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THE REGIONAL DIFFERENCES AND RANDOM CONVERGENCE OF URBAN RESILIENCE IN CHINA

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Abstract. This paper focuses on calculating resilience index of 282 cities in China from 2012 to 2019, to analysis the regional differences and random convergence. We use the entropy method to calculate the urban resilience index, adopt the Dagum Gini coefficient method to analyze the regional differences and the sources, explore the variation coefficients method and beta convergence model to diagnose the convergence mechanism. The conclusions are: (1) The urban resilience in China is at a medium and low level with a stable growth tendency, with a significant regional unbalance of "higher in east, and lower in other regions". As the sub-resilience, there is a big gap in the regional difference of the resilience structure with good performance in social resilience and economic resilience, poor in ecological resilience and infrastructure resilience. (2) The Gini coefficient of urban resilience continuously decreases with the regional unbalance narrowing accordingly. The Gini coefficients in different regions have a phased convergence tendency, and the hypervariable density contribution and intra-regional differences contribution are the main sources of differences in urban resilience. (3) The urban resilience in China and eastern region has σ convergence, while China and all regions have significant absolute β and conditional β convergence. Therefore, this paper proposes to continuously accelerate the urban resilient construction, make up for the shortcomings, and narrow the regional development gap, to promote the healthy and orderly development of cities.

Keywords: urban resilience index, regional differences, random convergence, China.

JEL Classification: O21, P25, Q57, R11, R58.

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Introduction

In recent years, the urban construction with technology as the core has achieved remarkable results (Eduardo, 2020). Even under the shock of major public emergencies, cities become more resilience with the help by smart technology (Ahad et al., 2020), and urban governance is more effective (Johnson et al., 2020; Lu et al., 2019; Chang, 2021). Actually, up to December 2020, there are more than 95% sub-provincial cities and 83% prefecture-level cities have promoted the construction of smart cities in China. However, shocked by the uncertain factors such as financial risk and major public emergencies, the urban resilience differs greatly: (1) the pilot cities as Hangzhou, Shanghai, and Shenzhen are more resilience; and (2) there is significant regional unbalance. Therefore, scientifically and systematically analyzing the resilience development degree of cities, exploring the differences and driving factors of urban resilience development in different regions are of great practical significant for improving the construction of urban resilience and the efficiency of urban governance in China.

Resilience, widely used in ecology, refers to the stable state of ecosystem, and gradually applied to the fields of ecological resilience, social ecological resilience and urban resilience (Folke, 2006). In 2002, the concept of "resilient city" was introduced into the study of cities and disaster prevention (Motesharrei et al., 2016), making cities resilient to shocks and stresses in order to ensure that the welfare of society has become a major concern for academics, emergency management practitioners and governments (Chmutina et al., 2016). City is a comprehensive system that includes economic, social, medical, infrastructure and other elements. Scholars have studied urban disaster prevention (UN-Habitat, 1996), economic recovery (Hill et al., 2008), and social sustainability (Godschalk, 2003; Christensen & Krogman, 2012) to explain the characteristics of urban resilience from different perspectives. And a more unified view defines urban resilience as "the ability of a city or urban region to resist, absorb, adapt to and recover from acute shocks and chronic stresses to keep critical services functioning, and to monitor and learn from on-going processes through city and cross-regional collaboration, to increase adaptive abilities and strengthen preparedness by anticipating and appropriately responding to future challenges" (Labaka et al., 2019; Smart Mature Resilience, 2016). Based on the existing research (Jha et al., 2013; The World Bank, 2008), this paper argues that urban resilience composed of ecological resilience, economic resilience, social resilience and infrastructure resilience, and strengthen the ability to quickly recover from shocks as major disaster or other uncertain emergencies. However, how to define the urban resilience is a complicated task. Cities can offer various smart applications such as smart transportation, industry 4.0, smart banking, among others, for boosting the life quality of citizens (Majeed et al., 2021). There is a weak connection between smart targets and sustainability goals (Bifulco et al., 2016), despite the proven role of advanced Information and Communications Technology (ICT), especially big data analytics and its applications, in supporting cities in moving towards sustainability (Angelidou & Psaltoglou, 2017; Batty et al., 2012; Bibri, 2018; Bibri & Krogstie, 2020). As the driving force for cities shifts from ICT to the internet of things (IoT), especially the application of blockchain and big data, urban governance is more "smart", and the ability to perceive and manage potential risk is stronger. Hence, urban construction provides an effective plan to the improvement of urban resilience (Xiao & Xie, 2021).

In China, construction of smart city was proposed in 2012, and that of "resilient city" was in 2020 in the "14^{th} Five-Year Plan" (Website of central Government of the People's Republic of China, 2020). However, some basic knowledge of resilient cities is still vague, which will be seriously detrimental to China's goal of building resilient cities. To this end, this paper will start from the following aspects in order to provide some basic directional guidance for the construction of China's smart resilient cities, including: (1) What is the development degree of smart resilient cities? (2) What are the spatial characteristics of smart resilient cities? (3) What are the convergence mechanisms of smart resilient cities? The current literature has not given practical evidence ever. Therefore, we focus on smart resilient cities, and attempt to expand it from the following aspects, which are also the innovations of this paper: (1) Research method: this paper uses the Dagum Gini coefficient method to analyze the differences in smart resilient cities. Consider the scale differences of the sample, we observed the regional differences and sources of smart resilient cities in China, and then compare the regional characteristics of East, Central, West, and Northeast China respectively. (2) Research content: analyze the influence of different factors on the convergence mechanism of smart resilient cities, and use the variation coefficient method and β convergence mechanism of smart resilient cities in China and different regions, and provide targeted reference to realize the construction of smart resilient cities.

1. Methodology and data

1.1. Evaluation index system of urban resilience

Urban resilience refers to the ability of one city suitable to uncertain. Based on the current researches (Schlör et al., 2018; Zhou et al., 2021; Feldmeyer et al., 2021; Shi et al., 2021), according to the conception understanding of urban resilience, and combined with the actual development situation of smart resilient cities, this paper constructs a smart resilient city evaluation index with four aspects as ecological resilience, economic resilience, social resilience and infrastructure resilience. (1) The urban ecological resilience refers to the self-recovery ability when faced with risk in urban development process. And the observe of that ability mainly come from two aspects: one is the ability to enhance the urban ecology, the other is the ability to destroy it. Therefore, this paper uses the green cover rate of build-up areas, the per capita green area of parks, the harmless treatment rate of domestic garbage, and the comprehensive utilization rate of industrial solid waste, to reflect the former; and we use the industrial sulfur dioxide emissions, industrial wastewater emissions, and industrial smoke (dust) emissions, to measure the latter. The seven indicators above form the basement for calculating urban ecological resilience.

