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Article

The Impact of Typhoons on Agricultural Productivity—Evidence from Coastal Regions of China

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Abstract: The impact of natural disasters on agricultural production has garnered global attention. This study takes typhoons as an example, employing their movement paths to construct a difference-in-differences (DID) model and combining survey data from Rural Fixed Observation Spots to estimate changes in agricultural productivity from coastal regions of China, including Guangdong, Fujian, and Zhejiang provinces. This study finds that typhoons significantly deteriorate local agricultural productivity. Specifically, the planting income per mu and planting income per capita of rural households have decreased by 11% and 14%, respectively, while agricultural total factor productivity (TFP) has dropped by 3.7%. The decline in productivity can be attributed to two channels. Firstly, typhoons directly damage crops, leading to reduced total output. Secondly, in anticipation of typhoons, rural households increase asset input but reduce labor input and intermediate goods, resulting in the misallocation of agricultural inputs, which further diminishes productivity. The cost-benefit analysis indicates that to compensate for 20% of the negative impact of typhoons on agricultural productivity, local financial funds ranging from 3.4 million to 20 million yuan are required. Therefore, it is imperative for the Chinese government to strengthen the natural disaster warning system and improve farmland water conservancy infrastructure to mitigate the misallocation of agricultural inputs by rural households.

Keywords: agricultural productivity; agricultural inputs allocation; natural disasters; typhoons

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1. Introduction

Agricultural productivity is a fundamental indicator of the quality of agricultural development. Improving agricultural productivity not only enhances agricultural competitiveness but also significantly promotes economic structural transformation (Cao & Birchenall, 2013; Gollin et al., 2021; Lewis, 1954; Ranis & Fei, 1961). According to the classic Cobb-Douglas production function, agricultural productivity is influenced by asset inputs (Cui, 2023), labor inputs (Shi, 2018), land use (Chari et al., 2021), technological progress (Kantor & Whalley, 2019), and institutional changes (Lin, 1992). In addition to these traditional factors, numerous studies have identified natural disasters, such as extreme temperatures, floods, and droughts induced by climate change, as significant disruptors of agricultural production, leading to severe losses in productivity (Burke & Emerick, 2016; Chen & Gong, 2021; Chen & Chen, 2018; Lesk et al., 2016).

Natural disasters exacerbated by climate change are becoming increasingly frequent. Typhoons are among the natural disasters with the highest frequency and most severe global impacts. Previous research has documented their adverse effects on economic growth (Cavallo et al., 2013; Deryugina et al., 2018; Elliott et al., 2015; Strobl, 2011), industrial production (Elliott et al., 2019), residents' wealth (Kahn, 2005; Pugatch, 2019), and education levels (Lin et al., 2021). In the context of agricultural production, typhoons disrupt the supply of agricultural products and induce abnormal fluctuations in market prices (Bao et al., 2023; Gagnon & López-Salido, 2020; Kinnucan, 2016).

China's coastal areas, particularly those located on the northwest side of the Pacific, are frequently affected by typhoons (Lin et al., 2021). Typhoons can significantly impact agricultural productivity through two primary mechanisms. Firstly, the strong winds and heavy rainfall associated with typhoons can cause crop lodging and farmland flooding, directly damaging crops and reducing production efficiency. Secondly, rural households often adjust their production inputs to mitigate the impact of typhoons, leading to input distortions that indirectly diminish agricultural productivity. This study constructs a difference-in-differences (DID) model to evaluate the impact of typhoons on agricultural productivity. The findings suggest that typhoons notably impair local agricultural productivity. Specifically, planting income per mu and planting income per capita of rural households have decreased by 11% and 14%, respectively, while agricultural total factor productivity (TFP) has declined by 3.7%. Moreover, the impact of typhoons on agricultural productivity varies significantly with the geographical characteristics of the village, including the organizational capacity represented by the density of village cadres and the land transfer ratio. Mechanism analysis reveals that both the direct destruction of crops by typhoons and the distortion of input allocation by rural households are the main channels of deteriorating agricultural productivity.

This study contributes to literature in several aspects. Firstly, by utilizing the exogeneity of typhoon paths, it effectively reduces the estimation bias of natural disasters on agricultural productivity. This allows for the precise delineation of treatment and control groups, enabling accurate estimation of the impact on agricultural productivity (Angrist & Pischke, 2009). This methodology not only enhances our understanding of the specific effects of typhoons but also provides insights into the broader implications of related natural disasters, such as earthquakes, droughts, and floods. Secondly, this study confirms the sudden impact of environmental changes on agricultural productivity. While Burke & Emerick (2016) and Chen & Gong (2021) have focused on the long-term effects of climate change on agricultural farming adaptability and productivity, this study specifically investigates the short-term impact of typhoons. It emphasizes the inadequate coping mechanisms of farmers and underscores the importance of government intervention. Thirdly, the mechanism analysis demonstrates how typhoons alter rural households' behavior and, consequently, reduce agricultural productivity. While numerous studies have assessed the impact of natural disasters on agricultural production (Chen & Chen, 2018; Lesk et al., 2016), few have delved into the intermediate mechanisms driving farmers' responses. By deeply exploring the behavioral mechanisms of farmers when facing typhoon impacts, this study provides valuable insights into how government agencies can guide farmers to mitigate the adverse effects of natural disasters and implement effective agricultural production.

2. Research Background and Methods

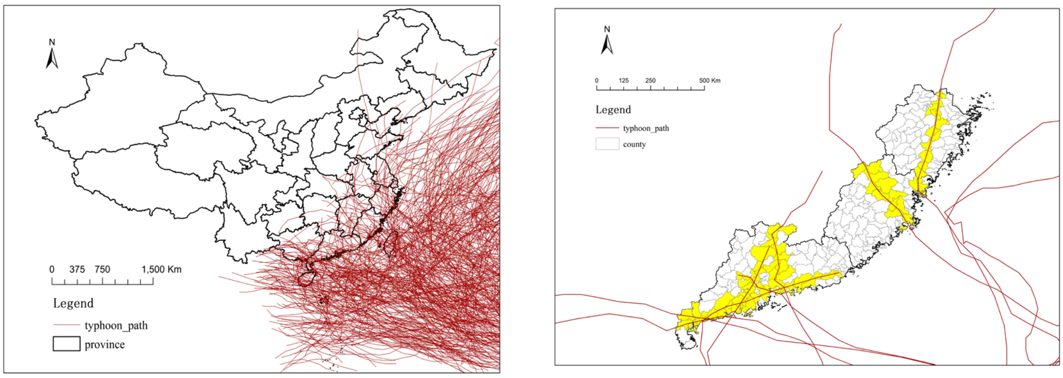
2.1. Research Background: Typhoons in Coastal Regions of China

China frequently experiences typhoons, with an average of 7.4 typhoons of magnitude 8 or above on the Beaufort scale annually (Lin et al., 2021). The main affected areas are coastal provinces such as Guangdong, Fujian, Hainan, Zhejiang, and Guangxi. From 1993 to 2006, the average annual economic losses from typhoons in Zhejiang reached 7.73 billion yuan, while Fujian, Guangdong, and Hainan experienced losses of 3.14 billion, 2.06 billion, and 1.11 billion yuan, respectively (Zhang et al., 2009).

