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Determinants of Regional Economic Resilience to Economic Crisis: Evidence from Chinese Economies

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Abstract: The severity of the 2007–2008 economic crisis and the spatial heterogeneity of its impact have accelerated the study of regional economic resilience. The economic crisis has affected most parts of the world, and its impact is highly heterogeneous within China. The aim of this study was to explore the determinants of regional economic resilience across 284 Chinese cities from 2003–2018. Both nation-based and province-based regional economic resilience were examined. A multilevel logistic regression model was established, finding a disparity of provincial effects on regional performance during the economic crisis. Regional economic resilience is significantly affected by provincial trajectories, economy size, and resources. There are five significant determinants of economic resilience: income inequality, innovation, government intervention, human capital, and financial development. The results provide evidence for the government to design region-based policies, taking into consideration the size and the resources of the region's economy to build a resilient wall to defend against external shocks and to form a basis for sustainable development.

Keywords: economic resilience; determinants; regional disparities; multilevel logistic regression model

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1. Introduction

In December 2007, the economic crisis broke out from the United States, which affected the global economy, ending in June 2009 [1]. Although the crisis affected most parts of the world, its impact was highly heterogeneous across countries. Moreover, the impact within countries was also heterogeneous, and the ability of regions to resist and recover from the crisis was different. This geographical heterogeneity of regions facing economic downturn is considered as a way to test whether a region is resilient [2]. According to Martin (2012), an economic recession may permanently damage productivity and employment opportunities [3]. The severity of an economic crisis and the spatial heterogeneity of its impact accelerate the study of regional economic resilience.

For regional research, the analysis of labor, work, and skills is crucial to the development of a new path which could reintegrate innovation and production into economic development strategies, so as to reduce inequality, improve productivity, and build resilient regional economies [4]. Some countries and organizations have already accelerated the construction of resilient cities, such as the 100 Resilient Cities Program launched by the Rockefeller Foundation and the 2030 Sustainable Development Goals (SDGs) issued by the United Nations [5,6]. As the largest developing country in the world, China has accelerated pace in the urbanization process since the reform and opening up, so as to build resilient cities [7]. However, only a few Chinese cities have achieved the building of high-level resilient cities [8,9]. In China, the progress of building resilient cities is complex and involves various influencing factors [10,11].

The ability of a region to withstand and recover from external shocks has been linked to both soft (social capital) and hard determinants (human capital and infrastructure), as well as network exploitation and economy agglomeration [12]. Similarly to previous studies [12–14], this study focused on exploring the comprehensive understanding of factors influencing regional economic resilience. Currently, the research on how pre-crisis determinants impact reaction and recovery faced during an economic crisis is still scarce. Moreover, there is little research focus on how determinants, such as income inequality and government intervention, impact regional economic resilience in a large developing country. In this study, we aimed to fill this gap.

This study aimed to explore how regions react facing economic crisis, and it empirically discussed the determinants of regional economic resilience. Firstly, this study describes the changes in employment of the regional economy and indicates the internal connection between the period of growth and recession. Moreover, this study adopted resilience perspectives at provincial and national levels to provide systematic evidence for the asymmetric impact of the economic crisis on Chinese economies. Thirdly, we examined how the pre-crisis (2003–2007) determinants impact post-crisis (2008–2018) performance. Taking into account the city size (relatively small and large economies) and the resource hierarchy (resource-based and synthetic economies), we compared the differences between small and large economies as well as resource-based and synthetic economies. This research investigated cities in China, providing evidence that regional heterogeneity exists within a large economy; this can contribute to the resilience literature in developing countries. Good governance is important to strengthen regional economic resilience [15]; thus, we aimed to provide evidence for governments to conduct effective and regional-based policies and to contribute to sustainable development.

This article is structured as follows: Section 2 focuses on data selection, resilience definition and its determinants, resilience indicator measurement, determinants of regional resilience, and analytical methods; Section 3 presents and discusses the empirical results; Section 4 concludes the article.

2. Methods

2.1. Data

There are 34 provincial administrative regions in China, including 23 provinces, five autonomous regions, four municipalities directly under the central government, and two special administrative regions. This study selected 22 provinces (excluding Taiwan due to a lack of data), four autonomous regions (excluding the Tibet Autonomous Region due to a lack of data), and four municipalities directly under the central government, yielding a total of 30 provincial administrative regions as the sample of this study. Prefecture-level cities are relatively independent and complete regional units of administrative divisions in China. According to the data released by the National Bureau of Statistics in China, 2020, there are 293 prefecture-level cities and four municipalities directly under the central government (Beijing, Tianjin, Shanghai, and Chongqing). In order to maintain the continuity of the data analyzed in this study, we excluded two kinds of regions: those lacking relevant data (Lhasa) and those cities that were not established as prefecture-level cities until 2010 (such as Shigatse, Changdu, Nyingchi, Shannan, Naqu, Sansha, Danzhou, Haidong, Tulufan, Hami, Tongren, and Bijie). This study selected 284 prefecture-level and above-prefecture-level cities (nested in 30 provincial administrative regions) in China from 2003 to 2018. The data of this study were acquired from the China City Statistical Yearbook, the China Statistical Yearbook for Regional Economy, and the National Bureau of Statistics in China [16,17].

According to the city-size division standard published by the State Council of China in 2014, the 284 cities were divided into relatively large economies and small economies according to their permanent population. Large economies had a population size $\geq$ 5 million, and small economies had a population size < 5 million [18]. According to this division standard, there were 102 large economies and 182 small economies included in this study. Furthermore, the State Council of the People's Republic of China identified a total of 262 resource-based cities in the "national sustainable development plan for resource-based cities (2013–2020)" in 2013 [18]. This study included 108 resource-based cities and 176 synthetic cities.

2.2. Resilience and Its Determinants

The concept of resilience is becoming more and more popular in economics, especially in urban and regional economics and economic geography [19]. It was first proposed and applied in ecosystems by Holling (1973), who identified resilience and stability as two aspects of a system's response to shocks [20]. Holling (1973) defined resilience as the ability of a system to absorb the changes of state variables, driving variables, and parameters and keep them unchanged. Stability is the ability of a system to return to the original equilibrium after being temporarily disturbed [20]. Relevant studies have identified three different methods to conceptualize the regional resilience framework, namely, engineering, ecology, and evolution [3]. Engineering resilience focuses on the resistance of a system to shocks and its ability to go back to the original equilibrium during the pre-crisis period. Ecological resilience is defined as the absorption ability of a system before changing its structure and building a new equilibrium. Evolution refers to the ability of a region to "rebound forward", i.e., to respond to shocks by adjusting and changing its functions. In this case, resilience does not necessarily mean returning to the original status, but it is possible to reach a new equilibrium [21,22].

Generally speaking, disparity of resilience is the reason why economies perform differently within a country [3,23]. Some researchers defined resilience as the ability of a region or an economy to maintain or restore its original status facing external shocks [24]. The affected areas are considered resilient if they at least return to their previous growth path within 4 years, and vice versa. Other researchers believe that resilience refers to the "ability to resist or recover from market, competition, and environmental shocks" of a regional economy [19]. They believe that the recovered economic system may not return to the status before the shock [3,25]. Therefore, resilience could be addressed as a process with four procedures: vulnerability (the sensitivity of workers and companies to external shocks), resistance (the initial effect of the shock on an economy), robustness (how workers and companies adjust and adapt to shocks), and recoverability (the extent, nature, and path of recovery for a region's economy) [19].

There are several kinds of external shocks: emergencies, macroeconomic fluctuations, and structural changes [26,27]. Among them, macroeconomic resilience has actually been the central issue of most studies on regional economic resilience published so far: how regions are affected by and recover from the recession. How territories differ in terms of economic resilience within and across countries have attracted the interests of researchers. In regional studies, identifying the influencing factors of regional employment growth and the growth path is essential.

Severe inequality is considered to be the structural cause of great recessions [28–31]. In addition, severe inequality also reduces an economy's ability to resist recession. Although researchers have focused on the role of income inequality in economic growth [32–34], the research on the role of income inequality in economic resilience and stability is limited. So far, there is little research that focused on the relationship between inequality and resilience. Lewin et al. (2018) examined the data of 639 urban areas in the United States and found that, after the economic crisis, counties with higher inequality were more likely to fall into recession [35]. Rahe (2019) extended this study to all counties in the United States and found that a higher degree of income inequality led to a higher unemployment rate in densely populated areas [36].

