Estimating dynamic interactive linkages among urban agglomeration, economic performance, carbon emissions, and health expenditures across developmental disparities

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Abstract

This work analyzed the dynamic interactive causal links among urban agglomeration, economic performance, carbon emissions, and health expenditures across developmental disparities in China. To this end, this work developed a health expenditures-augmented growth model to introduce health expenditures and carbon emissions as a shift factor of total factor productivity. A block of simultaneous equations is developed based on the health expenditures-augmented growth modeling framework. The System-variant/Difference-variant Generalized Method of Moments is employed to estimate the block of simultaneous equations in order to deal with the potential endogeneity of the variables used. Based on empirical results, the core findings are as follows: first, a Pendroni cointegration-based long-run stable association is verified. Second, the urban agglomeration exhibited a bidirectional positive causal linkage with the gross domestic product (GDP) growth and health expenditures growth. Third, the health expenditures growth demonstrated a bidirectional positive causal linkage with carbon emissions growth and GDP growth. Fourth, a unidirectional mixed causal linkage—positive (negative) for linear form (squared form) of urban agglomeration—existed from urban agglomeration to carbon emissions growth. Fifth, there is a negative causal linkage operating from carbon emissions growth to GDP growth. However, there is mixed causal linkage—positive for a linear form of GDP growth, and negative for the squared form of GDP—operating from GDP growth to carbon emissions growth. These findings exhibited consistency in the type of causal linkages across the developmental disparities and hence showed robustness. Nevertheless, the findings showed disparities in the degree of impact across the developmental disparities. In this regard, the

strength of causal linkage is the largest (moderate/lowest) for highly (moderately/least) developed regions of China. Based on empirical results, inferences are extracted and discussed.

Keywords: Urban agglomeration; Economic performance; Carbon emissions; Health expenditures; Health expenditures-augmented growth model.

Nomenclature			
Variables		***Methods***	
HE	Health expenditures	AR	Autoregressive
UBA	Urban agglomeration	AR (1)	AR of order one
UBA^2	Squared UBA	AR (2)	AR of order two
GDP	Gross domestic product	ADF	Augmented Dicky-Fuller
GDP^2	Squared GDP	PP	Phillips-Perron
CE	Carbon emissions	LLCT	Levin-Lin-Chu test
K	Physical capital	IPST	Im-Pesaran-Shin test
Acronyms		DWH	Durbin-Wu-Hausman
		GMM	Generalized Method of Moments
EC	Eastern China	IPCC	Intergovernmental Panel on Climate Change
CC	Central China	***Symbols***	
WC	Western China		
P-value	Probability value	I (1)	Integrated of order one
Abbreviations		Y	Aggregate production
		A	Total factor productivity
NBSC	National Bureau of Statistic of China	L	Labor input
EKC	Environmental Kuznets Curve	ξ	Error term
CNY	Chinese Yuan	'i'	ith provincial division
Highly dev.	Highly developed	't'	tth time
Moderately dev.	Moderately developed	$\alpha, \beta, \gamma, \theta$	Elasticities
Least dev.	Least developed	g	Growth rate form

1. Introduction

For the past few decades, the linkages among urban agglomeration, economic performance, environmental quality, and health expenditures have become increasingly important in the literature of developed as well as developing world. To begin with the general understanding of the subject matter, the Chinese economy experienced a considerably substantial surge in the urban-rural population ratio, which is the ratio of urban population (100,000 persons) to the rural population (100, 000 persons), from 0.57 unit points in 2000 to 1.47 unit points in

2018 (Fig. 1). Meanwhile, the average growth rate of gross domestic product (GDP) has been around 9.9% during the last three decades (WDI[1], 2018). Concerning the health expenditures in China, the government health expenditures increased from 70,952 million CNY[2] in 2000 to 1,639,913 million CNY in 2018. In the meantime, the social health expenditures raised from 117,194 million CNY to 2,581,078 million CNY, whereas out-of-pocket health expenditures rushed from 250,717 million CNY to 1,691,199 million CNY. Further, the carbon emissions boosted from 3,349.65 megatons in 2000 to 10,065 megatons in 2018. The figures for health expenditures, urban-rural population ratio, economic performance, and carbon emissions present interesting rising trends in China. Thus, it seems interesting to investigate their mutual connections. Also, it seems even more interesting to delve into those connections while considering the developmental disparities across Chinese regions.

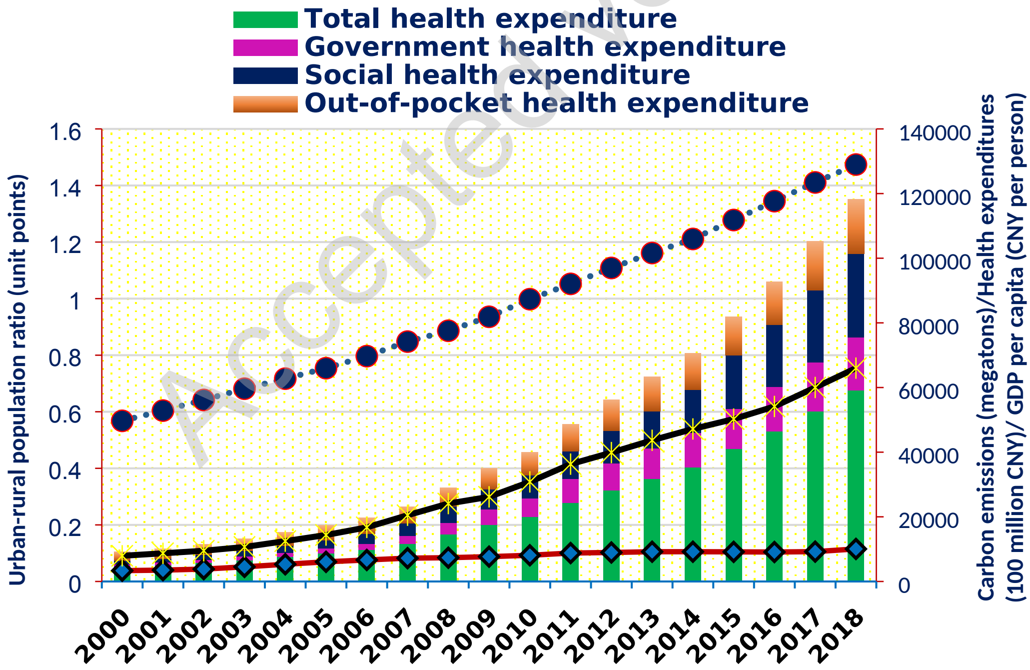

Fig. 1. Outline of total health expenditures, government health expenditures, social health expenditures, out-of-pocket health expenditures, carbon emissions, per capita GDP, and urban-rural population ratio in China

Source: Authors' own calculations based on data sourced from the National Bureau of Statistics (2017, 2018)

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[1] World Development Indicators

[2] Chinese currency unit called Chinese Yuan

As a further argument, the regional developmental distribution of Chinese provinces motivates the conduction of this research. In this respect, the 29 provinces of China can be divided into three regions—namely, eastern China (EC) which is highly developed (highly dev.), central China (CC) which is moderately developed (moderately dev.), and western China (WC) which is least developed (least dev.). The location of these regions is depicted in Fig. 2. Also, the three regions have obvious disparities in terms of the level of urbanization and gross domestic product (GDP). Fig. 2 presents the GDP (billion CNY) as well as urban-rural population ratio (unit points) for the three regions in time intervals 2000, 2005, 2010, and 2018. For all the time intervals, the values of both variables remained highest for EC (highly dev.), moderate for CC (moderately dv.), and lowest for WC (least dev.) regions. It draws clear distinction across the three regions with the heterogeneous levels of development.

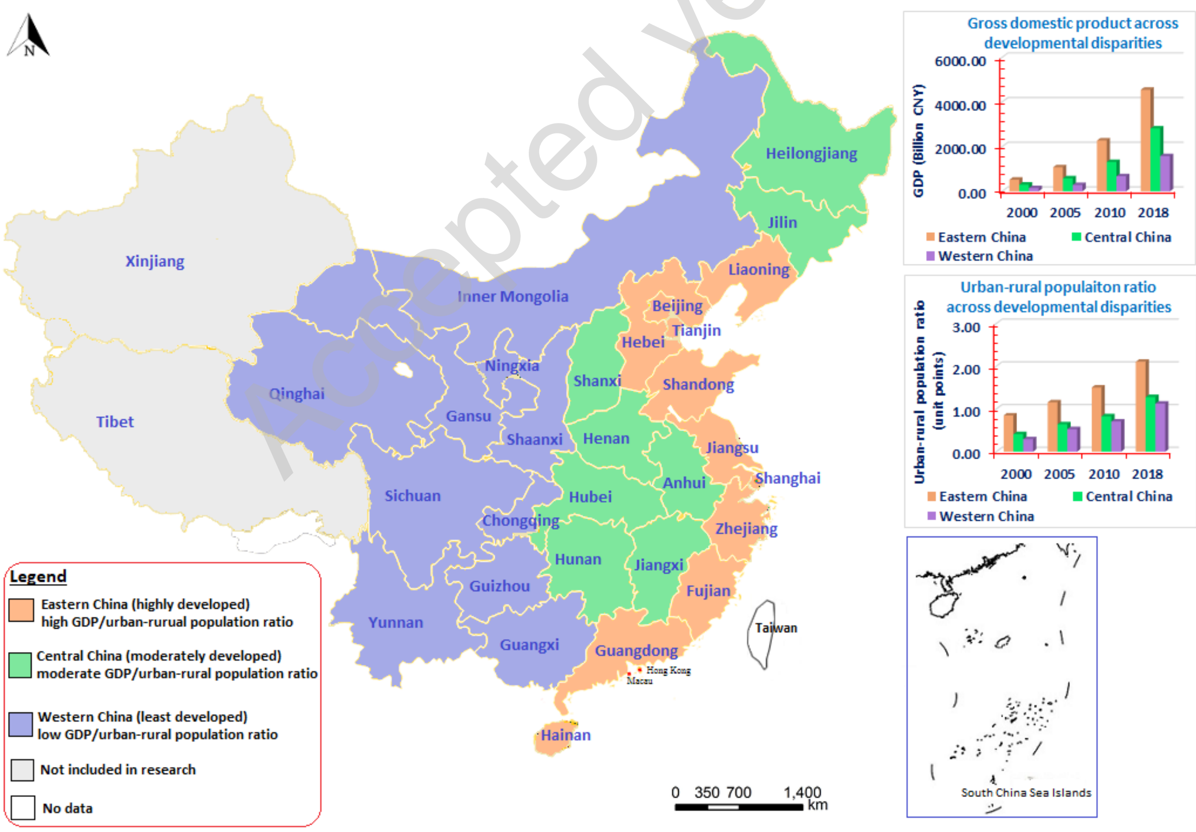

Fig. 2. Map of regional distribution of China across urban and economic developmental disparities
Source: Authors' own drawing.

