Is there a tradeoff between nature reserves and grain production in China?

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Abstract

China is committed to increase its nature reserves coverage up to 18% by the end of 2035. Concerns associated with natural reserve expansion include local grain production restraint and its threat to national food security since agricultural activities are limited in designated natural reserve zones. Grain production has always been one of the top national priorities as it links to national food security. This paper uses an unbalanced panel data with 940 counties from 1989 to 2018 and time-varying difference-in-difference (DID) methodology to estimate the impact of National Nature Reserves (NNRs) on the local agricultural production. Our results indicate that the establishment of NNRs would reduce the average grain production by 4.4% at the county level, and the impact is more intense in high-yield areas. As the NNRs policy proceeds, the treatment effects gradually decline afterwards. The negative impact might be due to (I) direct impact: less fertilizer and pesticide usage and the destruction from wildlife and (II) indirect impact: farmland restrictions within NNRs. To mitigate the negative effect on grain production, we suggest more supportive policies on productivity improvement should be promulgated to the counties that implement nature reserve policy, especially in the early phase of the NNRs and in the high-yield areas.

Keywords: nature reserves; grain production; difference-in-difference

JEL：Q58；Q57；Q56;

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Introduction

It has increasingly been recognized on the interdependence between protected areas and human activities at social and economic levels (Ferraro, Hanauer, & Sims, 2011; Ferraro & Hanauer, 2011; Gülez, 1992). Protected areas, such as national parks and nature reserve zones, serve as practical approaches for promoting a sustainable livelihood, updating production pattern, and alleviating poverty for social and economic development. Literature has repeatedly addressed the rewards in preserving such areas as an active environmental strategy. Owino et al. (2012) investigate 573 small-scale farmers practicing crop farming and livestock keeping nearby a peri-urban national park in central Kenya, and most of them support the conservation policy as they regard it as a potential for the future economic development of the area, especially through ecotourism to improve incomes. Similar results are found by Sims (Sims, 2010), estimating with 31 wildlife sanctuaries and 57 national parks that protected areas boost local consumption by 4.5% and reduce poverty by 10.3%. Therefore, national governments are taking steps to establish and expand nature reserve zones in their areas.

China now has the second-largest nature reserve area in the world, following the U.S. In 1956, the Chinese government established its first national nature reserve (NNR) in Zhaoqing, Guangdong, in an effort to maintain its biodiversity and perform scientific research. Over the past 60 years, the Chinese government established 2,750 nature reserve zones with a total area of 1.47 million square kilometers, accounting for 14.86% of national territories (Ministry of Ecology and Environment, 2017). Some studies show that the NNRs policy has generated positive impacts in China. For instance, wild Crested Ibis population reached more than 2000 from 7 after the Crested Ibis NNR was established in 1981 to 2017. Around 150 highly endangered wild pandas inhabit the Wolong

NNR in Sichuan, China. It attracted more than 200,000 visitors each year[1](Wei et al., 2020). As the NNR policy progresses, China aims to increase its nature reserve coverage to 18% by the end of 2035 (China State Council, 2019).

Expanding protected areas might generate an internal conflict with agricultural production. However, only a few studies have been conducted to investigate the impact of nature reserve zones on food security, and the results are mixed. On the one hand, ecologists emphasize that biodiversity regimes of natural protected areas contribute to agricultural productivity in farming areas. Protected areas have the function of (1) preventing excess surface runoff and so protecting cultivated land from erosion (de Moraes et al., 2017; de Oliveira et al., 2017), (2) habituating for crop pollinators and crop pest predators (Brandon et al., 2005; Devictor et al., 2007; Rodrigues et al., 2004; Venter et al., 2014), and (3) enriching agrobiodiversity by providing different crop species and varieties, which farmers select for suitability in their locations (Thrupp, 2000). But contradictory facts are reported at the practice level. Zhang et al. (2019) discover that the wheat production loss is around 45% in the core area of the waterfowl protected area in Anhui, China. Izquierdo & Grau (2009) also points out that the growing global demand for food and other agri-products provides incentives for transforming protected areas into agricultural land. Koemle et al. (2018) find that Natura 2000 program which protects biodiversity in Europe has a negative impact on land rent. To the best of our knowledge, most of the existing studies lack generalizability. Hence, a more comprehensive and robust assessment is needed. As the novelty of this paper, we explore the causal effect of NNRs on grain production from 1989 to 2018 at the county level rather than individual case studies, aiming to provide a broad view on the impact of NNRs on food supply in China.

In this paper, we use the county-level panel data collected from 940 counties from 1989 to 2018, within which 187 counties own at least one NNR. To assess the NNR policy's effect on grain production, we employ a time-varying difference-in-difference (DID) model (Beck et al., 2010; Deshpande & Li, 2019; Petrick & Zier, 2011). Our finding suggests the average grain production of

[1] https://en.wikipedia.org/wiki/Wolong_National_Nature_Reserve

the treatment county is 4.4% lower than that of control counties at a 5% significance level overall. The impact is stronger in high-yield counties and in major grain-producing provinces. In contrast, within the low-yield and nonmajor areas where the agricultural conditions are less favorable, the NNRs' policy impact is not significant instead. Moreover, the effect changes over time. The effect is relatively intense in the beginning but declines gradually afterwards. Lower production caused by NNRs can be explained in two aspects: (I) direct impact: the reduced use of chemical controls such as fertilizers and pesticides and the rising number of wildlife activities in agricultural sites, and (II) indirect impact: farmlands are changed and recovered to protected areas to be in line with the NNRs restraints. However, as crop production may benefit from improved ecology in the long term, the negative impact would gradually decrease. As the fact that grain loss caused by NNRs undermine food supply, the government should pay more attention to the balance between grain production and environmental protection implementations. More supportive policies and funds should be allocated to the major grain-producing areas with nature reserves at the beginning of the NNRs establishment. To be more concrete, the government should keep investment in grain productivity to offset the negative impact of NNRs on food security. Subsidies on income for grain loss and trainings for farmers to diversify their income sources are also encouraged.

The remainder of the paper proceeds as follows. Section II briefly introduces the evolution of NNRs in China and graphically illustrate our research conceptual framework. Section III describes the data and econometric methodology, while Section IV discusses core results in our research. In the final section, we provide conclusions.

Background and Conceptual Framework

In this section, we will briefly introduce the history, current situation, and policy contents of nature reserves in China. We will also describe the potential gains and costs of implementing NNR policies on agricultural production.

2.1 Policy evolution of national nature reserves

The objective of establishing NNRs is to protect and preserve ecological systems where rare and endangered wildlife species and plants are naturally concentrated. Once the nature reserve is set, the designated zone will be authorized for protection and administration independently. The policy aims to forestall biodiversity loss and species distinction. The total area of nature reserves has been increasing over time. The nature reserve area is nearly doubled since 1996, reaching a total area of 1.47 million square kilometers (km^2) in 2018, making China the second-largest area after the U.S. The nature reserves preserve 35 km^2 of wild forests, 20 km^2 of wetland, and more than 300 endangered species, accounting for 90.5% of ecological systems and 85% of total wildlife and plant species in China (National Park Administration, 2019).

[Insert Figure 1-4]

The Chinese government is committed to enforcing strict conservation measures to minimize the damage caused by human activities. In 1994, the Chinese State Council formulated *the Regulation of the People's Republic of China on Nature Reserves* (RPRCNR) to strengthen the enforcement and management of nature reserves. The regulation stipulates that minimal agricultural activities should be undertaken in nature reserves. Therefore, establishing nature reserve zones would curb planting and cultivating activities. In some cases, local farmers and households are forced to abandon their land, resulting in a loss of agricultural labor input. For instance, a survey of 600 farmers who inhabit the peripheries of the NNR in Shaanxi, China, finds cultivated land resources are deficient as land use is controlled and regulated in protected areas (Song et al., 2015). Nearly 34.4% of the local farmers lose their land because of NNRs, and 80.9% of the farmers need abandon their land and make a living in the non-NNR places as migrant workers due to the scarcity of arable land.