The global economic crisis in 2008 had heterogeneous impacts on the economic structure of various regions, leading to a unique local knowledge space [37,38]. Under this circumstance, the technological coherence and resilience of a region may determine, to a certain extent, the severity of impact on the economy and the time required for the economy to return to the original level of innovation, employment, and prosperity. Moreover, human capital provides the basis for generating new knowledge and innovation and for creating new market opportunities, which contribute to overcoming the crisis. Acs et al. (2006) tested the relationship between regional human capital and the survival rate of new enterprises in the labor market of the United States. They found that the impact of human capital on the survival rate of enterprises in the period of economic recession is weaker than that in the period of growth [39]. Wolman et al. (2017) analyzed 361 cities in the United States for more than 40 years and put forward specific suggestions on how to strengthen regional resilience. In the medium term, economies facing economic difficulties need to diversify their economies and support innovation and entrepreneurship. In the long run, metropolitan areas such as Detroit and Cleveland need to invest in human capital [40].

Government intervention may negatively affect regional recovery from the crisis. In the long run, it may cause regional dependence on fiscal expenditure and weaken viability under the crisis. There is little research focusing on how government intervention impacts economic resilience. Guo and Xu (2019) found a negative relationship between government intervention and regional resilience [41]. When entering the adjustment period, the reallocation of production resources and the transformation and upgrading of industrial structure are inseparable from the support of the financial sector [19]. Eraydin (2015) indicated the positive relationship between financial development and resilience by testing Turkish regions [42]. Du et al. (2019) examined cities in the Pearl River Delta of China and also found a positive impact of financial development on economic resilience [43].

The previous evidence lacks consensus on the direction and strength of the determinants of regional economic resilience; to the best of our knowledge, there is no study that focused on the pre-crisis determinants of regional economic resilience in 284 Chinese cities using a nested dataset. This study attempts to fill this gap by presenting and comparing the results of Chinese cities. The research question of this study was whether pre-crisis determinants such as income inequality, innovation, government intervention, human capital, and financial development impact regional economic resilience. The main hypothesis was that the lower the income inequality and government intervention, the greater the ability of an economy to resist and recover from an external shock. Another hypothesis was that the higher innovation, human capital, and financial development, the stronger the regional economic resilience. The difference of city size and resource endowment makes the capability of economies to withstand and recover from external impact differently. Some researcher suggest relatively large economies may perform better when facing external shocks because of agglomeration economies [44], while resource-based economies with a singular industrial structure may have lower economic resilience [45]. Thus, this study also focused on the question whether the response of Chinese economies to the 2008 economic crisis can be influenced by differences in the size and the resources of economies.

2.3. Resilience Indicator

Previous studies used a variety of methods and indicators to illustrate regional economic resilience [46]. In fact, there is no unified method to measure resilience, and the increasing diversity of indicators may further weaken the clarity and practicability of the concept of resilience [19,47]. The existing indices have not been confirmed to a large extent, and the past indices have proved inaccurate in predicting the resilience of economies to the recent economic crisis [48]. So far, most of the achievements of economic geography and regional economics depend on traditional economic indicators, such as employment and per capita gross domestic product [3,49–51]. Therefore, this study set out to test regional economic resilience from the perspective of the employment growth rate, in line with previous studies [13,51,52].

Following Faggian et al. (2018), Giannakis and Bruggeman (2020, 2021), and Lagravinese (2015), national-based regional economic resilience can be expressed as follows [51–53]:

$$R^N = [(E^R{}_t - E^R{}_{t-1})/E^R{}_{t-1} - (E^N{}_t - E^N{}_{t-1})/E^N{}_{t-1}]/\,|(E^N{}_t - E^N{}_{t-1})/E^N{}_{t-1}|, \quad (1)$$

where R represents regional economic resilience, E^R represents employment at the regional level, E^N represents employment at the national level, $t-1$ is the first year of the economic crisis (2008), and t represents the last year of the economic recovery period (2018).

If R^N is positive, the relative employment loss of the region is smaller (or the relative employment gain is higher) and/or the recovery speed is faster than the average employment change of the whole country, i.e., the economic resilience of the region is higher than the national average. If R^N is negative, it means that the regional economic resilience is lower than the national average.

Province-based regional economic resilience can be expressed as follows:

$$R^P = [(E^R{}_t - E^R{}_{t-1})/E^R{}_{t-1} - (E^P{}_t - E^P{}_{t-1})/E^P{}_{t-1}]/\,|\,(E^P{}_t - E^P{}_{t-1})/E^P{}_{t-1}\,|, \quad (2)$$

where E^P represents employment at the provincial level. Similar to R^N, a positive R^P represents a smaller employment loss of the region (or higher employment gain) and/or a faster recovery speed than the provincial average, i.e., the province-based regional economic resilience is higher than the provincial average. If R^P is negative, it means that the regional economic resilience of the region is lower than the provincial level.

2.4. Determinants of Regional Economic Resilience

Referring to the relevant literature on regional economic resilience, this study indicates the determinants of disparity in resisting and recovering from the impact of recession in different cities of China. Regional resilience is affected by the inherent characteristics that support its previous growth path [19]. According to Giannakis and Bruggeman (2020), temporary fluctuations, such as droughts, may affect agricultural regions [52]. Therefore, this study computed the average value of all influencing factors from 2003–2007. The discussion of how pre-crisis determinants impact regional performance is useful to understand the heterogeneous response of different regions during and after the crisis [54]. Based on previous studies, income inequality was measured by the Gini coefficient (GINI). We selected fiscal expenditure for science and technology as a measurement of innovation. Government intervention was measured by the ratio of public finance expenditure (excluding fiscal expenditure for science and technology) divided by the gross regional product. According to our hypothesis, economies with higher human capital and financial development are better able to resist and recover following the crisis. We used the number of students in colleges and universities per 10,000 people to measure human capital, and we used the ratio of balance of bank deposits and loans/gross regional product to measure financial development. The growth rate of total industrial output was used to measure manufacturing, and the ratio of investment in fixed assets/gross regional product was used to measure investment in fixed assets that can express the ability of governance. The share of the population older than 65 years was used to measure the population structure, and the percentages of employment in the urban individual economy and the private economy were used to measure entrepreneurship. Table 1 shows the descriptive statistics of all determinants.

Table 1. Descriptive statistics of nine explanatory variables used in regression models.

Variables	Definition	Minimum	Maximum	Average
GINI	Gini coefficient	0.06	0.44	0.19
INNO	Ln (fiscal expenditure for science and technology)	5.75	13.26	9.51
GOV	(Public finance expenditure—fiscal expenditure for science and technology)/gross regional product (%)	0.04	0.49	0.11
HUMCAP	Ln (number of students in colleges and universities per 10,000)	−3.77	4.19	0.64
FIN	Balance of bank deposits and loans/gross regional product	0.73	6.58	1.86
INDO	Growth rate of total industrial output (%)	4.70	134.12	60.51
FASSE	Investment in fixed assets/gross regional product (%)	16.00	93.44	46.17

Table 1. *Cont.*

Variables	Definition	Minimum	Maximum	Average
AGE65	Share of population older than 65 years (%)	8.67	16.20	12.33
ENTR	Employment in urban individual economy and private economy/population (%)	2.00	21.00	6.29

Source: National Bureau of Statistics: 2004–2019.

2.5. Analytical Methods

National-level factors affect regional economic resilience [55,56]; thus, a multilevel logistic regression was used in this study to assess determinants of regional economic resilience and regional resilience variance caused by disparities between provinces. This study used a nested structure, i.e., 284 cities (level 1) nested within 30 provinces (level 2). The independent variables were assumed to be statistically significant at the 10% level. All calculations were performed using the STATA 15 econometric software package and HLM 6.08. All figures were portrayed using ArcGIS 10.5 (ESRI, Redlands, CA, USA).

The dependent variable, regional economic resilience, was assumed as a dichotomous dependent variable.

$$\begin{gathered} Yij = 1, \text{ if } R^N \geq 0, \\ Y_{ij} = 0, \text{ if } R^N < 0. \end{gathered} \tag{3}$$

A two-level logistic regression model was constructed as follows:

(a) Null model:

$$\begin{gathered} \text{Prob } (Y_{ij} = 1) = p_{ij}, \\ \text{Log } (p_{ij}/(1 - p_{ij})) = \gamma_{00} + u_{0j}, \end{gathered} \tag{4}$$

(b) Full model:

$$\begin{gathered} \text{Log } (p_{ij}/(1 - p_{ij})) = \beta_{0j} + \beta_{ij}X_{qij}, \\ \beta_{0j} = \gamma_{00} + \gamma_{ij} + u_{0j}, \end{gathered} \tag{5}$$

where p_{ij} is the probability of $Y_{ij} = 1$, X_{qij} is the predictor q for city i in province j, and u_{0j} is the level 1 random effect; here, we assumed that the random term u_{0j}~N (0, σ^2).

The between-group variation can be measured by the intraclass correlation coefficient (ICC) [57]. For a logistic regression model, σ^2 is $\pi^2/3$. Thus, Equation (6) simply states that the intraclass correlation is the proportion of group-level variance compared to the total variance.

$$\text{ICC} = \sigma_b{}^2/(\sigma_b{}^2 + \sigma^2), \tag{6}$$

where σ^2 represents the within-group variance, and $\sigma_b{}^2$ indicates the between-group variance. ICC < 0.059 represents low within-group correlation; 0.059 < ICC < 0.138 represents moderate within-group correlation; ICC > 0.138 represents high within-group correlation, which indicates the necessity of conducting multilevel regression [58].