During the period of our study, typhoons had a significant impact on agricultural production in China's coastal areas for several reasons. Firstly, the typhoon warning and monitoring system was not fully established until the 1980s (Wen, 2004). Secondly, the time and location of typhoon landfall are difficult to predict (Lin et al., 2021), making it difficult for local farmers to make corresponding adjustments to agricultural production. Thirdly, many people in these areas make their livings from agriculture, which is particularly vulnerable to typhoons (Xu et al., 2005). Finally, inadequate infrastructure exacerbates the impact of typhoons. Prior to the 1980s, many dams in China were poorly constructed and unable to effectively protect against flooding caused by typhoons. (Jia-bi & Dong-ya, 2009). These factors pose serious threats to agricultural production in coastal regions.

This study proposes the following mechanisms to explain how typhoons lead to significant declines in agricultural productivity. First, the direct mechanism involves the destruction of crops due to the strong winds and heavy rains associated with typhoons, resulting in immediate agricultural losses. Second, the indirect mechanism involves pre-landfall adjustments by rural households aimed at mitigating typhoon damage. These adjustments often disrupt optimal decision-making regarding the allocation of agricultural inputs, leading to misallocation and, consequently, a decline in agricultural productivity. Adamopoulos et al. (2022) attribute the stagnation in China's agricultural productivity from 1993 to 2002 to the misallocation of agricultural inputs due to land policy constraints. Similarly, Chen and Gong (2021) show that the ability of rural households to adjust production inputs flexibly significantly reduces the negative impact of extreme temperatures on agricultural productivity. These studies highlight the importance of input allocation in determining agricultural productivity, making the "typhoon shock—factor allocation distortion—agricultural productivity decline" mechanism a plausible explanation.

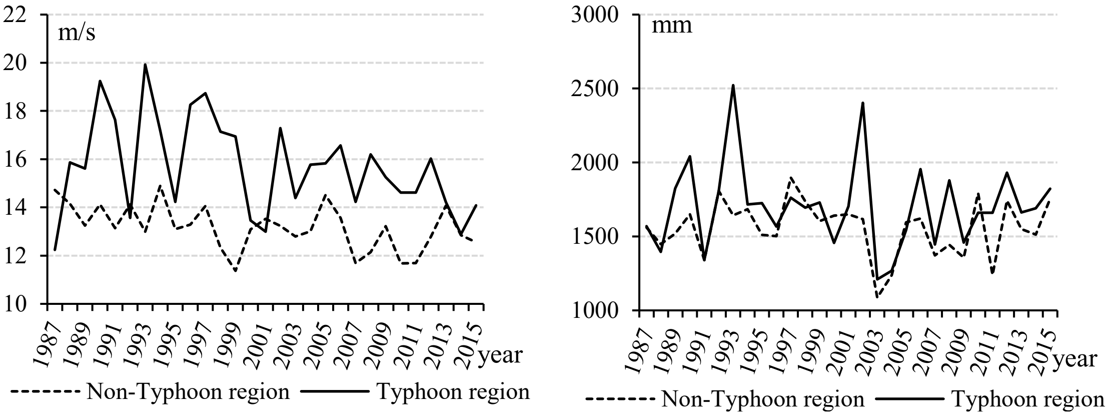
Figure 1 (a) illustrates the movement paths of typhoons in the Northwest Pacific from 1986 to 2015, highlighting the frequency with which China's coastal areas were affected. I obtained agricultural production data for the coastal provinces of Guangdong, Fujian, and Zhejiang from the Rural Fixed Observation Spot of the Chinese Ministry of Agriculture. Figure 1 (b) shows the intersection area of the typhoon track and the sample counties; the shaded area indicates a higher degree of impact and the non-shaded area indicates a lower degree of impact. Since typhoon movement is a natural phenomenon, I categorize the shaded areas as the treatment group and the unshaded areas as the control group. Then I compare the agricultural productivity gap between these two groups before and after the typhoons' landfall to accurately estimate the impact of typhoons.



(**a**) (**b**)

Figure 1: (**a**) Typhoons landed in China (1986−2015); (**b**) Typhoons landed in coastal counties (2008).

In addition, Figures 2 (a) and (b) illustrate the average maximum wind speed and average rainfall in sample counties, distinguishing between areas affected by typhoons and those that are not. On average, the annual maximum wind speed in non-typhoon areas is generally below 14 meters per second, whereas it can reach 16 meters per second or even 20 meters per second in typhoon-affected areas. Such increases in wind speed can easily cause crops to fall or even be destroyed. The average annual rainfall in typhoon-affected areas is significantly higher than in non-typhoon areas. The heavy rains not only directly damage the soil where crops grow but also frequently trigger floods that can completely destroy farmland. To mitigate the negative impacts of typhoons and reduce agricultural losses, rural households often take temporary measures such as dredging ditches, reinforcing crops, and expediting harvests before the typhoon makes landfall. These remedial actions can have a notable impact on the allocation of agricultural inputs and production, leading to deviations in agricultural productivity from normal status.



(**a**) (**b**)

Figure 2: (**a**) Typhoon and average wind speed; (**b**) Typhoon and average rainfall.

2.2. Model Setting and Data Description

I employ a standard two-way fixed effects (TWFE) regression model to estimate the influence of typhoons on agricultural productivity:

$$Y_{ict} = \alpha + \beta Typhoon_{ct} + \gamma \mathbf{X} + \theta_i + \delta_t + \varepsilon_{ict} \quad (1)$$

Here, Y_{ict} represents the agricultural productivity of rural households i in region c during year t , measured by crop production. $Typhoon_{ct}$ is an indicator variable that takes the value of 1 if region c was affected by a typhoon in year t, and otherwise 0. As shown in Figure 1 (b), if the area intersects with the typhoon track in a given year, $Typhoon_{ct}$ equals 1; otherwise, it equals 0. This setting is similar to Bao et al. (2023). $\mathbf{X}$ denotes the control variables, including the fixed assets (*FAS*) of rural households, labor working days (*WDY*) in planting, land size (*LSZ*), and intermediate inputs (*INP*) in planting. Except for $Typhoon_{ct}$, which is a dummy variable, other variables are in logarithmic form. θ_i represents the rural household fixed effect, δ_t is the year fixed effect, and ε_{ict} is the random disturbance term.