(2) Urban economic resilience is a main factor in smart resilient cites. It refers to the ability of quickly recovery and adjust the industry structure to adopt the changes when faced with unknown economic press and shocks. And we can calculate that ability from micro and macro aspects, and microeconomic resilience calculated by two indicators of the average salary employees and the saving per capita, and the macroeconomic resilience calculated by GDP per capita, investment in fixed assets, GDP per capita, and the proportion of tertiary

industries. (3) Urban social resilience is the main guarantee to realize the economic recovery and stable development. It is calculated by the four aspects as number of college students, unemployed rate, the number of doctors, and Internet broadband access households. (4) Urban infrastructure is the life line of one city, including the municipal public engineering facilities and public life services facilities, and it is an important carrier of urban development. The urban infrastructure resilience reflects the ability to ensure the continuity of key services and quickly recover order in life when faced emergencies and unknown changes. This paper chooses five indicators, as water consumption, electricity consumption, per capita public bus, road area, and public library collections, to calculate the urban infrastructure resilience.

Table 1 is the detailed evaluation index system of urban resilience of this paper.

1.2. Evaluation method of smart resilient city index

The advantage of entropy method is to weaken the subjectivity of index weight, and more suitable for index evaluation data with clear logic (Shi et al., 2020). Therefore, this paper adopts entropy method to measure the smart resilient city index, as:

$$\begin{cases} x_i' = \dfrac{x_i - \min\{x_1,\ldots,x_n\}}{\max\{x_1,\ldots,x_n\} - \min\{x_1,\ldots,x_n\}} \\ p_i = (1+x_i') / \sum_{i=1}^{n}(1+x_i') \\ e_j = -k\sum_{i=1}^{n} p_i \times \ln(p_i),\ k = 1/\ln(n) \end{cases}. \quad (1)$$

In formula (1), x_i' represents the standardized value of x_i. Similarly, the negative standardized value of x_i is $x_i' = \dfrac{x_i - \max\{x_1,\ldots,x_n\}}{\max\{x_1,\ldots,x_n\} - \min\{x_1,\ldots,x_n\}}$, p_i represents the weight of samples, e_j is the information entropy of index j, and n is the number of cities, and we obtain the weight of different samples as:

$$w_j = d_j / \sum_{j=1}^{m} d_j, d_j = 1 - e_j. \quad (2)$$

In formula (2), d_j is the value of index j, and the smart resilient city index $resil_i$ can be calculated as:

$$resil_i = \sum_{j=1}^{m} w_j \times x_i'. \quad (3)$$

1.3. Dagum Gini coefficient decomposition

This paper uses the Dagum Gini coefficient method to calculate and decompose the regional differences and sources of the smart resilient city index, and the results are calculated by the software of Matlab R2016a. Compared with other methods, the advantage of Dagum Gini index is that the imbalance of different regions is divided into three parts: intra-regional, inter-regional imbalance, and hypervariable density (Kakamu, 2016). And the hypervariable density refers to the regional imbalance caused by the overlap between regions. Referring

Table 1. The urban resilience evaluation index system and descriptive statistics

Target layer	Criterion layer	Index layer	Unit	Max.	Min.	Mean
Urban resilience	Urban ecological resilience	Industrial sulfur dioxide emissions per unit of GDP	Tons/100 million CNY	760.19	0.00	17.10
		Industrial wastewater discharge per unit GDP	Tons/10,000 CNY	215.16	0.01	2.59
		Industrial smoke (dust) emissions per unit of GDP	Tons/100 million CNY	4232.98	0.02	12.39
		Harmless treatment rate of domestic garbage	%	145.40	5.49	99.84
		Comprehensive utilization rate of industrial solid waste	%	189.51	0.24	89.73
		Green coverage rate of built-up area	%	158.11	0.39	40.65
		Green area of per capita park in the district	Square meter	716.64	0.09	10.39
	Urban economic resilience	Average salary of employees	10,000 CNY	17.32	0.50	5.52
		Per capita savings balance in the district	10,000 CNY	117.21	0.15	3.06
		GDP per area	100 million /square kilometer	66.78	1.09	14.57
		Investment in fixed assets	100 million CNY	21884.90	36.01	1267.64
		GDP per capita in the district	10,000 CNY	642.18	0.82	4.77
		Proportion of tertiary industries in the district	%	81.83	11.47	41.41
	Urban social resilience	Number of college students of ten thousand population in the district	Person	1754.91	0.80	100.32
		The proportion of registered unemployed persons in the population	%	127.22	0.03	4.09
		Number of doctors per 10,000 population in the district	Person	315.83	0.00	22.20
		Number of Internet broadband access households	10,000 households	246.48	0.10	6.40
	Urban infrastructural resilience	Per capita water consumption in district	Ton	293.73	0.06	7.68
		Per capita road area per person at the end of the year	Square meter	37494.00	0.59	14.17
		Number of buses per 10,000 people	Vehicles	904.00	0.17	4.25
		Electricity consumption per capita in the district	KWh	4507.10	0.08	221.36
		Per capita public library collections in the district	Volume	937.24	0.14	39.05

to the calculate method of Dagum (1997), the Gini coefficient G of the smart resilient city index can be calculated as:

$$G=\frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{hr}\right|}{2n^2\zeta}. \quad (4)$$

In formula (4), k represents the number of regions. According to the standards of National Development and Reform Commission, we divided the region of China into four parts: East, Central, West and Northeast[1], therefore $k = 4$; $n = 282$, is the number of cities; n_j, n_h represents the number of cities in region j and region h respectively; y_{ij}, y_{hr} represents the urban resilience index of city i in region j, and city r in region h respectively; ζ represents the average value of the urban resilience index of all sample. And the greater the Gini coefficient G, the greater difference in the urban resilience index between regions.

First, sort the average values of the urban resilience index between regions, and then divide the Gini coefficient of the urban resilience index into three parts: intra-regional difference contribution G_w, inter-regional net value difference contribution G_b, and hypervariable density contribution G_t, and $G = G_w + G_b + G_t$. Define p_j as the proportion of the number of sample cities in region j to the total number of cities n, and $p_j = n_j/n$; s_j is the proportion of total resilience index in region j to the sum of all sample cities, and have $s_j = n_j\zeta_j/n\zeta$. And the Gini coefficient G_{ij} in region j, intra-regional difference contribution G_w, and Gini coefficient G_{jh} in region h can be expressed (Domma et al., 2018; Miao et al., 2021; Lv et al., 2021) as:

$$G_{jj}=\frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|y_{ji}-y_{hr}\right|}{2n_j^2\zeta_j}; \quad (5)$$

$$G_w=\sum_{j=1}^{k}G_{jj}\zeta_j s_j; \quad (6)$$

$$G_{jh}=\frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{hr}\right|}{n_j n_h(\zeta_j+\zeta_h)}. \quad (7)$$

Further, set d_{jh} as the different value of the urban resilience between region j and region h, and it is the resilience index mathematical expectation value if $y_{ij}-y_{hr} > 0$. And set p_{jh} as the hypervariable primary moment, which is the resilience index mathematical expectation if $y_{hr} - y_{ij} > 0$; D_{jh} represents the relative influence of the urban resilience index between region j and region h, and function F is the cumulative density function of the urban resilience index of region $j(h)$.

$$d_{jh}=\int_0^{\infty}dF_j(y)\int_0^{y}(y-x)dF_h(x); \quad (8)$$

$$p_{jh}=\int_0^{\infty}dF_h(y)\int_0^{y}(y-x)dF_j(x); \quad (9)$$

$$D_{jh}=\frac{d_{jh}-p_{jh}}{d_{jh}+p_{jh}}. \quad (10)$$

[1] According to the standard, East region include Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan; Central region include Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan; West region include Inner Mongolia, Guangxi, Yunnan, Chongqing, Sichuan, Guizhou, Shaanxi, Gansu, Ningxia, Xinjiang and Tibet; Northeast region include Liaoning, Jilin, and Heilongjiang.