The existing body of knowledge remained deficient in the following significant areas: (1) The empirical causal linkage between urban agglomeration and health expenditures has been categorically overlooked. The understanding of their underlying connection is essential. On the one hand, an urban sprawl without agglomeration effects may impede the economic growth (Guan et al., 2020) and health expenditures. On the other hand, urban agglomerated regions may transmit significant promotional impacts on economic performance through economies of scale (Chen et al., 2019). Consequently, areas with high economic performance may deliver improved health facilities and thus promote the health expenditures. (2) The consideration of the interactive linkages among urban agglomeration, economic performance, carbon emissions, and health expenditures in a framework of simultaneous equations remained unnoticed by the existing studies. The simultaneous equation approach has an advantage over the single-equation approach, as the latter does not allow to deal with simultaneities and thus cannot help estimating the endogenous relationships (Lütkepohl et al., 2020). Since a potential two-way linkage between the variables cannot be estimated through a single-equation approach, adopting a simultaneous equations framework is required. (3) Incorporating health expenditures as a predictor of total factor productivity in the aggregate production function has not been considered previously. From an economic point of view, public health expenditures help improving public health that may directly contribute to workers' productive efficiency (Hlafa et al., 2019). As a result, it may serve as an important determinant of economic performance. Against this background, the incorporation of health expenditures in the production function is useful for providing an in-depth understanding of their mutual linkages. (4) Finally, to date, the interactive impact mechanism-based analysis of the variables of interest has not been taken into account across developmental disparities. Those impact mechanism may work differently across regional disparities. For instance, a region with high urban agglomeration and economic development may extend better health facilities for the public, and vice versa.

In the purview of the above-stated shortcomings of the existing literature, this research investigates the dynamic interactive impact mechanism among urban agglomeration, economic performance, carbon emissions, and health expenditures for data of 29 provincial units of Chinese municipalities and administrative regions. The current research distinguishes itself from previous researches and thus contributes to the pool of knowledge and provides empirical insights in the following ways. First, this research augments the production function-based economic growth modeling framework to accommodate health expenditures as a predictor of total factor productivity. Second, this research establishes a block of four simultaneous equations to tackle the endogeneity and to deal with the simultaneities among the variables of research. Third, from the empirical standpoint, this research systematically employs a series of pre-analysis tests—namely, a Durbin-Wu-Hausman (DWH) test of endogeneity, Levin-Lin-Chu test (LLCT) and Im-Pesaran-Shin test (IPST) of unit root analysis, and Pedroni cointegration tests, to test whether the data are well-behaved for final estimations. Fourth, it employs a System-variant and the Difference-variant of Generalized Method of Moments (GMM) to estimate the dynamic panel data. Fifth, the empirical outcomes are estimated for three different levels of development to capture whether there are disparities in the empirical findings across the developmental disparities.

The rest of this research is organized as follows. Section 2 is based on a brief literature review. Section 3 details the methods, including data, modeling, pre-analysis, and estimation approach. Section 4 describes the empirical results, causal linkages, and diagnostic test results. Also, it explains the policies, limitations, and future research directions. And, Section 5 concludes the research.

2. Literature review

The research on linkages among urban agglomeration, economic performance, environmental quality, and health expenditures can be classified into the following spectra of research.

The first spectrum of research was based on testing the environmental Kuznets curve (EKC) hypothesis, primarily proposed by Grossman and Krueger (1995), which involved the linkages between economic performance and various hazardous emissions such as carbon emissions, sulfur emissions, ammonia emissions, and particulate matter. The researches under this spectrum came to conclude that, for most of the hazardous emissions, economic performance injects an elementary stage of environmental degradation, and after that fetches a stage of revitalizing the environmental quality. Though those researches largely confirmed the existence of EKC, however many of them found various shapes of EKC and thus leaving the nature of association inconclusive. For illustration, most recently, Chen et al. (2020) for data of Chinese prefecture-level cities, Suki et al. (2020) for quarterly data of Malaysia, and He and Lin (2019) for Chinese provinces proved the existence of conventional EKC. However, Pontarollo and Muñoz (2020) for Ecuador, and Zhou et al. (2019) for the Yangtze River Delta, among other researches, were unable to confirm the existence of conventional EKC.

Furthermore, Moutinho et al., (2020) considered the twelve OPEC[3] economies to explore the presence of EKC employing data from 1992 through 2015. They uncovered that economic growth in those economies failed to mitigate the carbon emissions, and thus the presence of a U-shaped curve was verified. In another study, Pontarollo and Serpieri (2020) investigated the existence of land built-environment-based EKC in 42 counties of Romania during 2000-2014. For this, they employed the spatial analysis, did not find the presence of EKC in the studied regions. They further substantiated that Romanian urbanization was merely the

[3] Oil Producing and Exporting Countries

manifestation of the expansion of urban regions. Another empirical research explored the deforestation-based EKC in 114 global economies (Caravaggio, 2020). It exhibited the presence of the EKC in those economies for all the income groups. In their work, Churchill et al. (2020) employed the non-parametric approach to examine the EKC in eight states of Australia. Their findings verified the conventional EKC for all the states. They observed the peak of EKC in 2010. Another study by Boubellouta and Kusch-Brandt (2020) analyzed the e-waste-based EKC in selected 30 economies of Europe from 2000 to 2016. As an analytical tool, they used the GMM approach, and found the support for the EKC in the European region under consideration.

The second spectrum of research was based on the linkages between health expenditures and environmental quality. It received less traction of researchers as compared to the first spectrum of research. The researches in this field examined the impact of health expenditures on hazardous emissions, mostly carbon emissions, and found a positive impact of the former on the latter. Some researchers tested and found a positive impact of carbon emissions on health expenditures, including, among others, Apergis et al. (2018) for time series of the United States and Chaabouni et al. (2016) for developing countries categorized into low, middle, and high-income levels. Nevertheless, Zaidi and Saidi (2018) found a negative impact of those emissions on health expenditures for the data of African countries. Another research by Narayan and Narayan (2008) measured the influence of the environment on healthcare spending in eight selected OECD[4] economies from 1980 to 1999. They exposed the short-run promotional effects of economic output and carbon emissions on healthcare spending. Further, the sulfur emissions imparted a positive influence on healthcare spending in the long-run. Most recently, Ahmad et al. (2020) tested the impact of healthcare spending

[4] Organisation for Economic Co-operation and Development

and land urbanization on carbon dioxide emissions. They adopted the STIRPAT[5] framework for this purpose. They revealed a positive bilateral relationship between land urbanization and the growth of healthcare spending. Additionally, the carbon dioxide emissions promoted the healthcare spendings in China. Eventually, Weisz et al. (2020) examined the impact of carbon emissions on Austrian healthcare by using health industry data from 2005 to 2014, and found a significant positive impact of the same. To sum up, the researches belonging to this spectrum found linkage of mixed nature between health expenditures and carbon emissions.

The third spectrum of research was based on linkages between health expenditures and economic performance. Most of the researches in this spectrum estimated the income elasticity of health cost, including Kurt (2015) for the data of Turkey and Chaabouni and Saidi (2017) for data of low, middle, and upper-middle-income countries, among others. The former research found a positive direct and negative indirect impact of government health expenditures on economic performance. In contrast, the latter research found positive unidirectional causality from health expenditures to economic performance. Furthermore, some of the studies focused and found the impact of health shock variation on health expenditures, including, among others, Bernal-Delgado et al. (2020) for Spanish time-series data, and Wang et al. (2018) for 22 different countries. A recent work by Tandon et al. (2020) conducted an investigation in 155 economies around the globe form 2000 to 2017 regarding the links of healthcare spending with economic growth, public health expenditures, and suitable conditions of the macroeconomy. They found that public health expenditures and economic growth introduced significant contributions to the healthcare spending.

The fourth spectrum of research was based on the linkage of urban agglomeration with the environment and economic performance. In this field, the urban agglomeration is found to have a unidirectional positive impact by some researches, including Han et al. (2019) for data

[5] Stochastic Impacts by Regression on Population, Affluence and Technology

of 287 prefecture-level cities of China, Khan and Awan (2017) for cities of Punjab province of Pakistan, and Tripathi (2013) for 59 megacities of India. However, those researches failed to test the simultaneous linkage between urban agglomeration and economic performance. Finally, the fifth spectrum of research focused on the linkage between urban agglomeration and environmental quality. These researches showed two types of findings—namely, emissions reduction impact, and emissions promotion impact. On the one hand, the emissions reduction impact was found by Yu et al. (2020), which employed the STIRPAT model for the data of Chinese provinces, Han et al. (2018) which applied spatial analysis on 283 cities of China, and Chen et al. (2019) that used Theil-Kaya model for data of Pearl River Delta of China. On the other hand, the emissions promotion impact was revealed by, among others, Bai et al. (2019) for the data of Chinese cities, and Ahmad et al. (2019) for the data of Chinese provinces. Thus, researches in this domain remained inconclusive on the nature of the linkage between urban agglomeration and carbon emissions.

Moreover, Alvarado et al. (2020) studied the causal links among urbanization, non-renewable energy, and economic output in selected 110 economies worldwide from 1971 through 2017. They applied the dynamic OLS cointegration method. And found a unidirectional causality from urbanization to economic output in the low-income economies. In a different research, ŠATROVIĆ and DAĞ (2019) investigated the influence of urbanization and energy use on economic growth in 34 OECD countries during 1996-2015. They revealed the positive and exponentially growing impact of urbanization on economic growth in the short-term. In addition, Frick and Rodríguez-Pose (2018) considered urban agglomeration of 68 world economies for testing its impact on their economic growth. They built a modified data version of the built-land and found the absence of any uniformity in the relationship between urbanization and economic growth. In their research, Chen et al. (2018) analyzed the influence of urbanization, along with energy use structure, and economic activity, on particulate matter ($PM_{2.5}$) emissions in global economies from 1998 to 2014. They unveiled that economic activity and urbanization promoted the emissions in the global as well as sub-samples. Bakirtas and Akpolat (2018) explored the causal linkages of energy use and urbanization with economic production in six newly emerging markets from 1971 through 2014. They used the mutual causality approach and found causality running from energy use and urbanization to economic production. In a recent study, Wang et al. (2020) studied 136 global economies for investigating the impact of urbanization on urban residential energy utilization from 1990 to 2015. They found heterogeneous findings across the considered economies. Urbanization boosted the energy utilization in developing economies, while it reduced energy use in the developed economies.