The data sources are as follows. First, agricultural productivity indicators are from the Rural Fixed Observation Spots sample survey conducted by the Agricultural Economic Research Center of the Ministry of Agriculture and Rural Affairs of China. This survey covers 11 provinces, including Shanxi, Jilin, Zhejiang, Fujian, Jiangxi, Henan, Hubei, Hunan, Guangdong, Sichuan, and Gansu, providing a comprehensive sample distribution. Coastal areas including Guangdong, Fujian, and Zhejiang are selected as the study samples. Second, typhoon data is from the China Meteorological Administration's Tropical Cyclone Data Center. This dataset includes the position and intensity of tropical cyclones in the Northwest Pacific (including the South China Sea, north of the equator, and west of longitude 180°E) every 6 hours since 1949. By using the typhoon's longitude and latitude, I adopt ArcGIS software to map the typhoon paths and identify the affected areas within the sample data.

Table 1. Descriptive statistics.

	Variables	Variable description	Count	Mean	SD	Min	Max
dependent variables	*Ln(NINC_PM)*	*NINC_PM* = net income of planting/sown area	28490	5.68	1.23	0	9.01
	Ln(NINC_PC)	*NINC_PC* = net income of planting/labor force	28490	5.84	1.30	0	9.87
	Ln(TFP)	total factor productivity of planting	28490	2.76	0.86	1.26	7.29
independent variables	*Typhoon*	landed = 1； otherwise = 0	28490	0.17	0.37	0	1
	Max_wind	m/s	28490	13.36	3.43	8.08	30.95
	Ave_rain	mm	28490	1.58	0.31	1.04	2.49
	Ln(AFE)	agricultural fiscal expenditure (10 million yuan)	11517	0.89	0.54	0.24	2.70
baseline control variables	*Ln(FAS)*	original value of productive fixed assets(yuan)	28490	6.97	1.50	3.71	11.67
	Ln(WDY)	labor input of planting (day)	28490	1.36	0.50	0.26	3
	Ln(LSZ)	cultivated land area (mu)	28490	4.87	0.77	1.10	5.88
	Ln(INP)	operating expenses of planting (yuan)	28490	6.56	1.21	3.43	12.72
village control variables	*Ln(VPOP)*	population size	28262	7.70	0.75	6.16	8.90
	Log(VLSZ_PC)	land size per capita(mu/per_capita)	28029	0.77	0.31	0.23	2.22
	Log(VFAS_PC)	fixed assets per capita(yuan/per_capita)	27924	2.41	1.09	0.49	6.24
	VR_Sex	sex ratio	28262	1.04	0.08	0.82	1.21
	VP_Lab	proportion of labor force	28101	0.54	0.09	0.34	1.18
climate control variables	*D_Sun*	sunshine duration (100 days/year)	28490	1.76	0.17	1.17	2.24
	Max_tem	maximum temperature (celsius)	28490	37.58	1.33	33.47	43.20
	Min_tem	minimum temperature (celsius)	28490	−0.72	3.95	−13.94	8.29
	Ave_tem	average temperature (celsius)	28490	19.73	2.03	15.48	24.38
other dependent variables	*Ln(GOTP_PM)*	*GOTP_PM* = grain output/sown area	28490	5.63	1.18	0	7.51
	Ln(GOTP_PC)	*GOTP_PC* = grain output/labor force	28490	5.47	1.29	0	7.21
	Ln(GTFP)	total factor productivity of grain production	28490	3.95	1.33	−3.09	5.12
	Cap_dist	capital distortion (refer to Appendix)	28490	0.05	0.22	0	3.76
	Lab_dist	labor distortion (refer to Appendix)	28476	1.87	2.94	0	17.16
	Total_dist	total input distortion (refer to Appendix)	28476	0.99	0.37	0	2.13

The dependent variables include the average net income per mu of planting (*NINC_PM*), the average net income per capita of planting (*NINC_PC*), and the total factor productivity (*TFP*) of planting. *NINC_PM* is calculated by dividing the total net income from family planting by the sown area, while *NINC_PC* is obtained by dividing the total net income from family planting by the household labor force. *TFP* is estimated by using the Cobb-Douglas production function (Cao & Birchenall, 2013; Lin, 1992). The core independent variable is whether a rural household in a county was affected by a typhoon. For robustness checks, annual maximum wind speed and annual average rainfall are also considered, with data sourced from the national meteorological science data sharing platform. Among the control variables, fixed assets (*FAS*) are measured by the original value of productive fixed assets owned by rural households, labor input is measured by working days (*WDY*) in planting, land size (*LSZ*) represents the area of land managed by rural households, and intermediate inputs (*INP*) are quantified by the operating expenses of planting. To address potential issues with missing variables, village-level, and climate control variables are included in the regression model. To mitigate the impact of extreme outliers, all continuous variables are winsorized at the 1% level, and observations with only one occurrence or abnormal samples with zero dependent variables in 1993 are excluded. Descriptive statistics for the main variables are presented in Table 1.

3. Benchmark Regression Results

3.1. Baseline Regression

In the baseline regression analysis, I utilize the intersection of the typhoon path with specific areas as the criterion for determining typhoon landfall and subsequently examine its impact on agricultural productivity. The estimation results presented in Table 2 confirm that typhoon shocks have a significant negative effect on agricultural productivity. Specifically, models (1−2) demonstrate that in areas affected by the typhoon, the average net income per mu and net income per capita of rural households decreased by 11% and 13.9%, respectively. These results are statistically significant at the 1% level. Model (3) substitutes the dependent variable with the total factor productivity (*TFP*) of crop production and finds that the *TFP* growth rate in planting decreased by 3.72% significantly after the typhoon landed. Even after adding control variables for inputs such as assets, labor, land, and intermediate goods of rural households in models (4−6), the conclusions remain unchanged.

Table 2. Regression results of typhoon impact on agricultural productivity.

Variable	**Model(1)** ***Ln(NINC_PM)***	**Model(2)** ***Ln(NINC_PC)***	**Model(3)** ***Ln(TFP)***	**Model(4)** ***Ln(NINC_PM)***	**Model(5)** ***Ln(NINC_PC)***	**Model(6)** ***Ln(TFP)***
Typhoon	−0.110***	−0.139***	−0.0372***	−0.102***	−0.115***	−0.0375***
	(0.0157)	(0.0171)	(0.00731)	(0.0158)	(0.0163)	(0.00735)
Ln(FAS)	-	-	-	−0.000620	−0.0299***	−0.00251
	-	-	-	(0.00735)	(0.00765)	(0.00409)
Ln(WDY)	-	-	-	0.222***	0.380***	0.0254**
	-	-	-	(0.0197)	(0.0193)	(0.0125)
Ln(LSZ)	-	-	-	−0.274***	0.398***	0.0364**
	-	-	-	(0.0336)	(0.0332)	(0.0174)
Ln(INP)	-	-	-	0.0753***	0.191***	−0.0274***
	-	-	-	(0.0151)	(0.0146)	(0.00975)
Household Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,490	28,490	28,490	28,490	28,490	28,490
R^2	0.528	0.525	0.798	0.538	0.594	0.798

Notes: *NINC_PM*-net income per mu; *NINC_PC*- net income per capita; *TFP*- total factor productivity of planting; *FAS*- fixed assets; *WDY*- working days; *LSZ*-land size; *INP*-intermediate inputs. *** p<0.01,** p<0.05,* p<0.1; Standard errors clustered at the household level are in parentheses.

