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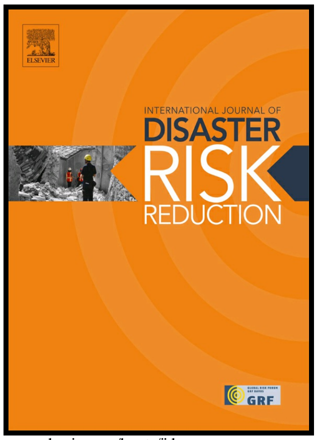

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Disaster-mitigating and general innovative responses to climate disasters: Evidence from modern and historical China

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Abstract

In studies on the effects of climate disasters, positive aspects are often overlooked. However it is important to accurately estimate the long-run impact of these disasters. This study presents the first attempt to investigate the innovative response to climate disasters in modern and historical China. For modern China, using panel data of up to 31 provinces from 2005 to 2013 and the Generalized Methods of Moments (GMM) technique, this study suggests that past climate disasters have led to an increase in the number of disaster-mitigating patents. These patents also boost innovations in other fields, which indicate that there exists a spillover effect in technological progress. The paper further investigates five major province groups in modern China and finds that disaster-mitigating patents not only respond to local disasters but serve as feedback to disasters occurring in neighboring provinces as well. Additionally, this study creatively uses the time-series data from 11 A.D. to 1910 A.D. to analyze the historical case with the Ordinary Least Square (OLS) method. The results show that climate disasters only spurred innovations in disaster mitigation fields and not in others, meaning that innovation spillovers did not exist in historical China. This study provides practical implications for policymakers and governments. They should introduce incentives to encourage and increase investment in research and technological development sectors after climate disasters.

Keywords: climate disasters; innovations; spillover effect; disaster-mitigating patents

1. Introduction

There is a growing consensus that climate change could worsen some natural disasters [1]. Over the past few decades, global warming had raised the frequency of extreme climatic events. As a result the world has been suffering from more climate disasters than geological disasters [2]. Climate disasters constitute 75% to 80% of all natural disasters [3]. They principally include floods, droughts, hail, frost and cyclones. Economic losses resulting from climate disasters are tremendous and, with a rise in the frequency of climate disasters, continue to increase [4]. The United Nations claim that in 2014, climate disasters resulted in economic losses totaling over 40 billion US dollars around the world.

Furthermore, climate disasters can lead to either negative or positive impacts on the economy and society. On the negative side, they can cause extensive damage, both in history and modern society. For instance, Vu and Hammes [5] claims that a disaster with a 1% increase in the percentage of population killed is associated with a fall in output of about 47 billion RMB in China. From the perspective of history, Wang et al. [6] and Zhang [7] confirm that floods in ancient China often damaged the agriculture in the Huaihe River district. Chen [8,9] argues that climate shocks played an important role in nomadic conquest and peasant uprisings, indirectly impeding economic development. Overall, climate disasters negatively influence the economy and cause people to alter their risk perceptions [10].

Recently, however, increased attention has been paid to the positive impact of climate disasters. It is possible for people to adapt climate changes, by mitigating disasters' harm, creating business opportunities and adjusting social ecological systems in response to incurred climate impacts [11]. As a matter of fact, Skidmore and Toya [10] argue that climate disasters are positively correlated with human capital accumulation and GDP growth. Cuaresma et al. [12] claim that disasters seem as "creative destruction" to some extent, because they could increase productivity and capital investment. These conclusions are confirmed in several recent studies. Kousky [13] finds that areas more prone to disasters invest more in reducing hazards, which serves as a future climate change adaptation. Birkmann et al. [14] indicate that climate disasters can generate large resource inflows for financing and supporting reconstruction as well as rehabilitation of disaster areas. Cunado and Ferreira [15] argue that moderate floods often result in a positive impact on per capita GDP growth in over one hundred developing countries.

According to Callaghan [16], disasters decreasing the amount of the factors of production would spur innovations that reduce the use of them. In other words, technological innovation is also of great importance in mitigating climate disasters. If the innovative response works out well and timely, economic losses will decrease and disaster resilience will increase [17]. On the one hand, innovations equip people with useful tools to cope with climate hazards. Shaw et al. [18] find that hazard reduction in

Asia has benefitted from the invention of early warning systems which forecast climate disasters. Moreover, technical innovations in construction enhance the resilience of buildings and infrastructures to various climate disasters. Using panel data of up to 28 countries in Europe over a period of 26 years, Miao and Popp [19] further find that the increase of disaster-mitigating innovations corresponds to the severity of natural disasters in the last five years. On the other hand, innovations resulting from climate disasters are beneficial for post-disaster economic development. As an example, drought-resistant crops are being developed to adapt to possible droughts and the effects of global warming, which would contribute greatly to farming all over the world [20]. Consequently, many patents based on new agricultural technologies are being registered, such as new freeze-resistant crops, as well as new fertilizers. Neumayer et al. [21] also suggest that private investments in disaster prevention and public damage mitigation policies spur innovations. Thus, climate disasters seem to be powerful inducements for technological progress.

Another important conclusion of Cunado and Ferreira [15] is that some disasters such as floods have a direct positive effect on agricultural growth rates, as well as an indirect effect on growth rates in other sectors. Why does this indirect effect exist? Our paper finds two main reasons. First, although climate disasters directly spur disaster-mitigating innovations, technology transfer among different fields are becoming more frequent [22,23]. Second, human abnormal behaviors like suicidal tendencies usually arise in the aftermath of natural disasters [24]. To satisfy security needs, people tend to make efforts in innovations that fight against mental issues and save lives [25]. In this case, it is of importance to identify the spillover effect of disaster-mitigating innovations on other patent applications.

China has a long history of recording climate disasters, like floods and droughts, which date back to 200 B.C. Successive dynasties and regimes gave their full attention to preventing disasters [26]. Nowadays, the economic losses due to climate disasters increase by approximately 30% per year on average in China [27]. Although China provides a good case study of the issue, no research empirically studies the relationship between climate disasters and innovations in China with both a modern and historical view.

This research presents the first attempt to reveal the causal link between climate disasters and innovations, both in modern and historical China, based on current knowledge. The study also creatively demonstrates the spillover effect of disaster-mitigating innovations and the impact of climate disasters on local innovations in neighboring provinces. The objective of the study is to provide policymakers and governments with practical implications for technological innovation.

The study selects the Generalized Methods of Moments (GMM) technique, based on Roodman [28], to estimate the panel of modern China. This study investigates modern China with data from 31 provinces from 2005 to 2013 and identifies the causal link between disaster-mitigating innovations and climate disasters. Moreover, disaster-mitigating patents could spur patent applications in all fields. Empirical analysis results show that 1 year lagged climate disasters significantly spur disaster-mitigating patents. A positive correlation can be found between disaster-mitigating patents and the total number of patent applications. It also demonstrates the impact of climate disasters on local disaster-mitigating innovations in neighboring provinces.

