Optimizing Resource Allocation for Regional Employment Governance: A Dynamic Fuzzy-Set QCA Analysis of Low-Carbon Pilot Cities in China

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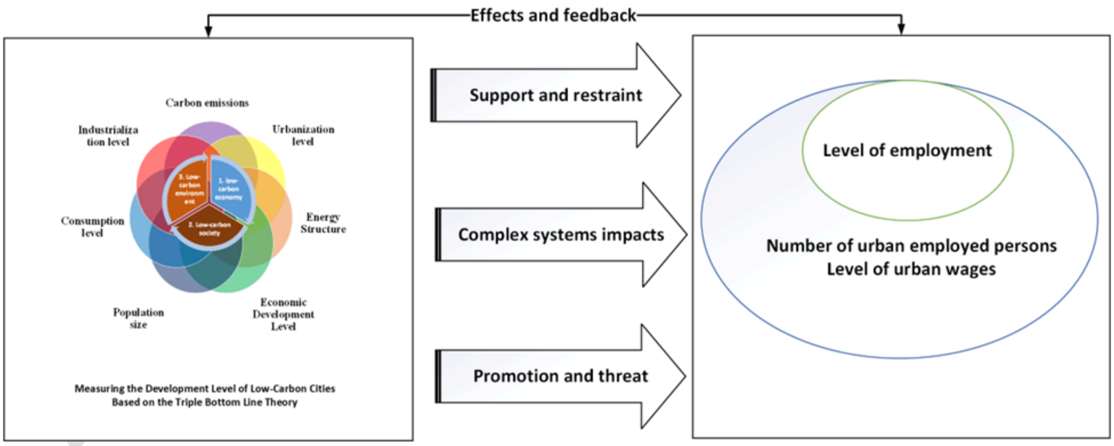
Graphical abstract



Abstract

This study employs a dynamic fuzzy-set qualitative comparative analysis (fsQCA) approach, utilizing panel data from 121 low-carbon pilot cities in China from 2007 to 2019. Grounded in complex systems theory and the triple bottom line framework (Economy-Society-Environment), the research aims to optimize resource allocation to enhance regional employment governance performance. The key findings include that the initial implementation of low-carbon policies resulted in a short-term decline in employment levels, with minimal long-term impact on overall employment figures but a significant effect on high-level urban wages. Significant disparities in employment levels were observed among pilot cities, driven by regional population sizes and economic development levels. Four development models for low-carbon cities were identified: human resources-driven, energy transition-driven, industrial cluster-driven, and comprehensive factor-driven models. These models provide strategic pathways for promoting low-carbon urban development and enhancing employment. The findings offer valuable insights into governance strategies for China's low-carbon pilot cities, facilitating the context-specific promotion of sustainable urban development and improved employment opportunities.

Keywords: Dynamic fsQCA；Employment governance；Low-carbon pilot cities；Resource allocation；Sustainable urban development

Highlights:

1. Developed a comprehensive evaluation system combining complex systems theory and the triple bottom line framework.
2. Explored the complex relationship between low-carbon urban transformation and employment levels.
3. Dynamic fsQCA was used to examine temporal and spatial disparities.
4. Findings reveal heterogeneous short-term and long-term impacts of low-carbon policies on employment.
5. Identified four unique development models for low-carbon cities.

Abbreviations table：

Full Forns	Abbreviatlons
Industrialization Level	IND
Energy Structure	ENE
Economic Development Level	ECO
Population Size	POP
Consumption Level	CON
Carbon Emissions Decline	CAR
Number of Urban Employed Persons	EMP
Level of Urban Wages	WAG
fuzzy-set Qualitative Comparative Analysis	fsQCA

1.Introduction

China is urgently addressing global warming as the world's second-largest economy and the largest carbon emitter (Chen et al., 2024). However, China's past development model, which relied on resource-intensive consumption and cheap labour, has exacerbated conflicts between humans and nature despite generating material wealth(Xue et al., 2022). China faces one of the most severe environmental challenges globally(Wolf et al., 2022). These issues indicate that China's economic sustainability can no longer rely on large-scale resource consumption, and the development of low-carbon cities has become an inevitable trend for high-quality, sustainable development(Di et al., 2023).

Since 2010, China's National Development and Reform Commission has initiated the first batch of national-level low-carbon province and city pilot projects, releasing the second and third batches of pilot city lists in 2012 and 2017 (Li et al., 2018). To better achieve carbon peak targets, China continuously explores decarbonization approaches at the city level (Shan et al., 2022). Low-carbon pilot cities actively explore green and low-carbon development models and paths suitable for their conditions, providing demonstrations and experiences for the low-carbon development of Chinese cities(L. M. Chen et al., 2023; W. Chen et al., 2023).

However, the development of low-carbon cities constitutes a comprehensive and profound systemic transformation of economic and social systems (Wang et al., 2018), inevitably impacting various domains such as investment, production, circulation, and consumption (Raff et al., 2019). In this transformation process, employees across multiple sectors must face adjustments, competition, and elimination regarding job positions and work methods (Crato & Paruolo, 2019). Therefore, an important and urgent question is how China's ongoing development of low-carbon cities can achieve carbon reduction goals while ensuring employment stability (Mathiesen et al., 2011). Existing research indicates that elucidating the complex relationship between low-carbon city development and employment is not straightforward (Maslach et al., 2001; Mathiesen et al., 2011). Some studies suggest that developing low-carbon cities results in significant layoffs within highly energy-intensive and polluting industries, restraining employment opportunities (Pearl-Martinez et al., 2016).

Conversely, other findings indicate that the trend towards low-carbon economic and societal transformation could guide or compel companies to engage in clean production, thus creating opportunities for green employment (Wang et al., 2021). Furthermore, research points out differing short-term and long-term effects of low-carbon city development on employment (Ren et al., 2020). Research on developing low-carbon cities in China primarily focuses on assessing their economic and environmental impacts. More literature is needed to examine the social effects, and even fewer studies are required to investigate the influence of low-carbon city pilot policies on employment(Ren et al., 2020).

Against this backdrop, this study will focus on the impact of China's low-carbon city pilot policies on employment, aiming to delve into the complex configurational relationships between low-carbon urban development and employment This paper addresses the following questions: What is the mechanism linking the development of low-carbon cities with employment levels? Over time, are there differences in the impact of developing low-carbon cities on employment levels in the short term versus the long term? In spatial terms, do different types of low-carbon cities have varying effects on employment levels? This paper attempts to expand the existing literature in three aspects: Firstly, this paper employs a complex systems configurational analysis approach to delve into the impact of low-carbon city transformation on regional employment levels. This method offers a new theoretical perspective to the field, aiming to uncover results that are challenging to obtain through traditional econometric methods. Through dynamic fuzzy-set Qualitative Comparative Analysis (fsQCA) methods, this paper seeks to reveal insights beyond what can be obtained through conventional statistical analysis, offering a fresh research perspective on a comprehensive understanding of the impact of low-carbon city transformation on regional employment levels. Secondly, this paper not only focuses on the impact of low-carbon city transformation on employment but also delves into the underlying theoretical mechanisms.

Drawing from resource allocation theory, the research identifies 11 configurations and four adaptation models for achieving high-level regional employment, elucidating the differences in employment levels among low-carbon pilot cities. This in-depth theoretical analysis contributes to a deeper understanding of the driving paths and mechanisms through which the development of low-carbon cities affects regional employment levels. Finally, to ensure the reliability of research results, this paper employs enhanced standard analysis and the Tibot panel model to validate the configurational analysis results. This step further enhances the credibility of the research, indicating that the results are robust.

This paper provides new theories and methods for the research field of low-carbon city transformation and regional employment levels through the perspective of complex systems configurational analysis, in-depth theoretical mechanism analysis, and reliability validation of results. It contributes to a deeper understanding of the complex relationship between low-carbon urban development and employment levels and offers more targeted policy recommendations. The paper consists of seven main sections: introduction, theoretical framework, research methods and data sources, analysis of research results, robustness tests, discussion , and conclusion.

2.Literature review

2.1 Literature on the effect of environmental regulation on employment

How does environmental regulation affect employment? Scholars hold varying viewpoints on this issue(Berman et al., 2001). Firstly, assessments of the impact of environmental regulation on overall economic employment have revealed complexity(Lahteenmaki-Uutela et al., 2021). Researchers(Goodstein & Polasky, 2017), based on a review of large-scale macroeconomic models, found that out of nine studies, seven indicated that employment would increase, one showed a decrease, and one had mixed effects. The conclusions drawn from these nine studies suggest that while environmental regulation does have some impact on employment, the magnitude of this impact is not substantial. On the other hand, Hazilla and Kopp (Hazilla & Kopp, 1990), as well as general equilibrium assessments by Jorgenson and Wilcoxen(Jorgenson & Wilcoxen, 1990), operate under the assumption of full employment, where labour demand equals labour supply. Consequently, Palmer often conclude that environmental regulations reduce job opportunities(Palmer et al., 1995). However, these models typically overlook underemployment situations, where individuals might voluntarily reduce work hours or choose to be unemployed(Crato & Paruolo, 2019). In practice, according to surveys conducted by the U.S. Department of Labor, environmental regulations only result in the reduction of approximately 650 related jobs per year, less than one-tenth of one per cent of all significant layoffs in the United States.

Furthermore, research into the impact of environmental regulations on specific industries reveals diversity in findings(Guo & Yuan, 2020). Some early studies suggested (Song et al., 2021)that the electricity sector experienced significant job losses as environmental regulations increased. However, recent research indicates that even when considering factors like inducements for factories to exit or deterring new factories(Cai et al., 2020), there is no evidence suggesting that environmental regulations reduce labour demand(Du et al., 2021). A study focused mainly on refineries in the Los Angeles area found that the impact of environmental regulations on employment might be minimal. It may increase employment. An additional explanation for the limited effect on employment, as demonstrated in the empirical study by Stern(Stern et al., 2001), is that environmental regulations target industries with relatively fewer jobs, which are capital-intensive. Industries such as refineries(Morgenstern et al., 2002), chemicals, cement, transportation, and other heavy industries are energy-intensive (Napp et al., 2014) . For capital-intensive industries like pulp and paper (Hafstead & Williams III, 2018), the price elasticity of industry demand is significantly lower than that of product demand(Sheng et al., 2019). Suppose all firms in the industry face similar cost-increasing regulatory changes, and product demand is inelastic. In that case, the individual firm's output may only experience a slight decrease due to environmental regulations(Liu et al., 2018). In such a scenario, the negative impact on employment from the output elasticity of labour demand is likely dominated by the positive effect of technological innovation and marginal technical substitution rates between labour, leading to a net increase in employment due to regulation(Morgenstern et al., 2002).