3.2. Endogeneity Discussion

The occurrence of typhoons is a natural phenomenon and cannot be controlled by humans. Therefore, typhoons exhibit strict exogeneity. Despite this, completely eliminating endogeneity problems in econometric regression analysis remains challenging. There are three main sources of endogeneity in econometric models: omitted variables, measurement error, and reverse causality.

First, concerning reverse causality, the formation and movement of typhoons are influenced by temperature, atmospheric pressure, and the Earth's rotation. Agricultural productivity cannot affect these factors, thereby the issue of reverse causation is eliminated.

Secondly, although I have controlled for variables related to rural household agricultural inputs in the baseline regression, omitted variables may still exist. For instance, villages with larger populations may possess stronger organizational capabilities in responding to typhoons, which could impact agricultural productivity. Moreover, villages with larger land areas per capita are more likely to engage in large-scale agricultural operations and enhance productivity. However, larger agricultural land sizes also experience more severe impacts from typhoons, resulting in greater declines in productivity. To minimize the influence of related factors, Models (1–3) in Table 3 include additional control variables at the village level, such as population size, land size per capita, fixed assets per capita, sex ratio, and labor force proportion. Following this adjustment, the core regression results remain unchanged. Furthermore, climate change affects both the frequency and intensity of typhoons and directly impacts agricultural production. Models (4–6) introduce regional-level control variables like annual sunshine duration, maximum temperature, minimum temperature, and average temperature. The fundamental regression results remain robust after considering these variables.

Table 3. Consider omitted variables.

Variable	Model(1) *Ln(NINC_PM)*	Model(2) *Ln(NINC_PC)*	Model(3) *Ln(TFP)*	Model(4) *Ln(NINC_PM)*	Model(5) *Ln(NINC_PC)*	Model(6) *Ln(TFP)*
Typhoon	−0.134***	−0.144***	−0.0360***	−0.122***	−0.128***	−0.0323***
	(0.0162)	(0.0167)	(0.00759)	(0.0163)	(0.0168)	(0.00772)
Add village control variables						
Ln(VPOP)	0.300**	0.356***	0.0668	0.232**	0.279**	0.0566
	(0.122)	(0.125)	(0.0670)	(0.118)	(0.122)	(0.0665)
Log(VLSZ_PC)	−0.214***	−0.190***	−0.0975***	−0.186***	−0.158***	−0.0957***
	(0.0293)	(0.0351)	(0.0285)	(0.0297)	(0.0353)	(0.0280)
Log(VFAS_PC)	−0.00252	−0.0239**	−0.00344	−0.00826	−0.0288**	−0.00484
	(0.0111)	(0.0112)	(0.00589)	(0.0111)	(0.0113)	(0.00593)
VR_Sex	0.0477	−0.134	−0.186**	0.0813	−0.0997	−0.186**
	(0.128)	(0.137)	(0.0756)	(0.128)	(0.136)	(0.0750)
VP_Lab	−0.518***	0.116	−0.0432	−0.459***	0.154	−0.0386
	(0.137)	(0.137)	(0.0848)	(0.139)	(0.137)	(0.0843)
Add climate control variables						
D_Sun	-	-	-	−0.0465	0.0450	−0.141***
	-	-	-	(0.0816)	(0.0817)	(0.0360)
Max_tem	-	-	-	−0.00241	−0.00823	−0.000566
	-	-	-	(0.00862)	(0.00801)	(0.00378)
Min_tem	-	-	-	−0.0579***	−0.0701***	−0.0208***
	-	-	-	(0.00764)	(0.00755)	(0.00328)
Ave_tem	-	-	-	0.134***	0.129***	0.0158
	-	-	-	(0.0327)	(0.0360)	(0.0192)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,846	27,846	27,846	27,846	27,846	27,846
R^2	0.543	0.599	0.798	0.544	0.601	0.799

Notes: Control variables include baseline control variables in Table 1. *VPOP*-population size in village level; *VLSZ_PC*-land size per capita in village level; *VFAS_PC*-fixed assets per capita in village level; VR_Sex-sex ratio in village level; *VP_Lab*-labor force proportion in village level; *D_Sun*-annual sunshine duration; *Max_tem*-maximum temperature; *Min_tem*-minimum temperature; *Ave_tem*-average temperature

Finally, concerning measurement error, while I accurately determine the affected areas based on historical typhoon paths, the assumption of homogeneity in assigning the impact of typhoons to the treatment group each year introduces some discrepancies. This is because typhoon intensity varies from year to year. The impact of typhoons primarily stems from strong winds and heavy rains. Therefore, I substitute the independent variables with other weather variables to analyze the impact of typhoons. Models (1–3) in Table 4 demonstrate that as the maximum wind speed increases, the average net income per mu, net income per capita, and total factor productivity of planting decline more significantly. Similarly, Models (4–6) use annual average rainfall as the independent variable and reveal that in areas with higher rainfall, agricultural productivity is notably lower. Thus, replacing other typhoon-related weather variables does not substantially alter the baseline regression results of this study.

Table 4. Consider measurement error.

Variable	Model(1) *Ln(NINC_PM)*	Model(2) *Ln(NINC_PC)*	Model(3) *Ln(TFP)*	Model(4) *Ln(NINC_PM)*	Model(5) *Ln(NINC_PC)*	Model(6) *Ln(TFP)*
Max_wind	−0.0233***	−0.0204***	−0.0102***	-	-	-
	(0.00235)	(0.00237)	(0.00108)	-	-	-
Ave_rain	-	-	-	−0.376***	−0.335***	−0.170***
	-	-	-	(0.0288)	(0.0289)	(0.0135)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,846	27,846	27,846	27,846	27,846	27,846
R^2	0.545	0.601	0.799	0.547	0.602	0.800

Note: Control variables include baseline control variables, village control variables, and climate control variables in Table 1.

3.3. Robustness Test

To assess the robustness of the baseline regression model, I perform supplementary tests. Initially, I modified the indicators of agricultural productivity. Models (1–3) in Table 5 substitute the dependent variables with grain output per mu (*GOTP_PM*), grain output per capita (*GOTP_PC*), and estimated grain total factor productivity (*GTFP*) to mitigate the effects of crop price fluctuations on planting net income indicators. The regression outcomes reveal that typhoons notably decrease agricultural productivity, as evidenced by grain production, aligning with the baseline regression results.