This study further models to investigate innovative responses to climate disasters in historical China. According to Chen's [8,9] work, he uses time series data from 11 A.D. to 1910 A.D. and defines each decade as an observation. This study gets 190 observations as time-series data and uses the Ordinary Least Square (OLS) to investigate innovative responses to climate disasters in historical China [8,9]. It finds that climate disasters which occurred in a given decade have had a positive impact on disaster-mitigating innovations in the next decade in historical China. The above findings confirm that the study provides valuable insight onto the economics of climate disasters. The present study contributes to researches by estimating the cost of climate disasters. Innovations are outcomes of the disasters, and should be particularly emphasized when estimating the long-run impact of disasters.

The rest of the paper is organized as follows: Section 2 reviews the literature; Section 3 presents the empirical model; Section 4 introduces the data and provides statistical analysis; Section 5 investigates and discusses empirical analysis results, and the final section concludes.

2. Empirical model

To discover how climate disasters boost innovation in modern China, this study first emphasizes risk perception. Risk is the key factor that spurs innovation, as people are generally reluctant in taking risks. In other words, someone's risk perception ($R_{i,t}$) greatly affects their self-protection decisions [29]. According to Cameron and Shah [30], individuals who had recently suffered from a natural disaster display a high level of risk aversion. Moreover, Miao and Popp [19] suggest that a region's capability to deal with disasters ($C_{i,t}$) as well as its baseline hazard ($B_{i,t}$) influences people's risk perception. Baseline hazard is measured by the frequency of geological disasters. For example, globally, 81 percent of all earthquakes occur in countries located along the "Ring of Fire" in the Pacific Ocean. Therefore, people living in this area perceive a stronger risk of earthquakes. In China, the province of Sichuan suffers more debris flow compared to the Hubei province, and as the result, suffers a higher baseline hazard. The paper models the perceived risk ($R_{i,t}$) as follows:

$$R_{i,t} = f_R\left(\sum_{n=1}^{N} D_{i,t-n}, B_{i,t}, C_{i,t}\right) \quad (1)$$

where $D_{i,t-n}$, a pre-determined variable free of endogeneity, denotes the lag of climate disaster damage.

Many researches focus on how the characteristics of an area can reduce disaster damages. Toya and Skidmore [31] and Kousky [13] show that the region with higher incomes ($Y_{i,t}$), higher education levels ($E_{i,t}$), greater openness ($O_{i,t}$), and stronger financial institutions ($I_{i,t}$) suffer fewer losses. In addition to this, the government spending ratio ($G_{i,t}$) correlates to how the region can withstand the disaster shocks [32]. Hence, the model $C_{i,t}$ is detailed as follows:

$$C_{i,t} = f_c(Y_{i,t}, I_{i,t}, E_{i,t}, O_{i,t}, G_{i,t}, K_{i,t-1}) \quad (2)$$

where $I_{i,t}$ refers to the financial system and institutions, and $K_{i,t-1}$ denotes existing knowledge stocks in year t. Miao and Popp's [19] study show that regions usually pay significant attention to prior exposure to disasters and can attain technological progress from it.

Disaster-mitigating Innovations ($INN_{i,t}$) in China, in response to climate disasters, principally depend on the perceived risk, income, government action, institutions, knowledge stocks, and human capital [33]. Using the variables mentioned above, we have the following function:

$$INN_{i,t} = f_I(R_{i,t}, Y_{i,t}, G_{i,t}, I_{i,t}, K_{i,t-1}, E_{i,t}) \quad (3)$$

Combining Equation (1), (2), and (3), we have the relationship presented in Equation (4):

$$INN_{i,t} = f_I(\sum_{n=1}^{N} D_{i,t-n}, B_{i,t}, Y_{i,t}, I_{i,t}, E_{i,t}, O_{i,t}, G_{i,t}, K_{i,t-1}) \quad (4)$$

Since the study decides to use the fixed-effects model, Equation (4) can be rewritten as follows:

$$INN_{i,t} = f_I(\sum_{n=1}^{N} D_{i,t-n}, B_{i,t}, Y_{i,t}, I_{i,t}, E_{i,t}, O_{i,t}, G_{i,t}, G_{i,t} \times E_{i,t}, K_{i,t-1}, \eta_i, \gamma_t) \quad (5)$$

where η_i controls the unobserved time-invariant heterogeneity across provinces and γ_t denotes the year fixed effect, which controls time-varying factors for all provinces. Moreover, the paper introduces the interaction term $G_{i,t} \times E_{i,t}$ to identify the quality of education in different provinces.

This study wonders whether disaster-mitigating innovations can spur patent applications ($inn_{i,t}$). We identify the Equation (6) as follows:

$$inn_{i,t} = f_i(INN_{i,t}) \tag{6}$$

Since the lag of disaster damage works as one of the independent variables, the paper mainly selects the GMM technique, based on Roodman [28], to estimate the dynamic panel of modern China. The robust standard error is used and is clustered by province.

The study also models to investigate innovative responses to climate disasters in historical China. "China" here refers to the central Chinese dynasty. Chen [8,9] provides good samples to study the subject. According to his work, this paper defines each decade as an observation and gets 190 observations as time-series data. The Ordinary Least Square (OLS) is used here. D'_t denotes the number of climate disasters in the decade t. We have to control two variables: whether or not China was unified (U_t), and whether or not China was under the protection of the Great Wall (W_t) [8]. Since the paper focuses on climate disasters, it should also control other disasters (D''_t) including earthquakes, landslides, and locusts. Select important culture systems (S_t), such as the Chinese imperial examination system, may affect innovations. Moreover, land (L_t) and populations (I_t) serve as important factors affecting each dynasty. Hence, the following function represents the historical case:

$$INN'_t = f'_I(\textstyle\sum_{n=1}^{N} D'_{t-n}, D''_t, U_t, W_t, L_t, S_t, P_t) \tag{7}$$

In the historical case, the paper also compares Equation (6) with (7) to identify the results obtained in the modern case. $inn_{i,t}$ serves as a proxy of acknowledged important innovations in all fields from 11 A.D to 1910 A.D.

3. Data and analysis

In empirical analysis, the paper needs proxies for variables in Equation (4) and (6). As the dependent variable, $INN_{i,t}$ is measured by disaster-mitigating patents, which is obtained from the China Patents Database. The study has obtained the amount of disaster-mitigating patents by searching for keywords that are related to climate disasters (includes but is not limited to drought; floods, landslide, debris flows and typhoons; hailstorms; freezing weather and snowstorms). These are climate disasters classified by the Chinese Statistical Yearbook. The present study groups multiple types of natural hazards and calculates the sum. This database can also show which institution a patent belongs to. As for co-inventors' patents, we only pay attention to the locations of institutions that have final ownership of patents. Figure 1 shows the number of disaster mitigating patents in each province from 2005 to 2013. Here the International Patent Classification (IPC) code is not used for searching for two reasons. First, it is difficult to distinguish whether the patent is invented due to climate disasters by IPC code. Second, a particular disaster could spur disaster-mitigating patents in different field. For example, drought might spur innovations in both farming and breeding fields that respectively links to A01C and A01F according to the IPC code. In this case, searching for keywords can be an easier way to identify the appropriate patents.