Moreover, based on the Porter hypothesis(Porter & Linde, 1995), an increasing number of researchers have found that when the market competition environment becomes more intense and uncertain, some firms tend to increase their research and development (R&D) investments and generate more innovations (Qingbin et al., 2017). This has received support from several empirical studies (Pearl-Martinez et al., 2016). However, some scholars (Voytenko et al., 2016) emphasize that production factors are, to some extent, "trapped," meaning they cannot freely flow between firms or industries in the short term. This implies that when facing adverse shocks, firms have limited ability in the short term to respond by changing factor inputs or exiting the market. Firms must adapt by innovating in production technology or management practices(Di, Chen, Shi, Cai, & Zhang, 2024) . As firm-level innovation carries positive externalities, adverse macroeconomic shocks may, under specific conditions, enhance firm-level productivity and promote long-term overall economic growth.

Scholars have previously investigated the impact of environmental regulations on employment using econometric methods. They often employ techniques such as difference-in-differences or other econometric models to analyze data, aiming to derive comparisons and causal inferences to understand better how environmental regulations affect employment. However, recent scholars believe that the impact of environmental regulations on employment is a complex and diverse issue, requiring comprehensive consideration of multiple factors.

2.2. Literature on Low-carbon city construction

Since the initiation of the first batch of low-carbon city pilot policies in China in 2010, scholars have conducted in-depth research into various impacts of this policy. Research in this area encompasses theoretical aspects, such as the concept(Yang et al., 2013), framework(Khanna et al., 2014), policies(Voytenko et al., 2016), and public participation related to low-carbon cities, as well as empirical aspects(Yu & Zhang, 2021), with a primary focus on assessing the environmental and economic effects of low-carbon pilot city policies (Pan et al., 2022).

When assessing the environmental effects of the low-carbon city pilot policies, some studies have analyzed their impact on Green Total Factor Energy Efficiency (GTFEE) and carbon emissions (Wen et al., 2022). For instance, Some scholars(Gao et al. 2022)utilized city-level data from 2006 to 2019 and employed the Difference-in-Differences (DID) method to investigate the effects of low-carbon city policies on urban Green Total Factor Energy Efficiency (GTFEE) and its underlying mechanisms. Their research found that these policies significantly enhance urban GTFEE. On the other hand, certain studies in the literature have explored the impact of low-carbon city pilot policies on carbon emissions efficiency (CO_2) (Liu et al., 2022).

When assessing the economic effects of the low-carbon city pilot policies, some scholars (Song et al., 2020) have examined their impact on total factor productivity at the city and enterprise levels. Chen, based on data from listed companies between 2005 and 2019, found that the low-carbon city pilot policies primarily promoted the improvement of enterprise total factor productivity through technological innovation and optimizing resource allocation efficiency(Chen et al., 2021). Another study by Wang employed a Difference-in-Differences (DID) model, identifying the positive impact of the low-carbon economic policies implemented in China in 2012 on urban Green Total Factor Productivity (GTFP) and explaining its transmission mechanism(Wang et al., 2023).

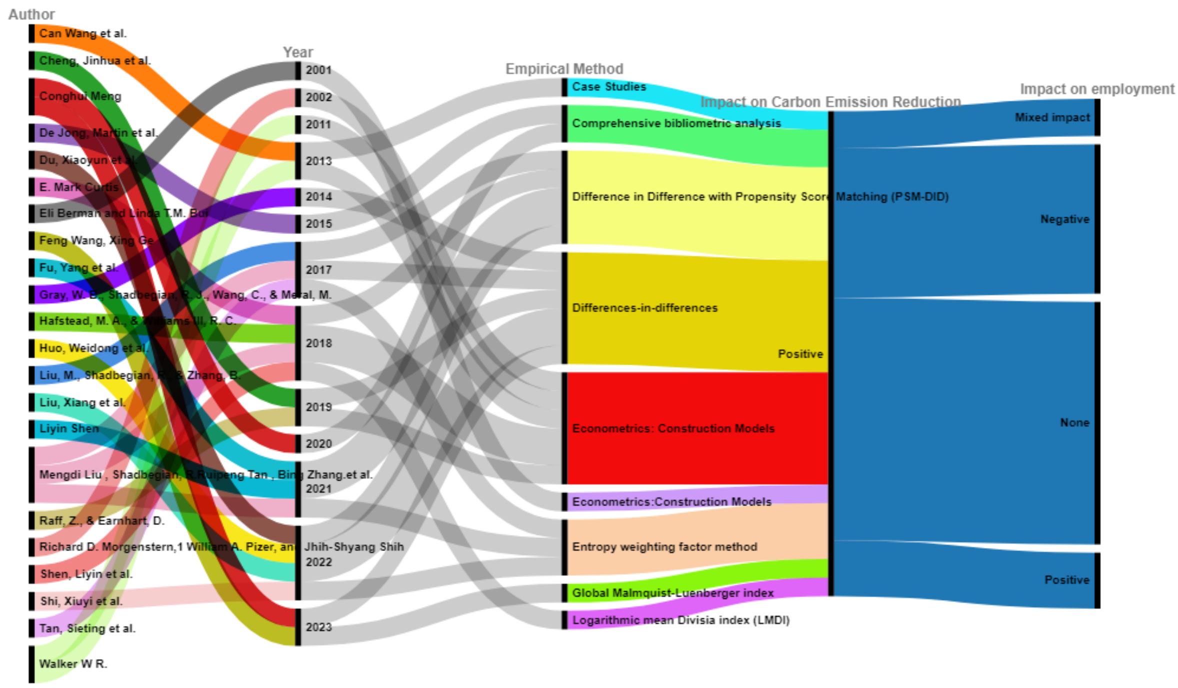
While there is a considerable body of research on the impact of environmental regulations on employment (Refer to Figure 1), these studies typically rely on the paradigm of traditional econometrics(Gilli & Winker, 2009), focusing primarily on the linear relationship between environmental regulations and labour demand(Marin & Mazzanti, 2013). So far, more research needs to be done from the perspective of complex configurations to delve into the intricate relationship between environmental regulations and employment. Therefore, this paper aims to enrich this research field by employing dynamic fsQCA methods, focusing on the multifaceted causal relationships, causal asymmetry, and various complexities in the relationship between low-carbon pilot cities and regional employment levels.

It is essential to emphasize that, despite existing literature evaluating the impacts of low-carbon city pilot policies, most of this research has concentrated on assessing the policy's environmental and economic effects, lacking a comprehensive evaluation of its social impacts, and particularly, its impact on employment(Moss et al., 2010). However, employment is pivotal in achieving high-quality and sustainable development in China's economic and social stability. Hence, the significance of this study lies in filling this research gap, contributing to a more holistic understanding of the impact of low-carbon city pilot policies, and providing robust support and recommendations for policy formulation.***2.3. Gaps in the literature***Although existing studies have evaluated the impact of low-carbon city pilot policies from a broader literature perspective, most have focused on their environmental and economic effects, needing a comprehensive assessment of their social impacts, particularly on employment. However, employment is crucial to China's economic and social stability and achieving sustainable development. Therefore, the significance of this study lies in filling this research gap, comprehensively and profoundly understanding the impact of low-carbon city pilot policies, and providing vital support and recommendations for relevant policy formulation.

In developed countries, the impact of environmental regulations on employment has been a long-standing and widely studied topic. Academia holds diverse perspectives on the influence of environmental regulations on employment. Studies have shown that environmental regulations' impact on employment is insignificant and varies across different industries. Although some sectors may be affected, others may only experience minor impacts or even see a slight increase in employment. Additionally, environmental regulations stimulate corporate innovation, potentially generating positive long-term employment effects. Currently, numerous scholars employ econometric methods, such as difference-in-differences or other quantitative models, to study the impact of environmental regulations on employment. These methods aid in obtaining comparisons and causal inferences from data, providing a clearer understanding of the impact of environmental regulations on employment. However, recent research has recognized the complexity and diversity of the impact of environmental regulations on employment, necessitating a comprehensive consideration of multiple factors.

In contrast, for developing countries like China, the impact of low-carbon city development on employment is more significant and intricate. Against rapid industrialization and urbanization, China faces pressures to accelerate sustainable development and address environmental challenges. Therefore, developing low-carbon cities aims to reduce carbon emissions and improve environmental quality. It is also perceived as a significant economic opportunity, potentially creating new employment opportunities in the job market. Academic attention on low-carbon city development in China typically revolves around theoretical aspects, such as conceptual frameworks, policies, public participation, and empirical research evaluating environmental and economic impacts.

Existing research primarily employs traditional econometric paradigms (as shown in Figure 1), focusing on the linear relationship between environmental regulations and labour demand, lacking in-depth exploration of the intrinsic connections between ecological regulations and employment from the perspective of complex configurations. Therefore, this paper will utilize the dynamic fuzzy-set Qualitative Comparative Analysis (fsQCA) method, focusing on the multi-factor causal relationships, causal asymmetry, and other complexities between low-carbon pilot city policies and regional employment levels, thereby enriching this research field. By filling this gap in the existing literature, this study contributes to a comprehensive and in-depth understanding of the impact of low-carbon city pilot policies. It provides solid theoretical support and practical policy recommendations for relevant policy formulation.**Figure 1. A bibliometric chart**



3. Theoretical Mechanism

Urban low-carbon transformation is a complex systematic project that requires careful consideration of multiple objectives, including economic, social, and environmental goals(De Boer et al., 2016) . The Triple Bottom Line (TBL) framework proposed by Elkington (Elkington, 1998) provides theoretical support, suggesting that a low-carbon economy, society, and environment form a dynamic and complex system. This study explores how various key indicators under these three dimensions affect regional employment levels using the dynamic fuzzy set qualitative comparative analysis (dynamic fsQCA) method (as illustrated in the Graphical abstract).

Firstly, the concept of a low-carbon economy emphasizes a transition from traditional industrialization to more environmentally friendly and sustainable industrialization(Grossman & Krueger, 1991). This includes adjusting the energy structure, improving energy efficiency, and developing green industries. At this level, it is essential to consider urban economic growth, optimizing industrial structures, and the sustainable use of energy. Developing a low-carbon economy helps reduce greenhouse gas emissions and promotes urban economic prosperity. There is a close relationship between industrial structure, urbanization level, and emission reduction, which is also tightly linked to economic growth. As income levels rise, these factors change significantly, profoundly influencing urban economic structures. In this trajectory, the impact of economic growth on environmental quality shifts from negative to positive. With the continuous strengthening of environmental regulations, the industrial sector gradually adopts more environmentally friendly technologies to meet the growing demand for a cleaner environment while reducing carbon emissions. This stage of progress is known as the technology effect. Meanwhile, the growth rate of the tertiary sector surpasses that of the secondary industry, transitioning the urban economy from capital-intensive to knowledge-intensive. Investment in research and development activities can stimulate economic growth while enhancing environmental management technology, thereby improving environmental quality.