Table 5. Robustness check.

Variable	Model(1)	Model(2)	Model(3)
	Change the indicators of agricultural productivity		
	Ln(GOTP_PM)	*Ln(GOTP_PC)*	*Ln(GTFP)*
Typhoon	−0.0830***	−0.0303**	−0.0493***
	(0.0163)	(0.0127)	(0.0151)
Control Variables	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes
Observations	27,846	27,846	27,846
R^2	0.613	0.768	0.723

Notes: Control variables include baseline control variables, village control variables, and climate control variables in Table 1. *GOTP_PM*-grain output per mu; *GOTP_PC*--grain output per capita; *GTFP*- total factor productivity of grain production.

Secondly, to mitigate the influence of migration and farmland abandonment on agricultural production, Models (1–2) in Table 6 exclude samples with zero planting income for that year and re-run the regression. The findings demonstrate that the adverse impact of typhoons on agricultural productivity remains significant. Thirdly Models (3–5) exclude the sample from the year 1999, which includes specific abnormal observations. The regression outcomes suggest that the detrimental effect of typhoons endures.

Table 6. Robustness check.

Variable	Model(1) Eliminate samples with zero output *Ln(NINC_PM)*	Model(2) *Ln(NINC_PC)*	Model(3) Eliminate abnormal year 1999 *Ln(NINC_PM)*	Model(4) *Ln(NINC_PC)*	Model(5) *Ln(TFP)*
Typhoon	−0.0625***	−0.0682***	−0.0728***	−0.0780***	−0.0141*
	(0.0119)	(0.0121)	(0.0151)	(0.0155)	(0.00762)
Control Variables	Yes	Yes	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes	Yes	Yes
Observations	27,527	27,527	26,946	26,946	26,946
R^2	0.679	0.727	0.586	0.641	0.813

Notes: Control variables include baseline control variables, village control variables, and climate control variables in Table 1.

Finally, I exclude the impact of other policies. Before the implementation of the rural tax and fee exemption reform, rural households were required to pay agricultural taxes and fees, which significantly affected their farming enthusiasm. Additionally, the land transfer rate plays a crucial role in promoting the efficient concentration of farmland and forming large-scale agricultural operations, directly impacting productivity. Models (1–3) in Table 7 include variables for tax and fee burden of rural households and land transfer rate to control for the impact of rural tax policies and land transfer policies. The regression results do not change significantly.

To eliminate the interference from policies that vary over time at the provincial level, such as the household contract responsibility system and family planning system gradually implemented by each province, Models (4–6) include the interaction term of province and year. After controlling for these effects, the regression coefficient is slightly reduced but remains negative and significant.

Table 7. Exclude the impact of other policies.

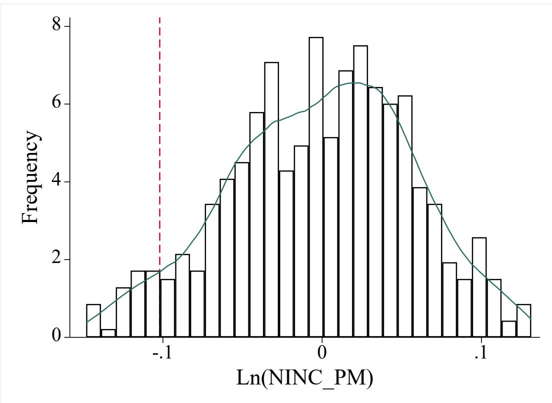
Variable	Model(1) *Ln(NINC_PM)*	Model(2) *Ln(NINC_PC)*	Model(3) *Ln(TFP)*	Model(4) *Ln(NINC_PM)*	Model(5) *Ln(NINC_PC)*	Model(6) *Ln(TFP)*
Typhoon	−0.122***	−0.129***	−0.0324***	−0.112***	−0.0990***	−0.0121
	(0.0163)	(0.0168)	(0.00772)	(0.0188)	(0.0194)	(0.00890)
Agri_tax	−0.000398	−0.140**	−0.106***	−0.00556	−0.162**	−0.108**
	(0.0865)	(0.0636)	(0.0387)	(0.0955)	(0.0765)	(0.0427)
Agri_fee	0.0490	0.0337	0.0237	0.0249	0.00764	0.0197
	(0.0383)	(0.0386)	(0.0155)	(0.0365)	(0.0424)	(0.0151)
Land_tf	−0.0588	0.0446	−0.0210	−0.0545	0.0355	−0.0329
	(0.0405)	(0.0438)	(0.0274)	(0.0393)	(0.0421)	(0.0259)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes
Year×Prov Fixed_effects	No	No	No	Yes	Yes	Yes
Observations	27,846	27,846	27,846	27,846	27,846	27,846
R^2	0.544	0.601	0.799	0.562	0.617	0.810

Notes: Control variables include baseline control variables, village control variables, and climate control variables in Table 1. *Agri_tax*-agricultural tax burden; *Agri_fee*-agricultural fee burden; *Land_tf*-land transfer rate

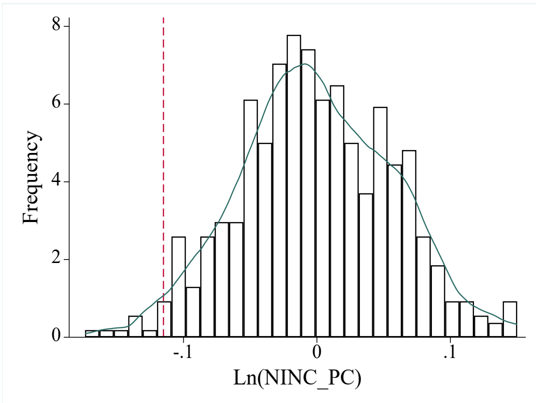
3.4. Permutation Test

The exogeneity of the typhoon movement path is crucial to ensure that the baseline regression estimate is unbiased. To verify this assumption, I conducted a permutation test. Initially, during our study period, the total number of typhoons hitting each region was 136. So I randomly selected 136 samples from the regional panel data as the treatment group and assigned a value of 1 to the simulated typhoon variable; otherwise, the value was 0 for the control group. Subsequently, I re-estimate the coefficients according to regression equation (1). This process is repeated 500 times to obtain the distribution of the estimated coefficients for different productivity indicators. Finally, I conduct a comparative analysis with the regression results from Models (4–6) in Table 2.

