Formal Credit Accessibility and Productivity Resilience to Natural Disasters: Evidence from the Qinghai-Tibetan Plateau of China

Yan Zhang[a,1], Zekuan Dong[b,*], Yuan Ning[a]

[a] *State Key Laboratory of Herbage Improvement and Grassland Agro-ecosystems, College of Pastoral Agriculture Science and Technology, Lanzhou University, Lanzhou, China*

[b] *Department of Agricultural, Food, and Resource Economics, Michigan State University, MI, USA*

Abstract

This study examines how formal credit accessibility (FCA) affects the productivity resilience and recovery of pastoral households following natural disasters. Employing a staggered Triple-Differences (staggered DDD) approach on household-level panel data from the Qinghai-Tibetan Plateau (QTP) in China, we find that households with access to formal credit perform a 4.3%–5.6% higher recovery in total factor productivity (TFP) within two years after natural disasters compared to those without such access, and their TFPs even surpass their own pre-disaster productivity levels. These findings highlight the pivotal role of FCA in enhancing disaster recovery, reducing poverty, and promoting ecological sustainability in vulnerable pastoral regions.

Keywords: Livestock productivity; Credit; Qinghai-Tibetan Plateau; Disaster

JEL Codes: D24 Q12 Q14 Q54

---

[1] All authors contributed equally to this work.

* Corresponding author: Zekuan Dong. Email: dongzeku@msu.edu.

Funding: The authors would like to acknowledge funding from the National Natural Science Foundation of China (72303086), National Center of Pratacultural Technology Innovation (under way) Special fund for innovation platform construction (CCPTZX2024QN08), the Leading Scientist Project of Qinghai Province (2023-NK-147), the Consulting Project of Chinese Academy of Engineering (2024-XZ-56).

1 Introduction

Coping with natural disasters is one of the core chapters of the agricultural production history of mankind. Over recent decades, the frequency, intensity, and economic losses associated with natural disasters have increased markedly due to climate change (Coronese et al., 2019; Newman and Noy, 2023; Rahmstorf and Coumou, 2011). Consequently, agricultural sectors face growing threats from these natural disasters (Lobell and Di Tommaso, 2025; Kuwayama et al., 2019). The Qinghai–Tibet Plateau (QTP)—also known as the Tibetan Plateau, Qingzang Plateau, or the "Third Pole"—is the world's largest and highest plateau and hosts one of the most fragile ecosystems on Earth (Xia et al., 2021; You et al., 2020; Wang, Tan, and Fan, 2022). The QTP region has been experiencing warming at a rate approximately three times the global warming rate for more than fifty years (Qiu, 2008). This rapid climate change has triggered diverse environmental responses, including permafrost degradation, glacier melt, ecological system changes, desertification, as well as more frequent and severe natural disasters such as floods, droughts, and landslides (Qiu, 2008; Feng et al., 2020; Qiu, 2016; You et al., 2020). As a result, pastoralist in QTP face increasing challenges in balancing ecological sustainability with grazing activities, as well as the growing production risks from natural disasters (Qiu, 2016).

Financial instruments such as insurance, credit, and government subsidies play vital roles in disaster coping and risk management (Moahid et al., 2023; Freebairn, 1983). Credit—whether formal or informal—can help smooth income and consumption, safeguard food security and productive assets, and avoid the transmission of poverty among disaster-affected populations (Janzen and Carter, 2019; Khandker, 2007; Mozumder et al., 2009). A strand of literature also shows that credit access enhances farm productivity through channels such as technological adoption, efficiency improvement, and improved scale and mix efficiency (Jimi et al., 2019; Dong, Lu, and Featherstone, 2012; O'Donnell, 2012). Although credits can bring many benefits to agricultural production, rural households in the QTP exhibit loan balances roughly 50% lower than the China average and experience slower credit growth (See Figure D1).

This paper investigates the effects of formal credit accessibility (FCA) on pastoral households' total factor productivity (TFP) resilience and post-disaster recovery. Specifically, we employ the staggered triple-differences (staggered DDD) and event study methods to analyze the observations of 553 pastoral households in QTP during 2015 to 2018. We find that the pastoral households with FCA, compared to those without FCA, perform about 4.3% to 5.6% better in TFP recovery after being hit by natural disasters. Dynamic analysis further reveals that, relative to one year before disasters, the TFPs of those pastoral households with FCA would recover about 5.6% more than those without FCA one year after the natural disaster, and about 7.3% more two years afterward. Moreover, TFP for pastoral households with FCA even surpasses their own pre-disaster levels by about 2.5%. These results remain robust across alternative estimation strategies and TFP calculation methods.

In the literature strands of credit accessibility, natural disasters, and productivity, most prior studies have linked only two of these three dimensions. For instance, existing work examines how credit affects agricultural productivity (Jimi et al., 2019; Dong, Lu, and Featherstone, 2012; Zhang et al., 2023), how natural disasters impact productivity (Vigani and Kathage, 2019), or how credit serves as a coping mechanism for disaster shocks (Khandker, 2007) To the best of our knowledge, the study most closely related to ours is Moahid et al. (2023), which explored the effects of agricultural credit on production input expenditure among disaster-affected households. However, due to their use of cross-sectional data, they could only compare input levels across affected farms with or without credit access, without establishing reliable comparisons with unaffected farms or capturing dynamic responses. Although they employ propensity score matching (PSM) methods, endogeneity concerns remain. By contrast, our panel data combined with the usage of staggered DDD framework and PSM method allows for more detailed comparisons and reliable causal identification. We also extend the analysis beyond input decisions to productivity outcomes.

This paper also contributes by providing new insights for agricultural management and poverty alleviation in ecologically vulnerable regions. Our empirical evidence shows that FCA enhances pastoral households' productivity resilience and facilitates post-disaster recovery to levels even exceeding pre-disaster benchmarks. These effects may help reduce the risk of disaster-induced poverty. Moreover, given the ecological fragility of the QTP, the productivity benefits associated with FCA may allow pastoral households greater flexibility in balancing grazing intensity with ecosystem protection. Hence, governments and financial institutions should expand formal credit availability, along with complementary financial risk management tools such as insurance and mutual aid funds, as part of rural development and poverty alleviation strategies. Policymakers might also consider easing credit requirements and increasing lending during post-disaster periods. Such policies not only accelerate recovery but also mitigate environmentally damaging behaviors such as overgrazing in the aftermath of disasters.

The remainder of the paper is arranged as follows. Section 2 provides a background of our study areas and data collection. Section 3 describes our methodology and provides summary statistics. Section 4 reports empirical results, and Section 5 provides a series of robustness checks. Section 6 concludes with policy implications.

2 Background and Data

2.1 Background of QTP

The QTP, with an area spanning about 3.1 million square kilometres and an average elevation of more than 4300 m above sea level (asl), is the world's largest and highest plateau (Du et al., 2004; Zhang, 2021). Approximately 2.58 million square kilometers (about 83.7%) of the QTP are situated within China, while the remaining about 0.5 million square kilometers extend into India, Pakistan, Tajikistan, Afghanistan, Nepal, Bhutan, Myanmar, and Kyrgyzstan (Zhang, 2021). The QTP areas in China are distributed in provinces of Xizang, Qinghai, Xinjiang, Sichuan, Gansu, and Yunnan with the areas of about 1171, 696, 305, 263, 101, and 46 thousand square kilometers, respectively (Zhang, 2021). And about 97% of the areas of the Xizang and Qinghai Provinces are located in QTP (Zhang, 2021).

The QTP, as the Earth's third largest store of ice following the Antarctic and Arctic, serves as the "Asian water tower" that gives rise to many great rivers like the Indus, Ganges, Brahmaputra, Yangtze, and Yellow rivers. The downstream basins of these five rivers provide fresh water for over 1.4 billion people (over 20% of the global population), thus the QTP plays an important role in global water and food security (Qiu, 2008; Immerzeel, Van Beek, and Bierkens, 2010).

The ecosystems in QTP are extremely fragile but play an important role in climatic regulation, water and soil retention, biodiversity conservation, carbon balance, and other environmental issues (Liu et al., 2018; Wang, Tan, and Fan, 2022). However, these vulnerable ecosystems in QTP are under threat from climate change, human activity, and natural hazards. In the past fifty years, the temperature in QTP has been increasing by about 0.3°C per decade, which is approximately three times the global warming rate (Qiu, 2008). This rapid climate change leads to various environmental responses like permafrost degradation, glacier melt, ecological system changes, desertification, as well as more frequent and intense natural disasters such as floods, droughts, and landslides (Qiu, 2008; Feng et al., 2020; Qiu, 2016; You et al., 2020).

The grasslands, which make up nearly two-thirds of the plateau, support livestock grazing as the dominant form of land use in QTP (Harris, 2010; Qiu, 2016). And these grasslands have been suffering from degradation for several decades (Chen et al., 2014; Liu et al., 2018). Although the causes of rangeland degradation remain inconclusive, "over-stocking of livestock, unscientific livestock management, historical-cultural impediments to adopting modern livestock management concepts, global climate change", "excessive herbivory and soil disturbance from small mammals", "rapid changes in socio-economic systems" and "alteration of land tenure arrangements" are proposed as the reasons of the degradation (Harris, 2010).

Due to the complex landscape, harsh natural environment, extremely fragile ecosystem, and rapid environmental changes, residents in QTP have a lower income level but experience more loss from natural disasters. For example, during 2010-2023, the annual average per capita GDP was only about 39,954 Chinese yuan (CNY) in Xizang Province, 42,061 CNY in Qinghai Province, but 59,653 CNY for the whole China mainland. While in the meantime, the annual average direct economic loss per capita from natural disasters is about 548 CNY in Xizang Province, 685 CNY in Qinghai Province, but only 256 CNY for China. Combining these two strands of data, we can see that, due to natural disasters, Xizang loses about 1.77% of its annual GDP, Qinghai loses 2.33%, while this ratio for China mainland is only 0.52%[1]. Since the QTP area is less developed but more disaster-suffered, it's important to explore the potential strategies to cope with natural disasters and alleviate poverty.

2.2 Data

The major data used in this study are the survey data from pastoral households in Gansu, Qinghai, and Xizang Province. In 2017, the grassland areas of Xizang, Qinghai, and Gansu were 70.68, 40.79, and 5.92 million hectares, respectively, and the total production values of the livestock sector were 9.22, 18.30, and 30.90 billion CNY, respectively[2]. And these three provinces take up about 76% of the area of the whole QTP. Thus, taking these three provinces as our study areas can well represent the conditions of the livestock sector in QTP areas.