2.2 Conceptual framework of nature reserves on grain yield

The designation of natural reserves implications for agricultural production from multiple channels is shown in Figure 5. On the one hand, natural reserves restrict human activities such as agricultural production in certain areas. Chemical fertilizers and pesticides are limited. These NNRs implementations affect the grain yield directly. Besides, as farmlands should be transformed back to protected areas, grain production would decrease correspondingly with declined planting areas. On the other hand, biodiversity enhancement in the natural reserves could enhance agricultural production through ecosystem services such as pollination, biological control, water purification, and soil nutrient protection (Tscharntke et al., 2005). The aggregate results might be uncertain and need to be verified empirically.

[Insert Figure 5]

2.3 Potential benefits and costs of nature reserves for agriculture production

To better understand the impact mechanism of nature reserves on agriculture, we categorize potential benefits and costs of NNRs on agricultural production as follows:

- **Costs of nature reserves**. Firstly, counties with reliable and profitable crop production would regard the payoff of NNRs less attractive (Brandon et al., 2005). Secondly, to minimize human activities within the boundaries of NNRs, the government must resettle farmers and villagers to new places. The ecomigration and land use change reduce the agricultural labors since farmers without land need to make a living as migrant workers in the urban area. Monetary compensations are more common than the compensation of cultivated land during the process of eco-migration (McElwee, 2010). Thirdly, since irrigation systems, roads, or other infrastructures are not allowed to be constructed within the NNRs, a higher cost to maintain agricultural productivity is incurred due to the lack of market access and efficient facilities (Gurrutxaga et al., 2011; Koemle, 2018; Li et al., 2020; Symes et al., 2016). Finally, wild animals within the NNRs might approach farmland and search for food, resulting in production loss. (Hou & Wen, 2012; Zhang, 2019).
- **Gains of nature reserves.** Firstly, the NNRs improve soil conservation and water restoration while providing an environmental-friendly and sustainable place for insects and animals. For example, rainforests and wetlands act as natural sponges. They reduce

droughts, purify water, and participate in the process of soil formation. Secondly, the NNRs also could promote agricultural production through pollination and biological control (Tscharntke et al., 2005). The positive externality might eventually be transformed into the advantages for agriculture activities, enhancing the farmland yield (Balmford et al., 2002; Wei et al., 2014). Thirdly, another critical function of nature reserve is to protect, restore, and recreate natural habitats for valuable, distinct, and endangered species. Nature reserves also provide abundant germplasm for seedbanks. Agricultural scientists use biological resources for breeding high-yield, stress-tolerant, and nutritious varieties (Ragamustari & Sukara, 2019; Scherer et al., 2017).

The discussion above may explain why extensive human activities and commercial developments continue to grow within protected areas. In areas where agriculture fails to provide secured crop productions but with high natural value, there are potential conflicts between conservation and agricultural activities. According to the research of Jones et al. (Jones et al., 2018), one-third of global protected land is under intense human pressure. The same critic goes for China's practices, especially at the local level, and there is evidence showing that human activities have damaged NNRs implementations (Xu et al., 2015). It is crucial to understand the tradeoff between nature reserves and local agricultural activities. Resistance could rise from farmers whose economic benefits are affected negatively.

Data and empirical model

3.1 Data

This paper uses an unbalanced panel data that includes 10,622 observations from 940 counties in China between 1989 and 2018[2]. Within 940 counties, 187 counties possess at least one national nature reserve. The treatment group contains 1,761 observations, which accounts for 19.8% of the

[2] The data is generated by deleting the top 1% and bottom 1% of the original dataset to avoid the impact of extreme values of the variables.

total observations. In terms of the geographical distribution of NNRs, 187 treated counties are distributed in 13 provinces (Figure 6). As shown in Figure 7, the average production of the treatment counties between 1989 and 2018 is 295.2 tons, which is 146.2 tons less than that in counties without treatment. Figure 8 shows that the average production of the NNRs treated observations is 301.5 tons, which is also smaller than that of the control group (438.4 tons). Both figures suggest a negative correlation between the establishment of NNRs and grain production.

[Insert Figure 6-8]

The primary dependent variable is grain production (ton) at the county level from 1989 to 2018. The information on grain production is from the National Statistical Bureau in China (NSBC) (National Bureau of Statistics, 2019). The data refers to the total amount of grain produced in one calendar year. Grains include rice, wheat, corn, sorghum, millet, as well as potatoes and beans. Beans are calculated by the dried beans after pod removal; potatoes (including sweet potatoes and potatoes, excluding taro and cassava) are calculated as converting 5kg of fresh potatoes into 1kg of grain equivalent. The statistical bureau in each county reports the data. Since the effect of NNR would not be differentiated by crops, here in this paper, it should be incorrect to use separated grain production information to test the NNRs on the varying grain types like rice, wheat, or maize individually. As the shortage of grain types data within or nearby the NNRs, using selected crop rather than the sum might generate the risk of downwards bias. For instance, if one selected crop's production is reported at the county-level, but the crop is not located in or around the NNRs zone, then the estimators could not reflect the causal correlation between NNRs and grain productions. To minimize the heterogeneity within the production information, we use the fixed effects model in our estimation since, in most counties, the principal crop types usually are fixed and would not change dramatically along with time. The information on our key independent variable of the NNRs is extracted from *the List of National Nature Reserves* issued by the Ministry of Ecology and Environment in China (MEEC). The list was recently updated in 2019, containing information on name, location, establishment date, type, administrative district, etc. The list shows 312 nature reserve areas are established after 1989, indicating the protected land has been vigorously established over time.

To control the county-specific, time-dependent changes in a county's agricultural production, we use the EPS dataset[3] to collect information on the agrarian input factors, including consumption of chemical fertilizers, total power of agricultural machinery, employment in the agricultural sector and grain planting area. The data is collected by the Statistic Yearbook of each province each year and compiled by the EPS dataset correspondingly. To be more specific, (1) Consumption of chemical fertilizers in agriculture: this variable refers to the volume (1,000 tons) of chemical fertilizers applied in agriculture per year. Chemical fertilizers include nitrogenous fertilizer, phosphate fertilizer, potash fertilizer, and compound fertilizer. We use the amount of chemical fertilizer calculated in pure nutrient in our dataset. The pure nutrient refers to the amount of nitrogen fertilizer, phosphate fertilizer and potassium fertilizer converted into the 100% components of nitrogen, phosphorus pentoxide and potassium oxide, respectively. Compound fertilizer is converted according to its main components. (2) Total power of farm machinery (10,000 KWH): this variable represents the total power consumption of machinery used in planting and other agricultural activities. The power of machinery and electric motors is converted from horsepower to watts for comparison. (3) Agricultural employment (10,000 people): this variable refers to the labor force engaged in farming and other agricultural activities at the county level. (4) Grain planting area (1,000 hectare): it refers to farmland that is plowed repeatedly for growing crops.

3.2 Empirical strategy

In our paper, we follow the Beck et al. (2010) time-varying DID specification to evaluate the policy impact of NNRs on grain production. We set up the following regression model (Proof in Appendix A),

$$y_{it} = \delta_0 + \mathbf{\Pi_i} + \mathbf{T_t} + \tau D_{it} + \delta_k \boldsymbol{X_{itk}} + \varepsilon_{it}, \qquad t = 1989, \dots, 2018; \; i = 1, \dots, 187,$$

[3] The EPS is a leading China data provider that collect and display market and demographic dataset on its platform.