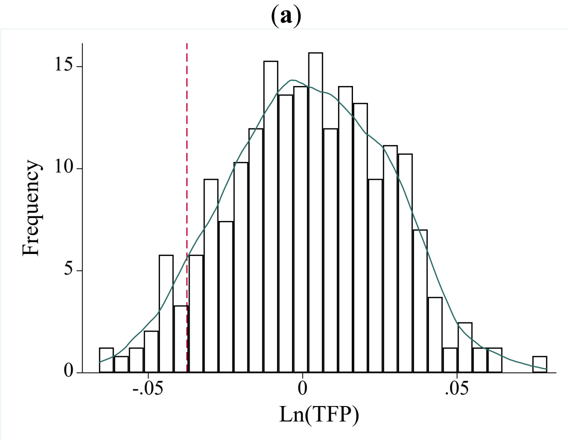
Figures 3 (a), 3 (b), and 3 (c) display the distribution of estimated coefficients for the simulated impact of typhoons on net income per unit of planting, net income per capita of planting, and total factor productivity of planting, respectively. The simulated false coefficients are distributed approximately normally around zero, while the true values of the baseline regression, indicated by the dotted line, are situated at the periphery of the false coefficient distribution. This confirms that the treatment effect of typhoon impacts on agricultural productivity in the baseline regression does not encompass the influences of other unobservable variables.



(**a**)



(**b**)



(**c**)

Figure 3: (**a**) Simulated typhoon and *Ln*(*NINC_PM*); (**b**) Simulated typhoon and *Ln*(*NINC_PC*); **(C)** Simulated typhoon and *Ln*(TFP).

3.5. Heterogeneity Analysis

The characteristics of villages and rural households can either worsen or alleviate the impact of typhoons. I employ the following regression model to examine the heterogeneous effects from three perspectives: village geographical environment, rural organizational capabilities, and land transfer level:

$$Y_{ict} = \alpha + \beta Typhoon_{ct} \times Z_{(i)ct} + \delta Typhoon_{ct} + \varphi Z_{(i)ct} + \gamma \boldsymbol{X} + \theta_i + \delta_t + \varepsilon_{ict} \quad (2)$$

Here, $Z_{(i)ct}$ represents the characteristics of the village or rural household, including whether the village is located in a plain area (*Plain*), village cadre density (*Cdensity*), and the proportion of rural household contracted land in the total cultivated land (*Tsland*). The remaining variables are consistent with the baseline regression.

Models (1–3) in Table 8 demonstrate that villages situated in plain areas exacerbate the negative effects of typhoons on agricultural productivity compared to those in hills and mountains.

This is due to their proximity to the sea, leading to higher typhoon intensity. Moreover, plain areas are more susceptible to post-typhoon disasters like flooding.

Table 8. Heterogeneity analysis.

	Model(1)	**Model(2)**	**Model(3)**
		Geographical heterogeneity	
	Ln(NINC_PM)	***Ln(NINC_PC)***	***Ln(TFP)***
Typhoon ×Plain	−0.186***	−0.181***	−0.0552***
	(0.0445)	(0.0442)	(0.0165)
Typhoon	−0.0837***	−0.0719***	−0.00530
	(0.0206)	(0.0215)	(0.00997)
Plain	0.686***	0.756***	0.300***
	(0.0819)	(0.0817)	(0.0265)
Observations	27,846	27,846	27,846
R^2	0.565	0.620	0.811
	Model (4)	**Model (5)**	**Model (6)**
		Organizational capability heterogeneity	
	Ln(NINC_PM)	***Ln(NINC_PC)***	***Ln(TFP)***
Typhoon ×Cdensity	0.0953**	0.102**	0.0180
	(0.0444)	(0.0429)	(0.0214)
Typhoon	−0.141***	−0.130***	−0.0180*
	(0.0227)	(0.0230)	(0.0106)
Cdensity	0.198***	0.249***	0.0646
	(0.0592)	(0.0565)	(0.0440)
Observations	27,846	27,846	27,846
R^2	0.562	0.618	0.810
	Model (7)	**Model (8)**	**Model (9)**
		Land transfer heterogeneity	
	Ln(NINC_PM)	***Ln(NINC_PC)***	***Ln(TFP)***
Typhoon ×Tsland	0.0824	0.111*	0.0842***
	(0.0620)	(0.0590)	(0.0299)
Typhoon	−0.125***	−0.117***	−0.0261***
	(0.0221)	(0.0219)	(0.00935)
Tsland	−0.0722*	0.0128	−0.0503*
	(0.0410)	(0.0434)	(0.0269)
Observations	27,846	27,846	27,846
R^2	0.562	0.617	0.810
Control Variables	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes

Notes: Control variables include baseline control variables, village control variables, and climate control variables in Table 1. *Plain*-Whether the village is located in a plain area; *Cdensity*-Village cadre density; *Tsland*-The proportion of rural household contracted land in the total cultivated land.

Second, models (4–6) demonstrate that as the proportion of cadres in the village increases, the negative impact of typhoons is significantly weakened. This is due to the influential role of grass-roots organizations in mitigating the effects of disasters. Village cadres can promptly convey information from higher-level governments about typhoon warnings and preventive measures, then help farmers take effective measures to reduce the serious impact of typhoons on agricultural production. Finally, models (7–9) show that when rural households hold a higher share of transferred land from others, the negative effect of typhoons on planting productivity is reduced. The implementation of policies such as the “Rural Land Contract Law of the People’s Republic of China” legally guarantees the stability of farmland, which can improve the scale of agricultural land and agricultural productivity (Chari et al., 2021). Rural households with a higher share of transferred land may be more skilled in agricultural production and have more flexible and effective measures to withstand the negative impact of typhoons.

4. Mechanism Analysis

4.1. Direct Mechanism

The direct impacts of typhoons on agricultural production are usually reflected in the destruction of production conditions, crop damage, and even labor casualties. Therefore, it is essential to investigate how typhoons directly decrease crop yield due to their strong winds or heavy rains. Models (1–2) in Table 9 indicate that typhoons did not significantly affect the sown area of planting or the number of family laborers. In other words, rural households' enthusiasm for agricultural farming remains strong despite the typhoons. The reason is that the agricultural planting period is generally at the turn of spring and summer, and typhoons mostly occur in summer and autumn. Therefore, farmers in coastal areas are unlikely to change their agricultural production plans due to subsequent typhoons. Moreover, the stable number of household laborers suggests that the typhoon-related casualties in our study are not severe. Therefore, the decrease in output cannot be solely attributed to a reduced labor force.

Second, Model (3) in Table 9 demonstrates that using the total net income from planting as a measurement indicator, typhoons significantly reduced agricultural productivity. Given that the decline in planting enthusiasm and the decrease in laborers are not core factors contributing to agricultural productivity loss, the substantial decrease in the net income from planting confirms the direct influence of typhoons on agricultural output.

Table 9. Verification of direct mechanism.

	Model(1) *Ln(Sown)*	**Model(2)** *Ln(Labor)*	**Model(3)** *Ln(Nincome)*
Typhoon	0.00466	0.00720	−0.103***
	(0.00952)	(0.00474)	(0.0203)
Control Variables	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes
Year×Prov Fixed_effects	Yes	Yes	Yes
Observations	27,782	27,813	27,846
R^2	0.603	0.547	0.610

Notes: Control variables include baseline control variables, village control variables, and climate control variables in Table 1. *Sown*-Sown area of planting; *Labor*-The number of rural household labor force; *Nincome*-Net income of planting.

