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Influence of Natural Disaster Shock and Collective Action on Farmland Transferees' No-Tillage Technology Adoption in China

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Abstract: Climate change in natural disasters such as droughts and floods has caused people to adopt, extend, and diffuse adaptive agricultural technologies. Meanwhile, the development of the farmland leasing market has pushed agricultural laborers to migrate from rural to urban areas, resulting in less participation in collective action. It is generally believed that no-tillage technology lessens the agricultural production risks instigated by climate change and natural disasters. However, previous literature has given little attention to this phenomenon, especially in the context of China. So, to fill this gap, the current study explores the influence of natural disaster shock and collective action on farmland transferees' no-tillage technology adoption using the data of 621 farmland transferees from Shaanxi, Gansu, and Ningxia provinces, China. By using Heckman's two-stage and moderating-effect models, the findings initially reveal that in the sample, 249 farmland transferees adopt no-tillage technology, accounting for 40.10% of farmland transferees. The farmland area in which no-tillage technology is adopted accounts for 23.90% of the total farmland area. Natural disaster shock exerts a positive and significant influence on transferees' no-tillage technology adoption, i.e., if the intensity of natural disaster shock increases by one unit, the adoption rate and adoption degree will increase by 24.9% and 9.5%, respectively. Meanwhile, collective action also positively and significantly impacts transferees' no-tillage technology adoption. If the number of transferees participating in collective action increases by one unit, the adoption rate and degree will increase by 13.3% and 6.5%, respectively. Further, it is found that collective action positively moderates the relationship between natural disaster shock and the adoption of no-tillage technology by farmland transferees. Additionally, educational level, agricultural income, farmland area, etc., are also found to influence transferees' no-tillage technology adoption significantly. Moreover, based on gender and organizational participation differences, the findings reveal that the effects of natural disaster shock and collective action are heterogeneous. The results propose that policymakers should take countermeasures such as providing training in no-tillage skills, raising no-tillage subsidy standards, and guiding long-term farmland transference.

Keywords: climate change; farmland transfer; technology adoption; Heckman two-stage model

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1. Introduction

Recently, climate change has emerged as the most crucial hazardous phenomenon adversely influencing the environment [1,2]. The evidence reveals that the link between climate change and human activities, such as increasing greenhouse gas emissions and decreasing forest area in the past 50 years, has reached 90% [3,4]. The fifth report of the IPCC points out that global warming caused by human activities in the past 130 years has increased to 0.85 °C, and the global average temperature increase is also likely to reach more than 1.5 °C by the end of the 21st century [5]. Thus, climate change, characterized by global warming, has significantly changed the geophysics (e.g., water evaporation and back-reflectivity), geotherm dynamics (e.g., atmospheric circulation and ocean currents changes), and biochemistry (e.g., the production and decomposition of organic matter), thereby accelerating the occurrence and development of natural disasters such as various meteorological and marine disasters [6]. Agriculture is the most vulnerable to climate change and natural disasters [7]. Natural disasters such as droughts and floods caused by global climate change have negatively influenced agricultural production in both developed and developing countries, especially in marginalized and deprived areas with low income and weak adaptive capacities, where they possibly suffer more severe economic damage [8,9]. Much of the literature states that climate change and natural disasters exacerbate water- and food-security issues [10,11]. Additionally, COVID-19 also disrupted the international agricultural supply chain, trade, and finance, further aggravating the global food crisis [12]. Consequently, improving agriculture's capacity to cope with natural disasters has become the focus of academicians and researchers around the globe [13,14].

In this regard, no-tillage technology has emerged as a crucial phenomenon with multiple advantages; for example, it helps with storing water, improving soil structure and quality, resisting soil erosion, and improving crop yield [15,16]. It has dual favorable attributes both for the economy and ecology. As Chan and Pratley [17] reported, no-tillage technology can significantly reduce soil and wind erosion and improve the ability to consolidate soil, increase fertilizer, and resist lodging. Specifically, no-tillage technology refers to the use of openers for sowing, and it is required that the amount of soil tilled does not to exceed 25% of the farmland area [18]. Except for sowing and fertilization, no-tillage technology has no adverse effect on the soil before the crops are harvested. No-tillage technology is also used in conjunction with other technologies, such as stubble mulching, straw returning, and biological weeding [19]. Considering the resources and environmental conditions, no-tillage technology has various types, such as no-tillage of paddy fields, no-tillage of paddy- and dry-field rotation, and no-tillage of dry fields [20,21]. About 51% of no-tillage technology is adopted in North America. However, in the context of China, it accounts for only 10.48% of the total farmland area, and that is why the adoption rate of no-tillage technology in China is relatively low [22].

In the prevailing literature, it is proposed that farmers opt for no-tillage technology in conservation tillage technologies (e.g., no-tillage, straw returning, and subsoiling) [23,24]. These technologies are complementary and work better together. Consequently, only a few studies discuss farmers' no-tillage technology adoption, and only a few focus on analyzing the influencing factors of farmers' adoption of conservation tillage technologies. In the context of individual and family characteristics, Cai and Cai [25] and Fei et al. [26] argued that education level, political identity, and part-time degrees positively and significantly influence farmers' adoption of conservation tillage technologies. Qiu et al. [22], in the context of farmers' cognition, believed that farmers with risk aversion and perceived risks are inclined to adopt a combination of straw returning + no-tillage or deep loosening. Further, from policy perspectives, Kurkalova et al. [27] and Zhang et al. [28] revealed that government subsidies drive farmers' adoption of conservation tillage technologies. Li et al. [29] stated that the cognitive and economic benefits positively affect farmers' adoption of conservation tillage technologies. A few studies also focus on exploring the drivers of farmers' no-tillage technology adoption. In this regard, D' Emden et al. [30] used the survey data of Australia's southern and western growing regions. They found that the cost of herbicides and weeds is the main factor influencing farmers' adoption of no-tillage technology. Moreover, Xia [31], in the case of Shaanxi, China, believed that risk preference, publicity and training, and cultivated land area have positive incentive effects on farmers' adoption of no-tillage technology. Unfortunately, previous studies have not focused on the wide-ranging social changes regarding farmers' no-tillage technology adoption, such as farmland transfer.

In 2020, China's farmland transfer exceeded 471 million mu (1 mu = 0.0667 hectare), and more than 200 million farmers migrated to cities for work [32]. The transfer of farmland profoundly influenced the economy and social structure in rural areas of China. Firstly, driven by the non-agricultural income effect, the rural-urban migration of large numbers of laborers has led to the drain of rural elites and technical talents, and rural areas have fallen into the dilemma of public-affairs governance and rural collective action, such as rural environmental degradation and collective infrastructure disrepair [33–35]. The study of Cai and Cai [25] found that the proportion of migrant households inhabited village collective action. Secondly, it is believed that farmland transfer provides excellent and mechanized conditions for agriculture on a large scale and also accelerates the transference of rural surplus labor to urban areas [36]. Thus, the farmland transferee acts as a leading implementer of new agricultural technology adoption [35]. Thirdly, farmland transfer accelerates modern agricultural production, represented by the moderate scale, and promotes the adoption of new agricultural technologies based on mechanization [37]. Meanwhile, farmland transfer makes the transferee an "elite" in the governance of rural public affairs. It enables them to contribute to agricultural production efficiently, thus resolving the dilemma of collective action [38].

Based on the above discussion, it is apparent that there are still some gaps in the previous literature that are worthy of exploring. In climate change economics, the emphasis is placed on reducing greenhouse gas emissions and disaster risk by opting for environmentally promising technologies [39]. Compared with traditional cultivating technologies, no-tillage technology has emerged as a pronounced method to cope with natural disasters and is given priority in arid and semi-arid regions to boost agricultural yield. Unfortunately, previous studies have not considered the role of natural disaster shock in farmland transferees' no-tillage adoption. Moreover, no-tillage technology provides dual attributes both to the economy and ecology. The former involves farmers' private interests, but the latter is a public product that requires collective consultation and joint adoption to exert its ecological effect. Unfortunately, previous studies have not considered the influence of collective action on farmers' no-tillage technology. Consequently, The main purpose of this paper is to explore the influence of natural disaster shock and collective action on the adoption of no-till technology by farmland transferees. The main contributions of this paper are as follows. Firstly, considering the background of farmland transfer, natural disaster shock and collective action are incorporated into the analytical framework for farmland transferees' no-tillage technology adoption, which can enrich relevant fundamental theories such as public management and agricultural technology economy. Secondly, the Heckman two-stage model is employed to empirically analyze the influence of natural disaster shock and collective action on farmland transferees' no-tillage technology adoption to explore factors influencing the adoption of no-tillage technology by farmland transferees. Finally, the moderating-effect model is used to test the moderating effect of collective action on the impact of natural disasters on farmland transferees' no-tillage technology adoption.

The rest of the paper is organized as follows. Section 2 highlights the theoretical and conceptual framework, and Section 3 describes the methodology. Section 4 reports and discusses the findings based on the empirical results. In the Section 5, conclusions are drawn, and some policy implications are proposed. Finally, the limitations of the study are also presented in the last section.

2. Theoretical and Conceptual Framework

2.1. The Influence of Natural Disaster Shock on Farmland Transferee's No-Tillage Technology Adoption

"China's Blue Book on Climate Change (2018)" pointed out that China is more prone to climate change and natural disasters such as heavy precipitation and heat waves [40] that adversely affect agricultural yield and income in China's arid and semi-arid regions [41,42]. Previous studies have debated the causal relationship between natural disaster shock and farmers' innovative technology adoption. Some scholars have introduced the concepts of "vulnerability assessment and adaptation of livelihood strategies" to discuss the degree of vulnerability and the adaptation strategies adopted by farmers in climate change [43,44]. Farmers with low vulnerability, strong industrial dependence, and weak livelihood flexibility are likely to adopt new agricultural technologies to cope with natural disasters [45,46]. However, other scholars have explained the concepts of "livelihood resilience and alternative livelihood strategies" [47,48]. They believe that, accompanied by the increased intensity of natural disasters, if the livelihood resilience of the affected farmers is weak, they are likely to adjust their industrial structure or engage in other activities to maintain their family welfare with alternative livelihood strategies [49,50]. In practice, the family industry of the transferee is mainly the moderate-scale operation of farmland. The agricultural industry is highly dependent, and the cost of seeking alternative livelihood industries is relatively high. The transferee is more inclined to adopt no-tillage technology to improve the capacity of soil to store water, improve soil's physical structure, and increase the lodging resistance of crops, finally reducing the influence of natural disasters on agricultural production. According to the above research, the study proposes the following assumption:

Hypothesis 1. *Natural disaster shock has a positive effect on transferees' no-tillage technology adoption.*

2.2. The Impact of Collective Action on Transferee's No-Tillage Technology Adoption

Collective action, an externalized manifestation of shared consciousness, profoundly impacts individuals' consciousness and behaviors [51]. Although collective action mainly solves dilemmas in the governance of "public affairs", some scholars have found that collective action is vital in quasi-public affairs, such as the promotion and diffusion of climate-resilient technology. In their studies, Jia et al. [52] and Li et al. [53] unveiled that soil- and water-conservation technologies are the attributes of quasi-public goods, and collective action has a good effect on boosting soil- and water-conservation technology adoption by farmers. Other scholars also believe that soil- and water-conservation technologies with positive externalities are usually carried out in collective action [52]. Additionally, collective action enables coherence in action through coordinated group action and information sharing. Meanwhile, collective action can mobilize private resources and encourage farmers to invest labor and financial resources under cooperation, to improve the insufficient supply of rural public goods and structural imbalances [53,54]. Liu and Ravenscroft [55] proposed that collective action can form an internal supervision mechanism of mutual trust among organizational members, saving on the cost of information search, and avoiding the inadequate supply of public goods caused by weak external supervision. The multiple effects of no-tillage technology can be maximized when adopted and promoted on a moderate continuous-scale operation, so it has a prominent quasi-public property attribute. Additionally, some scholars also state that farmers are less sensitive to agricultural technology due to their low education levels. In this regard, collective action will likely promote farmers to actively adopt no-tillage technology by coordinating village collective awareness and activities [56,57]. Hence, this paper proposes the following assumptions:

Hypothesis 2. *Collective action has a positive incentive effect on transferees' no-tillage technology adoption.*

2.3. The Moderating Effect of Collective Action in Natural Disaster Shock Influencing Farmer's No-Tillage Technology Adoption

Natural disaster shock also influences farmers' choices of adaptive livelihood strategy by raising public awareness of cooperation and collective action [58]. Specifically, when the impact of natural disaster shock on transferees' no-tillage technology adoption is uncertain, collective action led by the "elite" can promote mutual assistance and cooperation among farmers, which is conducive to opting for and the dissemination of no-tillage technology. On the one hand, when resource users are exposed to natural disaster risk damage, the management of public resources requires collective action and cooperation [59]. If farmers participate in collective action, their decision to adopt no-tillage technology is expected to be influenced by other farmers. Farmers often adopt no-tillage technology given group supervision and the peer effect. On the other hand, farmland transferees who implement large-scale farmland management are usually industry leaders and technical experts within the village, acting as initiators and organizers of village collective actions, and can ensure the orderly development of village collective action [60,61]. Hence, collective action is vital in organizing, coordinating, sharing, and supervising when dealing with economic losses and resource allocation problems caused by natural disaster shock. Based on the above discussion, the study proposes the following assumptions and the theoretical framework used in the current study is showed in Figure 1.

Hypothesis 3. *Collective action positively moderates transferees' no-tillage technology adoption affected by natural disaster shock.*

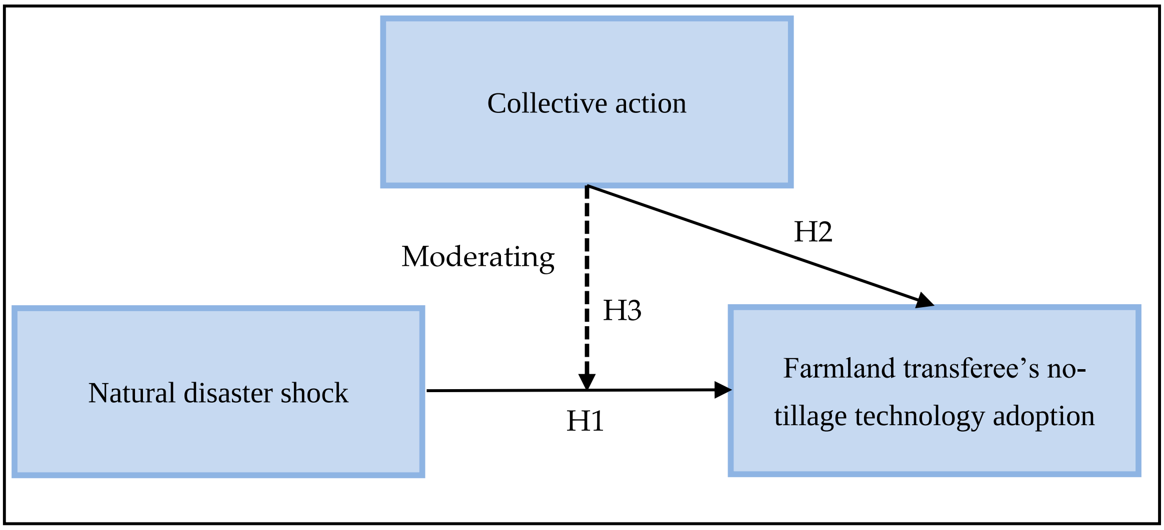

Figure 1. The theoretical framework used in the current study.

3. Data and Methodology

3.1. Data Sources

The study data were obtained through field questionnaires from Shaanxi, Gansu, and Ningxia provinces of China from January to February 2019 (Figure 2). The main reasons for selecting these sample sites are as follows: firstly, these provinces are located in the monsoon climate zone and the Loess Plateau, China, where seasonal heavy precipitation and drought are alternately superimposed. Secondly, these provinces are economically impoverished areas, where many rural laborers have migrated, and the scale of farmland transfer is enormous. The phenomenon of "hollow villages" is seriously profound. Thirdly, these provinces are China's pilot areas for modern agriculture in arid and semi-arid regions. The agricultural department has extensively promoted climate-adaptive agricultural technologies such as no-tillage technology in these areas, which are excellent representatives to meet the study objectives.

Further, the field survey was conducted using stratified and random sampling. The research team randomly selected 2 to 4 counties from each province, and then, randomly selected 3 to 5 sample townships from each county. Considering that the number of villages under the jurisdiction of each town is different, 4 to 8 villages from each town were randomly selected. Lastly, respondents were randomly selected from each village.

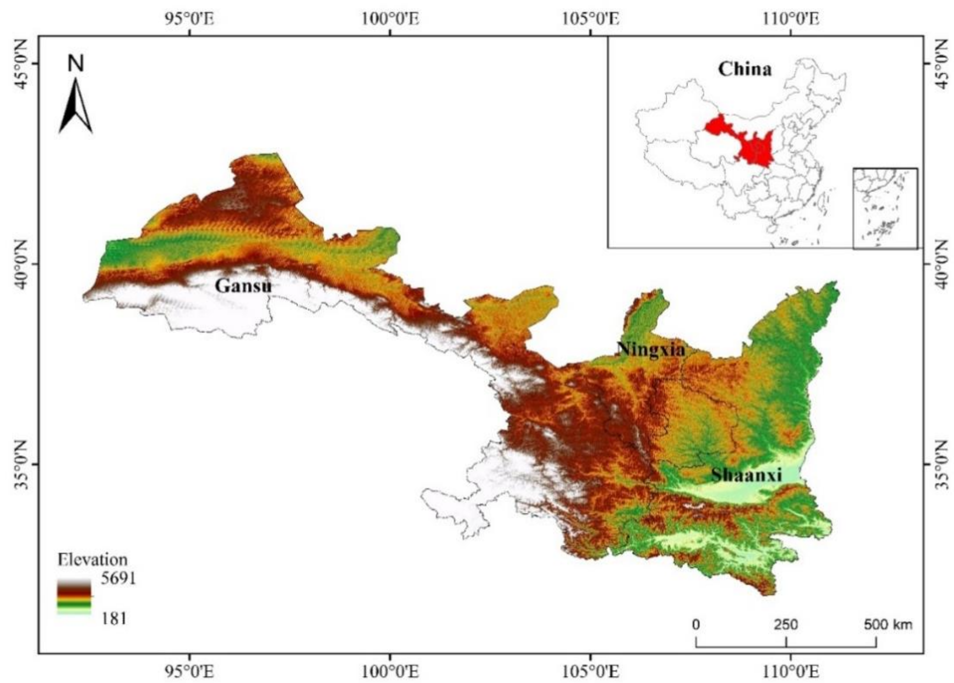

Figure 2. Map of the study area (source: ArcGIS 10).

This paper used the calculation formula of the minimum sample size to obtain the surveyed sample with a 3% error value and a 95%confidence level. A total of 1496 questionnaires were distributed in the survey. A total of 1450 samples were recovered and 46 samples were not recovered. Further, 85 households with missing information, 62 households with invalid questionnaires, and 682 households with non-transferred farmland samples were excluded; finally, 621 sample households transferring farmland were retained for empirical analysis. Among them, 185 households were from Shaanxi, 219 from Gansu, and 217 belonged to Ningxia. The content of the questionnaire survey involved individuals' characteristics, family situations, policies and environmental conditions, natural disaster shock, collective action, farmers' no-tillage technology adoption, etc. Before the formal questionnaire survey, the research team conducted a preliminary survey in Zhangye city, Gansu Province, and then, the questionnaire contents were further revised and modified.

The primary characteristics of the farmland transferees in the sample are shown in Table 1. It can be seen that 60.397% of the transferees are between 41 and 60 years old, and the age structure is relatively large. About 41.717% of the transferees have 6–9 school years, and the education level is low. Further, 46.699% of the transferees have a cultivated area of more than 10 mu. In comparison, 96.779% have an agricultural income of less than CNY 30,000, and the agricultural management efficiency is generally low. Meanwhile, the number of family laborers is mainly 1–2 people, and rural labor resources are scarce. Around 89.211% of the transferees are not village officials, and the awareness and ability of their political participation are weak. Additionally, 31.401% of transferees have loans, and their credit stress is relatively high. Moreover, 55.395% of the transferees have not received government no-tillage skill training, and their skill level is relatively low.

Table 1. Descriptive statistics of individual characteristics.

Variables	Classification	Sample Size	Proportion (%)
Age	20–40	51	8.213
	41–60	375	60.397
	>60 year	195	31.401
Educational level	0–5	196	31.562
	6–9	259	41.717
	>9 year	166	26.731
Farmland area	0–5	204	32.850
	6–10	127	20.451
	>10 mu	290	46.699
Agriculture income	0–3	601	96.779
	4–5	15	2.415
	>5 CNY ten thousand	5	0.805
Family labor	1–2	290	46.699
	3–4	248	39.356
	>4 people	83	13.366
Village officials	Yes	67	10.789
	No	554	89.211
Credit stress	Yes	195	31.401
	No	426	68.599
Training in no-tillage technology	Yes	277	44.606
	No	344	55.395

Note: 1 mu = 0.0667 hectares; CNY (Chinese Yuan) 1 = USD 0.148.

3.2. Variable Selection

3.2.1. Core Explanatory Variables

The first core explanatory variable is natural disaster shock. The impact of natural disasters has become important because of poverty among farmers in some developing countries [62,63]. Natural disasters frequently occur in China, with about 70% of rural households suffering from natural disaster shock. Natural disasters are the catastrophic consequences of extreme events in the biosphere, lithosphere, hydrosphere, and atmosphere [64]. Considering the overall benefit of no-tillage technology in water storage, moisture conservation, and the reduction in water and wind erosion, the average number of natural disasters such as drought, sandstorms, rainstorms, landslides, and debris flow in the survey area in the past three years was selected as the intensity of natural disaster shock. We obtained the data through the questionnaire item "Are you severely affected by natural disasters? (1 = rarely severe, 2 = less severe, 3 = average, 4 = severe, 5 = very severe)". According to the descriptive statistics in Table 2, compared with other natural disasters, the intensity of drought and rainstorms is higher, with an average of 4.429 and 4.203, respectively, and the average intensity of the transferees suffering from a natural disaster is 3.871.

Table 2. Descriptive statistics of natural disasters.

Natural Disasters	Mean	S.D.
Drought	4.429	1.231
Sandstorm	3.726	1.051
Rainstorm	4.203	1.109
Landslide	3.408	0.832
Debris flow	3.587	0.855
Mean	3.871	1.016

The second core explanatory variable is collective action. Drawing on Bisung [61] and Jia et al. [65] on the measurement indicators of collective action, this study described the transferee participation in collective action from four aspects: cognitive level, realization degree, organizational role, and contribution degree. First, the transferee's understanding level of the collective action system, rules, funds, content, and meaning can reflect the cognitive level of collective action. Second, the transferee's judgments on the improvement of income, the environment, relationships, and infrastructure reflect the realization degree of the scale economy of participation in collective action. Thirdly, the functional role of the transferee in the organization demonstrates their organizational role in collective action. Finally, the capital contribution and the proportion of meetings attended by participants in the village collective action represent the contribution degree of the transferee joining collective action (Table 3).

