Land Titling, Selection, and Fertilizer Use Efficiency in China

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Abstract

Excess fertilizer use is a major source of non point pollution in agriculture. This paper studies whether strengthening rural land rights can reduce fertilizer overuse in China. I exploit the staggered rollout of the national land certification program from 2013 to 2020 across counties and estimate causal effects using difference in differences methods with multiple periods, linked to a household panel from the National Fixed Point Survey and environmental data. Three findings emerge. First, clarifying land tenure reduces chemical fertilizer intensity at the household level by about 8.35%, and it induces shifts toward organic inputs, both on the extensive and the intensive margins. Second, a decomposition shows that roughly 60% of the decline is an incentive effect from secure tenure and about 40% is a reallocation effect as land moves toward more productive operators. Third, county level nitrous oxide emissions fall by about 2.82% after certification, closely matching a 2.92% reduction predicted from the estimated decline in fertilizer intensity, and water quality indicators improve in treated areas. Correspondingly, the reduction in fertilizer use is accompanied by significant improvements in related water quality indicators, particularly a decline in CODMn and NH_4-N. The results indicate that property rights reforms can mitigate agricultural pollution by correcting resource misallocation and by changing input choices within farms.

1 Introduction

Agriculture significantly contributes to global environmental degradation, largely due to the excessive use of chemical fertilizers. Each year, over half of nitrogen and phosphorus fertilizers applied worldwide end up as pollutants, severely harming soil and water resources and generating greenhouse-gas emissions comparable to those of major industrial economies (Del Rossi et al., 2023).[1] China is among the countries suffering the most from fertilizer overuse: despite having only about 9% of global cropland, it accounts for over 30% of global fertilizer consumption, far exceeding sustainable usage levels.

[1]For reference, Japan emitted approximately 1,082.6 Mt CO_2 ($\approx 1.08\,\mathrm{Gt}$) in 2022, ranking as the fifth-largest emitter globally.

Weak land rights and distorted land markets are well documented drivers of low farm productivity in developing economies (Lagakos and Waugh, 2013; Adamopoulos and Restuccia, 2014; Gollin et al., 2014); do these same forces also distort chemical input use and worsen agricultural pollution, and if so, through reallocation across farmers or incentives within farms?

In this paper, I empirically examine how strengthening land property rights mitigates agricultural pollution by correcting resource misallocation in farm production. First, I document sizable misallocation in Chinese agriculture using the standard total factor productivity framework from the macro development literature. Drawing on household level panel data, I estimate each plot's permanent productivity component via a fixed effects regression and recover marginal products of land and fertilizer under a Cobb-Douglas technology. I then construct farm level distortions, defined as deviations of actual inputs from the efficient margin implied by equalized marginal products. I show clear evidence of distortion: smaller and less productive farms apply fertilizer at much higher rates despite lower returns, indicating that frictions in the land market have kept a substantial share of farmland in inefficient hands.

Next, I leverage the staggered rollout of China's 2013 to 2020 land certification program as a natural experiment. In recent years, China launched a comprehensive land-titling reform (issuing land certificates and documenting plot rights) to secure farmers' long-term use rights. Strengthening land rights can mitigate pollution through two key channels. First, The reallocation effect: with transferable, well-defined rights, less productive farmers become more willing to lease out or sell land, allowing more efficient farmers to consolidate landholdings. Second, the incentive (property rights) effect: farmers with secure, long-term tenure invest in better farming practices and soil quality, reducing reliance on quick fixes like excessive fertilizer. Together, these mechanisms improve environmental efficiency via internal reallocation of productive resources. Exploiting variation in the timing of land certificate issuance across counties, I implement a difference in differences design to identify the causal impact of improved tenure security on fertilizer use and soil management. Clarifying land rights reduces chemical fertilizer intensity at the household level by approximately 8.35%. Moreover, households in newly certified counties adopt significantly more organic fertilizers, both extensively and intensively. This result demonstrates that secure tenure incentivizes long term soil stewardship rather than short term quick fixes through excessive chemical fertilizer applications.

Further, I propose and implement an empirical framework to separately quantify the reallocation effect and the property rights effect. The standard difference in differences estimates at the household level cannot directly yield aggregate changes in fertilizer use, due to shifts in land allocation after the reform. Specifically, more productive households expanded their operational scale. To address this, I classify households into four groups based on their land rental status after reform: "no change," "rent in," "rent out," and "both." I demonstrate that the aggregate reduction in fertilizer usage can be derived from a weighted aggregation of group-specific difference in differences estimates, with weights corresponding to each group's post-reform land share. The reduction observed in the "no change" group purely reflects the property rights effect. Using this decomposition, I find that approximately 40% of the total decline in fertilizer use intensity is driven by the reallocation effect, while the remaining 60% is attributable to the property-rights effect.

Combining environmental monitoring data that track indicators of non-point source pollution, including nutrient runoff and water contamination, I find that county level N_2O emissions decreased by 2.82% following the land tenure reform. This observed decline closely matches the predicted reduction of 2.92%, derived from the estimated decrease in fertilizer use intensity. Data from water quality monitoring stations further confirm improvements in fertilizer related pollution indicators in the areas subject to reform.

This study contributes to three strands of literature. First, it advanced research on resource misallocation in agriculture. Prior work has demonstrated that distortions in factor markets, whether arising from insecure land tenure, labor market frictions, or constraints in credit allocation, create wedges between farms' marginal products and explain substantial cross-country gaps in agricultural productivity (Lagakos and Waugh, 2013; Adamopoulos and Restuccia, 2014; Gollin et al., 2014; Bustos et al., 2016). I extend this literature by showing that these farm-level distortions not only reduce aggregate output and slow structural transformation but also amplify non-point source pollution. By trapping land in the hands of less productive operators, these distortions induce overuse of chemical fertilizers, one of agriculture's most ubiquitous intermediate inputs.

Secondly, my analysis contributes to the growing body of empirical research on the economic benefits of secure land property rights. Prior work has documented how insecure property rights discourage farmers from making productivity-enhancing investments, such as irrigation systems or soil fertility improvements (Jacoby et al., 2002; Jacoby and Mansuri, 2008; Goldstein and Udry, 2008). This tenure insecurity also constrains labor mobility, binding rural households to their land, reducing cross-sectoral and rural-urban migration, and ultimately hindering structural transformation (De Janvry et al., 2015; Lagakos et al., 2023; Adamopoulos et al., 2024). I extend this literature by highlighting the previously unexplored environmental gains from secure land rights. Distinct from the classic Coasean framework wherein well-defined property rights facilitate bargaining to internalize externalities (Muller and Mendelsohn, 2009; Behrer et al., 2021), I demonstrate that clarified land tenure prompts producers to internally adjust their farming practices and input choices.

Third, this work relates to the literature examining agriculture's environmental externalities and their health implications. Prior studies have extensively documented the detrimental effects of excessive fertilizer and pesticide use, highlighting negative impacts on water quality, biodiversity, and human health. For instance, Dias et al. (2023) and

Skidmore et al. (2023) show that intensive pesticide applications significantly increase infant mortality rates in downstream populations in Brazil, while Lai (2017), Perry and Moschini (2020), and Fletcher and Noghanibehambari (2024) document reduced life expectancy resulting from prolonged exposure to agricultural chemicals. By linking land property rights reform directly to reductions in chemical fertilizer intensity and measurable improvements in environmental quality, this study suggests that improving resource allocation efficiency through tenure security is beneficial for mitigating environmental concerns raised by agricultural production.