A second analysis was applied for province-based regional economic resilience. A logistic model was constructed to account for the effects of the independent variables on regional resilience to the crisis using 25 provinces and 279 cities (Beijing, Shanghai, Chongqing, Tianjin, and Qinghai were excluded as each consisted of only one city).

A third analysis was applied for large and small cities to capture the impacts of the size of regions. As discussed previously, 284 cities were divided into two groups: large (102) and small (182) economies. Two multilevel logistic regressions were applied using national-based resilience.

Finally, a multilevel logistic analysis was applied for resource-based economies and synthetic economies to capture the impacts of the resources of regions. This study divided the 284 cities into two groups: 108 resource-based economies and 176 synthetic economies. Two multilevel logistic regressions were also applied using national-based resilience.

In order to examine multicollinearity of the predictor variables, this study used the variance inflation factor (VIF). VIF < 5 denotes that the model has no multicollinearity and that the model is well constructed, and vice versa [59].

3. Results and Discussion

3.1. National- and Province-Based Regional Economic Resilience

This study computed the national-based and province-based regional economic resilience of 284 cities (As shown in Table A1 in Appendix A.1). The average national-based resilience was −0.02. For small cities, the average resilience (−0.11) was lower than that of large cities (0.14). The average resilience of resource-based economies was 0.05, while the average resilience of synthetic economies was −0.06. The spatial distribution of national-based regional economic resilience is portrayed in Figure 1, which illustrates the disparity in the ability of regions to resist and recover from the economic crisis. The regional economic resilience was clearly affected by provincial patterns. Significant differences were indicated between eastern and northeastern China. More precisely, most cities in Zhejiang, Jiangsu, Fujian, and Shandong were resilient to recession. Conversely, most cities in Heilongjiang, Jilin, and Liaoning were not resilient to economic crisis. Furthermore, a heterogeneity of resilience could be observed within provinces, such as Guangdong, Anhui, and Hunan. Guangdong was the province with the highest dispersion of resilience to economic downturn; resilience ranged from Dongguan (7.12) to Jieyang (−1.31). However, a homogeneous pattern existed in some provinces, such as Heilongjiang and Liaoning.

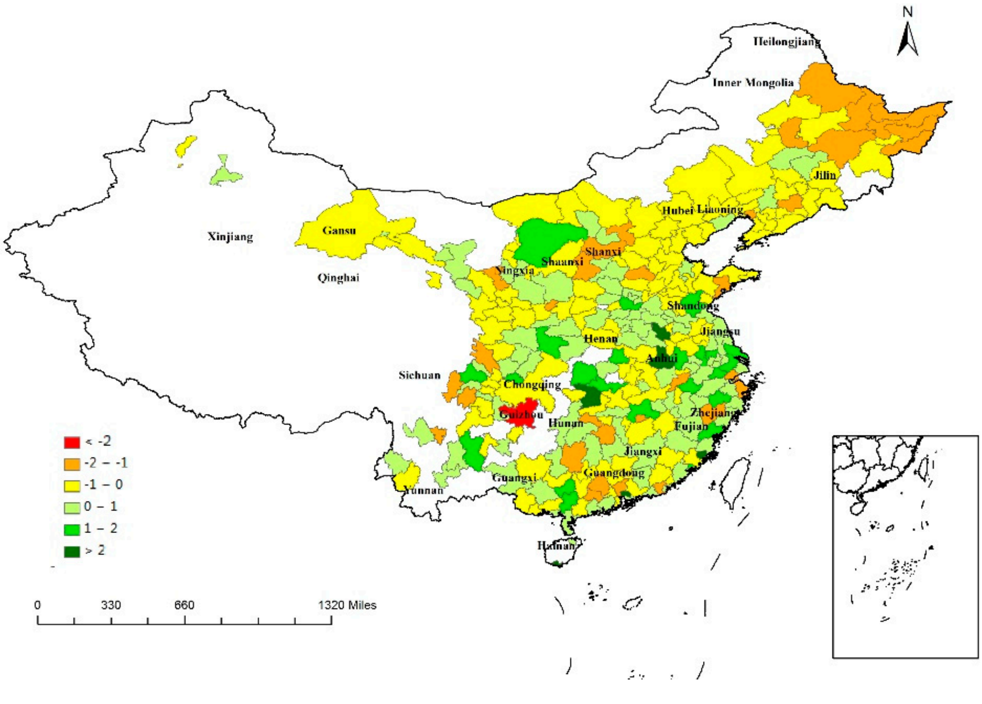

Figure 1. National-based resilience across 284 cities.

Figure 2 shows the geographical distribution of province-based regional economic resilience. Heilongjiang was the province with the widest dispersion of resilience; resilience ranged from 3.44 (Mudanjiang) to −4.43 (Hegang). Eighteen of the 25 provincial capital cities were more resilient to recession than their provincial average, indicating their improved capabilities to withstand and recover from external shocks.

3.2. Determinants of Regional Economic Resilience

The results of multilevel logistic regression models are presented in Tables 2–4. This study accounted for the multicollinearity problem and found no multicollinearity between variables. This study also computed the ICC as discussed in the previous section. The ICC for all regions was 0.22 (0.18 for small regions and 0.20 for large regions); the values being above 0.059 indicated the need for multilevel regression.

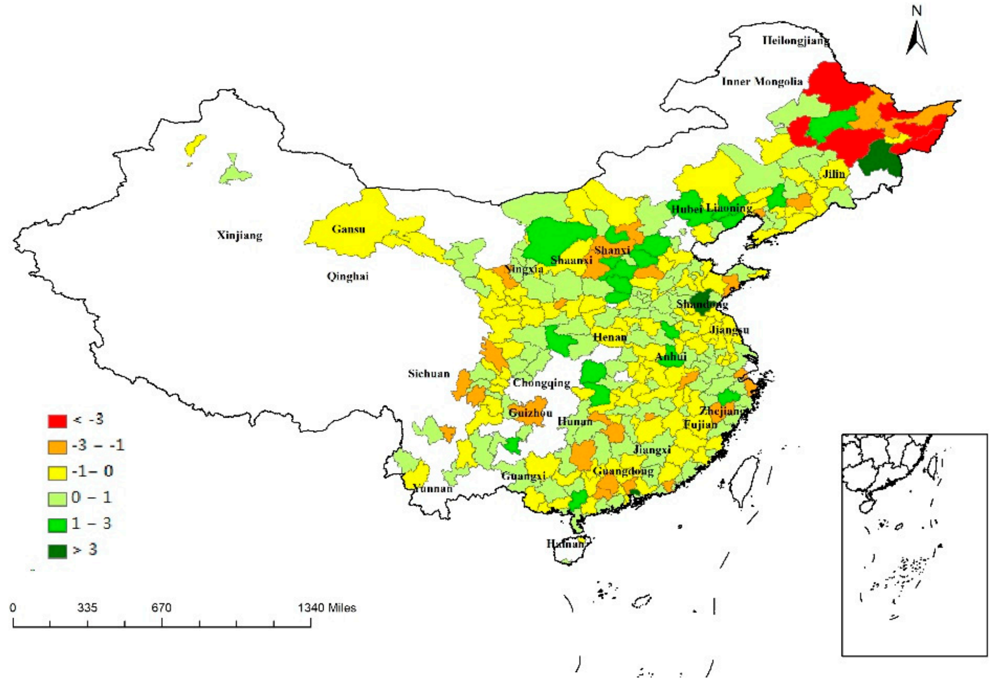

Figure 2. Province-based resilience across 279 cities. Source: portrayed by using file from Ministry of Natural Resources, People's Republic of China.

Table 2. Odds ratios of pre-crisis (2003–2007) determinants of national-based resilience using a multilevel logistic regression model and a logistic model for province-based resilience.

	Two-Level Logistic Model	**Logit Model**
GINI	0.015 **	0.224 *
INNO	1.779 **	1.444 *
GOV	0.874 ***	0.904 ***
HUMCAP	1.657 **	1.763 *
FIN	2.731 ***	3.059 ***
INDO	1.006	1.011
FASSE	1.000	1.003
AGE65	5.036	0.916
ENTR	0.922	0.881
Constant	0.007 *	0.024 *
Log likelihood	−411.004	356.293
p-value	0.000	0.000
No. of obs.	284	279

*** significant at the 0.01 level (2-tailed). ** significant at the 0.05 level (2-tailed). * significant at the 0.1 level (2-tailed). Source: calculated by using data from the National Bureau of Statistics: 2004–2019.