Table 3. Descriptive statistics of collective action.

Variables	Assignment	Mean	S.D.
Understanding system	The transferee's understanding of the collective action system (do not understand at all = 1 − understand very well = 5)	2.843	1.139
Understanding rules	The transferee's understanding of collective action rules (do not understand at all = 1 − understand very well = 5)	3.087	1.134
Understanding funds	The transferee's understanding of collective action funds (do not understand at all = 1 − understand very well = 5)	2.549	1.168
Understanding content	The transferee's understanding of collective action content (do not understand at all = 1 − understand very well = 5)	3.268	1.126
Understanding meaning	The transferee's understanding of collective action meaning (do not understand at all = 1 − understand very well = 5)	3.188	1.166
Increasing income	The effect of collective action on increasing income (very bad = 1 − very good = 5)	2.744	1.170
Improving environment	The effect of collective action on improving environment (very bad = 1 − very good = 5)	3.052	1.191
Improving villager relations	The effect of collective action on improving villager relations (very bad = 1 − very good = 5)	3.334	1.167
Improving infrastructure	The effect of collective action on improving infrastructure (very bad = 1 − very good = 5)	3.438	1.229
Organizational role	The functional role of the transferee in the organization (bystander = 1, participant = 2, manager = 3, leader = 4, initiator = 5)	3.653	0.993
Proportion of meeting participation	Number of transferees attending training/number of training sessions organized	0.781	0.387
Proportion of capital contribution	The amount that transferees contributed/the amount they were asked to contribute	0.492	0.085

The exploratory factor analysis method was used to measure the degree of the transferees' participation in collective action. The results show that the KMO (Kaiser–Meyer–Olkin) value is 0.782, and the approximate chi-square value of the Bartlett sphericity test is 3385.802 (sig = 0.000), indicating that the variables that characterize collective action have high correlation or commonalities, and are suitable for exploratory factor analysis. According to Kaiser's criterion, common factors with eigenvalues greater than 1 were selected. By extracting the common factor and variance contribution rate, the factor score value of different dimensions of the collective action was calculated. The calculation formula is as follows:

$$F_j = \beta_{j1}X_1 + \beta_{j2}X_2 + \cdots + \beta_{jp}X_p, j = 1,2,3,4 \tag{1}$$

where F_j is the score value of the transferee's j-th factor, X_i–X_p is the transferee's participation degree of collective action (cognitive level, realization degree, organizational role, and contribution degree), and $\beta_{j1} - \beta_{jp}$ is the corresponding coefficient of each dimension. Finally, each common factor's variance contribution rate (0.269, 0.237, 0.100, and 0.085) was weighted. The factor scores of the four dimensions of collective action were summed to obtain the transferees' participation degree in collective action. The specific calculation formula is as follows:

$$\text{Collective action} = (0.269 \times F_1 + 0.237 \times F_2 + 0.100 \times F_3 + 0.085 \times F_4)/0.690 \quad (2)$$

3.2.2. Explained Variable

From the perspective of technical economics, the previous literature on farmers' technology adoption mainly includes the adoption decision and degree [66,67]. The current study takes transferees' no-tillage technology adoption as an explained variable, which reflects both the adoption decision and degree. The adoption decision of no-tillage technology is a discrete binary variable. If the transferee chooses to adopt no-tillage technology, a value of 1 is assigned; otherwise, the value is 0. The adoption proportion of no-tillage technology represents the adoption degree, that is, the proportion of the area of no-tillage technology adopted to the total farmland area, a continuous variable between 0 and 1.

3.2.3. Control Variables

Following the previous studies of Mao et al. [68], Ahmed et al. [69], and Musyoki et al. [70], this paper selected control variables such as age, education level, village officials, agricultural income, farmland area, family labor, credit stress, farmland lease term, and training inno-tillage technology. Like social capital such as village officials, individual endowments such as age and education level have always been especially important factors affecting farmers' technology adoption [28]. The input level of agricultural production factors such as farmland area and family labor directly affect the benefits of agricultural technology [36]. In fact, agricultural technology adoption is fundamentally dependent on cost–benefit measures, and agricultural income growth will also feedback and increase the rate of agricultural technology adoption [67]. Meanwhile, as for capital-intensive agricultural technologies, family credit pressures also act as an important external driving force for technology adoption [65]. Additionally, the farmland lease term represents the stability of agricultural management rights and has a positive effect on the adoption of agricultural technologies [23]. Of course, for small farmers, government skill training has become an important factor in improving farmers' skill constraints. Additionally, with Ningxia as the comparison group, the two regional dummy variables of "are you located in Shaanxi?" and "are you located in Gansu?" were set. The descriptive statistical analysis of all the variables is shown in Table 4.

Table 4. Descriptive statistics of variables.

Variables	Measurement	Mean	S.D.	Relevant Literature
Explained variable				
Adoption decision	Adoption = 1, non-adoption = 0	0. 401	0.382	Wongnaa et al. [71]
Adoption degree	Proportion of the farmland area adopted to the total farmland area	0.239	0.084	Mello et al. [72]
Core explanatory variables				
Natural disaster shock	The average intensity of natural disasters (Table 2)	3.871	1.016	District et al. [43]
Collective action	The results of factor analysis (formula 2)	0.000	1.000	Gelo et al. [57]
Control variables				
Age	Actual age (year)	52.602	10.473	Li et al. [73]
Education level	Actual school time (year)	5.863	3.656	Lauwere et al. [74]
Village officials	Are there any village officials at home? (yes = 1, no = 0)	0.107	0.309	Castro Campos [75]

Table 4. *Cont.*

Variables	Measurement	Mean	S.D.	Relevant Literature
Agricultural income	Family agricultural income (CNY ten thousand)	1.501	1.732	Kiriyama et al. [76]
Farmland area	Actual farmland area (mu)	11.935	12.933	Qiu et al. [77]
Family labor	The actual number of family laborers (people)	3.028	1.491	Chhogyel et al. [9]
Credit stress	Does the family have a loan? (yes = 1, no = 0)	0.314	0.314	Jumpah et al. [78]
Farmland lease term	Term of farmland transfer lease contract (year)	3.152	0.805	Si et al. [23]
Training inno-tillage technology	Does the government carry out no-tillage technical training? (yes = 1, no = 0)	0.446	0.497	Musafiri et al. [79]
Dummy variables				
Are you in Shaanxi?	Yes = 1, no = 0	0.379	0.485	Si et al. [80]
Are you in Gansu?	Yes = 1, no = 0	0.383	0.487	

3.2.4. Empirical Estimation

To meet the study objective, the current study employed Heckman's two-stage approach because the explained variables included the two stages of the adoption decision and adoption degree. If the transferee does not adopt no-tillage technology, the adoption degree cannot be directly observed, so there is an issue with sample selection. Meanwhile, the explanatory factor group in the second stage (outcome equation) should be a complete subset of the explanatory factor group in the first stage (selection equation), so in the selection model, at least one explanatory variable should not appear in the second-stage equation [81–83]. Referring to the study by Tan and Lu [84], the "distance between the transferee and agricultural department" was selected as the identification variable. If the distance is closer, the transferee is more trained inno-tillage technology by the agricultural department, and it is more likely that the transferee will make an adoption decision. However, the adoption degree of no-tillage technology depends on various factors, such as technology costs and benefits, and the distance has no direct causal relationship with the adoption degree. Thus, the model is built as follows:

$$y_{li} = X_{1i}\alpha + \mu_{1i} y_{1i} = \begin{cases} 1 y_{1i}{}^{*} > 0 \\ 0 y_{1i}{}^{*} \leq 0 \end{cases} \tag{3}$$

$$y_{2i} = X_{2i}\beta + \mu_{2i} y'_{2i} = \begin{cases} b y_{li} > 0 \\ 0 y_{1i} \leq 0 \end{cases} \tag{4}$$

where Equation (3) represents the selection equation in the first stage, and Equation (4) is the result equation in the second stage. The subscript I indicates the i-th sample farmland transferee, y_{li} indicates whether the transferee adopts no-tillage technology, and y_{2i} indicates the adoption degree of the transferee's no-tillage technology. X_{1i} and X_{2i} represent the explanatory variables of the two equations, respectively. The subscript $y_1{}^{*}$ refers to the unobservable latent variable, and b signifies the adoption degree of the transferee's no-tillage technology adoption. If $y_{1i}{}^{*} > 0$, y_{2i}, it can be observed. α, β are the parameters to be estimated, and μ_{1i}, μ_{2i} represent the residuals, all of which follow the normal distribution. The conditional expectation for the transferees' adoption degree of no-tillage technology is expressed as follows:

$$\begin{aligned} & E(y_{2i}|y_{2i} = c) = E(y_{2i}|y_{1i}{}^{*} > 0) = E(X_{2i}\beta + \mu_{2i}|X_{li}\alpha + \mu_{1i} > 0) \\ & = E(X_{2i}\beta + \mu_{2i}|\mu_{1i} > -X_{1i}\alpha) = X_{2i}\beta + E(\mu_{2i}|\mu_{1i} > -X_{1i}\alpha) \\ & = X_{2i}\beta + \rho\sigma\mu_2\lambda(-X_{1i}\alpha) \end{aligned} \tag{5}$$

In formula (5), σ is the standard deviation and $\lambda(\cdot)$ is the inverse Mills rate function. The correlation coefficient between y_{1i} and y_{2i} is ρ. When $\rho = 0$, y_{2i} will not be affected by y_{1i}. When $\rho \neq 0$, y_{2i} will be impacted by y_{1i}. Additionally, there is a sample selection error. Furthermore, the interaction terms "natural disaster shock" and "collective action" were added to Heckman's two-stage model to verify the moderating effect of collective action in the influence of natural disaster shock on the transferees' no-tillage technology adoption.

4. Results and Discussion

4.1. Statistical Inference

Before the causality is identified, it is initially necessary to test the correlation between variables to verify the requirements of subsequent causal regression [85,86]. This study categorized transferees' decisions to adopt no-tillage technology into the adoption group and the non–adoption group to explore the relationship between the core explanatory variables and the explained variables. Meanwhile, the average adoption degree was taken as the center point, and the adoption degree was divided into two groups, i.e., high and low. Further, the independent samples *t*-test was used to analyze the differences between the impact of natural disaster shock and collective action of the transferees' no-tillage technology adoption (Table 5). The adoption decision shows significant differences at the 1% level regarding the intensity of natural disaster shock and the degree of participation in collective action between the adoption and non-adoption groups. The differencesare0.708 and 0.953, respectively. From the adoption degree, there are significant differences at a 5% significance level in the intensity of natural disaster shock and the degree of participation in collective action between the high and low groups. The differences are 0.602 and 0.946, respectively, indicating that there may be a positive correlation between natural disaster shock, collective action, and the transferees' no-tillage technology adoption.

Table 5. The results of the independent samples *t*-test.

Variables	Adoption Decision		Adoption Degree		Difference A–B	Difference C–D
	Adoption Group—A	Non-Adoption—B	High Group—C	Low Group—D		
Natural disaster shock	4.225	3.517	4.172	3.570	0.708 ***	0.602 **
Collective action	0.441	−0.512	0.520	−0.426	0.953 ***	0.946 **

Note: The significance levels at 1% and 5% are represented by *** and **, respectively. Source: authors' computation.