Taking the other important determinants of carbon emissions into account, most recently, Shahbaz et al. (2020) applied the bootstrap bounds testing procedures to investigate the impact of the financial sector, research and development, economic output, and energy use on carbon emissions in the United Kingdom. They confirmed the equilibrium relationship of carbon emissions with its determinants. They further emphasized that research and development mitigated the emissions. In contrast, the financial sector and energy use promoted the carbon emissions. Then, Rahman and Vu (2020) considered urbanization, renewable energy use, international trade, and economic output in terms of their influence on carbon emissions in Canada and Australia. They employed a bounds testing method on data from 1960 to 2015. Their short-term findings showed a positive (negative) influence of economic output on carbon emissions in Australia (Canada). While, in the long-term, trade and economic output increased carbon emissions in Canada. Additionally, Ullah et al. (2020) investigated the impact of renewable energy use and trade openness on carbon emissions for the time series of Pakistan from 1998 to 2017. They observed a positive (negative) influence of trade (renewable energy use) on carbon emissions during the study period. Besides, Jiang and Guan (2016) studied the driving factors of carbon emissions at a global level. The revealed that those emissions grew substantially in the developing world due to coal utilization. Conversely, the carbon emissions upsurged most markedly in the developed world in the face of heavy dependence on natural gas. Lastly, Wang et al. (2019) performed a consumption- as well as production-based analysis of carbon emissions in Kazakhstan. They concluded that the construction industry was the main contributor to the emissions.

Summing up the literature gaps, first, it is noted that no research is known to examine the empirical causal linkage between urban agglomeration and health expenditures. Second, it is further learned that no empirical work is known to explore the interactive impact mechanisms among urban agglomeration, economic performance, carbon emissions, and health expenditures, simultaneously. Third, from an economic viewpoint, it is also noticed that none of the research is known to accommodate health expenditures as a predictor of total factor productivity in the aggregate production function. Finally, to date, no research is known to consider the interactive impact mechanism-based analysis of the variables of interest across developmental disparities.

3. Methods

3.1. Health expenditures-augmented growth model

A Cobb-Douglas production function is considered, following Ahmad and Jabeen (2019), along with an additional exogenous component of total factor productivity (A):

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha} L^{1-\alpha}_{i,t} (UBA_{i,t})^{\psi} \qquad (1)$$

Where Y denotes the economy's aggregate output, K denotes the capital input, L denotes the labor element of the production function, and UBA refers to the urban agglomeration. Moreover, 'i' denotes the index term of provincial units, and 't' denotes the time dimension of panel data.

As a next step, it has been opined that hazardous emissions, like Carbon emissions (CE), have a significant contribution in determining the total factor productivity (Rusiawan et al., 2015; Ahmad and Zhao, 2018). Furthermore, health expenditures (*HE*) improve public health and hence may enhance the productive efficiency of people (Kumara and Samaratunge, 2019; Hlafa et al., 2019). In this way, HE may scale up the total factor productivity. Following this, taking all else constant as a norm of modeling, the CE and HE can be substituted as shift components for A in Eq. (1):

$$Y_{i,t} = K_{i,t}^{\alpha} L^{1-\alpha}_{i,t} (UBA_{i,t})^{\psi} (CE_{i,t})^{\phi} (HE_{i,t})^{\tau} \qquad (2)$$

Following Ahmad and Jabeen (2019), Eq. (2) is normalized by L and is further subjected to natural logarithmic operation to have the following expression:

$$lny_{i,t} = \alpha lnk_{i,t} + \psi lnUBA_{i,t} + \phi lnCE_{i,t} + \tau lnHE_{i,t} \quad (3)$$

The Eq. (3) is the per-worker form of the model. The difference operation is applied to obtain the growth form of Eq. (3) as follows:

$$\mathrm{g}_{y_{i,t}} = \alpha \mathrm{g}_{k_{i,t}} + \psi \mathrm{g}_{UBA_{i,t}} + \phi \mathrm{g}_{CE_{i,t}} + \tau \mathrm{g}_{HE_{i,t}} \qquad (4)$$

In Eq. (4), g indicates the growth rate form of the variables. Furthermore, Eq. (4) can be written in econometric expression as follows:

$$\mathrm{g}_{y_{i,t}} = \alpha \mathrm{g}_{k_{i,t}} + \psi \mathrm{g}_{UBA_{i,t}} + \phi \mathrm{g}_{CE_{i,t}} + \tau \mathrm{g}_{HE_{i,t}} + \xi_{i,t} \qquad (5)$$

Where ?? is the stochastic error term of the model. The model in Eq. (5) is termed as "*health expenditures-augmented growth model*." From Eq. (5), a block of four equations is established on a simultaneous basis among the four variables as follows:

$$\mathrm{g}_{y_{i,t}} = \alpha_1 \mathrm{g}_{k_{i,t}} + \alpha_2 \mathrm{g}_{UBA_{i,t}} + \alpha_3 \mathrm{g}_{CE_{i,t}} + \alpha_4 \mathrm{g}_{HE_{i,t}} + \xi_{i,t,1} \qquad (6)$$

$$\mathrm{g}_{UBA_{i,t}} = \beta_1 \mathrm{g}_{k_{i,t}} + \beta_2 \mathrm{g}_{y_{i,t}} + \beta_3 \mathrm{g}_{CE_{i,t}} + \beta_4 \mathrm{g}_{HE_{i,t}} + \xi_{i,t,2} \qquad (7)$$

$$\mathrm{g}_{CE_{i,t}} = \gamma_1 \mathrm{g}_{k_{i,t}} + \gamma_2 \mathrm{g}_{UBA_{i,t}} + \gamma_3 \mathrm{g}_{y_{i,t}} + \gamma_4 \mathrm{g}_{HE_{i,t}} + \xi_{i,t,3} \qquad (8)$$

$$\mathrm{g}_{HE_{i,t}} = \theta_1 \mathrm{g}_{k_{i,t}} + \theta_2 \mathrm{g}_{UBA_{i,t}} + \theta_3 \mathrm{g}_{CE_{i,t}} + \theta_4 \mathrm{g}_{y_{i,t}} + \xi_{i,t,4} \qquad (9)$$

Given the block of simultaneous equations (Eqs. 6-9), the testable hypotheses are documented as: (1) urban agglomeration and health expenditures are probable to have a positive linkage with economic performance, (2) economic performance and urban agglomeration are negatively related to carbon emissions, (3) health expenditures is expected to manifest a positive linkage with urban agglomeration and carbon emissions.

3.2. Description of data and summary statistics

3.2.1. Data

The data used in this work consist of 29 provincial units of China, covering the time period of 1999-2018. The urban population is employed to quantify urban agglomeration. The data on gross regional product is obtained to serve as the gross domestic product of provincial units. The total investment in fixed assets proxied for the physical capital. Table 1 reports the detailed elaborations of the variables, along with data sources. Moreover, the methodological flow of the study is presented in Fig. 3.

Table 1
Definitions of variables and regional samples.

Data	Explanations of variables	Estimation variables	Source
Carbon dioxide emissions (Mt)	For provincial units of China, there is no official data on Carbon emissions (CE). Therefore, following Fan et al., (2019), Wu et al. (2020), and Ahmad et al. (2019), we have calculated the data on CE according to IPCC (2014) and converted it into per capita form. For estimation purposes, the CE data is transformed into the growth rate form.	Carbon emissions growth	NBSC (2017, 2018)
Health expenditures (100 million CNY)	Data on health expenditures are corrected for CPI (preceding year=100) inflation and converted into per capita form, which is finally transformed into the growth rate.	Health expenditures growth	NBSC (2017, 2018)
Gross regional product (100 million CNY)	Gross regional product is corrected for CPI (preceding year=100) converted into per capita form and then transformed into growth form.	Economic performance	NBSC (2017, 2018)
Urban population (10,000 persons)	Data on the urban population is divided by the total population to obtain the urban population proportion of the total population. This ratio form variable is used as urban agglomeration	Urban agglomeration	NBSC (2017, 2018)
Total investment in	It refers to the size, growth, and structure of the investment in fixed assets. It is normalized by	Physical capital growth	NBSC (2017, 2018)

the fixed assets (100 million CNY)	population size and converted into growth form.
Regions	**Provincial units**
EC (highly dev.)	Tianjin, Beijing, Hebei, Zhejiang, Shanghai, Jiangsu, Fujian, Hainan, Shandong, Liaoning, Guangdong.
CC (moderately dev.)	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Hunan, Henan, Hubei.
WC (least dev.)	Guangxi, Ningxia, Chongqing, Sichuan, Inner Mongolia, Yunnan, Shaanxi, Qinghai, Guizhou, Gansu.

Notes: NBSC: National Bureau of Statistics of China, **CNY:** Chinese Yuan, **Mt:** million tons. **IPCC:** Intergovernmental Panel on Climate Change, **dev.:** developed, **CPI:** consumer price index. Tibet and Xinjiang are excluded from the analysis based on data unavailability.