Therefore, the inter-region differences of net value G_b and inter-region hypervariable density G_t are:

$$G_b = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} D_{jh} (p_j s_h + p_h s_j); \tag{11}$$

$$G_t = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} (1 - D_{jh})(p_j s_h + p_h s_j). \tag{12}$$

1.4. Convergence mechanism

σ convergence. σ convergence refers to the process in which the dispersion of the urban resilience index decreases continuously over time. The traditional measurement indicator includes coefficient of variation and Theil index. According to the current research (Kong et al., 2019; Malakar et al., 2018; Matos & Faustino, 2012), this paper chooses the coefficient of variation method, as:

$$\sigma_j = \frac{\sqrt{\left[\sum_i^{n_j} (resil_{jt} - \overline{resil_{jt}})^2 \right] \Big/ n_j}}{\overline{resil_{jt}}}. \tag{13}$$

β convergence. β *c*onvergence is to examine the resilience development tendency of the cities between regions from the perspective of growth rate. And it shows that the growth rate of regions with lower resilience index is increasing gradually, catching up the regions with the higher index, and finally reaching to convergence (Vu, 2013; Diaz Dapena et al., 2016).

β *c*onvergence can be divided into absolute β convergence and conditional β convergence. Absolute β convergence refers to the convergence tendency that only considers the urban resilience index itself, while the conditional β convergence is added to control a series of other factors.

The absolute β convergence model based on panel data is

$$\ln\left(\frac{resil_{i,t+1}}{resil_{i,t}} \right) = \alpha + \beta \ln resil_{i,t} + \mu_i + \upsilon_i + \varepsilon_{it}. \tag{14}$$

In formula (14), μ_i refers to the region fixed effect, υ_i refers to the time fixed effect, ε_i is the random error item.

The conditional β convergence model adds a series of control variables to the absolute convergence model, as:

$$\ln\left(\frac{resil_{i,t+1}}{resil_{i,t}} \right) = \alpha + \beta \ln resil_{i,t} + X_{i,t} + \mu_i + \upsilon_i + \varepsilon_{it}. \tag{15}$$

After Hausman's test, this paper uses the fixed-effect model to estimate the coefficients of β convergence. When $\beta < 0$ is significant, it indicates that the urban resilience index have converged, otherwise, it diverges. And the convergence velocity b calculated as: $b = -\ln(1 + \beta)/T$, and $T = 7$.

1.5. Variable description and data sources

Variable description. In Table 1, we clearly explain the appraise index, and describe the control variable here with β conditional convergence model. This paper analyzes the impact of different factors on urban resilience index from five aspects, as: economic condition, employment, fiscal condition, industrial structure and population condition. *Economic condition* is represented by GDP per capita (*rgdp*); *Employment condition* is represented by the unemployment rate (*unempr*); *Fiscal condition* is represented by the fiscal deficit rate (*fisd*), and calculated by the formula as (expenditure of fiscal – income of fiscal)×100/GDP; *Industrial structure* is calculated by the proportion of the add value of secondary industry in GDP (*strut*); *Population condition* is represented by the population density (*density*).

Data sources. Without special declare, the data above are from the "*China Statistical Yearbook*", "*China City Statistical Yearbook*", WIND and ESP data. The sample period is 2012–2019 since China began to construct smart cities in 2012. We add missing data according to interpolation and form a panel data with 282 cities. To reduce the influence by variance, this paper has carried logarithmic processing on the control variables. Table 2 shows the data descriptive statistics of variables.

Table 2. Descriptive statistical analysis of variables

Variable	Mean	Std. Dev.	Min	Max	N
lnrgdp	10.58	0.70	8.81	12.93	1692
lndensity	5.76	0.91	1.63	7.88	1692
lnunempr	1.46	0.63	–1.88	4.03	1692
lnrreisl	0.04	0.13	–0.97	0.97	1410
lnfisd	–2.50	0.97	–9.61	–0.04	1673
lnstrut	–0.17	0.45	–2.04	1.68	1692
lnresil	–2.420	0.557	–3.589	–0.228	1692

2. Dynamic evolution of the urban resilience

2.1. Evolution tendency of the urban resilience

Figure 1 shows the evolution tendency of the urban resilience from 2012 to 2019 in China. According to the calculate results, the mean value of the urban resilience of all sample in China (ttle) decreased from 0.0988 in 2012 to 0.0805 in 2019 with an annual average decline rate of 2.88%, and fluctuated between 0.001 to 0.022. It indicates that the urban resilience in China is at a relatively low level and have great potential to grow higher. Since 2012, the Chinese governance has implemented series policies focusing on planning guidance, construction standard, and coordinated organization, which provided a stronger guideline and rule guarantee for the urban resilient construction. Actually, 95% of cities (included the country-level city) in China has constructed smart cities, and the resilience level has steadily improved before 2018. However, constrained with the regional imbalance of economical and geographical resource, the urban resilience in China is still in a lower level, and influenced by the potential impact from COVID-19, and the urban resilience decreased in 2019.