Secondly, building a low-carbon society involves adjusting population size and consumption levels (Peretto & Smulders, 2002). The size of the urban population directly impacts resource utilization and the environment. Promoting low-carbon lifestyles and consumption patterns can reduce resource waste and carbon emissions. A low-carbon society encourages increased attention to environmental protection, sustainable development, and reducing carbon footprints. The impact of economic development level, energy structure, population size, and consumption level on the environment can be divided into three types: scale, technology, and structure effect. As population size, consumption level, and economic development level increase, these factors, in turn, raise regional pollution levels, a phenomenon known as the scale effect. According to neoclassical growth theory, economic growth is driven by human capital and technological innovation. Therefore, the growth of population and consumption levels will lead to the optimization of human capital, economic development level, and energy structure, producing a technological effect that benefits environmental quality.

Moreover, the structure effect is influenced by regional resource distribution and environmental policies. Different cities have comparative advantages in the low-carbon transformation process, such as capital-intensive, labour-intensive, resource-rich, and resource-depleted cities. These cities continuously optimize their economic structures and resource allocation to reduce carbon emissions. Additionally, the policy environment for low-carbon urban transformation is usually stricter, potentially causing different cities to experience varying impacts from the structure effect.

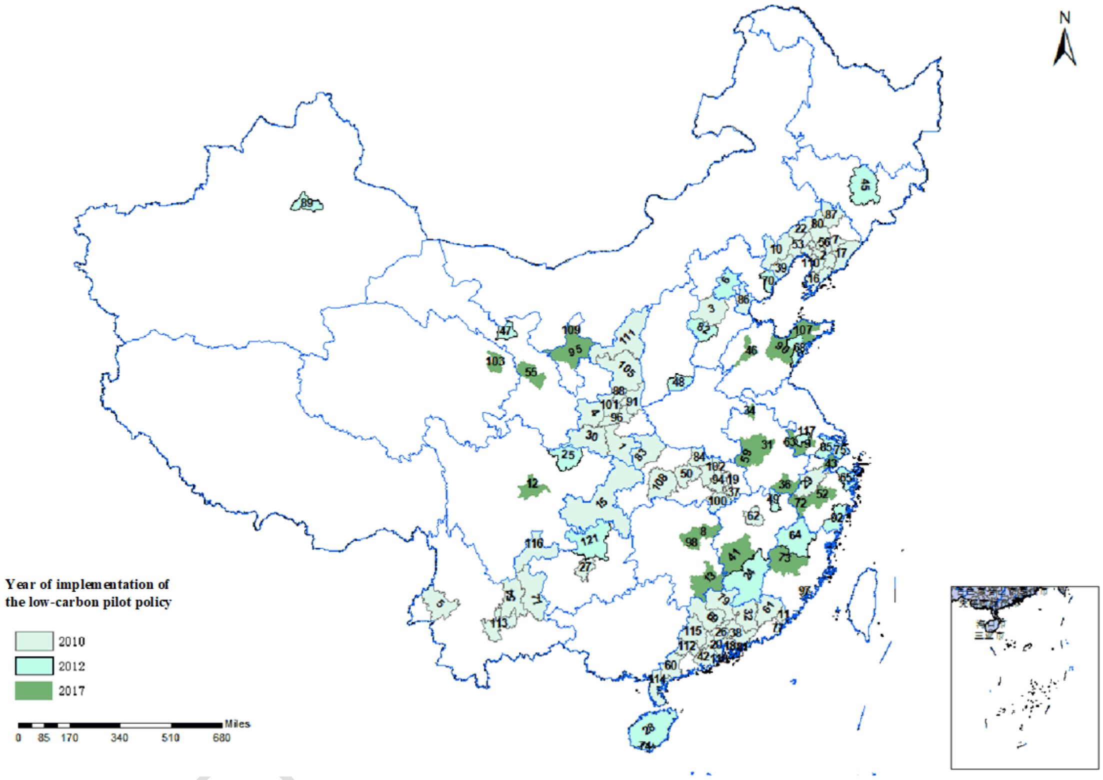
Specifically, the low-carbon economy dimension includes potential conditions such as industrialization level, energy structure, and economic development level. These conditions affect greenhouse gas emissions and are closely related to urban economic prosperity (Wang et al., 2021). The low-carbon society dimension focuses on factors like population size and consumption levels, which affect environmental quality through scale, technology, and structure effects (Di et al., 2023). The low-carbon environment dimension emphasizes the relationship between urbanization level and carbon emission control, requiring scientific urban planning and environmental management measures(Wang et al., 2020). These seven key indicators collectively reflect the comprehensive performance of urban low-carbon development, helping to reveal the various complex paths affecting employment and deepening the understanding of how low-carbon city policies impact employment.

4. Data

China's three phases of low-carbon city pilot policies were launched in July 2010, November 2012, and January 2017. To comprehensively account for the implementation timeline and lag effects of these pilot policies while ensuring the operational feasibility of this study, we have chosen the start dates of the three phases as 2010, 2013, and 2017 (as shown in Figure 2). This decision follows the methodology of Zheng (Zheng et al. 2021), wherein all prefecture-level cities in provinces involved in the low-carbon pilot program were treated as low-carbon pilot cities. Under this sample processing strategy, the earliest was considered if a city had multiple policy implementation start times (Shi and Xu 2022).

It is essential to clarify that the statistical scope of this study includes only prefecture-level cities within the provinces involved in the low-carbon pilot program; county-level towns are not included. This study employs panel data from 2007 to 2019. Carbon emission data are sourced from the CEADs database(Shan et al., 2019), jointly maintained by expert teams from the UK, the US, and China. This database focuses on emission accounting methods and applications in China and other emerging economies. Data related to industrialization, urbanization, energy structure, economic development, population size, consumption level, urban employment, and urban wage levels are obtained from the "China City Statistical Yearbook." This yearbook compiles central statistical data related to the socioeconomic development of cities at all levels across the country, provided by relevant government departments of each city. This sample selection approach simplifies the research design, enhances research feasibility, and ensures the consistency and comparability of the analysis. By clearly defining the start time and scope of low-carbon pilot cities, this approach helps ensure the accuracy and scientific rigour of the study, laying a solid foundation for the credibility of the research results.

Figure 2. Map of low-carbon pilot cities



Notes:

1.Ankang	17.Dandong	33.Huai'an	49.Jingdezhen	65.Ningbo	81.Shenzhen	97. Xiamen	113.Yuxi
2.Anshan	18.Dongguan	34.Huaibei	50.Jingmen	66.Panjin	82.Shijiazhuang	98. Xiangtan	114.Zhanjiang
3.Baoding	19.Ezhou	35.Huanggang	51.Jingmen	67.Pu'er	83.Shiyan	99. Xiangyang	115.Zhaoqing
4.Baoji	20.Foshan	36.Huangshan	52.Jinhua	68.Qingdao	84.Suizhou	100. Xianning	116.Zhaotong
5.Baoshan	21.Fushun	37.Huangshi	53.Jinzhou	69.Qingyuan	85.Suzhou	101. Xianyang	117.Zhenjiang
6.Beijing	22.Fuxin	38.Huizhou	54.Kunming	70.Qinhuangdao	86.Tianjin	102. Xiaogan	118.Zhongshan
7.Benxi	23.Fuzhou	39.Huludao	55.Lanzhou	71.Qujing	87.Tieling	103. Xining	119.Zhuhai
8.Changsha	24.Ganzhou	40.Hulunbuir	56.Liaoyang	72.Quzhou	88.Tongchuan	104. Xuancheng	120.Zhuzhou
9.Changzhou	25.Ganzhou	41.Ji'an	57.Lijiang	73.Sanming	89.Urumqi	105. Yan'an	121.Zunyi
10.Chaoyang	26.Guangzhou	42.Jiangmen	58.Lincang	74.Sanya	90.Weifang	106. Yangjiang	
11.Chaozhou	27.Guiyang	43.Jiaxing	59.Lu'an	75.Shanghai	91.Weinan	107. Yantai	
12.Chengdu	28.Haikou	44.Jieyang	60.Maoming	76.Shangluo	92.Wenzhou	108. Yichang	
13.Chenzhou	29.Hangzhou	45.Jilin	61.Meizhou	77.Shantou	93.Wuhai	109. Yinchuan	
14.Chizhou	30.Hanzhong	46.Ji'nan	62.Nanchang	78.Shanwei	94.Wuhan	110. Yingkou	

15.Chongqing	31.Hefei	47.Jinchang	63.Nanjing	79.Shaoguan	95.Wuzhong	111. Yulin	
16.Dalian	32.Heyuan	48.Jincheng	64.Nanping	80.Shenyang	96.Xi'an	112. Yunfu	

5. Dynamic fsQCA analysis

Traditional QCA methods, constrained by theoretical and data limitations, heavily rely on cross-sectional data, making it challenging to explore longitudinal configurational effects. However, since 2010, the National Development and Reform Commission (NDRC) has launched three phases of low-carbon city pilot projects in China. The first phase began on July 19, 2010, involving five provinces and eight cities. The second phase was confirmed on November 26, 2012, comprising one province and 28 cities. The third phase commenced on January 7, 2017, encompassing 41 cities and four districts. These three phases of low-carbon city pilot projects represent a continuous series of events along the timeline. Single cross-sectional data configurations cannot adequately elucidate interactive effects' causal relationships and temporal dimensions.

To address this, this study's research design employs a dynamic QCA analysis method to enhance rigour. This approach draws on relevant theories and methods proposed by scholars such as Garcia-Castro(Castro et al., 2016). It leverages the R programming language to bridge the gap between panel data and QCA. This enables an in-depth examination of configurational relationships under time effects and enhances the precision of configurational analysis through Enhanced Standard Analysis (ESA).

Dynamic QCA offers two advantages over traditional QCA methods(Boratyńska, 2016). First, it employs measurements across three dimensions: between, within, and pooled. This allows for a more comprehensive capture of configurational consistency across different sizes and their interrelationships. Second, dynamic QCA (Soares et al., 2016) uses Consistency Distance to describe the extent of consistency variation across time and case dimensions, thus more accurately reflecting the evolving characteristics of causal relationships over time.

Using this dynamic QCA method facilitates a deeper understanding and explanation of the dynamic impact processes and influencing factors of low-carbon city development on employment levels. This provides policymakers with a more targeted theoretical basis, helping better address urban development's complexity and diversity and offering practical support for achieving sustainable development goals.