The remainder of the paper is organized as follows. Section 2 provides background on China's fertilizer overuse situation and agricultural land institutions as well as recent reforms. Section 3 describes the data sources and presents descriptive evidence on fertilizer misallocation and farm productivity. Section 4 introduces the empirical strategy leveraging the staggered policy rollout, followed by the main difference-in-differences results on fertilizer intensity. Section 5 decomposes the treatment effect into reallocation and incentive channels, while Section 6 traces the environmental impacts of the reform, examining changes in N_2O emissions and water quality.

2 Background

2.1 Fertilizer overuse in China

Fertilizer, especially synthetic nitrogen, was one of the key innovations of the Green Revolution because it can greatly improve crop yields (Schultz, 1964; Evenson and Gollin, 2003). Yet when applied in excess it generates multiple forms of environmental damage (Galloway et al., 2008). In soils it alters chemical balances and microbial communities, raising pest and disease pressure, acidifying soils, and causing surface sealing, all of which undermine fertility and reduce future yields (Liu et al., 2016).[2] Unused fertilizer dissolves in rain and irrigation water and then leaches into rivers, lakes, and aquifers as nitrates that render freshwater unsafe to drink and drive harmful algal blooms (Tilman, 1999). Other nitrogen compounds volatilize or are transformed by soil microbes into nitrous oxide, a potent greenhouse gas, and agriculture is the largest global source of these emissions (Liu et al., 2022).

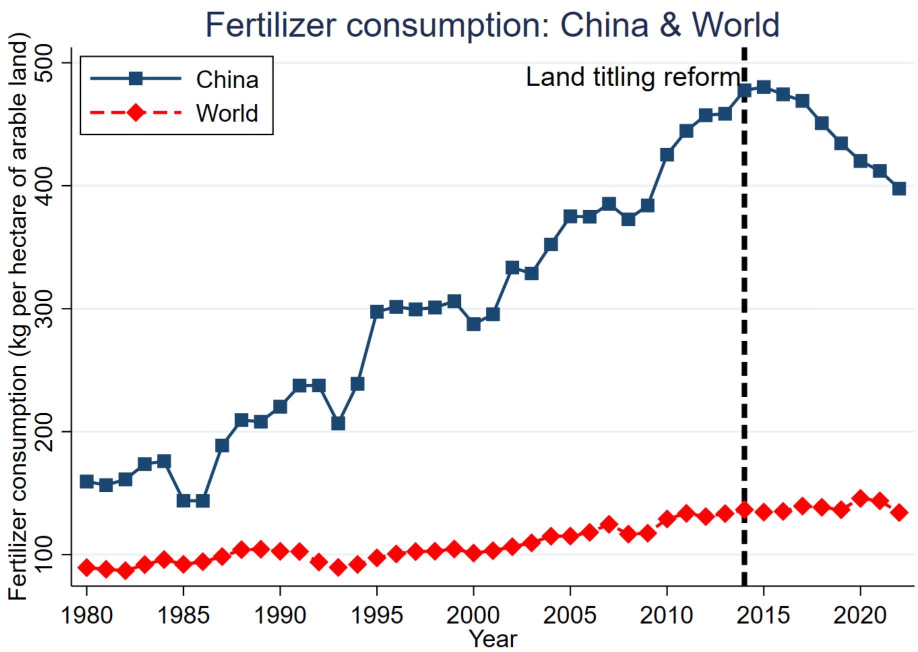
China is now the world's largest fertilizer user, yet it applies far more than agronomic guidelines recommend. Although Chinese cropland is under 9% of the global total, it accounts for over 30% of all fertilizer use (Liu et al., 2016). China achieves only 28% nitrogen use efficiency, measured as crop nitrogen uptake over fertilizer applied, compared

[2]For example, excess nitrogen raises pest and disease incidence, acidifies soils, and leads to surface sealing, each of which ultimately lowers soil productivity.

with about 48% worldwide and 70% in the United States[3] (Xu et al., 2024). This low efficiency together with high input drives severe pollution.

Several factors help explain China's excessive fertilizer use. Although synthetic fertilizer became common only after the 1980s, most farmers lack training and practical knowledge on field specific recommendations for timing, rates, and nutrient mixes, so they follow the simple rule of thumb that "more is better" (Lin et al., 2021). Government subsidies and the fast growth of the domestic fertilizer industry have kept prices low (Huang et al., 2013). Finally, insecure land tenure discourages farmers from taking into account the long term costs of soil degradation; they have little incentive to preserve or build soil fertility when they are unsure they will reap the future gains (Jacoby et al., 2002). Figure 1 plots fertilizer use intensity in China and the world from 1980 to 2022 using FAO data. The vertical line marks the start of land titling in China in 2014. Before 2014, fertilizer use in China rose far above the world average, and after 2014 it began to fall.

Figure 1: Fertilizer use intensity of China and world



Notes: This figure plots fertilizer use intensity in agricultural production, measured as kilograms of fertilizer applied per hectare of arable land, for China (solid blue line) and the world (dashed red line) from 1979 to 2022. The vertical black dashed line marks the rollout of China's land-titling policy beginning at 2014. Following this reform, China's fertilizer intensity shows a notable decline trend.

2.2 Land titling policy

Since the founding of the People's Republic of China in 1949, rural land policy has gone through several major reforms. The first land reform in the early 1950s redistributed

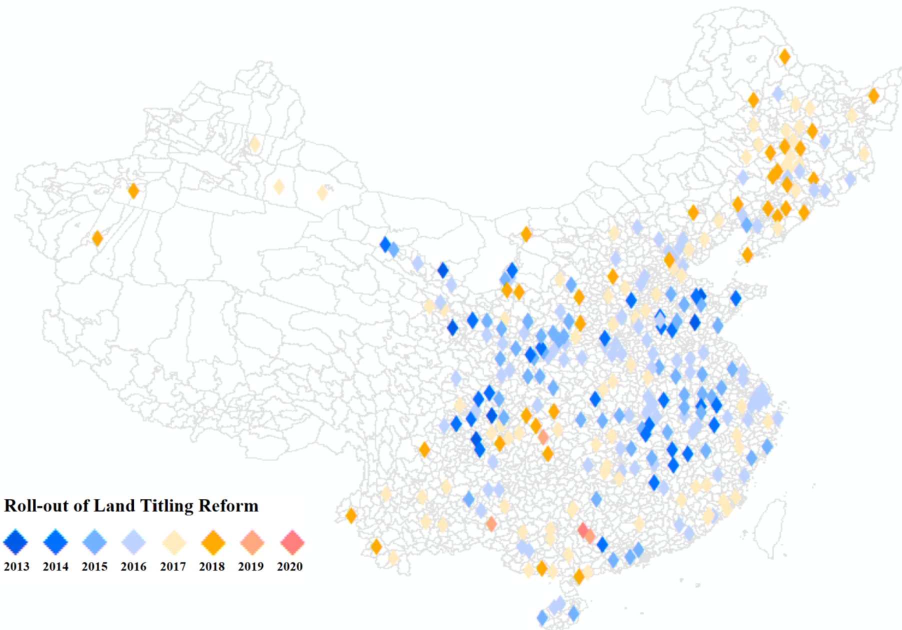
[3]Nitrogen use efficiency is defined as the ratio of crop nitrogen uptake to nitrogen fertilizer applied.

land from landlords to tenant farmers, briefly restoring private ownership and giving cultivators clear rights to the land. This arrangement was short lived. In the mid 1950s, the government launched forced collectivization, which led to the People's Commune system. Under collective ownership, individual incentives were weak and agricultural productivity suffered because property rights were unclear.