4.2. Indirect Mechanism

When faced with typhoons, rural households will make adjustments in agricultural input allocation to minimize potential losses. However, these adjustments are often unexpected and unintentional, which can lead to a relative distortion in input allocation and a negative deviation in agricultural productivity.

First, I examine the impact of typhoons on rural households' agricultural input decisions. The dependent variable of the baseline regression model is replaced with the agricultural inputs of rural households. Models (1–4) in Table 10 indicate that typhoons do not have a significant impact on the scale of land cultivated by rural households. However, rural households notably increase their investment in fixed assets while reducing labor time and intermediate inputs. The land cultivated by rural households is allocated based on the "rural land contract management system" and acquired through land transfers from other rural households. Therefore, the scale of land farming is not directly influenced by the occurrence of typhoons.

Additionally, rural households need to reinforce crops or clear farmland drainage to mitigate the impact of typhoons. The implementation of such measures necessitates investment in fixed assets like windproof brackets, iron and wood farm tools, and drainage machinery, which accounts for the rise in fixed assets. Conversely, the adverse weather conditions caused by typhoons impede rural households' engagement in on-site farming. The destruction of farmland also complicates planting, while crop damage decreases the demand for intermediate inputs. Models (5–7), which analyze agricultural inputs per mu as the dependent variable, demonstrate similar behavioral patterns among rural households.

Table 10. Changes in agricultural inputs.

	Model(1) *Ln(LSZ)*	Model(2) *Ln(FAS)*	Model(3) *Ln(WDY)*	Model(4) *Ln(INP)*	Model(5) *Ln(FAS_PM)*	Model(6) *Ln(WDY_PM)*	Model(7) *Ln(INP_PM)*
Typhoon	−0.0113	0.0581***	−0.0453***	−0.0684***	0.0856***	−0.0424***	−0.0708***
	(0.00767)	(0.0218)	(0.0115)	(0.0167)	(0.0240)	(0.0115)	(0.0154)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Prov Fixed_effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,846	27,846	27,846	27,846	27,846	27,846	27,846
R^2	0.672	0.633	0.633	0.681	0.657	0.499	0.700

Notes: Control variables include village control variables and climate control variables in Table 1. *FAS_PM*-original value of productive fixed assets per mu; *WDY_PM*-labor input of planting per mu; *INP_PM*-operating expenses of planting per mu.

In general, the arrival of typhoons prompts rural households to temporarily adjust their agricultural inputs by substituting labor and intermediate inputs with fixed assets. Further discussion is needed to determine whether this adjustment in agricultural inputs leads to misallocation. To assess whether typhoons distort the input allocation of rural households, I first calculate the distortion index of agricultural production and then analyze it as the dependent variable in the baseline regression.

Table 11. Agricultural input distortions.

	Model(1) *Cap_dist*	Model(2) *Lab_dist*	Model(3) *Total_dist*
Typhoon	0.00920**	0.141***	0.0130**
	(0.00445)	(0.0404)	(0.00598)
Control Variables	Yes	Yes	Yes
Household Fixed_effects	Yes	Yes	Yes
Year Fixed_effects	Yes	Yes	Yes
Year×Prov Fixed_effects	Yes	Yes	Yes
Observations	27,846	27,833	27,833
R^2	0.470	0.635	0.677

Notes: Control variables include baseline control variables, village control variables, and climate control variables in Table 1. The calculation process of *Cap_dist, Lab_dist,* and *Total_dist* can be referred to in Appendix.

Models (1–2) in Table 11 demonstrate that typhoons significantly increased the degree of distortion in rural households' capital investment and exacerbated the distortion in labor input. The rise in investment in fixed assets and the decline in labor input caused by the typhoon led to a deviation in the capital and labor inputs from the typical endowment of rural households. This unexpected adjustment in factor inputs creates distortions, with labor distortions exceeding capital distortions. This is attributed to the fact that capital investment has traditionally played a minor role in China's agricultural production, which relies more heavily on labor and intermediate goods. Since the capital stock of agricultural production is low and the capital fluctuation range is limited, the impact of capital distortion is relatively small; on the contrary, since agricultural production mainly relies on labor input, the typhoon has caused a reduction in agricultural working days and the phenomenon of labor idleness has become more obvious, which has a greater impact on input distortion. Combining the distortions in capital and labor inputs, Model (3) shows that the overall distortion in rural households' input allocation worsened due to typhoon impacts. I conclude that the involuntary substitution of fixed assets for labor in the aftermath of a typhoon is a key factor contributing to the distortion of overall input allocation. Thus, the hypothesis of "typhoon impact—distortion of input allocation—decline in agricultural productivity" proposed in the theoretical analysis of this study is fully supported by empirical evidence.

5. Cost-Benefit Analysis

Through the above analysis, we understand that typhoons significantly reduce agricultural productivity. An important question is whether the government's financial investment in agriculture can mitigate this negative impact. Model (1) in Table 12 uses "expenses for agriculture, forestry, water, and electricity" (*AFE*) from the "Financial Statistics of Prefectures, Cities, and Counties Nationwide" for the years 1993 to 2007 as a proxy for local government's agricultural fiscal expenditures. These models include interaction terms between the typhoon variable and *AFE* to assess their effects.

Model (1) indicates that local government's agricultural fiscal expenditures effectively mitigate the decline in agricultural productivity, as measured by the net income per mu of planting. Specifically, if the government were to double its agricultural fiscal expenditure, the local net income loss per mu could be reduced by 18.5%. With an average agricultural fiscal expenditure of 19.47 million yuan per year in the sample, an increase of approximately 20 million yuan in local government expenditures would offset nearly 20% of the drop in agricultural productivity caused by typhoons. This represents the estimated lower limit of the efficiency of government agricultural fiscal expenditures in suppressing typhoon-related agricultural losses.

Furthermore, data from 2003 to 2006 reveal that local government "water conservancy and meteorological expenditures" account for about 17% of the total "agriculture, forestry, water, and electricity expenses." Therefore, if the positive effect of government fiscal expenditure on reducing agricultural productivity decline is attributed solely to water conservancy and meteorological construction, then an increase of 3.4 million yuan in these expenditures could counteract nearly 20% of the decline in agricultural productivity caused by typhoons. This estimate provides the upper limit of the efficiency of government agricultural fiscal expenditures in mitigating typhoon-related impacts.

Table 12. Cost-Benefit analysis of agricultural production expenditures.