5.1. Measurement and calibration

Pre-calibration of the conditions and outcomes is necessary as part of the preparatory work for fsQCA analysis. This pre-calibration involves calibrating the considered conditions and outcomes (original values) into fuzzy set membership scores ranging from 0 to 1, following Ragin's (2008) (Ragin et al., 2008) framework. To ensure data consistency and coverage, this study carried out a unified calibration of the data based on existing theories (Fiss, 2011)， and previous research(Boratyńska, 2016).

Using a direct calibration method, this study set the 95th percentile, 50th percentile, and 5th percentile as calibration anchor points based on the characteristics of the variables, representing full membership, crossover points, and no membership, respectively. The specific calibration results are presented in Table 1. This study uniformly transformed the condition and outcome variables into positive values, setting their calibration points at the 95th, 50th, and 5th percentiles. This calibration process ensures consistency and accuracy in subsequent analyses at the within-case, cross-case, and overall levels. The application of this method, grounded in previous research and theoretical foundations, contributes to enhancing data comparability and the scientific rigour of the analysis.

Table 1. Descriptive statistics and calibration

Variables	IND	URB	ENE	ECO	POP	CON	CAR	EMP	WAG
Numbers	1573	1573	1573	1573	1573	1573	1573	1573	1573
Average	48.378	56.560	0.414	10.601	5.896	15.546	12.372	3.690	4.860
SD	10.950	11.043	0.144	0.706	0.694	1.219	0.816	0.946	2.199
Skewness	0.020	0.011	-0.249	-0.570	-0.215	-0.195	0.078	0.605	0.948
Kurtosis	0.520	-0.164	-0.726	2.927	0.838	2.531	-0.282	0.118	1.483
Minimum	16.160	28.240	0.010	4.600	3.780	5.470	9.950	1.100	1.220
Maximum	90.380	89.600	0.720	13.060	8.140	18.880	14.650	6.650	17.320
Affiliation (95%)	65.510	70.700	0.630	11.693	6.905	17.643	13.671	5.504	8.766
Intersection(50%)	48.250	57.100	0.440	10.633	5.865	15.461	12.377	3.529	4.511
Unaffiliated (5%)	30.412	39.246	0.176	9.408	4.786	13.667	11.073	2.303	1.989

Notes: IND= Value added of secondary industry as a proportion of regional GDP. URB= Share of urban population in total population. ENE= Ratio of coal consumption to total energy consumption. ECO= Log of regional GDP per capita. POP=Logarithm of total city year-end population. CON=Log of total retail sales of social consumer goods. CAR=Log of urban CO2 emissions decline. EMP=Log of the average number of urban workers on the job. WAG=Log of the average wage of urban workers on the job.

5.2. Necessity analysis

The necessary condition analysis in dynamic fsQCA (Castro et al., 2016) is an independent process used to assess whether individual conditions (possibly more than one) are necessary or essentially necessary for the occurrence of the outcome. In critical condition analysis, the criterion for determining necessity is when the consistency level exceeds 0.9; the condition variable is considered an essential condition for the outcome variable. In dynamic QCA panel data analysis, when the adjustment distance is less than 0.1, high consistency suggests that the condition variable may be necessary. However, when the adjustment distance exceeds 0.1, further investigation is required to ascertain its necessity.

The results of this analysis are shown in Table 2, with the outcome variables being the average number of on-duty employees and the urban wage level. The seven condition variables related to industrialization level, urbanization level, energy structure, economic development level, population size, consumption level, and carbon emissions reduction (IND, URB, ENE, ECO, POP, CON, and CAR) all exhibit a summarized consistency level of less than 0.9. This indicates that these factors are not necessary conditions for the outcome variables. Nevertheless, as the consistency adjustment distance for all these factors is more significant than 0.1, it suggests further analysis. In Appendix A, we provide scatter plots to determine whether these factors are necessary. It should be emphasized that this analytical approach helps determine which conditions are essential or essentially required for outcome variables, enhancing our understanding of these conditions' roles in dynamic fsQCA analysis.

Table 2. Analysis of necessity for Employment levels (High-EMP and High-WAG).

Condition		Outcome		Outcome	
		High-EMP		High-WAG	
		consistency	coverage	consistency	coverage
IND	High	0.649	0.633	0.589	0.559
IND	Low	0.684	0.686	0.738	0.720
URB	High	0.707	0.680	0.751	0.703
URB	Low	0.586	0.596	0.532	0.527
ENE	High	0.597	0.607	0.544	0.539
ENE	Low	0.715	0.687	0.776	0.726
ECO	High	0.808	0.789	0.837	0.796
ECO	Low	0.544	0.544	0.512	0.499
POP	High	0.844	0.803	0.700	0.649
POP	Low	0.515	0.530	0.605	0.606
CON	High	0.893	0.883	0.797	0.767
CON	Low	0.510	0.504	0.543	0.522
CAR	High	0.862	0.859	0.731	0.709
CAR	Low	0.517	0.507	0.584	0.557

5.3. Sufficiency analysis

Sufficiency analysis (Ragin et al., 2008) aims to identify different combinations of conditions that meet specific criteria for the occurrence of outcomes. To ensure the sufficiency of observations in the context of low-carbon cities, the membership scores of outcomes must consistently exceed the membership scores of combinations of conditions. This analysis is based on a truth table, which enumerates all logically possible combinations of conditions and outcomes, including high-EMP and low-EMP. Four conditions are considered in this context, resulting in 2^7 = 128 logically possible configurations. Each configuration is characterized by values of 0 and 1, where 0 indicates the absence and 1 indicates the presence of each condition. A condition's membership score for a low-carbon city observation is assigned based on a threshold value of 0.5; a score greater than 0.5 indicates the presence of the condition, while a score of 0.5 or less indicates its absence.Further consideration is given to two solutions, namely the intermediate solution and the parsimonious solution, employing a nested approach involving both solutions.

For each outcome, namely, High-Level Employment (High-EMP) and High-Level Urban Wages (High-WAG), we have adopted the presentation format for fsQCA analysis results as proposed by Ragin (Ragin et al., 2008) and Fiss (Fiss, 2011). The advantage of this presentation format lies in its ability to demonstrate the relative importance of each condition within the configuration.Here, ● signifies the presence of a condition, indicating that the condition variable takes a higher value, while ⊗ means the absence of a condition, indicating that the condition variable takes a lower value. Large circles represent "core conditions," small circles represent "peripheral conditions," and blank spaces denote that the presence of the condition variable is inconsequential for the outcome.

6. Panel data breakdown of fsQCA results

This section aims to analyze the dynamic fsQCA results across different years and cities using panel data. As previously mentioned, this approach utilizes techniques introduced by Castro (Castro et al., 2016) and elaborated upon by Guedes (Guedes et al., 2016), with further technical details provided in Appendix A. Here, we employ a three-step process to assess the consistency and coverage between the conditional variables and outcome variables in the city-year dataset. The first step involves evaluating the overall consistency of the entire panel, which is measured using POCO scores. The second step entails using BECONS values for each year from 2007 to 2019. Regardless of whether the overall consistency (POCONS) is high or low, the presence of significant BECONS distance between years may indicate the existence of consistent solid set-theoretic relationships in specific years, suggesting a temporal dimension to these relationships. Finally, WICONS values are utilized to measure the coverage of low-carbon cities across different configurations, aiding in explaining regional disparities. This approach comprehensively explores the dynamic fsQCA results, considering variations across time and location.

6.1 High-EMP

Table 3 presents sufficient conditions, precisely six driving pathways, to explain the high level of on-the-job employees. Each column represents a possible configuration of conditions. The overall solution consistency is 0.97, indicating that among all 121 low-carbon city transformation cases that satisfy these six types of condition configurations, 97% exhibit a high level of on-the-job employees. The solution coverage is 0.552, implying that these six condition configurations can explain 55.2% of the cases of low-carbon city transformation regarding high on-the-job employee levels. Both solution consistency and coverage are higher than the critical threshold, demonstrating the effectiveness of the empirical analysis. These six favourable configurations are sufficient conditions for developing low-carbon cities with high levels of on-the-job employees. Among them, HRD1, HRD2, HRD3, and HRD4 belong to the Human Resource-Driven category, while ETD1 and ETD2 fall into the Energy Transition-Driven category.Within the configurations HRD1, HRD2, HRD3, and HRD4, the presence of three essential conditions—namely, "population size," "consumption level," and "carbon emissions reduction"—plays a pivotal role. These configurations collectively represent a pathway driven by the human resources model, showcasing how it contributes to achieving high employment levels. In Figure 3, we delve into the evolving dynamics of BECONS values from 2007 to 2019, drawing comparisons to POCONS (represented by the dashed horizontal line). The fluctuations in the 13 BECONS values across different years are evident through the adj-distance of

BECONS. Notably, for HRD1, HRD2, HRD3, and HRD4, the consistency adjustment distances are consistently less than 0.1. This suggests that over the long term, from 2007 to 2019, the influence of low-carbon city development on employment numbers does not display significant temporal variations.

Nevertheless, it is worthwhile to explore short-term variations as well. Upon closer examination, a fascinating trend emerged in 2013, where we observed a collective decrease in consistency. This trend became even more pronounced in 2017. This intriguing pattern may be closely linked to the timing of policy implementations, precisely aligning with the initiation of the second batch of low-carbon pilot city policies in November 2012 and the subsequent rollout of the third batch in January 2017. This detailed analysis provides valuable insights into the dynamic relationship between low-carbon urban development and employment numbers. It underscores the importance of considering both long-term and short-term perspectives when evaluating the impact of policy interventions on employment outcomes.

In Figure 4, we present an analysis of the WICONS values among the 121 low-carbon pilot cities to compare the differences in coverage between these regions. The configurations represented by HRD1, HRD2, HRD3, and HRD4 suggest that even when a city's level of industrialization is relatively low, as long as its population size, consumption level, and carbon emission reduction level are high, the city's employment level can remain high. This phenomenon is particularly pronounced in tourist-oriented cities, exemplified by five Type II significant cities (as defined by the Chinese State Council, with a permanent population ranging from one to three million): Chizhou (No. 14), Quzhou (No. 72), Suizhou (No. 84), Xuancheng (No. 104), and Huangshan (No. 36). These five cities exhibit relatively low levels of industrialization.