The total number of patent applications in province i in year t is from the Chinese Statistical Yearbook on Science and Technology, which is used to measure $inn_{i,t}$. It should clarify that more than one *patent holder* (not co-inventor) can share a patent application. For instance, if the patent is applied by two patent holders in Hebei and Hubei respectively, both two provinces keep a record of one application. And if this application fails and the two holders apply again, the number of applications will change to 2. Figure 2 and 3 show the number of patent applications in 2013 in each province except Taiwan and its average growth rate from 2005 to 2013 respectively. From the two figures, it is clear that patent application is positively correlated to economic development. Wealthy provinces such as Jiangsu, Zhejiang, Guangdong, Beijing, and Shanghai have more patent applications. However, the growth rate of patent applications shows no relationship with economic development.

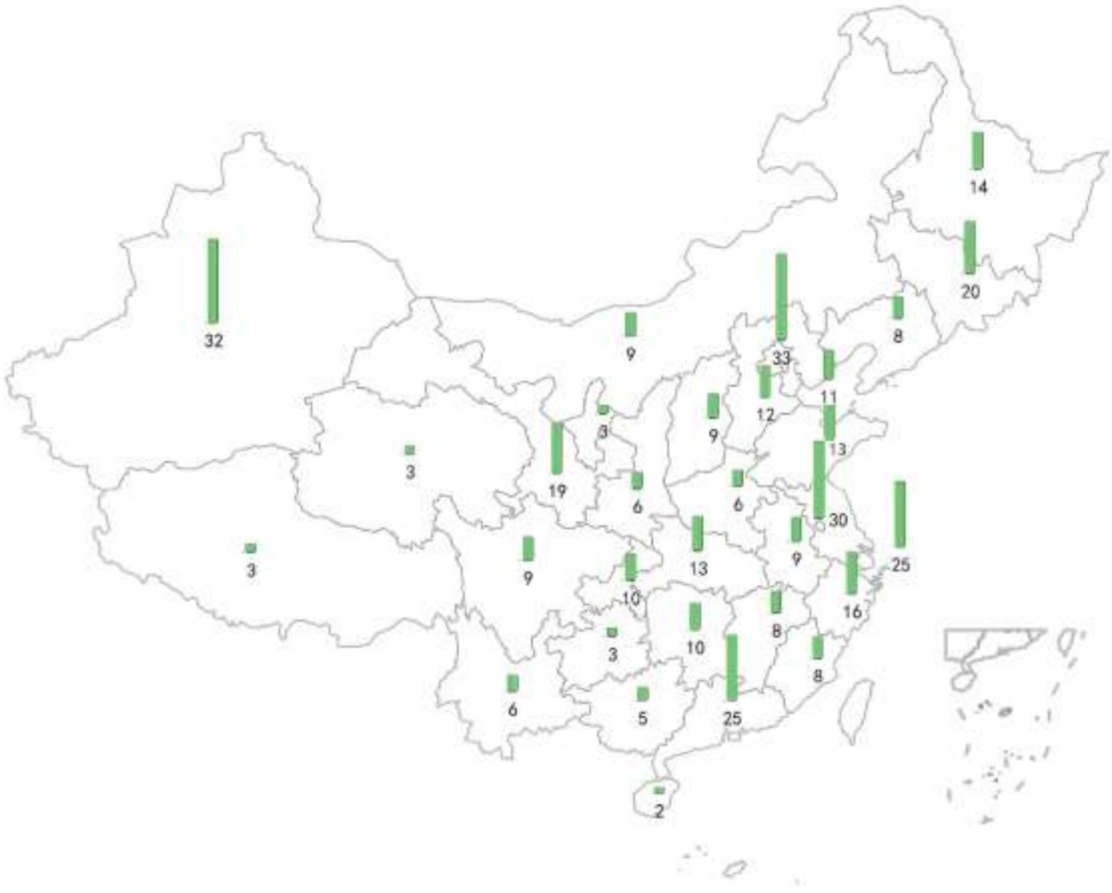

Figure 1. Disaster-mitigating patents in each province (2005-2013)

Note: The figure suggests that provinces with a strong scientific research power (eg. Shanghai and Beijing) or with more disasters (eg. Xinjiang and Zhejiang) contribute more to disaster-mitigating patents.

Data source: China Patents Database.

Figure 2. Total patent applications in each province (2013)

Data source: Chinese Statistical Yearbook on Science and Technology.

Figure 3. Average growth rate of total patent applications in each province (2005-2013)

Data source: Chinese Statistical Yearbook on Science and Technology.

The key independent variable, $D_{i,t}$, is measured by climate disaster damage in each province. The climate disasters, as classified in the Chinese Statistical Yearbook, denote four kinds of disasters: drought; floods, landslide, debris flows and typhoons; hailstorms; freezing weather and snowstorms. More precisely, according to Miao and Popp [19], the paper introduces disaster damage intensity as a proxy. Both economic losses and human fatalities can measure damage from climate disasters. Our proxy for $D_{i,t}$ is represented by victims divided by total population ($D_{a,i,t}$) or economic losses divided by GDP ($D_{b,i,t}$) in province *i* in given year *t*. The data is obtained from the Resource and Environment section of Chinese Statistical Yearbook.

B_i denotes baseline hazard for province i, which mostly depends on its location [34].

The paper uses two variables to measure the hazard: the frequency of earthquakes ($B_{a,i,t}$) and the frequency of debris flow in a province in a given year ($B_{b,i,t}$). Unless the variables are controlled, our estimations will show considerable bias, seeing as geological disasters also spur innovations. Figure 4 generally reveals which province suffers a greater baseline hazard.

$Y_{i,t}$ and $E_{i,t}$ respectively refer to income per capita and the average level of educational attainment. We obtain the data of these two variables from the Chinese Statistical Yearbook. The paper utilizes public expenditure of the local government divided by GDP in year t to measure $G_{i,t}$. As for $O_{i,t}$, the total export and import divided by GDP is a suitable proxy [35].

It is acknowledged that there exists no perfect measurement for social institution $I_{i,t}$. The paper thus drops $I_{i,t}$ for two main reasons. First and foremost, not much difference, particularly in social systems, can be found among the provinces of China. Second, government spending, economic conditions, and education levels can be proxies for $I_{i,t}$ because the three proxies play key roles in boosting the development of social institutions [36, 37].