4.2. The Influence of Natural Disaster Shock and Collective Action on the Transferees' No-Tillage Technology Adoption

The study employed Heckman's two-stage model to empirically analyze the influence of natural disaster shock and collective action on the transferees' no-tillage technology adoption (Model 1). Further, the interaction terms "natural disaster shock" and "collective action" were in corporated into the model (Model 2). Meanwhile, a standard deviation treatment was performed before the variable interaction to remove the correlation between the interaction term and the construction variables. The estimation results based on the Heckman model in Table 6 show that the LR values are 4.201 and 4.225, respectively, which are found to be significant at the 5% level; the Wald chi-square values are 43.312 and 44.801, respectively, which are also found to be significant at the 1%level, indicating the overall model fit. Meanwhile, the reverse Mills rate (probability of potential adoption decision) negatively and significantly influences the transferees' adoption degree and signifies that anomitted variable affects both the decision adoption and adoption degree; that is, there is the problem of sample selection bias. Additionally, the distance between the transferees and the agricultural department showed a positive and significant impact on the transferees' adoption decisions at a 1% significance level, indicating that the identification variable in the Heckman two-stage model is appropriate.

Table 6. Estimation results based on Heckman's two-stage model.

Variables	Model 1		Model 2	
	First Stage: Adoption Decision	Second Stage: Adoption Degree	First Stage: Adoption Decision	Second Stage: Adoption Degree
Natural disaster shock	0.249 *** (0.079)	0.095 * (0.053)	0.212 *** (0.067)	0.091 * (0.050)
Collective action	0.133 *** (0.050)	0.065 * (0.035)	0.105 *** (0.048)	0.042 * (0.023)
Natural disaster shock * collective action	——	——	0.192 * (0.101)	0.074 * (0.044)
Age	0.008 (0.018)	0.105 (0.093)	0.012 (0.015)	0.091 (0.096)
Education level	0.063 ** (0.030)	0.013 *** (0.005)	0.033 ** (0.015)	0.022 *** (0.008)
Village officials	0.089 (0.063)	0.044 (0.028)	0.102 (0.068)	0.025 (0.015)
Agricultural income	0.171 *** (0.063)	0.090 ** (0.040)	0.152 *** (0.057)	0.125 ** (0.058)
Farmland area	0.075 ** (0.032)	0.048 ** (0.020)	0.081 ** (0.035)	0.033 ** (0.014)
Family labor	0.104 (0.009)	0.015 (0.012)	0.084 (0.070)	0.012 (0.009)
Credit stress	0.011 (0.009)	0.064 (0.046)	0.014 (0.012)	0.052 (0.037)
Farmland lease term	0.172 *** (0.055)	0.185 *** (0.066)	0.146 *** (0.048)	0.149 *** (0.054)
Training inno-tillage technology	0.138 *** (0.044)	0.141 *** (0.045)	0.142 *** (0.044)	0.129 *** (0.041)
Are you in Shaanxi?	0.012 (0.008)	0.049 (0.036)	0.016 (0.010)	0.042 (0.030)
Are you in Gansu?	0.075 (0.054)	0.013 (0.008)	0.072 (0.051)	0.016 (0.010)
Distance between the transferee and agricultural department	0.046 *** (0.016)	——	0.019 *** (0.007)	——
Constant term	–4.207 *** (0.614)	17.389 * (9.243)	–4.254 *** (0.688)	17.997 * (10.203)
Log-likelihood value	179.124		179.259	
Wald chi-square value	43.312 ***		44.801 ***	
LR value	4.201 **		4.225 **	
Inverse Mills rate	–6.395 ***		–6.578 **	

Notes: Marginal effects are reported in the table, and standard errors are presented in parentheses. The significance levels at 1%, 5%, and 10% are represented by ***, **, and *, respectively. Source: authors' computation.

Moreover, according to the estimation results in Model 1, the findings revealed that the natural disaster shock positively and significantly influenced the transferees' adoption decisions and adoption degree at 1% and 10% significance levels, respectively. The marginal effects are 0.249 and 0.095, respectively, indicating that if the intensity of natural disaster shock increases by one unit, the adoption rate and adoption degree will increase by 24.9% and 9.5%, respectively; thus, assumption H1 is confirmed. Previous studies also unveiled a causal relationship between greenhouse gas emissions, climate change, and natural disaster shock [87,88]. This could reflect that the intensity of natural disaster shock followed an increasing trend before carbon peaks and carbon neutralization, which inevitably affects the global agricultural industry chain, especially in coastal countries and some deprived developing countries [89,90]. Developing countries bear the damaging consequences of significant carbon emissions in developed countries with fragile adaptation, which inevitably encourage farmers in developing countries to improve their climate adaptability. Consistent with the studies of Andati et al. [91], Kifle et al. [92], and Akimowicz et al. [93], our results also confirm the impact of climate change and natural disasters on farmers' adoption of adaptive technologies. In the sampled area, the impact of natural disasters causes crops to delay suitable growth intervals and germination, stop tillering, and depredate spikelets. Meanwhile, the decline in soil fertility and resilience caused by traditional farming further aggravates the farmland damage caused by natural disasters [94,95]. Farmland transferees tend to adopt no-tillage technology to cope with the adverse effects of natural disasters. Hence, no-tillage technology has emerged as an advantageous phenomenon with multiple benefits to cope with natural disasters such as droughts and floods, and is regarded as a viable path to mitigate the impacts of natural disasters. However, the study contradicts the findings of Ding et al. [96], who revealed that natural disasters are highly heterogeneous, and drought promotes farmers' adoption of tillage technology. In contrast, floods have an inhibitory effect on farmers' adoption of no-tillage technology. The reason is that there may be a causal relationship between flood disasters and the reduction in rural arable land [97,98]. Additionally, the current study confirms that natural disaster shock affects the transferees' adoption decisions and the adoption degree of no-tillage technology. Consistent with the studies of Tan et al. [99] and Kaluszka and Krzeszowiec [100], owing to the transferees' 'fuzzy aversion', the determined probabilistic risk preference showed a more significant effect on adoption decision. Therefore, with greater natural disaster shock, the transferee's adoption degree of no-tillage technology is not likely to follow the same growth trend as their adoption decision. Finally, inconsistent with the studies of Bijttebier et al. [101], Harperet al. [102], and Foguesatto and Machado [103], our study focuses on exploring and confirming the facilitation effect of natural disaster shocks on farmland transferees rather than all farmers' no-tillage technology adoption in the context of farmland transfer, just as Si et al. [37] statethat the farmland transferee becomes the main practitioner or operator of modern agriculture represented by moderate scale and mechanization.

Moreover, it is also found that collective action has a positive and significant impact on the transferees' adoption decisions and adoption degree of no-tillage technology at 1% and 10% significance levels, respectively, with marginal effects of 0.133 and 0.065, indicating that if the transferees' participation degree of collective action increases by one unit, the adoption rate and adoption degree of no-tillage technology will increase by 13.3% and 6.5%, respectively; thus, assumption H2 is also confirmed. The findings are consistent with the studies of Chen et al. [20], Li et al. [29], and Chidambaram [104]. The findings confirmed the incentives for collective action in providing quasi-public goods such as no-tillage adoption. No-till technology's economic and ecological attributes make the transferee less willing to adopt it. However, collective action can improve the inefficiency of quasi-public goods supply on two levels: on the one hand, inconsistent with the studies of Wang et al. [38], Takeda et al. [56], and Gelo et al. [57], our study confirms that the greater the number of large-scale farmland transferees, the stronger the collective leadership; moreover, the binding and organizational power of collective action can promote another transferee to implement incomplete rational production behavior or adopt technology with intertemporal economic properties. On the other hand, the inconsistency between the transferees' individual and collective rationality is also likely to induce the adoption of no-tillage technology. Fortunately, consistent with the studies of Corsi et al. [105] and Orsi et al. [106] collective action has a self-adjusting and reshaping function, prompting the transferee to adopt no-tillage technology through collective negotiation, group supervision, and peer effects. Additionally, the results also show that the effect of collective action on the transferees' decision to adopt no-tillage technology is greater than the effect on the adoption degree. A possible reason is that the endowment of farmland transferees is highly heterogeneous, and their demands for public affairs are differentiated, which limits collective action's continuous supply capacity [107].

According to Model 2, the interaction terms between natural disaster shock and collective action are also significant at 10%. The marginal effects are 0.192 and 0.074, indicating that if the transferees' participation degree in collective action increases by one unit, the impact of natural disaster shock on the adoption rate and adoption degree of no-tillage technology will increase by 19.2% and 7.4%, respectively, thus endorsing the assumption H3. Additionally, the findings portray the following possible explanations: firstly, natural disasters affect the transferee's adoption of no-tillage technology naturally and passively, which requires the transferee to have high technical perception, education level, and operational skills. This endowment advantage is difficult for developing Chinese farmers [108,109]. Of course, consistent with the findings of Mi et al. [110] and Tesfaye et al. [111], even farmers with superior endowments may reduce their willingness to adopt agricultural technology in the face of natural disasters. However, compared with the formal system, the consultation system, organizational rules, resource allocation, and information supply provided by collective action can effectively improve the uncertainty of natural disasters [53,54,56]. Secondly, farmland transferees also suffer economic losses caused by natural disasters. In this regard, collective action can significantly improve transferees' agricultural income by reducing transaction costs, controlling product quality, expanding product sales channels, and increasing bargaining power [112–114], which is also the core driving force behind the transferees' continued adoption of no-tillage technology. Thirdly, adopting no-tillage technology requires mechanized implementation, so collective action is likely to improve infrastructure in rural areas and build a mutual sharing mechanism of no-tillage machinery for members [115–117]. All these factors enable transferees to improve their adoption rate and degree of no-tillage technology.

The results also showed that some control variables significantly influence the transferees' adoption decisions and degree of no-tillage technology. Specifically, educational level positively and substantially impacts the adoption decision at 5% and 1%, respectively, and the marginal effects are 0.063 and 0.013, indicating that if the educational level increase by 1 year, the adoption rate and adoption degree of no-tillage technology will increase by 6.3% and 1.3%, respectively. The results correspond well with the study of Kumar et al. [118], who also revealed that educational facilities in rural areas help farmers adopt agricultural technology. Education level is the basis of capital endowment, which determines the ability of farmers to acquire, use, and disseminate agricultural technology information [119]. Agricultural income also showed a positive and significant impact on the adoption decision and adoption degree at1% and 5%, respectively. The marginal effects are 0.171 and 0.090, indicating that if agricultural income increases by CNY 10,000, the adoption rate and adoption degree will increase by 17.1% and 9.0%, respectively. The findings of Lampach et al. [120] also showed that agricultural income promotes farmers' adoption of capital-intensive agricultural technologies. No-tillage adoption is also capital-intensive, requiring mechanized farming and agricultural income investment. Likewise, the results of the farmland area also showed a positive and significant influence on the transferees' adoption decisions and adoption degree of no-tillage technology at a 5% level. The marginal effects are 0.075 and 0.048, indicating that if the farmland area increases by 1 mu, the adoption rate and adoption degree of no-tillage technology will increase by 7.5% and 4.8%, respectively. Consistent with the studies of Ola and Menapace [121] and Chen et al. [122], the findings stated that the promotion and expansion of modern agricultural technology are possible in large-scale farmland areas, which leads to the orderly connection between small farmers and modern agriculture.