In response to poor agricultural performance under collectivization, China introduced the Household Responsibility System (HRS) in the late 1970s. Ownership remained collective at the village level, but operating rights were assigned to individual households. Although farmers gained autonomy to farm their plots, village committees frequently reallocated land based on demographic changes such as household size, which continued to undermine land tenure security. Prior studies document large economic costs of insecure land rights, including weaker incentives for long term investment and inefficient resource allocation.

To further clarify rights and improve land use efficiency, the central government announced a comprehensive land titling program in the 2013 "No. 1 Document," with nationwide implementation starting in 2014. The program conducted systematic cadastral surveys to measure and map plots, and then issued standardized land certificates that clearly defined each household's rights and obligations. Crucially, the reform sharply limited the authority of village collectives to reassign land, thereby strengthening the security and stability of household land tenure.

Figure 2: Land titiling policy roll out in China



Notes: This figure illustrates the geographic and temporal variation in the implementation of China's land titling policy. The map indicates the timing of land titling policy completion in counties where NFP data villages are located. The nationwide rollout of the program commenced in 2014 and achieved universal coverage by the end of 2019.

By reducing tenure uncertainty and clarifying land rights, the policy aimed to raise agricultural productivity through two channels. First, clearer rights ease selection, allowing land to flow to more capable and productive farmers. Second, secure tenure encourages practices that emphasize long term sustainability and soil stewardship, reducing behaviors driven by short term gains at the expense of future productivity.

3 Data and Motivating Evidence

3.1 Data sources

To examine how land titling reform affects farmers' fertilizer use efficiency and environmental outcomes, we draw on four main data sources:

National Fixed Point Survey (NFP)

The primary data source for our analysis is the National Fixed Point Survey (NFP), a longitudinal panel conducted since 1986 by the Research Center for Rural Economy of the Chinese Ministry of Agriculture. Approximately 300 villages are sampled each round, and within each village 50 to 100 households are randomly selected and tracked over time. The survey records detailed information on agricultural production, employment, consumption, and intermediate inputs. Rigorous multi stage quality checks during data collection ensure minimal measurement error (Benjamin et al., 2005).

A potential limitation of the NFP is its lack of plot level identifiers and land quality measures, which in other settings can confound estimates of misallocation.[4] However, two pieces of evidence help to allay this concern. First, Adamopoulos et al. (2022) construct a village level land quality index using GAEZ data and find that the standard deviation of log land productivity across Chinese villages is only 0.096, less than half of the 0.21 dispersion they report for the Philippines. Second, Liu et al. (2010) conduct plot level surveys in the same NFP villages in 2010 and also document very limited variation in soil quality. They show that village collective leaders, when allocating plots to households, systematically account for observable quality differences, thereby equalizing land quality across operators.

Descriptive statistics for the NFP variables used in our regressions are reported in Table 1, Panel A. We restrict the sample to households engaged in agriculture, drop non farm households, and exclude observations missing information on input use.[5] In Panel B, we report village year aggregates of several controls, including land per capita, cropland

[4]Another limitation is the absence of plot level rental contract data, so we cannot track plot transactions before and after the reform.

[5]Although most survey rounds record only fertilizer purchases, volatilization makes on farm storage rare, so annual purchase approximates usage. In the Appendix we compare the one year with both purchase and usage data and find them effectively identical.

area, crop income per capita, and the average fertilizer price. These variables capture local resource endowments and input market conditions at the village level.

Land Titling Policy Timing and Socioeconomic Controls

County year implementation dates for the rural land titling program are hand collected from local agricultural bureau websites and annual government work reports, then merged with a broad set of time varying covariates at both the county and prefecture levels. In Panel C (2007 to 2022, county year), we include total population (ten thousand people), GDP (ten thousand yuan), and the shares of primary and secondary industry in GDP to capture local economic scale and structural change. In Panel D (also 2007 to 2022, city year), we add measures of industrial activity, including industrial wastewater discharge (ten thousand tons), sulfur dioxide emissions (tons), and smoke emissions (tons), as proxies for manufacturing intensity. These socioeconomic and environmental controls are used to account for general equilibrium effects of land titling on the broader economy in later regressions.

N_2O Emissions

Gridded N_2O emissions come from the EDGAR database, an independent global dataset of anthropogenic greenhouse gas and air pollution emissions maintained by the European Commission's Joint Research Centre. EDGAR uses international statistics and a consistent IPCC methodology to produce national totals and $0.1^\circ \times 0.1^\circ$ grid maps with yearly, monthly, and hourly data. We overlay these grid cells on county boundaries and sum annual emissions to construct county year totals.

Surface Water Quality

Water quality data are from the National Real time Surface Water Quality Monitoring System of the Ministry of Ecology and Environment. Monthly station level readings of pH, dissolved oxygen, permanganate index, and ammonia nitrogen at 149 sites are averaged and aggregated to the county year panel.

3.2 Measuring Misallocation in Agricultural Production

Before presenting the empirical regressions, we first document patterns that reveal misallocation in both land use and fertilizer application. We also describe the framework used to measure farm level productivity misallocation and fertilizer input intensity, drawing on detailed micro panel data for Chinese households. The framework is closely related to (Adamopoulos et al., 2022; Chen et al., 2023).

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A. Household Year (2010-2017)					
Crop sown area (ha)	33,493	1.07	17.95	0	1,733.33
Fertilizer purchased (kg)	31,780	747.67	1,475.02	0	168,750
Fertilizer intensity (kg/ha)	30,861	1,403.25	4,666.01	0	487,500
Imputed manure value (CNY)	21,954	20.20	150.35	0	6,600
Household income (CNY)	41,783	61,891.06	92,057.30	0	5,001,780
Household laborers (persons)	40,292	2.50	1.18	0	6
Panel B. Village Year (2010-2017)					
Village population (persons)	2,112	2,121.19	1,783.97	95	23,639
Land per capita (ha/person)	2,087	0.50	1.18	0	15.73
Cropland per capita (ha/person)	2,050	0.13	0.18	0	1.51
Crop income per capita (CNY/person)	2,034	54.73	327.32	0	7,364.71
Fertilizer price (CNY/kg)	2,083	2.68	5.16	0.39	200
Panel C. County Year (2007-2022)					
Total population (10 k people)	4,262	63.93	44.68	7	577
GDP (10,000 CNY)	4,633	2,590,000	4,410,000	49,630	92,703,104
Primary industry share	4,633	0.19	0.11	0.00	0.75
Secondary industry share	4,633	0.43	0.16	0.03	1.29
Panel D. City Year (2007-2022)					
Wastewater discharge (10 kt)	3,337	6,845.25	8,777.90	7	96,501
SO_2 emissions (tons)	3,903	41,249.29	50,265.03	2	683,000
Smoke emissions (tons)	3,336	30,582.77	131,000	34	5,168,812

Notes: In this table we report summary statistics of data. Panel A reports household–year data from the National Fixed Point Survey (2010–2017); Panel B reports village–year socioeconomic controls (2010–2017); Panel C reports county–year macroeconomic data (2007–2022); Panel D reports city–year environmental controls (2007–2022).