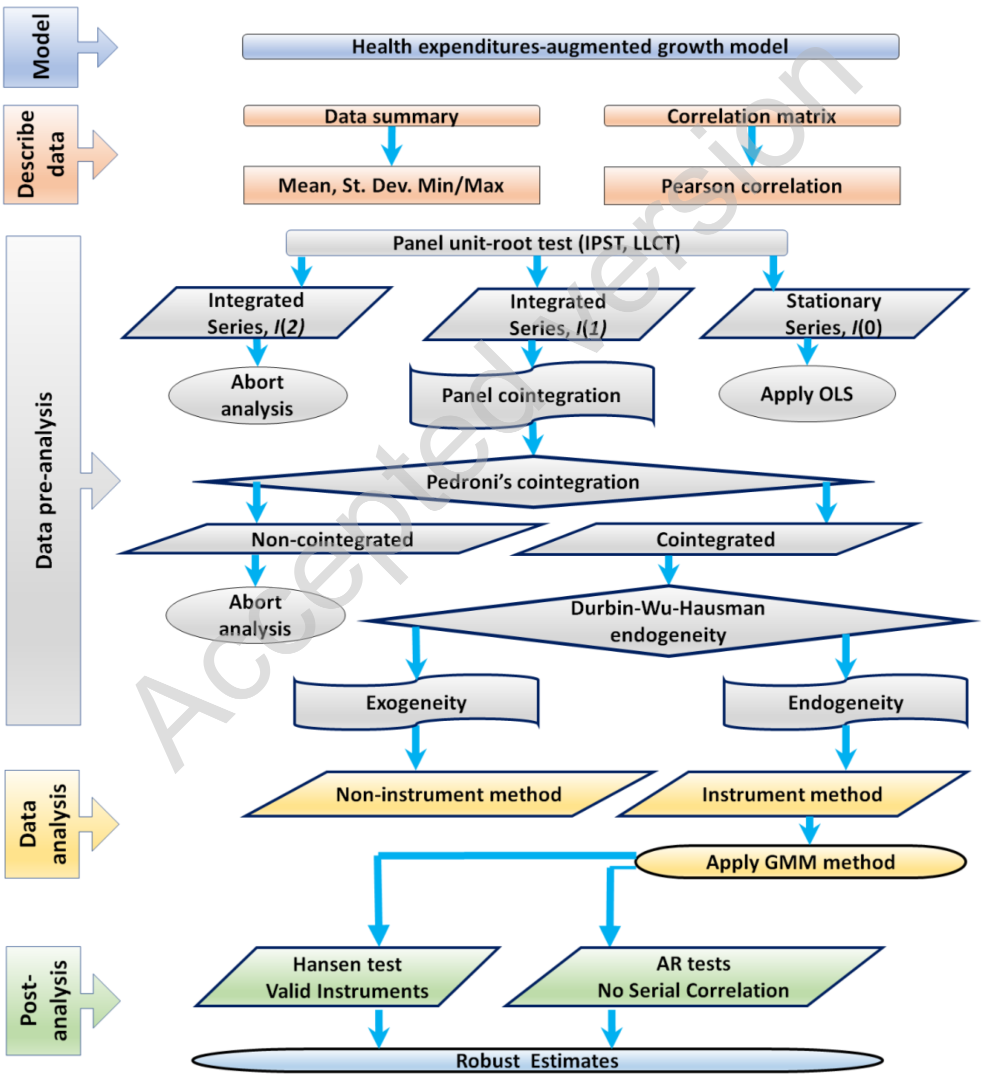

Fig. 3. Methodological flow of study

Notes: IPST: Im-Pesaran-Shin test, **LLCT:** Levin-Lin-Chu test, ***I*(0):** Zero order integration, **OLS:** ordinary least square.

3.2.2. Descriptive statistics

Table 2 provides a description of statistics, including observations of variables, mean, standard deviation (Std. Dev.), minimum, and maximum values of those variables. The data are based on balanced panels as each of the variables comprises of 580 (full data set), 220 (EC), 160 (CC), and 200 (WC) observations. GDP growth demonstrated the largest value of standard deviation, whereas K growth showed the smallest value. It implies that GDP growth exhibits the highest volatility, while K growth is least volatile and hence demonstrated the most persistent behavior across the provincial units in China. Furthermore, the mean value of GDP is observed to be the largest, while that of K growth is found the smallest. Additionally, the minimum and maximum values showed the greatest range for GDP growth. On the whole, GDP growth exhibited the least persistent behavior along with the largest mean and range values across all the samples.

Table 2
Statistical summary of variables

	Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
Full data set	UBA	580	0.1628	0.0437	0.1126	0.2061
	GDP growth	580	0.3982	0.1785	0.2103	0.5735
	CE growth	580	0.1590	0.0372	0.1138	0.1926
	HE growth	580	0.2173	0.0410	0.1726	0.2559
	K growth	580	0.1098	0.0127	0.0829	0.1307
EC (highly dev.)	UBA	220	0.1926	0.0632	0.1274	0.2591
	GDP growth	220	0.4182	0.1274	0.2843	0.5462
	CE growth	220	0.1825	0.0573	0.1287	0.2411
	HE growth	220	0.2027	0.0574	0.1465	0.2603
	K growth	220	0.1973	0.0135	0.1682	0.2096
CC (moderately dev.)	UBA	160	0.1826	0.0483	0.1320	0.2312
	GDP growth	160	0.3657	0.0937	0.2731	0.4572
	CE growth	160	0.1765	0.0923	0.0823	0.2706
	HE growth	160	0.2236	0.0634	0.1802	0.2858
	K growth	160	0.1356	0.0206	0.1150	0.1559
WC (least dev.)	UBA	200	0.1382	0.0381	0.1002	0.1743
	GDP growth	200	0.3025	0.0526	0.2475	0.3551
	CE growth	200	0.1382	0.0643	0.0625	0.2007
	HE growth	200	0.1560	0.0374	0.1173	0.1945
	K growth	200	0.0681	0.0166	0.0403	0.0821

Notes: EC: eastern China, **CC:** central China, **WC:** western China, **UBA:** urban agglomeration, **GDP:** gross domestic product, **CE:** carbon emissions, **HE:** health expenditures, **K:** physical capital.

3.2.3. Coefficients of the correlation matrix

The coefficients of the correlation matrix are presented in Table 3. It has provided the values of correlation coefficients among study variables. The value of the coefficient demonstrates the degree of correlation between the variables under consideration. As evident from Table 3, UBA has a positive correlation with all the variables, having the highest degree of correlation with GDP growth and the lowest degree of correlation with K growth across all the samples. Similarly, GDP growth exhibited a positive correlation with all the variables, except CE growth. GDP growth showed a negative correlation with CE growth for all the samples. The strongest correlation between GDP growth and K growth is observed for all the samples. Finally, HE growth is found in a positive correlation with all the variables, having the greatest degree of correlation with GDP growth, while the smallest degree is observed with CE growth across all the samples under consideration.

Table 3
Coefficient correlation matrix

	Item	UBA	GDP growth	CE growth	HE growth	K growth
Full data set	UBA	1.0000				
	GDP growth	0.4917	1.0000			
	CE growth	0.3652	-0.5634	1.0000		
	HE growth	0.3027	0.4938	0.2341	1.0000	
	K growth	0.2928	0.5647	0.2736	0.2643	1.0000
EC (highly dev.)	UBA	1.0000				
	GDP growth	0.5271	1.0000			
	CE growth	0.4027	-0.6142	1.0000		
	HE growth	0.3483	0.5001	0.2588	1.0000	
	K growth	0.3127	0.5081	0.2384	0.2865	1.0000
CC (moderately dev.)	UBA	1.0000				
	GDP growth	0.4292	1.0000			
	CE growth	0.2946	-0.4563	1.0000		
	HE growth	0.2531	0.4027	0.1836	1.0000	
	K growth	0.2274	0.4263	0.2193	0.2059	1.0000
WC (least dev.)	UBA	1.0000				
	GDP growth	0.3162	1.0000			
	CE growth	0.2019	-0.3139	1.0000		
	HE growth	0.1524	0.2973	0.1427	1.0000	

K growth	0.0935	0.3211	0.1738	0.1392	1.0000

Notes: EC: eastern China, **CC:** central China, **WC:** western China, **UBA:** urban agglomeration, **GDP:** gross domestic product, **CE:** carbon emissions, **HE:** health expenditures, **K:** physical capital. The values are coefficients of correlation. All the values are significant at 1%.

3.3. Data pre-analysis

3.3.1. Panel data unit root test

In addition to the endogeneity test, panel data unit root tests are employed to examine the stationary feature of the panel data. In this regard, Levin-Lin-Chu's (2002) test (LLCT) and Im, Pesaran, Shin's (2003) test (IPST) are applied. Both of the tests have statistical power to deal with the small sample bias problem of panel data, and both follow the asymptotic features. The null hypothesis for both tests is that panel data series have a unit root process. Table A.1 shows the unit root results at both levels and differences (see Appendix A). The tests are estimated both with constant and with the trend. Concerning the level form, the probability values failed to reject the null hypothesis and thus proved that all the panel data series have a unit root. On the other hand, all of the panel data series turned stationary at first difference as the probability values are significant at 1% for most of the cases. And thus, the null hypothesis of unit root is rejected. These findings are consistent across all the given samples. In this way, the variables are $I(1)$, i.e., they are integrated of order one. When all the panel data series are $I(1)$, Pedroni cointegration is the optimal choice to test whether the panel data series are cointegrated and share long-run trends (Pedroni, 2004).

3.3.2. Pedroni's panel cointegration

According to econometric literature, it has been posited that even if the panel data series have unit root feature at the individual level, if the estimated errors of those series form some linear combination, then they are said to be cointegrated. And those panel data series will attain equilibrium path in the long-term (Engle and Granger, 1987; Pedroni, 1999). In light of this, this work has employed Pedroni's (2004) cointegration, which is the advanced modification to that devised by Engle and Granger (1987). Pedroni cointegration is based on two classes of tests called "within-dimension" and "between dimension" tests. The "within-dimension" test provides four kinds of statistics, while "between dimension" estimates three kinds of statistics. Since it has been argued that Phillips-Perron (PP) and Augmented Dicky-Fuller statistics are most robust and reliable, therefore the results for these two statistics are reported. This work has applied Pedroni cointegration on all the given panel data samples, and the statistical results are reported in Table A.2 (see Appendix A). The null hypothesis is no cointegration exists for panel data series, which have a unit root property. The findings showed that, for both classes of tests, the statistical values are significant at 5, 1, and 0.1%. Thus, it suggested that the panel data series are cointegrated for all models and for all the panel data samples. It validated the existence of long-run equilibrium linkage among UBA, GDP growth, CE growth, HE growth, and K growth.

3.3.3. Durbin-Wu-Hausman test of endogeneity

It has been suggested by empirical studies that variables like GDP, CE, and K sometimes suffer from the problem of endogeneity (Chaabouni and Saidi, 2017; Zhang et al., 2019; Li et al., 2020). In the face of that scenario, the ordinary least square estimator provides inconsistent estimates and thus ruling out the possibility of employing a fixed or random-effects model of panel data. Thereby, Davidson and Mackinnon (1993) recommended estimating the Durbin-Wu-Hausman (DWH) test of endogeneity, which estimates the augmented regression. The augmented regression incorporates the errors of each potentially endogenous variable as a function of the exogenous variable. The significant probability values successfully reject the exogeneity of the estimated residuals of GDP growth, CE growth, and K growth. Hence, the test results of the exogeneity of residuals of estimated augmented regressions demonstrated the existence of endogeneity for all three variables. Table 4 shows the DWH exogenous residuals test results.

Table 4
Durbin-Wu-Hausman exogeneous residuals test results.

Variable	Estimate	F-statistic	Probability value	Exogenous
GDP growth_resid	0.010	13.25	0.00	No
CE growth_resid	0.047	15.42	0.00	No
K growth_resid	0.006	12.31	0.01	No

Notes: GDP: gross domestic product, **CE:** carbon emissions, **K:** physical capital. resid indicates residuals.