Our survey was conducted in August and September 2017 and 2019, asking for their information for 2015-2017 and 2016-2018, respectively. The survey collected pastoral households' demographics, like ages, family members, education, health, etc. It also asks about their production information, like the number of different livestock, working hours, grassland conditions, grazing inputs, production and living facilities, income, expenditure, and credit conditions, etc.

The survey uses stratified random sampling procedures. Firstly, 4-6 counties are randomly selected according to the grassland areas and intensity of livestock production in each province. Secondly, 3 townships are randomly selected in each county

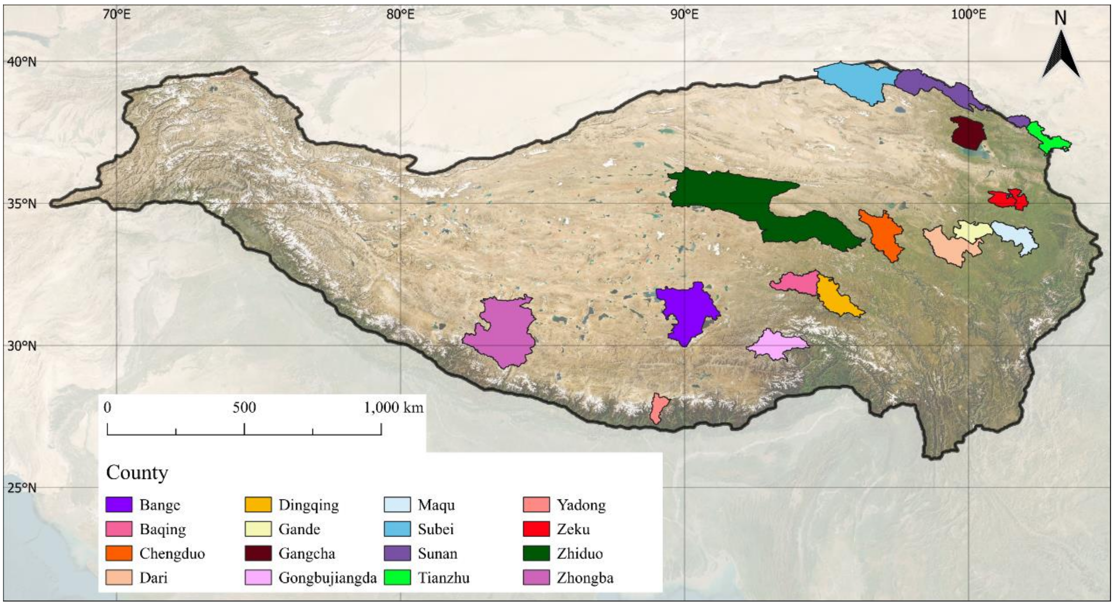
[1] The data reported in this paragraph is from National Bureau of Statistics of China.

[2] Data is from National Bureau of Statistics of China.

according to the intensity of livestock production. Thirdly, 2 sample villages were randomly selected in each town. And finally, 6 pastoral households were randomly selected in each village. Generally, in Xizang Province, the counties of Baqing, Zhongba, and Bange were selected, as they conduct large-scale livestock production. Yadong, Gongbujiangda, and Dingqing counties were selected as examples of a smaller production scale. In Qinghai Province, the counties of Gangcha, Zeku, and Zhiduo were randomly selected as they have a larger scale of livestock production. Chengduo, Dari, and Gande counties were randomly selected because of their smaller livestock production scale. In Gansu province, Maqu County and Tianzhu County were selected, as they conduct large-scale livestock production. Sunan County and Subei County were selected as examples of a smaller production scale (Feng et al., 2021). The areas of these counties are shown in Figure 1.

In addition, to more accurately measure pastoral households' grassland input, we account not only for the grassland areas but also for heterogeneity in land quality by incorporating the biomass indicator of net primary productivity (NPP, kgC/m²/year). NPP reflects the amount of organic dry matter accumulated by vegetation per unit area and time (Imhoff et al., 2004) and is derived from remote sensing data in the infrared and near-infrared spectral bands. We calculate total net primary productivity (TNPP, kgC/year) by multiplying grassland area by NPP. The NPP data are obtained from NASA's Earth Science Data Systems Program (MOD17A3HGF Version 6.1), which provides global NPP estimates at a spatial resolution of 500 meters.

Figure 1. The QTP area and our study counties



Note: QTP and counties boundary data from the Institute of Tibetan Plateau Research of China Academy of Science

Finally, a total of 574 questionnaires were collected from the two studies in Gansu, Qinghai, and Xizang. After excluding 21 invalid questionnaires, a total of 553 valid questionnaires were obtained, with an effective rate of 96.34%. Among these 553 pastoral households, 215 are in Xizang Province, 199 are in Qinghai Province, and 139 are in Gansu Province. We distributed surveys in Gansu and Qinghai in 2017, asking for their information for 2015-2017, and we distributed surveys in Xizang in 2019, asking for their information for 2016-2018. Thus, a final set of unbalanced data with 1659 observations is constructed for further analysis.

3 Methodology and Summary Statistics

In this section, we first introduce a stochastic frontier analysis (SFA) to estimate the pastoral households' productivity. We then employ a staggered triple difference (staggered DDD) method to estimate the effects of formal credit accessibility (FCA) on pastoral households' productivity resilience to natural disasters. Finally, we apply an event study analysis to decompose the effects of credit accessibility on the productivity recovery and test for parallel trend assumptions.

3.1 TFP Estimates

Stochastic frontier analysis, proposed by Aigner et al. (1977) and Meeusen and Vanden Broeck (1977), is widely used in estimating TFP and shows advantages in production analyses in agricultural sectors (Chen and Gong, 2021; Latruffe et al., 2017; Key and Sneeringer, 2014). Following Chen and Gong (2021), we employ a Transcendental Logarithmic (T-L) form of SFA to estimate the TFP of the pastoral households. The model is shown as follows:

$$y_{it} = \alpha_0 + \alpha_1 l_{it} + \alpha_2 k_{it} + \alpha_3 n_{it} + \alpha_4 {l_{it}}^2 + \alpha_5 {k_{it}}^2 + \alpha_6 {n_{it}}^2 + \alpha_7 l_{it} k_{it} + \alpha_8 l_{it} n_{it} + \alpha_9 k_{it} n_{it} + \lambda_t - u_{it} + v_{it} \quad (1)$$

where y_{it} is the natural logarithm of the livestock income of pastoral households i at time t, l_{it}, k_{it}, and n_{it} are the logarithms of the labor, capital, and TNPP, respectively. λ_t captures the year fixed effects, u_{it} is the non-negative normal stochastic term that accounts for the technical inefficiency of livestock production, and v_{it} accounts for the measurement errors. We estimated the technical inefficiency based on an ML random-effects time-varying efficiency decay model proposed by Battese and Coelli (1992). Finally, we have the logarithm form of TFP estimation calculated by $\ln TFP_{it} = \alpha_0 + \lambda_t - u_{it}$.

For robustness, we also provide several alternative approaches for TFP estimates in Appendix A. Firstly, instead of T-L model, we employ a traditional Cobb-Douglas (C-D) stochastic frontier model (Chen and Gong, 2021) in the form:

$$y_{it} = \alpha_0 + \alpha_1 l_{it} + \alpha_2 k_{it} + \alpha_3 n_{it} + \lambda_t - u_{it} + v_{it} \quad (2)$$

Considering that we will include both household and year fixed effects in the following staggered DDD approaches, we further provide an alternative SFA without the year fixed effects term (i.e., λ_t) in Equation (2). This model aligns more closely with Battese and Coelli (1992).

3.2 Staggered Triple-Differences (Staggered DDD)

The DID and DDD methods are widely used in empirical areas, such as policy evaluations and assessments of natural disasters (Cai, Chen, and Gong, 2016; Carvalho et al., 2021; Deryugina, Kawano, and Levitt, 2018). Staggered DDD models are also popular when treatment timings are various (Chen et al., 2023; Hansen and Wingender, 2023; Bar-Gill, Brynjolfsson, and Hak, 2024; Wang et al., 2024).

To exam the effects of formal credit accessibility on the pastoral households' productivities after hit by natural disasters, we estimate the following staggered DDD model:

$$\begin{aligned} \ln TFP_{it} = \beta_0 + \beta_1 Post\ Disaster_{it} \times FCA_i + \beta_2 Post\ Disaster_{it} + \boldsymbol{\pi}\mathbf{X}_{it} \quad (3) \\ + \theta_t + \varphi_i + \varepsilon_{it} \end{aligned}$$

where $\ln TFP_{it}$ is the logarithm form of TFP of pastoral household i at year t calculated by the SFA shown in Section 3.1. $Post\ Disaster_{it}$ is a dummy variable equal to one if pastoral household i had been affected by any natural disasters[1] prior to year t[2]. FCA_i is an indicator equal to one if a household i holds any loans from a

[1] For natural disasters, we include those reported by pastoralists, such as droughts, snow disasters, extreme heat events, windstorms, sandstorms, floods, hailstorms, rodent outbreaks, and other hazards.

[2] For example, if pastoral household A was affected by a natural disaster in 2016, then $Post\ Disaster_{A,2017}$ and $Post\ Disaster_{A,2018}$ would equal to 1. Noticed that $Post\ Disaster_{A,2016}$ would still equal to 0, which means that, instead of switching $Post\ Disaster_{it}$ to 1 in the year the pastoral household hit by a disaster, we only make it equal to 1 in all the following years. This definition aligns with literature using one-year-lagged treatment for natural disaster analysis (Barrot and Sauvagnat, 2016; Liebenehm, Schumacher, and Strobl, 2024; Beland and Oloomi, 2019). In practical terms, this choice is motivated by the following three considerations. Firstly, since we only have year-level survey data, it's hard to identify a more exact occurrence time of a disaster, so a disaster that happens at the end of a year may generate minor impacts to the TFP of the year. Secondly, since the core interest of this research lies in understanding how credit accessibility affects a pastoral household's productivity resilience and recovery, it takes time for pastoralists to take actions like getting loans, reinvesting, and changing management strategy to resume and improve production after a natural disaster. Thus, defining $Post\ Disaster_{it}$ to 1 in the years following the disaster can better capture the roles of credit accessibility during the productivity recovery. Thirdly, our event study results in Section 4.2 verify that the TFP

bank or credit union in at least one year of the study period, which represents their accessibility to formal credit. $\mathbf{X}_{it}$ is a series of control variables like pastoralists' age, education level, family members, etc. The details of these controls can be seen in Table 1. Variables θ_t and φ_i are time and household level fixed effects, respectively. The household-level fixed effects control unobserved time-invariant differences across household, such as location and climate. The time-level fixed effects control for unobserved household-invariant factors, such as output prices and policy changes. ε_{it} is the error term.