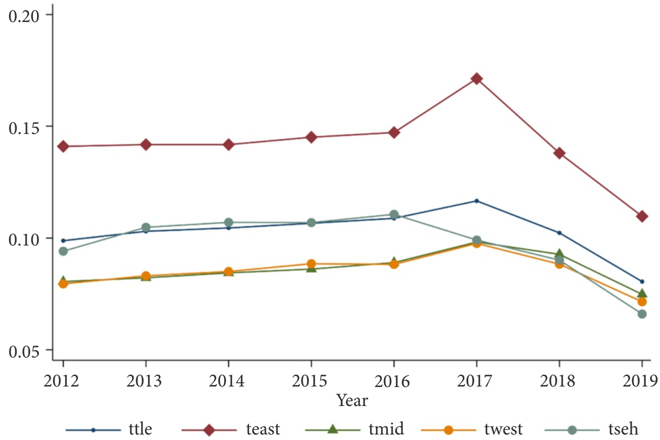


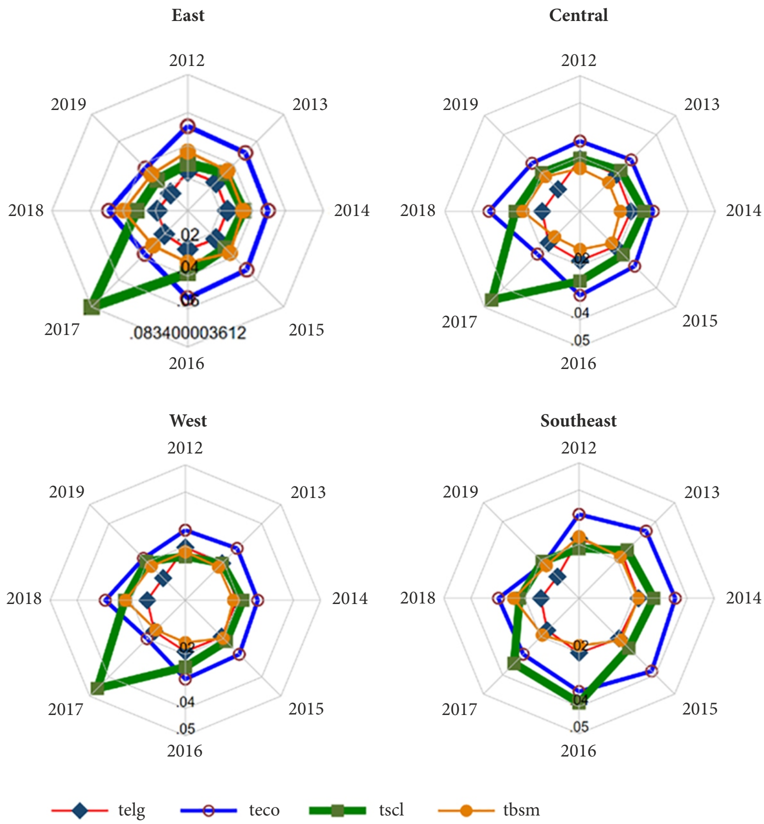
Figure 1. Trends of the urban resilience in China and four regions from 2012 to 2019

By region, the urban resilience (teast) in the eastern region has steadily decreased from 0.1410 in 2012 to 0.1097 in 2019, with an annual decline rate of 3.539%, and it grew slowly from 2012 to 2016 with annual average growth rate of 2.14%, while that decreased 20.54% in 2019 compared to 2018. The urban resilience in central region (tmid) is lower than that in eastern region, with an index value between 0.07 and 0.098, and it is in a fluctuated decreasing stage, with a steadily annual growth rate of 2.39% from 2012 to 2018, and a sharply decline rate of 19.36% in 2019. The urban resilience (twest) in western region is lower than that in central region, with a resilience value between 0.07 and 0.097, and it is also in a steadily decreasing stage, with decline rate significantly reaching to 19.05% in 2019. However, the urban resilience in western region steadily grew from 2012 to 2018 with annual average growth rate of 1.76%, similar with central region. The urban resilience in northeastern region (tseh) is lower than central region, with an index value between 0.066 and 0.091. It fluctuates slowly, while the decreasing rate significantly dropped to 26.7% in 2019. It can see that the urban resilience in eastern region is higher than that in other regions, which benefits from the earlier construction in eastern region. Especially Beijing and Fujian, who issued smart city construction plan in 2012, 2014 respectively, own rich experiences in promoting the urban resilience. Besides, eastern region is relative developed in China, the economic foundation of the urban resilience is better than other regions.

From the development tendency, we can see that the urban resilience in the four regions grew stably from 2012 to 2016, and the growth rates in 2017 are different with that decreased obviously in 2017 to 2019. Among them, the growth rate of urban resilience in eastern, central and western region are accelerated obviously in 2017, mainly due to the increasing number of cities which have taken urban construction plan after 2016, and the scale effect has led to a significant increase in the urban resilience. We can also see that the growth tendency in the three regions turns to decrease after 2017, especially in 2018 and 2019. In 2017, China earthquake administration promulgated a plan included "The resilience of urban and rural", and it was a firstly national formal issue about urban resilience with resilience construction standard, and the downward tendency above is mainly due to the policy lagged effect of implementing the new resilience construction standard and the potential impact from COVID-19. However, with the population decrease, the weak industrial transformation, especially the faked GDP data from 2011 to 2014 of some cities in northeastern region, there is a weaken basement to promote the urban resilience in northeastern region, and the resilience growth rate decrease sharply in 2017 to 2019, which obviously different from other regions.

Further, analyze the change characteristics of urban resilience sub-item in different regions. Figure 2 shows the trends in sub-items of the urban resilience in China and four regions from 2012 to 2019. In eastern region, the resilience sub-item distributes relatively evenly, and the relatively higher sub-item are the economic resilience in 2019, followed by the infrastructure resilience, the social resilience and the ecological resilience; From the growth fluctuations perspective, the economic resilience, the social resilience, the ecological resilience and the infrastructure resilience shows a trend of "increase first and then decrease", with social resilience the most fluctuated. It indicates that the urban resilience sub-items in the eastern regions are higher in economic resilience and social resilience, and the ecological resilience and infrastructure resilience fluctuated downward. As the developed area in China, the eastern region has sufficient financial and fiscal resource and advanced technology to promote urban resilience, especially in the economic resilience and social resilience. While in the new time, China strengthened the economic development quality not the economic scale and growth rate, especially in eastern region, and the economic transformed pressure constraints the economic resilience growth rate. The more continuously serious climate problem as the fog and haze in the Yangtze River Delta and Beijing-Tianjin-Hebei region in recent years, weakened the ecological resilience in the eastern region, and the local government continuously strengthen the infrastructure construction and promote the urban infrastructure resilience. While the potential impact of the COVID-19 leaded to the sharply decreasing in the economic resilience, the social resilience, and the infrastructure resilience.

Similar to the eastern region, in 2019, the economic resilience is also the higher resilient sub-items of cities in the central region, followed by ecological resilience and infrastructure resilience. The difference is that all sub-items are lower than these in eastern region. From the perspective of growth fluctuate, the economic resilience show "increase first and then decrease", the infrastructure resilience and the social resilience have a steady fluctuated growth trend, and the ecological resilience show a steadily decreasing trend, indicating that social resilience is the higher sub-item of urban resilience in central regions, and the economic resilience, the ecological resilience, and the infrastructure resilience have more improving space. Recently, the economic development in central region always maintained a relatively higher growth rate. The welfare effects of economic growth, and the construction of the people's livelihood and welfare always strengthened by the local government, and enhance more investment in the public infrastructure construction as metro railway, electricity charge station, which accelerated the improvement of the social resilience and the infrastructure resilience in central region. However, the industrial structure in central region is dominated by the secondary industry, and some cities are under great pressures in the transformed process from the high pollution and high energy consumption industry, which restricts the improvement of the economic resilience and ecological resilience.



Note: teco, tscl, telg, tbsm refers to urban economic resilience, social resilience, ecological resilience, and infrastructure resilience respectively.

Figure 2. Trends in sub-items of the urban resilience index in China and four regions from 2012 to 2019

Similar to central region, the social resilience and the economic resilience are still the higher resilient sub-items of cities in western region and northeastern region, compared to the ecological resilience, and the infrastructure resilience. From the perspective of growth fluctuated, the economic resilience and the infrastructure resilience are both in the trend of "increase first and then decrease", the social resilience increases steadily, and the ecological resilience is in a continuous decline trend. It indicates that urban social resilience is still higher in the western region and northeastern region, and urban economic resilience, ecological resilience and infrastructure resilience still have much room for improvement. The welfare effects of the economic growth of cities and the government's continuous effects in the construction of the people's livelihood and welfare are also driving forces for the rapid growth of social resilience in western region and northeastern region, while the relatively weaken economic foundation and the existing ecological environmental pressure are the mainly constraints to the increasing of the other resilience.