(1)

where y_{it} represents the grain production for county i in year t. In terms of the treatments in multiple periods, D_{it} is a binary variable where D_{it} = 1 means the treatment of NNR program in year t, whereas D_{it} = 0 means untreated counties. We construct vector $\boldsymbol{D_i} = (D_{i1}, \dots, D_{iT})$ as an indicator to describe the history of the NNR program for each observation. The coefficient τ in Equation (1) is the critical estimator that reflects the difference between the counterfactual effects. If τ is positive, NNRs increase the treated counties' grain production, whereas NNRs decrease production if τ is negative. $\boldsymbol{X_{itk}}$ is a set of control variables, including consumption of chemical fertilizers, total power of agricultural machinery, planting area, and agricultural labor employment. The $\mathbf{\Pi_i}$ and $\mathbf{T_t}$ variables account for unobservable characteristics of county-specific and time-specific confounders. Specifically, $\mathbf{T_t}$ is incorporated to control unobserved effects such as technology change. While $\mathbf{\Pi_i}$, a state-specific dummy variable, controls time-invariant characteristics such as crop types and rotations, soil quality, landscape, weather conditions, etc. ε_{it} is the idiosyncratic disturbance term for county i in year t with $E(\varepsilon_{it}) = 0$.

3.2.1 Empirical model specification

Since we have no prior knowledge of the actual specification of the production function, we apply the first-order Taylor expansion (Cobb-Douglas function) to construct it. The specification of empirical model is in Equation (2).

$$\ln y_{it} = \alpha_0 + \tau_{CD} D_{it} + \sum_k \alpha_k ln X_{ikt} + \boldsymbol{T_t} + \mathbf{\Pi_i} + \varepsilon_{it}.$$

(2)

In Equations (2), all variables are measured in logarithmic form except for D_{it} (The treatment of NNRs). The parameter of D_{it}, τ_{CD} can be regarded as difference-in-difference estimators, measuring the impact of NNRs on the grain production at the county level.

3.2.2 Endogeneity analysis

The county-specific, unobserved factors like local landscapes and ecological systems are important determinants of how NNR counties are selected. Thus, it is reasonable to presume $cov(D_{it}, \mathbf{\Pi_i}) \neq 0$, which violates the ignorability assumption. However, the fixed effects approach solves the endogeneity issue by differencing each observation from its county-group means to meet the assumption of ignorability. Here, Equation (2) could be rewritten as,

$$y_{it} - \overline{y_i} = \tau(D_{it} - \overline{D_i}) + \delta_k(X_{ikt} - \overline{X_{ik}}) + (\varepsilon_{it} - \bar{\varepsilon_i}). \quad (3)$$

Equation (3) eliminate the effects due to unobserved, time-invariant characteristics across the time since the source of endogeneity ($\mathbf{\Pi_i}$) is dropped from differencing.

3.2.3 Mechanism analysis

Here we follow Baron & Kenny (1986) model to explore the path of NNRs affecting the grain production. From Figure 5, we find there might be mediation processes existed in terms of farmland use change between the establishment of NNRs and grain production. Based on our conceptual framework, we decompose the policy effects into two aspects: (1) Direct effects: the NNRs restraints chemical fertilizer and promote the wild animal activities, which decrease the grain yield correspondingly. (2) Indirect effects: according to the RPRCNR, once the NNRs are established, farmland should be transformed back to protected land. Therefore, the planting area variable is the (hypothesized) mediator that is transmitted the causal effect of NNRs to production. To test our hypothesis, we construct Equation (4) to (6) as follows,

$$\ln y_{it} = \gamma_0 + \gamma_{CD} D_{it} + \sum_{k+1} \gamma_{k+1} lnX_{ik+1,t} + \mathbf{T_t} + \mathbf{\Pi_i} + \varepsilon_{it}. \quad (4)$$

$$\ln X_{1it} = \beta_0 + \beta_{CD} D_{it} + \sum_{k+1} \beta_{k+1} lnX_{ik+1,t} + \mathbf{T_t} + \mathbf{\Pi_i} + \varphi_{it}.$$

(5)

$$\ln y_{it} = \alpha_0 + \eta_{CD} D_{it} + \alpha_1 \ln X_{1it} + \sum_{k+1} \alpha_{k+1} lnX_{ik+1,t} + \mathbf{T_t} + \mathbf{\Pi_i} + \omega_{it}.$$

(6)

In our framework, Equation (4) to (6) are used to estimate the direct and indirect effects of the NNRs. Specifically, the direct effect is measured by η_{CD} as the path from NNRs to grain production, while the indirect effect is equivalent to the product of the path from NNRs to planting areas (β_{CD} in Equation (5)) and the path from planting areas to grain production (α_1 in Equation (6)). If γ_{CD}, β_{CD}, τ_{CD} and α_1 are significant, we could verify farmland use change is at least one of the mediators in our NNRs analysis (Agler & De Boeck, 2017; Baron & Kenny, 1986; Judd & Kenny, 1981).

Results and Discussion

The estimation results of Equation (2) are reported in Table 2. Table 3 presents the test results of parallel-trend assumption of DID. In Table 4, we divide our dataset into quantile groups by average grain yield. Next, in Table 5, we employ the data from major grain-producing provinces and nonmajor grain-producing provinces separately. Next, we employ the lagged year treatment variable from 1 to 3 years to determine the variation in treatment effect over time in Table 6. Furthermore, we test the mechanism of NNRs on grain production in consideration of mediation effect and display the results in Table 7. The results are consistent among all specifications, demonstrating our results are robust and reliable.

[Insert Table 1]

4.1 The establishment of NNRs policy

Using the panel data mentioned above, we obtain the estimates for Cobb-Douglas production function specifications shown in Table 2. We see that the establishment of NNRs has a significant negative impact on grain production in column (1). The grain production of the treated counties is

4.4% less than that of the control ones at a 5% significance level. As discussed in the earlier section, the establishment of nature reserves affects the grain production with mixed consequences. From Table 2, we conclude the negative effect is dominant in our observation period. In column (2), we use the year trend variable rather than the year fixed effect to estimate the NNRs policy, the result also indicates that NNRs' impact on the grain production is significantly negative. As the likelihood ratio test favors the fixed-effect model specification, thus we would use the two-way fixed effect for our following discussion.

The negative estimate implies an internal tradeoff between food security and the NNR zone regulation. Since grain production has always been one of the top national priorities, a 4.4% decline would trigger a concern on the stability of food supply. Thence, the government should keep improving the grain productivity of the counties with NNRs and offset the negative impact. Moreover, a 4.4% decrease in grain production would generate a considerable income loss for local farmers. The result could partially explain the cause of increasing human pressure in the establishment of NNRs. The resistance would become more intense in counties where farmers' primary income is from farming activities.

[Insert Table 2]

4.2 Other covariates estimation

We now discuss the estimation results of other variables separately. In Table 2, we find the coefficients of input variables are consistent with our expectations. The variables of agricultural employment, fertilizer, area, and machinery positively affect the grain production at the 1% significance level. The coefficient of agricultural employment input is 0.0504, and the coefficient of machinery input and fertilizer is 0.0312 and 0.0316 each. It means that a 1% increase in agricultural employment, machinery and fertilizer could generate a 0.0504% , 0.0312%, and 0.0316% increase in our dependent variable, respectively. In our estimation model, the area variable plays the most important role in promoting production increase. If the grain area expands by one percent, the grain production of the county will increase by 0.875% at a 1% significance level. Furthermore, we use the Wald test to verify whether the grain production function is in line with the homogeneity assumption. The result indicated the sum of input factors estimates is not significantly different from one, indicating the homogeneity assumption is well-satisfied. To capture the technological change, we involve the year dummy and year trend variables in our models. They are significantly positive in the model, implying the technology plays a positive role in grain production growth.