In this framework, the coefficient of the staggered DID term $Post\ Disaster_{it}$ (i.e. β_2) picks up the effects of disasters on pastoral households' TFP. And the interaction term $Post\ Disaster_{it} \times FCA_i$, which is the primary variable of interest, captures the triple differences effects: that is, whether pastoral households with and without formal credit accessibility would share different TFP changes after suffering from natural disasters. Notice that in the two-way fixed effects (TWFE) regressions we don't include singleton variables like FCA_i, $Disaster_i$ (indicates if household i had reported any natural disasters during the whole study period), or the interaction $FCA_i \times Disaster_i$. This is because we have already control for household-level fixed effects, so these variables would be omitted for collinearity. However, in some regression specifications, we add them to the regressions when we exclude the household-level fixed effects.

3.3 Event Study Analysis

The staggered DDD analysis estimates the aggregated effects of formal credit on TFP change gaps in all the periods after natural disasters. However, a more interesting topic would be the effects' dynamics in individual periods leading up to or following the natural disaster. Moreover, an event study analysis also contributes in the following two ways. First, it tests for the parallel-trends assumption, which is critical in the validity and unbiasedness of a DID or DDD approach (Roth, 2022; Wang et al., 2024; Sun and Abraham, 2021). Second, previous literature has shown that a static TWFE staggered DID estimate could be uninterpretable as it equals a weighted average of all possible DID estimators (Goodman-Bacon, 2021; Baker, Larcker, and Wang, 2022). Also, the variation of treatment timing, the changes of treatment effects over time (i.e., dynamic treatment effects), and the treatment effects heterogeneity could lead to biased static

---

differences between our control and treatment groups are minor in the year disasters occur but significant in the following years. Thus, if we define $Post\ Disaster_{it}$ to 1 in the disaster-occurrence year, it may significantly underestimate the role of credit accessibility. Despite all the reasons discussed above, we provide a robustness check in Section 5.2 where we also define $Post\ Disaster_{it}$ to 1 in the disaster-occurrence year, the results are still robust and show the significant effects of formal credit accessibility.

staggered DID estimators (Goodman-Bacon, 2021; Baker, Larcker, and Wang, 2022; Sun and Abraham, 2021; de Chaisemartin and D'Haultfoeuille, 2020).

We apply an event study analysis in the following form:

$$\ln TFP_{it} = \beta_0 + \sum_{r=-2}^{2} (\beta_1^r Post\ Disaster_{it}^r \times FCA_i + \beta_2^r Post\ Disaster_{it}^r) + \boldsymbol{\pi}\mathbf{X}_{it} + \theta_t + \varphi_i + \varepsilon_{it} \tag{4}$$

Where $Post\ Disaster_{it}^r$ are binary variables taking the value 1 if the pastoral household i reports natural disasters in the year $t-r$, and taking the value 0 otherwise. For example, if the pastoral household A reported natural disaster in 2016, and we have their records from 2015 to 2017, then $Post\ Disaster_{A,2015}^{1} = Post\ Disaster_{A,2016}^{0} = Post\ Disaster_{A,2017}^{-1} = 1$, and $Post\ Disaster_{A,2015}^{r=-2,-1,0,2} = Post\ Disaster_{A,2016}^{r=-2,-1,1,2} = Post\ Disaster_{A,2017}^{r=-2,0,1,2} = 0$. Thus, we are able to capture the dynamic treatment effects from the formal credit accessibility on TFP in different periods leading up to or following the natural disasters.

Although an event-study would be a great supplement to static DDD estimations, the canonical event-study estimators can not fully resolve the problems discussed above (Baker, Larcker, and Wang, 2022; Sun and Abraham, 2021), thus, in Section 5.2, we further provide discussions and robustness checks using alternative estimators developed in the econometrics literature for addressing these biases.

3.4 Summary Statistics

Table 1 presents definitions and summary statistics for the variables used in the SFA described in Section 3.1 and our baseline staggered DDD approach described in Section 3.2. For natural disasters, we include those reported by pastoralists, such as droughts, snow disasters, extreme heat events, windstorms, sandstorms, floods, hailstorms, rodent outbreaks, and other hazards.

Table 1. Variable definitions and summary statistics

Variables	Description	Mean	SD	Min	Max
Variables used in SFA and the estimated TFPs					
Pastoral income (Y)	Total livestock income (10,000 CNY), including selling sheep, wool, and dairy products	4.92	6.44	0.00	71.79
Capital input (K)	Purchase of farm inputs, such as expenditure on purchasing forage and livestock, and the present value of production machinery (10,000 CNY)	3.52	5.99	0.01	54.70
Labor input (L)	Number of working months of labor in household livestock husbandry (months)	20.69	10.68	1	70
TNPP (N)	Total grassland net primary productivity capacity (kgC/year) = Family-run grassland area * net primary productivity (NPP, kgC/m^2/year).	1119503	3132464	16	32754266
ln (TFP)	Natural logarithm of estimated TFPs	-1.12	1.05	-6.78	0.34
Variables used in the staggered DDD model					
$Post\ Disaster_{it}$	Dummy variable equal to 1 if pastoral households i had been affected by any natural disasters before year t	0.15	0.36	0	1
FCA	Whether participation has formal credit accessibility (No=0, Yes=1)	0.55	0.50	0	1
Age of HH	Age of head of household	49.93	12.77	20	93
Education of HH	Years of schooling for the head of household	2.22	3.31	0	16
Average age	Average age of the labor force	35.66	6.74	15.00	58.50
Number of laborers	Number of labor force with age between 15 and 60	3.42	1.43	1	8
Dependency ratio	Family dependency ratio (elderly over 60 years old and children under 15 years old in the total family population)	0.32	0.22	0.00	0.83
Smartphone	Whether have smartphones (No=0, Yes=1)	0.63	0.48	0	1
Savings	Family savings (CNY)	36184	54520	1000	600000
House	Value of the houses (CNY)	180085	202717	0	1300000
Average subsidy	Average subsidy per square meter of grassland	0.21	3.16	0.00	72.96
Number of livestock	Number of livestock raised (100 sheep units)	2.95	2.68	0.05	26.65
Cost of hiring	Hiring cost (10000 CNY) for livestock husbandry	0.18	0.72	0	10
Insurance	Whether to purchase livestock production insurance (No=0, Yes=1)	0.55	0.50	0	1
Cooperative membership	Whether joining the cooperative (No=0, Yes=1)	0.16	0.36	0	1
Training	Whether to receive agricultural training (No=0, Yes=1)	0.08	0.28	0	1
NDVI	Normalized Difference Vegetation Index, a vital indicator of vegetation growth status and nutritional information	0.54	0.22	0.00	0.88
Mortgage	Whether the pasture can be used as collateral (No=0,	0.29	0.45	0	1

	Yes=1)				
Distance	Distance to the nearest road (kilometer)	14.53	43.90	0	700
Number of observations			1659		

Notes: The input and output variables used in SFA are in logarithm forms when calculating, i.e., variables Y, L, K, and N correspond to the logarithm forms y, l, k, and n.

Since pastoralist usually cultivate multiple categories of livestock, sheep units were often used to calculate aggregated livestock numbers. 1 sheep = 1 sheep unit; 1 goat = 0.9 sheep units; 1 cattle/yak = 5 sheep units; 1 horse = 6 sheep units; 1 camel = 7 sheep units.

4 Empirical Results

In this section, we first report the TWFE staggered DDD estimation obtained from Equation (3). Some alternative specifications are also provided for robustness. We then report the results of the event study analysis in Figure 2 by applying the model shown in Equation (4). Broadly speaking, we find that pastoral households with FCA perform better in TFP resiliencies and recovery after natural disasters. The event study shows that the TFP differences are not significant in the year that natural disasters hit, but are significant in the following years.

4.1 Staggered DDD Results

Table 2 reports our baseline staggered DDD results for analyzing the effects of FCA on pastoral households' TFP resilience after natural disasters. Columns (1)-(4) report the results without control variables listed in Table 1, while Columns (5)-(8) include controls. Columns (1) and (5) don't include any fixed effects, Column (2) and (6) only include household-level fixed effects, Column (3) and (7) only include year-level fixed effects, and Column (4) and (8) include both year and household-level fixed effects. Noticed that Column (1), (3) (5), and (7) don't have household-level fixed effects, so we also include variables FCA_i, $Disaster_i$, and $FCA_i \times Disaster_i$ into regressions. For robustness, all the standard errors are clustered at the household level.

Based on the coefficient estimations for the variable $Post\ Disaster_{it}$, we can see that natural disasters generally bring negative impacts to pastoral households' TFP, especially to those without FCA. The direction of the effect is in accordance with intuition. Specifically, Columns (2) and (6) of Table 2, where we only control for household-level fixed effects, suggest that the TFP of pastoral households without FCA will statistically significantly decrease by about 6.5%-6.7% after suffering from natural disasters. For the rest of the specifications, although not significant, they still suggest similar negative impacts from natural disasters.

As for the estimators of $Post\ Disaster_{it} \times FCA_i$, which is the primary variable of interest, they suggest that the pastoral households with FCA perform better in TFP resilience and recovery after natural disasters. Although the estimators of $Post\ Disaster_{it} \times Credit_i$ in Column (1), (3), (5), and (7), where we exclude household-level fixed effects, are not statistically significant, they are all positive and suggest potential advantages that pastoral households with FCA have in TFP resilience and recovery after natural disasters compared to those without FCA. Moreover, once household-level fixed effects are controlled (Column (2), (4), (6), (8)), the estimations are positive and statistically significant. Generally, based on the TWFE estimations, the TFPs of pastoral households with FCA recovery 4.3%-5.2% more than those without FCA after being hit by natural disasters. Noticed that TFPs of the pastoral households with FCA are originally about 18.1% to 29.1% higher than those without FCA[1], which means the post-disaster TFPs gaps between the two groups will be about 22.4% to 34.3%[2]. Pastoral households with FCA gain comparative benefit from natural disasters compared to those without FCA.