The paper constructs existing knowledge stocks $K_{i,t}$ in detail. According to Lee and Huang [38], knowledge stocks mainly depend on current and past flows of human capital on the research and development department. It is expressed as below with the perpetual inventory model:

$$K_{i,t} = S_{i,t} + (1 - \rho)K_{i,t-1} \tag{8}$$

where $S_{i,t}$ denotes the full-time equivalent of research and development personnel in province i in year t. The data is from the Chinese Statistical Yearbook on Science and Technology. ρ denotes the depreciation rate of human capital, which the paper assumes to be 5% following Luo and Zhao [39]. For $K_{i,2005}$, we have:

$$K_{i,2005} = S_{i,2005} + (1 - 5\%)K_{i,2004} \tag{9}$$

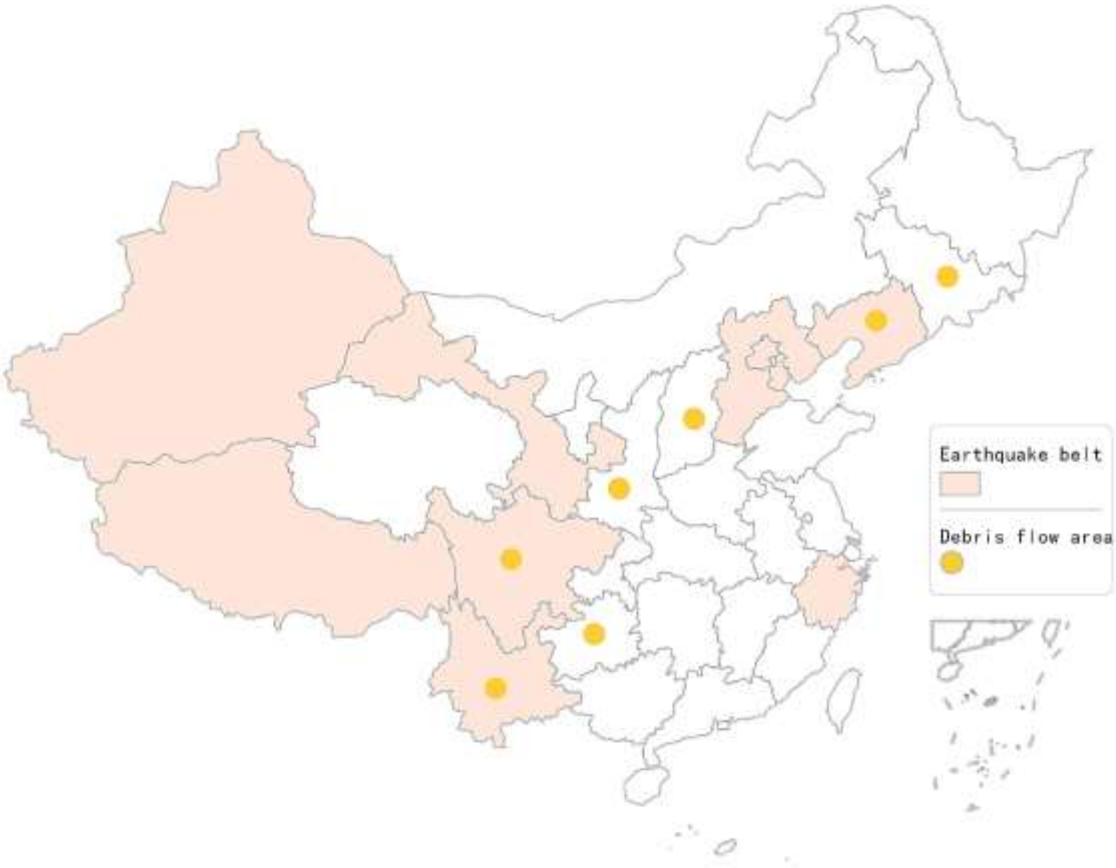

Figure 4. Baseline hazard

Data source: Chinese Statistical Yearbook on the Environment.

As for endogeneity, this study pays attention to lagged knowledge stocks. First, this term has the characters similar to lagged disaster-mitigating innovations and patent applications that are predetermined. Second, the disaster impacts may also be predetermined in the sense that any earlier efforts of innovation as a response to past disaster shocks may help decrease the victims and alleviate economic losses of subsequent similar disasters. To solve the endogeneity, we set an instrument for 1 year lagged knowledge stocks using 4 years lagged knowledge stocks. As 3 years lagged disasters' impact are taken into consideration, the instrument is no longer a function of innovations or patent applications in current year.

Another source of endogeneity is that climate disasters and patents may have impacts on each other. Since it takes time to apply new patents, these patents are believed to reduce the intensity of the disasters in the years following rather than in the current and past years. With a robust standard error, the paper can, to a considerable extent, avoid serial correlation of patents resulting from the model setting. Table 1 provides descriptive statistics of major variables from 2005 to 2013.

Table 1. Descriptive statistics of major variables from 2005 to 2013

	Abbreviation	Mean	Standard deviation	Maximum	Minimum	n
Dependent variable						
Disaster-mitigating patents	$INN_{i,t}$	2.198	2.717	19	0	186
Log patent applications	$inn_{i,t}$	4.174	0.730	5.703	2.209	186
Independent variables						
Disasters intensity a (human fatality intensity)	$D_{a,i,t}$	0.299	0.194	0.998	0.000	279
Disasters intensity b (economic loss intensity)	$D_{b,i,t}$	0.014	0.019	0.176	0.000	279
Log GDP per capita (RMB)	$Y_{i,t}$	4.502	0.216	4.989	3.995	186
Average level of educational attainment (year)	$E_{i,t}$	8.692	1.111	12.084	4.552	186
Openness	$O_{i,t}$	0.311	0.375	1.588	0.035	186
Government spending ratio	$G_{i,t}$	0.250	0.190	1.291	0.087	186
Logged knowledge stocks	$K_{i,t}$	5.195	0.593	6.296	3.338	186
Frequency of earthquake	$B_{a,i,t}$	0.254	0.703	4	0	186
Frequency of debris flow	$B_{b,i,t}$	0.069	0.294	2	0	186
Instrument variables						
4 years lagged knowledge stocks	-	4.448	0.560	5.453	2.692	186

Note: “GDP” refers to nominal GDP. In the empirical analysis, the paper uses real GDP to calculate log GDP per capita.

As for the historical part, the paper uses time series data from 11 A.D to 1910 A.D. It selects this period for two reasons. First, during the period, 190 observations can be obtained if each decade is seen as an observation. Second, during this period, accurate times of all innovations were recorded.

