

Article

Configurational Pathways for the Coordinated Development of County Industry and Employment from the Perspective of Inclusive Growth

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Abstract

During the stage of high-quality economic development, the synergy between advancing county industrial structure and employment growth has become a key issue in county governance. Although existing studies confirm that industrial structure has both creation and substitution effects on employment, few have adopted a configurational perspective to reveal how combinations of multiple factors can jointly promote both advanced county industrial structure and employment growth, thereby achieving industry-employment synergy. From the perspective of inclusive growth, this study incorporates six factors-economic level, financial level, innovation level, human capital, fiscal expenditure, and agricultural resources-into a unified analytical framework under the dimensions of efficiency and equity. Using a mixed method that combines dynamic QCA and regression analysis, and taking 1128 Chinese counties as the sample, this study explores configurational pathways that can simultaneously achieve advanced county industrial structure and inclusive employment growth. The findings are as follows: (1) Four configurational pathways lead to advanced county industrial structure: market-driven with efficiency priority (C1), endowment-substituted with factor concentration (C2), endowment-dependent with efficiency-equity coordination (C3), and talent-innovation dual-driven with government assistance (C4). (2) These four pathways differ in their effectiveness in promoting industry-employment synergy. Configurations C1, C2, and C3 achieve coordinated development of county industry and employment, whereas configuration C4 promotes advanced county industrial structure but inhibits employment growth. The conclusions reveal multiple equivalent pathways for synergistically enhancing county industry and employment, providing a basis for local governments to formulate context-specific industry-employment coordination policies.

Keywords: efficiency; equity; industrial structure; employment; mixed method

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1. Introduction

As China's economy transitions toward high-quality development, the synergy between advanced county industrial structure and employment growth has become increasingly important in regional governance and public policy. High-quality development requires not only sustained growth in economic aggregate but also a transformation of the development model, optimization of economic structure, and a shift in growth drivers [1]. During this process, the labor force inevitably moves across industries and regions in response to industrial restructuring [2], and overall employment conditions directly affect people's livelihoods. Therefore, whether advanced county industrial structure and employment growth can be achieved synergistically has become a key factor for regional high-quality development. This is especially true for county areas, which connect cities and villages. These areas serve both as the main front for industrial gradient transfer and as carriers for achieving common prosperity. However, compared with central cities, counties generally face challenges such as weak industrial bases, a shortage of quality jobs, and severe brain drain [3]. How to synergistically promote both advanced county industrial structure and the qualitative and quantitative expansion of employment at the county level is a practical challenge for county governance and an important question for academic research.

In practice, although some counties have achieved a shift toward high-value-added industries through technological innovation and financial support—leading to job growth—others have seen low-skilled workers squeezed out during industrial transformation and upgrading. This is often due to human capital mismatches, insufficient financial security, and other factors, which in turn affect overall employment. Existing studies have confirmed the complex relationship between industrial structure and employment. Some studies find that the tertiary industry has a relatively strong capacity to absorb labor [4], suggesting that advancing industrial structure can help expand employment to some extent [5]. However, other studies point out that industrial upgrading may negatively affect employment, because new technologies accompanying the transformation prompt firms to hire more highly skilled employees [6], producing two opposite effects simultaneously: directly replacing low- to medium-skilled workers while creating new jobs [7]. Further research reveals that the creation and substitution effects of industrial structure on employment depend on the synergistic influence of multiple factors, such as institutional and policy conditions. Therefore, it is necessary to adopt a configurational perspective to investigate how combinations of multiple factors can simultaneously promote advanced county industrial structure and achieve county employment growth.

Inclusive growth theory offers a theoretical entry point for addressing the above issues. The theory emphasizes that economic growth should pursue not only efficiency gains but also the fair sharing of development outcomes [8]. This aligns well with the need to achieve social goals—such as expanding employment opportunities and narrowing income gaps—during industrial transformation and upgrading. China's 15th Five-Year Plan Outline explicitly prioritizes high-quality full employment and calls for stronger industry–employment coordination. This underscores that industrial transformation and upgrading must not come at the expense of employment; the two must be advanced together. Accordingly, from the perspective of inclusive growth, this study incorporates efficiency and equity into the same analytical framework and selects six antecedent conditions to operationalize these two dimensions. Specifically, the efficiency-dimension antecedents are economic level, financial level, and innovation level, while the equity-dimension antecedents are human capital, fiscal expenditure, and agricultural resources. See Section 2.2.1 for the theoretical basis of selecting these six antecedents. Together, these six antecedents form a complex system that influences the synergy between county industry and employment across both the efficiency and equity dimensions. Given that the mixed

method combining Qualitative Comparative Analysis (QCA) with regression analysis is well-suited for investigating complex systems, this study adopts this mixed method. Using Chinese counties as the research sample, it explores configurational pathways that can simultaneously achieve advanced county industrial structure and inclusive employment growth. The study focuses on two main questions: (1) From the perspective of inclusive growth, which specific combinations of efficiency and equity elements can achieve advanced county industrial structure? (2) Can these combinations simultaneously improve county employment levels, and do some combinations promote advanced county industrial structure while inhibiting employment? Accordingly, compared with existing studies, this paper makes three distinct contributions. First, by applying a mixed method that combines dynamic QCA with regression analysis, it introduces configurational analysis into research on industry–employment synergy, thereby overcoming the limitations of single-factor net effect testing. Second, it operationalizes the efficiency and equity dimensions of inclusive growth theory into six antecedent conditions, revealing how multi-factor combinations interact to affect industry–employment synergy. Third, it focuses on the county unit rather than the national or urban level, thus providing a more targeted basis for formulating context-specific policies to coordinate industry and employment.

The remainder of this paper is organized as follows. Section 2 presents the literature review and model construction. Section 3 describes the research design. Section 4 reports the research results and analysis. Section 5 concludes with the research findings, implications, and limitations.

2. Literature Review and Model Design

2.1. Literature Review

2.1.1. Theoretical Relationship Between Industrial Structure and Employment

The relationship between industrial structure and employment has long been a central concern in economics. As early as classical economics, scholars recognized a connection between the two. Adam Smith argued that a finer division of labor improves production efficiency and expands industrial scale, which in turn creates new production links and business areas, thereby attracting more labor into production. David Ricardo pointed out that countries can promote industrial prosperity and drive employment growth by specializing in production according to their comparative advantages. Early development economics further advanced this understanding. The Petty-Clark theorem holds that as an economy grows, the labor force gradually shifts from the primary industry to the secondary and then to the tertiary industry, highlighting the impact of industrial development on total employment growth and employment structure transformation [9]. Kuznets' theory of industrial structure further notes that during industrialization, the secondary industry's capacity to absorb labor gradually increases. However, in the middle and late stages, secondary industry employment tends to saturate, and the tertiary industry—due to its employment inclusiveness—becomes the key to absorbing labor [10]. Collectively, these theories suggest that industrial structure has a unidirectional positive effect on employment growth.

As theoretical research has deepened, scholars have gradually recognized that industrial structure does not only positively affect employment. From the perspective of technological progress, as industrialization matures, advancing industrial structure is accompanied by innovations in production technology, which may generate employment displacement effects. Skill-Biased Technological Change (SBTC) suggests that technological progress tends to benefit high-skilled workers in improving productivity rather than helping low-skilled workers retain their jobs. This implies that when new technologies are applied on a large scale, workers engaged in routine and standardized tasks are easily

replaced [11]. Such differential effects compress employment opportunities for middle- and low-skilled workers, thereby widening income gaps [12]. Task-Biased Technological Change (TBTC) further argues that technological progress replaces routine, rule-based tasks, which are concentrated in middle-skill jobs. This leads to job polarization, characterized by the expansion of high- and low-end jobs and the contraction of middle-skill jobs [13]. Global value chain theory also holds that when a country's industry shifts from processing and assembly to research and design, two employment effects occur simultaneously: demand for high-skilled labor rises, while low-skill jobs are transferred to low-cost regions due to cost pressures [14]. These theories collectively demonstrate that the impact of industrial development on employment is non-neutral; that is, the effect of advancing industrial structure on employment depends on the relative strength of creation and displacement effects. On this basis, most existing studies examine the relationship between industry and employment from a synergistic perspective. Endogenous growth theory reveals the bidirectional interaction between industrial upgrading and human capital. On the one hand, shifting industry toward high-value-added segments requires a more skilled workforce. On the other hand, high-level human capital accumulation can, through innovation and knowledge spillovers, further promote advanced county industrial structure [15]. Together, these theoretical studies reveal the complexity of the employment effects of industry.

2.1.2. Empirical Relationship Between Industrial Structure and Employment

In addition to the theoretical studies discussed above, many scholars have conducted extensive empirical research on the impact of industrial structure on employment. Some studies suggest that advancing industrial structure helps expand employment scale or improve employment quality. For example, using regional data from the United States, Yazgan et al. found that manufacturing employment shares in high-income and middle-income countries successively peaked and then continued to decline, while the service sector became the main engine of employment growth [16]. This indicates that as the industrial structure gradually shifts toward a service-oriented economy, it exerts a positive effect on employment. From the perspective of technological progress, Hötte et al. argue that technological change accompanying industrial restructuring can have a long-term positive impact on employment by creating new jobs and new industries [17]. This suggests that, in the long run, the creation effect of industrial restructuring on employment often offsets the displacement effect. Similarly, Alcorta's research shows that industrialization effectively absorbs labor through the direct expansion of industrial sectors and their indirect spillover effects on related supporting industries, thereby promoting employment growth [18].

However, some studies argue that advancing industrial structure can also negatively affect employment. Using U.S. labor market data, Acemoglu and Restrepo found that industrial robots have a significant displacement effect on manufacturing employment: adding one robot per thousand workers reduces the employment-to-population ratio by 0.18 to 0.34 percentage points and lowers wages by 0.42% [19]. Mondolo further notes that technology-intensive advancement, particularly digitalization and automation, may reduce relative or even absolute labor demand. In the manufacturing sector, the displacement effect often outweighs the creation effect [13]. Feng et al. also show that structural unemployment risk cannot be ignored during economic development, and industrial upgrading may exacerbate employment difficulties for specific groups [20]. Taken together, these empirical studies indicate that the relationship between industrial structure and employment remains unclear, with even contradictory findings.