3.4. Estimation method

This work established a block of four simultaneous equations involving economic performance, urban agglomeration, carbon emissions, and health expenditures. The previous literature suggested the existence of endogeneity issues; for instance, Ahmad and Khan (2018) indicated the existence of endogeneity while considering the relationship between physical capital and economic performance. Further, Shahbaz et al. (2017) opined the possible occurrence of endogeneity and the reverse causation in consideration of simultaneous equations. In light of these arguments, the GMM has been argued to give unbiased and efficient estimates even in the presence of endogeneity. This work has applied the System-variant as well as the Difference-variant of GMM estimator extended by Blundell and Bond (2000). The GMM estimator involves the lag of the dependent variable as the independent variable, which evaluates the convergence and dynamic feature of each model. This work has considered two variants of GMM; System-variant is applied for the full data set, whereas the Difference-variant is applied for the regional samples, including EC (highly dev.), CC (moderately dev.), and WC (least dev.) to avoid small sample bias of panel data. As a further argument, the alternative panel methods, including random and fixed effects models, are not employed because GMM has an additional advantage over those estimators in controlling the correlation problem between the lag dependent variable and the stochastic error term. The conventional estimators are unable to handle this issue and thus leaving the GMM as the optimal choice for this work. The block of four simultaneous equations (6-9) can be rewritten following Blundell and Bond (2000):

$$g_{y_{i,t}} = \alpha_0 + \alpha_1 g_{y_{i,t-1}} + \alpha_2 g_{k_{i,t}} + \alpha_3 g_{UBA_{i,t}} + \alpha_4 g_{CE_{i,t}} + \alpha_5 g_{HE_{i,t}} + \xi_{i,t,1} \quad (10)$$

$$g_{UBA_{i,t}} = \beta_0 + \beta_1 g_{UBA_{i,t-1}} + \beta_2 g_{k_{i,t}} + \beta_3 g_{y_{i,t}} + \beta_4 g_{CE_{i,t}} + \beta_5 g_{HE_{i,t}} + \xi_{i,t,2} \quad (11)$$

$$g_{CE_{i,t}} = \gamma_0 + \gamma_1 g_{CE_{i,t-1}} + \gamma_2 g_{k_{i,t}} + \gamma_3 g_{UBA_{i,t}} + \gamma_4 g_{y_{i,t}} + \gamma_5 g_{HE_{i,t}} + \xi_{i,t,3} \quad (12)$$

$$g_{HE_{i,t}} = \theta_0 + \theta_1 g_{HE_{i,t-1}} + \theta_2 g_{k_{i,t}} + \theta_3 g_{UBA_{i,t}} + \theta_4 g_{CE_{i,t}} + \theta_5 g_{y_{i,t}} + \xi_{i,t,4} \quad (13)$$

where α_0, β_0, γ_0 and θ_0 indicate the drift elasticities of the Eqs. (10-13), respectively; and, α_1 , β_1, γ_1 and θ_1 are the coefficients of convergence variables of the four equations, respectively. Where α_1, β_1, γ_1 and $\theta_1 < 0$ imply the convergence of respective models. It means that after any arbitrary shock, the model will converge to an equilibrium. The α_2 , α_3, α_4 and α_5 are the influence absorbers of growth form variables involving physical capital, urban agglomeration, carbon emissions, and health expenditures, respectively, on economic performance. Next, the β_2 , β_3, β_4 and β_5 are the influence absorbers of growth form variables involving physical capital, economic performance, carbon emissions, and health expenditures, respectively, on urban agglomeration. After that, the γ_2 , γ_3, γ_4 and γ_5 are the influence absorbers of growth form variables involving physical capital, urban agglomeration, economic performance, and health expenditures, respectively, on carbon emissions. Finally, the θ_2 , θ_3, θ_4 and θ_5 are the influence absorbers of growth form variables involving physical capital, urban agglomeration, carbon emissions, and economic performance, respectively, on health expenditures.

4. Results and discussion

4.1. Convergence variables

For all models and in the case of all studied samples, the elasticity coefficients of convergence variables remained negatively statistically significant. It authenticated the existence of the dynamic property of the model. It entails that if series meet some shock, the series will converge to an equilibrium with a speed of convergence shown from the value of elasticity of convergence. These elasticity coefficients are given in Tables 5-8.

4.2. The dynamic model of urban agglomeration

In the estimated dynamic model of urban agglomeration, GDP growth posed a positive and statistically significant impact on urban agglomeration. The elasticity coefficients are given as 1.273 (Full data set), 1.536 (EC), 1.028 (CC), and 0.784 (WC). It is obvious that the impact of GDP growth is strongest in EC (highly dev.) and weakest in WC (least dev.), whereas the impact is moderate in CC (moderately dev.). This is named as *"development level-based industrial growth impact"* (Fig. 4). It means the relatively developed regions with industrial growth attract the rural workers to migrate to the city and promote urban agglomeration, and relatively less developed regions have relatively fewer industries and thus promote less urban agglomeration. Next, CE growth induced a neutral impact on urban agglomeration. After that, HE growth imparted a positive and statistically significant impact on urban agglomeration. The elasticity coefficients of HE growth are given as 0.327 (full data set), 0.269 (EC), 0.338 (CC), and 0.369 (WC). In this regard, the WC (least dev.) showed the strongest impact, while EC (highly dev.) exhibited the weakest impact. This is named as *"development level-based health infrastructure impact"* (Fig. 4).

This is probably because least developed regions extend health expenditures to promote construction sector activities and spend relatively more on health infrastructure than on public health benefits like health insurance (Ari and Sentürk, 2020). In this way, urban agglomeration promotion is relatively fast. On the other hand, relatively more developed regions offer more public health benefits rather than spending much on health-related infrastructure activities and therefore promote relatively less urban agglomeration. Moreover, K growth showed a positive and statistically significant impact on urban agglomeration, with the strongest impact in EC (highly dev.) and the least strong impact in WC (least dev.). These empirical outcomes are given in Table 5.

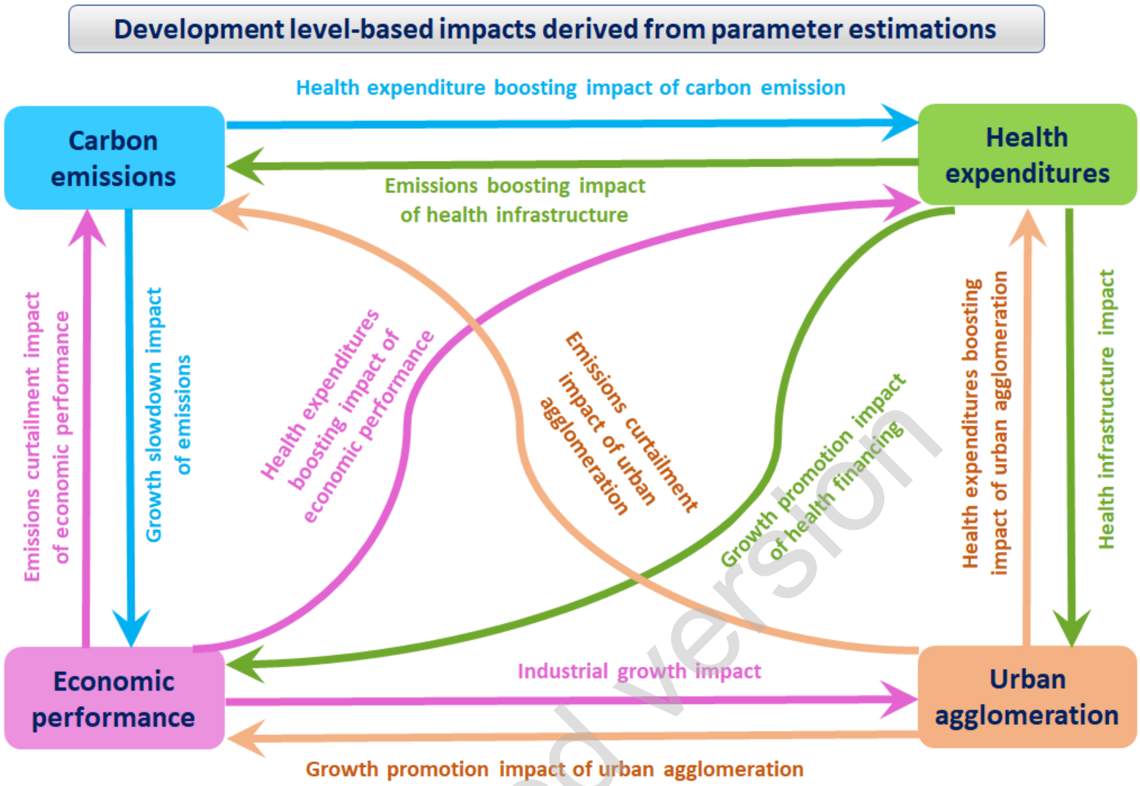

Fig. 4. Outline of development level-based estimated links among urban agglomeration, economic performance, carbon emissions, and health expenditures in China

Table 5
Estimations of the dynamic model of urban agglomeration

Dependent variable: Urban agglomeration				
Items	Full data set	EC (highly dev.)	CC (moderately dev.)	WC (least dev.)
Independent variables				
Lagged level of UBA	-0.811*** (0.229)	-0.758*** (0.182)	-0.834*** (0.241)	-0.723*** (0.160)
GDP growth	1.273*** (0.359)	1.536*** (0.340)	1.028** (0.354)	0.784*** (0.221)
CE growth	0.162 (0.130)	0.281 (0.161)	0.273 (0.267)	0.110 (0.045)
HE growth	0.327*** (0.682)	0.269*** (0.074)	0.338** (0.117)	0.369*** (0.107)
K growth	0.132*** (0.031)	0.149*** (0.032)	0.118** (0.041)	0.076*** (0.024)
Diagnostic tests				
Hansen test (p-value)	0.818	0.799	0.836	0.992
AR (1) test (p-value)	0.002	0.006	0.027	0.034
AR (2) test (p-value)	0.263	0.472	0.394	0.536
No. of observations	551	209	152	190
Provincial units	29	11	8	10

Notes: EC: eastern China, **CC:** central China, **WC:** western China, **UBA:** urban agglomeration, **GDP:** gross domestic product, **CE:** carbon emissions, **HE:** health expenditures, **K:** physical capital, **AR:** auto-regressive, **P-**

value: probability value. *** indicates $p < 0.01$, ** indicates $p < 0.05$. Brackets ( ) contain the values of robust standard errors.