4.3 Test of parallel-trend assumption

One of the assumptions in time-varying DID is the difference between the treatment and control group should be constant before the NNRs, or saying "parallel-trend assumption". To test the assumption, we follow Giovanni and Marco (2019)'s approach and construct the following regression model In Equation (7). We select a seven-year window, spanning from three years before the NNRs until three years after the NNRs. The $D_{it}^{-\omega}$ is one for counties in the ωth year before NNRs, while D_{it}^{ω} equals one for counties in the ωth year after NNRs.

$$\ln y_{it} = \rho_0 + \rho_1 D_{it}^{-3} + \rho_2 D_{it}^{-2} + \rho_3 D_{it}^{-1} + \rho_4 D_{it} + \rho_5 D_{it}^{1} + \rho_6 D_{it}^{2} + \rho_7 D_{it}^{3} + \sum_k \alpha_k lnX_{ikt} + \boldsymbol{T_t} + \boldsymbol{\Pi_i} + \varepsilon_{it} \qquad (7)$$

We plot the trend of treatment effect in Figure 9, we could visually observe that the difference between the treatment and control group is close to zero before the establishment of NNRs, while, since the second year after the treatment, the gap fades away gradually. This is in line with the result of F-test on $\rho_1 = 0$, $\rho_2 = 0$, $\rho_3 = 0$. Our result indicates that the F-test is not significant and parallel-trend assumption is well passed. Thus, we could safely say that previous the NNRs policy, the treatment counties and control counties share the common change trend as expected.

[Insert Table 3 and Figure 9]

4.4 Sensitivity model analysis

4.4.1 Sensitivity model analysis of different subgroups

Furthermore, we are interested in the variation of the impact of NNRs within different subgroups, we test the heterogeneity in two approaches. (1) We apply the quantile sample sorted by the average grain yield. In Table 4, we use the top 1% to 25%, top 26% to 50%, top 51% to 75%, and top 76% to 100% to estimate the grain production function. The coefficients in the high-yield groups (top 1% to 25% and top 26% to 50%) are negative and significant at a 5% level for the latter one. However, in the second half of our dataset (51% to 75%; top 76% to 100%), the impact of NNR turns to be insignificant. The heterogeneous effects indicate that the NNRs play a different role in different regions. (2) We divide our dataset into the major grain-producing provinces and nonmajor grain-producing provinces in Table 5,. The former subgroup includes Inner Mongolia, Liaoning, Jilin, Jiangxi, Jiangsu, Henan, and Hubei, while the latter includes Shanxi, Zhejiang, Guangxi, Hainan, Guizhou, Gansu, and Qinghai. The estimate in column (1) in Table 5 is -0.0815 at a 5% significance level, while the coefficient turns to be insignificant for the nonmajor production province sample. The results in Table 4 and Table 5 consistently imply that the NNR regulation has a more intensive negative impact on the counties with high grain yield and resilient ecological conditions, but the role of NNRs on grain production for the low-yield areas still call for more evidence to explore. It might because the low-yield counties or nonmajor production areas are concentrated in areas where environmental conditions are fragile and unsuitable for agricultural activities. Therefore, the NNRs could rehabilitate the ecological systems and improve their farming conditions, eventually counteracting the production decline rendered by the agricultural activities restrictions.

[Insert Table 4-5]

4.4.2 Sensitivity model analysis of lagged NNR treatment

In a dynamic context, the policy effect might vary with the length of the county exposure to it, which is usually referred as the “dynamic treatment effect” (Callaway & Sant’Anna, 2018; Dettmann et al., 2019). To verify the change of NNR effect over time after the displacement, we measure the lagged effect of the treatment from the first to the third lagged year after the NNRs establishment. According to the results in Table 6, we find a declined effect of the NNRs treatments in our observation. We could observe the policy effects are significantly negative one year after the policy carries out, but the effect gradually decreases to zero. While the third to the fourth year of the NNRs treatments (second to third-year lags) are not significantly different from zero with much smaller parameters. The estimates reflect the variation of NNR effects as the policy proceeds.

The outcome aligns with the policy implementation experience in China. At the early stage of the NNRs establishment, the policy would become more stringent and robust due to the pressure of evaluation and supervision from the central government. Therefore, we could observe a noticeable decline in grain production. However, this impact could not hold persistently. The trend of declined impact could be attributed to two aspects: First, since there is a tradeoff between the agricultural production and NNRs, agricultural activities might rebound if the regulation relaxes along with time. Second, in the long term, the ecological benefits of NNRs might take effect gradually and become dominant in the following years.

[Insert Table 6]

4.5 Mechanism analysis of NNRs on grain production

Columns (1) to (3) in Table 7 confirm that the NNRs generate a negative impact on grain production through agricultural land use restriction. Without controlling planting areas, the reduced model in Column (1) indicates that the NNRs are negatively correlated with the grain production at a 1% significance level with which the parameter value is equivalent to -0.093. However, in the full model in Column (3) planting area variable included, the impact is still significantly negative at a 5% significance level, but the coefficient drops to -0.044. Considering the NNRs also significantly decrease the agricultural planting areas (Columns (2)), we could confirm planting areas partially mediate the effect of NNRs on grain production at the county level.

In Table 7, we further explore the relationship between the NNRs and agricultural productivity. Column (4) indicates the NNRs also negatively affect the grain yield by 4.37% at a 5% significance level. This indicates there might be a second pathway that NNRs curtail production except farmland use restriction. As aforementioned in Section 2.3, lower yield caused by NNRs can be explained by the reduced use of chemical controls such as fertilizers and pesticides and the rising number of wildlife activities in agricultural sites.

[Insert Table 7]

Conclusions and policy implications

In response to worldwide global warming and biodiversity loss, the nature reserve zone has become a prevalent practice to rehabilitate ecological systems. Nowadays, China has 2,750 nature reserve zones, of which 474 are at the national level. According to the Ministry of Ecology and Environment in China, the total nature reserve area accounts for 14.86% of China's national land territory. In the past decades, nature reserve policies have made significant achievements in rebuilding a sustainable environment and ecological system. However, along with the expansion of nature reserve areas, the concern arises whether it might threaten the national food security since limited agriculture activities are allowed to continue within the zone. Is there a tradeoff between grain production and NNRs policy? Our research aims to examine the relationship between environmental protection implementations of the NNRs and food security in China.

To evaluate the impact of nature reserve policy, we construct a county-level panel data between 1989 to 2018 and apply a time-varying DID model to empirically estimate the potential effect. The dataset has 940 counties with 10,622 observations, within which 940 counties possess at least one nature reserve. The empirical results show that the average grain production in the county with NNRs policy would be 4.4% smaller than that of control counties, which demonstrates there is a tradeoff between NNRs and grain production. The impact is stronger in the high-yield subgroups and the major grain-producing areas. But within the low-yield and nonmajor areas where the agricultural conditions are less favorable, the NNRs' role of the grain production is not significant instead. In terms of lagged effects, the paper finds the earlier stages of the NNRs policy implementation have a much larger impact than that of the later years. The mechanism analysis in our paper verifies two paths from NNRs to grain production. (1) The NNRs policy constrains the agricultural inputs within the boundary, leading to fewer usage of fertilizers and pesticides. The grain yield declines directly. (2) The NNRs policy recovers the farmlands within the nature reserves into protected areas, indirectly reducing the grain production at the county level.

The tradeoff between NNRs and food security sheds light on the concerns of NNR expansion on agricultural activities. (1) Generally, in order to relieve the conflicts between food security pressure and NNRs, we suggest supportive funds should be allocated to improve the agricultural productivity in the counties with NNR treatments. For instance, low-carbon agriculture should be developed in the NNRs areas. (2) Since the tradeoffs occur much higher in high-yield areas, requiring the central government to have a more careful strategy in selecting sites. Avoiding the farmland with productive crop potentials chosen as nature reserves could alleviate the conflict between the protected land and farming activities. Besides, for the areas where land is not desirable for crop production, setting aside for NNRs should be encouraged. (3) It is worth pointing out that the negative impact is more intensive in the early stage of the NNR establishments. Therefore, more supporting policies on productivity and moderate assessment on food security should be executed in these NNR regions in the beginning years.