2.1.3. Moderating Mechanisms of the Complex Relationship Between Industrial Structure and Employment

A large body of research has further explained the complex relationship between industrial structure and employment, arguing that this complexity arises from the moderating role of multiple factors. From a temporal perspective, Zhao et al. found that regional digital transformation initially hurts employment quality but follows a U-shaped trajectory over time, revealing the complex effects of industry and labor skill levels on employment quality [21]. From the perspective of technological progress, Balsmeier et al. found that mechanized digital technology is associated with an increase in high-skilled employment and a decrease in low-skilled employment, with a positive net effect. In contrast, non-mechanized digital technologies such as e-commerce or cooperative support systems have no significant impact on employment [22]. From the perspective of regional differences, Li et al. found that employment structure optimization in eastern and northeastern China benefits from industrial green development, while the corresponding coefficients for western and central regions are not significant. Further analysis by Li et al. revealed that after accounting for the interaction between industrial green development and technological innovation, the positive impact on employment structure becomes significant across all four regions [23].

The above studies provide theoretical and empirical foundations for understanding the relationship between industrial structure and employment. However, from a methodological perspective, the existing literature largely focuses on testing the net effects of single factors. It pays limited attention to how multiple factors can synergistically drive advanced county industrial structure and improve employment levels from a configurational perspective. Regarding the unit of analysis, most existing empirical research concentrates on the national or urban level, while insufficient attention has been given to counties as the fundamental governance units linking urban and rural areas. From a theoretical perspective, when analyzing the employment effects of industrial structure upgrading, existing studies often rely solely on the logic of technological substitution, failing to incorporate efficiency improvement and benefit sharing into the same analytical framework. Inclusive growth theory has long emphasized that economic growth should balance efficiency and equity. The efficiency dimension focuses on the optimal allocation of production factors, while the equity dimension stresses the equalization of development opportunities in education, healthcare, and employment [24]. Introducing this inclusive growth perspective—which advocates the interdependence of efficiency and equity—into the study of industrial structure and employment has two implications. On the one hand, we should examine how efficiency-dimension factors (e.g., economic level, financial level, innovation level) drive advanced county industrial structure. On the other hand, we should explore how equity-dimension factors (e.g., human capital, fiscal expenditure, agricultural resources) help secure employment opportunities and mitigate structural unemployment. This approach reveals how factors from different dimensions can achieve the dual goals of advanced county industrial structure and employment growth through configurational effects. Accordingly, this study adopts the efficiency-equity framework from the inclusive growth perspective to uncover the multiple concurrent causal paths that synergistically promote advanced county industrial structure and employment growth at the county level.

2.2. Model Design

2.2.1. Selection of Antecedent Conditions

Inclusive growth theory holds that economic growth should pursue not only efficiency gains but also the fair sharing of development outcomes. High-efficiency growth

that fails to benefit the majority of workers can hardly be called inclusive. Conversely, overemphasizing fair distribution at the expense of efficiency also prevents sustainable development. Thus, efficiency and equity are not simple substitutes; they can achieve synergy through specific combinations of conditions. This theoretical perspective suggests that whether industrial upgrading and employment growth form a synergistic relationship does not depend on any single factor, but on how efficiency- and equity-dimension elements work together. That is, under certain configurations, multiple elements can match each other to form a virtuous cycle, jointly promoting advanced county industrial structure while benefiting more workers.

From this perspective, traditional regression analysis is well suited for estimating the average effect of a single factor. In reality, however, county development conditions are often shaped by multiple intertwined factors, making it difficult to isolate the role of any one factor. Some counties have a strong economic foundation but weak innovation vitality; others are rich in agricultural resources but lack human capital; still others have considerable fiscal capacity but an underdeveloped financial system. Given such heterogeneous backgrounds, the development pathways that actually work are correspondingly diverse. This suggests that studying industry–employment synergy at the county level requires attention to which combinations of factors produce desirable outcomes. Inclusive growth theory itself implies this path diversity: different counties can choose development models suited to their own advantages, and as long as efficiency and equity complement each other, achieving the dual goals of advanced county industrial structure and employment growth is possible.

Configurational analysis is well suited to capturing these complex causal relationships among multiple factors. Rather than estimating the net effect of a single factor, it focuses on how multiple factors combine to produce outcomes. It recognizes that different condition combinations can achieve the same goal and identifies which combinations can simultaneously promote advanced county industrial structure and employment growth. This aligns with inclusive growth theory's concern for balancing efficiency and equity. Therefore, from an inclusive growth perspective, the synergy between advanced county industrial structure and employment growth cannot be achieved by efficiency-dimension or equity-dimension factors alone, but rather arises from specific combinations of factors across both dimensions. Accordingly, this study maps six antecedent conditions—economic level, financial level, innovation level, human capital, fiscal expenditure, and agricultural resources—onto the two dimensions of efficiency and equity, as follows.

On the efficiency dimension, economic level provides the material foundation for industrial transformation. Financial level ensures that firms can access affordable credit to support industrial upgrading. Innovation level supplies the technological impetus for shifting toward high-value-added activities. These three antecedents are expected to enable an advanced county industrial structure; however, their direction and strength of influence often depend on the presence and combination of equity-dimension conditions. On the equity dimension, human capital determines the skill level of the local workforce, directly affecting workers' ability to meet new job requirements after industrial upgrading. Fiscal expenditure reflects the government's capacity to provide public goods and social protection, helping to buffer the negative employment effects of technological substitution. Agricultural resources capture a county's capacity for agricultural production based on natural conditions, providing resources for labor-absorbing industries such as ecotourism and specialty agriculture, thereby partially offsetting job losses from automation or technological upgrading. Unlike the efficiency-dimension antecedents, these three equity-dimension factors do not directly drive advanced county industrial structure; rather, they primarily contribute to the inclusiveness of employment outcomes.

Together, the three efficiency-dimension and three equity-dimension factors offer a concise and theoretically grounded operationalization of the inclusive growth perspective. We acknowledge that these six antecedents do not exhaust all possible determinants. Nevertheless, they represent the constructs most frequently emphasized in the existing literature on industry–employment synergy. Other potentially omitted variables—such as digital infrastructure and cultural service supply—are discussed in Section 5.4, and we call for future research to further extend this analytical framework.

2.2.2. The Relationship Between Key Elements and Advanced County Industrial Structure

Economic Level and Advanced County Industrial Structure. Economic level reflects a region's overall development by integrating various production factors over a given period. Counties with a high economic level tend to have greater capital accumulation, which provides material support for technological innovation, talent attraction, and infrastructure construction. This facilitates the transformation from traditional agriculture-oriented industries to technology- and knowledge-intensive sectors [25]. Moreover, as economic development improves, residents' consumption power rises and their demand becomes more diversified, favoring high-quality and personalized products. This encourages existing firms to invest more capital in service industries such as information technology and cultural tourism, thereby contributing to industrial transformation and upgrading [26]. In addition, a higher economic level often indicates a more active local market and a better business environment. These conditions promote the flow of production factors—capital, knowledge, and management—toward high-efficiency industries, helping firms enhance their market competitiveness and stimulating advanced county industrial structure. Based on this, this study proposes Hypothesis 1:

H1. *Economic level can affect advanced county industrial structure.*

Financial Level and Advanced County Industrial Structure. Financial level refers to the development degree of a region's financial market over a given period, which relates to the efficiency of resource allocation. Counties with a high financial level often have a more complete financial market system. As a result, local enterprises have more diversified financing channels, which help them engage in technology research and development (R&D), equipment renewal, and other activities using stable capital supply. This effectively alleviates the financing constraints faced during industrial transformation and upgrading [27]. At the same time, a high financial level means that local financial institutions can guide capital toward efficient technology- and knowledge-intensive industries through various mechanisms, thereby optimizing resource allocation and promoting local industrial transformation and upgrading. However, the financial level may also have a threshold effect on advanced county industrial structure [28]. When the financial development level is low, financial resources tend to flow to traditional industries with longer duration and greater stability, which may solidify the county's industrial structure. Only when the financial level reaches a certain threshold does its positive impact on industrial structure become more prominent. Based on this, this study proposes Hypothesis 2:

H2. *Financial level can affect advanced county industrial structure.*

Innovation Level and Advanced County Industrial Structure. Innovation level reflects a county's knowledge output and efficiency in transforming scientific and technological achievements over a given period. Counties with a high innovation level often

have more abundant scientific research resources. This not only facilitates process upgrading and technological renovation in traditional industries but also fosters new industries and business forms—such as intellectual property services—through knowledge spillover. These changes drive the county's industrial structure toward technology- and knowledge-intensive sectors [29]. In addition, a high innovation level usually indicates a vibrant local innovation climate and a well-established mechanism for transforming scientific achievements. These conditions create a favorable environment that attracts external capital and labor to local high-efficiency industries, thereby facilitating an advanced county industrial structure [30]. However, in county areas, the role of innovation in promoting advanced industrial structure may also depend on local innovation infrastructure. Only when the innovation level matches the local industrial base can innovation truly promote industrial transformation and upgrading. Based on this, this study proposes Hypothesis 3:

H3. *Innovation level can affect advanced county industrial structure.*

Human Capital and Advanced County Industrial Structure. Human capital measures a region's educational and cultural level over a given period. Counties with a high level of human capital can provide high-quality labor, which helps meet the demand of high-end manufacturing and modern service industries, thereby promoting the shift toward technology- and knowledge-intensive sectors [31]. Moreover, a higher level of human capital implies that local employees have stronger overall skills. This helps county enterprises overcome technical bottlenecks, achieve technological renovation, and upgrade products, thus facilitating the transformation and upgrading of the entire industrial system [32]. However, the positive effect of human capital on advanced county industrial structure likely depends on the match between human capital and industrial demand. If the education system does not align with actual industrial needs, or if local supporting facilities cannot ensure labor supply, high-quality workers may choose to move to larger cities. This would inhibit the positive impact of human capital on advanced county industrial structure. Based on this, this study proposes Hypothesis 4:

H4. *Human capital can affect advanced county industrial structure.*

Fiscal Expenditure and Advanced County Industrial Structure. Fiscal expenditure refers to the amount of funds invested by a local government to perform public functions over a given period. On the one hand, counties with higher fiscal expenditure often have more developed infrastructure. This reduces logistics costs between industries, supports the agglomeration of high-end manufacturing and the development of modern services, and attracts external enterprises to locate in the county, thereby affecting its industrial structure [33]. On the other hand, a higher level of fiscal expenditure also implies better public services, such as education and healthcare [34]. This improves the living environment and helps attract high-quality talent from outside to the county, which indirectly influences the advanced county industrial structure. In addition, higher fiscal expenditure means that the local government has stronger macroeconomic control. It can guide social capital toward emerging high-tech industries through measures such as tax incentives [35], thereby helping to alleviate the risks enterprises face during transformation and upgrading. However, a high level of fiscal expenditure may also indicate greater government intervention in enterprises. This can increase transaction costs for firms during transformation and upgrading, potentially hindering advanced county industrial structure [36]. Based on this, this study proposes Hypothesis 5:

H5. *Fiscal expenditure can affect advanced county industrial structure.*

Agricultural Resources and Advanced County Industrial Structure. Agricultural resources measure the foundation and scale of agricultural production that relies on natural conditions in county areas, primarily reflected in the abundance of land, biological, and water resources. A high level of agricultural resources in a county often implies superior cultivated land, distinctive agricultural products, and a favorable agro-ecological environment. These conditions provide the material basis for developing local specialty industries such as deep-processing of agricultural products, ecological agriculture, and rural tourism, thereby promoting green industrial transformation and upgrading [37]. Moreover, abundant agricultural resources usually indicate a sound local natural environment, which can attract talent with high living quality requirements to move to the county [38] and also create suitable conditions for the establishment of knowledge- and technology-intensive industries. Furthermore, a higher level of agricultural resources helps the county form a differentiated agricultural competitive advantage, avoiding homogenized competition with surrounding areas, and assists existing enterprises in improving their industrial system by developing characteristic agricultural industry chains. However, an excessively high level of agricultural resources may bring negative effects. When agricultural resources are too abundant, the county economy may become overly dependent on traditional crop farming or resource-based agriculture, and a large number of production factors may remain locked in the low-value-added agricultural sector [39]. This, in turn, hinders the transformation and upgrading of the industrial structure toward high-end manufacturing and modern service industries. Based on this, this study proposes Hypothesis 6:

H6. *Agricultural resources can affect the advanced county industrial structure.*

2.2.3. Construction of the Analytical Framework

Existing research reports ambiguous or even contradictory relationships between the six key elements-economic level, financial level, innovation level, human capital, fiscal expenditure, and agricultural resources-and the advanced county industrial structure. This ambiguity arises mainly because the effect of any single antecedent condition on industrial structure upgrading may be contingent on other factors. Thus, focusing exclusively on individual factors is insufficient for identifying pathways to achieve advanced county industrial structure. In reality, the process of upgrading county industrial structure often involves numerous interdependent factors. Especially in county areas, the synergistic effects of certain non-economic dimensions deserve due consideration. The configurational perspective views organizations as entities composed of multiple interrelated components [40]; therefore, it is essential to analyze multiple conjunctural causal paths leading to an outcome from a holistic standpoint [41]. Consequently, this perspective is well suited to examining the complex causal relationships between the six key elements and advanced county industrial structure. It can reveal the internal mechanisms through which different key elements interact and mutually influence one another, thereby affecting advanced county industrial structure. Based on this, this study adopts a configurational perspective to construct a theoretical model for investigating the influencing factors of advanced county industrial structure.

Although the configurational perspective helps identify factor combinations that achieve advanced county industrial structure, different combinations may have significantly different impacts on county employment levels. Both theoretical and empirical evidence suggests that the relationship between industrial structure upgrading and employment growth is not simply linear. If a county's industrial structure upgrading shifts toward service-oriented industries, it often exhibits a strong inclusive employment growth effect. However, if it converges toward technology- and knowledge-intensive industries, it may compress employment opportunities for low-skilled workers. Specifically, when a

county has high levels of innovation and human capital, these factors can jointly drive industrial structure toward technology-intensive industries. If, at the same time, fiscal expenditure on livelihood protection is insufficient, this may aggravate unemployment risks for low-skilled workers. Therefore, different combinations of the six key elements may not only constitute different pathways to advanced county industrial structure but also directly or indirectly exert different impacts on county employment levels. Based on this, this study constructs the theoretical model shown in Figure 1 and proposes Hypothesis 7. This hypothesis aims to explore factor combinations that can simultaneously promote advanced county industrial structure and enhance county employment levels, thereby avoiding situations where factor combinations used to promote industrial upgrading instead suppress employment.

H7. *The six antecedent conditions can synergistically affect advanced county industrial structure and county employment levels.*

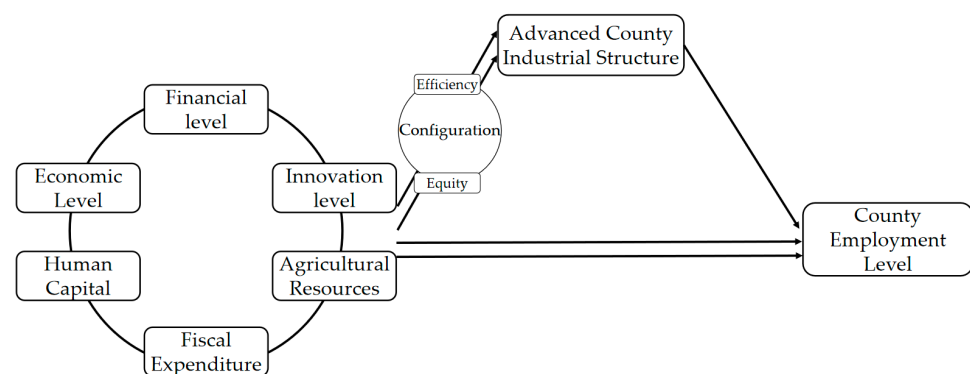


Figure 1. Theoretical model for achieving industry-employment synergy.

3. Research Design

3.1. Method

To explore configurational pathways that can synergistically promote advanced county industrial structure and improve county employment levels, this study adopts a mixed method that combines dynamic QCA with regression analysis. This mixed method is based on the approach proposed by Du et al. [42]. It can analyze how combinations of antecedent conditions evolve over time while also addressing the limitations of traditional statistical methods when dealing with complex causal systems. The uniqueness of a complex causal system lies in the fact that independent variables, mediating variables, and dependent variables can all be complex systems comprising multiple key elements.

First, Qualitative Comparative Analysis (QCA) is a case-oriented research method. Its methodological core rests on three assumptions of causal complexity: (1) conjunctural causality-multiple antecedents jointly lead to an outcome; (2) equifinality-different combinations of conditions can produce the same outcome; and (3) asymmetry-the presence of a condition may lead to an outcome, but its absence does not necessarily imply the absence of the outcome [43]. This study adopts dynamic QCA as the first-stage analytical method because advanced county industrial structure is often driven by multiple factors, whereas traditional regression analysis can only identify the net effect of a single variable. Moreover, dynamic QCA extends standard QCA by incorporating the time dimension, allowing it to capture both time effects and individual effects of configurational pathways [44]. This enables a more comprehensive understanding of how multiple antecedents work together on the outcome variable through synergistic or substitution relationships at different time stages.

Second, although dynamic QCA can identify combinations of conditions that lead to an outcome, it cannot quantify the influence of each configurational pathway on subsequent variables. Therefore, this study adopts regression analysis in the second stage. The difference between this stage and traditional regression analysis lies in the independent variable, which is the set membership score of each case on each identified configurational pathway for promoting industrial structure upgrading. Specifically, for each identified configurational pathway, we use subset and intersection logic in fuzzy-set operations to calculate the set membership score of each county on that configuration. This score reflects the degree of match between the county's characteristics and the corresponding configurational pathway. Using this method, we can further test the direct and indirect effects of these configurational pathways on employment levels.

Finally, combining dynamic QCA with regression analysis compensates for the lack of time effects in traditional static QCA while retaining the rigor of statistical inference. This combination addresses the core question of how multiple antecedent conditions jointly drive industrial structure upgrading and employment promotion. If only a single method were used, the resulting configurational pathways might promote advanced county industrial structure but inhibit county employment levels. Therefore, this study adopts a mixed method that combines dynamic QCA based on panel data with regression analysis. Specifically, in the first-stage dynamic QCA, several configurational pathways that achieve advanced county industrial structure are identified. Each configurational pathway is a combination of specific antecedent conditions. Then, using subset and intersection logic in fuzzy-set operations, we calculate the set membership score of each county on each of these four configurations. This score, ranging from 0 to 1, reflects the degree of match between the county's actual conditions and a given configurational pathway. A higher score indicates that the county's characteristics more closely align with that pathway. Finally, this set membership score is used as the independent variable, and county employment level as the dependent variable, in a regression analysis. Thus, combining dynamic QCA with regression analysis allows this study both to identify configurational pathways that lead to advanced county industrial structure and to quantitatively evaluate the differential effects of these pathways on employment growth. Figure 2 illustrates the step-by-step implementation of this mixed method, from dynamic QCA to regression analysis.

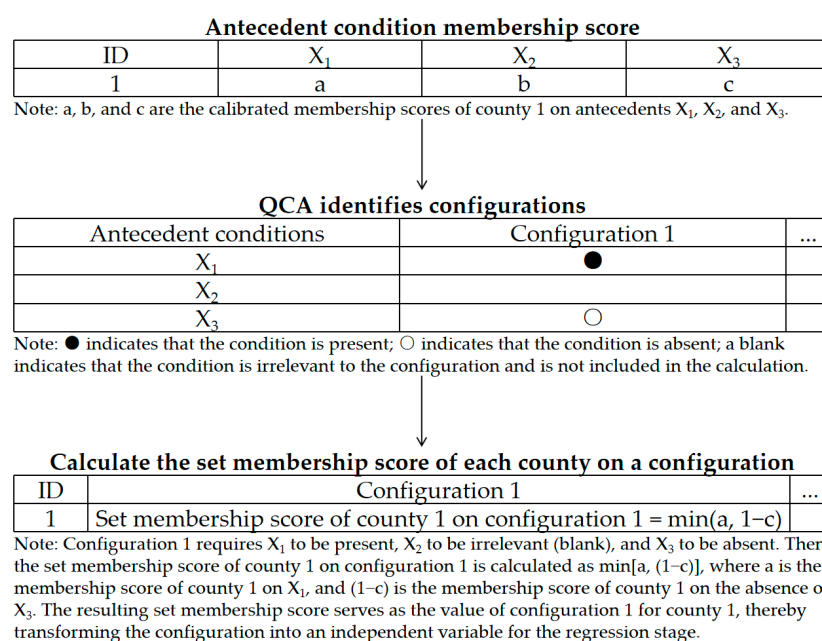


Figure 2. Schematic diagram of the mixed method analysis procedure.

