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ARTICLE

Impact of Economic Development Levels and Disaster Types on the Short-Term Macroeconomic Consequences of Natural Hazard-Induced Disasters in China

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Abstract The relationship between natural hazard-induced disasters and macroeconomic growth has been examined widely on global and national scales, but little research has been focused on the subnational level, especially in China. We examined the impacts of natural hazard-induced disasters on the regional growth in China based on subnational panel data for the period from 1990 to 2016. First, we used the number of people affected and the direct economic losses as the measures of the scale of disasters. Then, we used the direct damages of meteorological disasters and earthquakes as disaster measures separately to examine the impacts of different disaster types. Finally, we performed intraregional effects regressions to observe the spatial heterogeneity within the regions. The results show that the adverse short-term effects of disasters is most pronounced in the central region, while the direct damage of disasters is a positive stimulus of growth in the whole of China. However, this stimulus is observed in a lagged way and is reflected differently—meteorological disasters in central and eastern China and earthquakes in western China are related to regional growth. The results demonstrate that the short-term macroeconomic impacts of these disasters in the three geographical regions of China largely depend on regional economic development levels and the disaster types.

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1 Introduction

There is a consensus that natural hazard-induced disasters pose a threat to the stable and sustainable development of society and its economic systems. The Wenchuan Earthquake of May 2008 in China, the Great East Japan Earthquake and Tsunami of March 2011, and the costly (USD 95 billion) Hurricane Harvey of August 2017 in the United States have shown alarming impacts of major disasters (UNISDR and CRED 2017). The occurrence and severity of such disasters, especially climate-related ones, have greatly increased in recent years (IPCC 2012; Wu et al. 2018). According to a report by the World Bank, the real cost of natural hazard-induced disasters to the global economy is a staggering USD 520 billion per year, with disasters pushing 26 million people into poverty every year (Hallegatte et al. 2017). At a time when costs in human and financial terms ensue from climate shocks, disasters will continue to create new risks and disrupt government budgets, thus limiting development trends (UNISDR and CRED 2017). Therefore, studies about the relationship between disasters and economic development have attracted increasingly more attention (Sawada and Takasaki 2017).

Natural hazard-induced disasters cause human and economic losses, which may in turn affect economic growth of countries and regions. Previous studies can be grouped into estimates of short-term impacts and long-term impacts (Kousky 2014). Long-term impacts are generally considered to be at least 3 years and can sometimes be measured in decades (Noy and DuPont 2016). A typical way to detect this impact is to compare the ex post level of economic development to its level before a disaster. Common approaches include the input–output tables method (Hallegatte 2008; Wu et al. 2012; Okuyama and Santos 2014; Koks et al. 2015), the computable general equilibrium (CGE) method (Kajitani and Tatano 2018; Xie et al. 2018), and statistical-econometric techniques (Cerra and Saxena 2008; Husby et al. 2013). When examining country-level data, several studies have found that disasters have little to no effect in the long run, with wealthy countries eventually returning to their long-term equilibrium, while poor countries, as well as small island states, show less resilience (Pelling and Uitto 2001; Cavallo et al. 2010). Generally, the controversy about the long-term consequences of disasters and the arguments for long-term creative destruction still exist (Skidmore and Toya 2002; Jaramillo 2010; Hsiang and Jina 2014; Kousky 2014). Noy and DuPont (2016) indicated that different postdisaster experiences in different cases are the hidden reasons for this disagreement.

Short-term impacts of disasters are discussed more widely. Albala-Bertrand (1993) looked at statistics of 28 natural hazard-induced disasters in 26 countries for the period 1960–1979 using a simple before-and-after comparison of variables, including Gross Domestic Product (GDP), its growth rate, and inflation rate up to 3 years after disasters. He found that GDP is not affected, and GDP growth is slightly positively stimulated by these disasters. Noy (2009) undertook another multicountry study using the Emergency Events Database (EM-DAT) data for a panel of 109 countries for the period 1970–2003. He aggregated all rapid-onset disaster events in a year, weighted by month of occurrence. The results show that in developing countries natural disasters have a negative impact on GDP growth of approximately 9%. For Organisation for Economic Co-operation and Development (OECD) countries, there is a slightly positive impact of less than 1%. Hochrainer (2009) took an approach that developed a counterfactual projection of GDP and then compared this to the actual value of GDP after disasters. Based on his sample of 225 large natural disaster events from 1960 to 2005, he found that the negative impact of disasters on GDP lasts for up to 5 years, with a median reduction of 4% compared to a baseline of 5 years after disasters. A majority of multicountry studies confirms that more intense disasters have a larger negative impact on output and growth (Raddatz 2007; Hochrainer 2009; Strobl 2011; Cavallo et al. 2013; Fomby et al. 2013). Noy and Nualsri (2011) found that procyclical fiscal policy in response to disasters may aggravate negative outcomes on the macroeconomy in developing countries. Another strand of short-term impact research focuses on a single country and/or single disaster type (Noy and Vu 2010; Vu and Hammes 2010; Anttila-Hughes and Hsiang 2013; Deryugina 2013; Elliott et al. 2015). Part of the research uses econometric methods for the multicountry studies. In addition to these examples, a couple of sector-specific studies try to detect the winners and losers of natural disasters (Hsiang 2010; Loayza et al. 2012; Fomby et al. 2013).

Limited by the fact that reliable and higher-resolution data for different natural hazard-induced disasters at the subnational regional scale are not available in every country, however, the relationship between different disasters and output growth in a single country have rarely been discussed. Raddatz (2007) and Loayza et al. (2012) studied cross-country panel datasets and found that geological disasters (mainly referring to earthquakes) do not have a significant impact, while meteorological events (droughts and floods) reduce GDP per capita.