Table 3. Odds ratios of pre-crisis (2003–2007) determinants of national-based regional economic resilience, using a multilevel logistic regression model for 182 small regional economies (left) and 102 large regional economies (right).

	Small Economies	**Large Economies**
GINI	0.015 *	0.019 *
INNO	1.944 *	0.876
GOV	0.889 **	0.770 **
HUMCAP	1.611 ***	1.560 *
FIN	2.502 ***	5.776 ***

Table 3. *Cont.*

	Small Economies	Large Economies
INDO	0.992	1.046 *
FASSE	1.009	0.990
AGE65	1.283	3.275
ENTR	0.950	0.903
Constant	0.001 **	0.586
Log likelihood	−266.506	−146.468
p-value	0.018	0.018
No. of obs.	182	102

*** significant at the 0.01 level (2-tailed). ** significant at the 0.05 level (2-tailed). * significant at the 0.1 level (2-tailed). Source: calculated by using data from the National Bureau of Statistics: 2004–2019.

Table 4. Odds ratios of pre-crisis (2003–2007) determinants of national-based regional economic resilience, using a multilevel logistic regression model for 108 resource-based economies (left) and 176 synthetic economies (right).

	Resource-Based Economies	Synthetic Economies
GINI	0.045 *	0.026 *
INNO	1.985 **	2.065 **
GOV	0.968	0.752 ***
HUMCAP	1.749	1.507 ***
FIN	0.267 *	2.814 ***
INDO	1.019	0.990
FASSE	0.969	1.025 *
AGE65	5.493	4.623
ENTR	0.905	0.944
Constant	0.001 *	0.005 *
Log likelihood	−157.695	−255.217
p-value	0.011	0.003
No. of obs.	108	176

*** significant at the 0.01 level (2-tailed). ** significant at the 0.05 level (2-tailed). * significant at the 0.1 level (2-tailed). Source: calculated by using data from the National Bureau of Statistics: 2004–2019.

Table 2 presents a negative relationship between income inequality (GINI) and regional economic resilience in the multilevel logistic regression model and the logit model. A 1% increase in GINI could decrease resilience 0.015 times in the multilevel logistic regression model and 0.224 times in the logit model. This result supports the findings by Lewin et al. (2018) indicating that income inequality has a negative impact on regional resilience according to 639 US urban counties from 2006 to 2010 [35]. Rahe (2019) extended this study to all counties in the United States and considered unemployment [36]. They found that high income inequality may increase the unemployment rate in counties with a large population and reduce the unemployment rate in the smallest counties. Severe income inequality decreases a region's ability to withstand recession. As income inequality intensifies, income is largely concentrated in the hands of high-income families. The overall marginal propensity of an economy to consume is expected to decline; thus, the recession may be exacerbated and lead to a lower resilience [35]. The highest GINI was found in eastern, western, and northeastern China, such as Heilongjiang, Beijing, Guangdong, and Zhejiang (Figure 3).

Table 2 shows a negative relationship between government intervention (GOV) and regional resilience in both models, supporting the earlier findings by Guo and Xu (2019). Guo and Xu (2019) found a negative relationship between GOV and regional resilience using data from 27 provinces in China between 2005 and 2016 [41]. The government has to provide financial assistance in the face of external shocks. Although this assistance may be effective in the recovery from crisis, in the long run, it may cause regional dependence on fiscal expenditure and weaken viability under the crisis. The regions with a low level of

GOV were mainly located in the east of China, and the regions with a high level of GOV were found in the northern regions (Figure 4). The government has decided to first develop eastern China since reform and opening-up in 1978. This policy has allowed great progress in east cities, along with less government intervention in more developed regions.

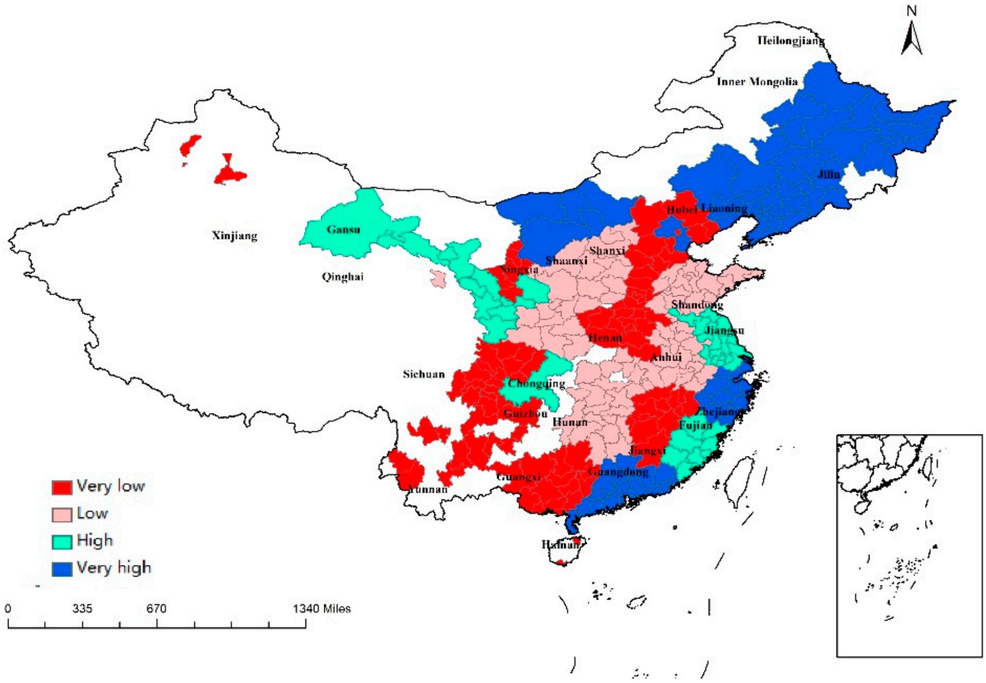

Figure 3. Regional values of GINI.

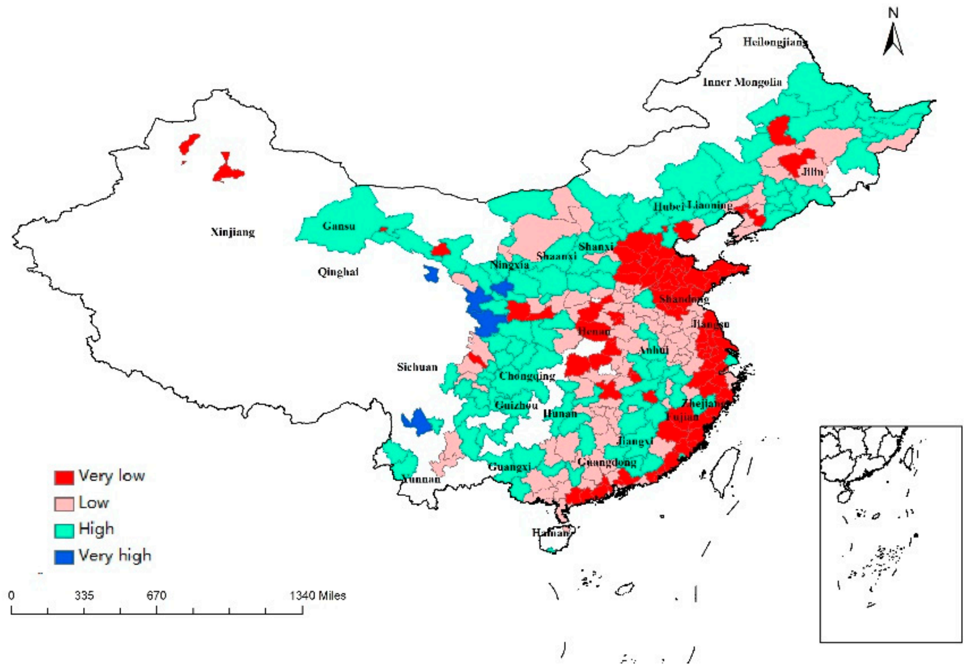

Figure 4. Regional values of GOV.

On the contrary, the results in Table 2 indicate a significant positive effect of innovation (INNO) in shaping regional resilience. Technology-driven innovation was expressed by the fiscal expenditure for science and technology (support for science and technology activities) in this study. Zeng (2018) suggested that the relationship between innovation and regional resilience is positive according to a study of 31 provinces of China from 2006 to 2015 [60], while Bristow and Healy (2018) also found a positive relationship between innovation capacity and regional resilience using the data of European regions between 2001 and 2011 [61]. Innovation is an essential factor to enhance the competitiveness and resilience of regions [62,63]. Technology-driven innovation may help regions to break negative path dependence, promote industrial transformation and upgrading, and build ability to deal with economic crisis. The innovation process changes the dynamic ability of firms; thus, regions with more innovative entrepreneurs are more resilient [19]. The geographical distribution of INNO is portrayed in Figure 5. Cities in eastern China also had a higher level of innovation due to the "reform and opening-up" policy.