3.2. Data Sources

This study selects Chinese counties as the research cases. The sample covers 1128 counties nationwide (including counties, municipal districts, county-level cities, autonomous counties, etc.) after excluding those with missing data. The reasons are as follows. (1) Using the county as the unit of analysis allows for a more detailed examination of the relationship between advanced county industrial structure and the labor market. (2) The counties are distributed across eastern, central, western, and northeastern China, ensuring sufficient heterogeneity in the antecedent conditions of this study. Moreover, unlike regression models, QCA cannot control for the influence of irrelevant variables by including control variables. However, using different regions within the same country as research cases helps control for factors such as cultural background. Therefore, by taking Chinese counties as the research cases, this study simultaneously satisfies the requirements of heterogeneity and homogeneity [43].

Considering the lagged effects of antecedent conditions on advanced county industrial structure and county employment levels, this study sourced data as follows. Data on economic level, innovation level, human capital, fiscal expenditure, and agricultural resources were obtained from the China County Statistical Yearbook (County and City Volume) for the years 2021–2023 (which contain statistical data for 2020–2022). Innovation level data came from the patent database of the China National Intellectual Property Administration for 2020–2022. Data on advanced county industrial structure were taken from the China County Statistical Yearbook (County and City Volume) for 2022–2024 (containing data for 2021–2023). Data on county employment levels were drawn from the Statistical Bulletins of National Economic and Social Development of provinces or prefecture-level cities for 2022–2024, as well as the Statistical Yearbooks of provinces or prefecture-level cities for 2025 (all of which contain statistical data for 2022–2024).

It should be noted that the time span of this study covers the period of the COVID-19 pandemic. This choice does not ignore the pandemic's disruption but is based on the following considerations. First, data availability determines the boundaries of the time span. For county-level data, several indicators had considerable missing values before 2019, whereas data completeness after 2020 is relatively high. Second, although the pandemic represents an extreme shock, it also provides an external shock scenario for observing the complex relationship between industry and employment. Under this shock, differences in factor endowments across counties in the efficiency and equity dimensions become amplified, which helps identify configurational pathways that might remain hidden under normal conditions. In other words, if a configurational pathway can robustly promote advanced county industrial structure and employment growth even under pandemic conditions, its applicability under normal conditions is more credible. Third, this study does not rely exclusively on results from this special period. In the robustness tests, we supplement the analysis with subsamples. We also candidly discuss the limitations of this time span in Section 5.4 and call for future research to validate our findings using pre-pandemic data.

3.3. Variable Measurement

3.3.1. Outcome Variable

County Employment Level (CEL). County employment level measures the labor force absorption capacity of county areas and reflects the strength of local livelihood security. Existing studies often use indicators such as non-agricultural employment, the number of employed staff, or the registered unemployment rate. However, these data suffer from low availability. Therefore, this study measures county employment level as the ratio of newly created urban jobs to the registered resident population. The rationale is

that newly created urban jobs represent the total number of people who achieved initial employment or re-employment through various channels in a given county within a year, which reflects the activity of the local labor market. Standardizing by the registered resident population avoids the interference of scale effects.

3.3.2. Mediator Variable

Advanced County Industrial Structure (ACIS). Advanced county industrial structure measures the process by which a regional economy transitions from a lower to a higher level. This process is characterized by the industrial focus shifting from the primary industry to the secondary and tertiary industries, with the share of the tertiary industry rising continuously relative to the secondary industry. Therefore, this study uses the industrial structure hierarchy coefficient (*isu*) to measure advanced county industrial structure. It is calculated as $isu = I_1 + I_2 \times 2 + I_3 \times 3$, where I_i represents the proportion of value added of industry i to the total output value. This ratio directly reflects whether the county's economic structure is gradually transitioning from an industrial to a service orientation—that is, whether the industrial structure is becoming more advanced. The larger the index value, the higher the level of advanced county industrial structure.

3.3.3. Antecedent Variables

Economic Level (EL). Economic level reflects a county's comprehensive economic strength and development stage. To address the issue that gross domestic product (GDP) is not directly comparable across counties due to differences in population size, this study measures economic level as the ratio of regional GDP to the year-end registered resident population [45]. This indicator objectively measures the economic value created per unit of population in each county. It reflects the county's overall production efficiency while allowing for comparability across counties with different population sizes through population standardization.

Financial Level (FL). Financial level measures the supply of financial resources and the efficiency of resource allocation in a county. This study uses the ratio of year-end outstanding loans of financial institutions to regional GDP as the indicator of financial level [46]. This ratio reflects the intensity of credit support provided by banking and non-banking financial institutions to various economic entities in the county, thereby capturing the supply level and activity of financial resources. Standardizing by regional GDP enables comparison of credit support across counties with different economic scales.

Innovation Level (IL). Innovation level measures a county's technological innovation vitality and knowledge creation capacity. This study uses the ratio of the number of patent applications to the year-end registered resident population as the indicator of innovation level [47]. The number of patent applications includes all invention, utility model, and design patent applications submitted to the China National Intellectual Property Administration by enterprises, research institutions, universities, and individuals in the county during the reporting period. This metric captures the activity level of regional innovation. Standardizing by registered resident population ensures comparability across counties with different population sizes.

Human Capital (HC). Human capital measures the knowledge reserve of the labor force in county areas. The number of students enrolled in primary and secondary schools directly reflects the supply level of basic education services. This study measures human capital as the ratio of the number of primary and secondary school students to the registered resident population. The number of primary and secondary school students refers to the total enrollment in ordinary primary schools, junior high schools, and senior high schools in the county. This reflects the coverage of basic education and the scale of the

future labor reserve. Standardizing by registered resident population also helps eliminate the impact of differences in population base.

Fiscal Expenditure (FE). Fiscal expenditure measures the government's supply of public services through public finance. This study measures fiscal expenditure as the ratio of local general public budget expenditure to regional GDP [48]. Local general public budget expenditure refers to government funds allocated to general public services and other areas, reflecting the degree of government intervention in regional economic and social development. Standardizing by regional GDP eliminates the interference of differences in regional GDP on total expenditure.

Agricultural Resources (AR). Agricultural resources measure the foundation and scale of agricultural production that relies on natural conditions in county areas. Following the System of National Accounts definition that the primary industry produces goods "derived directly from nature (including plantations, forestry, pastoralism, and fisheries)" [49], this study uses the value added of the primary industry as the indicator of agricultural resources. Due to the lack of consistent data on natural resource stocks (e.g., cultivated land area) at the county level [50], this output-based proxy is a necessary strategy in empirical research. Notably, this variable captures a double-edged role. On one hand, a higher level of agricultural resources indicates stronger natural conditions for production. On the other hand, an excessively high dependence on such resources may create path dependence and hinder industrial upgrading, as suggested by the natural resource curse literature [51]. Therefore, using the value added of the primary industry allows this study to reflect both the foundational role of agricultural resource endowment and its potential negative consequences for industrial transformation.

3.3.4. Control Variables

Considering that factors beyond the six key antecedents may also affect advanced county industrial structure and county employment levels, this study includes the following control variables in the second-stage regression analysis to avoid potential bias due to omitted variables. (1) **Population Size (PS).** Measured as the natural logarithm of the year-end total registered resident population. This variable controls for the scale effect on total employment due to differences in population base across counties [52]. (2) **Savings Rate (SR).** Measured as the ratio of household savings deposit balance to GDP. The household savings level not only reflects a region's potential consumption capacity and capital accumulation but also indirectly affects the employment absorption capacity of the local labor market through its influence on consumer demand and investment vitality [53]. (3) **Intensity of Tax Cuts and Fee Reductions (ITCFR).** Measured as the ratio of local general public budget revenue to regional GDP. A lower tax burden can stimulate corporate investment and expansion, which in turn raises labor demand and promotes regional employment [54]. (4) **Traditional Infrastructure (TI).** Measured as the ratio of fixed telephone subscribers to the year-end registered resident population. The adequacy of traditional communication infrastructure directly affects the efficiency of employment information dissemination and the matching efficiency between workers and jobs, thereby influencing rural labor force employment decisions and migration patterns [55].

4. Research Results and Analysis

4.1. Stage 1: Using Dynamic QCA to Identify Configurational Pathways for Achieving Advanced County Industrial Structure

4.1.1. Variable Calibration

This study uses the direct calibration method to convert each variable into a fuzzy-set membership score. Due to the lack of recognized external standards at the county level-

such as national statistical thresholds or policy classification criteria—to define high, medium, and low levels of each condition, we follow common practice in mainstream QCA research [56]. Specifically, we set the 75th percentile, median, and 25th percentile of the sample data as the calibration anchors for full membership, the crossover point, and full non-membership, respectively. This choice implies that, for each antecedent condition, the top 25% of counties are considered to have high membership (i.e., the condition is present), the bottom 25% are considered to have low membership (i.e., the condition is absent), and the middle 50% exhibit varying degrees of partial membership. This approach aligns with the asymmetric distribution characteristics of county-level data and preserves the differences among counties in the sample.

To ensure that the calibration results are not sensitive to the choice of specific percentiles, we adjust the full membership and full non-membership anchors by two percentage points up and down from the original 75%, 50%, and 25% anchors. Specifically, we test anchor sets of 73%, 50%, and 27% as well as 77%, 50%, and 23%. The sufficiency analysis results based on these alternative calibrations yield configurational pathways that are completely consistent with the original results, indicating that the calibration anchors are robust (see Section 4.1.6 for details). In addition, to avoid excluding cases with a calibrated membership score of exactly 0.5 from subsequent analyses, we replace all membership scores of 0.5 with 0.501. The membership score of each case in non-advanced county industrial structure is obtained as the negation (1 minus) of its membership score in advanced county industrial structure. Tables 1 and 2 present the calibration anchors and descriptive statistics for each variable.

Table 1. Calibration anchor points.

Variables		Calibration Anchor Points		
		Full Membership	Cross Over Point	Full Non-Membership
Antecedent variables	EL	6.774	4.270	2.916
	FL	11.60	8.518	6.229
	IL	12.67	5.657	2.714
	HC	1.377	1.165	0.925
	FE	3.119	2.028	1.372
	AR	5.299	3.147	1.751
Outcome variable	ACIS	2.368	2.283	2.181

Note: Economic Level (EL), Financial Level, (FL), Innovation Level (IL), Human Capital (HC), Financial Expenditure (FE), Agricultural Resources (AR), Advanced County Industrial Structure (ACIS). The same below.

Table 2. Descriptive statistics of each variable.