I model each farm's production with a Cobb Douglas technology featuring heterogeneous household specific productivity. In particular, output per labor day for household i in year t is

$$y_{it} = (As_i)^{1-\gamma}\big(L_{it}^{\alpha}F_{it}^{1-\alpha}\big)^{\gamma}. \tag{1}$$

Here A is the common sector level productivity factor, s_i is the permanent idiosyncratic productivity of household i, L_{it} is labor adjusted land area (hectares per labor day), F_{it} is labor adjusted fertilizer use (kilograms per labor day), $\alpha \in (0, 1)$ is the land share parameter, and $\gamma < 1$ governs decreasing returns to scale. Under an undistorted allocation, differences in s_i alone would drive scale choices, equalizing marginal products across farms.

From Equation (1) I define two measures. First, physical total factor productivity (TFPQ) is

$$\text{TFPQ}_{it} \equiv (As_i)^{1-\gamma}, \tag{2}$$

which abstracts from input use and reflects each farm's technical efficiency. Second, revenue productivity (TFPR) is

$$\mathrm{TFPR}_{it} \equiv \frac{y_{it}}{L_{it}^{\alpha} F_{it}^{1-\alpha}}, \tag{3}$$

which captures effective output per composite input bundle. I recover the permanent household component of each series by estimating $\log \mathrm{TFPQ}_{it}$ and $\log \mathrm{TFPR}_{it}$ with household by year fixed effects, removing common shocks, and exponentiating the residuals to obtain time invariant levels TFPQ_i and TFPR_i.

Following the literature, I set $\gamma = 0.54$ and $\alpha = 0.75$. For each household year observation, net value added Y_{it} is computed by subtracting intermediate input costs and wage payments from agricultural revenue, and I normalize Y_{it}, L_{it}, and F_{it} by total labor days (family and hired). To isolate persistent productivity, I estimate

$$\log \mathrm{TFPQ}_{it} = \mu_i + \beta_t + \varepsilon_{it}, \tag{4}$$

where μ_i and β_t are household and year fixed effects and ε_{it} is a transitory shock. I then purge village level heterogeneity by regressing μ_i on village dummies and using the residuals ζ_i. Marginal products of land and fertilizer are

$$\mathrm{MPL}_{it} = \gamma\alpha \frac{Y_{it}}{L_{it}}, \tag{5}$$

$$\mathrm{MPF}_{it} = \gamma(1-\alpha) \frac{Y_{it}}{F_{it}}. \tag{6}$$

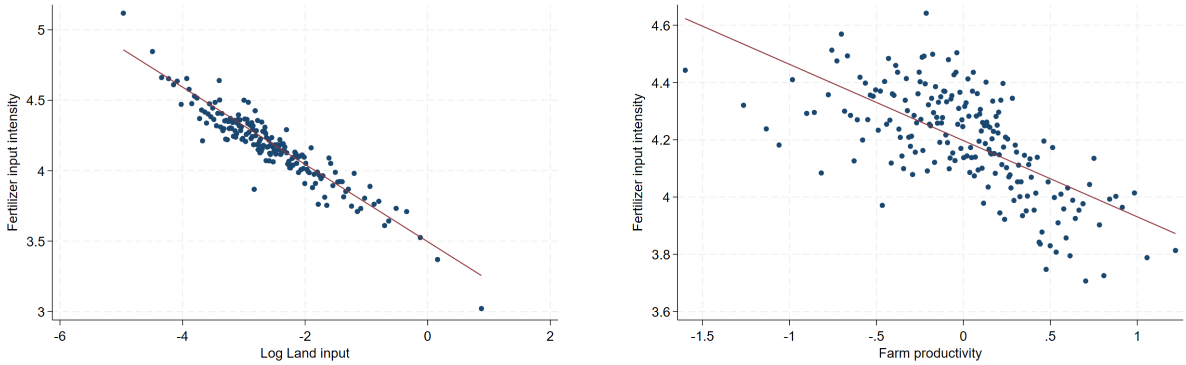
3.3 Stylized Facts On Fertilizer Use Efficiency

Fertilizer use intensity varies substantially across households. Figure 3 shows scatter plots of farm level fertilizer intensity (kilograms of fertilizer per hectare after normalizing by labor days) against farm characteristics. Panel (a) plots intensity against log land size (normalized by labor days); Panel (b) plots intensity against farm productivity. In both cases the fitted lines slope downward, indicating that larger and more productive farms apply less fertilizer per unit of land.

In a frictionless, common technology setting à la Samuelson, the efficient allocation of land requires that land inputs scale proportionally with farm productivity, so that more productive farmers operate larger areas. In addition, the marginal product of land should be invariant to productivity, since first order conditions require that marginal factor products are equalized across producers.

Figure 4 shows that this benchmark fails in our data period in China. Panel (a) plots log land area per labor day against the permanent idiosyncratic productivity measure (log TFPQ). Rather than a clear upward trend, many low productivity households remain on small plots, suggesting that insecure and informal land rights constrain exit and

Figure 3: Farm characteristics and Fertilizer use intensity



(a) By farm size (b) By productivity

Notes: This figure shows household fertilizer use intensity by farm characteristics. The y-axis in both panels measures fertilizer use intensity in kilograms of fertilizer per hectare after normalizing by labor days. Panel A plots fertilizer intensity against log land area per labor day, while Panel B plots fertilizer intensity against farm productivity, which is a pure idiosyncratic permanent component of productivity (log TFPQ) estimated from equation 4. As shown in both panels, large farm and productive farm tend to use fertilizer less intensively.

reallocation (Adamopoulos et al., 2024). Panel (b) plots average land output (log Y/L) against log TFPQ and shows a strong positive relationship, consistent with more productive farms achieving higher yields on the land they operate.

We next examine how household productivity relates to fertilizer returns. Figure 5 documents this relationship. Panel (a) plots average fertilizer productivity (log value added per kilogram of fertilizer) against the permanent idiosyncratic productivity component (log TFPQ) estimated from Equation (4). In an efficient, frictionless allocation, returns would be equalized across farms; instead, we observe a strong positive relationship.

Panel (b) shows the marginal product of fertilizer, computed as $\gamma(1-\alpha)\,Y_{it}/F_{it}$, plotted against log TFPQ. Again, there is an upward slope, indicating that more productive farms face higher marginal gains from additional fertilizer. These patterns point to input misallocation across households.