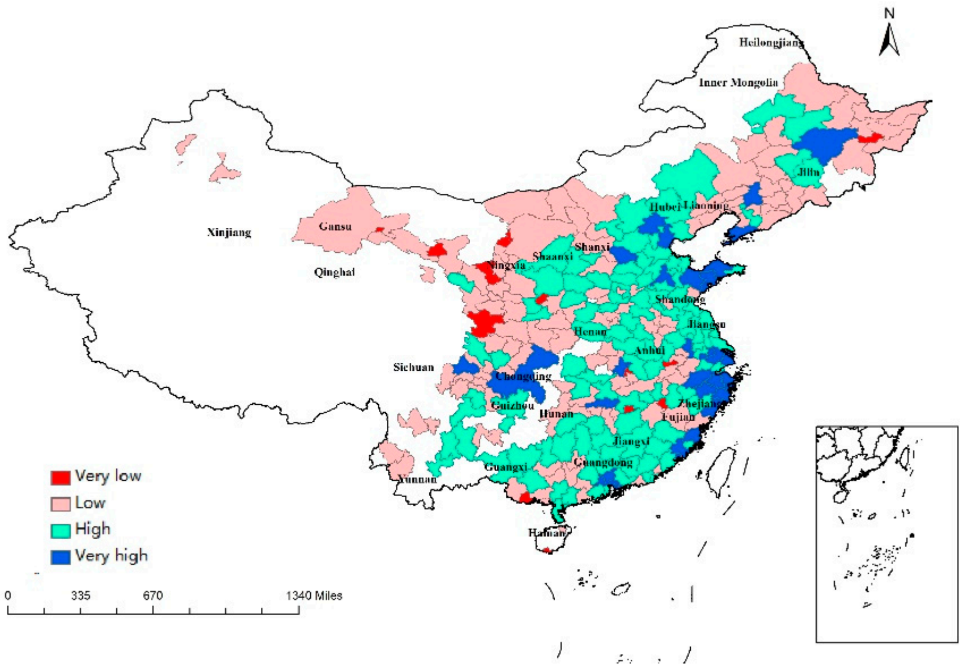

Figure 5. Regional values of INNO.

Furthermore, this study found a significant positive relationship between human capital (HUMCAP) and regional resilience (Table 2). Investments in education may improve human resources and increase productivity, which may explain differences across regions during growth and crisis periods [64]. Di Caro (2015) used years of education attainment to measure human capital from 1992 to 2012 in Italy and found a positive relationship between human capital and economic resilience [65]. Crescenzi et al. (2016) also took human capital into account and found a positive relationship between human capital and regional resilience by studying NUTS 2 regions of European countries from 2004 to 2010 [62], while Östh (2015) also found a positive relationship between education attainment and spatial economic resilience [66]. Generally speaking, cities with high human capital and knowledge production may have high productivity and high return on skills, which makes these areas more attractive to companies and labor. In addition, the concentration of people with high human capital is conducive to the growth of consumption facilities [67]. This in turn further attracts human capital and talent [68]. The geographical distribution of HUMCAP is portrayed in Figure 6. Similar to the geographical distribution of INNO, due to a higher level of development, talented people were more likely to agglomerate in high-technology cities, mostly located in eastern China.

In addition, there was a significantly positive relationship between financial-development level (FIN) and the ability of cities to resist and recover from the economic crisis in both models. More precisely, the odds of regions with a high financial-development level to resist and recover from the recession were 2.73 times greater than of those with a poor financial-development level for all regions in the multilevel logistic model. This result is consistent with a previous study by Eraydin (2015) indicating a positive relationship between the financial-development level and regional performance to resist and recover from economic downturn according to Turkish regions [42]. Moreover, Du et al. (2019) adopted data from the Pearl River Delta of China from 2008–2016 and found that FIN has a positive impact on regional resilience [43]. After entering the adjustment period, the reallocation of production resources and the transformation and upgrading of industrial structure are inseparable from the support of the financial sector [19]. In addition, Du et al. (2019) also suggested that regions with more bank deposits and loans may perform better during and after the financial crisis [43]. The geographical distribution of FIN is portrayed in Figure 7. In order to test the robustness of the above results, this study provided robust test by changing measurement of economic resilience in Table A2 in Appendix A.2.

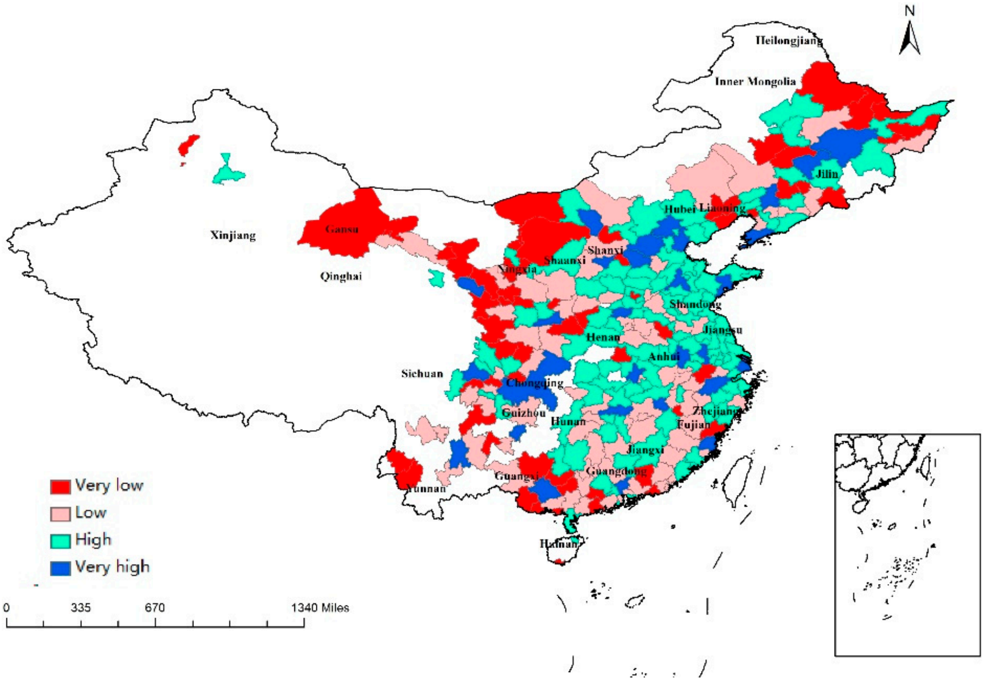

Figure 6. Regional values of HUMCAP.

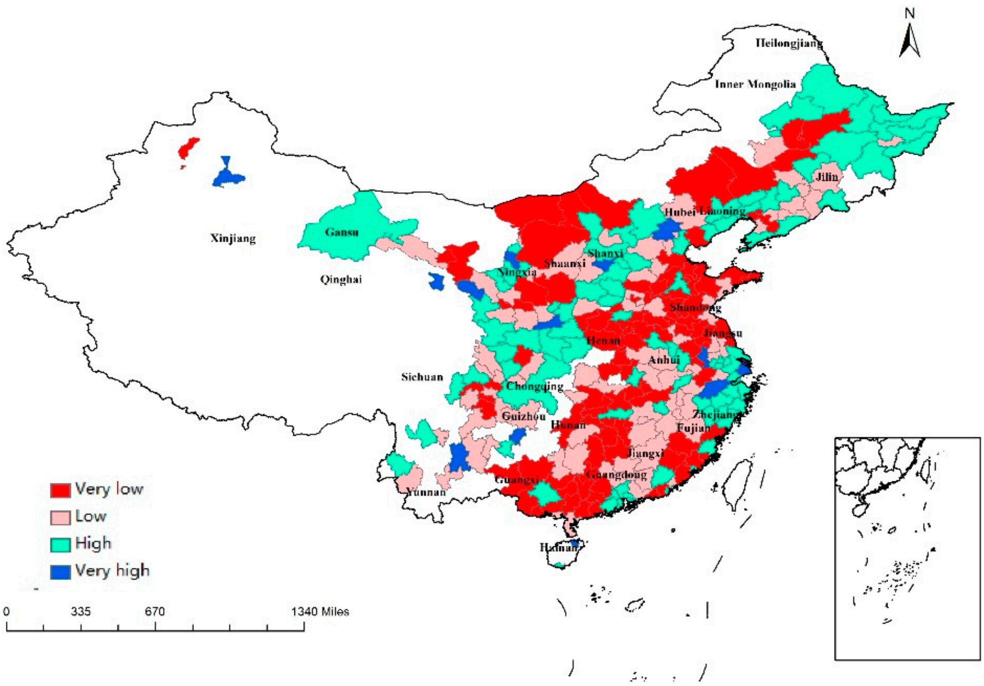

Figure 7. Regional values of FIN, classified into four quartiles (very low to very high). Source: portrayed by using file from the Ministry of Natural Resources, People's Republic of China.