2.2. The resilience analysis of the different cities

According to the relationship between the standard deviation and mean value of the urban resilience index, cities can be divided into four types as leading-type (red), advanced-type (blue), catching-up-type (yellow), and undeveloped-type (gray). Taking sample in 2019 as example, the resilience index is used to classify different types of cities, as shown in Figure 3. In general, the catching-up cities in whole sample are dominated (191), followed by advanced-type (51), leading-type (34), and only one undeveloped-type. The cities in eastern region are dominated in the type of leading-type and advance-type, and dominated in catch-up type of western and northeastern regions. Specially, the eastern region includes 19 leading-type cities, 28 advanced-type cities, and 41 catching-up cities, and the percentage of advanced-type and leading-type cities in eastern region is 53.41%; The number of the advanced-type cities in central, western and northeaster regions are 68, 60, 25 respectively, account for 85%, 73.17% and 80.65% of the total in the region correspondingly. Therefore, the types of cities in different regions still have common characteristics.

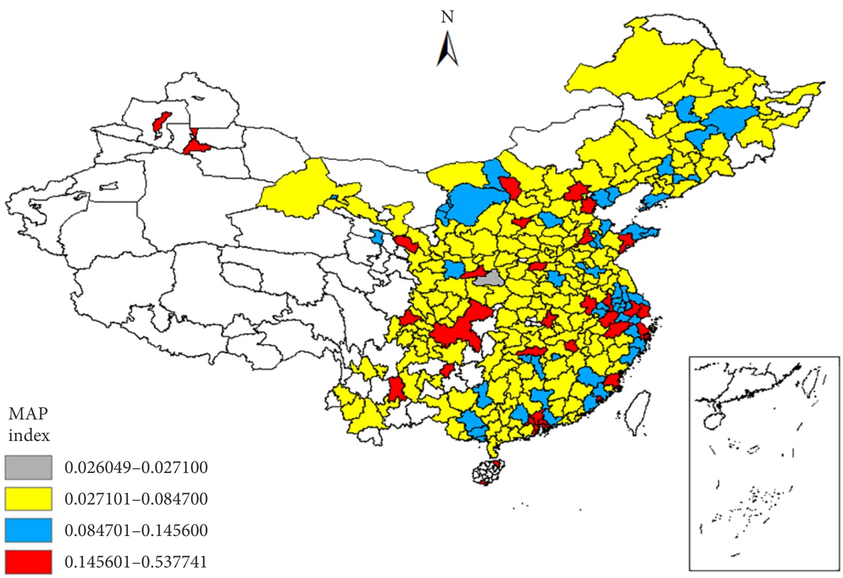


Figure 3. Types of the cities in 2019

3. The regional different of the urban resilience

3.1. The Gini coefficient of the urban resilience

Figure 4 shows the Gini coefficient trends of the urban resilience in 2012–2019. From the perspective of the national trends, the Gini coefficient of the urban resilience (gt) decrease from 0.3129 in 2012 to 0.3187 in 2019 with the highest point in 2014. It indicates that the urban resilience differences across the country are gradually narrowing, and the urban resilience is converging in general. Among them, the Gini coefficients decreased obviously from 2012 to 2014, while volatility declined from 2014 to 2019. Before 2014, urban construction

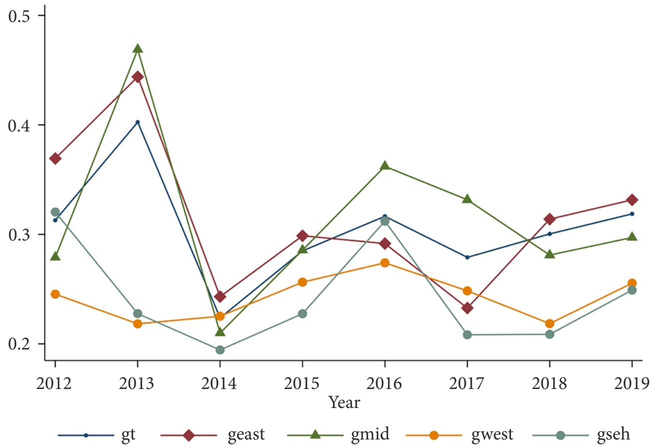


Figure 4. The Gini coefficient trends of the urban resilience in 2012–2019

in China is in the initial stage, and the urban resilience converges at a low level. Since 2014, most cities in China began to promote urban construction, especially followed a new resilience construction in 2018 and impacted by the potential risk of COVID-19 in 2019, and the resilience differences between cities have begun to appear, and show an improving and converging trend.

In terms of different regions, the Gini coefficient of the urban resilience in the eastern region and northeastern region decline from 0.3693, 0.3204 in 2012 to 0.3315, 0.2491 in 2019, with the annual descent rate of 1.53%, 3.53% respectively, indicating a convergence trend. The Gini coefficient of urban resilience in east shows continuously decrease, while "decrease-increase-decrease" in northeast. The convergence characteristics are different. As mentioned above, most cities in eastern region and some cities in northeastern region promote the construction of smart city earlier than other regions, which narrowing the resilience gap of the cities in regions. The Gini coefficients of the urban resilience in central region (g_mid) and western region (g_west) increase from 0.2790, 0.2454 in 2012 to 0.2971, 0.2554 in 2019, with the annual growth rate of 0.90%, 0.57% respectively. It indicates that there is a divergence trend of the urban resilience. The Gini coefficient in central region shows a fluctuating trend of "increase-decrease-increase-decrease", and "decrease-increase-decrease" in western region. Specifically, in 2019, the Gini coefficient of urban resilience in central region and western region decline 6.38%, 2.32% respectively, compared to the Gini coefficient of the urban resilience in 2016, and the convergence characteristics showed a phased nature.

As pointed out above, there are relatively large differences in economic development between cities in the central and western regions, and there are large differences in time and supporting policy for urban resilience construction in different cities, which also leads to the uneven development within the region. After 2016, China had implemented series substantive action policies to promote the smart city construction as "New Smart City Evaluation Index (2016)", which provided practical standards for the smart city construction in the central and western regions, and was conducive to narrowing the internal gap between different cities. And it also leads the Gini coefficient of urban resilience in the central and western regions, as well as the eastern and northeastern regions, have a significant year-on-year decline in 2019.

3.2. The regional differences of the urban resilience

Further, observe the differences in the Gini coefficient of the urban resilience index between different regions. In Figure 5, in general, the Gini coefficient of the urban resilience index between regions has greatly changed, meaning obvious differences between regions, and showing two fluctuating trends of "decrease-increase-decrease" and "decrease-increase-decrease-increase". Among them, the downward trend in 2012–2014 is more obvious, indicating that the difference of resilience between regions has narrowed. Compared to that, the fluctuated upward trend in 2014–2016 indicates that the difference of resilience between regions has enlarged. The downward trend from 2017 to 2019 is obvious, indicating that the difference of resilience between regions has narrowed again. While the downward trend from 2016 to 2017, and the upward trend from 2017 to 2019 is also obvious, indicating that the difference of resilience between regions has enlarged again. However, the differences in the Gini coefficient of the urban resilience index between different regions in 2019 are lower than the differences in 2014, indicating that the difference of resilience between regions narrowed in general.