Aiming to contribute to the knowledge on whether there is a significant impact on the macroeconomy and the difference between meteorological and geological disasters, this study examined the subnational regional data from China, one of the world's fastest-growing major economies, over the past three decades, 1990–2016. We focused on the short-term postdisaster state in China for several reasons. First, along with global climate change and the rapid development of the economy and rapid urbanization, China is one of the countries most affected by natural hazard-induced disasters. The variety of disaster events, the high frequency of disasters, and the vast areas affected make results more robust in a regional examination and less susceptible to the impact of outliers (Noy and Vu 2010). Second, under the influence of natural and human factors, China's natural hazard-induced disaster risks show obvious east–west differentiation (Shi et al. 2017). Due to the instability of the monsoon, meteorological disasters such as floods and typhoons occur frequently in China, with an annual average of approximately seven typhoons making landfall in the southeastern coastal areas (Xu et al. 2013). Local or regional droughts occur in most years. Most of China is located at the intersection of the Asia-Europe plate, the Indian plate, and the Pacific plate. The active geotectonic movements cause frequent earthquakes. Therefore, China has the most earthquakes in the world, accounting for approximately 33% of global, land-based, destructive earthquakes (Shi et al. 2017). Third, the unique "whole-nation system"[1] in China ensures that even after a

[1] "Whole-nation system" in China means that the state uses administrative resources and policy instruments to concentrate or allocate limited human, material, financial, and technical resources to establish a strategic target within a certain time limit or under specific conditions. The system plays a key role in responding to major disasters (for example, the 2008 Wenchuan Earthquake) (Shi et al. 2013).

major disaster such as the 2008 Wenchuan Earthquake, assistance from the whole country helps to ensure housing reconstruction completion within 3 years (Tse et al. 2014; Wu et al. 2014), which complicates the examination of the long-term impacts of natural hazard-induced disasters.

2 Data and Methods

The data analyzed in this study are natural hazard-induced disaster impact records and socioeconomic data. To account for the impact of disaster measures and disaster types, we estimate two sets of equations for showing the impact of economic development levels on macroeconomic consequences in eastern, central, and western China.

2.1 Data

We used two types of data in this study (Table 1). The first type is the data on natural hazard-induced disaster impacts for the 31 provinces, municipalities, and autonomous regions of China's mainland from 1990 to 2016, which is available from the China Civil Affairs Statistical Yearbook (CCASY) (Ministry of Civil Affairs of China 2017). Recorded disasters include earthquakes, droughts, floods, tropical cyclones, gales/hail, and low temperature/snowstorms. In this study, we treat all of these occurrences, except earthquakes, as meteorological disasters (Wu et al. 2018). According to previous studies, the number of people affected and the amount of direct economic loss were the two most commonly used disaster measures (*DM*) (Raddatz 2007; Anttila-Hughes and Hsiang 2013); thus the affected population (*AFP*) and the direct economic loss (*DEL*) for all natural hazard-induced disasters by province/year were extracted. Next, we wanted to obtain the impact records of both meteorological disasters and earthquakes, respectively. Earthquake disaster event impact records are available from the China Earthquake Yearbook (China Earthquake Administration 2017). We used the method of Wu et al. (2018) to derive the meteorological disaster impact data series—the disaster impact records from all natural hazard-induced disasters obtained earlier ($DM_{\text{disasters}}$, that is, *AFP* or *DEL*) as a whole, minus the earthquake part ($DM_{\text{earthquake}}$), reflects the impact of meteorological disasters. It is formulated as

$$DM_{\text{meteor}} = DM_{\text{disasters}} - DM_{\text{earthquake}}. \quad (1)$$

Earthquake impact records from the China Earthquake Yearbook do not include information on the number of people affected. Therefore, our impact records of two natural hazard-induced disaster types can only be expressed through direct economic losses. In this way, a direct economic losses dataset for meteorological disasters (*Meteor*) and earthquakes (*Eq*) by province/year can be constructed.

Considering that the impact of a specific natural hazard-induced disaster on the macroeconomy depends on the magnitude of the disaster relative to the size of the economy, we divide the number of people affected by the provincial population size in the year prior to the current year and divide the direct economic loss by provincial GDP values the year before.

The second type of data is the provincial data for other macroeconomic variables, including provincial GDP growth, retail sales as a proxy for trade, highway mileage as a proxy for infrastructure, school enrollments as a proxy for education, and the proportion of the primary industry, which are available from the Chinese Socioeconomic Development Statistical Database.[2] Data on trade were divided by the provincial GDP values and were expressed as a percentage of output. For school enrollments, we sum up primary, secondary, and college enrollments and divide them by population. Data on highway mileage were also divided by population. Note that all economic values were deflated to the 2015 constant Chinese Yuan (CNY). Specifically, the nominal economic losses were deflated by the consumer price index (CPI), and GDP values were deflated by the GDP deflator (Wu et al. 2018). The CPI and GDP deflator of China were available in the World Development Indicators from the Word Bank.[3] Information about the variables and their sources is summarized in Table 1.

Considering that the level of development and the geographic characteristics of the 31 provinces are quite different, China can generally be divided into three regions. The western region of China includes Qinghai, Tibet, Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Xinjiang, Gansu, Ningxia, and Guangxi Provinces / Autonomous Regions / Municipality. The central region of China includes Inner Mongolia, Heilongjiang, Jilin, Shanxi, Henan, Anhui, Hubei, Jiangxi, and Hunan Provinces / Autonomous Region. The eastern region of China includes Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan Provinces / Municipalities. We then aggregate data and report descriptive statistics for variables in Table 2 for ready reference.

2.2 Methods

The benchmark estimation equation of this study is from Noy and Vu (2010), in which a provincial-level analysis in

[2] http://data.cnki.net/.

[3] https://datacatalog.worldbank.org/dataset/world-development-indicators.

Table 1 Data sources of the study on macroeconomic consequences of natural hazard-induced disasters in China, 1990–2016

Variable	Definition	Source
GDPG	GDP growth	Chinese Socioeconomic Development Statistical Database (CSDSD, http://data.cnki.net/)
AFP	Number of people affected from all natural hazard-induced disasters (% last year's population)	China Civil Affairs Statistical Yearbook (Ministry of Civil Affairs of China 2017)
DEL	Direct economic loss from all natural hazard-induced disasters (% last year's GDP)	China Civil Affairs Statistical Yearbook
Meteor	Direct economic loss from meteorological disasters (% of last year's GDP)	Calculated by Eq. 1
Eq	Direct economic loss from earthquake disasters (% of last year's GDP)	China Earthquake Yearbook (China Earthquake Administration 2017)
TRADE	Total retail sales (% of GDP)	CSDSD (http://data.cnki.net/)
EDUC	School enrollment rate (% of population)	CSDSD (http://data.cnki.net/)
INFRA	Highway mileage as infrastructure (km per person)	CSDSD (http://data.cnki.net/)
PRIMA	Proportion of the primary industry	CSDSD (http://data.cnki.net/)