Appendix

A.1 Proof of Time-varying DID specification as Two-way fixed effects

The estimation strategy incorporates the DID estimator into a conventional panel regression (Dettmann et al., 2019). The canonical DID model is a *2 × 2 case* that refers to two analyzed groups and two time periods. The estimator is the coefficient of the interaction of the treatment group dummy and the post-treatment-period dummy (Wing et al., 2018). But the two-group two-periods DID model could not accommodate the cases that involve treatment exposures in multiple groups and varying periods. We consider an estimation strategy associated with heterogeneous treatment effects in a panel data context. To assess the impact of NNRs on grain production, we build a DID with two-way fixed effects model (Beck et al., 2010; Deshpande & Li, 2019; Petrick & Zier, 2011). The mechanism in this design is as follows. We construct counterfactuals to counties affected by NNRs by comparing counties that experience the same NNR policy a few years later or never. The difference is the treatment effect of the NNRs.

We consider the case where county i is a participant or nonparticipant in the NNR program in each period t. In terms of the treatments in multiple periods, D_{it} is a binary variable where D_{it} = 1 means the treatment of NNR program at year t, whereas D_{it} = 0 means untreated counties. We construct vector $\boldsymbol{D_i} = (D_{i1}, \dots, D_{iT})$ as an indicator to describe the history of the NNR program for each observation. For completeness, we also denote $y_{it}(1)$ and $y_{it}(0)$ the counterfactual grain production in the treated and untreated counties, respectively.

To identify the impact of the NNR program with no selection bias, we here, following Woodridge's approach (Wooldridge, 2010), assume $\boldsymbol{D_i}$ and ($y_{it}(1)$, $y_{it}(0)$) should be independent conditional on the unobserved heterogeneity $\mathbf{\Pi_i}$ and $\mathbf{T_t}$ and observable characteristics X_{it}, which is widely called the assumption of ignorability (or unconfoundedness) of treatment (Rosenbaum & Rubin, 1983). Mathematically, the ignorability should be in conditional mean independence as following,

$$\left(y_{it}(1), y_{it}(0)\right) \perp \boldsymbol{D_i} \mid X_{it}, \mathbf{\Pi_i}, \mathbf{T_t}.$$

$$E[y_{it}(g)|\,\boldsymbol{D_i}, X_{it}, \mathbf{\Pi_i}, \mathbf{T_t}] = E[y_{it}(g)|\, X_{it}, \mathbf{\Pi_i}, \mathbf{T_t}], \qquad g = 0{,}1. \tag{A.1}$$

To note that the ignorability assumption imposes a strict exogeneity on the treatment assignment $\boldsymbol{D_i}$. In terms of the observed outcome expressed as $y_{it} = y_{it}(0) + D_{it}E[y_{it}(1) - y_{it}(0)]$, it is straightforward to rewrite $E[y_{it}(g)|\,\boldsymbol{D_i}, X_{it}, \mathbf{\Pi_i}, T]$ as follows,

$$E[y_{it}(g)|\,\boldsymbol{D_i}, X_{it}, \mathbf{\Pi_i}, \mathbf{T_t}] = E(y_{it}(0)|X_{it}, \mathbf{\Pi_i}, \mathbf{T_t}) + D_{it}E[y_{it}(1) - y_{it}(0)|X_{it}, \mathbf{\Pi_i}, \mathbf{T_t}]. \tag{A.2}$$

The treatment effect we are interested in is measured by $E[y_{it}(1) - y_{it}(0)|X_{it}, \mathbf{\Pi_i}, \mathbf{T_t}]$. To proceed with the identification, we make a set of assumptions on Equation (A.2): (i) The treatment effect is equal to τ and constant across counties and time. The assumption is the so-called common-effects assumption (Petrick & Zier, 2011). (ii) $E(y_{it}(0)|X_{it}, \mathbf{\Pi_i}, \mathbf{T_t})$ could be expressed as a linear and additively separable specification, which is widely used in causal inference literature (Angrist & Pischke, 2019; Khandker et al., 2009). (iii) We impose the homogeneity assumption on the parameters of our observed covariates X_{it}, indicating β_k is not varying within each observable variable. (iv) No carryover effects. We assume for each given county i, the NNR implement at year t is randomized conditional on the realized treatment in previous years, but without conditioning on the previous grain yield outcome (Imai & Kim, 2019). Then the Equation (A.2) leads to,

$$y_{it} = \mathbf{\Pi_i} + \mathbf{T_t} + \delta_k \boldsymbol{X_{itk}} + \tau D_{it} + \varepsilon_{it}\,, \qquad t = 1, \ldots, T, \qquad k = 1, \ldots, K. \tag{A.3}$$

The coefficient τ in Equation (A.3) is the critical estimator that reflects the difference between the counterfactual effects. $\boldsymbol{X_{it}}$ is a set of control variables. Equation (A.3) leads to a DID analysis with two-way fixed effects.

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Table 1 Summary statistics

No.		Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
1		Nature reserve area	0/1	10,622			0	1
2		Year		10,622			1989	2018
1	Production Function	Grain production	1000 Ton	10,622	396.95	664.60	0.26	9843.70
2		Grain area	1000 Hectare	10,622	69.34	96.74	0.07	1245.45
3		Fertilizer	1000 Ton	10,622	41.10	74.66	0.03	1038.99
4		Machinery power	1000 Kwh	10,622	527.49	612.31	0.80	7334.82
5		Agri-employment	1000 Persons	10,622	191.55	297.33	0.20	4229.20
1	Yield Function	Yield	Ton/Hectare	10,622	5.30	1.63	0.86	9.38
2		Fertilizer usage per hectare	Ton/Hectare	10,622	0.57	0.39	0.05	3.35
3		Machinery power per hectare	Kwh/Hectare	10,622	9.88	8.15	1.26	90.63
4		Agri-employment per hectare	Persons/Hectare	10,622	3.245	2.063	0.458	17.892

Table 2 The impact of NNRs on grain production by counties in 1989-2018

	Production	
VARIABLES	(1)	(2)
Treatment	-0.0442**	-0.0697***
	(0.0203)	(0.0203)
Area	0.875***	0.891***
	(0.0109)	(0.0107)
Fertilizer	0.0316***	0.0401***
	(0.00627)	(0.00623)
Machinery	0.0312***	0.0371***
	(0.00567)	(0.00525)
Agri-employment	0.0504***	0.0257**
	(0.0106)	(0.0105)
Year trend		0.0161***
		(0.000434)
Constant	1.978***	1.874***
	(0.110)	(0.106)
Year fixed-effect	Yes	No
County fixed-effect	Yes	Yes
Observations	10,622	10,622
R-squared	0.657	0.636
Number of counties	940	940
Likelihood ratio test	628.09***	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3 Test of the parallel trend assumption

VARIABLES	Production
Treatment_pre3	0.00576
	(0.0235)
Treatment_pre2	-0.0350
	(0.0435)
Treatment_pre1	-0.181*
	(0.108)
Treatment	0.158
	(0.132)
Treatment_lag1	-0.233
	(0.199)
Treatment_lag2	0.0844
	(0.120)
Treatment_lag3	0.0330
	(0.0651)
Area	0.862***
	(0.0513)
Fertilizer	0.0518***
	(0.0180)
Machinery	0.00684
	(0.0186)
Agri-employment	0.00468
	(0.0259)
Constant	2.460***
	(0.511)
Year fixed-effect	Yes
County fixed-effect	Yes
Observations	10,622
Number of county code	612
R-squared	0.641
Test of the parallel trend assumption: $\boldsymbol{\rho_1 = \rho_2 = \rho_3 = 0}$	
F (3, 611)	1.47
Prob > F	0.2206