The paper finds special proxies that consider data accessibility and historical situations. Here $INN_{i,t}$ refers to the number of innovations in a decade. The paper measures innovations in two ways. One is disaster-mitigating innovation ($INN_{i,t}$). The information of this kind of innovation, collected by Shao [40] from Chinese history, aims directly at reducing damages (e.g. wind measuring devices and earth thermometers). Shao's paper divides disaster-mitigating innovations into four kinds: farming techniques; farming systems; storing techniques; seeds breeding and introducing. These innovations effectively mitigate loss of disasters. Another is the so-called "important innovation" ($inn_{i,t}$). The 85 important innovations are from all fields, mainly including mathematics, machines and weaponry, which are officially identified by the Chinese Academy of Science [41]. D_t' and D_t'' are measured by the number of climate disasters in a decade and the data is from Chen et al. [42]. The paper introduces W_t and U_t based on Chen [8]. An overview of cultural systems in China shows the understandings of culture systems [43], which help us to form S_t as a dummy variable. The paper defines $S_t = 1$ when the imperial examination system exists and $S_t = 0$ when the recommendatory system exists in China. As for L_t and P_t, Liang [44] gives us a detailed summary. As mentioned above, the paper defines each decade as an observation and gets 190 observations in total. Table 2 provides descriptive statistics of major variables from 11 A.D. to 1910 A.D as follows:

Table 2. Descriptive statistics from 11 A.D. to 1910 A.D.

	Abbreviation	Mean	Standard deviation	Maximum	Minimum	n
Dependent variable						
Number of disaster-mitigating innovations	$INN_{i,t}$	0.263	0.436	1	0	190
Number of important innovations	$inn_{i,t}$	0.311	0.464	1	0	190
Independent variables						
Number of climate disasters	D_t'	21.722	21.508	106	0	190
Whether unified	U_t	0.717	0.451	1	0	190
Whether under protection of the Great Wall	W_t	0.612	0.488	1	0	190
Number of other disasters	D_t''	4.303	4.374	22	0	190
Culture systems	S_t	0.684	0.446	1	0	190
Farmland (million squared kilometers)	L_t	6.559	3.328	17.6	2.18	190
Population (ten million)	P_t	8.856	8.203	39.9	1.4	190

4. Results and discussion

The paper uses GMM to identify the impact of climate disasters on innovations in modern China. GMM is a proper method for two reasons. First, it can solve the endogeneity problem (such as knowledge stocks and disasters impact, discussed in Section 3). Second, even if the error terms are self-correlated or of heteroscedasticity, the estimates are robust. Moreover, since the amount of disaster-mitigating innovations and patent applications is a natural number, it is appropriate to use count-data model. In the paper, Poisson regression is selected for the modern case because the dependent variables are not over dispersion. It should be noted that there does not exist a mature strategy to eliminate endogeneity in a Possion regression. To some extent, the results can show robustness.

4.1. Impact of local climate disasters

Table 3 presents the estimated results using economic loss intensity as the disaster intensity. Since Kousky [13] indicates that past impacts play a more important role in affecting disaster-stricken areas, the paper uses the intensities of climate disasters during the past three years to capture past impacts. The results show that climate disasters in the past year have a significant impact on local innovations. If disaster intensity in the year t-1 increases by 0.1, then the number of disaster-mitigating patents in year t will soar by 1.6 in Model (2). In general, the coefficients of disaster intensity in year t are not significant because disasters have mixed impacts on innovations as soon as they occur. Skidmore and Toya [10] also support this conclusion. They claim that both negative and positive impacts exist when disasters have just happened, and the positive effect may be stronger given a few years. In Model (4), the Poission regression almost indicates the same results: disaster intensity significantly boosts the disaster-mitigating patents.

Now we turn to other variables. Log GDP per capita has no significant impact on disaster-mitigating patents. This conclusion seems a little different from other papers that use many countries as sample data. In China, there exists a mismatch between disaster-mitigating innovations and disaster intensity. Many relatively poorer provinces suffer from severe disasters but they do not have enough resources to invent new techniques. In this way, wealthier provinces shoulder this responsibility. It is surprising that the Government spending ratio has no effect on the patents. As is their duty, governments build medical institutions and schools and also pour funds into disaster prevention. We assume that these activities can dampen the enthusiasm for innovations. The impact of knowledge stocks in the past year is positively significant as we set an instrument for it using 4 years lagged knowledge stocks. Miao and Popp [19] suggest that the knowledge stock serves as a building block for future innovations and could also inspire more innovations. The present study argues that the latter mechanism plays a more important role in China nowadays. The interaction term of log GDP per capita and the average level of educational attainment is used to test whether the quality of education affects innovations. In wealthier areas, schools provide better education than in other areas. The coefficient of this term is not significant and shows that there does not exist a remarkable difference in the quality of education. As we suggest, the mobility of students eliminates this difference. A student can receive their primary education in the Hubei province for instance, but gain a higher education in another province.

In Table 4, the victim intensity is used to measure disasters results. Model (5) and Model (6) again indicate that the past one-year loss intensity has a significant and positive impact on disaster-mitigating patents. The results are, in general, the same as Model (3) and Model (4). These results support our robust main conclusion: climate disasters with higher intensities contribute more to the increase of the disaster-mitigating patents.

For other variables, the interaction term of GDP per capita and the average level of educational attainment is still not significant in Table 4. As discussed earlier, this term affects disaster-mitigating patents through multiple channels, and therefore, their final effect is somewhat unclear in comparison between economic losses and victims. As Miao and Popp [19] and Neumayer et al. [21] claim, openness is an important factor of a province's adaptive capacity, which in turn has a mixed effect on innovations. As a result, the coefficients of openness show no significant impact on the patents.

Table 3. Impact of economic loss intensity on disaster-mitigating patents

Disaster-mitigating patents	Model (1)	Model (2)	Model (3)	Model (4)
Disasters intensity in year t	0.349	11.446	10.370	5.307
	(8.154)	(10.778)	(10.447	(5.111
Disasters intensity in year t-1	14.553*	14.692*	15.961*	8.081*
	(7.961)	(8.136)	(8.565)	(5.041)
Disasters intensity in year t-2	-4.682	-2.526	-0.882	-5.765
	(7.077)	(6.195)	(5.545)	(8.134)
Disasters intensity in year t-3	6.447	6.774	6.471	4.061
	(5.543)	(5.465)	(4.913)	(4.165)
Log knowledge stocks in year t-1	1.842**	1.723**	1.844***	1.128***
	（0.745）	（0.700）	（0.661)	（0.388)
Log GDP per capita		-3.557	-3.436	4.640
		(6.650)	(6.688)	(5.710)
Average level of educational attainment		-3.360	-3.100	1.989
		(4.593)	(4.547)	(3.443)
Log GDP per capita × Average level of educational attainment		0.794	0.745	-0.395
		(0.930)	(0.921)	(0.700)
Government spending ratio		2.171	2.441	2.381*
		（2.247）	(2.266)	(1.436)
Openness		0.315	0.299	-0.091
		（0.816）	(0.806)	(0.226)
Frequency of debris flow			-0.844***	-0.861***
			(0.223)	(0.239)
Frequency of earthquake			-0.142	-0.063
			(0.186)	(0.105)
Constant	-7.434*	6.145	4.582	-29.566
	（4.166）	（31.596）	(32.025)	(26.496)
ADJ R^2	0.203	0.320	0.331	0.245
n	186	186	186	186
Year fixed effect	YES	YES	YES	YES
Province fixed effect	YES	YES	YES	YES
Number of provinces	31	31	31	31
Estimate method	GMM	GMM	GMM	Poisson
First-stage F value	805.06	742.49	607.86	-