Furthermore, if we combine the estimators of $Post\ Disaster_{it}$ and $Post\ Disaster_{it} \times FCA_i$ shown in Column (8), we can see that the TFPs of those pastoral households with FCA even over-recover beyond their pre-disaster levels by 2.5%[3] after natural disasters.

We believe two mechanisms may contribute to this phenomenon. Firstly, the means of production, such as facilities, grassland, and livestock, are damaged after natural disasters, so pastoral households need to reinvest (e.g., repairing facilities, purchasing new livestock, seeding) to resume production. In these reinvestment procedures, pastoralists with credit accessibility could have more flexible budget constraints to resume production faster, adopt more advanced technology/livestock breeds/grass species, and allocate resources more appropriately, thus leading to better TFP resilience and even overshooting the pre-disaster level. This mechanism aligns with previous studies that associate credit accessibility with productivity increasing through channels like technical change, efficiency improvement, and scale and mix efficiency (Jimi et al., 2019; Nordjo and Adjasi, 2020; Dong, Lu, and Featherstone, 2012; Guirkinger and Boucher, 2008; Moahid et al., 2023; Ciaian, Fałkowski, and Kancs, 2012). Another potential mechanism that results in the post-disaster TFP differences could be the effects of debt on labor usage and management practice. Pastoralists who access credit to resume production after natural disasters will face a higher debt ratio and interest

[1] See the coefficient estimators of FCA_i in Columns (1), (3), (5), and (7) in Table 2.

[2] 22.4%=18.1%+4.3%, 34.3%=29.1%+5.2%.

[3] 2.5%= (0.043-0.018) *100%, and this result is statistically significant at 5% level.

expense, which results in more financial pressure for the future. The household utility theory suggests that an increase in household expenditure would lead to more time allocated to work (Becker, 1965). Some empirical works also suggest that households with increasing debt will supply more labor through increasing working time and women's participation in the labor market (Zator, 2025; Del Boca and Lusardi, 2003; Fortin, 1995). Although we don't find a statistically significant working time difference between treatment and control groups, we believe pastoralists with higher debt may tend to work harder and manage labor more carefully and efficiently, which leads to a better TFP recovery or even over-recovery.

Generally speaking, our static staggered DDD analysis provides empirical evidence to support our hypothesis that FCA could improve pastoral households' TFP resilience and recovery capability after suffering from natural disasters. And the results even show that pastoral households with FCA exhibit higher TFP relative to their own pre-natural disaster levels.

Table 2. Baseline Staggered DDD results

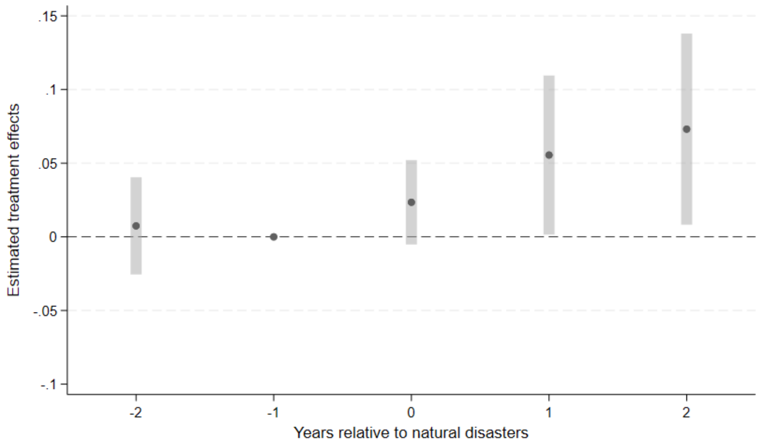
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$
$Post\ Disaster_{it} \times FCA_i$	0.230	0.062**	0.220	0.052**	0.239	0.051**	0.228	0.043**
	(0.163)	(0.025)	(0.160)	(0.020)	(0.145)	(0.024)	(0.145)	(0.020)
$Post\ Disaster_{it}$	-0.167	-0.067***	-0.180	-0.025	-0.193*	-0.065***	-0.196	-0.018
	(0.134)	(0.020)	(0.140)	(0.017)	(0.117)	(0.020)	(0.126)	(0.017)
FCA_i	0.291**		0.271**		0.190*		0.181	
	(0.121)		(0.121)		(0.114)		(0.113)	
$Disaster_i$	0.125		0.117		-0.028		-0.023	
	(0.151)		(0.148)		(0.138)		(0.138)	
$FCA_i \times Disaster_i$	-0.008		-0.011		0.094		0.085	
	(0.183)		(0.180)		(0.166)		(0.165)	
Constant	-1.332***	-1.115***	-1.313***	-1.121***	-1.908***	-2.349***	-1.818***	-1.737***
	(0.099)	(0.002)	(0.098)	(0.002)	(0.391)	(0.309)	(0.407)	(0.313)
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Household FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
N	1659	1659	1659	1659	1659	1659	1659	1659

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Standard errors reported in the parentheses are clustered at the pastoral household level. In Columns (1), (3), (5), and (7), we also include variables FCA_i, $Disaster_i$, and $FCA_i \times Disaster_i$.

4.2 Event Study Analysis

This section presents the regression results by applying the event study approach discussed in Section 3.3. These results can also serve as a test for parallel trend assumptions. Figure 2 plots the estimated coefficients of $Post\ Disaster_{it}^{r} \times Credit_{i}$ shown in Equation (4) before and following natural disasters. In particular, we set the coefficient estimator one year prior to the natural disaster as baseline (i.e., relative time=-1), and plot the rest of the coefficients with their 95% confidence intervals. Firstly, we can see that the coefficient estimator two years before the natural disasters (i.e., relative time=-2) doesn't significantly differ from the baseline. This suggests that, prior to the natural disasters, the treatment group and control group (with and without FCA) have relatively constant TFP gaps. In other words, they don't have significantly different pre-treatment trends. Secondly, the coefficient of the disaster-occurrence year (i.e., relative time=0) is not significantly different from the baseline, which means that we don't observe significant TFP gap changes in the disaster-occurrence year. Finally, the coefficients in one and two years after the natural disasters (i.e., relative time=1 and 2, respectively) are significantly higher than the baseline. This indicates that the TFP gaps between pastoral households with and without FCA start to get larger one year after the natural disasters. In other words, pastoral households with FCA began to show significantly better TFP resilience/recovery compared to those without FCA. Specifically, compared to the situation one year before the occurrence of natural disasters, the TFPs of those pastoral households with FCA would recover about 5.6% more than those without FCA one year after the natural disaster, and about 7.3% more two years following the natural disaster. This finding highlights our hypothesis: FCA could enhance pastoral households' productivity resilience and recovery capacity to natural disasters.

Figure 2. Event Study Analysis Results



Note: The figure plots the pre- and post-disaster TFP gap dynamics between our treated and control groups by setting the 1-year-before-disaster TFP gap as a baseline. The confidence intervals are plotted at a 95% level. The regression includes the control variables listed in Table 1, and standard errors are clustered at the pastoral household level.

5 Robustness

In this section, we conduct a number of additional analyses to gauge the reliability and robustness of our baseline results. We first apply the propensity score matching (PSM) method to our baseline model and report the results in Section 5.1. We then employ several advanced econometric methods to address potential estimation bias related to canonical TWFE DID/DDD estimators, the results are shown in Section 5.2. Furthermore, considering that different SFA models could affect our TFP estimations, we provide two alternative SFA models and rerun the regressions in Appendix A. We next redefine the indicator $Post\ Disaster_{it}$ equals 1 not only in the years following a natural disaster, but also in the disaster-occurrence year. The results are reported in Appendix B. Finally, as supplementary material, we provide some DID analyses separately about FCA and natural disasters. The discussions are shown in Appendix C.

5.1 PSM Staggered DDD Approach

PSM estimators (Rosenbaum and Rubin, 1983) are widely used along with DID or DDD methods to estimate treatment effects in empirical works (Labonne and Chase, 2011; Bravo-Ureta et al., 2021; Gilligan and Hoddinott, 2007).

The primary topic of interest in this study is whether the FCA can enhance pastoral households' productivity resilience and recovery capability to natural disasters. However, measuring TFP differences between pastoral households with and without FCA, as well as before and after natural disasters, even controlling for household-level characteristics, may give a biased estimation. This bias arises under two potential circumstances: there are unobserved factors that affect the probability of FCA or natural disasters' occurrences, and are also correlated with the TFP changes. Considering that the occurrences of natural disasters are almost ideal exogenous, the primary problem that may sabotage our study is the potential endogeneity of FCA. For example, the better-educated household heads may prefer formal credit and have easier access to it, and they may also perform better in post-disaster TFP recovery because they have a higher education level. Thus, as the TFP recoverability and FCA are both correlated with education level, the baseline approach may not be able to separate the FCA-led and education-led TFP recoverability. Thus, an ideal measure of the treatment effects of FCA should be built under a counterfactual scenario where we can compare the TFP outcomes between pastoral households that have FCA with the same pastoral households if they don't have FCA. Since the unobservability of this counterfactual construction is the key dilemma of impact evaluation, a PSM estimator could partially alleviate the potential bias by adjusting pre-treatment observable differences between the treatment (pastoral households with FCA) and the control groups (pastoral households without FCA).

Specifically, we generate a propensity function using a rich set of pastoral households' characteristics to estimate their propensity of getting FCA and match treatment pastoral households with the control groups that have similar FCA likelihoods. After using covariate imbalance diagnostics to evaluate several matching methods, we decided to employ the 5-nearest neighbors matching method with a logit model, which achieves good balancing between the treatment and control groups. Results from the logit regression are available in Table D1 of Appendix D, and the pre-match distribution of the propensity scores of treatment and control groups is shown in Figure D2 of Appendix D. The covariate imbalance testing results indicate that the two after-match groups are well-balanced (Table D2 of Appendix D).

We then rerun our baseline regressions after dropping 66 unmatched observations, and 13 more singleton observations are dropped. The regression results shown in Table 3 are highly consistent with our baseline approach, and the estimated coefficients even show increasing magnitude and significance. Specifically, the estimators of Columns (1), (3), (5), and (7) in Table 2 of our baseline approach, with which household-level fixed effects are excluded, are positive but not statistically significant. But in Table 3, these estimators are getting significant in 90% and have increasing magnitudes. And for those estimators in Columns (2), (4), (6), and (8) in Table 3, they are getting bigger and more significant compared to their cohorts in Table 2. Generally speaking, the TWFE PSM staggered DDD approach shows that the TFP resilience/recoverability to natural disasters of pastoral households with FCA is 4.8%-5.6% higher than that of those without FCA. Still, as the TFPs of the pastoral households with FCA are originally about 18.2% to 28.1% higher than those without FCA[1], the TFP recoverability difference will make the post-disaster TFP gaps be about 23% to 33.7%.