	Model(1)
	Ln(NINC_PM)
Typhoon×Ln(AFE)	0.185***
	(0.0594)
Ln(AFE)	−0.0259
	(0.0969)
Typhoon	−0.270***
	(0.0626)
Control Variables	Yes
Household Fixed_effects	Yes
Year Fixed_effects	Yes
Year×Prov Fixed_effects	Yes
Observations	10,971
R^2	0.396

Notes: Control variables include baseline control variables, village control variables, and climate control variables in Table 1. "Expenses for agriculture, forestry, water and electricity" were only disclosed from 1993 to 2002. This study uses the sum of "agricultural expenditures," "forestry expenditures," and "water conservancy and meteorological expenditures" as proxy indicators from 2003 to 2006. In 2007, this study uses "agriculture, forestry, and water expenditure" as a proxy indicator.

6. Conclusions

The threat of natural disasters to rural development has garnered attention from governments worldwide. This study focuses on coastal typhoons, identifying the affected treatment group and the unaffected control group based on their unique movement paths. Using a difference-in-differences (DID) model and survey data from the Rural Fixed Observation Spot of the Chinese Ministry of Agriculture, this study finds that typhoons significantly reduce the agricultural productivity of local rural households. Specifically, the average income per mu and per capita from planting decreases by 11% and 14%, respectively, while agricultural total factor productivity falls by approximately 3.7%. This provides quantitative evidence of the adverse effects of typhoons on agricultural production.

The mechanism through which typhoons exacerbate the decline in agricultural productivity operates through several channels. First, typhoons directly damage crops, reducing total output. Second, in anticipation of the typhoon, rural households significantly increase asset investment in agricultural production while reducing labor input and intermediate goods. This adjustment leads to a distortion in the allocation of agricultural inputs, further diminishing productivity. The adverse impact of typhoons is more pronounced in plain areas, whereas strengthening rural organizational capabilities and improving land circulation can substantially mitigate the negative effects. This implies that policies should enhance farmland and water conservancy infrastructure, consolidate the strength of rural grassroots organizations, and expand land circulation channels.

Finally, a cost-benefit analysis indicates that reducing the negative impact of typhoons on agricultural productivity by 20% within the context of China requires local financial support for agriculture amounting to approximately 3.4 million to 20 million yuan. This provides a reference for other developing countries in planning financial investments for typhoon prevention and control. To optimize the use of financial resources, future improvements should focus on streamlining spending processes, updating assessment systems, and developing disaster prevention strategies tailored to local conditions.

However, this study has the following limitations: First, this study focuses solely on the impact of typhoons in China's coastal regions, neglecting indirect consequences like supply chain disruptions and market fluctuations in inland areas resulting from shortages of agricultural products. Second, due to the lack of detailed data, this study has only conducted a preliminary examination of the effectiveness of government financial support for disaster prevention and has not yet proposed a comprehensive and practical improvement plan. These limitations highlight the need for additional research in the future.

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Appendix

Calculating the Distortion of Agricultural Inputs in Rural Households

Assume rural households use capital (K), labor (L), land (T), and intermediate goods (M) for agricultural production, following a Cobb-Douglas production function. Let total factor productivity be denoted as A, and output as Y:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} T_{it}^{\gamma} M_{it}^{\delta} \tag{A1}$$

In Equation A1, i represents the rural household and t represents the year, with the return to scale of the production function remaining unchanged ($\alpha + \beta + \gamma + \delta = 1$). The rural household's profit maximization problem is:

$$\max \left\{ P_{it} Y_{it} - (1+\tau_{Kit}) K_{it} P_{Kit} - (1+\tau_{Lit}) L_{it} P_{Lit} - P_{Tit} T_{it} - P_{Mit} M_{it} \right\} \tag{A2}$$

Due to the lack of detailed information on the prices of various agricultural inputs (P_{it}), I use the total income from agricultural production ($P_{it} Y_{it}$) directly. Hsieh and Klenow (2009) discussed productivity due to irrational allocation of capital and labor inputs under distorted factor prices. They assumed P_{Kit} and P_{Lit} represent the market prices of capital and labor, while $(1 + \tau_{Kit}) P_{Kit}$ and $(1 + \tau_{Lit}) P_{Lit}$ denote the distorted prices faced by enterprises, with τ_{Kit} and τ_{Lit} represent the degrees of distortion for capital and labor inputs, respectively.

This study focuses on the impact of typhoon disasters on rural households' adjustment of fixed assets or labor input, regardless of distorted input factor prices. This adjustment is reflected in the distortion of capital input $(1 + \tau_{Kit}) K_{it}$ and labor input $(1 + \tau_{Lit}) L_{it}$. I define the distortion of agricultural input as the total cost of inputs: $(1 + \tau_{Kit}) K_{it} P_{Kit}$ and $(1 + \tau_{Lit}) L_{it} P_{Lit}$. Here, τ_{Kit} and τ_{Lit} indicate the distortion of capital and labor factors, respectively. The calculation of the distortion index is similar to previous literature.

Assuming land is used free of charge ($P_{Tit} = 0$) and given the difficulty of obtaining data of intermediate inputs, I calculate only the distortions in capital and labor inputs. Based on the profit maximization conditions derived from Equations A1 and A2, we have:

$$\alpha P_{it} Y_{it} = (1+\tau_{Kit}) P_{Kit} K_{it} \tag{A3}$$

$$\beta P_{it} Y_{it} = (1+\tau_{Lit}) P_{Lit} L_{it} \tag{A4}$$

Thus, capital and labor input distortions can be expressed as:

$$1+\tau_{Kit} = \frac{\alpha P_{it} Y_{it}}{P_{Kit} K_{it}} \tag{A5}$$

$$1+\tau_{Lit} = \frac{\beta P_{it} Y_{it}}{P_{Lit} L_{it}} \tag{A6}$$

The overall factor distortion index for rural households can be defined as:

$$dist_{it} = (1+\tau_{Kit})^{\alpha} (1+\tau_{Lit})^{\beta} \tag{A7}$$

To measure capital and labor distortion, I utilize the following data: $P_{it}Y_{it}$ as the total income of agricultural planting; $P_{Kit}K_{it}$ as the original value of productive fixed assets; L_{it} as the number of days rural households worked in planting each year; and P_{Lit} as the opportunity cost of labor, estimated from the average income of migrant workers at the county level. All monetary values (P_{Lit}, $P_{it}Y_{it}$, $P_{Kit}K_{it}$ and P_{Lit}) are adjusted for inflation (with 1986 as the base year). Finally, α and β represent the output elasticity of capital and labor in the Cobb-Douglas production function as follows:

$$lnY_{it} = \alpha lnK_{it} + \beta lnL_{it} + \gamma lnT_{it} + \delta lnM_{it} + i\_fe + t\_fe + \varepsilon_{it} \tag{A8}$$

This regression model is used to estimate the coefficients for capital and labor inputs (α and β) and determine the degree of distortion in agricultural inputs ($dist_{it}$).

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