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4 The impact of NNRs on grain production at the county in 1989-2018 with quantile sample

	Grain Production			
	(1)	(2)	(3)	(4)
VARIABLES	0-25%	26-50%	51-75%	76-100%
Treatment	-0.102	-0.134**	0.215	0.0555
	(0.0677)	(0.0601)	(0.186)	(0.0566)
Area	0.905***	1.012***	0.872***	0.825***
	(0.0491)	(0.0336)	(0.0397)	(0.0531)
Fertilizer	0.0144	-0.00540	0.0304*	0.0507**
	(0.0379)	(0.0158)	(0.0162)	(0.0231)
Machinery	0.0414	0.00563	0.0174*	0.0120
	(0.0290)	(0.0152)	(0.00973)	(0.0138)
Agri-employment	0.0909	0.0692*	0.00129	0.00253
	(0.0875)	(0.0382)	(0.0275)	(0.0263)
Constant	1.340***	0.815***	2.091***	2.776***
	(0.507)	(0.283)	(0.418)	(0.583)
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	1,982	2,625	3,041	2,974
R-squared	0.520	0.721	0.798	0.793
Number of counties	212	235	247	246

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5 The impact of NNRs on grain production at the county in 1989-2018 with major production province and nonmajor production province

VARIABLES	Grain production (1) Major production provinces	 (2) Nonmajor production province
Treatment	-0.0815**	0.135
	(0.0392)	(0.104)
Area	0.853***	0.930***
	(0.0331)	(0.0353)
Fertilizer	0.0795***	-0.0220
	(0.0181)	(0.0157)
Machinery	0.0360***	0.0306**
	(0.0116)	(0.0122)
Agri-employment	0.0398	0.00139
	(0.0295)	(0.0364)
Constant	1.817***	2.394***
	(0.340)	(0.411)
County fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	6,368	4,254
R-squared	0.696	0.551
Number of counties	462	478

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6 The impact of NNRs on grain production at the county in 1989-2018 with lagged effects of policy

	Grain production		
	(1)	(2)	(3)
VARIABLES	One-year lag	Two-year lag	Three-year lag
Treatment_lag1	-0.0492**	-0.0870**	-0.119***
	(0.0218)	(0.0399)	(0.0449)
Treatment_lag2		0.0293	0.0480
		(0.0365)	(0.0520)
Treatment_lag3			0.0151
			(0.0391)
Area	0.867***	0.855***	0.888***
	(0.0115)	(0.0126)	(0.0133)
Fertilizer	0.0380***	0.0602***	0.0481***
	(0.00698)	(0.00787)	(0.00797)
Machinery	0.0353***	0.0273***	0.0263***
	(0.00575)	(0.00588)	(0.00586)
Agri-employment	0.0258**	0.00418	0.00395
	(0.0110)	(0.0116)	(0.0119)
Constant	2.390***	2.345***	2.079***
	(0.116)	(0.127)	(0.134)
County fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Observations	9,078	7,818	6,645
R-squared	0.674	0.682	0.678
Number of counties	901	858	779

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7 Mechanism analysis of NNRs on grain production

	Grain production	Area	Grain production		Yield	
VARIABLES	(1)	(2)	(3)	VARIABLES	(4)	(5)
Treatment	-0.0930***	-0.0558***	-0.0442**	Treatment	-0.0437**	-0.0697***
	(0.0262)	(0.0189)	(0.0203)		(0.0203)	(0.0203)
Area			0.875***	Fertilizer/hectare	0.0321***	0.0404***
			(0.0109)		(0.00624)	(0.00621)
Fertilizer	0.173***	0.161***	0.0316***	Machinery/hectare	0.0321***	0.0374***
	(0.00776)	(0.00561)	(0.00627)		(0.00559)	(0.00522)
Machinery	0.0850***	0.0615***	0.0312***	Agri-employment/hectare	0.0557***	0.0288***
	(0.00727)	(0.00525)	(0.00567)		(0.00888)	(0.00849)
Agri-employment	0.204***	0.176***	0.0504***	Year trend		0.0161***
	(0.0135)	(0.00972)	(0.0106)			(0.000434)
Constant	9.780***	8.435***	2.398***	Constant	1.906***	1.834***
	(0.0767)	(0.0554)	(0.110)		(0.0754)	(0.0684)
Year fixed effect	Yes	Yes	Yes	Year fixed effect	Yes	No
County fixed effect	Yes	Yes	Yes	County fixed effect	Yes	Yes
Observations	10,591	10,591	10,591	Observations	10,622	10,622
R-squared	0.972	0.981	0.983	R-squared	0.302	0.260

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

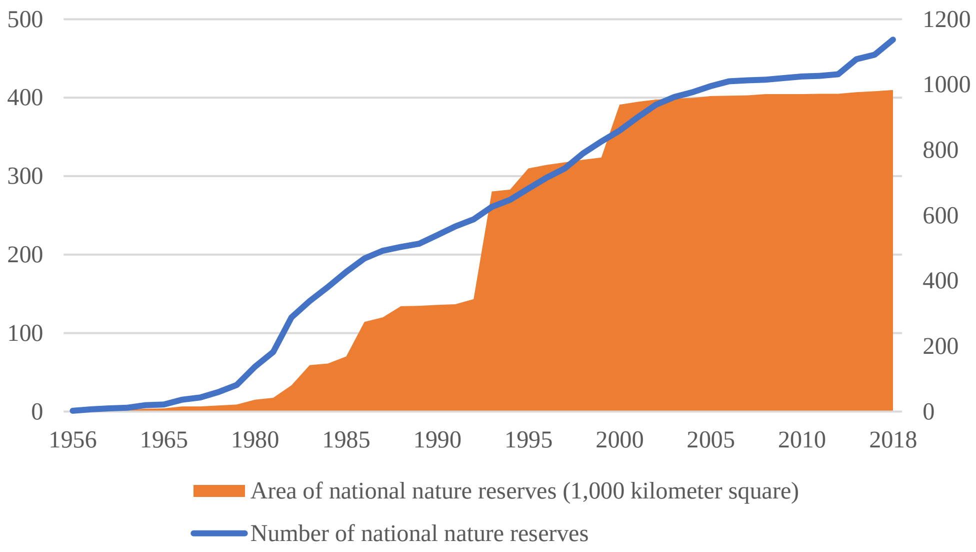

Figure 1 Number and area of national nature reserves in China (National-level)

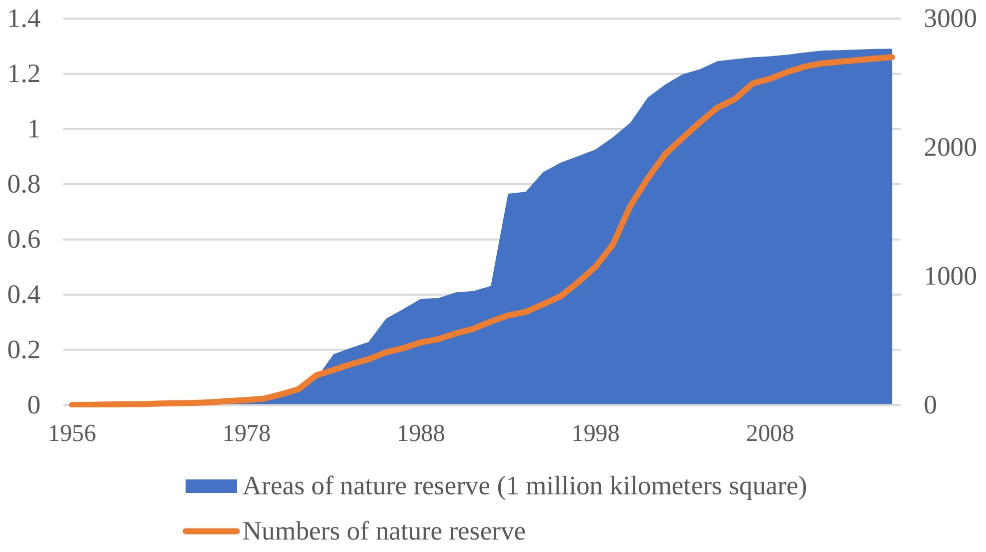

Figure 2 Number and area of national nature reserves in China (All-levels)