[1] See the coefficient estimators of FCA_i in Columns (1), (3), (5), and (7) in Table 3.

Table 3. PSM Staggered DDD results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$
$Post\ Disaster_{it} \times FCA_i$	0.304*	0.073***	0.281*	0.056***	0.287*	0.063**	0.267*	0.048**
	(0.166)	(0.026)	(0.163)	(0.021)	(0.151)	(0.025)	(0.150)	(0.020)
$Post\ Disaster_{it}$	-0.241*	-0.078***	-0.234	-0.031*	-0.245**	-0.075***	-0.236*	-0.025
	(0.138)	(0.021)	(0.143)	(0.018)	(0.123)	(0.021)	(0.132)	(0.018)
FCA_i	0.281**		0.264**		0.189*		0.182	
	(0.122)		(0.121)		(0.114)		(0.113)	
$Disaster_i$	0.146		0.138		-0.024		-0.019	
	(0.152)		(0.149)		(0.138)		(0.138)	
$FCA_i \times Disaster_i$	-0.029		-0.032		0.091		0.079	
	(0.184)		(0.181)		(0.166)		(0.165)	
Constant	-1.321***	-1.106***	-1.306***	-1.111***	-1.849***	-2.279***	-1.762***	-1.700***
	(0.099)	(0.002)	(0.098)	(0.001)	(0.400)	(0.314)	(0.416)	(0.324)
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Household FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
N	1593	1580	1593	1580	1593	1580	1593	1580

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Standard errors reported in the parentheses are clustered at the pastoral household level.

5.2 Advanced Staggered DDD Estimations

Although the TWFE DID approach is popular in previous empirical studies, some recent works have pointed out that the variation of treatment timing, the changes of treatment effects over time (i.e., dynamic treatment effects), and the treatment effects heterogeneity could lead to biased static staggered DID estimators (Goodman-Bacon, 2021; Baker, Larcker, and Wang, 2022; Sun and Abraham, 2021; de Chaisemartin and D'Haultfoeuille, 2020).

De Chaisemartin and D'Haultfoeuille (2020) show that the TWFE regressions estimate weighted sums of the average treatment effects (ATEs) in each group and period. And, if the ATEs are heterogeneous across groups or periods, the weights of some ATEs could be negative, which leads to the linear regression coefficient being biased or even opposite to the real ATEs (de Chaisemartin and D'Haultfoeuille, 2020). Later works, such as Callaway and Sant'Anna (2021), Sun and Abraham (2021), and Baker, Larcker, and Wang (2022), further extend the discussions to staggered DID settings and event study regressions, and they find similar problems related to the estimators.

Based on the potential problems shown above, we provide additional robustness checks using more advanced staggered DID estimators developed in this strand of econometric literature. Firstly, we apply the event study method proposed by Sun and Abraham (SA, 2021)[1], which utilizes the interaction-weighted (IW) method to estimate dynamic treatment effects in the presence of potential treatment effect heterogeneity. The corresponding results are presented in Panels (a) and (b) of Figure 3, where Panel (a) doesn't include our covariates (we set the covariates as our control variables listed in Section 3.4), but Panel (b) includes them. We can see that, compared to the original TFP gaps in the disaster-occurrence year, those pastoral households with FCA would perform about 2.5% to 3.1% better in TFP resilience/recoverability than those without FCA one year following the natural disaster, and about 5.1% to 6.0% higher two years following the natural disaster.

We then apply the DID with multiple periods estimator proposed by Callaway and Sant'Anna (CS, 2021)[2]. Summarized by Baker, Larcker, and Wang (2022), the methods proposed by CS and SA are closely related but have some differences. One major difference is that, while SA allows only for never-treated or last-treated groups as controls, CS also allows not-yet-treated units as controls. Thus, we further provide a robustness check applying the CS method and using observations never treated and

[1] Sun and Abraham (2021) provide a publicly-available Stata package (eventstudyinteract) to implement their IW estimators.

[2] We use the Stata package "csdid" to implement the method of Callaway and Sant'Anna (2021).

those not yet treated as the control group. The corresponding results with and without covariates are presented in Panels (c) and (d) of Figure 3, respectively. The results show that the TFP recoverability of those pastoral households that have FCA would be about 1.4% to 2.1% higher than those without FCA one year following the natural disaster, and about 3.1% to 5.1% higher two years following the natural disaster.

Finally, we employ the extended TWFE (ETWFE) estimator proposed by Wooldridge (2023)[1]. When addressing the staggered treatments, the ETWFE allows the "average treatment effect on the treated" (ATT) to vary by group and time, and allows us to limit the control groups to those never treated pastoral households to test for the parallel trend assumption. The ATT estimations with and without covariates are present in Panels (e) and (f) of Figure 3, respectively. The results suggest that, compared to the situation in the disaster-occurrence year, the TFP recoverability of those pastoral households that have FCA would be about 2.4% to 4.5% higher than those without FCA one year following the natural disaster, and about 5.0% to 11.0% higher two years following the natural disaster.

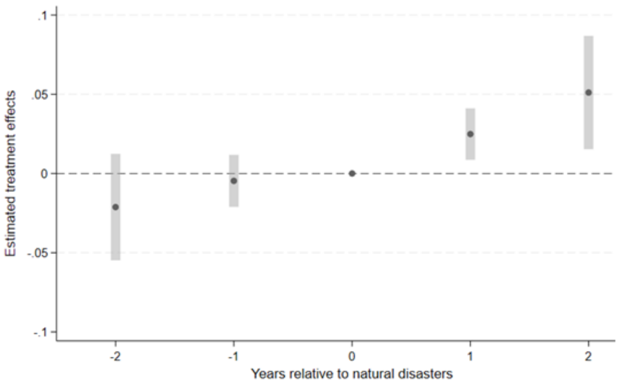
Generally speaking, the regression results using more advanced staggered DDD estimations are highly consistent with our baseline approach. This suggests that, after considering the potential treatment heterogeneities across groups or periods, we still find that pastoral households with FCA perform significantly better in TFP resilience and recovery after natural disasters than those without FCA.

5.3 Other Robustness Checks

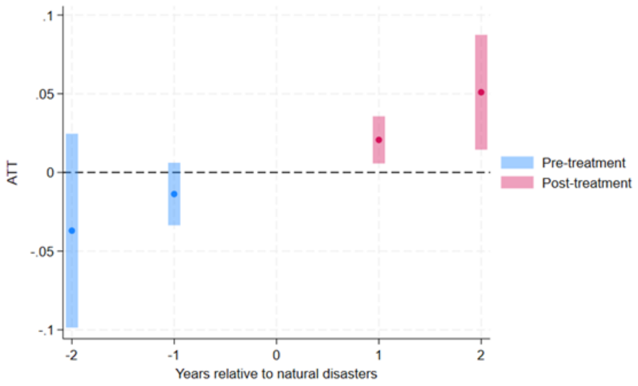
We also provide several other robustness checks. Firstly, we try two alternative SFA functions and re-run our baseline regressions to test if our findings are robust under different TFP estimation methods. The detailed discussion and results are available in Appendix A. Secondly, we redefine the indicator $Post\ Disaster_{it}$ would equal 1 not only in the years following a natural disaster, but also in the disaster-occurrence year. We rerun the regressions and present the results in Appendix B. Finally, we provide two robustness checks using staggered DID approaches to examine the effects of natural disasters or FCA on pastoral households' TFP separately. The detailed discussions are available in Appendix C.

[1] We use the Stata package "jwdid" to implement the ETWFE method of Wooldridge (2023).

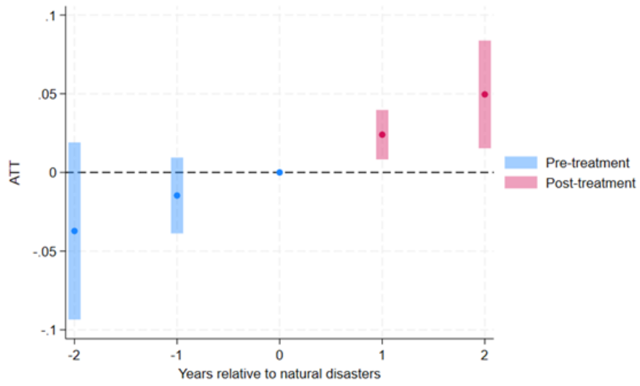
Figure 3. Robustness checks using advanced staggered DID estimators



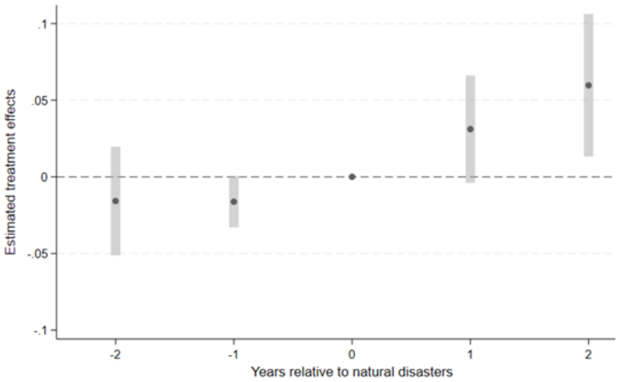
(a) SA approach without covariates



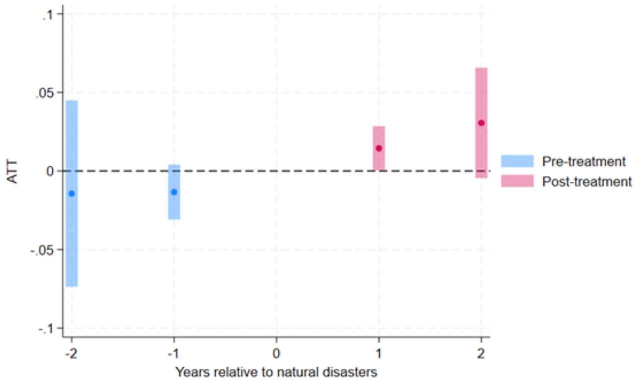
(c) CS approach without covariates



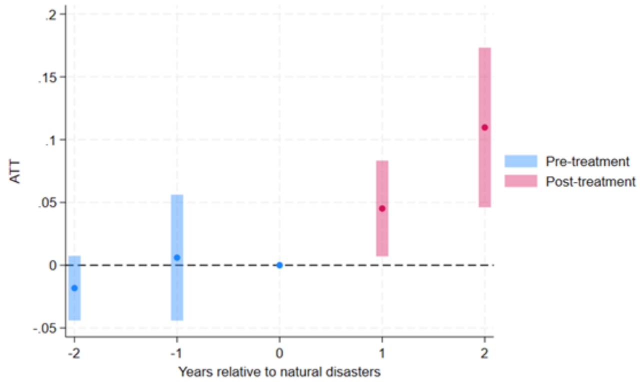
(e) ETWFE approach without covariates



(b) SA approach with covariates



(d) CS approach with covariates



(f) ETWFE approach with covariates

Note: The presented confidential intervals are at the 95% level. Panels (a) and (b) use the method provided by Sun and Abraham (2021). Panels (c) and (d) use the method of Callaway and Sant'Anna (2021). Panels (e) and (f) use the method proposed by Wooldridge (2023). Panels (a), (c), and (e) don't include any covariates, while Panels (b), (d), and (f) include our control variables (see Section 3.4) as covariates. Corresponding to our baseline setting where we define the treatment variable as equal to 1 in the years following the disaster-occurrence year, we present all the estimated treatment effects by comparing them to the estimator of the disaster-occurrence year. In other words, we set the estimator of the disaster-occurrence year as 0.