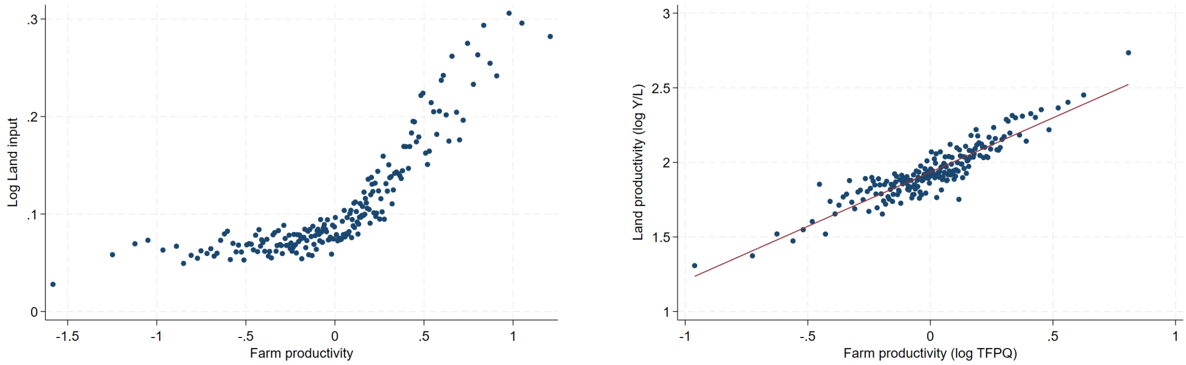
4 Empirical Results

4.1 Empirical specification

To estimate the causal effect of land titling on fertilizer use efficiency, we run a difference in differences regression that compares fertilizer intensity of farmers in counties that implement the land titling policy at different times:

$$Y_{ivct} = \beta\, Treat_{ct} + X'_{ivct}\gamma + \alpha_i + \eta_v + \phi_c + \lambda_t + \varepsilon_{ivct}, \tag{7}$$

Figure 4: Land Allocations by Farm Productivity.



(a) Land input

(b) Land productivity (Yield)

Notes: This figure shows the relationship between land allocation and household productivity. Panel (a) plots farm productivity, estimated as the permanent idiosyncratic component from equation 4 against land input per labor day, where land input is measured relative to total labor days supplied by the household. Many low productivity farms continue to operate small plots, indicating inefficient allocation. Panel (b) shows farm productivity against average land output, where land productivity is defined as value added per hectare. More productive farms achieve higher average land output.

where i indexes households, v villages, c counties, and t years. Y_{ivct} is fertilizer intensity for household i in village v, county c, year t; $Treat_{ct}$ equals one if county c has implemented land titling by year t and zero otherwise; X_{ivct} is a vector of time varying controls at the household, village and county levels; α_i and λ_t are household and year fixed effects; and ε_{ivct} is the idiosyncratic error term.

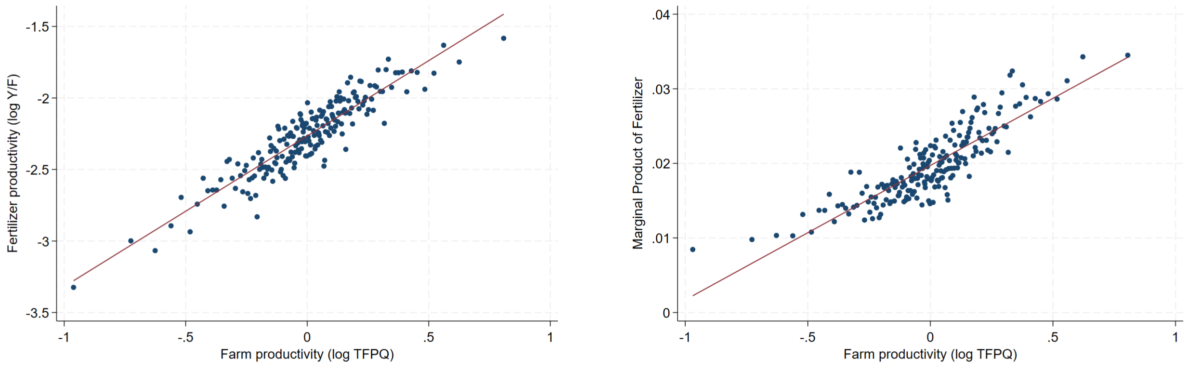
Because land titling is rolled out in a staggered fashion, the standard two way fixed effects estimator may produce biased estimates of the average treatment effect, as documented in recent econometrics literature (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). We therefore implement the Callaway and Sant'Anna (2021) estimator to recover valid treatment effect measures.

To capture the dynamic effects of land titling and to test the parallel trends assumption, we estimate an event study model with event dummies for each year relative to implementation from $l = -7$ to $l = 3$, along with household, village, county and year fixed effects and the same vector of controls. Formally:

$$Y_{ivct} = \sum_{l=-7}^{3} \beta_l \, \mathbf{1}\{t - \tau_c = l\} + X'_{ivct}\gamma + \alpha_i + \eta_v + \phi_c + \lambda_t + \varepsilon_{ivct}, \tag{8}$$

where $\mathbf{1}\{t - \tau_c = l\}$ equals one if county c first implemented titling l years before or after t. We omit the $l = -1$ dummy so that all β_l are interpreted relative to the year before titling. The sequence $\{\beta_l\}$ then traces out pre treatment trends and post treatment dynamics in fertilizer intensity.

Figure 5: Farm productivity and fertilizer productivity



(a) Average fertilizer productivity (log Y/F) (b) Marginal product of fertilizer

Notes: Panel (a) shows the relationship between log TFPQ (from equation 4) and average fertilizer productivity, defined as log value added per kilogram of fertilizer. Panel (b) shows TFPQ against the marginal product of fertilizer, computed as $\gamma(1-\alpha)Y_{it}/F_{it}$. Both panels display fitted linear trends, highlighting that more productive farms realize higher fertilizer returns.

4.2 Results

We first show that land titling significantly reduces fertilizer intensity. Following Equation (7), Table 2 reports the regression results. Column (1) includes only household and year fixed effects; the coefficient on the post-reform indicator is -0.0834, implying an 8.34% decline in fertilizer intensity in treated counties. In Column (2), we add household-level controls for labor endowment and annual income. While the separation theorem predicts no effect of these endowments on input choices, extensive evidence shows that rural labor market frictions make labor supply related to production decisions, such as the choice between intensive and extensive methods (Kaur, 2019; LaFave and Thomas, 2016; Benjamin, 1992). As shown in Column (2), the point estimate remains virtually unchanged. Column (3) further adds village-level socioeconomic controls (population, land per capita, agricultural labor, crop revenue per capita, and fertilizer price). Finally, Column (4) includes county-level controls (GDP per capita, primary industry share, and secondary industry share). Across all specifications, the post-reform coefficient remains negative and statistically significant at the 5% or 1% level.