Table 2 Descriptive statistics for the variables in the study on macroeconomic consequences of natural hazard-induced disasters in China, 1990–2016

Region	Western region: 297 observations[a]				Central region: 243 observations[b]				Eastern region: 297 observations[c]			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
GDPG	9.046	4.646	− 5.194	27.089	8.960	4.509	− 7.693	23.111	8.638	4.974	− 23.158	39.300
AFP	36.167	19.992	0	116.174	31.627	15.985	3.137	92.340	19.975	18.247	0	107.983
DEL	2.957	4.856	0	66.620	2.929	3.817	0.049	33.795	1.394	2.225	0	16.745
Meteor	2.413	2.691	0	29.665	2.917	3.814	0.049	33.795	1.391	2.223	0	16.745
Eq	0.544	4.161	0	65.683	0.012	0.096	0	1.343	0.003	0.019	0	0.209
EDUC	12.480	1.704	6.689	16.572	11.342	1.592	7.260	15.258	10.863	2.782	5.980	27.756
TRADE	31.960	6.585	19.117	57.886	34.591	6.159	21.835	51.943	33.784	6.074	22.976	53.196
INFRA	39.603	42.486	7.786	241.689	21.247	14.099	4.852	69.852	13.261	7.357	2.272	29.534
PRIMA	20.746	9.229	7.318	50.900	19.560	8.605	4.287	41.900	12.456	10.004	0.437	51.500

[a]The 297 observations = 11 Provinces / Autonomous Regions / Municipality in western China × 27 years (1990–2016)

[b]The 243 observations = 9 Provinces / Autonomous Region in central China × 27 years (1990–2016)

[c]The 297 observations = 11 Provinces / Municipalities in eastern China × 27 years (1990–2016)

Vietnam is presented. Our starting estimation is characterized by the following equation:

$$GDPG_{i,t} = \alpha_i^1 + \alpha_t^2 + \beta GDPG_{i,t-1} + \gamma DM_{i,t} + \chi DM_{i,t-1} + \phi X_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

where $GDPG_{i,t}$ is the value of the GDP growth rate (2015 price, CNY), i denotes a province, and t denotes time. α_i^1 and α_t^2 are the province and time fixed-effects, $DM_{i,t}$ is our measures for disaster magnitude as described in the previous section (*AFP* or *DEL*), and $X_{i,t-1}$ is the lagged control variable. β, γ, χ, and ϕ are coefficients to be estimated, and $\varepsilon_{i,t}$ is the error term. As such, the first set of regressions is specifically characterized by:

$$GDPG_{i,t} = \alpha_i^1 + \alpha_t^2 + \beta GDPG_{i,t-1} + \gamma AFP_{i,t} + \chi AFP_{i,t-1} + \phi X_{i,t-1} + \varepsilon_{i,t}, \tag{3}$$

$$GDPG_{i,t} = \alpha_i^1 + \alpha_t^2 + \beta GDPG_{i,t-1} + \gamma DEL_{i,t} + \chi DEL_{i,t-1} + \phi X_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

After the benchmark estimation, damage data of meteorological disasters and earthquakes replace the measures for all disaster types (*AFP* or *DEL*) that are collectively represented by the term $DM_{i,t}$. As such, the second set of regressions is specifically characterized by:

$$GDPG_{i,t} = \alpha_i^1 + \alpha_t^2 + \beta GDPG_{i,t-1} + \gamma Meteor_{i,t} + \chi Meteor_{i,t-1} + \gamma' Eq_{i,t} + \chi' Eq_{i,t-1} + \phi X_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

In these disaster impact and development regression equations, taking the lagged term of all the control variables can control the endogeneity problem, which makes the estimation results more interpretable (Noy 2009).

One of the advantages of panel data is that they can model the economic variable's dynamic behavior. According to economic theory, due to inertia or partial adjustment, some economic variables' current behavior depends on past behaviors, such as the adjustment of the GDP growth rate. In our estimated model, the lagged dependent variable is included in the independent variables, which make our panel data dynamic. Nickell (1981) proved that for "small T, large N" panels, the dynamic panel bias is comparable to T^{-1} in magnitude. Therefore, in these cases, the estimation method of the difference-GMM (difference generalized method of moments) or the system-GMM (system generalized method of moments) are usually adopted (Vu and Noy 2015). However, the panels we used in this study are "small N, large T" panels (N = 11/9/11, T = 27), so their bias was relatively small (Nickell 1981).

3 Results

Table 3 shows our baseline results. The coefficient estimates for *AFP* and its lagged values are reported in Columns (1a), (2a), and (3a), respectively, whereas the coefficient results for *DEL* and its lagged values are reported in the corresponding (b) columns. From this table, the impacts of the population affected (*AFP*) and the direct economic loss (*DEL*) present a similar direction of influence only in central China [see Columns (2a) and (2b)]. This implies that a 1% increase in the ratio of people affected to population (or a 1% increase in the ratio of direct damage to output) is associated with a decrease in GDP growth rate of 0.05 (or 0.25). However, such increases of stricken population and property losses in the central region bring the following year's growth, though the coefficients for lagged measures are relatively small. Interestingly, such lagged stimulus shows almost equal (80%) "resilience" (this refers to the degree of stimulus that can be achieved in the second year, compared to the level reduced in the first year) when measured by either *AFP* or *DEL* [see Columns (2a) and (2b)].

Here, we also sum the coefficients for the current and lagged values and report the *p* value for the significance of this sum. The sum of two values can be interpreted as a composite effect of a disaster in the short-term (Noy and Vu 2010; Vu and Noy 2015). These results are provided after each specification in the next column. However, in Table 3, the composite effect of both disaster measures in the three regions is not significant.

As for eastern China, the impact of the number of people affected (*AFP*) on the growth rate is an immediate negative, whereas the impact of the amount of damage (*DEL*) on the growth rate is a lagged positive [see Columns (3a) and (3b)]. In the western region, the impact of the affected population (*AFP*) on the growth rate is positive; this difference between the eastern and western regions could be ascribed to different types of dominant disasters (Jaramillo 2010). Therefore, we estimate the impact of direct economic loss from the different disaster types (Table 4).