6 Conclusion

Balancing ecological sustainability and economic development poses complex challenges in regions characterized by fragile ecosystems and underdeveloped economies, such as the QTP). In this paper, we analyze how formal credit can contribute to the productivity of pastoral households in the QTP area in the post-disaster scenery, based on survey data from 553 pastoral households across 16 counties between 2015 and 2018.

Our empirical results show that pastoral households with FCA outperform those without by approximately 4.3% to 5.6% in total factor productivity (TFP) recovery following natural disasters. Dynamic analyses further reveal that, relative to one year before disaster events, TFP among pastoral households with FCA recovers 5.6% more one year after and 7.3% more two years after natural disasters. Moreover, the TFP of pastoral households with FCA exceeds their own pre-disaster levels by about 2.5%.

These findings carry several important policy implications. Compared with insurance or post-disaster government transfers—which often impose substantial fiscal burdens—expanding credit access offers a less-burden mechanism for disaster recovery, as most loans are ultimately repaid. Furthermore, insurance or government transfers typically provide fixed compensation irrespective of heterogeneous monetary needs, which would bring resource misallocation in some circumstances. Meanwhile, credit allows rural households to choose borrowing amounts and repayment plans according to their specific needs, thereby promoting the efficiency of resource allocation. This flexibility may help explain the observed "over-recovery" of TFP among pastoral households with FCA.

In addition to economic benefits, enhanced productivity can contribute to ecological sustainability by enabling pastoralists to produce more efficiently with fewer biomass inputs. Overall, our findings provide robust evidence supporting credit expansion as an effective financial strategy for disaster mitigation, poverty reduction, and ecological balance in vulnerable pastoral regions.

References

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. Journal of Econometrics, 6(1), 21-37.

Barrot, J. N., & Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. The Quarterly Journal of Economics, 131(3), 1543-1592.

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. Journal of Productivity Analysis, 3(1), 153-169.

Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates?. Journal of Financial Economics, 144(2), 370-395.

Bar-Gill, S., Brynjolfsson, E., & Hak, N. (2024). Helping small businesses become more data-driven: A field experiment on eBay. Management Science, 70(11), 7345-7372.

Becker, G. S. (1965). A Theory of the Allocation of Time. The Economic Journal, 75(299), 493-517.

Beland, L. P., & Oloomi, S. (2019). Environmental disaster, pollution and infant health: Evidence from the Deepwater Horizon oil spill. Journal of Environmental Economics and Management, 98, 102265.

Bravo-Ureta, B.E., González-Flores, M., Greene, W. and Solís, D. (2021), Technology and Technical Efficiency Change: Evidence from a Difference in Differences Selectivity Corrected Stochastic Production Frontier Model. American Journal of Agricultural Economics, 103(1), 362-385.

Cai, H., Chen, Y., & Gong, Q. (2016). Polluting thy neighbor: Unintended consequences of China′ s pollution reduction mandates. Journal of Environmental Economics and Management, 76, 86-104.

Carvalho, V. M., Nirei, M., Saito, Y. U., & Tahbaz-Salehi, A. (2021). Supply Chain Disruptions: Evidence from the Great East Japan Earthquake. The Quarterly Journal of Economics, 136(2), 1255-1321.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. Journal of Econometrics, 225(2), 200-230.

Chen, M. A., Hu, S. S., Wang, J., & Wu, Q. (2023). Can blockchain technology help overcome contractual incompleteness? Evidence from state laws. Management Science, 69(11), 6540-6567.

Chen, S., & Gong, B. (2021). Response and adaptation of agriculture to climate change: Evidence from China. Journal of Development Economics, 148, 102557.

Chen, B., Zhang, X., Tao, J., Wu, J., Wang, J., Shi, P., ... & Yu, C. (2014). The impact of climate change and anthropogenic activities on alpine grassland over the Qinghai-Tibet Plateau. Agricultural and Forest Meteorology, 189, 11-18.

Ciaian, P., Fałkowski, J., & Kancs, D. A. (2012). Access to credit, factor allocation and farm productivity: Evidence from the CEE transition economies. Agricultural Finance Review, 72(1), 22-47.

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., & Roventini, A. (2019). Evidence for sharp increase in the economic damages of extreme natural disasters. Proceedings of the National Academy of Sciences, 116(43), 21450-21455.

De Chaisemartin, C., & D'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. American Economic Review, 110(9), 2964-2996.

Del Boca, D., & Lusardi, A. (2003). Credit market constraints and labor market decisions. Labour Economics, 10(6), 681-703.

Deryugina, T., Kawano, L., & Levitt, S. (2018). The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns. American Economic Journal: Applied Economics, 10(2), 202-233.

Dong, F., Lu, J., & Featherstone, A. M. (2012). Effects of credit constraints on household productivity in rural China. Agricultural Finance Review, 72(3), 402-415.

Du, M., Kawashima, S., Yonemura, S., Zhang, X., & Chen, S. (2004). Mutual influence between human activities and climate change in the Tibetan Plateau during recent years. Global and Planetary Change, 41(3-4), 241-249.

Feng, W., Lu, H., Yao, T., & Yu, Q. (2020). Drought characteristics and its elevation dependence in the Qinghai–Tibet plateau during the last half-century. Scientific Reports, 10(1), 14323.

Feng, X., Qiu, H., Pan, J., & Tang, J. (2021). The impact of climate change on livestock production in pastoral areas of China. Science of the Total Environment, 770, 144838.

Fortin, N. M. (1995). Allocation inflexibilities, female labor supply, and housing assets accumulation: Are women working to pay the mortgage?. Journal of Labor Economics, 13(3), 524-557.

Freebairn, J. W. (1983). Drought assistance policy. Australian Journal of Agricultural Economics, 27(3), 185-199.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. Journal of Econometrics, 225(2), 254-277.

Gilligan, D.O. and Hoddinott, J. (2007). Is There Persistence in the Impact of Emergency Food Aid? Evidence on Consumption, Food Security, and Assets in Rural Ethiopia. American Journal of Agricultural Economics, 89: 225-242.

Guirkinger, C., & Boucher, S. R. (2008). Credit constraints and productivity in Peruvian agriculture. Agricultural Economics, 39(3), 295-308.

Hansen, C. W., & Wingender, A. M. (2023). National and global impacts of genetically modified crops. American Economic Review: Insights, 5(2), 224-240.

Harris, R. B. (2010). Rangeland degradation on the Qinghai-Tibetan plateau: a review of the evidence of its magnitude and causes. Journal of Arid Environments, 74(1), 1-12.

Immerzeel, W. W., Van Beek, L. P., & Bierkens, M. F. (2010). Climate change will affect the Asian water towers. Science, 328(5984), 1382-1385.

Imhoff, M., Bounoua, L., Ricketts, T. et al. (2004). Global patterns in human consumption of net primary production. Nature, 429, 870–873.

Janzen, S. A., & Carter, M. R. (2019). After the drought: The impact of microinsurance on consumption smoothing and asset protection. American Journal of Agricultural Economics, 101(3), 651-671.

Jimi, N. A., Nikolov, P. V., Malek, M. A., & Kumbhakar, S. (2019). The effects of access to credit on productivity: separating technological changes from changes in technical efficiency. Journal of Productivity Analysis, 52(1), 37-55.

Kang, S., Xu, Y., You, Q., Flügel, W. A., Pepin, N., & Yao, T. (2010). Review of climate and cryospheric change in the Tibetan Plateau. Environmental Research Letters, 5(1), 015101.

Key, N. and Sneeringer, S. (2014). Potential Effects of Climate Change on the Productivity of U.S. Dairies. American Journal of Agricultural Economics, 96: 1136-1156.

Khandker, S. R. (2007). Coping with flood: role of institutions in Bangladesh. Agricultural Economics, 36(2), 169-180.

Kuwayama, Y., Thompson, A., Bernknopf, R., Zaitchik, B., & Vail, P. (2019). Estimating the impact of drought on agriculture using the US Drought Monitor. American Journal of Agricultural Economics, 101(1), 193-210.

Labonne, J., & Chase, R. S. (2011). Do community-driven development projects enhance social capital? Evidence from the Philippines. Journal of Development Economics, 96(2), 348-358.

Latruffe, L., Bravo-Ureta, B.E., Carpentier, A., Desjeux, Y. and Moreira, V.H. (2017). Subsidies and Technical Efficiency in Agriculture: Evidence from European Dairy Farms. American Journal of Agricultural Economics, 99: 783-799.

Liebenehm, S., Schumacher, I., & Strobl, E. (2024). Rainfall shocks and risk aversion: Evidence from Southeast Asia. American Journal of Agricultural Economics, 106(1), 145-176.

Liu, S., Zamanian, K., Schleuss, P. M., Zarebanadkouki, M., & Kuzyakov, Y. (2018). Degradation of Tibetan grasslands: Consequences for carbon and nutrient cycles. Agriculture, Ecosystems & Environment, 252, 93-104.

Lobell, D. B., & Di Tommaso, S. (2025). A half-century of climate change in major agricultural regions: Trends, impacts, and surprises. Proceedings of the National Academy of Sciences, 122(20), e2502789122.

Meeusen, W., & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. International Economic Review, 435-444.