4.3. The dynamic model of GDP growth

In the estimated dynamic model of GDP growth, UBA induced a positive and statistically significant impact on GDP growth for all the samples. Its elasticity coefficients are given as 0.135 (full data set), 0.146 (EC), 0.117 (CC), and 0.081(WC). Thus, it had the largest contribution in EC (highly dev.), and the smallest contribution is observed in WC (least dev.). This is termed as *"development level-based growth promotion impact of urban agglomeration"* (Fig. 4). It means that more developed regions support more urban agglomeration, which promotes GDP growth more rapidly, whereas relatively less developed regions are relatively less supportive of urban agglomeration and thus promote relatively less rapid GDP growth. Next, CE growth showed a negative and statistically significant impact on GDP growth for all the samples. Its elasticity coefficients are given as -0.208 (full data set), -0.229 (EC), -0.201 (CC), -0.136 (WC). As can be seen from magnitudes, carbon emissions offered the strongest impact in EC (highly dev.) and weakest impact in WC (least dev.). This is termed as *"development level-based growth slowdown impact of emissions"* (Fig. 4). It entails that more developed regions rely more on energy consumption to run industries, which produce heavy carbon emissions, having a relatively more adverse impact on GDP growth. On the other hand, relatively less developed regions run relatively fewer industries and thus produce a relatively low level of carbon emissions. It has a relatively less adverse impact on GDP growth in those regions. After that, HE growth posed a positive and statistically significant impact on GDP growth for all the samples. Its elasticity coefficients are observed as 0.130 (full data set), 0.141 (EC), 0.113 (CC), and 0.074 (WC). It is obvious from the magnitudes of elasticity coefficients that EC (highly dev.) showed the largest value, and WC (least dev.) showed the lowest value of impact elasticities. This is called the *"development level-based growth promotion impact of health financing"* (Fig. 4). It shows that relatively more developed regions invest more in the health sector and which promotes the efficiency of workers and thus imparting relatively more impact on GDP growth. On the contrary, relatively less developed regions make less spending in the health sector and thus promoting GDP growth with relatively less degree. In addition, K growth induced a positive and statistically significant impact on GDP growth, with the strongest impact in EC (highly dev.) and weakest impact in WC (least dev.). The empirical outcomes are presented in Table 6.

Table 6

Estimations of the dynamic model of GDP growth

Regressand: GDP growth				
Items	Full data set	EC (highly dev.)	CC (moderately dev.)	WC (least dev.)
Regressors				
Lagged level of GDP	-0.899*** (0.277)	-0.731*** (0.200)	-0.852** (0.294)	-0.898** (0.310)
UBA	0.135*** (0.033)	0.146*** (0.041)	0.117*** (0.036)	0.081** (0.028)
CE growth	-0.208*** (0.054)	-0.229*** (0.059)	-0.201** (0.069)	-0.136** (0.047)
HE growth	0.130*** (0.037)	0.141** (0.049)	0.113** (0.039)	0.074*** (0.020)
K growth	0.426*** (0.094)	0.493*** (0.104)	0.386*** (0.105)	0.219*** (0.061)
Diagnostic tests				
Hansen test (p-value)	0.735	0.574	0.839	0.984
AR (1) test (p-value)	0.028	0.001	0.041	0.050
AR (2) test (p-value)	0.613	0.362	0.593	0.271
No. of observations	551	209	152	190
Provincial units	29	11	8	10

Notes: EC: eastern China, **CC:** central China, **WC:** western China, **UBA:** urban agglomeration, **GDP:** gross domestic product, **CE:** carbon emissions, **HE:** health expenditures, **K:** physical capital, **AR:** auto-regressive, **P-value:** probability value. *** indicates $p < 0.01$, ** indicates $p < 0.05$. Brackets ( ) contain the values of robust standard errors.

4.4. The dynamic model of carbon emissions growth

In the estimated dynamic model of carbon emissions growth, the linear variable of UBA induced positive and statistically significant impact, while the squared form variable of UBA imparted a negative and statistically significant impact on CE growth. The elasticity coefficients of UBA in linear form are given as 0.184 (full data set), 0.199 (EC), 0.175 (CC), 0.102 (WC). Whereas, those of UBA in the squared form is given as -0.092 (full data set), -0.106 (EC), -0.075 (CC), and -0.062 (WC). For both linear and squared form variables, UBA showed the strongest impact in EC (highly dev.) and weakest impact in WC (least dev.). This is called *"development level-based emissions curtailment impact of urban agglomeration"* (Fig. 4). It implies that urban agglomerations in relatively more developed regions curtail carbon emissions relatively more aggressively, perhaps because of using more energy-efficient technologies or making use of smart buildings (Menegaki and Tugcu, 2018). Moreover, the environmental management systems have vital role to play in the emissions reduction in both urban and rural areas (Ikram et al. 2019). Contrariwise, relatively less developed regions curtail carbon emissions relatively less efficiently, perhaps because of using relatively less energy-efficient techniques in households and transport systems. Next, GDP growth in linear form contributed positively to carbon emissions growth, whereas it extended negative contribution in squared form for all the samples. Its elasticity coefficients in the level form are observed as 1.027 (full data set), 1.147 (EC), 1.003 (CC), and 0.815 (WC). While its elasticity coefficients for squared form variable are estimated as -0.198 (full data set), -0.209 (EC), -0.183 (CC), and -0.150 (WC). It revealed the strongest impact in EC (highly dev.) and weakest impact in WC (least dev.). This is termed as *"development level-based emissions curtailment impact of economic performance"* (Fig. 4). It means relatively more developed regions may spend more of GDP growth on emissions curtailment through the improvement of energy efficiency and switching to clean alternatives (Munasinghe et al., 2017). On the other hand, relatively less developed regions may spend relatively less part of GDP growth on emissions curtailment objectives. After that, HE growth imparted a positive and statistically significant impact on CE growth for all the samples. Its elasticity coefficients are estimated as 0.644 (full data set), 0.710 (EC), 0.619 (CC), and 0.502 (WC). It is obvious that HE growth showed a relatively more strong impact in EC (highly dev.) and relatively less strong impact in WC (least dev.). This is named as *"development level-based emissions boosting impact of health infrastructure"* (Fig. 4). It means health expenditures in relatively more developed regions promote more construction activities of health infrastructure and thus produce relatively more carbon emissions. On the contrary, relatively less developed regions promote relatively fewer construction activities of the health sector and thus bring about relatively fewer emissions. Finally, K growth showed a positive and statistically significant contribution to carbon emissions growth for all the samples, with a more vigorous impact in EC (highly dev.) and less vigorous impact in WC (least dev.). These empirical outcomes can be seen in Table 7.

Table 7
Estimations of the dynamic model of carbon emissions growth

Dependent variable: Carbon emissions growth				
Items	Full data set	EC (highly dev.)	CC (moderately dev.)	WC (least dev.)
Independent variables				
Lagged level of CE	-0.698*** (0.231)	-0.810*** (0.208)	-0.643*** (0.156)	-0.883** (0.304)
UBA	0.184*** (0.044)	0.199*** (0.044)	0.175*** (0.041)	0.102** (0.035)
GDP growth	1.027*** (0.216)	1.147*** (0.266)	1.003*** (0.290)	0.815*** (0.272)
HE growth	0.644*** (0.123)	0.710*** (0.167)	0.619** (0.213)	0.502*** (0.129)
K growth	0.277*** (0.078)	0.301*** (0.096)	0.265*** (0.064)	0.204*** (0.055)
UBA^2	-0.092*** (0.028)	-0.106*** (0.020)	-0.075*** (0.024)	-0.062*** (0.017)
GDP^2	-0.198*** (0.055)	-0.209*** (0.066)	-0.183*** (0.046)	-0.150*** (0.035)
Diagnostic tests				
Hansen test (p-value)	0.812	0.653	0.734	0.846
AR (1) test (p-value)	0.017	0.036	0.049	0.024
AR (2) test (p-value)	0.152	0.458	0.372	0.495
No. of observations	551	209	152	190
Provincial units	29	11	8	10

Notes: EC: eastern China, **CC:** central China, **WC:** western China, **UBA:** urban agglomeration, **GDP:** gross domestic product, **CE:** carbon emissions, **HE:** health expenditures, **K:** physical capital, **AR:** auto-regressive, **P-value:** probability value. *** indicates $p < 0.01$, ** indicates $p < 0.05$. Brackets ( ) contain the values of robust standard errors.

4.5. The dynamic model of health expenditures growth

In the estimated dynamic model of health expenditures growth, UBA induced positive and statistically significant contribution to HE growth for all the samples. Its elasticity coefficients are estimated as 0.118 (full data set), 0.136 (EC), 0.107 (CC), and 0.085 (WC). The estimates revealed that UBA has the most powerful impact in EC (highly dev.) and the least powerful impact in WC (least dev.). This is named as *"development level-based health expenditures boosting the impact of urban agglomeration"* (Fig. 4). It means urban agglomeration in relatively more developed regions promote relatively rapid economic performance, which provides an incentive to the authorities to spend more in the health sector and thus increasing the health expenditures. On the other way around, urban agglomeration in relatively weakly developed regions bring about relatively less rapid economic performance and hence may increase health expenditures with relatively less intensity. Next, GDP growth imparted a positive and statistically significant impact on HE growth for all the given samples. Its impact elasticities are estimated as 0.917 (full data set), 1.002 (EC), 0.861 (CC), 0.725 (WC). Its impact elasticity is with the highest magnitude in EC (highly dev.) and lowest in WC (least dev.). This is called *"development level-based health expenditures boosting impact of economic performance"* (Fig. 4). It means developed regions have the incentive to make relatively more expenditures in the health sector than relatively less developed regions. Furthermore, CE growth imparted a positive and statistically significant impact on HE growth, with a relatively more strong impact in EC (0.128), moderate impact in CC (0.80), and relatively less strong impact in WC (0.051). Its impact in the full data set remained less strong than EC but stronger than the other two regions. This is termed as *"development level-based health expenditures boosting impact of carbon emissions"* (Fig. 4). It entails that relatively more developed regions are relatively large emitter of carbon emissions and thus affect the public health. It raises the out-of-pocket health expenditures. This phenomenon is relatively less intense in relatively less developed regions. Finally, K growth imparted a neutral impact on health expenditures growth for all the samples. These empirical outcomes are given in Table 8.

Table 8
Estimations of the dynamic model of health expenditures growth

Dependent variable: Health expenditures growth

Items	Full data set	EC (highly dev.)	CC (moderately dev.)	WC (least dev.)
Independent variables				
Lagged level of HE	-0.764*** (0.185)	-0.780*** (0.219)	-0.813*** (0.248)	-0.725** (0.250)
UBA	0.118*** (0.026)	0.136*** (0.033)	0.107** (0.037)	0.085*** (0.024)
GDP growth	0.917*** (0.188)	1.002*** (0.289)	0.861** (0.297)	0.725*** (0.197)
CE growth	0.093*** (0.026)	0.128*** (0.031)	0.080*** (0.019)	0.051*** (0.016)
K growth	0.140 (0.095)	0.232 (0.124)	0.078 (0.039)	0.119 (0.056)
Diagnostic tests				
Hansen test (p-value)	0.731	0.846	0.759	0.866
AR (1) test (p-value)	0.029	0.041	0.013	0.008
AR (2) test (p-value)	0.711	0.318	0.302	0.382
No. of observations	551	209	152	190
Provincial units	29	11	8	10

Notes: EC: eastern China, **CC:** central China, **WC:** western China, **UBA:** urban agglomeration, **GDP:** gross domestic product, **CE:** carbon emissions, **HE:** health expenditures, **K:** physical capital, **AR:** auto-regressive, **P-value:** probability value. *** indicates $p < 0.01$, ** indicates $p < 0.05$. Brackets ( ) contain the values of robust standard errors.