Note: Clustered standard errors of provinces are in parentheses. ***, **, and * indicate a 1%, 5%, and 10% level of significance, respectively. A 2-step GMM is used with fixed effects of the year and province in models (1) to (3). The instrument variable, 4 years lagged knowledge stocks, passes the "weak instruments test". The minimum eigenvalue is more than 600, which can reject the original hypothesis that weak instrument exists. We set an instrument for disaster impact (disaster intensity) using population intensity. However, in the regression, population intensity does not serve as a good instrument. It does not significantly correlate with disaster intensity and the minimum eigenvalue is 0.24. Coincidentally, disaster intensity included in the regression cannot be recognized as endogenous variables by the Hausman test. The 4 years lagged knowledge stocks, instead of population intensity, is used as the instrument in further regressions. In Model (4), as a Poisson model is used, the paper includes log knowledge stocks in year t-1 as an independent variable.

Table 4. Impact of victims' intensity on disaster-mitigating patents

Disaster-mitigating patents	Model (5)	Model (6)
Disasters intensity in year t	0.860	0.233
	(1.827)	(0.828)
Disasters intensity in year t-1	2.477**	1.604**
	(1.166)	(0.583)
Disasters intensity in year t-2	-0.633	-0.312
	(1.222)	(0.723)
Disasters intensity in year t-3	-0.840	0.865
	(0.660)	(0.487)
Log knowledge stocks in year t-1	1.514***	1.204***
	(0.441)	(0.237)
Log GDP per capita	-2.331	6.237
	(7.021)	(5.099)
Average level of educational attainment	-2.862	2.739
	(4.879)	(3.266)
Log GDP per capita × Average level of educational attainment	0.690	-0.552
	(0.995)	(0.663)
Government spending ratio	2.760	2.901**
	(2.301)	(1.297)
Openness	0.431	-0.052
	(0.925)	(0.306)
Frequency of debris flow	-0.969***	-0.979***
	(0.224)	(0.262)
Frequency of earthquake	-0.151	-0.089
	(0.184)	(0.104)
Constant	1.250	-36.799
	(33.614)	(24.450)
ADJ R^2	0.325	0.242
First stage F value	563.74	-
Estimate method	GMM	Poisson

Note: Clustered standard errors of provinces are in parentheses. ***, **, and * indicate a 1%, 5%, and 10% level of significance, respectively. The 2-step GMM is used with fixed effects of the year and province in Model (5). We set an instrument for 1 year lagged knowledge stocks using 4 years lagged knowledge stocks. In Model (6), as a Poisson model is used, the paper directly includes log knowledge stocks in year t-1 as an independent variable.

Table 5. Spillover of disaster-mitigating patents on total patent applications

Log total patent applications **Disasters intensity measurement**	**Model (7)** **Economic losses**	**Model (8)** **Victims**
Predicted disaster-mitigating patents in year t	-3.617 (2.566)	-0.211.005 (0.190.081)
Predicted disaster-mitigating patents in year t-1	0.018 (0.071)	0.064 (0.057)
Disasters intensity in year t	38.786** (16.698)	0.151 (0.147)
Disasters intensity in year t-1	57.718**8 (25.492)	0.563**(0.267)
Disasters intensity in year t-2	-2.443 (1.740)	0.264 (0.192)
Disasters intensity in year t-3	25.797** (11.159)	-0.176* (0.088)
Log knowledge stocks in year t-1	8.421*** (3.133)	1.509** (0.097)
ADJ R^2	0.938	0.939

Note: Clustered standard errors of provinces are in parentheses. ***, **, and * indicate a 1%, 5%, and 10% level of significance, respectively. The 2-step GMM is used with fixed effects of the year and province. We set an instrument for 1 year lagged knowledge stocks using 4 years lagged knowledge stocks. Other controlled variables are not reported. As predicted disaster-mitigating patents are highly correlated with log knowledge stocks in year t-1 (correlation coefficient equals 0.76). The insignificant coefficient of the former does not mean it cannot spur patent applications. In Table 6, we drop log knowledge stocks in year t-1 to validate the impact of predicted disaster-mitigating patents on total patent applications.

Table 6. Spillover of disaster-mitigating patents on total patent applications (without lagged knowledge stocks as an independent variable)

Log total patent applications	Model (9)	Model (10)	Model (11)	Model (12)
Disasters intensity measurement	Economic losses	Economic losses	Victims	Victims
Predicted disaster-mitigating patents in year t	0.052*** (0.090)		0.070*** (0.084)	
Predicted disaster-mitigating patents in year t-1	0.004 (0.065)		-0.059 (0.060)	
Disaster-mitigating patents in year t		0.037*** (0.013)		0.037*** (0.012)
Disaster-mitigating patents in year t-1		0.025** (0.012)		0.017 (0.014)
ADJ R^2	0.942	0.778	0.943	0.761

Note: Clustered standard errors of provinces are in parentheses. ***, **, and * indicate a 1%, 5%, and 10% level of significance, respectively. GMM is used with fixed effects of the year and province and no endogenous variables are included in the regression since we drop lagged knowledge stocks in the year t-1. The table can clearly indicate that the spillover effect is significant. Model (9) and Model (11) are additional explanation for the spillover effect since predicted disaster-mitigating patents in the year t and t-1 can be highly correlated and influenced by each other's coefficient. However, if we use the real number of disaster-mitigating patents in the year t and t-1, the problem can be solved to some extent. Other controlled variables are not reported. Overall, the spillover effect exists.

Spillover effect is shown in Table 5 and Table 6. Though the coefficients of predicted disaster-mitigating patents in year t and t-1 are not significant in the models (7) and (8), it does not suggest that no spillover effect can be discovered. In fact, since log knowledge stocks in year t-1 are highly correlated with log total patent applications and predicted disaster-mitigating patents, multicollinearity problems exist in models (7) and (8). In this case, coefficients of predicted disaster-mitigating patents are not accurate.

Therefore, in models (9) and (11), the paper drops log knowledge stocks in year t-1. In economic loss and victim loss cases, respectively, predicted disaster-mitigating patents in year t can boost total patent applications by 5.2% and 7.0%. In models (10) and (12), we use the real number of disaster-mitigating patents in year t instead of predicted disaster-mitigating patents as independent variables. The results show that one additional disaster-mitigating patent can increase total patent applications by 3.7%. One advantage of models (10) and (12) is that there exists no close logical relation or numerical correlation between core independent variables in year t and t-1.

Overall, the results show that climate disasters positively affect total patent applications via disaster-mitigating patents. The so-called “spillover effect” exists in technological development. For example, the freeze-proof material that was initially used in agriculture to cover crops and prevent damages in low temperature has since been used on motor vehicles and water pipes. New ideas in technological development are being applied into more fields, especially in this modern society [24].