The results in the case of farmland lease term also showed a positive and significant impact on the transferee's adoption decisions and adoption degree of no–tillage-tillage technology at a 1% level, with marginal effects of 0.172 and 0.185, respectively; thisindicates that if the farmland lease term increases by 1 year, the adoption rate and adoption degree will increase by 17.2% and 18.5%, respectively. Consistent with the findings of Cao et al. [123] and Kehinde et al. [124], the farmland lease term represents the stability of land use rights and impacts farmers' production investment. Meanwhile, no-tillage technology has typical intertemporal economic properties. With a longer farmland lease term, the farmland transferee can increase the adoption of no-tillage technology [23]. Training in no-tillage technology also showed a positive and significant impact on the transferees' adoption decisions and adoption degree of no-tillage technology at a 1% level, with marginal effects of 0.138 and 0.141, indicating that if the transferee is trained in no-tillage technology, the adoption rate and adoption degree of no-tillage technology will increase by 13.8% and 14.1%, respectively. Previous researchers proved that those skill constraints are a bottleneck for small farmers in adopting modern technologies [125,126]. Thus, it is proposed that if the agricultural sector carries out no-tillage skill training, it can boost the transferees' technical knowledge and operation methods, benefit perception, and motivate them to adopt no-tillage technology.

4.3. Robustness Check

For the robustness check, the current study employed model replacement, variable substitution, and sample compression [11,67,105]. To further test the robustness, this paper relaxed the conditional constraints of the Heckman two-stage model. It used the Probit and Tobit models to estimate the impact of natural disaster shock and collective action on the transferees' adoption decisions and adoption degree of no-tillage technology. The robustness estimation results in Table 7 are consistent with the benchmark regression results (as shown in Table 6). The marginal effect value slightly increases, indicating that the Heckman two-stage model has good robustness.

Table 7. Results of the robustness test.

Variables	Model 3		Model 4	
	First Stage: Adoption Decision	**Second Stage: Adoption Degree**	**First Stage: Adoption Decision**	**Second Stage: Adoption Degree**
Natural disaster shock	0.289 *** (0.087)	0.115 * (0.061)	0.262 *** (0.077)	0.131 * (0.074)
Collective action	0.174 *** (0.061)	0.095 * (0.052)	0.145 *** (0.053)	0.074 * (0.042)
Natural disaster shock * collective action	——	——	0.231 * (0.125)	0.092 * (0.052)
Control variables	Controlled		Controlled	

Notes: Marginal effects are reported in the table, and standard errors are presented in parentheses. The significance levels at 1% and 10% are represented by *** and *, respectively. Source: authors' computation.

4.4. Heterogeneity Analysis

4.4.1. Heterogeneity Analysis Based on Gender

Due to various factors such as customs, role division, resource acquisition, and social discrimination, gender differences have always been the first factor in exploring and comparing the motivations of different-gendered farmers' behavior [127–129]. The study used grouped regression to analyze the impact of natural disaster shock and collective action on the adoption of no-tillage technology by different-gendered transferees. In the sample, there are 385 male-headed households and 236 female-headed households. The Model 5 and 6 estimation results (Table 8) show that natural disaster shock and collective action have a positive effect. Meanwhile, collective action still has a moderating effect. Inconsistent with the findings of Jia and Lu [32] and Si et al. [130], our study confirms that amale transferee is more willing to engage in prestigious and public-value affairs. At the same time, females are more concerned with handling family affairs and pays less attention to investment in agricultural production or technology adoption [131]. From implicit constraints, women are disempowered due to cultural restrictions. They encounter gender discrimination in public affairs and are even excluded from family investment decisions [132,133].

Table 8. Model estimation based on gender heterogeneity.

Variables	Male (Model 5)		Female (Model 6)	
	First Stage: Adoption Decision	Second Stage: Adoption Degree	First Stage: Adoption Decision	Second Stage: Adoption Degree
Natural disaster shock	0.103 ** (0.050)	0.095 * (0.051)	0.061 (0.072)	0.038 (0.054)
Collective action	0.071 * (0.061)	0.065 * (0.034)	0.045 (0.061)	0.066 (0.047)
Natural disaster shock * collective action	0.035 * (0.019)	0.022 * (0.012)	0.035 (0.075)	0.012 (0.020)
Control variables	Controlled		Controlled	
Sample size	385		236	

Notes: Marginal effects are reported in the table, and standard errors are presented in parentheses. The significance levels at 5% and 10% are represented by ** and *, respectively. Source: authors' computation.

4.4.2. Heterogeneity Analysis Based on Organizational Participation

The core path for small farmers integrating into the modern agricultural industry chain is organizational participation [134–136]. Organizational participation can affect farmers' production behavior through technology supply, information acquisition, standardized production, and product sales [137,138]. The study employed grouped regression to analyze the influence of natural disaster shock and collective action on the adoption of no-tillage technology by the different transferees. In the sample, there are 374 transferees joining cooperatives and 247not joining cooperatives. The Model 7 and 8 estimation results show (Table 9) that natural disaster shock and collective action positively and significantly influence the transferee who joins a cooperative but not the transferee who does not join a cooperative. Meanwhile, collective action also has a moderating effect. Consistent with the findings of Ma et al. [139], cooperatives enhance the enthusiasm of farmland transferees to participate in collective action and further augment the influence of collective action. Additionally, by obtaining the latest market, service, and technical information, cooperatives can motivate transferees to adopt no-tillage technology, improve agricultural products' quality and market competitiveness, and alleviate production losses caused by natural disasters [140,141].

Table 9. Model estimation based on organizational-participation heterogeneity.

Variables	Joining Cooperatives (Model 7)		Not Joining Cooperatives (Model 8)	
	First Stage: Adoption Decision	Second Stage: Adoption Degree	First Stage: Adoption Decision	Second Stage: Adoption Degree
Natural disaster shock	0.085 ** (0.041)	0.035 * (0.019)	0.072 (0.077)	0.035 (0.074)
Collective action	0.064 ** (0.032)	0.025 ** (0.012)	0.041 (0.053)	0.024 (0.042)
Natural disaster shock * collective action	0.021 * (0.012)	0.042 ** (0.020)	0.036 (0.125)	0.049 (0.052)
Control variables	Controlled		Controlled	
Sample size	374		247	

Notes: Marginal effects are reported in the table, and standard errors are presented in parentheses. The significance levels at 5% and 10% are represented by ** and *, respectively. Source: authors' computation.

5. Conclusions and Policy Implications

The Paris Agreement on Climate Change aims to keep the global average temperature rise within 2 °C of pre-industrial levels [142]. Climate change and natural disasters have become the most critical constraints for developing countries to eliminate poverty, food crisis, and public health issues [143,144]. Improving farmers' adoption of climate change-adapting technologies has become an essential issue in agricultural economics that needs to be solved urgently [145]. Meanwhile, the income gap between the rich and the poor and between rural and urban residents has also widened [146]. Moreover, industrial income growth has also attracted many rural laborers to migrate to cities, leading to the transference of farmland and the weakening of collective action in developing countries. In this vein, boosting farmland transferees' enthusiasm to participate in rural collective action has become the key to strengthening rural public-affairs governance [61].

Moreover, no-tillage technology not only has the advantage of coping with natural disaster shocks such as drought and floods, but also requires collective action to promote it. In practice, the technology adoption rate of farmland transferees is relatively low. Therefore, determining what key factors restrict farmland transferees' adoption of no-tillage technology is of great significance for promoting technology adoption and modern agricultural development. This study incorporates natural disaster shock and collective action into a unified analytical framework and employs Heckman's two-stage and moderating-effect model to explore the effects and path of natural disaster shock and collective action on the adoption of no-tillage technology by farmland transferees. The findings revealed that natural disaster shock and collective action positively and significantly influence transferees' no-tillage technology adoption. The effects of natural disaster shock and collective action on transferees' adoption decisions are more significant than their impact on the adoption degree. Moreover, some control variables, such as educational level, agricultural income, and farmland area, were also found to be significant in influencing transferees' no-tillage technology adoption. Additionally, it is found that collective action positively moderates the impact of natural disaster shock on the adoption of no-tillage technology by farmland transferees. If transferees' participation degree in collective action increases by one unit, the effects of natural disaster shock on the adoption rate and adoption degree of no-tillage technology will increase by 19.2% and 7.4%, respectively. Finally, heterogeneity analysis showed that natural disaster shock and collective action positively and significantly influenced the adoption of no-tillage technologies by male transferee, as did joining cooperatives.

This study provides some valuable insights for policymakers based on the research findings. Firstly, the government should focus on publicity and the training of farmland transferees and continuously improve their cognitive level concerning the harm of natural disasters and the function of no-tillage technology through diversified publicity modes such as media dissemination, centralized training, and typical demonstrations. Secondly, the government should cultivate elite groups that drive and develop rural industries and guide transferees to adopt and promote no-tillage technology through cooperation and mutual assistance. Meanwhile, the government should direct transferees to innovate the participation model and improve the organization of collective action and the level of participatory management. Thirdly, the government should raise the subsidy standard for no-tillage technology adoption and no-tillage machinery, which may effectively ease transferees' credit constraints and pressure. Meanwhile, the government should encourage long-term farmland transfer and continuously improve the scale and mechanization of agricultural production. Finally, the government should provide credit support for transferees, encourage them to extend the agricultural industry chain, increase the added value of agricultural products, create a scale effect and brand effect from high-quality products, and continuously increase the agricultural income and "adsorption" effect of no-tillage technology adoption.

6. Limitation

Of course, this study still has some shortcomings. Firstly, sample selection bias is caused by the transferees' adoption decisions, and explanatory variables that affect both the core and the explained variables are omitted. These issues may cause the endogeneity of model estimation. Limited by the sample data, the study did not find suitable instrumental variables to deal with. Secondly, the study only used natural disaster data over the past three years to measure the intensity of natural disaster shock. However, natural disasters are volatile over time, and short-term data may lead to biased results. Finally, transferees' participation in collective action is closely related to social capital, while social capital is highly heterogeneous. The study did not consider the heterogeneity of social capital. Of course, these issues provide focus and direction for future in-depth research.