4.6. Diagnostic tests

For the estimated models, diagnostic checks, including the Hansen test and AR test, are estimated to confirm the appropriateness and accuracy of the estimated results. In this regard, the Hansen test validated that the instruments used are appropriate. Further, AR (1) test showed the existence of serial correlation of errors, whereas AR (2) test confirmed that the findings are robust as the estimated errors revealed no serial correlation for this test. Therefore, the estimated empirics are robust and accurate in terms of implications based on those estimates. These statistical outcomes are given in the bottom panels of Table 5-8.

4.7. Derived causal links

A summary of derived causal links is depicted in Fig. 5. First, a bidirectional positive causal link existed health expenditures and economic performance. This is perhaps because a high level of health expenditures improves public health, which makes their working efficiency better. As a result, they extend more contribution to the economy and promote economic performance. On the other way around, regions with high economic performance have the incentive to enhance public health expenditures. This is consistent with the real scenario of the world economies. For instance, the United States ranks first in both economic growth and health expenditures (WDI, 2018). Contrastingly, the countries with low levels of development, such as Afghanistan, Burundi, and Burkina Faso, have poorly developed healthcare institutions and have their health spendings are also very low (WDI, 2018). In eight OECD countries, including Denmark, Ireland, Iceland, Austria, Norway, Switzerland, United Kingdom, and Spain, Narayan and Narayan (2007) uncovered a positive contribution of economic progress on health spending. Contrarily, Tandon et al. (2020) revealed that the public expenditures on health disproportionately increased in countries with low and middle income. Second, there existed a bidirectional positive causal link between urban agglomeration and economic performance. It posited that a high level of urban agglomeration increases economic activity and thus leads to high economic performance. On the other side, boosted economic performance means the promotion of industrial activities that need a workforce. Therefore, it may attract people to move towards urban primacies and thus promoting urban agglomeration. This finding coincides with those of Ahmad et al. (2019) and Ahmad and Jabeen (2019) in the context of Chinese provinces. They found that both economic growth and urbanization proved to be strong drivers of each other.

Third, a bidirectional positive causal link operated between health expenditures and carbon emissions. It means enhanced health expenditures to finance health infrastructure may increase carbon emissions as it involves construction-based activities. Contrarily, skyrocketed level of carbon emissions creates health hazards and may impact public health, which may increase the health expenditures. In this regard, Weisz et al. (2020) estimated the carbon footprint of the health industry of Australia. They found that around 14 percent of the carbon footprint declined in the Australian health industry associated with the use of renewables in the health industry. Fourth, there existed a bidirectional positive causal link between urban agglomeration and health expenditures. It revealed the scenario that enhanced urban agglomeration may support advanced health facilities and thus may escalate the health expenditures. On the flip side, more health expenditures may imply government investment in the health infrastructure. Better health facilities may promote rural-urban migration and thus giving support to urban agglomeration. In their work, Rehman et al. (2020) added that the population increased the carbon emissions in the transport sector in Pakistan and thus substantially added to the environetnal degradation. In contrast to the finding of this research, Friedson and Li (2015), using the FAIR health database, revealed that increased agglomeration of hospitals in the urban regions reduces the health expenditures due to the reduced cost of laboratory testing facilities.

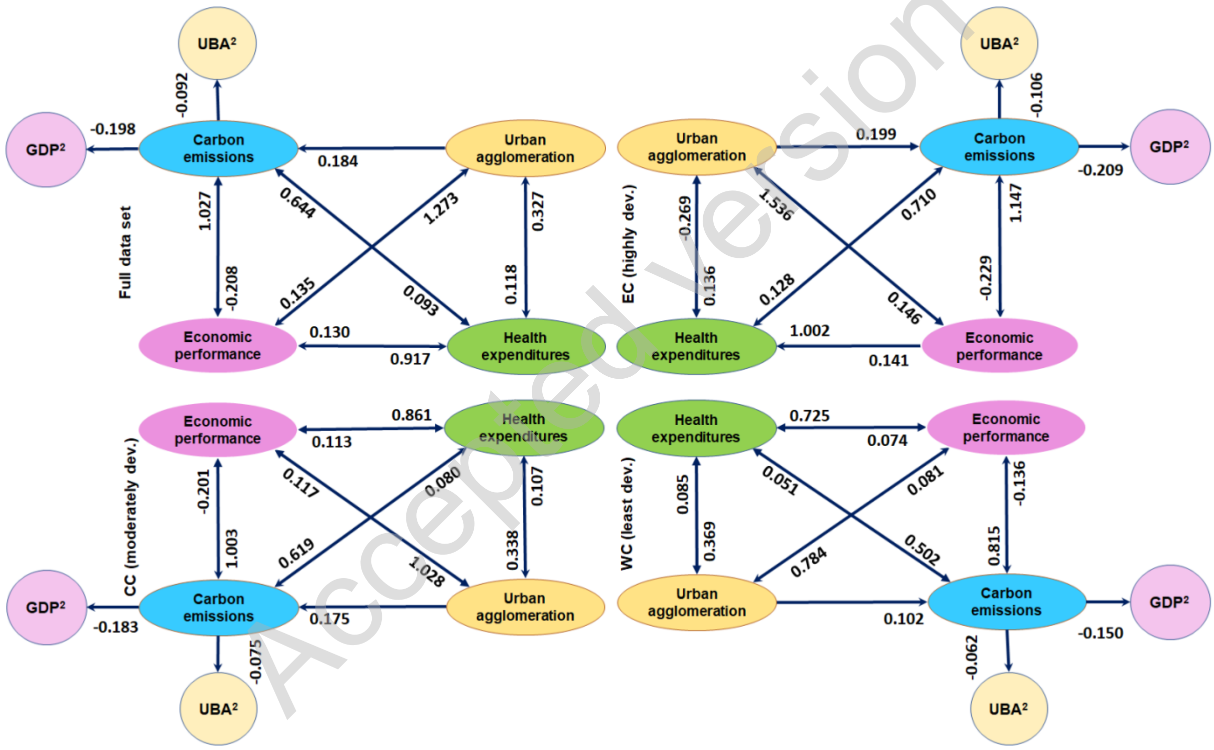

Fig. 5. Empirics-based contributions among urban agglomeration, economic performance, carbon emissions, and health expenditures.

Note: GDP: gross domestic product, **UBA:** urban agglomeration.

Fifth, there existed a unidirectional mixed causal link from urban agglomeration to carbon emissions. In this sense, the linear form of urban agglomeration established a positive link, while the squared term of urban agglomeration formed a negative link. The total impact of urban agglomeration is carbon emissions curtailment. It means that at a low level of development, urban agglomeration may add to carbon emissions, but for a high level of development, it may curtail emissions. It implies that a high level of urban agglomeration promotes economic performance, which may curtail carbon emissions. In this context, Bakirtas and Akpolat (2018) revealed a unidirectional causality emerging from urbanization to energy use from the perspective of emerging economies of Indonesia, Colombia, Kenya, Mexico, India, and Malaysia. Furthermore, Mendonça et al. (2020) estimated the impact of linear form population on carbon emissions in 50 greatest countries worldwide. They found the positive impact of the former on the latter. In the case of Canada and Australia, Rahman and Vu (2020) found the driving impact of the urban population on carbon emissions in the long-run. They further unveiled that post-Kyoto ratification in 2002 and 2007, Australia carbon emissions met declining trends; nevertheless, Canada failed to induce the mitigation effects. While studying global countries, Wang et al. (2020) unmasked that the boosted level of urban population was adding to the emissions in African countries without affecting their economic progress. Additionally, they interestingly found an insignificant difference in the impact of urbanization on those emissions in the Caribbean and Latin American economies. They argued that it was because of the negligible difference between urban and rural domestic energy use. Finally, also a unidirectional mixed causal link is found running from economic performance to carbon emissions. It this context, linear form GDP growth established a positive link with carbon emissions, whereas the squared term of GDP growth formed a negative link. It also supported the existence of the Environmental Kuznets Curve hypothesis. It suggests that the economic performance of regions at a low level of development promotes carbon emissions. Contrarily, the economic performance of regions at a high level of development curtails those hazardous emissions to promote environmental sustainability in terms of improving the environmental quality. This finding verified that of Boubellouta and Kusch-Brandt (2020) in European countries, which are well developed.

Their work found the presence of e-waste-based EKC in those countries. But, the results of this research did not align with those of Moutinho et al. (2020) in OPEC economies. They revealed a U-shaped curve and thus did not confirm the existence of EKC in those economies. Moreover, Ikram et al. (2020) found that India remained the strongest emitter of carbon emissions among the SAARC[6] economies. Besides, for the eight Australian territories, Churchill et al. (2020) found the same findings as this work found for the carbon emission-based EKC in the developed regions. Contrariwise, Pontarollo and Serpieri (2020) ended up with non- the existence of build-environment based EKC in 42 counties of Romania.

4.8. Policies, limitations, and future works

From empirical outcomes, it is inferred that a high level of health expenditures would reinforce rural-urban migration to enhance the urban agglomeration. This is because people respond to urban health facilities and thus move towards megacities. Another possible dimension is the health infrastructure spending by the government, which would attract the rural workforce towards cities to find employment and thus boosting the urban economic performance. This scaling-up of economic performance would provide an incentive to adopt sustainable production methods to mitigate hazardous emissions like carbon emissions. In return, emissions mitigation would implicate the mitigation of health risks and deliver a healthy and efficient workforce to the economy. It would not only further boost the economy but would also reduce the personal or out-of-pocket health spending. To sum up, this research suggests the reinforcement of health expenditures by the government. Furthermore, the policy impact across developmental disparities would be highly (moderately/least) powerful in highly (moderately/least) developed regions.