Our identification strategy relies on the assumption that, in the absence of land titling reform, treated and never-treated farms would have followed parallel trends in log fertilizer intensity. To verify this, we estimate the event study specification in Equation (8) using the Callaway and Sant'Anna estimator. Figure 6 plots the coefficients $\{\beta_l\}$ for each year l relative to the year before titling (normalized so $\beta_{-1}=0$), conditional on household and year fixed effects and a full set of household, village, and county controls. The pre-reform estimates are close to zero and never statistically significant at the 95% level, confirming parallel trends. After implementation, treated households exhibit a marked relative decline in fertilizer intensity, and this negative divergence persists through the end of our sample

Table 2: The effects of land titling on fertilizer use intensity

	Dependent variable: ln(Fertilizer input intensity)			
	(1)	(2)	(3)	(4)
Treatment effect	-0.0834**	-0.0879***	-0.139***	-0.151***
	(0.0334)	(0.0332)	(0.0366)	(0.0363)
Household controls		✓	✓	✓
Village controls			✓	✓
County controls				✓
Household FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean of dep. var. (kg/ha)	1403.25	1403.25	1403.25	1403.25
Observations	30,052	28,752	25,247	23,969

Notes: This table reports static CS DiD estimates using equation (7). The sample covers 2010 to 2017 at the household year level. Never treated observations serve as the control group. Household controls include labor force and annual income; village controls include population, land per capita, agricultural labor, crop revenue per capita, and fertilizer price; county controls include GDP per capita, primary industry share, and secondary industry share. Standard errors clustered at the county level in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

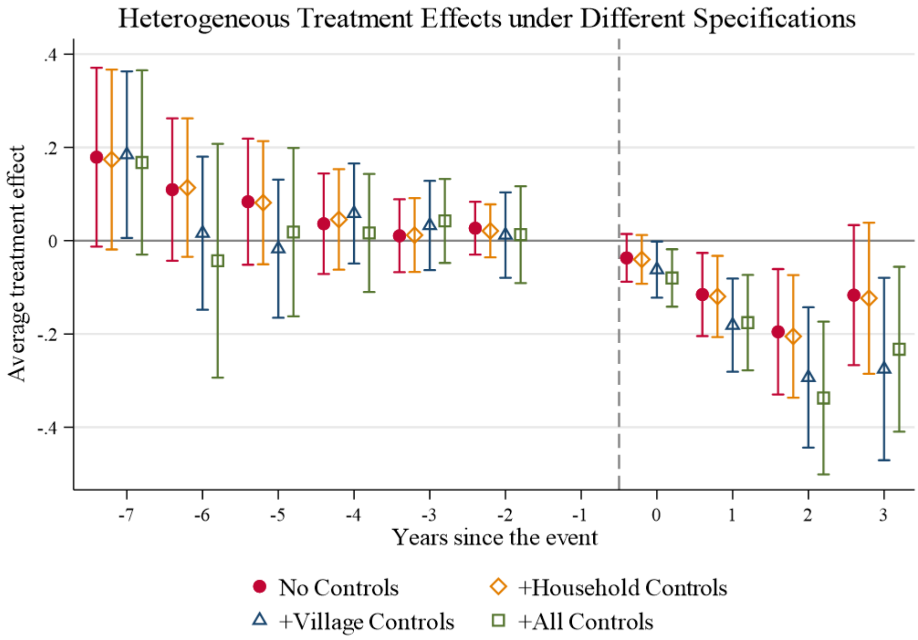
period.

Land titling may incentivize farmers to make long term soil-improving investments. We examine its effect on the use of farmyard manure, an organic fertilizer produced from livestock waste and crop residues. Unlike chemical fertilizers, manure is labor intensive to process and apply and yields benefits gradually through improved soil fertility and sustained productivity. Prior literature finds that insecure property rights discourage such investments because farmers cannot fully internalize future gains in China, Pakistan, and Ghana (Jacoby et al., 2002; Jacoby and Mansuri, 2008; Goldstein and Udry, 2008). To test this, we use household expenditures on farmyard manure (in yuan) as a proxy. Although the NFP does not record organic fertilizer quantities directly, expenditures approximate usage due to minimal on-farm storage. We convert expenditures into an imputed input value and estimate the difference in differences model in Equation (7). Table 3 reports the results. Column (1) shows a positive and statistically significant post-reform increase in manure use for the full sample. Columns (2) and (3) split the sample into "extensive" farmers (no manure use pre-reform) and "intensive" farmers (manure use pre-reform), with both groups exhibiting significant positive effects.

5 Decomposition

In this section, I decompose the overall reduction in fertilizer intensity into two channels: the selection channel, whereby land titling reduced barriers to trading land and reallocated

Figure 6: Dynamic Effects of Land Titling on Fertilizer Intensity (Event Study)



Notes: This figure shows event study result of coefficients β_l from equation (8), normalized at $\beta_{-1} = 0$. The figure shows the difference in log fertilizer intensity between treated and never treated counties, estimated with the CS DiD method including household and year fixed effects and household , village , and county level controls respectively. Shaded bands are 95 percent confidence intervals.

it toward more productive farmers; and the tenure incentive channel, whereby secure tenure leads farmers to internalize the future value of land and invest in long term soil management.

First, I assess heterogeneous effects of the reform by classifying households in treated counties based on changes in their operated land area. Households are divided into four groups: the "no change" group, whose land area remained almost unchanged (change rate below 5%) after reform; the "rent in" group, which expanded its area post reform (typically higher-productivity farmers constrained before); the "rent out" group, which reduced its area after titling (often lower-productivity households); and the "both" group, which both rented in and rented out land.[6] Table 4 presents the corresponding CS DiD estimates: Column (1) reports results for the full sample, while Columns (2)–(5) show group-specific coefficients for no change, rent in, rent out, and both groups, respectively.

Since land titling reforms also change the distribution of land across households, our household-level DID estimates recover the average treatment effect on treated households (ATETH). To assess how much of the total fertilizer savings is due to each channel, we focus on the average treatment effect per treated unit of land (ATETL). Multiplying this per-unit effect by the total treated land gives the aggregate fertilizer savings. A

[6] These "portfolio adjusters" may combine high underlying productivity with plot-level knowledge to optimally adjust land composition, yielding the largest treatment effects.

Table 3: Impact of Reform on Farmyard Manure Input

	Farmyard manure input (imputed value)		
Sample	Full sample	Intensive	Extensive
Post-reform year	19.91***	26.76***	18.96***
	(4.501)	(7.081)	(4.979)
Household FE	✓	✓	✓
Year FE	✓	✓	✓
Controls	✓	✓	✓
Observations	20,975	6,373	18,042

Notes: This table reports the impact of land titling reform on farmyard manure application. The dependent variable is the imputed value of manure expenditures in yuan. "Intensive" denotes households that used manure before the reform; "Extensive" denotes those that did not. All regressions include farmers in never treated counties as the control group. Standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Impact of Reform on Fertilizer Input Intensity by Transfer Status

Dependent variable:	ln(Fertilizer input intensity)				
Transfer Status	Full sample (1)	No Transfer (2)	Transfer In (3)	Transfer Out (4)	Both (5)
Post reform year	-0.0834**	-0.0772**	-0.1110**	-0.0642	-0.1940***
	(0.0334)	(0.0392)	(0.0521)	(0.0416)	(0.0694)
Household FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	30,052	22,275	6,719	9,727	5,497