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References

1. Abid, M.; Scheffran, J.; Schneider, U.A.; Ashfaq, M. Farmers' perceptions of and adaptation strategies to climate change and their determinants: The case of Punjab province, Pakistan. *Earth Syst. Dyn.* **2015**, *6*, 225–243. [CrossRef]
2. Fosu–Mensah, B.Y.; Vlek, P.L.G.; MacCarthy, D.S. Farmers'perception and adaptation to climate change: A case study of Sekyedumase district in Ghana. *Environ. Dev. Sustain.* **2012**, *14*, 495–505. [CrossRef]
3. Wreford, A.; Topp, C.F.E. Impacts of climate change on livestock and possible adaptations: A case study of the United Kingdom. *Agric. Syst.* **2020**, *178*, 102737. [CrossRef]
4. Walshe, R.A.; Seng, D.C.; Bumpus, A.; Auffray, J. Perceptions of adaptation, resilience and climate knowledge in the Pacific: The cases of Samoa, Fiji and Vanuatu. *Int. J. Clim. Chang. Strateg. Manag.* **2018**, *10*, 303–322. [CrossRef]
5. Jha, C.K.; Gupta, V. Farmer's perception and factors determining the adaptation decisions to cope with climate change: An evidence from rural India. *Environ. Sustain. Indic.* **2021**, *10*, 100112. [CrossRef]
6. Kalele, D.N.; Ogara, W.O.; Oludhe, C.; Onono, J.O. Climate change impacts and relevance of smallholder farmers'response in arid and semi–arid lands in Kenya. *Sci. Afr.* **2021**, *12*, e00814. [CrossRef]
7. Papa, C.; Nzokou, P.; Mbow, C. Farmer livelihood strategies and attitudes in response to climate change in agroforestry systems in Kedougou, Senegal. *Environ. Manag.* **2020**, *66*, 218–231. [CrossRef]
8. Khan, I.; Lei, H.; Shah, I.A.; Ali, I.; Khan, I.; Muhammad, I.; Huo, X.; Javed, T. Farm households'risk perception, attitude and adaptation strategies in dealing with climate change: Promise and perils from rural Pakistan. *Land Use Policy* **2020**, *91*, 104395. [CrossRef]
9. Chhogyel, N.; Kumar, L.; Bajgai, Y.; Hasan, M.K. Perception of farmers on climate change and its impacts on agriculture across various altitudinal zones of Bhutan Himalayas. *Int. J. Environ. Sci. Technol.* **2020**, *17*, 3607–3620. [CrossRef]
10. Chukwuone, N.A.; Amaechina, E.C. Factors affecting climate change coping strategies used by smallholder farmers under root crop farming systems in derived savannah ecology zone of Nigeria. *Environ. Dev.* **2021**, *39*, 100627. [CrossRef]
11. Tan, Y.; Sarkar, A.; Rahman, A.; Qian, L.; Memon, W.H.; Magzhan, Z. Does external shock influence farmer's adoption of modern irrigation technology?—A case of Gansu Province, China. *Land* **2021**, *10*, 882. [CrossRef]
12. Antwi–Agyei, P.; Nyantakyi–Frimpong, H. Evidence of climate change coping and adaptation practices by smallholder farmers in northern ghana. *Sustainability* **2021**, *13*, 1308. [CrossRef]
13. Bello, M.; Salau, S.E.; Galadima, O.E.; Ali, I. Knowledge, perception and adaptation strategies to climate change among farmers of central state Nigeria. *Sustain. Agric. Res.* **2013**, *2*, 107. [CrossRef]
14. Paudel, B.; Acharya, B.S.; Ghimire, R.; Dahal, K.R.; Bista, P. Adapting agriculture to climate change and variability in Chitwan: Long–Term trends and farmers'perceptions. *Agric. Res.* **2014**, *3*, 165–174. [CrossRef]

15. Chuang, L.; Hongyuan, Z.; Na, L. No–tillage mulching increases organic carbon and microbial diversity in moderately saline–alkali soil aggregates. *J. Agric. Eng.* **2019**, *35*, 116–124.
16. Thomas, G.A.; Titmarsh, G.W.; Freebairn, D.M.; Radford, B.J. No–tillage and conservation farming practices in grain growing areas of Queensland—A review of 40 years of development. *Aust. J. Exp. Agric.* **2007**, *47*, 887–898. [CrossRef]
17. Chan, K.Y.; Pratley, E.J. Soil structural decline and the trend were reversed. *Agriculture* **1998**, *4*, 129–143.
18. Ma, S.; Xie, L.; Zhu, G. Reflections on conservation tillage technology of black soil. *Maize Sci.* **2018**, *26*, 116–119.
19. Lu, Z.; Su, M. A review of soil and water conservation tillage measures. *Bull. Soil Water Conserv.* **1983**, *12*, 86–93.
20. Chen, Q.; Sun, T.; Song, C. Effects of no–tillage on soil physical properties and crop yield. *Grass Ind. Sci.* **2014**, *31*, 650–658.
21. Wei, H.; Wang, S.; Yang, W.; Sun, H.; Yin, L.; Deng, X. Integrated analysis of the effects of no–tillage and subsoil tillage on yield and water use efficiency of spring maize and winter wheat in the Loess Plateau. *Chin. Agric. Sci.* **2017**, *50*, 461–477.
22. Qiu, H.; Su, L.; Zhang, Y.; Tang, J. Risk appetite, risk perception and farmers' adoption of conservation tillage technology. *China Rural Econ.* **2020**, *12*, 59–79.
23. Si, R.; Lu, Q.; Aziz, N. Does the stability of farmland rental contract & conservation tillage adoption improve family welfare? Empirical insights from Zhangye, China. *Land Use Policy* **2021**, *107*, 105486. [CrossRef]
24. Si, R.; Zhang, X. The impact of the adoption of no–tillage technology on the income structure of households transferring farmland: Based on micro–empirical evidence in Shaanxi, Gansu and Ningxia. *Resour. Environ. Arid Areas* **2022**, *36*, 47–55.
25. Cai, R.; Cai, S. Empirical analysis of conservation tillage technology adoption and its impact on crop yield——Based on the survey data of rice growers in Anhui province. *Resour. Sci.* **2012**, *34*, 1705–1711.
26. Fei, H.; Liu, W.; Jiang, H. Willingness to adopt conservation tillage technology and analysis of group differences. *Rural Econ.* **2019**, *13*, 122–129.
27. Kurkalova, L.A. Cost–effective placement of best management practices in a watershed:Lessons learned from conservation effects assessment project. *J. Am. Water Resour. Assoc.* **2015**, *51*, 359–372. [CrossRef]
28. Zhang, T.; Yan, T.; Wang, Z. Social networks, income uncertainty, and self–employed women's adoption of conservation farming techniques. *Agric. Technol. Econ.* **2020**, *12*, 101–116.
29. Li, W.; Xue, C.; Yao, S.; Zhu, R. Farmers'adoption behavior of conservation tillage technology and its influencing factors: An analysis based on 476 farmers in the Loess Plateau. *China Rural Econ.* **2017**, *32*, 44–57.
30. D'Emden, F.H.; Llewellyn, R.S.; Burton, M.P. Adoption of conservation tillage in Australian cropping regions: An application of duration analysis. *Technol. Forecast. Soc. Chang.* **2006**, *73*, 630–647. [CrossRef]
31. Xia, J. *Behavioral Choice of Wheat Growers Using No–Tillage technology and Its Impact on Yield*; Northwest A&F University: Yangling, China, 2020.
32. Jia, R.; Lu, Q. The influence of working outside, female decision–making on the participation of farmers in collective action. *Agric. Technol. Econ.* **2019**, *12*, 122–134.
33. Cao, Y.; Zhang, X.; He, L. Collective Action in maintaining rural infrastructures: Cadre–farmer relationship, institution rules and their interaction terms. *Land Use Policy* **2020**, *99*, 105043. [CrossRef]
34. Fischer, E.; Qaim, M. Linking smallholders to markets:Determinants and impacts of farmer collective action in Kenya. *World Dev.* **2012**, *40*, 1255–1268. [CrossRef]
35. Villamayor–Tomas, S.; Sagebiel, J.; Rommel, J.; Olschewski, R. Types of collective action problems and farmers' willingness to accept agri–environmental schemes in Switzerland. *Ecosyst. Serv.* **2021**, *50*, 101304. [CrossRef]
36. Zhang, X.; Ye, Y.; Wang, M.; Yu, Z.; Luo, J. The micro administrative mechanism of land reallocation in land consolidation: A perspective from collective action. *Land Use Policy* **2018**, *70*, 547–558. [CrossRef]
37. Si, R.; Yao, Y.; Zhang, X.; Lu, Q.; Aziz, N. Exploring the role of contiguous farmland cultivation and adoption of No–tillage technology in improving transferees' income structure:Evidence from China. *Land* **2022**, *11*, 570. [CrossRef]
38. Wang, Y.; Chen, C.; Araral, E. The Effects of Migration on Collective Action in the Commons: Evidence from Rural China. *World Dev.* **2016**, *88*, 79–93. [CrossRef]
39. Vale, P.M. The changing climate of climate change economics. *Ecol. Econ.* **2016**, *23*, 12–19. [CrossRef]
40. China Meteorological Administration. *China's Blue Book on Climate Change*; China Meteorological Administration: Beijing, China, 2018.
41. Xin, Y.; Tao, F. Have the agricultural production systems in the North China Plain changed towards to climate smart agriculture since 2000? *J. Clean. Prod.* **2021**, *299*, 126940. [CrossRef]
42. Li, W.; Ruiz–Menjivar, J.; Zhang, L.; Zhang, J. Climate change perceptions and the adoption of low–carbon agricultural technologies: Evidence from rice production systems in the Yangtze River Basin. *Sci. Total Environ.* **2021**, *759*, 143554. [CrossRef]
43. District, R.; Dawadi, B.; Shrestha, A.; Hari, R.; Prasad, Y. Regional sustainability impact of climate change on agricultural production: A case of Rasuwa District, Nepal. *Reg. Sustain.* **2022**, *3*, 122–132. [CrossRef]
44. Chi, G.; Gao, J.; Wang, D.; Hagedorn, A.; Kelgenbaeva, K.; Smith, M.L.; Henebry, G.M. Agricultural production at the oblast level in post–Soviet Kyrgyzstan, 1990–2014: Implications of demographic and climate changes. *Res. Glob.* **2020**, *2*, 100027. [CrossRef]
45. Bauer, T.; de Jong, W.; Ingram, V.; Arts, B.; Pacheco, P. Thriving in turbulent times: Livelihood resilience and vulnerability assessment of Bolivian Indigenous forest households. *Land Use Policy* **2022**, *119*, 106146. [CrossRef]
46. Morshed, M.; Yaseen, M.; Saqib, S.E. Climate change impacts of drought on the livelihood of dryland smallholders: Implications of adaptation challenges. *Int. J. Disaster Risk Reduct.* **2022**, *80*, 103210. [CrossRef]