Moahid, M., Khan, G. D., Bari, M. A., & Yoshida, Y. (2023). Does access to agricultural credit help disaster-affected farming households to invest more on agricultural input?. Agricultural Finance Review, 83(1), 96-106.

Mozumder, P., Bohara, A. K., Berrens, R. P., & Halim, N. (2009). Private transfers to cope with a natural disaster: evidence from Bangladesh. Environment and Development Economics, 14(2), 187-210.

Newman, R., & Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. Nature Communications, 14(1), 6103.

Nordjo, R. E., & Adjasi, C. K. (2020). The impact of credit on productivity of smallholder farmers in Ghana. Agricultural Finance Review, 80(1), 91-109.

O'Donnell, C. J. (2012). Nonparametric estimates of the components of productivity and profitability change in US agriculture. American Journal of Agricultural Economics, 94(4), 873-890.

Qiu, J. (2008). China: The third pole. Nature, 454, 393–396.

Qiu, J. (2016). Trouble in Tibet. Nature, 529(7585), 142-146.

Rahmstorf, S., & Coumou, D. (2011). Increase of extreme events in a warming world. Proceedings of the National Academy of Sciences, 108(44), 17905-17909.

Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. American Economic Review: Insights, 4(3), 305-322.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics, 225(2), 175-199.

Vigani, M., & Kathage, J. (2019). To risk or not to risk? Risk management and farm productivity. American Journal of Agricultural Economics, 101(5), 1432-1454.

Wang, Q., Sun, X., Xiong, H., Wang, Q., & Zhang, B. (2024). Environmental taxes, environmental outsourcing, and pollution abatement: Evidence from Chinese industrial sewage discharge enterprises. Energy Economics, 133, 107480.

Wang, X., Yamauchi, F., & Huang, J. (2016). Rising wages, mechanization, and the substitution between capital and labor: evidence from small scale farm system in China. Agricultural Economics, 47(3), 309-317.

Wang, S., Tan, X., & Fan, F. (2022). Landscape Ecological risk assessment and impact factor analysis of the Qinghai–Tibetan plateau. Remote Sensing, 14(19), 4726.

Wooldridge, J. M. (2023). Simple approaches to nonlinear difference-in-differences with panel data. The Econometrics Journal, 26(3), C31-C66.

Xia, M., Jia, K., Zhao, W., Liu, S., Wei, X., & Wang, B. (2021). Spatio-temporal changes of ecological vulnerability across the Qinghai-Tibetan Plateau. Ecological Indicators, 123, 107274.

You, Q., Chen, D., Wu, F., Pepin, N., Cai, Z., Ahrens, B., ... & AghaKouchak, A. (2020). Elevation dependent warming over the Tibetan Plateau: Patterns, mechanisms and perspectives. Earth-Science Reviews, 210, 103349.

Zator, M. (2025). Working more to pay the mortgage: Household debt, interest rates, and family labor supply. The Journal of Finance, 80(2), 1171-1207.

Zhang, Y, Huang, Y., Zhang, F., Tang, Z. (2023). Effects of formal credit on pastoral household expense: Evidence from the Qinghai–Xizang Plateau of China. Journal of

Integrative Agriculture 2024, 23(5): 1774–1785.

Zhang, Y., Li, B., Liu, L., & Zheng, D. (2021). Redetermine the region and boundaries of Tibetan Plateau. Geographical Research. 2021, (6): 1543 -1553.

Appendix A. Robustness under alternative SFA models

In our baseline approach, we use a Transcendental Logarithmic stochastic frontier model to calculate the TFPs of pastoral households. Considering that different SFA models would lead to different TFP estimations, we turn to two alternative SFA models to test for robustness.

Firstly, following Chen and Gong (2021) we turn to a traditional Cobb-Douglas (C-D) stochastic frontier model in the form:

$$y_{it} = \alpha_0 + \alpha_1 l_{it} + \alpha_2 k_{it} + \alpha_3 n_{it} + \lambda_t - u_{it} + v_{it} \tag{A1}$$

where y_{it} is the natural logarithm of the livestock income of pastoral household i at time t, l_{it}, k_{it}, and n_{it} are the logarithms of the labor, capital, and TNPP, respectively. λ_t captures the year fixed effects, u_{it} is the non-negative normal stochastic term that accounts for the technical inefficiency of livestock production, and v_{it} accounts for the measurement errors.

After re-calculating the TFPs, we re-run our baseline staggered DDD regressions and present the results in Table A1.

Secondly, since we will include both household and year fixed effects in the staggered DDD approaches, we provide an alternative SFA without the year fixed effects term (i.e. λ_t) in Equation (A1). This model aligns more closely with Battese and Coelli (1992). The updated staggered DDD results are provided in Table A2.

Generally, the results are highly consistent with those of our baseline approaches. This suggests our findings are robust under different TFP estimation methods.

References

Chen, S., & Gong, B. (2021). Response and adaptation of agriculture to climate change: Evidence from China. Journal of Development Economics, 148, 102557.

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. Journal of Productivity Analysis, 3(1), 153-169.

Table A1. Staggered DDD results using the alternative SFA model of Chen and Gong (2021)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$
$Post\ Disaster_{it}$	0.251	0.061**	0.240	0.051***	0.262*	0.051**	0.252*	0.043**
$\times FCA_i$	(0.165)	(0.024)	(0.163)	(0.019)	(0.146)	(0.024)	(0.146)	(0.019)
$Post\ Disaster_{it}$	-0.170	-0.069***	-0.180	-0.023	-0.199*	-0.066***	-0.199	-0.017
	(0.137)	(0.020)	(0.143)	(0.017)	(0.118)	(0.020)	(0.128)	(0.016)
Constant	-1.404***	-1.178***	-1.387***	-1.184***	-2.001***	-2.195***	-1.918***	-1.712***
	(0.100)	(0.002)	(0.099)	(0.001)	(0.392)	(0.290)	(0.407)	(0.300)
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Household FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
N	1659	1659	1659	1659	1659	1659	1659	1659

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Standard errors reported in the parentheses are clustered at the pastoral household level.

Table A2. Staggered DDD results using the alternative SFA model of Battese and Coelli (1992)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$
$Post\ Disaster_{it}$	0.234	0.026***	0.229	0.024***	0.247*	0.026***	0.243*	0.020**
$\times FCA_i$	(0.160)	(0.009)	(0.159)	(0.009)	(0.142)	(0.010)	(0.142)	(0.009)
$Post\ Disaster_{it}$	-0.169	-0.080***	-0.189	-0.011	-0.204*	-0.052***	-0.205	-0.008
	(0.133)	(0.008)	(0.141)	(0.008)	(0.115)	(0.008)	(0.125)	(0.008)
Constant	-1.371***	-1.145***	-1.361***	-1.155***	-1.922***	0.573***	-1.900***	-1.478***
	(0.100)	(0.001)	(0.099)	(0.001)	(0.394)	(0.121)	(0.408)	(0.138)
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Household FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
N	1659	1659	1659	1659	1659	1659	1659	1659

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Standard errors reported in the parentheses are clustered at the pastoral household level.

Appendix B. Robustness by including the disaster-occurrence year as treated

In our baseline approaches, we define $Post\ Disaster_{it}$ as a dummy variable equal to one in the years after the disaster-occurrence year, which means we treat the TFP observations of the disaster-occurrence year as "untreated". This approach aligns with previous studies such as Barrot and Sauvagnat (2016), Liebenehm, Schumacher, and Strobl (2024), and Beland and Oloomi (2019). However, in some previous literature, they include observations of the disaster-occurrence or policy-implementation periods also as "treated" (Lai, 2017; Georgic and Klaiber, 2022; Cai, Chen, and Gong, 2016).

Our baseline approach is also informed by the following three practical considerations. Firstly, since we only have year-level survey data, it's hard to identify a more exact occurrence time of a disaster, so a disaster that happens at the end of a year may generate minor impacts to the TFP of the year. Secondly, since the core interest of this research lies in understanding how credit accessibility affects a pastoral household's productivity resilience and recovery, it takes time for pastoralists to take actions like getting loans, reinvesting, and changing management strategy to resume and improve production after a natural disaster. Thus, defining $Post\ Disaster_{it}$ to 1 in the years following the disaster can better capture the roles of credit accessibility during the productivity recovery. Thirdly, in our event study analyses in Section 4.2, we verify that the TFP differences between our control and treatment groups are minor in the year disasters occur but significant in the following years. Thus, if we define $Post\ Disaster_{it}$ to 1 in the disaster-occurrence year, it may significantly underestimate the role of credit accessibility.

Despite all the reasons discussed above, we provide a robustness check in this section where we also define $Post\ Disaster_{it}$ to 1 in the disaster-occurrence year, we re-run the staggered DDD regressions, and the results are presented in Table B1. Generally speaking, the results are still robust and show the significant effects of FCA. However, the magnitude and significance of estimated treatment effects decrease, which suggests that including the disaster-occurrence year also as "treated" would underestimate the effects of FCA, as the FCA-contributed TFPs differences are minor in the disaster-occurrence year but significant in the following years.

References

Barrot, J. N., & Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. The Quarterly Journal of Economics, 131(3), 1543-1592.

Beland, L. P., & Oloomi, S. (2019). Environmental disaster, pollution and infant health: Evidence from the Deepwater Horizon oil spill. Journal of Environmental Economics and Management, 98, 102265.

Cai, H., Chen, Y., & Gong, Q. (2016). Polluting thy neighbor: Unintended consequences of China′ s pollution reduction mandates. Journal of Environmental Economics and Management, 76, 86-104.

Georgic, W., & Klaiber, H. A. (2022). Stocks, flows, and flood insurance: A nationwide analysis of the capitalized impact of annual premium discounts on housing values. Journal of Environmental Economics and Management, 111, 102567.

Lai, W. (2017). Pesticide use and health outcomes: Evidence from agricultural water pollution in China. Journal of Environmental Economics and Management, 86, 93-120.

Liebenehm, S., Schumacher, I., & Strobl, E. (2024). Rainfall shocks and risk aversion: Evidence from Southeast Asia. American Journal of Agricultural Economics, 106(1), 145-176.