Specifically, the Gini coefficients of the urban resilience of eastern-central (ge_m), eastern-northeastern (ge_w), central-western regions (gm_w) increase 0.08%, 0.10%, 0.06% from 2012 to 2019, respectively. The Gini coefficient of the urban resilience of central-northeast (ge_se), central-northeast (gm_se) and west-northeast (gw_se) decrease 0.01%, 1.95%, 2.05% from 2012 to 2019, respectively. And the average value of the descent rate in 2012–2014 between above regions is 16.16%, that of the growth rate in 2014–2016 is 19.47%, and the average value of the descent rate in 2017 is 11.96%, showing a trend of "firstly convergence, then divergence and last convergence" in different time ranges before 2017. And the average value of growth rate in 2018–2019 between above regions is 7.57%, showing a divergence

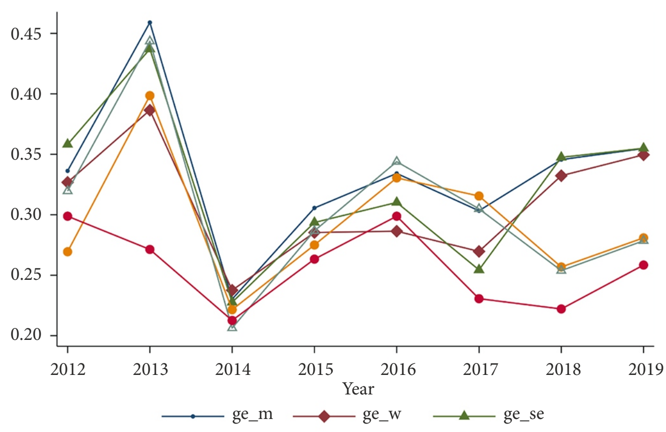


Figure 5. The Gini coefficient trends of the urban resilience in regions from 2012 to 2019

trend after 2018. Therefore, under the policy guided background of China strengthened the construction of smart city, especially implemented the new type smart city construction standard in 2016, which conducive to narrowing the resilience gap and promote the converged development of cities between different regions before 2017. However, after 2018, the potential risk of COVID-19 enlarged the development of cities between different regions.

3.3. The Gini coefficient decomposition of the urban resilience

Table 3 shows the Gini coefficient decomposition of the urban resilience in 2012–2019. The contribution rate variation of difference sources reflects the changes in the generation mechanism of the differences in the urban resilience. The hypervariable density contribution ratio (G_t) of the smart resilience is generally higher than the contribution rate of the intra-region (G_nb) and inter-region (G_w), with the rate ranges in 34.14–66.64%, which is the main source of the overall difference in the urban resilience; the contribution from the intrarregion is the second source, with the ratio ranges in 6.14–39.56%; the contribution from the inter-region is the third source, with the ratio floats around 27%.

From the perspective of the evolution characteristics of the different sources, the contribution ratio of the hypervariable density shows a downward trend, from 60.81% in 2012 to 37.81% in 2019, with an annual average decrease rate of 6.56%, indicating that there is more overlap in the resilience development of the cities across regions. The resilience index of some cities in the region with higher resilience index, may be lower than that of some cities in the regions with low index, which leaded by the development imbalance between regions. In 2013, the contribution ratio of the Gini coefficient of the urban resilience index of inter-region reached the stage highest point of 27.90%, and then fluctuate downward, reaching the lowest point of 6.14% in 2016, and reached to the highest point of 39.56% in 2018, with an annual average growth rate of 4.2% during 2013–2019, showing an enlarged difference between regions. From 2012 to 2019, the contribution ratio of the Gini coefficient of the urban resilience index of the intra-region fluctuated around 26.91% and the regional differences are relatively stable. In addition, the inter-regional contribution ratio has gradually approached the intra-regional contribution rate, and the effects of differences in the resilience of the cities between inter-region and intra-region have gradually converged.

Table 3. The Gini coefficient decomposition of the smart resilience index in 2012–2019

year	Intra-region		Inter-region		Hypervariable density	
	G_w	Contribution ratio	G_nb	Contribution ratio	G_t	Contribution ratio
2012	0.0842	26.92%	0.0384	12.27%	0.1903	60.81%
2013	0.1077	26.75%	0.1123	27.90%	0.1825	45.35%
2014	0.0606	27.10%	0.0207	9.26%	0.1424	63.65%
2015	0.0778	27.30%	0.0353	12.39%	0.1718	60.31%
2016	0.0862	27.23%	0.0194	6.14%	0.2109	66.64%
2017	0.0730	26.17%	0.0595	21.31%	0.1466	52.53%
2018	0.0790	26.29%	0.1188	39.56%	0.1026	34.14%
2019	0.0844	26.48%	0.1138	35.70%	0.1205	37.81%
Mean	0.0816	26.78%	0.0648	20.57%	0.1584	52.65%

4. The convergence mechanism of the urban resilience index

4.1. The σ convergence mechanism

Table 4 shows the σ convergence mechanism of the urban resilience in 2012–2019. From the national perspective, the variation coefficient of the urban resilience (gm_tt) fluctuated as "increase-decrease", indicating that the urban resilience shows convergence in general, and the regional imbalance of the urban resilience weaken.

From the regional perspective, the variation coefficient (gm_east) shows a fluctuated downward trend, and indicates a σ convergence trend of the urban resilience in eastern region. Among them, the decline ratio of the variation coefficients in eastern region is smaller in 2012–2018 with value of 3.35%, and higher in 2017 with 11.44%. However, the variation coefficients turn to upward with growth rate of 9.9%. It indicates a fluctuated σ convergence trend in eastern region. The variation coefficients (gm_west) shows a fluctuated "increase-decrease" trend in western region, with annual growth rate of 4.91% from 2012 to 2017, and obviously decline rate of 8.81% in 2017–2019, indicating a σ convergence tendency. The variation coefficients (gm_se) also shows a fluctuated "increase-decrease" trend in southeastern region, with annual growth rate of 1.78% from 2012 to 2017, and obviously decline rate of 8.45% in 2017–2019, indicating a σ convergence tendency. The variation coefficient in central region shows a fluctuated upward trend, with the annual growth rate of 2.24%, showing a more obviously divergence trend. Therefore, urban resilience in the eastern region and southeastern region shows a σ convergence, and western region has a σ convergence trend. And the resilience gap of the cities in central region is widening, and the regional resilience imbalance of the cities is prominent.

Table 4. The variation coefficient of the urban resilience in 2012–2019

year	gm_tt	gm_east	gm_midt	gm_west	gm_se
2012	0.7781	0.8039	0.5161	0.5616	0.4496
2013	0.7966	0.8063	0.5519	0.6445	0.4636
2014	0.7953	0.8038	0.5623	0.6403	0.4737
2015	0.8008	0.8040	0.5802	0.6724	0.4849
2016	0.7776	0.7636	0.5818	0.6777	0.4797
2017	0.7596	0.6762	0.5673	0.7138	0.4910
2018	0.6630	0.6551	0.5274	0.5680	0.4496
2019	0.7162	0.7200	0.6026	0.5935	0.4636

4.2. The β convergence mechanism

4.2.1. The absolute β convergence mechanism

After hausman test, this paper uses the fixed effect OLS model to estimate the absolute β convergence efficient, and estimated result shows in Table 5. The absolute β convergence coefficient of the urban resilience index in the overall and the four major regions are significantly negative at the 1% confidence level, indicating that there are absolute β convergence trends of the urban resilience in the overall and the four major regions, and the growth rate of different regions has been obviously enlarged, with convergence rate of 17.93%, 20.09%, 11.92%, 28.19%, 14.79%, respectively.