In order to explore whether the size of an economy may influence regional economic resilience, this study divided the sample into small and large economies to run a multilevel logistic regression model. The relationship between GINI and resilience was negative in both models. However, the relationship between INNO and resilience was weak in both cases, with only the value in small regions being significant at the 10% level. There was a significantly negative relationship between GOV and regional resilience for both small economies and large economies. According to Table 3, HUMCAP had a statistically significant impact on regional resilience in both cases. Table 3 also shows the highly positive contribution of FIN for both small and large economies, supporting the earlier findings by Du et al. (2019) and Eraydin (2015) [42,43]. Large regions with a high manufacturing industry (INDO) were more resilient to economic downturn than regions with low manufacturing shares, which is consistent with the studies by Brown and Greenbaum (2016), Su and Zhao (2020), and Di Caro and Fratesi (2018) [54,69,70]. Above all, the GINI, GOV, HUMCAP, and FIN of cities of different sizes had a significant impact on regional economic resilience. Large economies were more sensitive to GINI, FIN, and INDO, whereas small economies were more sensitive to INNO and HUMCAP. This may be because large economies usually take advantage of agglomeration economies, whereas small economies need more innovation and human capital to promote their development.

In addition, this study further analyzed whether the resource hierarchy influences post-crisis performance. According to Table 4, the relationship between GINI and resilience was negative for both resource-based economies and synthetic economies. In particular, INNO, as one of the most important determinants of regional economic resilience, had a highly significant positive impact on resilience for both resource-based economies and synthetic economies. Moreover, the impact of INNO on the resilience of synthetic economies was higher than that of resource-based economies. GOV had a negative impact on regional performance for both economies, but this was only significant for synthetic economies. For synthetic economies, the relationship between FIN and resilience was positive. However, FIN had a negative impact on resilience for resource-based economies unlike the other models. This may be because resource-based economies primarily rely on exploitation and processing of natural resources, and they may have been influenced by international resource price fluctuation due to the financial crisis [45]. Thus, the cost of resource-based economies is higher. Furthermore, this study found a positive effect of investment in fixed assets (FASSE) on regional economic resilience for synthetic economies, which is consistent with the previous findings [45,71]. For resource-based cities with a singular industrial structure, governments should promote their development by getting rid of the inertia of resource dependence. Thus, building a diversified regional system could improve the correlation and adhesion between enterprises and promote the spillover of knowledge and innovation.

This study analyzed determinants of regional economic resilience from 2003–2018, which included the 2008 financial crisis. The government issued four trillion CNY to boost the economy in 2010. With the implementation of this policy, China's economy maintained a high growth rate in the short term, such that most China's cities showed strong resilience. However, this policy caused negative effects as well, such as a waste of resources, increased government liabilities, overcapacity, and a high leverage of enterprise. With the Chinese government's economic growth target lowered year by year, the government gradually turned to the "new normal" stage in 2011, focusing on the quality of growth rather than speed. Regions located in the south and east of China are more developed than regions located in the west and northeast of China. As we discussed above, eastern China performed better during and after financial crisis, while Western China encountered a deeper recession. Thus, in order to build resilient cities, decreasing the level of income inequality and government intervention and increasing innovation, human capital agglomeration, and financial development are important for the long-term development of economies.

Building on previous research, this study explored how pre-crisis determinants impact post-crisis performance that may contribute to mitigate short-term recession of regional economies. Firstly, this study divided the period to pre-crisis and post-crisis, which could unveil the connection between the pre-crisis path and the capability of an economy to resist and recover from shocks. Besides, the methodology of this study was a multilevel logistic regression by using nested data (284 cities nested in 30 provinces), which was more appropriate for exploring both provincial and regional effects. Due to different specialization of cities and province-based policy, it is important to take both provincial and regional influencing factors into account. Moreover, this study also considered the size of economies and the resource hierarchy, which may contribute to developing policies according to the characteristics of economies. Finally, this study analyzed 284 cities in China, which could contribute to the resilience literature in developing counties.

The limitations of our study consist in the fact that the models lack attention paid to spatial and dynamic factors. Martin (2012) suggests that a dynamic rather than a static fashion may further improve resilience [3]. Further, the measurement of resilience was limited. Although we provided a robust test by replacing the measurement of resilience, there are emerging index and research methods to play roles in resilience. Additionally, the models did not contain policy factors. Strengthening regional-based policy is important to balance the capability of a region to resist and recover from external shocks. Finally, this study did not consider the renewal and reorientation ability. According to the concept of resilience, adjustment and path orientation are important to the sustainable development of economies.

4. Conclusions

This study analyzed regional economic resilience against the background of the 2008 financial crisis. According to the nested data for 284 Chinese prefecture-level and above prefecture-level cities from 2003 to 2018, combined with relevant studies, this article built an empirical analysis of the factors influencing regional economic resilience. The aim of this study was to find the internal connection between the period of growth (pre-crisis) and the recession (post-crisis). Thus, the results shown above indicated this connection. The results showed that pre-crisis determinants such as income inequality, innovation, government intervention, human capital, and financial development had a significant effect on regional economic resilience. The model results revealed that the financial-development level is the factor with the greatest positive impact on economic resilience, while government intervention had a strong negative impact on economic resilience. The positive impact of financial development was highest for large and synthetic economies, whereas the negative impact of government intervention was highest for small and resource-based economies. Improvements in the financial-development level across Chinese cities can help economies to build greater resilience. Less government intervention may reduce regional dependence on fiscal expenditure and enhance the viability of regional economies under the crisis.

We also found statistically significant differences for both national-based resilience and province-based resilience. Due to the development strategy built by the government, large economies and synthetic economies are mostly located in eastern and coastal China. Economies in eastern and coastal (such as Fujian, Zhejiang) China were more resilient when facing external shocks, which may be related to their lower income inequality and government intervention as well as their higher innovation, human capital, and financial-development level.

Taking into account the diversity of regions, this study provided evidence for the government to design region-based policies that could determine and develop high-quality governance and improve the efficiency of regional response mechanisms to build a resilient wall to defend against external shocks and to form a basis for sustainable development. Regional policies could target areas more prone to recession and could introduce structural policies to alleviate labor-market friction in these areas.

Future studies could further investigate the renewal and reorientation ability and could emphasize the long-term process of realizing the adjustment and path orientation of regional economic systems. Therefore, in the future, researchers could expand the data and optimize index selection by different means to deeply analyze the long-term evolution and influencing factors of regional economic resilience. Moreover, the impact of regional development policies on regional resilience should not be ignored. Future resilience evaluation frameworks should include policy factors, and innovative research should be conducted with diversified research perspectives and emerging research data and research methods.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Appendix A.1. National- and Province-Based Regional Economic Resilience

Table A1. National- and province-based regional economic resilience of 284 cities.

Cityid	City	Province	R^N	R^P
1	Beijing	Beijing	−0.11109	
2	Tianjin	Tianjin	−0.5843	
3	Shijiazhuang	Hebei	−0.25677	1.463781
4	Tangshan	Hebei	−0.87254	−0.57746
5	Qinghuangdao	Hebei	−0.45149	0.818291
6	Handan	Hebei	−0.95008	−0.83451
7	Xingtai	Hebei	−1.54113	−2.79384
8	Baoding	Hebei	−0.2054	1.634082
9	Zhangjiakou	Hebei	−0.66689	0.104271
10	Chengde	Hebei	−0.32209	1.24727
11	Cangzhou	Hebei	−0.93111	−0.77162
12	Langfang	Hebei	−0.69289	0.018063
13	Hengshui	Hebei	−0.88639	−0.62338
14	Taiyuan	Shanxi	0.146482	1.404865
15	Datong	Shanxi	−1.48236	−2.01179
16	Yangquan	Shanxi	−0.51664	0.013896
17	Changzhi	Shanxi	0.162884	1.43927
18	Jincheng	Shanxi	0.028696	1.157797
19	Suzhou	Shanxi	0.222703	1.564746
20	Jinzhong	Shanxi	0.098738	1.304717
21	Yuncheng	Shanxi	−0.96673	−0.9302