Notes: NC includes treated and never treated households with no additional transfers; In only includes those with transfer in only; Out only includes those with transfer out only; Both includes those with both transfer in and transfer out. Never treated observations serve as the control group. Standard errors clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

special case is the no-change group: by definition, these households experience no change in cultivated area, so their household-level ATETH equals their ATETL. Moreover, the invariance of their land holding means the selection channel is absent, so their estimate reflects only the tenure incentive channel. To implement this decomposition, we assume that the tenure incentive effect is constant across groups.[7]

We classify treated plots into four post-reform groups $g \in \{\text{NC}, \text{In}, \text{Out}, \text{Both}\}$: no change (NC), rent in only (In), rent out only (Out), and both rent in and rent out (Both). Let L_g be the total land in group g, $L_{\text{tot}} = \sum_g L_g$ the total treated land, and $\omega_g = L_g/L_{\text{tot}}$ the ex post land share. Denote by τ_g the group-specific DID estimate of the log change in

[7]There may still be within-group heterogeneity in tenure incentive effects. We require that average incentive effects are equal across groups in order to extrapolate the no-change coefficient to all treated land. More formally, this assumes that farmers' discount rates, which govern their valuation of long term soil improvements, are independent of their pre-reform productivity.

fertilizer intensity, $\Delta \ln(F/L)$.

The average log intensity change per unit land is the land weighted sum

$$\tau_{\text{land}} = \sum_g \omega_g \, \tau_g. \tag{9}$$

Because group NC has no land reallocation, its estimate

$$\tau_{\text{prop}} = \tau_{\text{NC}} \tag{10}$$

captures the pure property rights effect. The residual difference,

$$\tau_{\text{sel}} = \tau_{\text{land}} - \tau_{\text{prop}}, \tag{11}$$

is the selection effect. The share of the total effect due to each channel is given by $\tau_{\text{prop}}/\tau_{\text{land}}$ and $1 - \tau_{\text{prop}}/\tau_{\text{land}}$.

Table 5 presents each group's estimated treatment effect τ_g alongside its ex post land share ω_g. Aggregating these yields a land-weighted average effect of $\tau_{\text{land}} = -0.1298$. The tenure incentive effect, identified by the no-change group, is $\tau_{\text{prop}} = -0.0772$, so the selection effect is $\tau_{\text{sel}} = -0.0526$. Thus, roughly 60% of the total reduction in fertilizer intensity is driven by improved tenure security, while the remaining 40% reflects land reallocation toward more productive farmers.

Table 5: Land Shares and Group Specific Fertilizer Reduction Effects

Group	Share ω_g	Effect τ_g	Contribution $\omega_g \tau_g$
No transfer (NC)	0.1100	−0.0772	−0.0085
Transfer in only	0.4798	−0.1110	−0.0533
Transfer out only	0.0741	−0.0642	−0.0048
Both in and out	0.3265	−0.1940	−0.0633
Total	**1.0000**		**−0.1298**

Notes: This table presents the post reform share of operated land by group (ω_g) and the corresponding group specific treatment effect on fertilizer intensity (τ_g) estimated in Table 4. Weighting the estimates in column three by the shares in column two yields an aggregate effect of $\tau_{\text{land}} = -0.1298$.

6 Environmental Impacts

In this section we examine the environmental benefits from improved fertilizer use efficiency induced by land titling reform. Synthetic fertilizers such as urea $CO(NH_2)_2$, ammonium nitrate NH_4NO_3, and ammonium sulfate $(NH_4)_2SO_4$ supply nitrogen for crop uptake but, when applied in excess, undergo microbial nitrification and denitrification, producing nitrous oxide N_2O emissions (Matson et al., 1998; Xu et al., 2024). Excess inputs also alter soil chemistry and reduce microbial diversity, impairing soil health and long term fertility. Surface and subsurface runoff carries residual nutrients into rivers and lakes, with up to 70% of reactive nitrogen losses driving eutrophication and coastal hypoxia (Gu et al., 2023). We next examine two key environmental outcomes.

6.1 Effect on Nitrous Oxide

Nitrous oxide (N_2O) is a potent greenhouse gas with a 100-year global warming potential roughly 265 times that of CO_2 (Change, 2013). As the third largest anthropogenic GHG after carbon dioxide and methane, atmospheric N_2O concentrations have risen by about 40% between 1980 and 2020.[8] Agricultural soil management, particularly synthetic fertilizer application and manure handling, is the largest source of N_2O emissions, accounting for roughly 60 to 70% of the anthropogenic total globally.[9]

To assess how reform affects N_2O emissions, we estimate a county year difference in differences regression analogous to Equation (7), with $\ln(N_2O)$ as the outcome. Table 6 reports three specifications. Column (1) includes county and year fixed effects; the coefficient of -0.0173 implies a 1.73% reduction in N_2O emissions in treated counties. To account for general equilibrium effects—such as shifts in labor allocation or industrial output that also affect N_2O—we sequentially add controls. Column (2) adds county level controls for GDP per capita and arable land area. Column (3) further incorporates prefecture-level industrial SO_2 and dust emissions.[10] Across all specifications, the post-reform coefficient remains negative and statistically significant, indicating that land titling reform led to robust declines in N_2O emissions.

To verify the parallel-trends assumption and trace dynamic effects on N_2O emissions, Figure 7 plots event-study coefficients from Equation (8). Coefficients for the pre-reform period are statistically indistinguishable from zero, supporting parallel trends. After titling, counties display a persistent decline in $\ln(N_2O)$.

Finally, we compare the predicted effect on N_2O emissions implied by reduced fertilizer use with the directly observed effect from our county-year DID. From household-level regressions, land transfers reduce fertilizer intensity by 12.98% (SE = 0.0342). Since

[8] Data from (Change, 2013).

[9] See (FAO, 2021) and (Yang et al., 2024) for detailed emission accounting.

[10] Industrial SO_2 and dust emissions are reported only at the prefecture level in official yearbooks.

Table 6: Impact of Land Titling Reform on N_2O Emissions

	(1)	(2)	(3)
Dependent variable		*ln(N_2O)*	
Post-reform year	-0.0173**	-0.0252**	-0.0282**
	(0.00860)	(0.00989)	(0.0124)
County fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
County controls		Y	Y
City controls			Y
Observations	2,352	2,352	2,352