Table B1. Staggered DDD results by including the disaster-occurrence year as "treated"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$
$Post\ Disaster_{it}$	0.210	0.044*	0.201	0.028	0.192	0.048**	0.186	0.029*
$\times FCA_i$	(0.144)	(0.023)	(0.146)	(0.018)	(0.131)	(0.021)	(0.132)	(0.017)
$Post\ Disaster_{it}$	-0.109	0.011	-0.201	-0.020	-0.157	0.010	-0.228**	-0.013
	(0.116)	(0.019)	(0.125)	(0.015)	(0.102)	(0.018)	(0.112)	(0.015)
Constant	-1.332***	-1.131***	-1.313***	-1.119***	-1.901***	-1.745***	-1.797***	-1.794***
	(0.099)	(0.003)	(0.098)	(0.003)	(0.391)	(0.317)	(0.406)	(0.314)
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Household FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
N	1659	1659	1659	1659	1659	1659	1659	1659

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Standard errors reported in parentheses are clustered at the pastoral household level.

Appendix C. Staggered DID analyses

For supplementary, we discuss the effects of natural disasters or FCA on pastoral households' TFP separately. We first use a staggered DID approach to test the treatment effects of natural disasters, but ignore the potential TFP differences led by FCA. Specifically, we run the regressions in the following form:

$$\ln TFP_{it} = \beta_0 + \beta_1 Post\ Disaster_{it} + \boldsymbol{\pi}\mathbf{X}_{it} + \theta_t + \varphi_i + \varepsilon_{it} \tag{C1}$$

The definitions of the variables are the same as those in our baseline approaches (Section 3.2).

We reported the results in Columns (1) and (2) of Table C1, where Column (1) doesn't include control variables and Column (2) includes. We can see that the estimated coefficients of $Post\ Disaster_{it}$ are all positive but not significant. Notice that, in our baseline results shown in Table 2 and the PSM Staggered DDD results shown in Table 3, the estimated coefficients of $Post\ Disaster_{it} \times FCA_i$ are positive and significant, and the estimators of $Post\ Disaster_{it}$ are negative and significant. These comparisons further suggest our baseline findings: although the pooled effects of natural disasters on pastoral households' TFPs are not significant, these effects are heterogeneous over pastoral households with and without FCA. The TFPs of pastoral households without FCA decrease after natural disasters, while the TFPs of pastoral households with FCA increase a little.

Secondly, we use a simple fixed effect model to show the TFP differences between pastoral households with and without FCA. Specifically, we run the models in the following form:

$$\ln TFP_{it} = \beta_0 + \beta_1 FCA_i + \boldsymbol{\pi}\mathbf{X}_{it} + \theta_t + \varepsilon_{it} \tag{C2}$$

Notice that we only include year-level fixed effects but exclude household-level fixed effects. This is because the household-level fixed effects will make the variable FCA_i omitted because of collinearity. We reported the results in Columns (3) and (4) of Table C1, where Column (3) doesn't include control variables and Column (4) includes. We can see that the TFPs of those pastoral households with FCA are about 26% to 31% higher than those without FCA. These results, together with our baseline findings, suggest that these two groups of pastoral households have some original TFP gaps, and the natural disasters will further deepen the gaps.

Finally, we construct a staggered DID approach to analyze the singleton effect of formal credit usage (FCU). Specifically, we run the models in the following form:

$$\ln TFP_{it} = \beta_0 + \beta_1 FCU_{it} + \boldsymbol{\pi}\mathbf{X}_{it} + \theta_t + \varphi_i + \varepsilon_{it} \quad \text{(C3)}$$

While most variables are the same as above, the constructed variable FCU_{it} is a dummy variable equal to one if pastoral household i ever holds any debit from bank or credit union before or in the year t. Thus, the coefficient β_1 captures the effects of using the formal credit on the TFPs. The results are shown in Columns (5) and (6) of Table C1, where Column (5) doesn't include control variables and Column (6) includes. We can see that the coefficients of FCU_{it} are positive but not significant. These results suggest that using formal credit does not always increase the TFP.

These analyses further discuss the effects of FCA, natural disasters, and FCU on TFPs separately. And all the results do not conflict with our baseline findings.

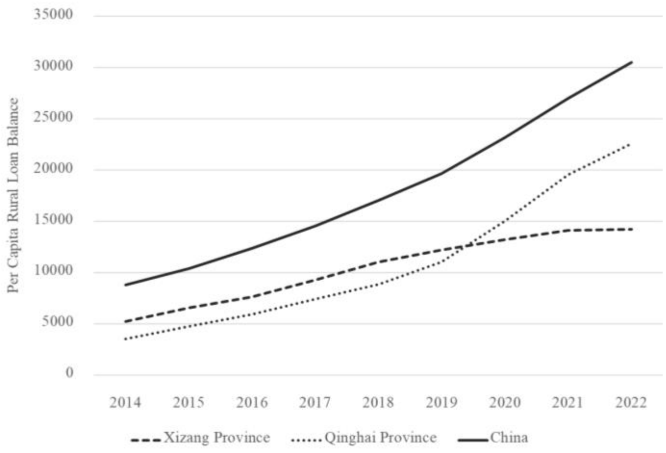
Table C1. Staggered DID results

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$	$\ln TFP_{it}$
$Post\ Disaster_{it}$	0.004	0.006	--	--	--	--
	(0.010)	(0.010)	--	--	--	--
FCA_i	--	--	0.308^{***}	0.264^{***}	--	--
	--	--	(0.091)	(0.084)	--	--
FCU_{it}	--	--			0.008	0.005
	--	--			(0.009)	(0.009)
Constant	-1.184^{***}	-1.812^{***}	-1.354^{***}	-1.951^{***}	-1.187^{***}	-1.787^{***}
	(0.001)	(0.302)	(0.075)	(0.399)	(0.004)	(0.299)
Controls	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1659	1659	1659	1659	1659	1659

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Standard errors reported in the parentheses are clustered at the pastoral household level.

Appendix D. Supplementary tables and figures

Figure D1 Per capita rural loan balances in Xizang, Qinghai, and China



Data source: National Bureau of Statistics of China

Figure D1 shows the dynamics of per capita rural loan balances in different regions of China in the past decade. We can see that, the rural population in Qinghai and Xizang provinces (two major provinces located on QTP) share a much lower per capita loans comparing to the average of China. Moreover, while Qinghai province has a growing trend of per capita rural loans similar to the state-average, Xizang province experiences a much lower growth.

Table D1 Estimating the propensity of FCA

Variables	FCA
Age of HH	-0.016***
	(0.005)
Education of HH	0.058***
	(0.018)
Average age	-0.008
	(0.009)
Number of laborers	0.188***
	(0.044)
Dependency ratio	0.311
	(0.260)
Smartphone	0.438***
	(0.119)
Savings	-0.000
	(0.000)
Home	0.000**
	(0.000)
Average subsidy	-0.026
	(0.025)
Number of livestock	-0.050**
	(0.021)
Cost of hiring	-0.208**
	(0.086)
Insurance	-0.227**
	(0.110)
Cooperative membership	0.163
	(0.151)
Training	0.135
	(0.199)
NDVI	-0.775***
	(0.258)
Mortgage	0.888***
	(0.122)
Distance	0.003**
	(0.001)
Constant	0.490
	(0.465)
N	1659

Note: After comparing several PSM specifications, we decided to use a logit model with a 5-nearest neighbors matching method to estimate the propensity score.

Figure D2 Pre-match distribution of the propensity scores of treated and untreated groups

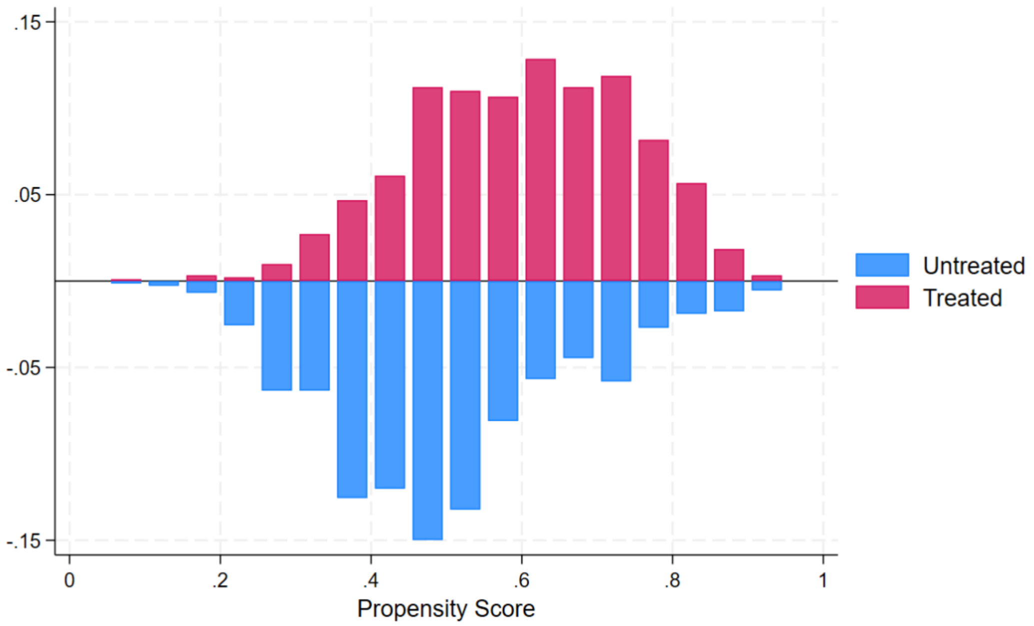


Table D2 Imbalance testing results for PSM after-match groups

Variables	Mean		%bias	t-test	
	Treated	Control		t	p>t
Age of HH	48.536	48.451	0.7	0.15	0.882
Education of HH	2.526	2.626	-3.1	-0.62	0.533
Average age	35.322	35.406	-1.2	-0.28	0.776
Number of laborers	3.555	3.560	-0.4	-0.08	0.940
Dependency ratio	0.314	0.302	5.2	1.15	0.250
Smartphone	0.695	0.697	-0.4	-0.09	0.927
Savings	35831	34059	3.2	0.73	0.463
Home	193740	190000	1.8	0.36	0.716
Average subsidy	0.090	0.094	-0.1	-0.05	0.962
Number of livestock	2.945	3.101	-5.8	-1.19	0.234
Cost of hiring	0.163	0.142	2.9	0.71	0.480
Insurance	0.538	0.540	-0.4	-0.07	0.940
Cooperative membership	0.171	0.148	6.3	1.33	0.185
Training	0.095	0.097	-0.8	-0.16	0.874
NDVI	0.530	0.516	6.1	1.27	0.203
Mortgage	0.363	0.363	-0.1	-0.02	0.985
Distance	17.097	15.182	4.5	0.88	0.382