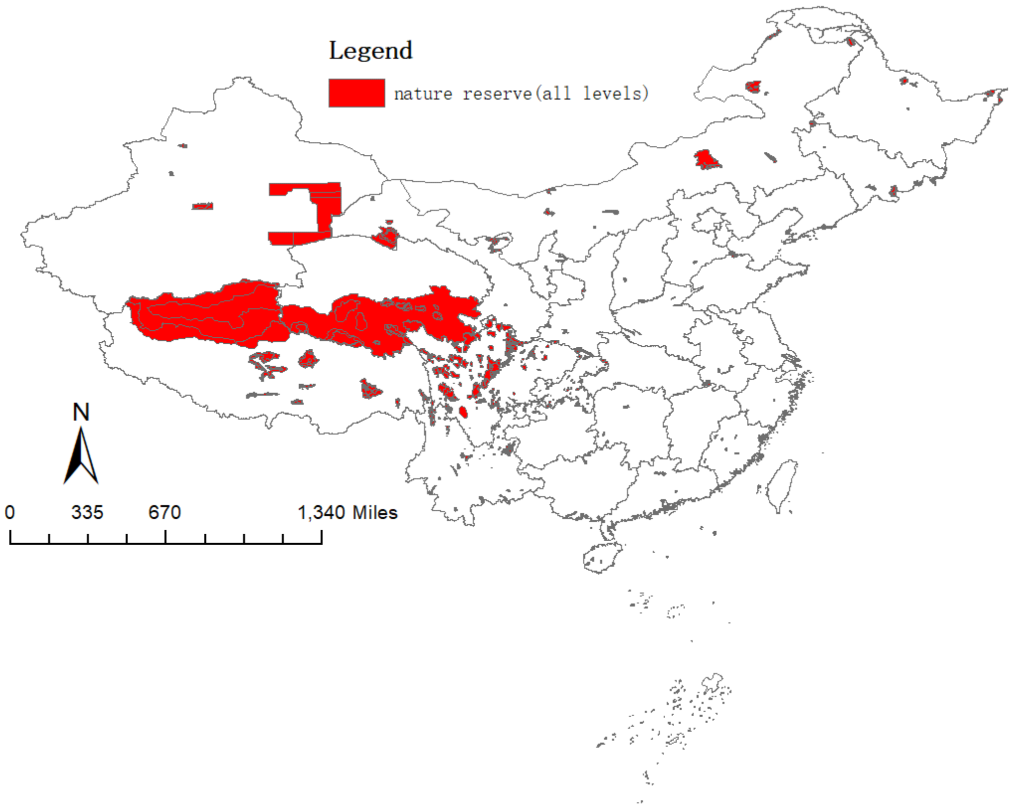

Figure 3 Geographic distribution of the nature reserves by area in China

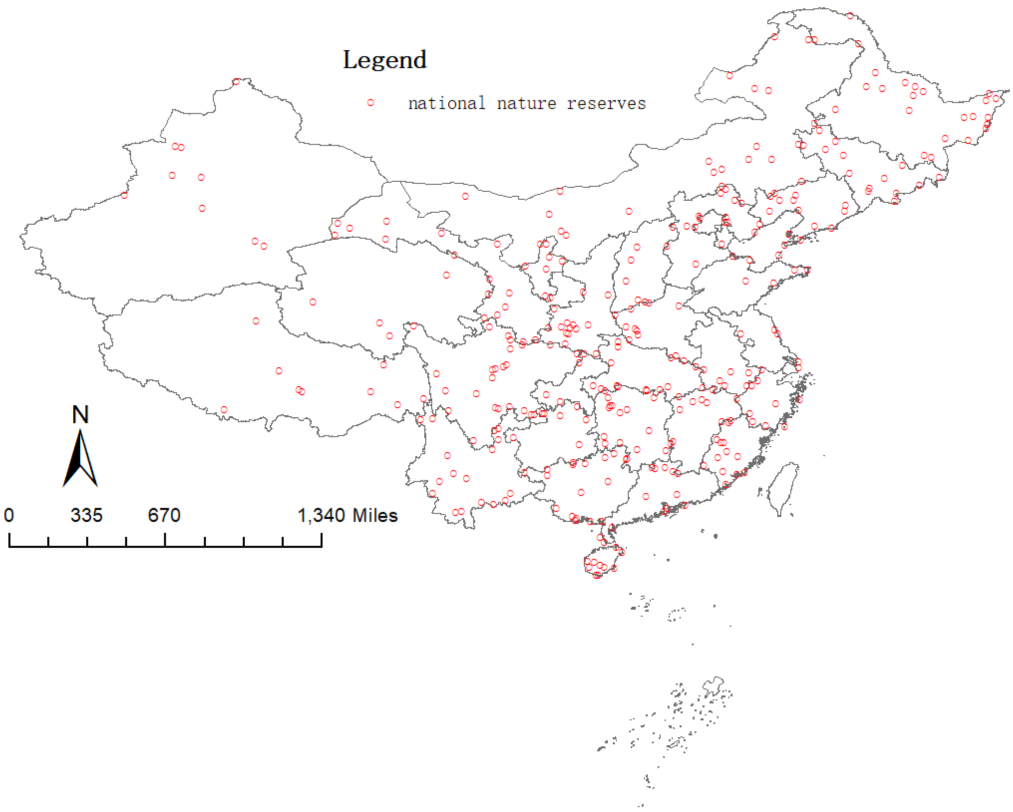

Figure 4 Geographic distribution of the nature reserves in China by projects (National-level)