Taking Chizhou City as an example, it was designated as China's first national ecological economic demonstration zone and consistently ranked at the forefront of Anhui Province in terms of total tourism reception and scale. In 2021, the service sector, dominated by the cultural and tourism industry, accounted for a substantial 45.7% of the GDP, reaching 100.42 billion RMB, with a growth rate of 10.2%. This placed Chizhou City third among the 41 cities in Anhui Province and the Yangtze River Delta region. Simultaneously, Chizhou City achieved a remarkable 15.7% growth in industrial value-added in 2021, ranking second in Anhui Province. These tourist-oriented cities provide valuable insights, demonstrating that in the development of low-carbon cities, a high level of employment can be achieved through the synergistic effect of critical factors such as population size, consumption level, and carbon emission reduction, even when the level of industrialization is relatively low. These findings offer important implications for urban development and sustainability policies.

In configurations ETD1 and ETD2, we delve into the dynamics of high employment levels driven by the transformation of energy structures. These configurations highlight the central role of four critical conditions: energy structure transformation, elevated economic development, consumption levels, and reduced carbon emissions. They shed light on how transitioning energy resources can positively impact employment outcomes.

Figure 5 provides a comprehensive view of how BECONS values evolved from 2007 to 2019, allowing for a direct comparison with the POCONS (dashed horizontal line in the graph) for reference. The 13 years of BECONS variation is captured through the adj-distance of BECONS. Remarkably, ETD1 and ETD2 exhibit consistency adjustment distances of less than 0.1. This suggests that when considering the long-term perspective (from 2007 to 2019), the development of low-carbon cities appears to have a relatively stable influence on employment levels without significant temporal fluctuations.However, a more detailed examination of the short-term dynamics reveals intriguing trends. 2013 consistency declined noticeably, with an even more pronounced drop in 2017. These trends are closely associated with the timing of policy implementations, precisely the second batch of low-carbon pilot city policies introduced in November 2012, followed by the launch of the third batch in January 2017.In summary, our analysis indicates that BECONS values remain relatively consistent over the long term, reflecting a stable relationship between low-carbon urban development and employment. Nevertheless, policy implementations exert a notable influence in the short term, particularly evident in 2013 and 2017. This finding underscores the dynamic interplay between policy factors and their impact on employment in the context of low-carbon urban development.In Figure 6, we illustrate the WICONS values among 121 low-carbon pilot cities and compare their differences in coverage. The configurations of ETD1 and ETD2 suggest that when a city undergoes a transition in its energy structure, experiences an elevation in economic development, witnesses an increase in consumption levels, and achieves a reduction in carbon emissions, it can maintain a high level of employment even if its industrial development is relatively weak.

These configurations can be exemplified by energy transition cities such as Zhenjiang (117), Changzhou (9), Foshan (20), Fushun (21), Jiaxing (43), Dongguan (18), and Zhuhai (119). Taking Zhuhai, Foshan, and Dongguan as examples, these three cities exhibit relatively high levels of economic development and have attracted a significant influx of external population in recent years. Overall, these three cities have a high degree of industrialization and have substantial potential for reducing carbon emissions in their industrial and energy sectors. By 2020, these three cities' combined GDP accounted for 21.62% of the entire province, with an average per capita GDP of 116,300 yuan, surpassing the provincial average. In terms of industrial structure, these cities show a relatively balanced distribution between the secondary and tertiary sectors, ranging from 40% to 55%. In recent years, they have been transitioning toward a more service-oriented economy.

Furthermore, these three cities have a relatively large number of large-scale industrial enterprises (especially Dongguan and Foshan), accounting for 35.96% of the total in the province. However, the total energy consumption of these enterprises only represents 17.63% of the province's total, indicating a significant decoupling between economic growth and carbon emissions in these cities. In recent years, these cities have notably optimized their energy consumption structure, especially Dongguan, which has significantly reduced the proportion of coal consumption. Between 2016 and 2020, the proportion of coal consumption in Foshan and

Zhuhai decreased from 20.68% and 5.11% to 18.48% and 4.52%, respectively. During the same period, Dongguan's coal consumption proportion significantly reduced from 41.18% to 27.45%, a reduction of nearly 15 percentage points.

These city characteristics suggest that high-level economic development and carbon reduction coexist, providing valuable insights for sustainable development and low-carbon transformation in other regions. The successful experiences of these cities can serve as valuable lessons for governments at all levels looking to promote sustainable development and low-carbon transitions.

Table 3.Suficiency analysis for Employment levels (High-EMP)

Conditional	**High-EMP**					
	Human resource driven				**Energy transition drive**	
IND	⊗				⊗	
URB			⊗	•		•
ENE			•	⊗	⨂	⨂
ECO		•			●	●
POP	●	●	●	●		
CON	●	●	●	●	●	●
CAR	●	●	●	●	●	●
Type of configuration	HRD1	HRD2	HRD3	HRD4	ETD1	ETD2
Consistency	0.970	0.981	0.974	0.977	0.969	0.958
PRI	0.933	0.961	0.922	0.944	0.926	0.907
Coverage	0.552	0.636	0.414	0.496	0.458	0.526
Unique coverage	0.004	0.027	0.021	0.008	0.006	0.025
Consistency adjustment distance between groups	0.020	0.016	0.016	0.016	0.020	0.016
Consistency adjustment distance within groups	0.111	0.089	0.089	0.089	0.111	0.111
Overall PRI				0.933		
Overall consistency				0.970		
Overall coverage				0.552		

Notes: The consistency and coverage values are over the whole data set of cases (not just from those configurations shown associated in strong membership terms).

Figure 3. BECONS values (2007–2019) for causal recipes HRD1, HRD2, HRD3, and HRD4 (High-EMP outcome)

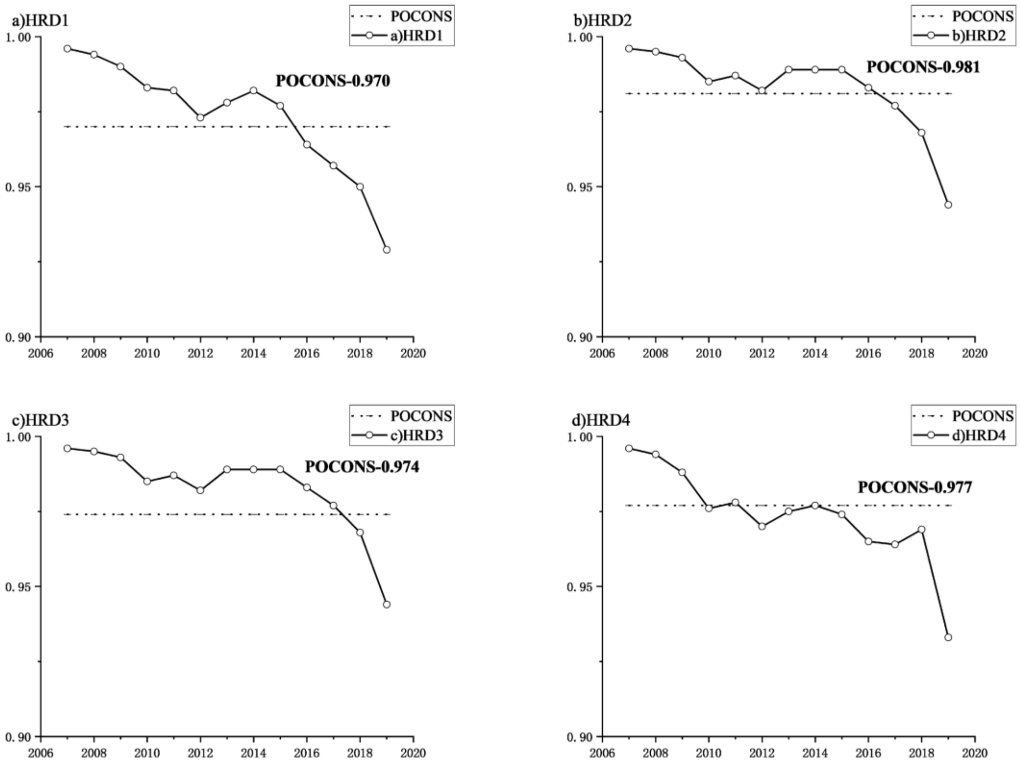


Figure 4. WICONS values across Low-carbon cities for causal recipes HRD1, HRD2, HRD3, and HRD4 (High-EMP outcome).

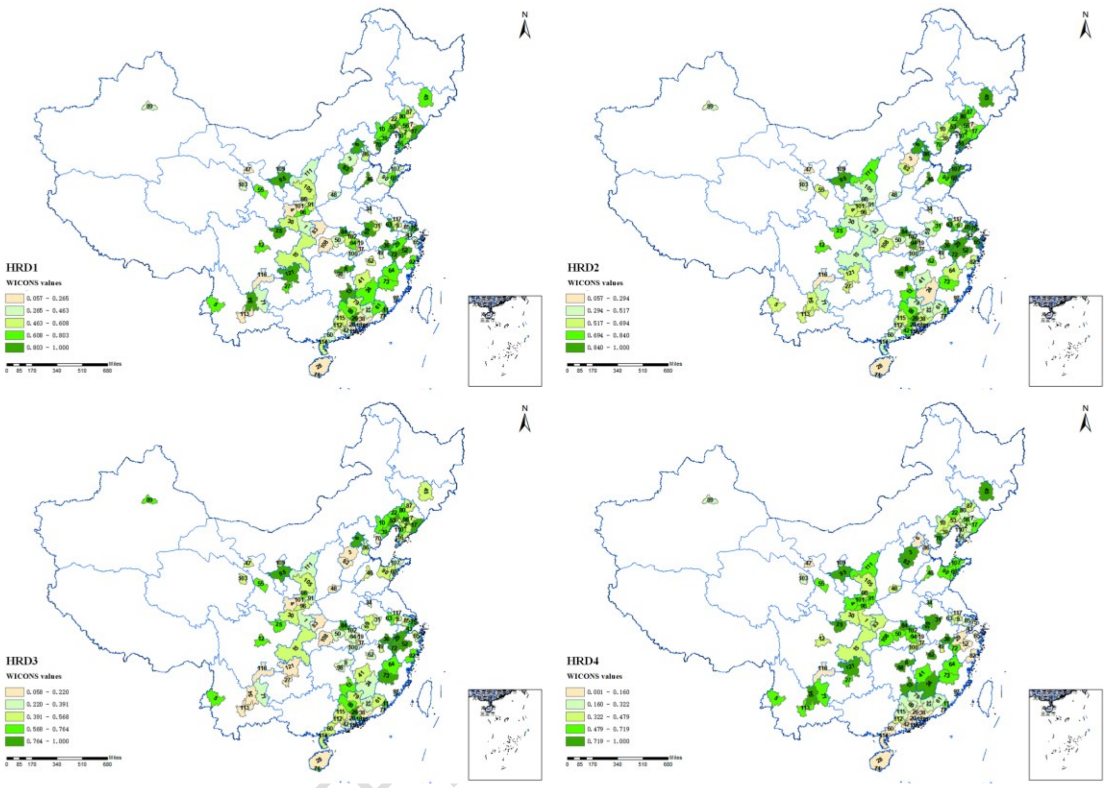


Figure 5. BECONS values (2007–2019) for causal recipes ETD1 and ETD2 (High-EMP outcome)