There are certain limitations of this work that shall be incorporated by the future works in this domain. Firstly, since the panel data series might not always have cross-sectional

[6] South Asian Association for Regional Cooperation

independence and slope homogeneity, their presence may bias the parameter estimates of the models. However, the GMM only allows the endogeneity and cannot incorporate both slope heterogeneity and cross-sectional dependence. Therefore, future works shall opt for the estimation method robust to these issues, along with the endogeneity problem. Secondly, the variable of the urban agglomeration was measured by the urban population proportion of the total population of the provinces. Nevertheless, it may not capture the full dynamics of the agglomeration effects. Therefore, future studies should also incorporate the area of urban land and urban population density to provide more comprehensive findings. Finally, this research used the variable of total health expenditures. The future research works should include the public health expenditures and out-of-pocket health expenditures to provide their comparative impacts.

5. Conclusions

This work developed a health expenditures-augmented growth model to introduce health expenditures and carbon emissions as a shift factor of total factor productivity. A block of simultaneous equations is developed based on the health expenditures-augmented growth model. A long-run cointegration is found among the variables by employing the Pedroni cointegration test. Two variants of the Generalized Method of Moments are employed to estimate the block of four simultaneous equations, in order to deal with potential endogeneity of the variable used. The main findings of this research are as follows. First, there is evidence of the long-run cointegrating equilibrium association among the variables of research. Second, the urban agglomeration exhibits bidirectional causal linkage with GDP growth and health expenditures growth. Third, health expenditures growth demonstrates bidirectional positive causal linkage with carbon emissions growth and GDP growth. Fourth, a unidirectional mixed causal linkage—positive for a linear form of urban agglomeration, and negative for the squared form of urban agglomeration—exists from urban agglomeration to carbon emissions growth. Fifth, there is a negative causal linkage operating from carbon emissions growth to GDP growth. However, there is mixed causal linkage—positive for a linear form of GDP growth, and negative for the squared form of GDP—operating from GDP growth to carbon emissions growth. These outcomes revealed consistency across developmental disparities in consideration of the type of causal linkages (positive/negative) and thus show robustness. Nevertheless, the findings show disparities in the degree of impact across the developmental disparities. In this regard, the strength of causal linkage is the largest for highly developed, moderate for moderately developed, and lowest for the least developed regions of China.

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Appendix A

Table A.1
Panel data unit root test results.

	Variable	At level				At first difference			
		LLCT		IPST		LLCT		IPST	
		Cons.	Trend	Cons.	Trend	Cons.	Trend	Cons.	Trend
Full data set	UBA	1.162	0.437	3.274	2.917	-10.263	-7.450	-13.274	-11.834
		(0.673)	(0.938)	(0.294)	(0.684)	(0.000)	(0.000)	(0.000)	(0.000)
	GDP growth	2.710	2.481	1.372	1.734	-3.564	-5.357	-8.473	-7.401
		(0.152)	(0.916)	(0.354)	(0.735)	(0.001)	(0.000)	(0.000)	(0.009)
	CE growth	2.939	1.023	4.362	3.286	-4.346	-4.926	-12.992	-8.746
		(0.274)	(0.139)	(0.119)	(0.562)	(0.000)	(0.000)	(0.000)	(0.000)
	HE growth	-1.095	-2.743	-3.282	-3.965	-17.206	-14.360	-10.465	-15.107
		(0.634)	(0.543)	(0.884)	(0.243)	(0.000)	(0.180)	(0.000)	(0.000)
	K growth	1.274	0.928	2.016	0.928	-6.470	-9.035	-5.385	-6.587
		(0.116)	(0.595)	(0.385)	(0.772)	(0.000)	(0.000)	(0.003)	(0.000)
EC (highly dev.)	UBA	2.764	3.291	3.835	4.262	-19.865	-13.574	-10.263	-8.364
		(0.183)	(0.564)	(0.183)	(0.824)	(0.000)	(0.000)	(0.000)	(0.000)
	GDP growth	3.290	4.273	4.723	4.273	-7.947	-6.584	-7.004	-6.480
		(0.645)	(0.223)	(0.129)	(0.538)	(0.000)	(0.000)	(0.000)	(0.000)
	CE growth	1.945	1.682	3.274	2.947	-5.486	-6.005	-9.001	-8.061
		(0.156)	(0.975)	(0.392)	(0.487)	(0.004)	(0.000)	(0.000)	(0.000)
	HE growth	-1.362	-1.765	-2.005	-2.158	-9.306	-9.950	-5.395	-6.018
		(0.337)	(0.199)	(0.485)	(0.237)	(0.000)	(0.000)	(0.000)	(0.000)
	K growth	0.953	1.006	1.932	2.459	-11.473	-11.812	-9.075	-9.450
		(0.128)	(0.366)	(0.652)	(0.264)	(0.000)	(0.000)	(0.000)	(0.000)
CC (moderately dev.)	UBA	1.274	2.483	0.994	1.332	-15.302	-16.835	-11.638	-10.284
		(0.648)	(0.284)	(0.170)	(0.284)	(0.000)	(0.000)	(0.000)	(0.000)
	GDP growth	4.320	3.947	2.429	3.001	-17.058	-14.360	-8.007	-7.380
		(0.177)	(0.260)	(0.248)	(0.190)	(0.000)	(0.000)	(0.000)	(0.000)
	CE growth	2.129	3.009	1.574	1.340	-10.043	-9.208	-13.294	-11.515
		(0.189)	(0.216)	(0.368)	(0.246)	(0.000)	(0.000)	(0.000)	(0.000)
	HE growth	-0.932	-1.002	-1.076	-1.362	-6.781	-7.995	-9.574	-9.965
		(0.125)	(0.198)	(0.382)	(0.756)	(0.000)	(0.000)	(0.000)	(0.000)
	K growth	1.382	1.927	0.485	0.857	-18.493	-18.068	-4.695	-5.035
		(0.245)	(0.136)	(0.174)	(0.293)	(0.000)	(0.000)	(0.002)	(0.000)
WC (least dev.)	UBA	2.184	2.902	1.372	1.946	-18.320	-16.906	-7.481	-6.906
		(0.736)	(0.653)	(0.284)	(0.295)	(0.000)	(0.000)	(0.000)	(0.000)
	GDP growth	1.785	1.475	2.048	2.676	-11.602	-11.879	-8.574	-5.375
		(0.257)	(0.210)	(0.185)	(0.579)	(0.000)	(0.000)	(0.000)	(0.000)
	CE growth	2.845	2.901	1.958	1.735	-10.048	-11.939	-6.594	-5.027
		(0.184)	(0.463)	(0.384)	(0.372)	(0.000)	(0.000)	(0.000)	(0.000)
	HE growth	-0.495	-0.997	-0.910	-1.012	-8.974	-6.690	-9.486	-8.501
		(0.865)	(0.120)	(0.623)	(0.180)	(0.000)	(0.004)	(0.000)	(0.000)
	K growth	0.988	0.725	1.337	1.264	-9.185	-10.009	-10.792	-5.302
		(0.493)	(0.522)	(0.279)	(0.945)	(0.000)	(0.000)	(0.000)	(0.003)

Notes: EC: eastern China, **CC:** central China, **WC:** western China, **UBA:** urban agglomeration, **GDP:** gross domestic product, **CE:** carbon emissions, **HE:** health expenditures, **K:** physical capital. **LLCT:** Levin-Lin-Chu test, **IPST:** Im, Pesaran, Shin test, **Cons.:** constant. Brackets ( ) contain the probability values.

Table A.2
Pedroni's panel cointegration test results.

Pedroni cointegration-based tests				
Model	Sample	Type of test	Within-dimension	Between dimension
UBA	Full data set	PP-statistic	-1.97[c]	-1.64[c]
		ADF-statistic	-2.15[c]	-1.78[c]
	EC (highly dev.)	PP-statistic	-3.08[b]	-2.91[b]
		ADF-statistic	-2.86[b]	-2.23[c]
	CC (moderately dev.)	PP-statistic	-3.77[a]	-3.80[a]
		ADF-statistic	-3.13[b]	-2.52[b]
	WC (least dev.)	PP-statistic	-1.82[c]	-2.63[b]
		ADF-statistic	-2.10[c]	-3.19[b]
GDP growth	Full data set	PP-statistic	-3.45[b]	-3.27[b]
		ADF-statistic	-3.99[a]	-4.01[a]
	EC (highly dev.)	PP-statistic	-3.65[a]	-3.71[a]
		ADF-statistic	-1.92[c]	-1.68[c]
	CC (moderately dev.)	PP-statistic	-3.31[b]	-2.97[b]
		ADF-statistic	-3.50[a]	-3.74[a]
	WC (least dev.)	PP-statistic	-2.28[c]	-2.17[c]
		ADF-statistic	-3.95[a]	-4.12[a]
CE growth	Full data set	PP-statistic	-2.89[b]	-3.01[b]
		ADF-statistic	-3.56[a]	-3.95[a]
	EC (highly dev.)	PP-statistic	-3.76[a]	-3.63[a]
		ADF-statistic	-2.55[b]	-2.69[b]
	CC (moderately dev.)	PP-statistic	-3.07[b]	-3.20[b]
		ADF-statistic	-3.91[a]	-4.12[a]
	WC (least dev.)	PP-statistic	-2.18[c]	-2.29[c]
		ADF-statistic	-3.40[b]	-3.26[b]
HE growth	Full data set	PP-statistic	-3.59[a]	-4.00[a]
		ADF-statistic	-3.33[b]	-3.15[b]
	EC (highly dev.)	PP-statistic	-3.24[b]	-2.96[b]
		ADF-statistic	-3.75[a]	-3.57[a]
	CC (moderately dev.)	PP-statistic	-2.99[b]	-2.86[b]
		ADF-statistic	-3.61[a]	-3.83[a]
	WC (least dev.)	PP-statistic	-2.85[b]	-2.90[b]
		ADF-statistic	-1.99[c]	-2.16[c]
K growth	Full data set	PP-statistic	-4.09[a]	-3.76[a]
		ADF-statistic	-3.47[b]	-3.21[b]
	EC (highly dev.)	PP-statistic	-2.98[b]	-2.55[b]
		ADF-statistic	-1.97[c]	-2.41[c]
	CC (moderately dev.)	PP-statistic	-3.64[a]	-3.53[a]
		ADF-statistic	-2.48[c]	-2.71[b]
	WC (least dev.)	PP-statistic	-4.11[a]	-3.87[a]
		ADF-statistic	-3.58[a]	-3.96[a]

Notes: EC: eastern China, **CC:** central China, **WC:** western China, **UBA:** urban agglomeration, **GDP:** gross domestic product, **CE:** carbon emissions, **HE:** health expenditures, **K:** physical capital. **PP:** Philip-Perron, **ADF:** Augmented Dicky-Fuller. [a] indicates probability < 0.001, [b] indicates probability < 0.01, [c] indicates probability < 0.05.

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