Variables		Mean	SD	Min	Max
Antecedent variables	EL	6.080	6.056	0.729	103.8
	FL	9.483	4.835	0.088	67.28
	IL	14.24	29.04	0.033	395.1
	HC	1.183	0.386	0.196	3.892
	FE	2.626	2.104	0.418	30.80
	AR	3.836	2.822	0.017	18.57
Outcome variable	ACIS	2.272	0.157	1.577	2.860

4.1.2. Necessary Condition Analysis

Before conducting the sufficiency analysis, we first perform a necessity analysis for each antecedent condition to determine whether any single condition constitutes a necessary condition for advanced county industrial structure. This study uses R version 4.5.2 for the necessity analysis, and the results are presented in Tables 3 and 4. Consistency is a key indicator for judging a necessary condition. If the consistency of an antecedent condition is greater than or equal to 0.9, that condition can be considered necessary for the outcome to occur. As shown in Table 2, the consistency of all antecedent conditions is below 0.9, indicating that none of the six antecedent conditions alone constitutes a necessary condition for advanced county industrial structure. Therefore, a sufficiency analysis is required.

Table 3. Analysis on the necessity of advanced county industrial structure.

Antecedent Variables		Pooled Consistency	Pooled Coverage	Between-Group Consistency-Adjusted Distance	Within-Group Consistency-Adjusted Distance
Efficiency	EL	0.619	0.634	0.088	0.572
	~EL	0.474	0.469	0.111	0.639
	FL	0.628	0.639	0.041	0.572
	~FL	0.471	0.469	0.067	0.605
	IL	0.652	0.678	0.075	0.504
	~IL	0.449	0.438	0.080	0.639
Equity	HC	0.58	0.587	0.023	0.572
	~HC	0.517	0.518	0.036	0.639
	FE	0.463	0.473	0.132	0.639
	~FE	0.632	0.627	0.090	0.572
	AR	0.507	0.517	0.083	0.605
	~AR	0.586	0.582	0.083	0.605

Note: “~” indicates negation.

Table 4. Analysis on the necessity of non-advanced county industrial structure.

Antecedent Variables		Pooled Consistency	Pooled Coverage	Between-Group Consistency-Adjusted Distance	Within-Group Consistency-Adjusted Distance
Efficiency	EL	0.455	0.461	0.158	0.673
	~EL	0.639	0.623	0.106	0.572
	FL	0.459	0.461	0.093	0.673
	~FL	0.641	0.63	0.065	0.572
	IL	0.417	0.427	0.139	0.639
	~IL	0.686	0.661	0.075	0.572
Equity	HC	0.512	0.511	0.021	0.639
	~HC	0.586	0.579	0.026	0.605
	FE	0.619	0.624	0.127	0.538
	~FE	0.478	0.468	0.155	0.673
	AR	0.574	0.578	0.041	0.572
	~AR	0.52	0.51	0.049	0.639

Note: “~” indicates negation.

In addition, we examine time and individual effects using between-group and within-group consistency-adjusted distances. If the consistency-adjusted distance exceeds 0.1 or 0.2, the pooled consistency is considered unstable, warranting further analysis [44].

The between-group consistency-adjusted distance measures the stability of consistency over time, while the within-group consistency-adjusted distance measures the stability of consistency across individual cases. As shown in Tables 3 and 4, the between-group consistency-adjusted distance for each variable is below 0.2, and although some variables exceed the 0.1 threshold, the pooled consistency remains relatively stable at the time level. In contrast, the within-group consistency-adjusted distance for each variable exceeds 0.2, indicating that the pooled consistency is highly unstable at the individual level. This may be because our study covers 1128 counties across China, and the large sample amplifies the heterogeneity in efficiency- and equity-dimension endowments across counties. Consequently, even when different types of counties follow the same pathway of industrial structure upgrading, their internal conditions differ substantially, leading to greater fluctuations in pooled consistency at the individual level.

For cases where the between-group consistency-adjusted distance falls between 0.1 and 0.2, we further examine the between-group consistency and coverage of the corresponding variables. Using R version 4.5.2, we analyze the seven situations in which the consistency-adjusted distance is between 0.1 and 0.2. The between-group results are presented in Table 5. The consistency level for each situation across all years is below 0.9, indicating that none of these situations constitutes a necessary relationship. Therefore, it is necessary to fully consider the interactions and influences among multiple variables. Furthermore, from 2020 to 2022, the consistency between low economic level and fiscal expenditure, on the one hand, and advanced county industrial structure, on the other, decreased year by year. This trend may be attributed to the increasing uncertainty of the macroeconomic environment and the impact of the COVID-19 pandemic in recent years. Specifically, during the pandemic, counties with low economic levels had insufficient momentum for industrial transformation and upgrading. Fluctuations in external demand further weakened the supporting role of their own resource accumulation in industrial structure upgrading. At the same time, county-level financial resources were increasingly concentrated on pandemic prevention and control and basic livelihood needs, leading to a relative reduction in special expenditures for industrial transformation and upgrading. This, in turn, weakened the driving role of fiscal expenditure in advancing the industrial structure. The above analysis further demonstrates that a single condition can hardly constitute a necessary condition for an advanced county industrial structure.

Table 5. Between-group data with consistency-adjusted distance greater than 0.1 and less than 0.2.

Case	Causal Configuration		2020	2021	2022
1	~EL and ACIS	Between-Group Consistency	0.525	0.458	0.444
		Between-Group Coverage	0.464	0.443	0.5
2	FE and ACIS	Between-Group Consistency	0.522	0.439	0.432
		Between-Group Coverage	0.469	0.462	0.489
3	EL and ~ACIS	Between-Group Consistency	0.393	0.463	0.509
		Between-Group Coverage	0.452	0.477	0.454
4	~EL and ~ACIS	Between-Group Consistency	0.699	0.63	0.59
		Between-Group Coverage	0.617	0.653	0.601
5	IL and ~ACIS	Between-Group Consistency	0.467	0.412	0.372
		Between-Group Coverage	0.447	0.441	0.393
6	FE and ~ACIS	Between-Group Consistency	0.691	0.568	0.598
		Between-Group Coverage	0.62	0.64	0.613
7	~FE and ~ACIS	Between-Group Consistency	0.408	0.523	0.501
		Between-Group Coverage	0.46	0.499	0.445

Note: “~” indicates negation.

4.1.3. Sufficiency Analysis

Based on the necessity analysis, the sufficiency analysis helps identify multiple combinations of antecedent conditions that can lead to an outcome, thereby revealing the multiple concurrent causal relationships between antecedents and the outcome. In QCA, the initial truth table is screened by setting three thresholds: the raw consistency threshold, the case frequency threshold, and the PRI consistency threshold. Referring to the calibration standards used in existing large-sample studies, this study sets the raw consistency threshold to 0.75, as a threshold greater than 0.75 ensures the reliability of the results [57]. The case frequency threshold is set to 20, which ensures that the configurations meeting or exceeding this threshold cover more than 80% of the cases [58]. The PRI consistency threshold is set to 0.6, as a threshold higher than 0.5 avoids the problem where a configuration simultaneously leads to both the occurrence and non-occurrence of an outcome [59].

In addition to the threshold settings described above, before identifying complex, intermediate, and parsimonious solutions, hypothetical assumptions about logical remainders must be made based on whether the presence or absence of an antecedent condition promotes the outcome. Since the influence of each antecedent condition on the outcome is not clear, this study assumes, in the counterfactual analysis, that either the presence or the absence of a single antecedent condition could potentially lead to advanced county industrial structure. Following these procedures, this study obtained configurational solutions that achieve advanced county industrial structure and presents them following the standard QCA methodological paradigm [40]. Specifically, conditions that appear in both the parsimonious and intermediate solutions are treated as core conditions, while those that appear only in the intermediate solution are treated as peripheral conditions. Based on this, this study takes advanced county industrial structure as the outcome variable in the sufficiency analysis and identifies four configurational pathways that achieve it, labeled C1, C2, C3, and C4. The results are presented in Table 6.

Table 6. Configuration of advanced county industrial structure.

Antecedent Variables	Advanced County Industrial Structure			
	C1	C2	C3	C4
EL	●	●	●	
FL	●	●		●
IL	●	●	●	●
HC			●	●
FE	○		○	●
AR		○	●	○
Consistency	0.862	0.871	0.816	0.832
PRI consistency	0.820	0.828	0.725	0.740
Raw coverage	0.282	0.201	0.183	0.112
Unique coverage	0.069	0.029	0.057	0.035
Between-group consistency-adjusted distance	0.021	0.015	0.018	0.031
Within-group consistency-adjusted distance	0.370	0.370	0.370	0.336
Solution consistency		0.826		
Solution PRI		0.775		
Solution coverage		0.425		

Note: ● = core conditions exist, ○ = core conditions are absent, ● = edge conditions exist, ○ = edge conditions are absent. The term “blank” indicates that the conditions may or may not be present in the configuration.

4.1.4. Between-Group Results Analysis

The between-group consistency-adjusted distances for the four configurations are all below 0.1, indicating no significant time effects. However, applying the panel-data-based dynamic QCA method reveals the dynamic characteristics of each configuration's consistency level over time, as shown in Figure 3. Closer inspection shows that the consistency levels of all four configurations remain above 0.8 from 2020 to 2022, indicating strong overall explanatory power, yet their dynamic patterns differ. Specifically, configurations C1, C2, and C3 exhibit a pattern of first decreasing and then increasing, while C4 shows a monotonic upward trend. The consistency of C1, C2, and C3 declined in 2021 compared to 2020, then rebounded in 2022. Among them, C3 rebounded the most, surpassing its 2020 level; C1 remained slightly below its 2020 level after the rebound; and C2 showed the smallest fluctuation and the strongest stability. C4 increased year by year without any decline. These dynamic differences can be understood from two perspectives: the general impact of external shocks and the internal structural differences across configurations.

The widespread decline in consistency across configurations in 2021 is closely related to the impact of the pandemic on county-level fiscal resources. In the early stage of the pandemic, local governments faced both additional expenditure pressure from epidemic prevention and control and the erosion of the tax base due to slowing economic activity. The local fiscal self-sufficiency rate dropped to 47.6% in 2020, the lowest level since 1994. With the general tightening of fiscal resources, both C1 (which has the absence of fiscal expenditure as a peripheral condition) and C4 (which has the presence of fiscal expenditure as a core condition) experienced disruptions in the allocation environment for production factors needed for industrial upgrading. Subsequently, as large-scale tax and fee reduction policies continued to take effect—with additional reductions exceeding 2.6 trillion yuan in 2020 and over 1 trillion yuan in 2021, followed by a combined tax and fee support policy in 2022—county-level fiscal pressures gradually eased, providing a crucial policy buffer for county industrial upgrading.