47. Campbell, D. Environmental change and the livelihood resilience of coffee farmers in Jamaica: A case study of the Cedar Valley farming region. *J. Rural Stud.* **2021**, *81*, 220–234. [CrossRef]
48. Arhin, P.; Erdiaw–Kwasie, M.O.; Abunyewah, M. Displacements and livelihood resilience in Ghana's mining sector: The moderating role of coping behaviour. *Resour. Policy* **2022**, *78*, 102820. [CrossRef]
49. Wale, E.; Nkoana, M.A.; Mkuna, E. Climate change–induced livelihood adaptive strategies and perceptions of forest–dependent communities: The case of Inanda, KwaZulu–Natal, South Africa. *Trees For. People* **2022**, *8*, 100250. [CrossRef]
50. Wang, Y.; Zhang, Q.; Li, Q.; Wang, J.; Sannigrahi, S.; Bilsborrow, R.; Bellingrath-Kimura, S.D.; Li, J.; Song, C. Role of social networks in building household livelihood resilience under payments for ecosystem services programs in a poor rural community in China. *J. Rural Stud.* **2021**, *86*, 208–225. [CrossRef]
51. Pierotti, R.S.; Friedson–Ridenour, S.; Olayiwola, O. Women farm what they can manage: How time constraints affect the quantity and quality of labor for married women's agricultural production in southwestern Nigeria. *World Dev.* **2022**, *152*, 105800. [CrossRef]
52. Jara-Rojas, R.; Bravo-Ureta, B.E.; Engler, A.; Díaz, J. An analysis of the joint adoption of water conservation and soil conservation in Central Chile. *Land Use Policy* **2013**, *32*, 292–301. [CrossRef]
53. Ayres, A.B.; Edwards, E.C.; Libecap, G.D. How transaction costs obstruct collective action: The case of California's groundwater. *J. Environ. Econ. Manag.* **2018**, *91*, 46–65. [CrossRef]
54. Willy, D.K.; Holm-Müller, K. Social influence and collective action effects on farm level soil conservation effort in rural Kenya. *Ecol. Econ.* **2013**, *90*, 94–103. [CrossRef]
55. Liu, P.; Ravenscroft, N. Collective action in implementing top–down land policy: The case of Chengdu, China. *Land Use Policy* **2017**, *65*, 45–52. [CrossRef]
56. Takeda, M.; Takahashi, D.; Shobayashi, M. Collective action vs. conservation auction: Lessons from a social experiment of a collective auction of water conservation contracts in Japan. *Land Use Policy* **2015**, *46*, 189–200. [CrossRef]
57. Gelo, D.; Muchapondwa, E.; Shimeles, A.; Dikgang, J. Aid, collective action and benefits to smallholders: Evaluating the World Food Program's purchase for progress pilot. *Food Policy* **2020**, *97*, 101911. [CrossRef]
58. Ostrom, E.; Cox, M. Moving beyond panaceas:A multi–tiered diagnostic approach for social–ecological analysis. *Environ. Conserv.* **2010**, *37*, 451–463. [CrossRef]
59. Cai, Q.; Zhu, Y. The impact of social capital and income gap on collective action in villages: Taking farmers' participation in the maintenance of small farmland water conservancy facilities as an example. *J. Public Adm.* **2016**, *13*, 89–100.
60. Tembata, K.; Takeuchi, K. Collective decision making under drought: An empirical study of water resource management in Japan. *Water Resour. Econ.* **2018**, *22*, 19–31. [CrossRef]
61. Bisung, E. Community based collective action for safe water in rural sub–Saharan Africa. *Water Secur.* **2021**, *13*, 100088. [CrossRef]
62. Rosas–mu, J. What can we learn about the natural disasters and multidimensional poverty link for artisanal fishery in Chile? *Mar. Policy* **2022**, *144*, 105225. [CrossRef]
63. Warr, P.; Aung, L.L. Poverty and inequality impact of a natural disaster: Myanmar's 2008 cyclone Nargis. *World Dev.* **2019**, *122*, 446–461. [CrossRef]
64. Alizadeh, B.; Hitchmough, J.D. How will climate change affect future urban naturalistic herbaceous planting? The role of plant origin and fitness. *Urban For. Green.* **2020**, *54*, 126786. [CrossRef]
65. Jia, R.; Lu, Q. Does land transfer promote the implementation of soil and water conservation measures for farmers in the Loess Plateau?—Analysis based on the mediating effect of collective action and the moderating effect of government subsidies. *China Rural Econ.* **2018**, *6*, 35–54.
66. Gao, Y.; Zhao, D.; Yu, L.; Yang, H. Influence of a new agricultural technology extension mode on farmers' technology adoption behavior in China. *J. Rural Stud.* **2020**, *76*, 173–183. [CrossRef]
67. Xie, H.; Huang, Y. Influencing factors of farmers' adoption of pro–environmental agricultural technologies in China: Meta–analysis. *Land Use Policy* **2021**, *109*, 105622. [CrossRef]
68. Mao, H.; Zhou, L.; Ying, R.Y.; Pan, D. Time Preferences and green agricultural technology adoption: Field evidence from rice farmers in China. *Land Use Policy* **2021**, *109*, 105627. [CrossRef]
69. Ahmed, Z.; Shew, A.M.; Mondal, M.K.; Yadav, S.; Jagadish, S.V.K.; Prasad, P.V.V.; Buisson, M.; Das, M. Climate risk perceptions and perceived yield loss increases agricultural technology adoption in the polder areas of Bangladesh. *J. Rural Stud.* **2022**, *94*, 274–286. [CrossRef]
70. Musyoki, M.E.; Busienei, J.R.; Gathiaka, J.K.; Karuku, G.N. Linking farmers'risk attitudes, livelihood diversification and adoption of climate smart agriculture technologies in the Nyando basin, South–Western Kenya. *Heliyon* **2022**, *8*, e09305. [CrossRef]
71. Wongnaa, C.A.; Apike, I.A.; Babu, S.; Awunyo–Vitor, D.; Kyei, A.B. The impact of adoption of artificial pollination technology in cocoa production: Evidence from Ghana. *J. Agric. Food Res.* **2021**, *6*, 100208. [CrossRef]
72. Mello, B.V.M.; Macchione Saes, M.S.; Carrer, M.J.; Meirelles de Souza Filho, H. The effect of meso–institutions on adoption of sustainable agricultural technology: A case study of the Brazilian Low Carbon Agriculture Plan. *J. Clean. Prod.* **2021**, *280*, 124334. [CrossRef]
73. Li, M.; Yan, X.; Guo, Y.; Ji, H. Impact of risk awareness and agriculture cooperatives' service on farmers' safe production behaviour: Evidences from Shaanxi Province. *J. Clean. Prod.* **2021**, *312*, 127724. [CrossRef]

74. De Lauwere, C.; Slegers, M.; Meeusen, M. The influence of behavioural factors and external conditions on Dutch farmers ' decision making in the transition towards circular agriculture. *Land Use Policy* **2022**, *120*, 106253. [CrossRef]
75. Castro Campos, B. The Rules–Boundaries–Behaviours (RBB) framework for farmers'adoption decisions of sustainable agricultural practices. *J. Rural Stud.* **2022**, *92*, 164–179. [CrossRef]
76. Kiriyama, H.; Matsuda, H.; Kamiji, Y.; Morita, S. Nitrogen stock and farmer behaviour under rice policy change in Japan. *J. Environ. Manag.* **2021**, *299*, 113438. [CrossRef] [PubMed]
77. Qiu, X.; Jin, J.; He, R.; Mao, J. The deviation between the willingness and behavior of farmers to adopt electricity–saving tricycles and its influencing factors in Dazu District of China. *Energy Policy* **2022**, *167*, 113069. [CrossRef]
78. Jumpah, E.T.; Adams, A.; Ayeduvor, S. Estimating yield and income effects of formal credit–based programme among tomato farmers in the Greater Accra Region of Ghana. *Sci. Afr.* **2020**, *9*, e00499. [CrossRef]
79. Musafiri, C.M.; Kiboi, M.; Macharia, J.; Ng, O.K.; Okoti, M.; Mulianga, B.; Kosgei, D.K.; Ngetich, F.K. Does the adoption of minimum tillage improve sorghum yield among smallholders in Kenya? A counterfactual analysis. *Soil Tillage Res.* **2022**, *223*, 105473. [CrossRef]
80. Si, R.; Zhang, X.; Yao, Y.; Zhang, S.; Wang, H. Unpacking the myth between increased government initiatives and reduced selling of dead live stocks in China: An approach towards exploring hidden danger of zoonotic diseases. *One Health* **2021**, *13*, 100344. [CrossRef]
81. Abbasi, S.; Ko, J.; Kim, J. Carsharing station location and demand: Identification of associated factors through Heckman selection models. *J. Clean. Prod.* **2021**, *279*, 123846. [CrossRef]
82. Lachos, V.H.; Prates, M.O.; Dey, D.K. Heckman selection–t model: Parameter estimation via the EM–algorithm. *J. Multivar. Anal.* **2021**, *184*, 104737. [CrossRef]
83. Sarma, P.K. Adoption and impact of super granulated urea (guti urea) technology on farm productivity in Bangladesh: A Heckman two–stage model approach. *Environ. Chall.* **2021**, *5*, 100228. [CrossRef]
84. Tan, Y.; Lu, Q. Effects of risk avoidance and social learning on farmers'adoption behavior of modern irrigation technology: An empirical analysis based on Heckman's sample selection model. *Resour. Environ. Yangtze River Basin* **2021**, *30*, 234–245.
85. Riccò, M.; Ranzieri, S.; Balzarini, F.; Bragazzi, N.L.; Corradi, M. SARS–CoV–2 infection and air pollutants: Correlation or causation? *Sci. Total Environ.* **2020**, *734*, 139489. [CrossRef] [PubMed]
86. Parise, C.V.; Spence, C.; Ernst, M.O. When correlation implies causation in multisensory integration. *Curr. Biol.* **2012**, *22*, 46–49. [CrossRef]
87. Osberghaus, D.; Fugger, C. Natural disasters and climate change beliefs: The role of distance and prior beliefs. *Glob. Environ. Chang.* **2022**, *74*, 102515. [CrossRef]
88. Cappelli, F.; Costantini, V.; Consoli, D. The trap of climate change–induced "natural" disasters and inequality. *Glob. Environ. Chang.* **2021**, *70*, 102329. [CrossRef]
89. Guo, A.; Wei, Y.; Zhong, F.; Wang, P. How do climate change perception and value cognition affect farmers' sustainable livelihood capacity? An analysis based on an improved DFID sustainable livelihood framework. *Sustain. Prod. Consum.* **2022**, *33*, 636–650. [CrossRef]
90. Petersen–rockney, M. Social risk perceptions of climate change: A case study of farmers and farm advisors in. *Glob. Environ. Chang.* **2022**, *75*, 102557. [CrossRef]
91. Andati, P.; Majiwa, E.; Ngigi, M.; Mbeche, R.; Ateka, J. Determinants of adoption of climate smart agricultural technologies among potato farmers in Kenya: Does entrepreneurial orientation play a role? *Sustain. Technol. Entrep.* **2022**, *1*, 100017. [CrossRef]
92. Kifle, T.; Ayal, D.Y.; Mulugeta, M. Factors influencing farmers adoption of climate smart agriculture to respond climate variability in Siyadebrina Wayu District, Central highland of Ethiopia. *Clim. Serv.* **2022**, *26*, 100290. [CrossRef]
93. Akimowicz, M.; Del Corso, J.P.; Gallai, N.; Képhaliacos, C. Adopt to adapt? Farmers' varietal innovation adoption in a context of climate change. The case of sunflower hybrids in France. *J. Clean. Prod.* **2021**, *279*, 123654. [CrossRef]
94. Shi, W.; Wang, M.; Liu, Y. Crop yield and production responses to climate disasters in China. *Sci. Total Environ.* **2021**, *750*, 141147. [CrossRef] [PubMed]
95. Yang, Y.; Li, K.; Wei, S.; Guga, S.; Zhang, J. Spatial–temporal distribution characteristics and hazard assessment of millet drought disaster in Northern China under climate change. *Agric. Water Manag.* **2022**, *272*, 107849. [CrossRef]
96. Ding, Y.; Schoengold, K.; Tadesse, T. The impact of weather extremes on agricultural production methods: Does drought increase adoption of conservation tillage practices? *J. Agric. Resour. Econ.* **2009**, *34*, 395–411.
97. Ianoş, I.; Ionică, C.; Sîrodoev, I.; Sorensen, A.; Bureţa, E.; Merciu, G.; Paraschiv, M.; Tălângă, C. Inadequate risk management and excessive response to flood disaster create unexpected land use changes and potential local conflicts. *Land Use Policy* **2019**, *88*, 104081. [CrossRef]
98. Parven, A.; Pal, I.; Witayangkurn, A.; Pramanik, M.; Nagai, M.; Miyazaki, H.; Wuthisakkaroon, C. Impacts of disaster and land–use change on food security and adaptation: Evidence from the delta community in Bangladesh. *Int. J. Disaster Risk Reduct.* **2022**, *78*, 103119. [CrossRef]
99. Tan, Q.; Huang, G.; Cai, Y.; Yang, Z. A non–probabilistic programming approach enabling risk–aversion analysis for supporting sustainable watershed development. *J. Clean. Prod.* **2016**, *112*, 4771–4788. [CrossRef]
100. Kaluszka, M.; Krzeszowiec, M. On risk aversion under fuzzy random data. *Fuzzy Sets Syst.* **2017**, *328*, 35–53. [CrossRef]