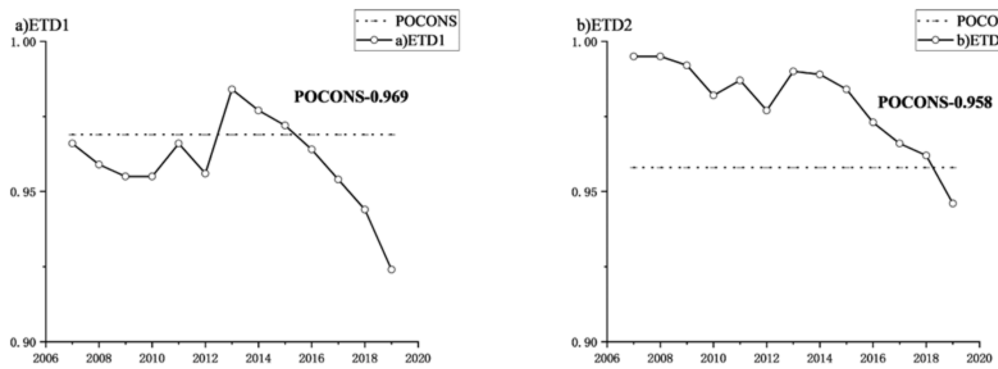
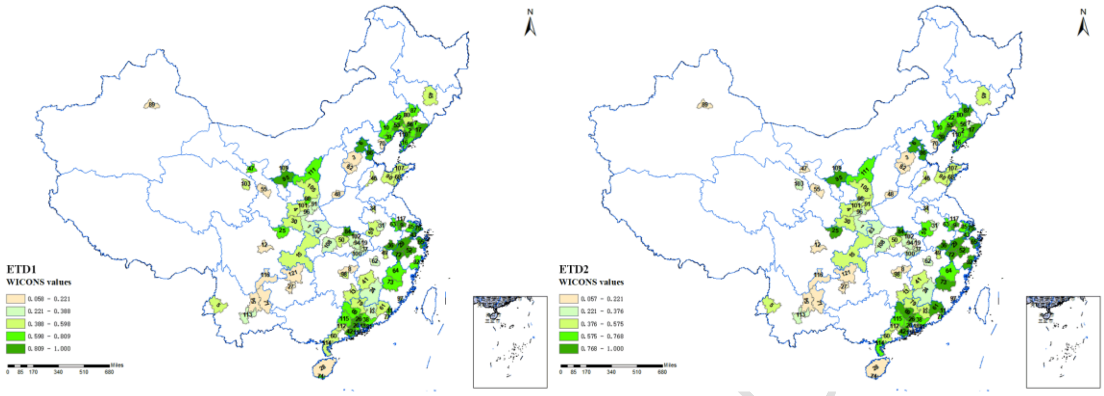


Figure 6. WICONS values across Low-carbon cities for causal recipes ETD1 and ETD2 (High-EMP outcome).



6.2 High-WAG

Table 4 presents sufficient conditions for explaining the generation of high-level urban wages, which encompass five distinct driving pathways. Each column represents a possible configuration of conditions. The overall solution consistency is 0.955, signifying that among the cities that meet these five condition configurations in the transformation cases of 121 low-carbon towns, 95.5% exhibit higher urban wage levels. The solution coverage stands at 0.483, indicating that these five condition configurations can account for 48.3% of the cases concerning the transformation of low-carbon cities in terms of high-level urban wages. Both solution consistency and coverage surpass the critical threshold, affirming the effectiveness of our empirical analysis. These five favourable configurations are sufficient condition combinations for the impact of low-carbon city transformation on high-level urban wages. Specifically, IGD1 and IGD2 belong to the Industry Group Drive category, while FFD1, FFD2, and FFD3 fall within the Full Factor Drive category.

Figures 7 and 9 describe the BECONS values' evolution from 2007 to 2019, alongside a comparison with the POCONS (represented by the dashed horizontal line in the graphs). The 13-year changes in BECONS are illustrated through the adj-distance of BECONS. The adj-distance values for IGD1, IGD2, FFD1, FFD2, and FFD3 are all greater than 0.1. This suggests that over the long term (from 2007 to 2019), there is a certain degree of heterogeneity in how low-carbon urban development impacts urban wage levels across different years. Further analysis of the BECONS values in Figure 5 reveals that higher consistency peaks emerge as time progresses, especially after 2012. In summary, if there are sufficient theoretical reasons to believe that the heterogeneity in urban wage levels after 2012 is due to the implementation of low-carbon pilot policies, this can be examined using annual BECONS analysis. For instance, if changes in industrial and energy structures occur in different cities each year due to low-carbon pilot policies, this hypothesis can be tested.

In Figure 8, we describe the WICONS values among 121 low-carbon pilot cities to compare the differences in coverage between these regions. The configurations of IGD1 and IGD2 suggest that when a city's urbanization level, energy structure transformation, economic development level, and consumption level are high, even if the city's pillar industries do not rely on the secondary sector, the city's wage level can remain high. Specific cases that can be explained include industrial structural transformation cities such as Dandong (17), Liaoyang (56), Wuzhong (95), Chaozhou (11), and Hangzhou (29).

As one of the typical cases, Hangzhou has seen a continuous increase in the proportion of the tertiary industry, accounting for over 68% in 2021. Especially the development of low-carbon and efficient industries, represented by the digital economy, has driven Hangzhou's low-carbon transformation. Data shows that in recent years, Hangzhou's carbon emissions per unit of GDP have decreased, reaching about 0.57 tons per 10,000 yuan of GDP in 2020, achieving economic growth and energy conservation.

For instance, Hangzhou has conducted energy-saving assessments on over 100,000 critical energy-consuming units in the city, requiring non-compliant enterprises to rectify their energy use. They have also conducted energy audits on 150 high-energy-consuming enterprises with an annual energy consumption of over 10,000 tons of standard coal, determining the energy baseline of key energy-consuming enterprises and identifying energy-saving opportunities. Hangzhou has intensified efforts in industrial structure adjustment, compelling enterprises to upgrade and transform. This has included eliminating and rectifying high-energy-consuming industries such as papermaking in Fuyang. Additionally, Hangzhou has allocated energy use quotas of more than 600,000 tons of standard coal to support over ten major industrial projects, including the Zhejiang Cloud Data Center, ensuring energy use for significant projects. This transformation highlights the importance of energy efficiency and structural adjustments in achieving low-carbon development and sustaining high wage levels in cities.

In Figure 10, we describe the WICONS values among 121 low-carbon pilot cities to compare the differences in coverage between these regions. FFD1, FFD2, and FFD3 configurations suggest that when a city's economic development level, population size, consumption level, and carbon emissions are all at high levels, this represents the path to achieving high-level urban wages driven by the full-factor model. As a specific illustrative case, Beijing (6), Baoji (4), Chengdu (12), Changzhou (9), Chenzhou (13), and Dongguan (18) are notable cities. Using Beijing as a typical example, it ranks at the forefront in terms of GDP total, per capita GDP, and other indicators of economic development quality. During the "Thirteenth Five-Year Plan" period, Beijing saw the cumulative exit of more than 2,000 general manufacturing companies, focusing on traditional high-energy-consumption industries such as building materials, machinery manufacturing, and processing. Beijing's tertiary sector accounts for a staggering 80%, ranking first among all cities in the country, with outstanding performance in modern service sectors such as technology services, finance, and the digital economy. These industries, characterized by lower carbon emissions, form the bedrock of Beijing's economy.

Table 4.Suficiency analysis for Employment levels (High-WAG)

Conditional	High-WAG				
	Industry Group Drive		Full Factor Drive		
IND	⊗	⊗	⊗	⊗	
URB	●	●	●		●
ENE	⊗	⊗		⊗	⊗
ECO	●	●	●	●	●
POP		⊗	●	●	●
CON	●		●	●	●
CAR		⊗	●	●	●
Type of configuration	IGD1	IGD2	FFD1	FFD2	FFD3
Consistency	0.955	0.951	0.953	0.952	0.931
PRI	0.898	0.802	0.885	0.886	0.840
Coverage	0.483	0.300	0.418	0.422	0.458
Unique coverage	0.019	0.015	0.021	0.024	0.061
Consistency adjustment distance between groups	0.128	0.116	0.132	0.140	0.176
Consistency adjustment distance within groups	0.055	0.066	0.055	0.055	0.066
Overall PRI			0.898		
Overall consistency			0.955		
Overall coverage			0.483		

Notes: The consistency and coverage values are over the whole data set of cases (not just from those configurations shown associated in strong membership terms).

Figure 7. BECONS values (2007–2019) for causal recipes IGD1 and IGD2 (High-WAG outcome)

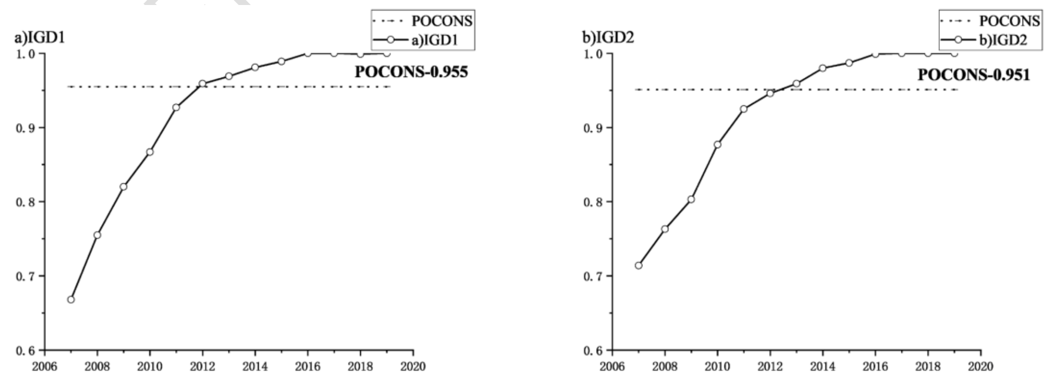


Figure 8. WICONS values across Low-carbon cities for causal recipes IGD1 and IGD2 (High-WAG outcome).