4.2. Impact of climate disasters in neighboring provinces

Given that globalization is rendering countries increasingly interdependent with each other, salient disaster shocks can generate a global effect by raising the risk perception in other countries [19]. This phenomenon also exists in China on a provincial level. For example, a typhoon named “Dujuan” resulted in heavy rain in Shanghai for 4 days and the transport system came to a standstill. Both the provinces Jiangsu and Zhejiang also suffered from the typhoon because their trades with Shanghai had to stop. From this stems the idea of further investigating the impact of climate disasters on neighboring provinces in China [45].

This problem is of great interest for two reasons. First, as Verdonlini and Galeotti [46] claim, since the flow of knowledge is related to distance, geographic proximity makes it possible for neighboring provinces to serve as potential markets for innovation in one province. Second, geographic proximity leads to provinces sharing similar environmental characteristics and having a similar baseline hazard [19]. The paper groups provinces according to the government's policy, geographic characteristics, and economic ties and chooses five groups, including 14 provinces, as observations (see Figure 5).

This study still uses victim intensity and economic loss intensity to measure the impact of local climate disasters. As for disasters in neighboring areas, the following equation represents the measurement of their impact:

$$D_{i,t,f,j} = \frac{\sum D_{s\neq i,t,l,j}}{n-1} \quad , s = 1,2,3 \ldots n \tag{10}$$

where $D_{i,t,f,j}$ represents the impact of disasters in neighboring provinces (f) on province i in year t for group j, and $D_{s\neq i,t,l,j}$ denotes the impact of local disasters (l) on province s in year t for group j. n represents the number of provinces for group j.

Table 7 presents the estimation results. First, it should be noted that, in models (13) and (15), coefficients of disaster intensity in year t-1 are respectively larger than those of models (3) and (5). It means that provinces in the economic regions can benefit more from climate disasters. One explanation is that economic or technological ties in a certain group can positively affect the outcomes of patents. Knowledge stocks are playing an increasingly important role as technological cooperation thrives.

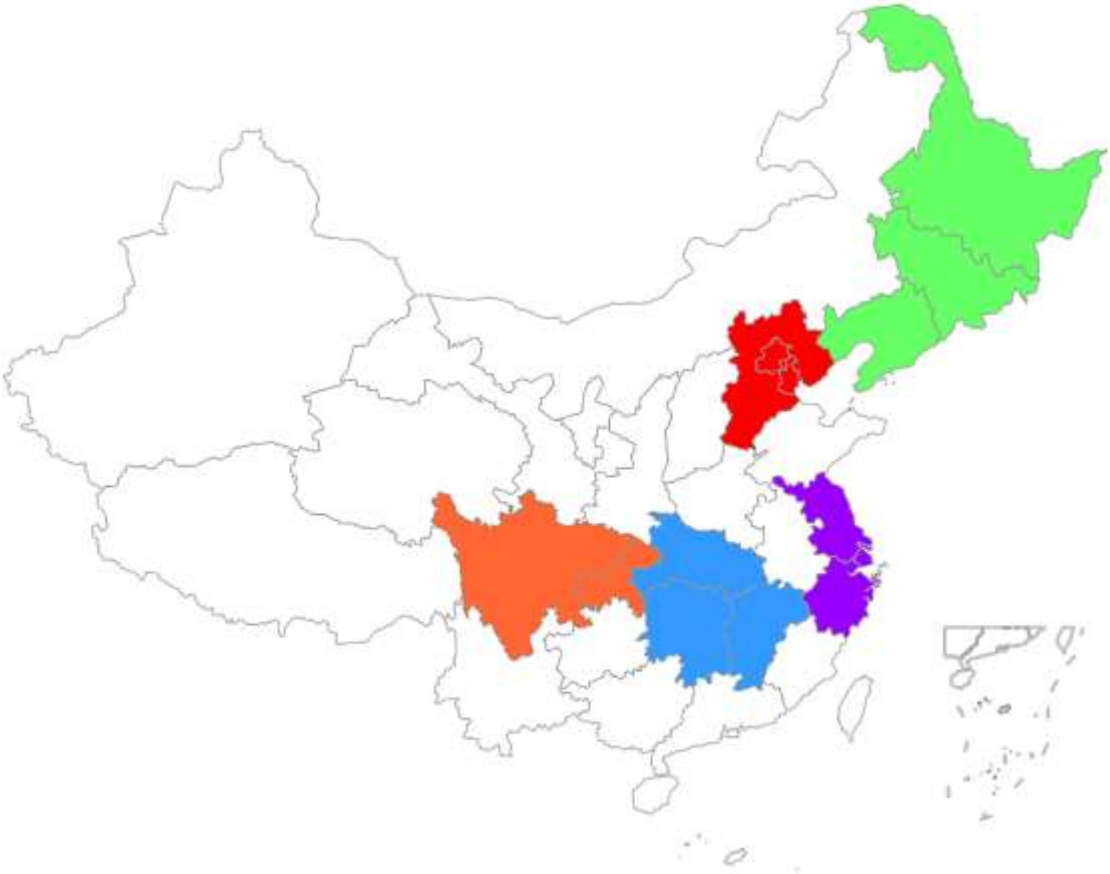

Figure 5. Provinces groups

Note: The paper groups provinces, according to government's policy, geographic characteristics and economic ties. The green region includes Heilongjiang, Jilin, and Liaoning, named the Dongbei industrial district. The red region includes Beijing, Tianjing, and Hebei, named the Jing-Jin-Ji district. The purple region includes Shanghai, Jiangsu, and Zhejiang, named the Changsanjiao district. The blue region includes Hubei, Hunan, and Jiangxi, named the province group in the middle reaches of the Changjiang River. Lastly, the orange region includes the Sichuan province and Chongqing, named the Chengyu economic region.