The signs of direct damage on the economic growth rate, as shown in Table 4, are almost the same as reported in Table 3. However, in this case they are reflected in specific disaster types. In the central and eastern regions of China, the impact of meteorological disasters is significantly correlated with the growth rate, whereas in western China the impact of earthquakes is significant.

Because of the positive significance of meteorological disaster impacts on growth in eastern China, we want to know if a province that is more seriously or frequently stricken is getting faster growth. We set Shanghai Municipality as the base group. Although Shanghai is commonly considered one of the cities most vulnerable and at risk to floods, it experienced the lowest direct damage of meteorological disasters among the eastern region provinces during our study period. We generate slope dummies for all other provinces and regress GDP growth on the direct economic losses of meteorological disasters (*Meteor*) with all control variables added, including the lagged value of GDP growth. Table 5 shows the results of benchmark variables. The coefficient of the *Meteor* in Column (1) reports the effect of meteorological disasters on the growth of Shanghai. Other results in Column (1) show the difference in coefficients of each province relative to the base group. A positive coefficient implies that a province enjoys higher GDP growth than the base group in the case of the same loss rate of meteorological disasters and vice versa. Additionally, the effects of meteorological disasters on the

Table 3 Effects of natural hazard-induced disasters on macroeconomic growth of the western, central, and eastern regions of China, 1990–2016

	Dependent variable: GDP growth											
	(1) Western region				(2) Central region				(3) Eastern region			
	(1a)		(1b)		(2a)		(2b)		(3a)		(3b)	
GDPG Lag	0.286***		0.301***		0.481***		0.474***		0.542***		0.542***	
	(0.000)		(0.001)		(0.002)		(0.001)		(0.000)		(0.000)	
AFP	0.0033	0.03			− 0.0506**	− 0.003			− 0.020*	− 0.008		
	(0.802)	(0.102)			(0.014)	(0.844)			(0.094)	(0.629)		
AFP Lag	0.0266***				0.0473**				0.012			
	(0.009)				(0.035)				(0.228)			
DEL			− 0.0141	− 0.011			− 0.246***	− 0.044			− 0.142	0.065
			(0.721)	(0.689)			(0.001)	(0.523)			(0.327)	(0.675)
DEL Lag			0.00315				0.202**				0.207**	
			(0.951)				(0.013)				(0.049)	
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	286		286		234		234		286		286	
Adjusted-R^2	0.478		0.468		0.662		0.667		0.485		0.49	
p value for F-test	0.000		0.000		0.000		0.000		0.000		0.000	

The table reports the change in GDP growth from natural hazard-induced disasters (including two disaster measures and their lag term) and the lagged GDP growth (dependent variable is GDP growth) in response to a 1 unit change in the variables. All added control variables are listed in Table 1. The associated *p* values for coefficients are given in parenthesis

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Due to the existence of lag terms in Eqs. 3 and 4, the number of observations for each region is fewer than that in Table 2

Table 4 Effects of meteorological disasters and earthquakes on macroeconomic growth of the western, central, and eastern regions of China, 1990–2016

	Dependent variable: GDP growth					
	(1) Western region		(2) Central region		(3) Eastern region	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Growth Lag	0.285***		0.393***		0.507***	
	(0.006)		(0.007)		(0.000)	
Meteor	− 0.0283	− 0.270	− 0.196**	− 0.010	− 0.109	0.098
	(0.855)	(0.176)	(0.011)	(0.924)	(0.457)	(0.581)
Meteor Lag	− 0.106		0.186**		0.207**	
	(0.271)		(0.025)		(0.027)	
Eq	− 0.00841	0.034	0.643	− 0.136	6.810	− 9.920
	(0.797)	(0.181)	(0.715)	(0.957)	(0.503)	(0.616)
Eq Lag	0.0421**		− 0.779		− 16.73	
	(0.018)		(0.436)		(0.135)	
Controls	Yes		Yes		Yes	
Observations	286		234		286	
Adjusted-R^2	0.498		0.634		0.463	
p value for F-test	0.000		0.000		0.000	

The table reports the change in GDP growth from natural hazard-induced disasters (including two disaster-types and their lag term) and the lagged GDP growth (dependent variable is GDP growth) in response to a 1 unit change in the variables. All added control variables are listed in Table 1. The associated *p* values for coefficients are given in parenthesis

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Due to the existence of lag terms in Eq. 5, the number of observations for each region is fewer than that in Table 2

growth of the other provinces are calculated by adding up the coefficient of each province to that of the base group. These province regression results and their *p* values are calculated in Column (2). Then, the sum of the current value and the lagged value for all provinces are reported in Column (3), including their *p* values for significance.

Table 5 shows that all the provinces with higher loss rates from meteorological disasters do not enjoy higher GDP growth than Shanghai does; though the table notes the coefficients for Shanghai are not statistically significant, that does not mean that the other provinces do not enjoy "creative destruction" for economic growth. Column (2) notes that the eastern provinces can also be suppressed by meteorological disasters. The composite effect of a single province in Column (3) might further imply information about a province's "resilience" characteristics. For example, Hainan Province is quite unusual for having significantly benefited from meteorological disasters.

Similarly, according to the results in Table 4, we did the same analysis for the central (see Table 6) and western regions (see Table 7). We set Henan Province as the base group since it was the least stricken area in the central region. Table 6 reports more information about the central provinces. It is clearly indicated that provinces with higher damage rates of meteorological disasters do have a lower GDP growth than the base group. The results of Column (1) show that meteorological disasters are definitely one of the factors hindering the development pace for the central provinces. While meteorological disasters can sometimes be positive (see Column (2) in Table 6, and Column (2) in Table 4), such "doughnut'' effects come at the expense of limited growth rates.