In addition, different combinations of antecedent conditions also shape each configuration's ability to withstand shocks and restore growth. Regional economic resilience theory suggests that when a regional economic system faces external shocks, its capacity to maintain function and restore growth depends on multiple factors, including social and environmental conditions. Empirical studies show that industrial agglomeration [60] and industrial diversity [61]—both structural characteristics of industry—significantly enhance county economic resilience. Moreover, as the quality of county economic development improves, the driving factors gradually shift toward comprehensive elements, with government expenditure, capital access, and human resources playing increasingly important roles.

Based on this analysis, configuration C2 has hard supporting elements from the efficiency dimension as its core conditions. These elements have low coupling with each other but high substitutability, which results in the smallest fluctuation and strongest stability. Configuration C3 includes both efficiency and fairness dimensions, with relatively diverse sources of elements. When one type of element is affected by a shock, other elements can play a buffering role. Therefore, C3 shows a noticeable decline under short-term shocks but quickly releases its multi-synergy advantages as the policy environment improves, achieving the largest rebound in 2022 and exceeding its pre-pandemic level. Configuration C1 has the absence of fiscal expenditure as a peripheral condition, making it highly dependent on market mechanisms and lacking government policy buffers. Consequently, after recovery, it remains below its initial level. Configuration C4 has the presence of fiscal expenditure as a core condition. The high concentration of its core elements makes it reliant on continuous policy support. The sustained expansion of active fiscal policy from

2020 to 2022 provided it with year-by-year increasing external support, thereby giving its consistency a monotonic increasing trend.

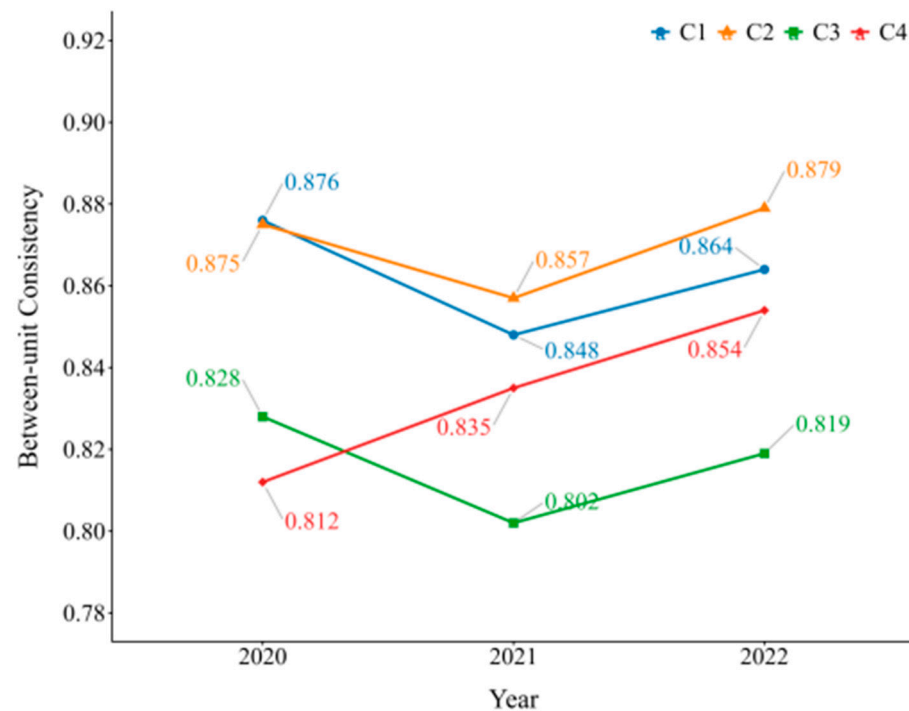


Figure 3. Between-group consistency changes in configurations C1 to C4.

4.1.5. Within-Group Results Analysis

The within-group consistency-adjusted distances for the four configurations are all above 0.33, far exceeding the empirical threshold of 0.2. This indicates significant individual effects, as shown in Figure 4. The scatter distribution patterns of the four configurations are similar. The proportion of counties with consistency above 0.8 is approximately 80% for each configuration, meaning that most counties match the four configurational pathways well. This further demonstrates that these four pathways have strong explanatory power for advanced county industrial structure. Furthermore, based on the specific within-group consistency data, about 12% of counties have consistency levels below 0.8 across all four configurations. These counties are listed in Appendix A. They are mostly concentrated in the western border areas, northeastern forest regions, Inner Mongolian pastoral areas, and mountainous areas of the central and western regions. These counties generally face challenges such as weak economic foundations and severe brain drain. For configurations C1 and C2, these counties have small economic aggregates, weak innovation vitality, and scarce financial resources. Even with the absence of fiscal expenditure (C1) or insufficient agricultural resources (C2), they still struggle to achieve an advanced county industrial structure. For configuration C3, although some counties—such as Ansai District, Cangxi County, and Hejing County—possess certain natural resources and labor reserves, their limited fiscal expenditure prevents the complementary effect between human capital and agricultural resources from effectively driving advanced county industrial structure. For configuration C4, although these counties have fiscal expenditure in name, their actual disposable fiscal capacity is limited. Their expenditure structure may be dominated by basic livelihood security, lacking guidance for industrial development. As a result, finance, innovation, and human capital cannot truly work together to promote an advanced county industrial structure.

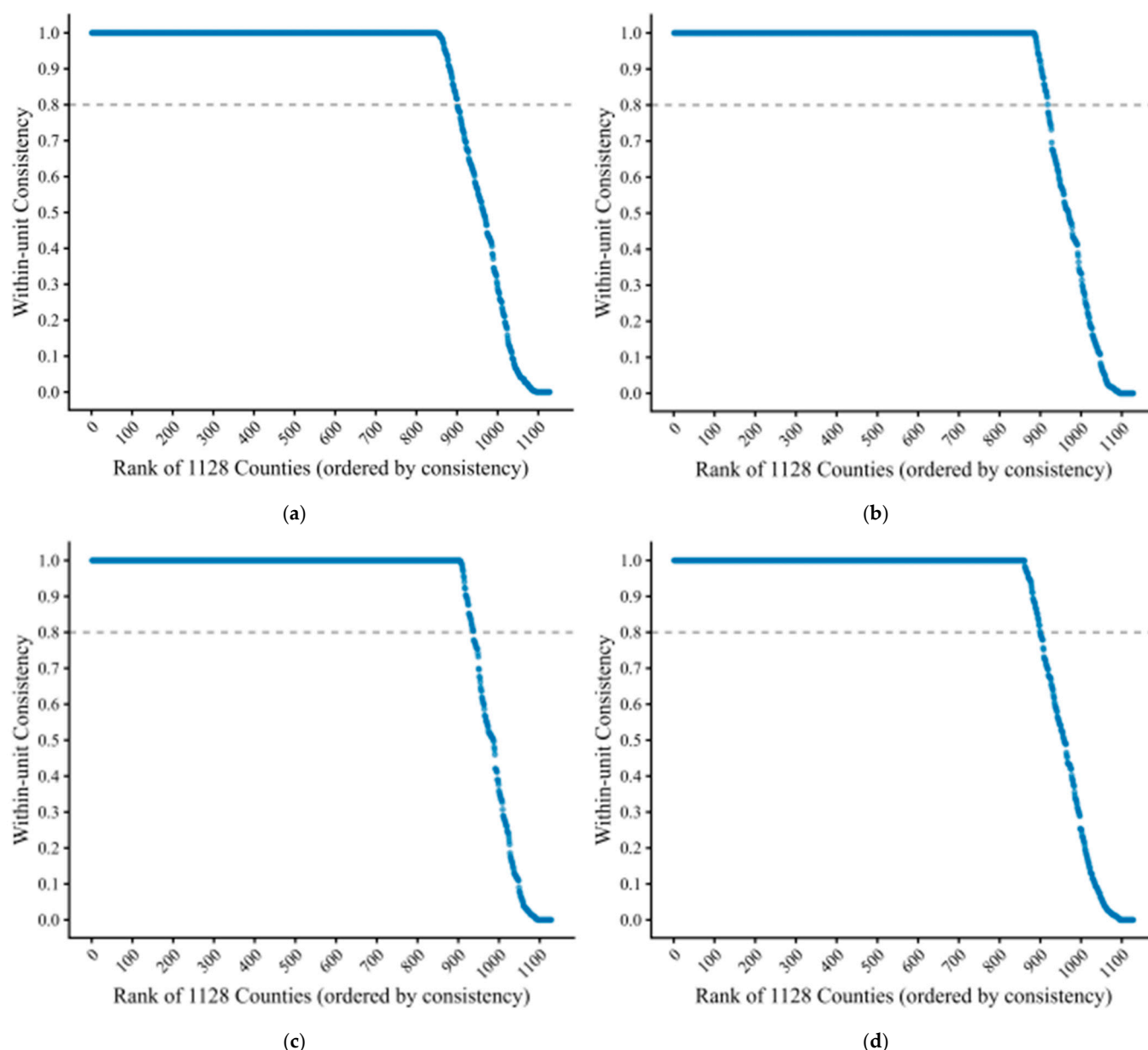


Figure 4. Within-group consistency changes in configurations C1 to C4: (a) Within-group consistency changes for C1. (b) Within-group consistency changes for C2. (c) Within-group consistency changes for C3. (d) Within-group consistency changes for C4.

4.1.6. Robustness Test for the QCA Analysis

To test the robustness of the above dynamic QCA results, this study assesses reliability by adjusting the calibration anchors, changing the case frequency threshold, and conducting subsample analysis. If the results obtained from these alternative specifications exhibit a clear subset relationship with the original results, the findings are considered robust [57]. Specifically: (1) After adjusting the calibration anchors to the 80th, 50th, and 10th percentiles, we obtained four configurations that are highly consistent with the original results. (2) After raising the case frequency threshold to 30, we again obtained four configurations that are highly consistent with the original ones. (3) Considering that the period from 2020 to 2022 includes the peak of the pandemic, we tested whether the configurational results are overly dependent on this special period. We excluded the 2020 data and re-ran the dynamic QCA using only the panel data from 2021 to 2022. The resulting four configurations remained highly consistent with the original ones. (4) After

fine-tuning the calibration anchors to the 77th, 50th, and 23rd percentiles, we obtained four configurations that are highly consistent with the original results. (5) After fine-tuning the calibration anchors to the 73rd, 50th, and 27th percentiles, we again obtained four configurations that are highly consistent with the original results. Detailed results are presented in Tables 7 and 8, indicating that the sufficiency analysis results have not changed substantially.

Table 7. Robustness test results (alternative specifications).