Table 7. Impact of climate disaster intensity on disaster-mitigating patents with neighboring provinces' shocks

Disaster-mitigating patents	**Model (13)**	**Model (14)**	**Model(15)**	**Model(16)**
Disasters intensity measurement	**Economic losses**	**Economic losses**	**Victims**	**Victims**
Local shocks				
Disasters intensity in year t	43.007	38.029	1.289	1.962
	(32.123)	(27.020)	(3.953)	(4.867)
Disasters intensity in year t-1	63.827***	64.495***	3.802*	3.414
	(18.752)	(18.357)	(2.340)	(3.318)
Disasters intensity in year t-2	12.715	11.714	-1.438	0.787
	(12.911)	(11.774)	(2.438)	(3.227)
Disasters intensity in year t-3	37.090**	29.664*	-1.299	0.271
	(17.389)	(18.227)	(1.959)	(2.422)
Log GDP per capita	20.678*	15.269	20.557	22.904
	(12.412)	(12.577)	(14.542)	(14.433)
Average level of educational attainment	15.275*	11.769	14.561	16.238**
	(8.422)	(7.361)	(9.310)	(7.806)
Log GDP per capita × Average level of educational attainment	3.202*	2.497	3.039	3.369*
	(1.739)	(1.570)	(1.958)	(1.650)
Government spending ratio	-9.287	-2.911	-0.049	7.251
	(8.194)	(7.011)	(8.380)	(7.320)
Log knowledge stocks in year t-1	5.443***.	5.797***	4.895**	4.433*
	(1.956)	(2.138)	(2.243)	(2.379)
Openness	-1.157	-1.811	-1.576	-1.014
	(1.358)	(1.111)	(1.497)	(1.175)
Neighboring provinces shocks				
Disasters intensity in year t		34.641**		0.546
		(15.427)		(3.949)
Disasters intensity in year t-1		-0.356		1.398
		(18.159)		(3.478)
Disasters intensity in year t-2		41.257***		-3.762
		(13.195)		(3.722)
Disasters intensity in year t-3		-27.533		-3.658
		(19.622)		(3.324)
ADJ R^2	0.518	0.553	0.460	0.491
First stage F value	38.59	29.06	52.17	41.89
n	84	84	84	84
Number of provinces	14	14	14	14

Note: Robust standard errors of provinces are in parentheses. ***, **, and * indicate a 1%, 5%, and 10% level of significance, respectively. The GMM is used with fixed effects of year and province. We set an instrument for 1 year lagged knowledge stocks using 4 years lagged knowledge stocks. Other controlled variables are not reported.

In terms of neighboring province shocks, the past one-year and two-year disaster intensities show a positive and significant effect on disaster-mitigating patents in Model (14). If disaster intensity in the past one-year or two-year increases by 0.1, the amount of disaster-mitigating patents will respectively rise by approximately 3.5 or 4.1. Thus, neighboring province shocks should never be ignored. Innovative responses to climate shocks cannot be confined to a certain geographic region. For instance, a drought in Guizhou province would not only boost developing drought-proof technologies in this province or even nearby provinces, but also all of China. However, neighboring provinces shocks are not significant in Model (16), which suggests that the victim case does not support the conclusion we discussed above in this paragraph. Differences in models (14) and (16) does not seem difficult to understand: neighboring shocks are more easily shown in the economic aspect instead of population aspect.

4.3. Impact of climate disasters in historical China

Table 8 shows the results of a general analysis for the historical case. Model (17) suggests that the number of climate disasters in the past decade has had a positive and significant impact on disaster-mitigating innovations, as so-called "patents" have not yet been defined in historical China. The main conclusion in the above sector is justified here as well, as past climate disasters had positively affected disaster-mitigating innovations. In the Model (18), important innovations is introduced as an explanatory variable. However, the coefficient is not significant, which suggests general important innovations cannot spur disaster-mitigating innovations.

As for other variables in Model (18), a soaring farming dominated population has an increasing need for disaster-mitigating innovations, and as the result, the population can boost innovations to some extent. Moreover, other disasters, aside from doing serious harm to agriculture, positively impact innovation. The results in Table 9 suggest that whenever a new disaster-mitigating innovation took place, it failed to spur innovations in other fields in historical China. In other words, the spillover effect does not exist in historical China.

Table 8. Impact of climate disasters on disaster-mitigating innovations (in historical China)

Disaster-mitigating patents Innovations	Model (17) Disaster-mitigating Innovations	Model (18) Disaster-mitigating Innovations
Number of climate disasters in decade t	-0.003 (0.033)	-0.002 (0.004)
Number of climate disasters in decade t-1	0.006** (0.003)	0.008** (0.003
Whether unified	-0.119 (0.155)	-0.183 (0.144)
Whether under protection of the Great Wall	0.053 (0.152)	0.058 (0.137)
Number of other disasters in decade t	0.020** (0.012)	0.020* (0.013)
Culture systems	-0.003 (0.124)	0.003 (0.122)
Farmland	-0.002 (0.014)	-0.004 (0.015
Population	0.085* (0.055)	0.119** (0.064)
Decade	-0.002** (0.001)	-0.005** (0.002)
Important innovations		-0.079 (0.057)
n	190	190

Note: Newey-west standard errors are in parentheses with lag term $p = 0.75\sqrt[3]{n}$. ***, **, and * indicate a 1%, 5%, and 10% level of significance, respectively. OLS is used.

Table 9. Spillover of disaster-mitigating innovations on important innovations (in historical China)

Important innovations	Model (19)
Disaster-mitigating innovations in decade t	0.185
	(0.362)
Disaster-mitigating innovations in decade t-1	0.021
	(0.374)
n	189

Note: Newey-west standard errors are in parentheses with lag term $p = 0.75\sqrt[3]{n}$. ***, **, and * indicate a 1%, 5%, and 10% level of significance, respectively. OLS is used and other controlled variables are not reported.

5. Conclusions and limitations

This study provides a credible answer that, whether in modern or historical China, innovations can serve as responses and adaptations to climate disasters. Using disaster-mitigating patents as the key dependent variable in the modern case, our empirical analysis suggests a stimulating effect of climate disaster intensities on the patents' creation. The paper also shows that climate disasters boost disaster-mitigating innovations in historical China. The above findings show significant implications for policymakers. Given that most disaster-mitigating patents were invented by the national research institutions and universities in China, encouraging more investment in public research and technological development (R&D) sectors after climate disasters would be effective and productive. However, for the private R&D sectors, just leave it up to the market.

In addition, the study reveals that disaster-mitigating patents can not only respond to local disasters but also to disasters from neighboring provinces. This result requires policymakers in one province to pay more attention to climate disasters occurring in nearby provinces because the transfer and diffusion of technologies could benefit local innovations. The impact of local disaster shock is larger than that of neighboring ones when provinces in a group forge close economic ties.

The present study confirms the spillover effect of disaster-mitigating patents on the total patent applications in modern China. In this case, we have revealed the mechanisms and the intensity of the spillover effect. Policymakers and regulators should learn and strengthen this positive externality.

A number of studies reveal the important role of climate changes in historical evolution. The analysis on historical China extends existing researches. As the conclusions of this paper, disaster-mitigating innovations serve as a result of climate disasters. The relation between disaster-mitigating innovations and climate disasters can never be over-emphasized in a historical evaluation, and deserves more attention and investigation in the future.

This study has limitations in the empirical research. China is still short of perfect patent data. In this case, it is difficult to identify the hazard-specific innovations and, for example, to test the link between flooding and flood-mitigation innovation instead of all innovations together. As shown in Table 1, the total number of disaster-mitigating patents range from 0 to 19 with a mean of 2.198. Thus, the number of specific disaster-mitigating patents equals 0 in many provinces for several of the years. We tried to regress specific disaster-mitigating patents on disaster intensity. However the results are not meaningful or robust. The present study leaves much to be desired on this part.

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