Observations	2,716	3,908
within_R^2	0.334	0.428

Notes: The dependent variable take the natural logarithm form. Standard errors are reported in parentheses.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 7. Heterogeneity: Main and non-main grain-producing areas. (DID model)

	Dependent variable: fertilizer use (yuan/mu)	
	(1) Non-main grain-producing areas	(2) Main grain-producing areas
$D_i \times Time_t$	-0.046**	-0.078***
	(0.020)	(0.030)
Other controls	YES	YES
Individual fixed effect	YES	YES
Time fixed effect	YES	YES
Constant	8.520***	5.894***
	(0.452)	(0.816)
Observations	2,364	4,260
within_R^2	0.375	0.475

Notes: The dependent variable take the natural logarithm form. Standard errors are reported in parentheses.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 8. The results of mediating effect (By three-step approach)

	Ln fertilizer	Farmland scale (*M1*, ln)	Ln fertilizer	Hire labor (*M2*, ln)	Ln fertilizer	Machine use (*M3*, ln)	Ln fertilizer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D_i \times Time_t$	-0.072*** (0.027)	0.061*** (0.021)	-0.058*** (0.018)	0.098 (0.145)	-0.070*** (0.021)	0.371*** (0.136)	-0.060*** (0.019)
Farmland scale (*M1*, ln)			-0.126*** (0.029)				
Hire labor (*M2*, ln)					-0.003** (0.001)		
Machine use (*M3*, ln)							-0.097** (0.043)
Individual fixed effect	YES	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES
Constant	5.785*** (0.579)	2.116*** (0.678)	5.117*** (0.622)	-7.658** (3.320)	5.455*** (0.856)	-5.023** (2.314)	5.326*** (0.789)
Observations	6,624	6,624	6,624	6,624	6,624	6,624	6,624
within_R^2	0.418	0.305	0.478	0.341	0.440	0.429	0.456

Notes: The dependent variable takes the natural logarithm form. Standard errors are reported in parentheses.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table 9. Decomposition of mediation effects of agricultural subsidy on fertilizer usage (By bootstrap).

Decomposition	Ln fertilizer (yuan/mu. year) Bias-corrected bootstrap		
	Coefficient	SE	Significance
Mediation path through a single variable			
Pathway 1: Farmland scale (a1*b1)	-0.006	0.003	**
Pathway 2: Hire labor (a2*b2)	-0.000	0.004	
Pathway 2: Machine use (a3*b3)	-0.035	0.001	***
Total indirect effect (*a1*b1+a2*b2+a3*b3*)	-0.041	0.015	***
Direct effect (c’)	-0.031	0.014	**
Total effect (*c*)	-0.072	0.027	***
Proportion of total effect mediated	56.943%		

Notes: SE represent 1000 re-sampling bootstrapped standard errors.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Appendix A. The results of mediating effect (By seemingly unrelated regression)

	Ln fertilizer	Agricultural land *(M1*, ln)	Hire labor (*M2*, ln)	Machine use (*M3*, ln)	Ln fertilizer
	(1)	(2)	(3)	(4)	(5)
$D_i \times Time_t$	-0.072*** (0.027)	0.052*** (0.019)	0.094 (0.245)	0.324*** (0.101)	-0.031*** (0.011)
Agricultural land (*M1*, ln)					-0.113*** (0.022)
Hire labor (*M2*, ln)					-0.004** (0.002)
Machine use (*M3*, ln)					-0.108*** (0.026)
Individual fixed effect	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES
Constant	5.785*** (0.579)	2.005*** (0.532)	-7.168** (3.256)	-5.187** (2.501)	6.125*** (1.758)
Observations	6,624	6,624	6,624	6,624	6,624
Adj_R^2	0.418	0.271	0.306	0.421	0.401

Notes: The dependent variable takes the natural logarithm form.Standard errors are reported in parentheses.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.