Last, we turn our attention to western China. We set Guangxi, Guizhou, Shaanxi, and Ningxia together as the base group because earthquakes there are quite rare compared to the other seven western provinces in the past three decades. Table 7 shows the results. Column (1) shows that not all the provinces with higher earthquake damage enjoy higher GDP growth than the base group. The negative signs imply that the growth rate of Chongqing, Gansu, and Xinjiang might be decreased in the case of earthquake occurrences. Nevertheless, the effect of earthquakes on the

Table 5 Intraregional effects of meteorological disasters on the macroeconomic growth of eastern China, 1990-2016

	Dependent variable: GDP growth		
	(1)	(2)	(3)
Meteor	0.189		2.435
	(0.932)		(0.463)
Meteor Lag	2.246		
	(0.468)		
Beijing	− 3.116	− 2.927***	− 2.378
	(0.141)	(0.003)	(0.125)
Beijing Lag	− 1.697	0.549	
	(0.647)	(0.604)	
Fujian	0.149	0.338	− 0.229
	(0.952)	(0.279)	(0.474)
Fujian Lag	− 2.813	− 0.567*	
	(0.403)	(0.073)	
Guangdong	− 1.198	− 1.009*	− 1.093
	(0.588)	(0.072)	(0.103)
Guangdong Lag	− 2.162	− 0.084	
	(0.477)	(0.782)	
Hainan	− 0.127	0.062	0.317***
	(0.954)	(0.284)	(0.002)
Hainan Lag	− 1.991	0.255***	
	(0.517)	(0.000)	
Hebei	− 1.575	− 1.386**	− 0.834*
	(0.497)	(0.043)	(0.082)
Hebei Lag	− 1.694	0.552	
	(0.628)	(0.372)	
Jiangsu	− 0.696	− 0.507**	− 0.146
	(0.746)	(0.012)	(0.534)
Jiangsu Lag	− 1.885	0.361	
	(0.506)	(0.260)	
Liaoning	− 0.511	− 0.322	0.197
	(0.806)	(0.253)	(0.461)
Liaoning Lag	− 1.727	0.519***	
	(0.564)	(0.008)	
Shandong	− 1.711	− 1.522**	− 1.536***
	(0.519)	(0.029)	(0.006)
Shandong Lag	− 2.260	− 0.014	
	(0.520)	(0.977)	
Tianjin	0.932	1.121	− 2.346
	(0.793)	(0.548)	(0.144)
Tianjin Lag	− 5.713	− 3.467	
	(0.265)	(0.145)	
Zhejiang	− 0.608	− 0.419	− 0.101
	(0.798)	(0.120)	(0.775)
Zhejiang Lag	− 1.928	0.318	
	(0.565)	(0.330)	
Controls	Yes		
Observations	286		
Adjusted-R^2	0.535		
p value for F-test	0.000		

The table reports the intraregional difference of change in GDP growth from meteorological disasters in eastern China. All added control variables are listed in Table 1. The associated *p* values for coefficients are given in parenthesis

***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively

macroeconomic growth rate in the three frequently and seriously stricken provinces (see He et al. 2018), Sichuan, Yunnan, and Qinghai, is statistically greater than zero. The possible reason is that postearthquake aid increases investment, which then brings prosperity.

4 Discussion

In this study, we examined the impacts of two disaster measures and two disaster types on a region's macroeconomic growth. Furthermore, we investigated the intraregional effects of significant natural hazard-induced disasters across the western, central, and eastern regions in China. We found that, from the perspective of either disaster measures or disaster types, natural hazard-induced disasters have distinct spatially heterogeneous effects on the regions.

4.1 Relationship between the Macroeconomic Impact of Natural Hazard-Induced Disasters and Development Level as Reflected in Disaster Measures

According to previous empirical studies on the macroeconomic impacts of natural hazard-induced disasters, the studies can be grouped into two substrands (van Bergeijk and Lazzaroni 2015). The first set of literature focuses on the direct cost of disasters, including populations affected and/or killed and economic damage (Cavallo et al. 2013; Neumayer et al. 2014; Raschky and Schwindt 2016). Another set of literature concentrates on the indirect cost of disasters, which is usually identified in terms of the effects on GDP/income (Vu and Hammes 2010; Strobl 2012; Fomby et al. 2013). In this study, we use two disaster measures—affected population (*AFP*) and direct economic loss (*DEL*), as direct disaster costs to detect indirect disaster costs. The Klomp and Valckx (2014) meta-analysis found that studies using monetary terms, that is, damage/GDP, as their measures tend to report a more significant

Table 6 Intraregional effects of meteorological disasters on the macroeconomic growth of central China, 1990–2016

	Dependent variable: GDP growth		
	(1)	(2)	(3)
Meteor	0.365		1.244
	(0.218)		
Meteor Lag	0.879**		
	(0.016)		
Anhui	− 0.639**	− 0.274***	− 0.010
	(0.033)	(0.000)	(0.919)
Anhui Lag	− 0.615**	0.264***	
	(0.042)	(0.005)	
Heilongjiang	− 0.661**	− 0.296*	− 0.487
	(0.049)	(0.053)	(0.200)
Heilongjiang Lag	− 1.070**	− 0.191	
	(0.011)	(0.456)	
Hubei	− 0.537*	− 0.172*	− 0.188
	(0.089)	(0.066)	(0.359)
Hubei Lag	− 0.895**	− 0.016	
	(0.015)	(0.904)	
Hunan	− 0.411	− 0.046	− 0.062
	(0.219)	(0.551)	(0.679)
Hunan Lag	− 0.771**	0.108	
	(0.038)	(0.189)	
Jiangxi	− 0.464	− 0.099	0.053
	(0.126)	(0.113)	(0.571)
Jiangxi Lag	− 0.727**	0.152**	
	(0.030)	(0.039)	
Jilin	− 0.609	− 0.244**	− 0.151
	(0.109)	(0.043)	(0.397)
Jilin Lag	− 0.786**	0.093	
	(0.047)	(0.309)	
Inner Mongolia	− 0.437	− 0.072	0.148
	(0.112)	(0.454)	(0.154)
Inner Mongolia Lag	− 0.659**	0.220**	
	(0.049)	(0.012)	
Shanxi	− 0.733**	− 0.368*	0.529**
	(0.023)	(0.089)	(0.042)
Shanxi Lag	0.0181	0.897***	
	(0.948)	(0.000)	
Controls	Yes		
Observations	234		
Adjusted-R^2	0.701		
p value for F-test	0.000		

The table reports the intraregional difference of change in GDP growth from meteorological disasters in central China. All added control variables are listed in Table 1. The associated *p* values for coefficients are given in parenthesis