101. Bijttebier, J.; Ruysschaert, G.; Hijbeek, R.; Werner, M.; Pronk, A.A.; Zavattaro, L.; Bechini, L.; Grignani, C.; Ten Berge, H.; Marchand, F.; et al. Adoption of non–inversion tillage across Europe: Use of a behavioural approach in understanding decision making of farmers. *Land Use Policy* **2018**, *78*, 460–471. [CrossRef]
102. Harper, J.K.; Roth, G.W.; Garalejić, B.; Škrbić, N. Programs to promote adoption of conservation tillage: A Serbian case study. *Land Use Policy* **2018**, *78*, 295–302. [CrossRef]
103. Foguesatto, C.R.; Machado, J.A.D. Adoption of sustainable agricultural practices in Brazil: Understanding the influence of socioeconomic and psychological factors. *Econ. J. Agribus. Dev. Emerg.* **2022**, *12*, 204–222. [CrossRef]
104. Chidambaram, S. How do institutions and infrastructure affect mobilization around public toilets vs. piped water? Examining intra–slum patterns of collective action in Delhi, India. *World Dev.* **2020**, *132*, 104984. [CrossRef]
105. Corsi, S.; Marchisio, L.V.; Orsi, L. Connecting smallholder farmers to local markets: Drivers of collective action, land tenure and food security in East Chad. *Land Use Policy* **2017**, *68*, 39–47. [CrossRef]
106. Orsi, L.; De Noni, I.; Corsi, S.; Marchisio, L.V. The role of collective action in leveraging farmers' performances: Lessons from sesame seed farmers' collaboration in eastern Chad. *J. Rural Stud.* **2017**, *51*, 93–104. [CrossRef]
107. Wang, Y.; Yiqing, S.; Shu, Q. Labor outflow, rural collective action and rural revitalization. *J. Tsinghua Univ.* **2022**, *37*, 173–187.
108. Hao, P.; He, S. What is holding farmers back? Endowments and mobility choice of rural citizens in China. *J. Rural Stud.* **2022**, *89*, 66–72. [CrossRef]
109. Wang, W.; Lan, Y.; Wang, X. Impact of livelihood capital endowment on poverty alleviation of households under rural land consolidation. *Land Use Policy* **2021**, *109*, 105608. [CrossRef]
110. Mi, Q.; Li, X.; Li, X.; Yu, G.; Gao, J. Cotton farmers'adaptation to arid climates: Waiting times to adopt water–saving technology. *Agric. Water Manag.* **2021**, *244*, 106596. [CrossRef]
111. Tesfaye, M.Z.; Balana, B.B.; Bizimana, J.C. Assessment of smallholder farmers'demand for and adoption constraints to small–scale irrigation technologies: Evidence from Ethiopia. *Agric. Water Manag.* **2021**, *250*, 106855. [CrossRef]
112. Nie, S.; Wang, Z.; Pujia, W.; Nie, Y.; Lu, P. Big data prediction of durations for online collective actions based on peak's timing. *Phys. A Stat. Mech. Its Appl.* **2018**, *492*, 138–154. [CrossRef]
113. Gyau, A.; Franzel, S.; Chiatoh, M.; Nimino, G.; Owusu, K. Collective action to improve market access for smallholder producers of agroforestry products: Key lessons learned with insights from Cameroon's experience. *Curr. Opin. Environ. Sustain.* **2014**, *6*, 68–72. [CrossRef]
114. Willy, D.K.; Ngare, L.W. Analysis of participation in collective action initiatives for addressing unilateral agri–environmental externalities. *Environ. Sci. Policy* **2021**, *117*, 1–7. [CrossRef]
115. Lv, L.; Gao, Z.; Liao, K.; Zhu, Q.; Zhu, J. Soil & Tillage Research Impact of conservation tillage on the distribution of soil nutrients with depth. *Soil Tillage Res.* **2022**, *225*, 105527. [CrossRef]
116. Liu, P.; Zhao, Y.; Ravenscroft, N.; Harder, M.K. Responsibility–driven collective action in the context of rapid rural depopulation. *J. Rural Stud.* **2020**, *75*, 48–56. [CrossRef]
117. Wang, R.; Tan, R. Patterns of rural collective action in contemporary China: An archetype analysis of rural construction land consolidation. *J. Rural Stud.* **2020**, *79*, 286–301. [CrossRef]
118. Kumar, A.; Takeshima, H.; Thapa, G.; Adhikari, N.; Saroj, S.; Karkee, M.; Joshi, P.K. Adoption and diffusion of improved technologies and production practices in agriculture: Insights from a donor–led intervention in Nepal. *Land Use Policy* **2020**, *95*, 104621. [CrossRef]
119. Curry, G.N.; Nake, S.; Koczberski, G.; Oswald, M.; Rafflegeau, S.; Lummani, J.; Peter, E.; Nailina, R. Disruptive innovation in agriculture: Socio–cultural factors in technology adoption in the developing world. *J. Rural Stud.* **2021**, *88*, 422–431. [CrossRef]
120. Lampach, N.; To–The, N.; Nguyen–Anh, T. Technical efficiency and the adoption of multiple agricultural technologies in the mountainous areas of Northern Vietnam. *Land Use Policy* **2021**, *103*, 105289. [CrossRef]
121. Ola, O.; Menapace, L. Smallholders' perceptions and preferences for market attributes promoting sustained participation in modern agricultural value chains. *Food Policy* **2020**, *97*, 101962. [CrossRef]
122. Chen, T.; Rizwan, M.; Abbas, A. Exploring the role of agricultural services in production efficiency in Chinese agriculture: A case of the socialized agricultural service system. *Land* **2022**, *11*, 347. [CrossRef]
123. Cao, Y.; Bai, Y.; Zhang, L. The impact of farmland property rights security on the farmland investment in rural China. *Land Use Policy* **2020**, *97*, 104736. [CrossRef]
124. Kehinde, M.O.; Shittu, A.M.; Adewuyi, S.A.; Osunsina, I.O.O.; Adeyonu, A.G. Land tenure and property rights, and household food security among rice farmers in Northern Nigeria. *Heliyon* **2021**, *7*, e06110. [CrossRef] [PubMed]
125. Okello, D.; Owuor, G.; Larochelle, C.; Gathungu, E.; Mshenga, P. Determinants of utilization of agricultural technologies among smallholder dairy farmers in Kenya. *J. Agric. Food Res.* **2021**, *6*, 100213. [CrossRef]
126. Yang, X.; Zhou, X.; Deng, X. Modeling farmers'adoption of low–carbon agricultural technology in Jianghan Plain, China: An examination of the theory of planned behavior. *Technol. Forecast. Soc. Chang.* **2022**, *180*, 121726. [CrossRef]
127. Unay–Gailhard, İ.; Bojnec, Š. Gender and the environmental concerns of young farmers: Do young women farmers make a difference on family farms? *J. Rural Stud.* **2021**, *88*, 71–82. [CrossRef]
128. Zhao, X.; Ju, S.; Wang, W.; Su, H.; Wang, L. Intergenerational and gender differences in satisfaction of farmers with rural public space: Insights from traditional village in Northwest China. *Appl. Geogr.* **2022**, *146*, 102770. [CrossRef]

129. Nidumolu, U.; Lubbers, M.; Kanellopoulos, A.; van Ittersum, M.K.; Roth, C.H.; Mishra, P.; Bagchi, N.S.; Majumdar, S.; Carter, L.; Rahman, M.W.; et al. Integrating gender and farmer's preferences in a discussion support tool for crop choice. *Agric. Syst.* **2022**, *195*, 103300. [CrossRef]
130. Si, R.; Zhang, X.; Yao, Y.; Lu, Q. Risk preference, health risk perception, and environmental exposure nexus: Evidence from rural women aspig breeders, China. *Soc. Indic. Res.* **2021**, *11*, 151–178. [CrossRef]
131. Doss, C.R.; Morris, M.L. How does gender affect the adoption of agricultural innovations? *Agric. Econ.* **2001**, *25*, 27–39. [CrossRef]
132. Yang, C. Gender, proportional policy and female participation: Taking the election of Tianjin Chuancun village committee as an example. *J. Cent. China Norm. Univ.* **2006**, *45*, 12–17.
133. Ali, M.P.; Kabir, M.M.M.; Haque, S.S.; Qin, X.; Nasrin, S.; Landis, D.; Holmquist, B.; Ahmed, N. Farmer's behavior in pesticide use: Insights study from smallholder and intensive agricultural farms in Bangladesh. *Sci. Total Environ.* **2020**, *747*, 141160. [CrossRef]
134. Ma, W.; Abdulai, A. Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy* **2016**, *58*, 94–102. [CrossRef]
135. Ma, W.; Abdulai, A. The economic impacts of agricultural cooperatives on smallholder farmers in rural China. *Agribusiness* **2017**, *33*, 537–551. [CrossRef]
136. Ma, W.; Abdulai, A. IPM adoption, cooperative membership and farm economic performance: Insight from apple farmers in China. *China Agric. Econ. Rev.* **2019**, *11*, 218–236. [CrossRef]
137. Ma, W.; Abdulai, A.; Goetz, R. Agricultural Cooperatives and Investment in Organic Soil Amendments and Chemical Fertilizer in China. *Am. J. Agric. Econ.* **2018**, *100*, 502–520. [CrossRef]
138. Ma, W.; Renwick, A.; Yuan, P.; Ratna, N. Agricultural cooperative membership and technical efficiency of apple farmers in China: An analysis accounting for selectivity bias. *Food Policy* **2018**, *81*, 122–132. [CrossRef]
139. Ma, W.; Zhu, Z. A Note: Reducing Cropland Abandonment in China—Do Agricultural Cooperatives Play a Role? *J. Agric. Econ.* **2020**, *71*, 929–935. [CrossRef]
140. Manda, J.; Khonje, M.G.; Alene, A.D.; Tufa, A.H.; Abdoulaye, T.; Mutenje, M.; Setimela, P.; Manyong, V. Does cooperative membership increase and accelerate agricultural technology adoption? Empirical evidence from Zambia. *Technol. Forecast. Soc. Chang.* **2020**, *158*, 120160. [CrossRef]
141. Mao, F.; Wang, X.; Kong, X. Financing service supply of farmers' professional cooperatives and its influencing factors. *China Soft Sci.* **2014**, *65*, 26–39.
142. Huang, M.T.; Zhai, P.M. Achieving Paris Agreement temperature goals requires carbon neutrality by middle century with far–reaching transitions in the whole society. *Adv. Clim. Chang. Res.* **2021**, *12*, 281–286. [CrossRef]
143. Li, W.; Yuan, K.; Yue, M.; Zhang, L.; Huang, F. Climate change risk perceptions, facilitating conditions and health risk management intentions: Evidence from farmers in rural China. *Clim. Risk Manag.* **2021**, *32*, 100283. [CrossRef]
144. WMO; UNDRR. *Climate and Weather Related Disasters Surge Five–Fold over 50 Years, but Early Warnings Save Lives–WMO Report*; WMO: Geneva, Switzerland, 2021.
145. Tessema, Y.M.; Asafu-Adjaye, J.; Shiferaw, B. The impact of conservation tillage on maize yield and input demand: The case of smallholder farmers in north-west Ethiopia. *Aust. J. Agric. Resour. Econ.* **2018**, *62*, 636–653. [CrossRef]
146. Zhong, S.; Wang, M.; Zhu, Y.; Chen, Z.; Huang, X. Urban expansion and the urban–rural income gap: Empirical evidence from China. *Cities* **2022**, *129*, 103831. [CrossRef]