Table 5. The absolute β convergence coefficient estimation of the urban resilience

Variable	(1)	(2)	(3)	(4)	(5)
	Overall	east	middle	west	southeast
lnresil	−0.715***	−0.755***	−0.566***	−0.861***	−0.645***
	(−28.46)	(−16.67)	(−12.31)	(−18.64)	(−8.26)
_cons	−1.754***	−1.610***	−1.458***	−2.285***	−1.614***
	(−27.95)	(−16.36)	(−12.05)	(−18.40)	(−8.08)
City controls	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES
R^2	0.580	0.734	0.562	0.568	0.563
N	1967	609	560	574	224

Note: *t* statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.2. The conditional β convergence mechanism

In further, we control the variables such as the GDP per capital, fiscal deficit, population density, unemployment rate and industrial structure, and the estimate result is in Table 6. The conditional β convergence coefficient of the urban resilience in the overall and the four major regions are significantly negative at the 1% confidence level, indicating that the conditional β convergence trends exist. It further confirms the convergence of the growth rate of the urban resilience, with the convergence rate of 19.69%, 22.71%, 12.36%, 31.66%, 16.96%, respectively. Therefore, after controlling a series of factors, the conditional convergence rate of β of the cities in most regions have decreased significantly, indicating that the reason that improving the urban resilience are more complicated excluded by the GDP per capita, fiscal deficit, population density, unemployment rate and industrial structure, which has decreased the decline rate of the urban resilience in different regions, and accelerated the urban resilience differences in different regions.

Table 6. The conditional β convergence coefficient estimation of the urban resilience

Variable	(6)	(7)	(8)	(9)	(10)
	All sample	East	Central	West	Southeast
lnresil	−0.748***	−0.796***	−0.579***	−0.891***	−0.695***
	(−30.15)	(−17.92)	(−12.60)	(−19.44)	(−9.11)
lnpgdp	1.165***	1.519***	−0.0571	1.257***	1.556**
	(5.75)	(4.66)	(−0.12)	(3.27)	(2.10)
lnpgdp2	−0.0490***	−0.0640***	0.00638	−0.0527***	−0.0689*
	(−5.26)	(−4.36)	(0.29)	(−2.99)	(−1.94)

End of Table 6

Variable	(6)	(7)	(8)	(9)	(10)
	All sample	East	Central	West	Southeast
lndensity	−0.0824**	−0.294***	0.00913	0.0112	−0.416***
	(−2.21)	(−3.72)	(0.09)	(0.16)	(−4.01)
lnunempr	−0.00886	0.0119	−0.0177	−0.00997	0.00599
	(−1.12)	(0.87)	(−1.37)	(−0.64)	(0.25)
lnfisd	0.0525	0.118	0.237	0.116	0.120
	(0.48)	(0.48)	(0.91)	(0.63)	(0.54)
lnstrut	0.179***	0.396***	0.310***	0.0603	0.156**
	(4.39)	(3.69)	(2.67)	(0.94)	(2.07)
_cons	−8.850***	−10.33***	−2.857	−9.972***	−8.997**
	(−8.19)	(−5.83)	(−1.21)	(−4.95)	(−2.37)
City controls	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES
R^2	0.602	0.757	0.577	0.592	0.624
N	1967	609	560	574	224

Note: *t* statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. The robustness test

4.3.1. The decomposition of the urban resilience index on the Theil index

By using the Theil index, we calculate the Gini index of the urban resilience development, to test the robustness of the Dagum Gini coefficients decomposition, and Table 7 shows the results. In Table 7, except for the Gini coefficients in the central region grew from 0.2331 in 2012 to 0.2554 in 2019 with a steadily upward trend, the Gini coefficients in all sample, the eastern region, the western region and the northeastern region shows a fluctuated downward trend, indicating a convergence trend in overall, the eastern region, the western region, and the northeastern region, and a divergence trend in the central region. In addition, the inter-difference (GE_W(a)) and the intra-difference (GE_B(a)) between different regions shows a downward trend, indicating a narrowing tendency of the urban resilience development between inter-regions and intra-region. Therefore, the conclusions are similar to the above accordingly, and the results decomposed by the Dagum Gini coefficient and the gamma convergence are reliable.

4.3.2. The robustness test on the β convergence

As mentioned above, the growth rate of the the urban resilience index before or after 2017 is different, and we choose the time breakpoint to test the robustness of the β convergence. Table 8 shows the results. In Table 8, the coefficients in the Panel A and the Panel B are significantly negative at the 1% confident level, and the coefficients in the Panel C and the Panel D are also significantly negative at the 1% confident level, indicating that the absolute β convergence and the conditional β convergence trends exists, and the results above is robustness and reliable.

Table 7. The robustness test estimation of the Gini coefficients

year	(11)	(12)	(13)	(14)	(15)	(16)	(17)
	All sample	East	Central	West	Southeast	GE_W(a)	GE_B(a)
2012	0.3246	0.3518	0.2331	0.2864	0.2230	0.1652	0.0374
2013	0.3382	0.3617	0.2347	0.3181	0.2305	0.1794	0.0367
2014	0.3425	0.3664	0.2416	0.3209	0.2390	0.1834	0.0369
2015	0.3480	0.3685	0.2497	0.3327	0.2474	0.1887	0.0355
2016	0.3424	0.3578	0.2443	0.3275	0.2408	0.1805	0.0356
2017	0.3428	0.3297	0.2237	0.3342	0.2441	0.1652	0.0468
2018	0.3002	0.3139	0.2185	0.2811	0.2172	0.1377	0.0270
2019	0.3184	0.3315	0.2554	0.2971	0.2335	0.1594	0.0266

Table 8. The robustness test estimation of the β convergence

Variable	(18)	(19)	(20)	(21)	(22)
	All sample	East	Central	West	Southeast
Panel A: The absolute β convergence before 2017					
lnresil	-0.866^{***}	-0.841^{***}	-0.842^{***}	-0.962^{***}	-0.798^{***}
	(−24.52)	(−10.78)	(−16.85)	(−15.17)	(−7.73)
_cons	-2.131^{***}	-1.797^{***}	-2.180^{***}	-2.553^{***}	-2.005^{***}
	(−24.24)	(−10.64)	(−16.63)	(−15.05)	(−7.61)
City controls	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES
R^2	0.419	0.507	0.549	0.442	0.371
N	1405	435	400	410	160
Panel B: The absolute β convergence after 2016					
lnresil	-0.990^{***}	-0.984^{***}	-0.715^{***}	-1.129^{***}	-1.152^{***}
	(−26.69)	(−18.04)	(−9.72)	(−15.49)	(−7.66)
_cons	-2.367^{***}	-2.067^{***}	-1.807^{***}	-2.834^{***}	-2.960^{***}
	(−27.77)	(−19.98)	(−10.07)	(−15.64)	(−7.77)
City controls	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES
R^2	0.783	0.800	0.765	0.813	0.800
N	562	174	160	164	64
Panel C: The conditional β convergence before 2017					
lnresil	-0.854^{***}	-0.762^{***}	-0.851^{***}	-0.951^{***}	-0.773^{***}
	(−23.71)	(−9.63)	(−16.48)	(−14.43)	(−6.71)
_cons	-12.76^{***}	-19.24^{***}	-16.49^{***}	-10.00^{***}	−11.61
	(−6.45)	(−4.15)	(−4.41)	(−2.81)	(−1.62)
Var. controls	YES	YES	YES	YES	YES