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Table 7 Intraregional effects of earthquake disasters on macroeconomic growth of western China, 1990–2016

	Dependent variable: GDP growth		
	(1)	(2)	(3)
Eq	0.651		1.063
	(0.251)		(0.129)
Eq Lag	0.412		
	(0.357)		
Chongqing	− 3.645**	− 2.994	− 2.621
	(0.014)	(0.117)	(0.200)
Chongqing Lag	− 0.0394	0.373	
	(0.966)	(0.782)	
Gansu	− 0.823*	− 0.172*	− 0.163
	(0.099)	(0.099)	(0.104)
Gansu Lag	− 0.403	0.009	
	(0.292)	(0.912)	
Qinghai	− 0.416	0.235**	0.202
	(0.430)	(0.045)	(0.158)
Qinghai Lag	− 0.445	− 0.033	
	(0.336)	(0.484)	
Sichuan	− 0.688	− 0.037	0.014
	(0.210)	(0.155)	(0.549)
Sichuan Lag	− 0.361	0.051**	
	(0.397)	(0.039)	
Xinjiang	1.183	1.834	− 1.316
	(0.411)	(0.104)	(0.424)
Xinjiang Lag	− 3.562***	− 3.150**	
	(0.007)	(0.021)	
Tibet	− 0.411	0.240	0.426
	(0.427)	(0.255)	(0.223)
Tibet Lag	− 0.226	0.186	
	(0.666)	(0.205)	
Yunnan	0.369	1.020**	1.463
	(0.612)	(0.036)	(0.110)
Yunnan Lag	0.0305	0.443	
	(0.951)	(0.492)	
Controls	Yes		
Observations	286		
Adjusted-R^2	0.479		
p value for F-test	0.000		

The table reports the intraregional difference of change in GDP growth from earthquakes in western China. All added control variables are listed in Table 1. The associated *p* values for coefficients are given in parenthesis

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

negative impact than studies that use the number of people affected as their natural disaster indicator. The result of the van Bergeijk and Lazzaroni meta-analysis (2015) found

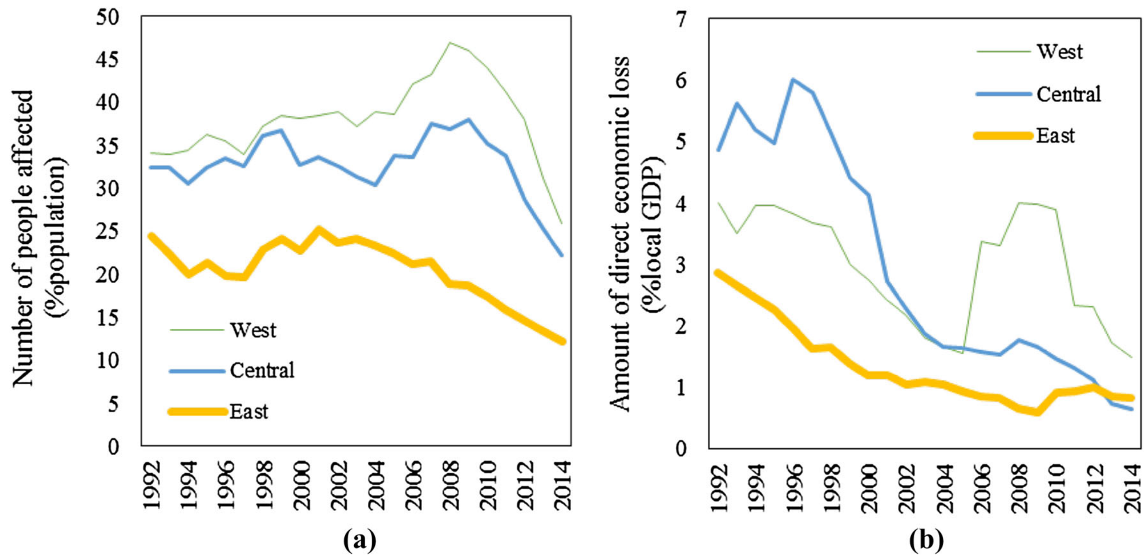

Fig. 1 Provincial average of the number of people affected (**a**) and the amount of direct economic loss (**b**) in the western, central, and eastern regions of China. A 5-year moving average is shown. **a**, **b** show that in the eastern region, a developed area, nonmonetary and monetary costs of natural hazard-induced disasters were lower than in the central and western regions

that different measures of disasters do not influence the tendency to report a negative or positive impact (except for disaster intensity) among indirect cost studies. However, our results in Table 3 demonstrate a spatial heterogeneity of disaster measure sensitivity. The nonmonetary term—population affected—is significant in the western region, while both nonmonetary and monetary terms show significant impact in the eastern region—although the two influences act in opposite ways. The consistency of the two disaster measures is reflected in the central region, whether from the sign or the ratio of current value and lagged value.

The Intergovernmental Panel on Climate Change (IPCC) report in 2012 stated confidently that the disaster-related economic losses are higher in developed countries, while the fatalities and loss rate (%GDP) are higher in developing countries (IPCC 2012). This means that a better level of development exacerbates the absolute consequences of disasters but increases the ability to maintain a relatively low rate of costs. In China, it is generally accepted that the western and the central regions belong to the underdeveloped or less-developed areas while the eastern region belongs to the developed area (Zhou et al. 2014). The spatial pattern of natural hazard-induced disaster variables in China is consistent with that of the IPCC report (Fig. 1).

Theoretically, the expansion of the affected population could reduce the efficiency of labor production and hinder the process of human capital accumulation and thus bring a reduction in growth. The Toya et al. (2010) reevaluation of the effects of human capital accumulation on macroeconomic growth proved that natural disasters play an unexpected role in the relationship between human capital and economic development by influencing changes in schooling. However, our results show a positive effect of the affected population (*AFP*) in the western and central regions of China, the underdeveloped regions, albeit a lagging effect [see Columns (1a) and (2a) in Table 3]. Compared with eastern China, differences in the degree of economic development and geographical environmental conditions (as well as the dominant disaster types discussed in the next section) should be a significant driver behind this effect (Zhou et al. 2014).