Antecedent Variables		Advanced County Industrial Structure											
		(1)				(2)				(3)			
		C1_1	C2_1	C3_1	C4_1	C1_2	C2_2	C3_2	C4_2	C1_3	C2_3	C3_3	C4_3
Efficiency	EL	●	●	●		●	●	●		●	●	●	
	FL	●	●		●	●	●		●	●	●		●
	IL	●	●	●	●	●	●	●	●	●	●	●	●
	HC			●	●			●	●			●	●
Equity	FE	○		○	●	○		○	●	○		○	●
	AR		○	●	○		○	●	○		○	●	○
Consistency		0.871	0.882	0.838	0.855	0.862	0.871	0.816	0.832	0.866	0.871	0.816	0.845
PRI consistency		0.814	0.822	0.722	0.733	0.820	0.828	0.725	0.740	0.825	0.828	0.726	0.758
Raw coverage		0.302	0.223	0.210	0.137	0.282	0.201	0.183	0.112	0.284	0.204	0.181	0.133
Unique coverage		0.064	0.026	0.058	0.037	0.069	0.029	0.057	0.035	0.070	0.030	0.055	0.035
Between-group consistency-adjusted distance		0.018	0.015	0.015	0.026	0.021	0.015	0.018	0.031	0.017	0.020	0.017	0.017
Within-group consistency-adjusted distance		0.336	0.336	0.336	0.303	0.370	0.370	0.370	0.336	0.355	0.355	0.355	0.323
Solution consistency			0.837				0.826				0.828		
Solution PRI			0.769				0.775				0.778		
Solution coverage			0.444				0.425				0.426		

Note: ● = core conditions exist, ○ = core conditions are absent, ● = edge conditions exist, ○ = edge conditions are absent. The term “blank” indicates that the conditions may or may not be present in the configuration.

Table 8. Robustness test results (fine-tuned anchors).

Antecedent Variables		Advanced County Industrial Structure							
		(4)				(5)			
		C1_4	C2_4	C3_4	C4_4	C1_5	C2_5	C3_5	C4_5
Efficiency	EL	●	●	●		●	●	●	
	FL	●	●		●	●	●		●
	IL	●	●	●	●	●	●	●	●
	HC			●	●			●	●
Equity	FE	○		○	●	○		○	●
	AR		○	●	○		○	●	○
Consistency		0.865	0.875	0.825	0.841	0.858	0.866	0.806	0.821
PRI consistency		0.818	0.825	0.724	0.736	0.822	0.830	0.725	0.741
Raw coverage		0.290	0.210	0.194	0.121	0.275	0.193	0.174	0.103
Unique coverage		0.067	0.028	0.058	0.036	0.071	0.030	0.057	0.035
Between-group consistency-adjusted distance		0.018	0.015	0.018	0.028	0.021	0.015	0.021	0.034
Within-group consistency-adjusted distance		0.336	0.336	0.370	0.336	0.370	0.370	0.404	0.370
Solution consistency			0.830				0.821		
Solution PRI			0.772				0.777		
Solution coverage			0.433				0.419		

Note: ● = core conditions exist, ○ = core conditions are absent, ● = edge conditions exist, ○ = edge conditions are absent. The term “blank” indicates that the conditions may or may not be present in the configuration.

4.2. Stage 2: Using Regression Analysis to Identify Configurational Pathways for Synergistically Achieving Advanced County Industrial Structure and Employment Growth

4.2.1. Descriptive Analysis

Based on the identification of four configurational pathways that promote advanced county industrial structure, this study employs regression analysis to test whether these four pathways also promote county employment levels. To do so, for each configuration (C1, C2, C3, C4), we use the set membership score of each county on that configuration as the explanatory variable. The explained variable is county employment level, and the mediating variable is advanced county industrial structure. We conducted descriptive statistics using Stata 17, and the results are presented in Table 9.

Table 9. Descriptive statistics results.

Variables		Measurement Method	Number	Mean	SD	Min	Max
Explained variable	CEL	Proportion of Newly Created Jobs	2960	11.20	8.175	0.432	98.43
Explanatory variables	C1	Set membership score of each county in C1	2960	0.165	0.276	0	0.999
	C2	Set membership score of each county in C2	2960	0.116	0.221	0	0.999
	C3	Set membership score of each county in C3	2960	0.113	0.207	0	0.994
	C4	Set membership score of each county in C4	2960	0.068	0.146	0	0.961
Mediator variable	ACIS	Industrial Structure Hierarchy Coefficient	2960	2.272	0.157	1.577	2.860
Control variables	PS	Natural Logarithm of Registered Population	2960	3.715	0.798	0.642	5.533
	SR	Household Savings Deposit Balance/GDP	2960	9.843	4.671	0.497	54.64
	ITCFR	Local General Public Budget Revenue/GDP	2960	5.643	2.847	0.630	35.65
	TI	Fixed Telephone Subscribers/Population	2960	8.470	7.773	0	68.92

Note: County employment level (CEL), Population size (PS), Savings ratio (SR), The intensity of tax cuts and fee reductions (ITCFR), Traditional infrastructure (TI).

4.2.2. Benchmark Regression Analysis

To test the total effects of configurations C1, C2, C3, and C4 on county employment levels, this study conducted regression analyses with the set membership scores of the four configurations as explanatory variables, county employment level as the dependent variable, and population size, savings rate, tax cut and fee reduction intensity, and traditional infrastructure as control variables. The analyses also controlled for year fixed effects and geographic location fixed effects (with regions divided into eastern, central, western, and northeastern China). The results are presented in Table 10. Configurations C1, C2, and C3 have a significant positive total effect on county employment levels, whereas configuration C4 has a significant negative total effect.

Table 10. Regression analysis results of four configurations on county employment level.

	Model 1	Model 2	Model 3	Model 4
C1	9.232 *** (0.554)			
C2		5.236 *** (0.656)		
C3			6.157 *** (0.739)	
C4				−3.605 *** (0.959)

PS	−1.430 *** (0.183)	−0.548 *** (0.187)	−1.230 *** (0.193)	−0.883 *** (0.189)
SR	−0.286 *** (0.030)	−0.355 *** (0.031)	−0.251 *** (0.032)	−0.305 *** (0.032)
ITCFR	0.541 *** (0.048)	0.600 *** (0.050)	0.637 *** (0.050)	0.690 *** (0.050)
TI	0.208 *** (0.019)	0.275 *** (0.019)	0.286 *** (0.018)	0.319 *** (0.018)
Constant	12.704 *** (1.088)	9.803 *** (1.109)	10.304 *** (1.111)	9.415 *** (1.118)
Year	YES	YES	YES	YES
Position	YES	YES	YES	YES
Number	2960	2960	2960	2960
R ²	0.288	0.238	0.239	0.225
Adjusted R ²	0.286	0.235	0.237	0.222

Notes: *** indicates $p < 0.01$. Standard errors are in parentheses.

4.2.3. Robustness Test for the Regression Analysis

To verify the robustness of the benchmark regression results, this study employs two approaches. First, we add two control variables to the original set: Population Density (PD), measured as the ratio of registered resident population to administrative area; and Industrialization Level (IL), measured as the logarithm of the number of industrial enterprises above a designated size. Population density reflects the spatial agglomeration of the county labor market. Higher population density typically implies a denser labor supply and a larger local market. This may promote industrial structure upgrading through labor pooling and knowledge spillovers, but it may also have complex effects on employment due to intensified competition [62]. Industrialization level reflects a county's industrial base and degree of industrial agglomeration. Counties with a higher level of industrialization tend to have more complete industrial chains and stronger employment absorption capacity, yet they may also face structural unemployment risks during the transformation of traditional industries [63]. The regression results are shown in Table 11. After adding these two control variables, the direction of the total effect of each configurational pathway on county employment level remains unchanged. Second, we winsorize all continuous variables at the 1st and 99th percentiles and then re-run the regressions. The results are presented in Table 12, and the total effect of each configuration remains significant.

Table 11. Regression analysis results of four configurations on county employment level after adding control variables.

	Model 1	Model 2	Model 3	Model 4
C1	6.771 *** (0.587)			
C2		2.482 *** (0.657)		
C3			4.205 *** (0.725)	
C4				−4.634 *** (0.919)
PS	−3.740 *** (0.265)	−3.824 *** (0.281)	−4.261 *** (0.268)	−4.351 *** (0.271)
SR	−0.172 ***	−0.171 ***	−0.108 ***	−0.110 ***

	(0.032)	(0.033)	(0.033)	(0.033)
ITCFR	0.470 ***	0.496 ***	0.508 ***	0.541 ***
	(0.048)	(0.049)	(0.048)	(0.049)
TI	0.142 ***	0.176 ***	0.175 ***	0.190 ***
	(0.019)	(0.019)	(0.019)	(0.019)
PD	0.022 ***	0.022 ***	0.024 ***	0.021 ***
	(0.005)	(0.005)	(0.005)	(0.005)
IL	1.973 ***	2.648 ***	2.620 ***	2.919 ***
	(0.196)	(0.191)	(0.188)	(0.185)
Constant	12.931 ***	10.455 ***	11.037 ***	10.107 ***
	(1.130)	(1.130)	(1.132)	(1.128)
Year	YES	YES	YES	YES
Position	YES	YES	YES	YES
Number	2960	2960	2960	2960
R ²	0.320	0.293	0.298	0.296
Adjusted R ²	0.318	0.290	0.295	0.293

Note: *** indicates $p < 0.01$. Standard errors are in parentheses.

Table 12. Regression analysis results of four configurations on county employment level after win-sORIZATION.

	Model 1	Model 2	Model 3	Model 4
C1	8.344 *** (0.497)			
C2		5.351 *** (0.586)		
C3			4.942 *** (0.668)	
C4				−3.453 *** (0.874)
PS	−1.446 *** (0.166)	−0.601 *** (0.169)	−1.212 *** (0.175)	−0.938 *** (0.171)
SR	−0.290 *** (0.028)	−0.360 *** (0.029)	−0.262 *** (0.030)	−0.306 *** (0.030)
ITCFR	0.540 *** (0.047)	0.603 *** (0.048)	0.651 *** (0.048)	0.704 *** (0.048)
TI	0.210 *** (0.018)	0.270 *** (0.018)	0.287 *** (0.017)	0.315 *** (0.017)
Constant	12.734 *** (0.990)	9.986 *** (1.004)	10.254 *** (1.012)	9.467 *** (1.015)
Year	YES	YES	YES	YES
Position	YES	YES	YES	YES
Number	2960	2960	2960	2960
R ²	0.311	0.266	0.259	0.249
Adjusted R ²	0.309	0.263	0.256	0.247

Note: *** indicates $p < 0.01$. Standard errors are in parentheses.