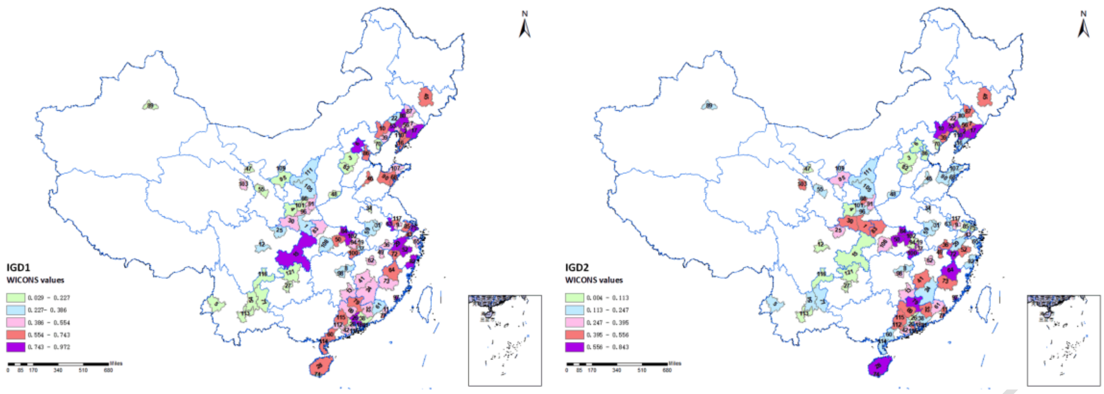


Figure 9. BECONS values (2007–2019) for causal recipes FFD1 ,FFD2 and FFD3 (High-WAG outcome)

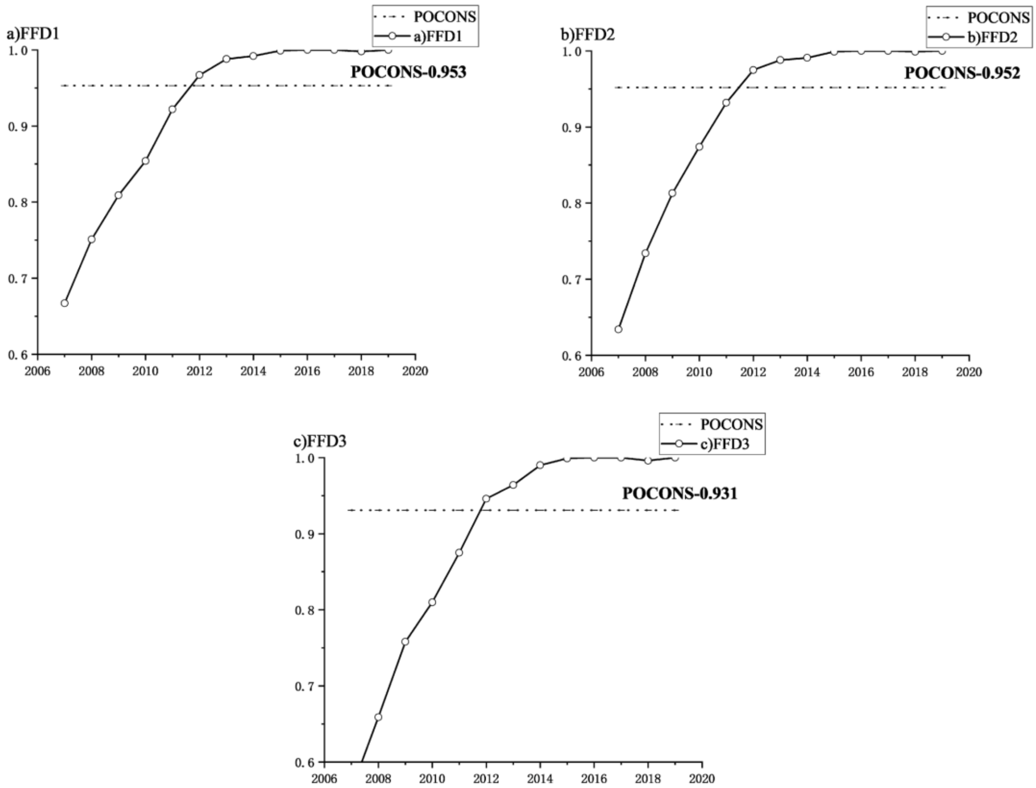
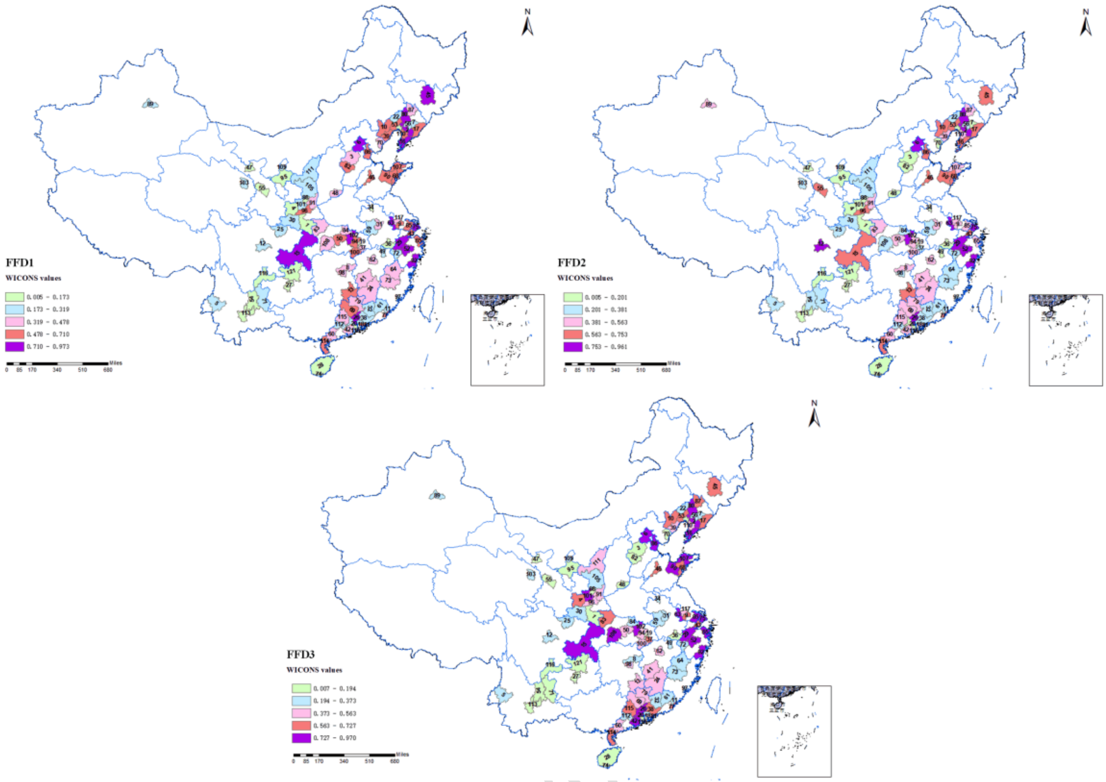


Figure 10. WICONS values across Low-carbon cities for causal recipes FFD1 ,FFD2 and FFD3 (High-WAG outcome)



7. Robustness test

The robustness testing section conducts robustness checks on the configurations generated in the fifth section based on outcome variables: high employment (HRD1, HRD2, HRD3, HRD4, ETD1, and ETD2) and high city wages (IGD1, IGD2, FFD1, FFD2, FFD3). The fsQCA, as a set-theoretic method, is considered robust when slight variations in operations result in subsets of solutions that do not alter the substantive interpretations of the research findings (Zhang & Du, 2019; Du et al., 2020). In this study, we employ two methods, enhanced standard analysis and Tobit panel regression, to validate the 11 configuration results obtained in the fifth section. These robustness tests aim to ensure the reliability and stability of our research findings.**7.1Enhanced standards analysis**

Based on a counterfactual analysis framework, enhanced standard analysis begins by simplifying assumptions to remove contradictions. Given the vast geographical expanse and varying resource endowments of urban regions in China, we focus solely on the necessity of economic development for regional employment levels. Determining their directional effects uniformly for other antecedent conditions is challenging, so we refrain from making directional assumptions, considering the remaining six condition variables as "present or absent." Ultimately, we obtain enhanced simple, intermediate, and complex solutions. Enhanced standard analysis primarily emphasizes intermediate enhanced solutions, complemented by enhanced simple solutions, to identify core and marginal conditions. Tables 5 and 6 present the overall configuration analysis results. Specifically, we identify three configurations for the result condition of high-level employment, further reinforcing the reliability of the previously mentioned HRD1, HRD2, HRD3, HRD4, ETD1, and ETD2 configurations. For the result condition of high-level urban wages, we identify five configurations, once again validating the reliability of the IGD1, IGD2, FFD1, FFD2, and FFD3 configurations. These enhanced standard analysis results ensure the reliability and stability of our research findings.

Table 5.Results of the enhanced criteria analysis (High-EMP)

Conditional	**Outcome(High-EMP)**		
IND	⊗		⊗
URB			
ENE			⊗
ECO		●	●
POP	●	●	
CON	●	●	●
CAR	●	●	●
Complex Solution	Enhanced 1	Enhanced 2	Enhanced 3
Consistency	0.970	0.981	0.969
PRI	0.933	0.961	0.926
Coverage	0.552	0.636	0.458
Unique coverage	0.053	0.137	0.036
Consistency adjustment distance between groups	0.005	0.004	0.005
Consistency adjustment distance within groups	0.020	0.016	0.020
Overall PRI	0.010	0.008	0.010
Overall consistency	0.111	0.089	0.111
Overall coverage		0.932	

Notes: The consistency and coverage values are over the whole data set of cases (not just from those configurations shown associated in strong membership terms).

Table 6.Results of the enhanced criteria analysis (High-WAG)

Conditional	**Outcome(High-EMP)**				
IND	⊗	⊗	⊗	⊗	
URB	●	●	●		●
ENE	⊗	⊗		⊗	⊗
ECO	●	●	●	●	●
POP		⊗	●	●	●
CON	●		●	●	●

CAR		⊗	●	●	●
Complex Solution	Enhanced 4	Enhanced 5	Enhanced 6	Enhanced 7	Enhanced 8
Consistency	0.955	0.951	0.953	0.952	0.931
PRI	0.898	0.802	0.885	0.886	0.84
Coverage	0.483	0.300	0.418	0.422	0.458
Unique coverage	0.019	0.015	0.021	0.024	0.061
Consistency adjustment distance between groups	0.129	0.117	0.133	0.141	0.177
Consistency adjustment distance within groups	0.056	0.067	0.056	0.056	0.067
Overall PRI			0.898		
Overall consistency			0.955		
Overall coverage			0.483		

Notes: The consistency and coverage values are over the whole data set of cases (not just from those configurations shown associated in strong membership terms).