End of Table 8

Variable	(18)	(19)	(20)	(21)	(22)
	All sample	East	Central	West	Southeast
City controls	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES
R^2	0.442	0.544	0.582	0.455	0.385
N	1405	435	400	410	160
Panel D: The conditional β *convergence after 2016*					
lnresil	-0.985^{***}	-0.992^{***}	-0.712^{***}	-1.081^{***}	-1.138^{***}
	(−25.38)	(−17.74)	(−9.32)	(−13.53)	(−6.00)
_cons	−2.600	-5.071^{*}	6.791	−4.201	−15.67
	(−1.38)	(−1.71)	(1.66)	(−1.09)	(−1.51)
Var. controls	YES	YES	YES	YES	YES
City controls	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES
R^2	0.789	0.824	0.790	0.834	0.842
N	562	174	160	164	64

Note: *t* statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Conclusions and policy implications

Conclusions

This paper establishes an urban resilience assessment index, calculates the resilience index of 281 cities in 2012–2019 by using the entropy method, and analyzes the regional differences and source of the urban resilience index in national level, eastern, central, western and northeastern regions by using the Dagum Gini coefficient method, and uses the variation coefficient method and convergence model to test the convergence characteristics. The conclusions are:

Firstly, the urban resilience index in China is at low to middle level in general, with steadily increasing tendency, and has enough improvement space. The index shows a spatial distribution patter as higher in eastern region and lower in others, indicating that there is the regional imbalance in urban resilience development. Specifically, the leading-type and advanced-type cities dominated in the eastern region, and catch-up type dominated in the central, western and northeastern regions. In the perspective of the resilient structure characteristic, the social resilience and economic resilience index are higher sub-item of the urban resilience in four regions, while lower in the ecological resilience and infrastructure resilience; in the characteristic of growth rate, the social resilience increases obviously in all four regions, economic resilience shows a trend of "first increase then decrease", and the fluctuation differences of the ecological resilience and infrastructure resilience are large. The foundation of economic development in different regions, the government's continuous efforts in people's livelihood and well-being, and the pressure on the regional ecological resources are the keys to the differences in the resilience structure of different regions.

Second, from the perspective of relative differences, the Gini coefficient of the urban resilience fluctuates downward in general, and regional difference of the urban resilience gradually narrows. Specifically, the Gini coefficient in eastern and northeastern regions shows a downward trend, and the inner differences stably narrow, indicating a convergence tendency; The Gini coefficient in central and western regions fluctuate upward, and the inner differences enlarged, but existed a phased divergence trend. And the urban resilience between regions shows convergence. The hypervariable density contribution is the mainly source of the overall difference of the urban resilience, the second source is intra-region contribution, and the third is the inter-region contribution. The policy uniformity is the important factor in narrowing the resilience gap of the cities in the four regions.

Third, from perspective of the convergence characteristic, the smart resilience in China and eastern region has obvious σ convergence, and the variation coefficient fluctuates downward and gap in urban resilience is widen, while there is an absolute β convergence and conditional β convergence across country and four regions. The absolute β convergence coefficients are significantly negative at 1% confident level, indicating that the resilience level of the cities in China will converge to the same steady-state level with time changes. In further, after controlling variables including economic condition, employment condition, fiscal condition, fiscal condition, industry structure and population condition, the conditional β convergence coefficients in China are significantly negative at 1% confident level, and the convergent speed of the conditional β convergent coefficient is slower than that of absolute β, showing that the control variables will reduce the convergence speed of the urban resilience in different regions.

Compared with the conclusions of the current studies, we have some interesting findings to previous studies. However, our studies have several limitations. First, the sample period ranged from 2012 to 2019. For data limitation, we did not expand the data to 2020, and statistical bias may underestimate the city resilience index. Second, this article analyzed the random convergence and related factors of the urban resilience in China, but did not explore the medium mechanism. Therefore, we may have to analyze the medium mechanism in the further study.

Policy implications

The analysis and conclusions of the study have broad policy implications for the development of the smart resilient city, as follows:

(1) *Accelerate the construction of urban resilience, and improve the resilience level of smart cities*. Face up to the objective facts that the urban resilience development in China is at a low level, prominent the fiscal guideline effects, enhance the fiscal and financial support to the resilience construction of cities. Strengthen top-level policy design of the resilience construction of cities, and highlight the importance of the resilience development in the construction process, and form a periodic update mechanism for the construction standards of the cities, emphasizing the functions and roles of advanced technologies as 5G and big data in the new smart city construction. In addition, the cities in central, western and northeastern regions, it should accelerate the policy design for the resilience development of cities, improve the fiscal expenditure

of the resilience construction of the cities, expand the pilot scope of the cities, to improve the resilience development level.

(2) *Make up the shortcoming and highlight the ecological and infrastructure construction.* Under the basic premise of continuing to promote the high-quality economic development of the cities, continue to give full play to the positive externalities of infrastructure, people's livelihood and other aspects of high-quality economic growth. Meanwhile, in the construction process of the urban resilience, especially in central and western region, need to strengthen the implementation of carbon neutral policies, and accelerate the greening and cleaning carbon emissions of the public transportation such as public bus and railway with zero-emission hydrogen energy, and increase the control of atmospheric pollutions as PM2.5, and continuously expand the urban gardening and greening coverage range, to improve the ecological resilience. In addition, it should be combined with the urban carrying capacity, continuing to promote the construction of infrastructure such as roads, medical care, and education, accelerate the coverage of infrastructures such as 4G/5G, establish urban big data centers such as smart city brains, improve the communication and smart emergency processing capabilities, to enhance the infrastructure resilience.

(3) *Plays demonstrative and leading effect and gradually narrow the development gap between different regions*. At present, the urban resilience index in central, western and northeastern region are lower than the national mean value. Although the national urban resilience index has a convergence trend, the regional gap between regions is still large, especially hypervariable density contribution caused by the regional overlapping is the primary reason for the gap in the resilience development of cities in different regions. Therefore, the country needs to plan as a whole linkage measures for the development of cities in different regions. In the one hand, cities in eastern region should be promote the resilience development, meanwhile it is necessary to accelerate the promotion of smart innovations, and continue to play a leading role in the resilience development of cities across country, and narrow the resilience gap between regions. In the other hand, other regions should be learning from the sample from the advanced regions, establish the regional resilience construction pilot site of the cities, and play a demonstrative role in improving the resilience level of surrounding cities, to continuously narrow the gap within the region.

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