4.2 Relationship between Macroeconomic Impact of Natural Hazard-Induced Disasters and Disaster Types

Jaramillo (2010) believed that different natural disasters could create different macroeconomic impact scenarios. This is related to the mechanism of damage caused by disasters. Compared with earthquakes, meteorological disasters occur more frequently and often at specific times of the year, which makes them easier to predict (Skidmore and Toya 2002). Chhibber and Laajaj (2008) considered that an earthquake is more likely to result in "build-back" or "build-back-better" because considerable reconstruction might trigger prosperity and eventually lead to technological change. Conversely, a drought may not bring much effect on economic growth because the loss is generally restricted to annual or seasonal production. Guo et al. (2015) hold the view that meteorological disasters in China had a marginally positive and causal relationship with growth from 1999 to 2011, while geological disasters had no significant impact on growth.

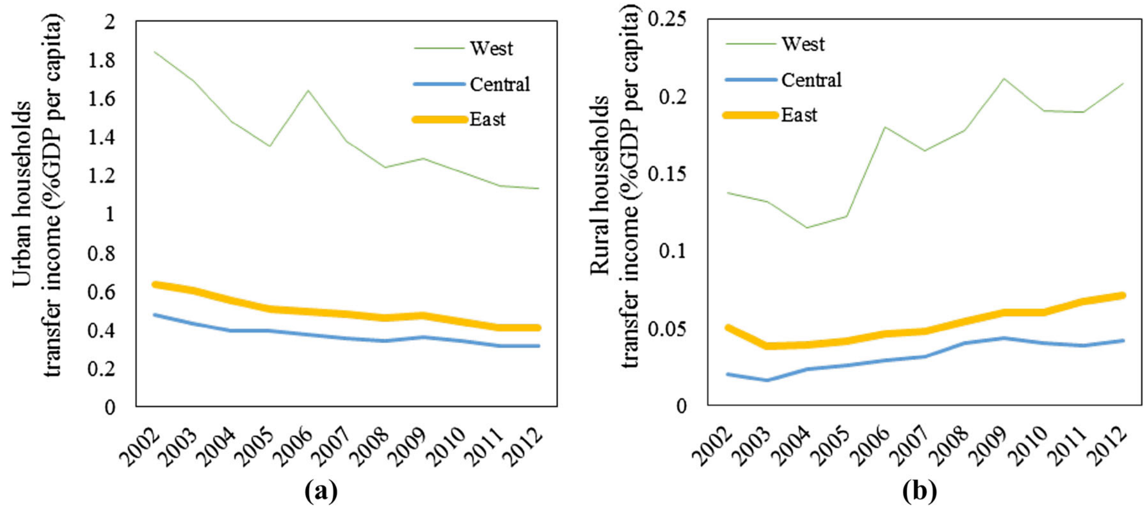

Fig. 2 Urban (**a**) and rural household (**b**) transfer income levels in the western, central, and eastern regions of China over the period from 2002 to 2012. Natural hazard-induced disasters caused considerable losses to the central region (see Fig. 1), whereas **a**, **b** show that households that lived here obtained the lowest level of transfer income

Our results show that impact on regional growth is related to the regionally "dominant" disasters. During our study period, more earthquakes occurred in the western region, while more meteorological and climatic disasters occurred in the central and eastern regions. The perception of these disasters may affect the propensity of government fiscal expenditures. To provide a basis for this conjecture, we collected data on transfer income from urban and rural households in each province from 2002 to 2012 (Fig. 2). These data are available from the Chinese Socioeconomic Development Statistical Database.[4] Here, transfer income refers to various transfer payments made by the state, work units, and social groups to households, including disaster relief funds, pensions, production subsidies, living allowances, and the reimbursement of medical expenses (National Bureau of Statistics of China 2017). In both urban and rural households, the provincial average relative transfer income (as the ratio of GDP per capita) is highest in the western region, followed by the eastern and lowest in the central regions. We believe that the occurrence of the lowest transfer income in central China should be related to the general lack of main sudden-onset disasters in the region, such as earthquakes. The long-lasting disaster periods of droughts and extreme temperatures, for example, brought huge losses but did not result in matching relief funds that could be reflected in household transfer income. Correspondingly, it can be argued that earthquakes in western China and storms in eastern China add to the instability of the local economies and to people's lives, as these rapid-onset natural disasters bring losses and demands at the moments the events occur. While the level of transfer income cannot fully represent households' postdisaster relief level, the low level of support provided by the governments of central China is a fact, which should be one of the drivers of differences in macroeconomic consequences of natural hazard-induced disasters.

4.3 Detect the Pattern of Macroeconomic Growth Impact of Natural Hazard-Induced Disasters

The ultimate goal of a large number of empirical studies over the past decade has been to portray a macroeconomic response to natural hazard-induced disasters, though the real situation is absolutely complex. Klomp and Valckx (2014) found empirical support for scenarios for climatic, geological, and hydrometeorological disasters. They attributed each disaster type to one of the four scenarios summarized by Chhibber and Laajaj (2008). Based on our empirical results (mainly Table 4), we also attempt to describe the specific scenarios of the three regions in China (Fig. 3).

First, by the end of 2016—the end of our research period, the provincial average per capita GDP of eastern China was about twice that of the western region, and that of the central region was slightly higher than the western region. Second, in the last 3 years of our research period, from 2014 to 2016, the eastern and the central regions' provincial average GDP growth was approximately 5%. The western region developed slightly faster, at a rate of about 6.5%. Therefore, the base level and benchmark slope of growth scenarios in the western, central, and eastern regions are identified.

[4] http://data.cnki.net/.