Table A1. *Cont.*

Cityid	City	Province	R^N	R^P
22	Yizhou	Shanxi	−1.31885	−1.66882
23	Linfen	Shanxi	−0.37607	0.308768
24	Lvliang	Shanxi	−1.50201	−2.05301
25	Huhehaote	Inner Mongolia	0.647102	0.792586
26	Baotou	Inner Mongolia	−0.36959	−0.31391
27	Wuhai	Inner Mongolia	−0.32789	−0.26852
28	Chifeng	Inner Mongolia	−0.34386	−0.28591
29	Tongliao	Inner Mongolia	−0.03096	0.054636
30	Erdors	Inner Mongolia	1.352074	1.559825
31	Hailaer	Inner Mongolia	−0.46514	−0.4179
32	Bayanzhuoer	Inner Mongolia	−0.04704	0.037131
33	Wulanchade	Inner Mongolia	−0.78522	−0.76625
34	Shenyang	Liaoning	0.122288	1.644333
35	Dalian	Liaoning	−0.94366	−0.86726
36	Anshan	Liaoning	−0.26315	0.736152
37	Fushun	Liaoning	−1.23556	−1.55503
38	Benxi	Liaoning	−0.5994	−0.05611
39	Dandong	Liaoning	−0.9087	−0.78487
40	Jinzhou	Liaoning	−0.631	−0.13056
41	Yingkou	Liaoning	−0.5708	0.011278
42	Fuxin	Liaoning	−0.86719	−0.68706
43	Liaoyang	Liaoning	−0.83911	−0.62092
44	Panjin	Liaoning	−1.13943	−1.32853
45	Tieling	Liaoning	−0.43092	0.340866
46	Zhaoyang	Liaoning	−0.02319	1.301552
47	Huludao	Liaoning	0.177666	1.774813
48	Changchun	Jilin	0.288544	0.521485
49	Jilin	Jilin	−0.32835	−0.20693
50	Siping	Jilin	−0.85818	−0.83254
51	Liaoyuan	Jilin	−0.77109	−0.72971
52	Tonghua	Jilin	−0.89205	−0.87253
53	Baishan	Jilin	−0.0421	0.131073
54	Songyuan	Jilin	0.482841	0.750907
55	Baicheng	Jilin	−0.46179	−0.3645
56	Haerbin	Heilongjiang	−1.57353	−3.63828
57	Qiqihaer	Heilongjiang	−0.61837	0.755532
58	Jixi	Heilongjiang	−1.63553	−3.9235
59	Hegang	Heilongjiang	−1.74667	−4.43474
60	Shuangyashan	Heilongjiang	−1.59252	−3.72567
61	Daqing	Heilongjiang	−1.4787	−3.20207
62	Yichun	Heilongjiang	−1.05992	−1.27564

Table A1. *Cont.*

Cityid	City	Province	R^N	R^P
63	Jiamusi	Heilongjiang	−1.00658	−1.03028
64	Qitaihe	Heilongjiang	−0.81709	−0.15858
65	Mudanjiang	Heilongjiang	−0.03457	3.44108
66	Heihe	Heilongjiang	−1.46661	−3.14645
67	Neihua	Heilongjiang	−0.27408	2.339288
68	Shanghai	Shanghai	0.300459	
69	Nanjing	Jiangsu	1.564261	0.412132
70	Wuxi	Jiangsu	0.565437	−0.13792
71	Xuzhou	Jiangsu	0.461362	−0.19523
72	Changzhou	Jiangsu	0.301605	−0.28321
73	Suzhou	Jiangsu	1.373144	0.306884
74	Nantong	Jiangsu	1.796283	0.539905
75	Lianyungang	Jiangsu	0.206234	−0.33573
76	Huaian	Jiangsu	−0.12028	−0.51554
77	Yancheng	Jiangsu	0.164331	−0.35881
78	Yangzhou	Jiangsu	0.445947	−0.20372
79	Zhenjiang	Jiangsu	1.006741	0.105107
80	Taizhou	Jiangsu	0.720402	−0.05258
81	Suqian	Jiangsu	−0.00178	−0.45028
82	Hangzhou	Zhejiang	0.757783	0.657364
83	Ningbo	Zhejiang	−1.44516	−1.41973
84	Wenzhou	Zhejiang	0.226893	0.156803
85	Jiaxing	Zhejiang	−1.41941	−1.39545
86	Huzhou	Zhejiang	1.11746	0.996493
87	Shaoxing	Zhejiang	0.195993	0.127668
88	Jinhua	Zhejiang	1.326105	1.193218
89	Quzhou	Zhejiang	0.925476	0.815477
90	Zhoushan	Zhejiang	−0.19715	−0.24302
91	Taizhou	Zhejiang	0.404764	0.324512
92	Lishui	Zhejiang	−1.51561	−1.48615
93	Hefei	Anhui	1.08804	0.304413
94	Wuhu	Anhui	0.701984	0.063241
95	Bengbu	Anhui	−0.58168	−0.73868
96	Huainan	Anhui	−0.46929	−0.66846
97	Maanshan	Anhui	0.705013	0.065134
98	Huaibei	Anhui	−0.58149	−0.73855
99	Tongling	Anhui	−0.12867	−0.45568
100	Anqing	Anhui	0.476086	−0.07788
101	Huangshan	Anhui	1.070805	0.293646
102	Chuzhou	Anhui	−0.10749	−0.44244
103	Fuyang	Anhui	0.954113	0.220748

Table A1. *Cont.*

Cityid	City	Province	R^N	R^P
104	Suzhou	Anhui	0.890161	0.180797
105	Liuan	Anhui	5.268123	2.915741
106	Haozhou	Anhui	2.342163	1.087873
107	Chizhou	Anhui	−1.57333	−1.35817
108	Xuancheng	Anhui	0.761145	0.1002
109	Fuzhou	Fujian	0.8043	−0.01145
110	Xiamen	Fujian	1.498696	0.369002
111	Putian	Fujian	2.597335	0.970932
112	Sanming	Fujian	0.552555	−0.14938
113	Quanzhou	Fujian	−0.00554	−0.45515
114	Zhangzhou	Fujian	0.932425	0.05875
115	Nanping	Fujian	0.586125	−0.13098
116	Longyan	Fujian	−0.10543	−0.50988
117	Ningde	Fujian	1.875216	0.575293
118	Nanchang	Jiangxi	0.547259	0.215881
119	Jingdezhen	Jiangxi	−0.307	−0.45542
120	Pingxiang	Jiangxi	−0.40354	−0.53129
121	Jiujiang	Jiangxi	−0.0971	−0.29048
122	Xinyu	Jiangxi	−1.07151	−1.0562
123	Yingtan	Jiangxi	0.72118	0.352553
124	Ganzhou	Jiangxi	0.825614	0.434621
125	Jian	Jiangxi	−0.56886	−0.6612
126	Yichun	Jiangxi	1.462779	0.935323
127	Fuzhou	Jiangxi	−0.00998	−0.22202
128	Shangrao	Jiangxi	0.225931	−0.03663
129	Jinan	Shandong	−0.66993	−0.38758
130	Qingdao	Shandong	−1.43154	−1.80071
131	Zibo	Shandong	−0.47438	−0.02474
132	Zaozhuang	Shandong	−0.49694	−0.06659
133	Dongying	Shandong	−0.67694	−0.40058
134	Yantai	Shandong	−0.43025	0.057156
135	Weifang	Shandong	−0.6611	−0.37118
136	Jining	Shandong	−0.36247	0.182921
137	Taian	Shandong	−0.27669	0.342082
138	Weihai	Shandong	−0.55127	−0.1674
139	Rizhao	Shandong	−0.37025	0.168486
140	Linyi	Shandong	1.831404	4.253566
141	Dezhou	Shandong	−0.31576	0.269583
142	Liaocheng	Shandong	−0.29385	0.310232
143	Binzhou	Shandong	0.040836	0.931233
144	Heze	Shandong	0.070261	0.985831

Table A1. *Cont.*

Cityid	City	Province	R^N	R^P
145	Zhengzhou	Henan	0.54524	0.282566
146	Kaifeng	Henan	0.269364	0.053586
147	Luoyang	Henan	0.415253	0.174676
148	Pingdingshan	Henan	−0.21199	−0.34594
149	Anyang	Henan	0.591732	0.321155
150	Hebi	Henan	0.306126	0.084099
151	Xinxiang	Henan	1.300494	0.909436
152	Jiaozuo	Henan	−0.70323	−0.75368
153	Puyang	Henan	−0.42632	−0.52384
154	Xuchang	Henan	0.057256	−0.12247
155	Luohe	Henan	0.337541	0.110174
156	Sanmenxia	Henan	−0.17706	−0.31695
157	Nanyang	Henan	−0.23032	−0.36116
158	Shangqiu	Henan	0.594604	0.323539
159	Xinyang	Henan	−0.10897	−0.26044
160	Zhoukou	Henan	0.072022	−0.11021
161	Zhumadian	Henan	0.435657	0.191611
162	Wuhan	Hubei	−0.20812	−0.30838
163	Huangshi	Hubei	0.380738	0.20592
164	Shiyan	Hubei	0.163261	0.015978
165	Yichang	Hubei	1.629116	1.296238
166	Xiangfan	Hubei	0.38812	0.212367
167	Ezhou	Hubei	−0.42163	−0.49486
168	Jinmen	Hubei	0.409257	0.230828
169	Xiaogan	Hubei	−0.62101	−0.66899
170	Jingzhou	Hubei	1.180686	0.904585
171	Huanggang	Hubei	−0.29478	−0.38407
172	Xianning	Hubei	−0.45912	−0.5276
173	Suizhou	Hubei	1.130519	0.860769
174	Changsha	Hunan	0.890677	0.869584
175	Zhuzhou	Hunan	0.18113	0.167953
176	Xiangtan	Hunan	−0.92194	−0.92282
177	Hengyang	Hunan	−1.62677	−1.61978
178	Shaoyang	Hunan	0.397515	0.381923
179	Yueyang	Hunan	−0.1575	−0.1669
180	Changde	Hunan	2.008414	1.974851
181	Zhangjiajie	Hunan	−0.52758	−0.53285
182	Yiyang	Hunan	−0.74386	−0.74671
183	Chenzhou	Hunan	0.359088	0.343925
184	Yongzhou	Hunan	0.474048	0.457603
185	Huaihua	Hunan	0.381726	0.366311