7.2 Panel Tobit Robustness Tests

The data in this study falls under the typical category of truncated data, with a left-censoring point at 0 and a right-censoring point at 1. This model is known as the "censored regression model," also called the Tobit model (Tobin, 1958). We consider a panel model for censored data based on the following assumptions:

$$y_{it}^{*} = x_{it}^{'}\beta + u_i + \varepsilon_{it}$$

Among these, y_i^{*} represents unobservable factors, $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^2)$ represents disturbances, u_i represents individual effects.

We initially conducted a mixed Tobit regression on the configurations, utilizing clustered robust standard errors. Subsequently, we performed a random-effects panel Tobit regression to examine the individual effects of low-carbon pilot cities. Robustness tests for the configurations generating high-performance low-carbon cities were conducted through Tobit regression in this study. The data in this study falls under the category of typical censored data, with a left-censoring point at 0 and a right-censoring point at 1. Even after Tobit regression, the results for the configurations remain statistically significant, as shown in Table 7.

Table 7.Panel Tobit robustness test

Configuration	Coefficient	Standard error	Z-statistic	chibar2
Resulting variables:EMP				
HRD1	0.095***	-0.024	4.000	1775.150
HRD2	0.060**	-0.024	2.530	1768.120
HRD3	0.319***	-0.022	14.290	1743.840
HRD4	0.039	-0.028	1.440	1708.580

ETD1	0.305***	-0.022	13.710	1678.710
ETD2	0.102***	-0.025	4.100	1708.580
Resulting variables:WAG				
IGD1	-0.524***	-0.029	-17.810	1309.250
IGD2	0.160**	-0.065	2.440	1312.180
FFD1	-0.488***	-0.053	-9.220	1221.590
FFD2	-0.491***	-0.056	-8.760	1169.070
FFD3	-0.558***	-0.067	-8.390	1390.140

Notes:*** p<0.01, ** p<0.05, * p<0.1

Through panel Tobit regression, we discovered that when the dependent variable is employment, the seven conditional factors (IND, URB, ENE, ECO, POP, CON, and CAR) tend to exhibit more complementary effects among them. The estimated coefficients for the six configurations, HRD1, HRD2, HRD3, HRD4, ETD1, and ETD2, are statistically significant at the 1% level, with HRD3 and ETD1 displaying marginal utilities exceeding 0.3, indicating a considerable positive impact of economic development-driven configurations on employment.

However, when the dependent variable is high-level urban wages, the estimated coefficients for IGD1, FFD1, FFD2, and FFD3 are significantly negative at the 1% level. This suggests there may be more substitution effects among the seven conditional factors or potential multicollinearity issues in the data. Upon further analysis, we found strong collinearity between urban consumption and urban wage levels within IGD1, FFD1, FFD2, and FFD3. This collinearity leads to endogeneity issues, which explain the significantly negative coefficients for these configurations.

According to Theodore W. Schultz's human capital theory(Schultz, 1960), when population growth slows down, the quality of labour (knowledge, technical skills, work capacity, and health) becomes more crucial for regional economic development. A considerable portion of overall consumption is invested in the workforce's continuous education and health management. This investment enhances the human capital of the labour force and contributes to long-term economic growth. Therefore, the increase in workforce quality resulting from improved consumption levels can positively impact regional wage levels, fostering a virtuous cycle of economic development and transforming human capital-intensive industries.

8. Discussion

The findings contribute to the broader literature on low-carbon city development and employment by elucidating the complex relationships and underlying mechanisms that drive these dynamics. Specifically, effective resource allocation in low-carbon pilot cities hinges on the interplay between environmental policies, economic incentives, and social initiatives. This aligns with the resource allocation theory, which posits that optimal resource distribution can enhance productivity and sustainability(Chen et al., 2024; Maslach et al., 2001). The study supports previous research indicating that low-carbon initiatives can stimulate green employment opportunities by compelling companies to adopt cleaner production methods(Di, Chen, Shi, Cai, Liu, et al., 2024; Yasir et al., 2020). However, it also highlights the short-term adverse effects on employment in high-polluting industries, corroborating findings from other studies (Di, Chen, Shi, Cai, & Zhang, 2024; Fan et al., 2023). The dynamic fsQCA approach allowed for identifying specific configurations and adaptation models that lead to high employment levels, providing a nuanced understanding that traditional econometric methods might overlook.

Despite these contributions, the study has several limitations. First, the reliance on data from low-carbon pilot cities in China limits the generalizability of the findings to other contexts. Future research should consider comparative studies involving low-carbon initiatives in different countries to enhance the robustness and applicability of the results. Second, the dynamic nature of QCA analysis means that the findings are contingent on the selected time frame and variables. Longitudinal studies could provide deeper insights into how these relationships evolve. Another limitation is the potential bias in data collection, as the study relies on secondary data sources that may only capture some relevant variables influencing employment outcomes. Future research could incorporate primary data collection methods like surveys or interviews to validate and expand upon the findings.

Future research should explore the following areas to build on these findings: conducting comparative studies across different countries and regions to understand how varying socio-economic contexts influence the relationship between low-carbon city development and employment; implementing longitudinal studies to track the long-term effects of low-carbon policies on employment and to identify potential lag effects not captured in cross-sectional analyses; incorporating primary data collection methods, such as field surveys and interviews, to validate secondary data findings and uncover additional variables impacting employment in low-carbon cities; and examining the specific impacts of individual policy measures within the broader framework of low-carbon city initiatives to identify the most effective strategies for enhancing employment. By addressing these limitations and pursuing these research directions, future studies can further advance the understanding of the complex interplay between low-carbon city development and employment.

9.Conclusions

This study employs dynamic fsQCA research methodology, focusing on 121 low-carbon pilot cities in China as case studies, to investigate the synergistic effects and driving pathways of China's low-carbon urban governance on employment from 2007 to 2019. It reveals the core conditions and their complex interactions that influence high-level employment and high-level urban wages from both temporal and regional dimensions.

First and foremost, by analyzing the impacts of seven conditional variables (IND, URB, ENE, ECO, POP, CON, and CAR) on high-level employment (High-EMP) and high-level urban wages (High-WAG), this study finds that none of the seven low-carbon urban development factors can independently serve as necessary conditions for elevating regional employment levels. This suggests that individual factors must be considered bottlenecks to significantly boost regional employment levels. Developing low-carbon cities leads to six driving pathways for high-level employment, broadly categorized into the Human Resources-Driven Model and the Energy Transition-Driven Model. Furthermore, the influence of low-carbon urban development on high-level urban wages is shaped by five driving pathways, categorized into the Industry Agglomeration-Driven Model and the Total Factor Productivity-Driven Model.

Secondly, this research illustrates the changing trends of the impacts of the seven conditional variables on employment levels (High-EMP and High-WAG) from 2007 to 2019, addressing previous research gaps. Notably, industrialization, energy structure, and carbon emission reduction have formed evident time effects on regional employment levels, particularly around 2016. This result validates the Porter-Clark theorem, helping us understand the relationship between the industrialization level of low-carbon cities and regional employment levels from the perspective of industrial development evolution. According to the theory of structural transformation, the equilibrium level of industrial structure, energy structure, and carbon emission reduction tends to approach reasonableness as economic development progresses, often involving structural changes that contribute to increased factor productivity.

In addition, we observe increasing time effects related to urbanization and consumption levels, especially around 2014. The rise in urbanization stimulates urban construction and infrastructure development, promoting the growth of various industries and thus creating more employment opportunities. With the increase in urbanization levels, urban scale and population size also continuously increase, further driving the improvement of employment levels. Economic development is another significant driving factor. During periods of economic prosperity, enterprises tend to expand, generating more job opportunities. Economic development also promotes technological innovation and scientific development, fostering the growth of emerging industries and further boosting employment levels. Consumption levels are also one of the crucial factors driving regional employment levels. As consumption levels rise, market demand increases accordingly, prompting businesses to increase production and operations and create more job opportunities. Finally, the time effects of economic development on regional employment levels are the most prominent among all conditional variables, particularly evident in regional employment and urban wage levels.

In summary, this research makes two primary theoretical contributions compared to previous studies on related topics. Firstly, past assessments of net employment gains or losses (Chen et al., 2024) often relied on traditional econometric models' increasing or decreasing marginal effects. These approaches have limitations because traditional quantitative methods are based on models that assume independence, unidirectional linear relationships, and causal symmetry among independent variables. They analyze the "net effects" of independent variables on dependent variables under the control of other factors, which cannot explain the complex causal relationships among interdependent variables. Therefore, this study adopts an analysis perspective based on holistic configurations, treating the research objects as configurations of different combinations of conditional variables. This approach integrates the advantages of case studies and variable studies and, through the dynamic fsQCA analysis method, explores the set relationships between factors and outcomes. This approach aids in addressing multiple concurrent causal relationships, causal asymmetry, and equivalence of various scenarios in understanding the impact of developing low-carbon cities on employment. Secondly, in previous research on related topics, there may have been a "time blind spot" issue, indicating a lack of consideration of the temporal dimension, thereby neglecting the influence of time on conditional configurations. To overcome this "time blind spot," this study improved upon previous work by using panel data. By comprehensively evaluating data for 13 years, including industrialization levels, urbanization levels, energy structures, economic development levels, population sizes, consumption levels, carbon emissions, average on-duty workers, and urban wage levels, this research used the dynamic QCA method. This method helps enrich the theoretical dynamism and theoretical saturation during the theoretical construction phase and forms robust configuration conclusions during empirical testing.

This study helps uncover results that traditional econometric methods cannot provide, contributing to expanding research in this field. By exploring the conditions and mechanisms that drive low-carbon urban development to affect employment levels from both temporal and regional perspectives, this research enhances our understanding of the driving pathways and mechanisms of low-carbon cities on employment levels. It promotes the development of low-carbon local towns and the improvement of employment levels in a context-sensitive manner.

Funding statement

1. Achievements of the Joint Doctoral Forum Program between Tianjin University and Qinghai Minzu University.

2.Qinghai Minzu University (23XJX01): Study on the Coupling Effect of Technology-Organization-Environmental Condition Configuration on the Performance of Low Carbon City Development in China.

3.Qinghai Minzu University (39D2023005): The Impact of Low-Carbon Urban Transformation on Regional Employment Levels.

4.Tianjin Research Innovation Project for Postgraduate Students (2022BKYZ029): The linkage of technology-organization-environment condition Configuration on the construction of low carbon city in China's development performance.

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