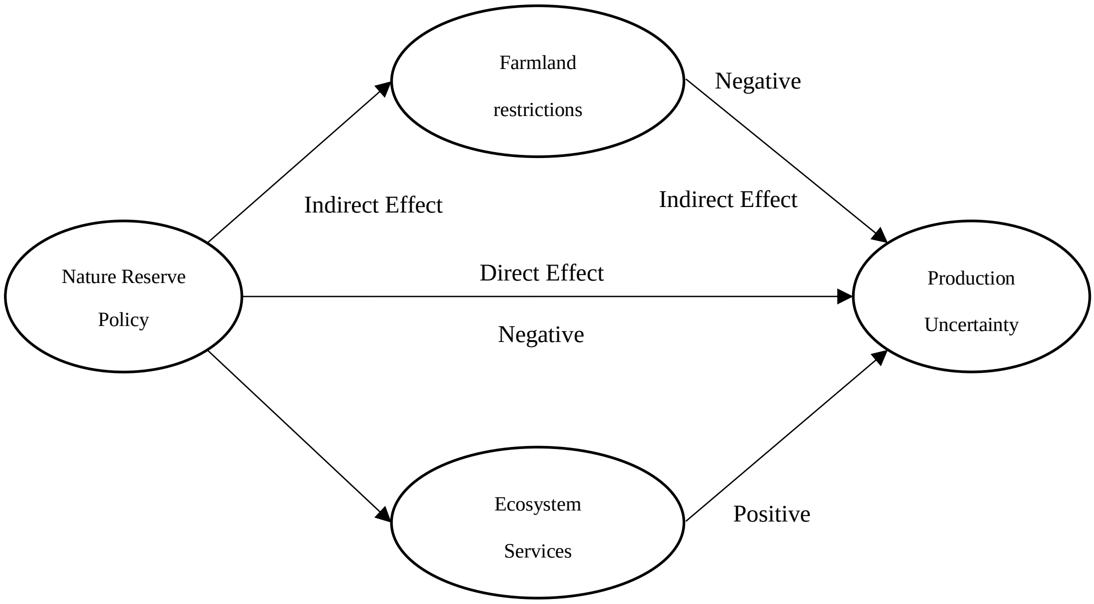

Figure 5 Conceptual framework of NNR on agricultural production

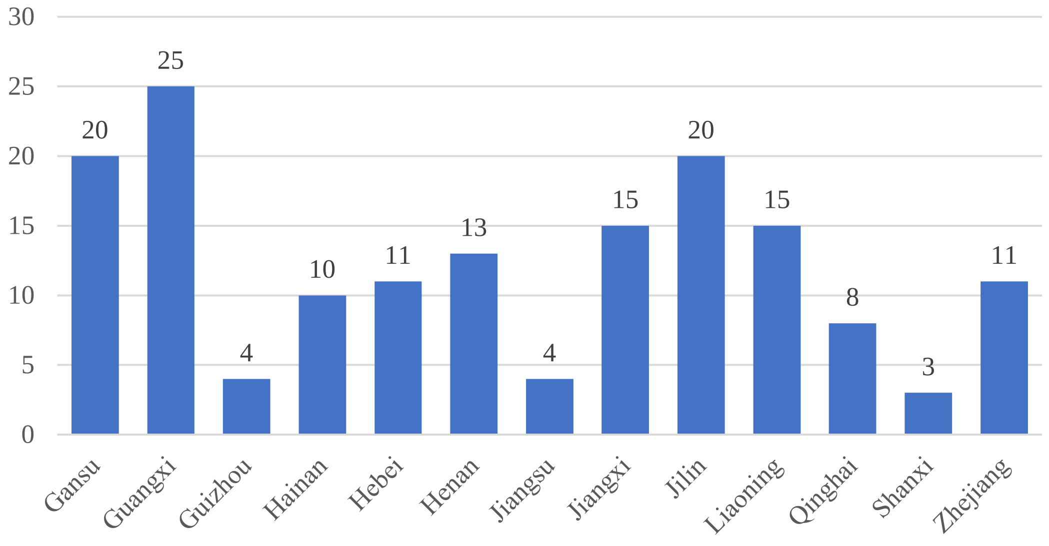

Figure 6 Geographical distribution of the NNRs samples by province

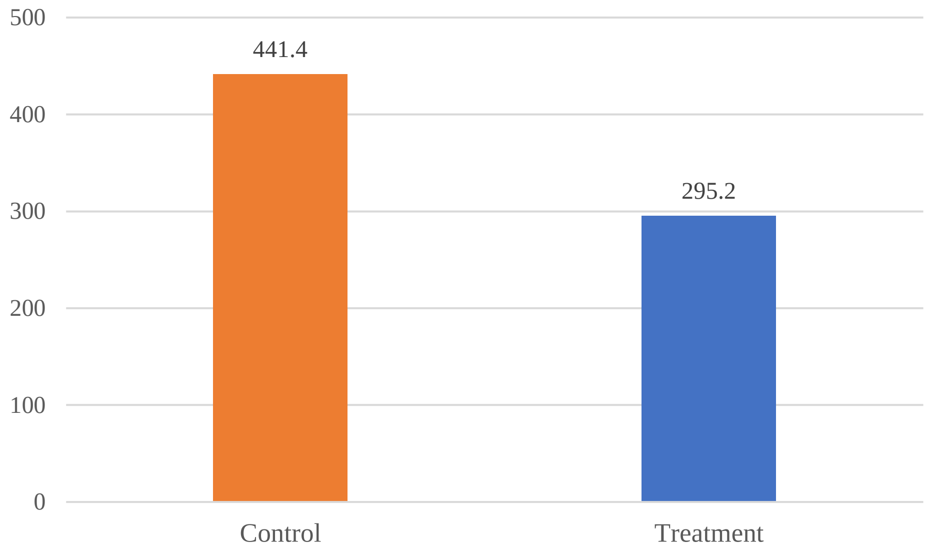

Figure 7 Average grain production by counties with and without NNR from 1989 - 2018

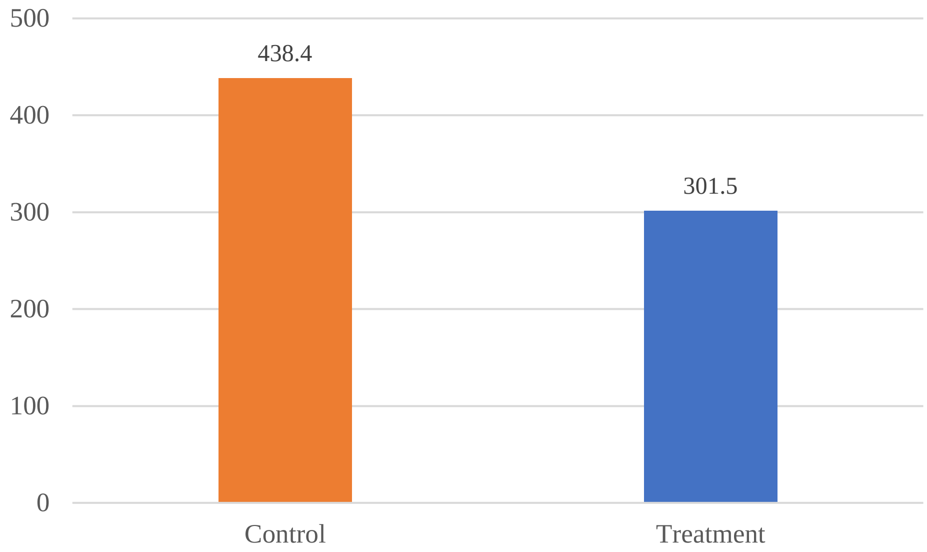

Figure 8 Average grain production by observations with and without NNR from 1989 -2018

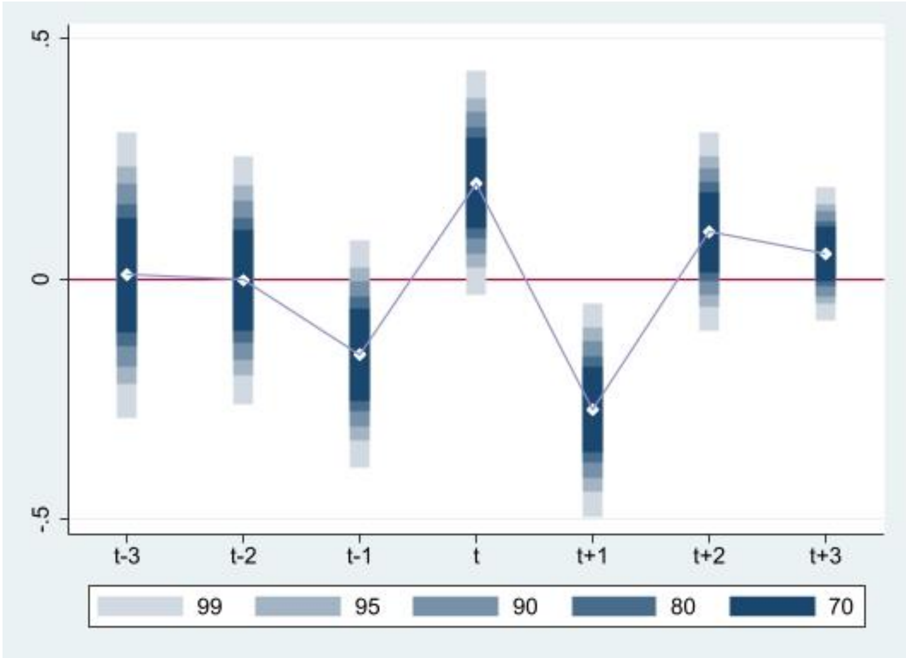

Figure 9 Test of pre-treatment parallel-trend assumption with time-varying treatment