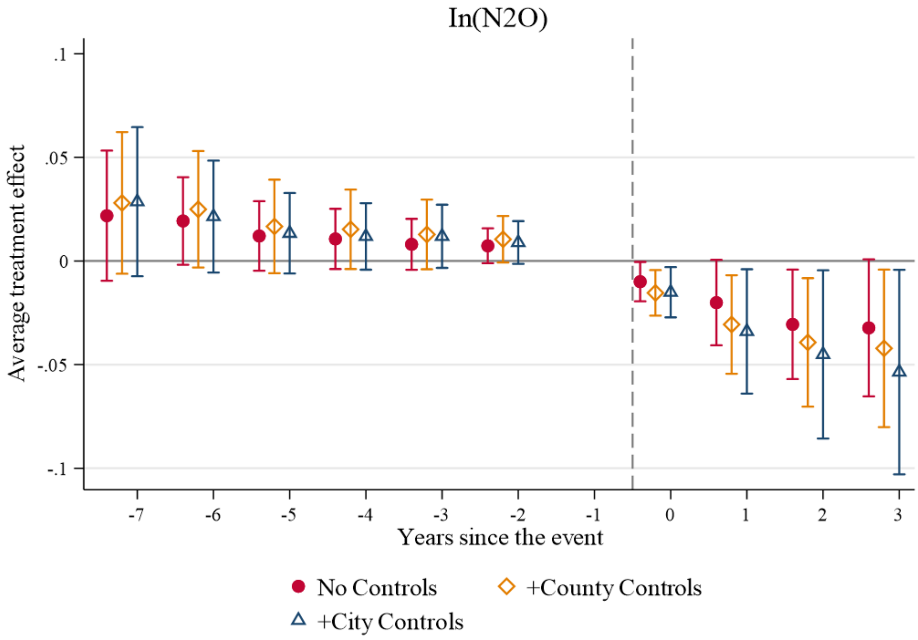
Notes: This table displays the impact of land titling reform on N_2O emissions. Regressions follow equation (7), with the dependent variable equal to the county-year log N_2O value aggregated from EDGAR data by administrative boundaries. Column (2) adds county level controls for GDP per capita and arable land area; column (3) further includes prefecture-level industrial SO_2 and dust emissions. Never treated and not yet treated counties form the control group, and all specifications include county and year fixed effects. Based on column (1), land titling reform reduced N_2O emissions by 1.26%. Standard errors clustered at the county level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

agricultural fertilizer accounts for roughly 22.5% of China's total N_2O emissions, this implies a nationwide reduction of

$$0.1298 \times 0.225 = 0.0292 \quad (2.92\%),$$

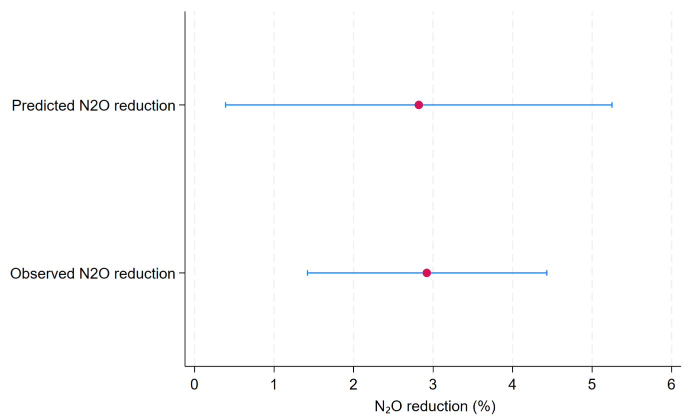
hereafter the "predicted" effect. Our county-year DID on ln(N_2O) yields a 2.82% decline (SE = 0.0124), hereafter the "observed" effect. Figure 8 plots these two estimates side by side, demonstrating close correspondence between predicted and observed reductions. The two estimates do not differ significantly.

Figure 7: Event-Study: Land Titling and County-Level N_2O Emissions



Notes: This figure shows event study result of coefficients β_l from equation (8), normalized at $\beta_{-1} = 0$. The figure shows the difference in log N_2O between treated and never treated counties, estimated with the CS DiD method including county and year fixed effects and county as well as city level controls respectively. Shaded bands are 95 percent confidence intervals.

Figure 8: Predicted versus Observed N_2O Emissions Reductions



Notes: This figure illustrates the close match between predicted and observed N_2O emissions reductions following land titling reform. The predicted reduction of 2.92% is obtained by multiplying the 12.98% decline in fertilizer intensity—estimated from the household-level DID specification (Eq. (7))—by the 22.5% share of fertilizer in China's N_2O emissions. The observed reduction of 1.94% is estimated from the county–year DID regression of $\ln(N_2O)$ on the reform indicator (Eq. (7)), as reported in Table 6, and comes with a 95% confidence interval that overlaps the implied interval for the predicted estimate, indicating no statistically significant difference between them. Both estimators use never-treated counties as controls and include county and year fixed effects plus relevant local controls.

6.2 Effect on Water Pollution

Agricultural runoff, driven by both surface and subsurface flow, carries chemical fertilizers into nearby rivers, lakes, and reservoirs, posing significant threats to aquatic ecosystems. Among various pollutants, nutrient-driven eutrophication—mainly caused by nitrogen and phosphorus compounds—has emerged as a key environmental concern in China's rural areas(Yu et al., 2019).

To examine how reduced fertilizer use impacts water pollution, I construct a coupled hydrologic-economic framework to overcome the spatial mismatch between administrative boundaries and ecological units. Water pollution data are obtained from approximately 244 monitoring stations across China, with observations recorded at monthly or biweekly frequencies.

A key challenge is that pollution spreads along hydrologic, not administrative, boundaries. To address this, I use hydrologic analysis to delineate watersheds, which allows me to accurately map each monitoring station to its upstream agricultural drainage area.

The core explanatory variable in this section is the share of farmland with confirmed property rights within each watershed. This variable captures the intensity of the land titling reform's implementation across space. The dependent variables are four widely used water quality indicators: chemical oxygen demand (CODMn), ammonium nitrogen (NH_4-N), dissolved oxygen (DO), and pH levels.

The regression results, presented in Table 7, show that CODMn and NH_4-N, both closely associated with fertilizer runoff-decline significantly following increased titling intensity. In contrast, DO and pH values remain statistically unchanged, consistent with their weaker direct link to nitrogen-based fertilizer application.

Table 7: Impact of Fertilizer Reduction on Water Pollution

Dependent variable	(1) CODMn	(2) NH_4-N	(3) DO	(4) pH
Treatment intensity	-0.166***	-0.212**	0.013	0.002
	(0.0612)	(0.0868)	(0.0499)	(0.0069)
Monitoringsite effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	1,503	1,503	1,503	1,503

Notes: This table reports the effect of fertilizer treatment intensity on four water quality indicators (CODMn, NH_4-N, dissolved oxygen, and pH). All regressions include monitoring site and year fixed effects. Standard errors clustered at the monitoring site level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

7 Conclusion

This paper asks whether clarifying land rights at scale can curb fertilizer overuse and through which channel. Using the staggered rollout of land certification and linking household panels to environmental monitors, I find that clarifying land rights reduces chemical fertilizer intensity by about 8.35% and shifts input use toward organic fertilizers on both the extensive and intensive margins. A decomposition shows that roughly 60% of the decline is a tenure incentive channel within farms and about 40% is a reallocation channel as land moves toward more productive operators. At the county level, nitrous oxide emissions fall by about 2.82%, closely matching a 2.92% reduction predicted from the micro estimate of fertilizer intensity, and water quality indicators that are closely tied to nutrient runoff improve in treated areas.

Taken together, the results show that strengthening land rights can deliver environmental gains in agriculture by correcting misallocation and by changing input choices within farms. Institutional reform aimed at securing tenure can therefore complement conventional environmental policy by lowering fertilizer intensity, improving soil stewardship, and reducing pollution at scale in a large developing economy.

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