Table A1. *Cont.*

Cityid	City	Province	R^N	R^P
186	Loudi	Hunan	−1.51698	−1.51121
187	Guangzhou	Guangdong	−1.21975	−1.23501
188	Shaoguan	Guangdong	−0.50528	−0.47093
189	Shenzhen	Guangdong	0.436537	0.536262
190	Zhuhai	Guangdong	−0.72095	−0.70158
191	Shantou	Guangdong	0.11597	0.193442
192	Foshan	Guangdong	−0.40845	−0.36739
193	Jiangmen	Guangdong	0.28294	0.372002
194	Zhanjiang	Guangdong	0.250871	0.337707
195	Maoming	Guangdong	−0.17425	−0.11692
196	Zhaoqing	Guangdong	−1.22821	−1.24405
197	Huizhou	Guangdong	−0.53061	−0.49802
198	Meizhou	Guangdong	−0.45549	−0.41769
199	Shanwei	Guangdong	0.535752	0.642365
200	Heyuan	Guangdong	0.379586	0.475357
201	Yangjiang	Guangdong	0.01007	0.08019
202	Qingyuan	Guangdong	−0.27257	−0.22207
203	Dongguan	Guangdong	7.123492	7.687429
204	Zhongshan	Guangdong	−0.57192	−0.5422
205	Chaozhou	Guangdong	−0.03841	0.028346
206	Jieyang	Guangdong	−1.31475	−1.3366
207	Yunfu	Guangdong	−1.20414	−1.21831
208	Nanning	Guangxi	0.138094	0.028772
209	Liuzhou	Guangxi	0.463053	0.322516
210	Guilin	Guangxi	−1.11879	−1.10738
211	Wuzhou	Guangxi	−0.14081	−0.22334
212	Beihai	Guangxi	0.800893	0.627905
213	Fangchenggang	Guangxi	−0.09698	−0.18372
214	Qinzhou	Guangxi	−0.20268	−0.27927
215	Guigang	Guangxi	1.189621	0.979292
216	Yulin	Guangxi	1.397779	1.167455
217	Baise	Guangxi	0.277851	0.155104
218	Hezhou	Guangxi	−0.3003	−0.36751
219	Hechi	Guangxi	−0.37315	−0.43337
220	Laibin	Guangxi	−0.08068	−0.16899
221	Chongzuo	Guangxi	−0.18622	−0.26439
222	Haikou	Hainan	0.756012	−0.10631
223	Sanya	Hainan	2.080534	0.567777
224	Chongqing	Chongqing	−0.0118	
225	Chengdu	Sichuan	1.387773	0.847688
226	Zigong	Sichuan	0.346122	0.041645

Table A1. *Cont.*

Cityid	City	Province	R^N	R^P
227	Panzhihua	Sichuan	−1.07356	−1.05692
228	Luzhou	Sichuan	0.681912	0.301484
229	Deyang	Sichuan	0.169929	−0.0947
230	Mianyang	Sichuan	−1.40085	−1.31018
231	Guangyuan	Sichuan	−0.31248	−0.46799
232	Suining	Sichuan	−0.2908	−0.45121
233	Neijiang	Sichuan	−0.59552	−0.68701
234	Leshan	Sichuan	−1.27323	−1.21143
235	Nanchong	Sichuan	0.681486	0.301154
236	Meishan	Sichuan	0.597725	0.236339
237	Yibin	Sichuan	−0.61184	−0.69964
238	Guangan	Sichuan	1.535255	0.96181
239	Dazhou	Sichuan	0.716645	0.328361
240	Yaan	Sichuan	−1.44421	−1.34373
241	Bazhong	Sichuan	0.543564	0.194429
242	Ziyang	Sichuan	−0.2715	−0.43628
243	Guiyang	Guizhou	−0.308	0.267204
244	Liupanshui	Guizhou	−0.10159	0.645183
245	Zunyi	Guizhou	−2.29372	−1.36893
246	Anshun	Guizhou	0.548663	1.835948
247	Kunming	Yunnan	0.007942	−0.14291
248	Qujing	Yunnan	1.038497	0.733414
249	Yuxi	Yunnan	0.30601	0.110551
250	Baoshan	Yunnan	0.483655	0.26161
251	Shaotong	Yunnan	−0.54346	−0.61179
252	Lijiang	Yunnan	0.963303	0.669473
253	Simao	Yunnan	0.212645	0.031159
254	Lincang	Yunnan	−0.11591	−0.24823
255	Xian	Shaanxi	0.121028	0.211093
256	Tongchuan	Shaanxi	−1.02695	−1.02912
257	Baoji	Shaanxi	−0.10214	−0.03001
258	Xianyang	Shaanxi	−0.87945	−0.86977
259	Weinan	Shaanxi	−0.82571	−0.8117
260	Yanan	Shaanxi	0.264379	0.365962
261	Hanzhong	Shaanxi	0.032731	0.115703
262	Yulin	Shaanxi	−0.10492	−0.033
263	Ankang	Shaanxi	1.114078	1.283927
264	Shangluo	Shaanxi	0.678829	0.813709
265	Lanzhou	Gansu	0.677763	0.515168
266	Jiayuguan	Gansu	0.906522	0.721757
267	Jinchang	Gansu	0.343099	0.212937

Table A1. *Cont.*

Cityid	City	Province	R^N	R^P
268	Baiyin	Gansu	−0.20667	−0.28355
269	Tianshui	Gansu	−0.18993	−0.26844
270	Wuwei	Gansu	0.225993	0.107179
271	Zhangye	Gansu	−0.469	−0.52046
272	Pingliang	Gansu	−0.11815	−0.20362
273	Jiuquan	Gansu	−0.04386	−0.13652
274	Qingyang	Gansu	0.488924	0.344629
275	Dingxi	Gansu	−0.7664	−0.78904
276	Longnan	Gansu	−0.89582	−0.90592
277	Xining	Qinghai	−0.18809	
278	Yinchuan	Ningxia	−0.04179	0.059206
279	Shizuishan	Ningxia	−0.06651	0.031879
280	Wuzhong	Ningxia	0.217087	0.345368
281	Guyuan	Ningxia	−0.11229	−0.01872
282	Zhongwei	Ningxia	−1.14909	−1.16481
283	Urumqi	Xinjiang	0.298819	0.130162
284	Kelamayi	Xinjiang	−0.55072	−0.60906

Source: calculated by using data from the National Bureau of Statistics: 2004–2019.

Appendix A.2. Robust Test

In order to test the robustness of the results, this study changed the calculation method of regional economic resilience. We followed Martin et al. (2016) [72] and used a counterfactual indicator to measure resilience.

$$\left(\Delta E_i^t\right)^c = g_N^{t,t-1} E_i^{t-1} \tag{A1}$$

where $g_N^{t,t-1}$ is the national employment growth rate, E_i^t represents the employment rate of region i, $t-1$ is the turning year into economic crisis (2008), and t represents the end year of the economic recovery period (2018). Then, the measurement of counterfactual resilience is as follows:

$$R^C = \left[\left(\Delta E_i^t\right) - \left(\Delta E_i^t\right)^c\right] / \left|\left(\Delta E_i^t\right)^c\right| \tag{A2}$$

The result shown in Table A1 is consistent with the baseline results above (Table 2), which shows that the baseline estimation in this study is robust.

Table A2. Odds ratios of pre-crisis (2003–2007) determinants of counterfactual resilience using a multilevel logistic regression model.

	Two-Level Logistic Model
GINI	0.011 *
INNO	2.102 ***
GOV	0.030 ***
HUMCAP	1.624 **
FIN	2.316 ***
INDO	1.014
FASSE	1.940
AGE65	1.280
ENTR	0.876
Constant	0.002 **

Table A2. *Cont.*

	Two-Level Logistic Model
Log likelihood	−386.885
p-value	0.000
No of obs	284

*** significant at the 0.01 level (2-tailed). ** significant at the 0.05 level (2-tailed). * significant at the 0.1 level (2-tailed). Source: calculated by using data from the National Bureau of Statistics: 2004–2019.

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