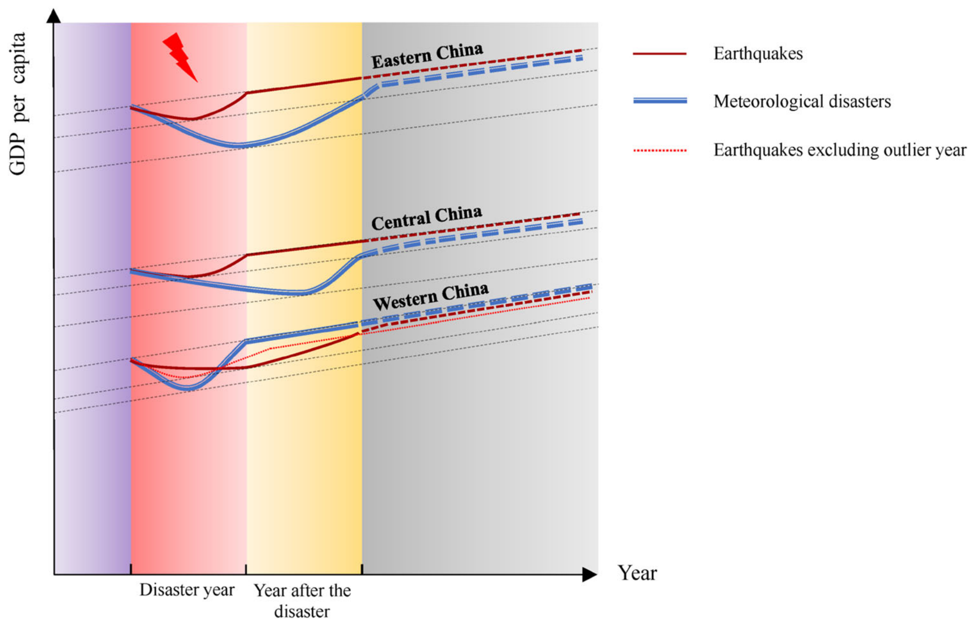

Fig. 3 Scenarios of the short-term per capita output impact of meteorological disasters and earthquakes in the western, central, and eastern regions of China. The slope of the dotted lines represents the current average GDP growth rate in each region. The points tangent to the dotted line are consistent with the estimation results in Table 4—that is, there is no statistically significant difference between current GDP growth rate at this point and the benchmark growth rate

Here, we treat each year as a "disaster year." The change of per capita output in "disaster year" and "year after the disaster" in Fig. 3 are only affected by the disasters that occurred during the "disaster year." Each "disaster year" is affected by the impact of past disaster years, but we did not incorporate impact from previous years in Fig. 3.

Earthquakes in the central and eastern regions cause an initial drop in output because of the destruction of both human and financial capitals. However, due to the stimulated inflow of external investment and the higher return on postdisaster capital, the output trajectory of the year can return to the baseline. Earthquakes will have a longer impact in the west, because it will still enjoy the positive stimulus of reconstruction investment until the end of the second year. Meteorological disasters have temporary effects on growth in the west. Compared with the east, the central region spends a longer time on implementing reconstruction investments—possibly due to financial and technical capacity constraints (Loayza et al. 2012). Note that financial constraints can be confirmed by the regional transfer incomes gap that was discussed earlier. In addition, Hallegatte et al. (2007) also highlighted that in developing countries technical constraints are driven by the imbalance between excess demand for certain skills and limited supply. These scenarios, however, are based on the inclusion of the 2008 Wenchuan Earthquake in our sample. When we exclude the outlier year 2008 from the sample, the positive impact of earthquakes in the western region is increased and advanced. Therefore, an outlier event could be a strong impediment to economic development in underdeveloped regions. Overall, short-term economic development scenarios are still robust even without excluding the outlier year.

4.4 Limitations of the Study

There are some limitations in our study. First, in recent years China's disaster impact statistics have gradually improved, but the uncertainty of disaster information still exists. Disaster impacts may often be systematically underreported in underdeveloped provinces, especially prior to the early 1990s (Zhang et al. 2009; Wu et al. 2018). Such biases are also serious in multicountry studies (Noy 2009). It is one of the reasons that we do regional scale estimation. Wu et al. (2018) considered data published by Chinese government agencies (such as the data we used in this study) as a beneficial supplement to reflect the regional disparity of missing disaster impact records of EM-DAT for regions in China.

Finally, as a fast-booming economy, in China the relationship between natural hazard-induced disasters and economic growth is closely related to the stage of the country's development. How disasters will change the pace of development in different regions in the future will rely on the form and effectiveness of current disaster management measures.

5 Conclusion

It was generally recognized by previous studies that natural hazard-induced disasters have negative impacts on national macroeconomic development. The impact of such disasters has become prominent in China; however, the relationship between the effects of different hazards and regional growth is still poorly understood. In this article, we present regional-level evidence on the effect on China's macroeconomic growth from natural hazard-induced disasters over the period 1990–2016. With detailed information in a "disaster year" instead of for a disaster event, our study contributes to two large strands of literature: the short-term impact and the indirect costs of disasters. With different specifications for regions of different development levels, we found that most regions in China have experienced adverse short-term impacts, and it was especially pronounced for the central region, where a 1% increase in direct damage from disasters may lead to an approximately 0.2% short-term decrease in the output growth rate.

To explore the reasons for this spatially heterogeneous response to disasters, we further show that meteorological disasters should be responsible for the macroeconomic impacts of the central and eastern regions, whereas earthquakes have more association with the western region's growth pace. However, even with meteorological disasters, the pattern of each region's macroeconomic response is still different. Such a heterogeneous response becomes more evident when we examined intraregional effects in the central and eastern regions, which demonstrates the robustness of our research results.

The high correlation between development levels, types of disaster, and regional growth in China challenges our understanding of the disaster management behaviors of local governments. In particular, the identified need based on our findings is in sharp contrast to the low transfer-income level of households in the central region. Furthermore, considering that the central region mainly experiences slow-onset but long-lasting disasters, the actual responses to natural hazard-induced disasters in the region indicate that the level of socioeconomic development and the type of disasters affect the development of the region.

From a policy perspective, people who manage disaster responses should understand that higher disaster losses do not necessarily imply that a province would have growth in the following year, although our empirical results show such tendencies in certain provinces. Loss compensation is the driving force of the postdisaster recovery, and social productivity and sustainable economic development are the economic basis of compensation for disaster losses. To this end, economic development is the most effective way to compensate for disaster losses. Note that government behavior objectively adjusts or restricts the relationship between natural hazard-induced disasters and macroeconomic development, even under market-economy conditions. Based on such an understanding, the government is required to take two measures to achieve a healthy relationship between natural hazard-induced disasters and economic development. One measure is to consider short- and long-term benefits while maintaining sustainable development. The other measure is to consider the benefits of affected provinces and the region/nation as a whole when considering multihazard compensation.

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