4.2.4. Endogenous Test

To further mitigate potential endogeneity concerns arising from reverse causality and omitted variables, this study uses one-period-lagged configurational membership scores as explanatory variables in regression analysis. Specifically, we replace the current values of C1, C2, C3, and C4 with their first-order lags, include the same control variables, and control for year and geographic location fixed effects. We then re-estimate the total effects

of each configuration on county employment levels. The results are presented in Table 13. The lagged terms of configurations C1, C2, and C3 still have a significant positive effect on employment levels, while the lagged term of C4 remains significantly negative.

In addition, we employ an instrumental variable (IV) approach with two-stage least squares (2SLS) estimation to further address endogeneity. Specifically, for each county, we use the mean of the independent variables of other counties within the same prefecture-level city as the instrumental variable. This IV satisfies the relevance condition because counties within the same prefecture-level city share similar policy environments, market conditions, and factor endowments; thus, the configurational membership scores of other counties are correlated with that of the focal county. At the same time, the configurational membership scores of other counties do not directly affect the focal county's employment level, satisfying the exclusion restriction. The 2SLS regression results are shown in Table 14. The first-stage F-statistics are all greater than 10, ruling out weak instruments. The second-stage results indicate that C1, C2, and C3 still have a significant positive effect on employment levels, while C4 has a significant negative effect, with coefficients and significance levels largely consistent with the benchmark regressions. These analyses demonstrate that our conclusions remain robust after controlling for potential endogeneity bias.

Table 13. Endogeneity Test Results with Lagged Independent Variables.

	Model 1	Model 2	Model 3	Model 4
L.C1	9.852 *** (0.701)			
L.C2		5.737 *** (0.810)		
L.C3			6.219 *** (0.939)	
L.C4				−2.498 ** (1.113)
PS	−1.310 *** (0.227)	−0.393 * (0.234)	−1.109 *** (0.242)	−0.728 *** (0.237)
SR	−0.324 *** (0.038)	−0.399 *** (0.039)	−0.287 *** (0.041)	−0.353 *** (0.040)
ITCFR	0.585 *** (0.061)	0.648 *** (0.063)	0.691 *** (0.062)	0.735 *** (0.063)
TI	0.220 *** (0.023)	0.292 *** (0.024)	0.305 *** (0.023)	0.336 *** (0.023)
Constant	12.188 *** (1.344)	9.382 *** (1.378)	9.758 *** (1.383)	9.090 *** (1.394)
Year	YES	YES	YES	YES
Position	YES	YES	YES	YES
Number	1832	1832	1832	1832
R ²	0.317	0.264	0.261	0.245
Adjusted R ²	0.314	0.260	0.258	0.242

Notes: * indicates $p < 0.1$, ** indicates $p < 0.05$, *** indicates $p < 0.01$. Standard errors are in parentheses.

Table 14. Endogeneity Test Results Using the Instrumental Variable Method.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
IV.C1	0.831 *** (0.020)							

C1		14.827 ***						
		(0.917)						
IV.C2			0.803 ***					
			(0.022)					
C2				8.905 ***				
				(1.175)				
IV.C3					0.795 ***			
					(0.022)			
C3						8.502 ***		
						(1.329)		
IV.C4							0.839 ***	
							(0.021)	
C4								−9.011 ***
								(1.620)
PS	0.037 ***	−1.834 ***	−0.016 ***	−0.392 **	0.042 ***	−1.407 ***	−0.014 ***	−1.058 ***
	(0.005)	(0.194)	(0.004)	(0.193)	(0.004)	(0.211)	(0.003)	(0.195)
SR	0.001	−0.260 ***	0.003 ***	−0.374 ***	−0.005 ***	−0.221 ***	0.004 ***	−0.269 ***
	(0.001)	(0.031)	(0.001)	(0.032)	(0.001)	(0.035)	(0.000)	(0.033)
ITCFR	0.002	0.463 ***	0.002 *	0.551 ***	0.002 *	0.624 ***	0.002 **	0.720 ***
	(0.001)	(0.050)	(0.001)	(0.052)	(0.001)	(0.050)	(0.001)	(0.051)
TI	0.006 ***	0.143 ***	0.005 ***	0.248 ***	0.003 ***	0.276 ***	0.001 ***	0.326 ***
	(0.000)	(0.021)	(0.000)	(0.020)	(0.000)	(0.019)	(0.000)	(0.019)
Constant	−0.239 ***	14.677 ***	−0.062 **	10.050 ***	−0.119 ***	10.640 ***	−0.018	9.322 ***
	(0.028)	(1.138)	(0.026)	(1.119)	(0.023)	(1.125)	(0.017)	(1.127)
Year	YES	YES	YES	YES	YES	YES	YES	YES
Position	YES	YES	YES	YES	YES	YES	YES	YES
Number	1794.51		1346.14		1324.03		1609.82	
R ²	62.549 ***		14.254 ***		4.452 **		17.585 ***	
Adjusted R ²	63.645 ***		14.265 ***		4.441 **		17.618 ***	

Notes: * indicates $p < 0.1$, ** indicates $p < 0.05$, *** indicates $p < 0.01$. Standard errors are in parentheses.

4.2.5. Mechanism Analysis

Based on the tests of the total effects of the four configurations on county employment levels, we further analyze their direct and indirect effects by incorporating advanced county industrial structure as a mediating variable into the regression model. The results are presented in Table 15. Specifically, Model 1 shows that advanced county industrial structure has a significant positive impact on county employment levels. Models 2 through 5 show that all four configurations have a significant positive indirect effect on county employment levels. That is, configurations C1, C2, C3, and C4 all enhance the employment-driving role of advanced county industrial structure. However, Models 2–5 also reveal that configurations C1, C2, and C3 have a significant positive direct effect on county employment levels, whereas configuration C4 has a significant negative direct effect. This negative direct effect likely explains why configuration C4 exhibits a significant negative total effect on county employment levels. Together, these results indicate that not every configurational pathway that promotes advanced county industrial structure also boosts employment; in particular, configuration C4 suppresses employment levels.

Table 15. Regression analysis results of four configurations and advanced county industrial structure on county employment level.

	Model 1	Model 2	Model 3	Model 4	Model 5
C1		9.000 ***			
		(0.566)			

C2			4.651 *** (0.681)		
C3				5.814 *** (0.741)	
C4					−4.380 *** (0.963)
ACIS	4.963 *** (0.963)	1.885 ** (0.945)	3.080 *** (0.995)	4.159 *** (0.959)	5.580 *** (0.970)
PS	−0.879 *** (0.188)	−1.455 *** (0.184)	−0.642 *** (0.189)	−1.298 *** (0.193)	−1.033 *** (0.190)
SR	−0.358 *** (0.032)	−0.298 *** (0.031)	−0.370 *** (0.031)	−0.279 *** (0.033)	−0.332 *** (0.032)
ITCFR	0.630 *** (0.050)	0.529 *** (0.049)	0.583 *** (0.050)	0.606 *** (0.050)	0.649 *** (0.050)
TI	0.288 *** (0.019)	0.201 *** (0.019)	0.264 *** (0.019)	0.266 *** (0.019)	0.291 *** (0.019)
Constant	0.410 (2.088)	9.170 *** (2.078)	4.127 * (2.142)	2.641 (2.086)	−0.827 (2.098)
Year	YES	YES	YES	YES	YES
Position	YES	YES	YES	YES	YES
Number	2960	2960	2960	2960	2960
R ²	0.228	0.289	0.240	0.244	0.234
Adjusted R ²	0.226	0.287	0.237	0.241	0.231

Notes: * indicates $p < 0.1$, ** indicates $p < 0.05$, *** indicates $p < 0.01$. Standard errors are in parentheses.

4.3. Interpretation of Configurational Pathways for Synergistically Achieving Advanced County Industrial Structure and Employment Growth

Using the panel-data-based dynamic QCA method, this study identified four configurational pathways that achieve advanced county industrial structure. Regression analysis further verified the impact of these four pathways on county employment levels. The consistency of all four configurations exceeds 0.8, indicating that they are sufficient conditions for explaining advanced county industrial structure. The overall coverage of the four configurations is 0.425, meaning they explain more than 42.5% of the county cases. Furthermore, configurations C1, C2, and C3 have significant positive total and direct effects on county employment levels, whereas configuration C4 has significant negative total and direct effects. This indicates that configurations C1, C2, and C3 can achieve synergy between county industry and employment, while configuration C4 cannot.

4.3.1. Interpretation of Configuration C1 Results

Market-driven, efficiency-first configuration (C1). This configuration has the presence of economic level, financial level, and innovation level as core conditions, and the absence of fiscal expenditure as a peripheral condition. Together, they form a typical efficiency-first driving mode for advanced county industrial structure. Among the four configurations, C1 has the most extensive raw coverage and unique coverage, indicating the strongest explanatory power, accounting for 28% of county cases. Typical examples of C1 include Kunshan City (2020–2022), Taicang City (2020–2022), Anji County (2020–2022), Yiwu City (2020–2022), Changshu City (2020–2022), Tonglu County (2020), Rudong County (2021), Shanggao County (2021–2022), and Jinhu County (2022).

Counties with a high economic level often possess substantial capital accumulation, which provides sufficient material support for technological innovation and talent attraction, and drives industrial transformation and upgrading through the accumulation of production factors such as talent, knowledge, and management. A higher financial level

implies a more developed local financial market system, which helps local enterprises alleviate financing constraints during industrial transformation and upgrading through diversified investment channels. Meanwhile, a higher innovation level facilitates technological transformation of traditional industries and can spawn new industries and business models. Under the joint effect of these three efficiency-dimension factors, the absence of fiscal expenditure further allows the market to spontaneously guide various production factors toward high-value-added industries, thereby promoting an advanced county industrial structure. Take Kunshan City as an example. This county-level city had high economic and innovation levels from 2020 to 2022. In 2021, the output value of its electronic information industry and equipment manufacturing industry exceeded 560 billion yuan and 280 billion yuan, respectively, and the number of high-tech enterprises reached 2264. The share of R&D investment in GDP increased from 2.8% to 3.9%. In such counties, the synergy of economy, finance, and innovation can spontaneously advance through market mechanisms without relying on large-scale fiscal investment. Another example is Yiwu City. In 2021, its industrial structure ratio reached 1.4:32.0:66.6, with a relatively high proportion of tertiary industry and nearly 800,000 market entities. Taicang City has formed industrial clusters worth hundreds of billions of yuan in sectors such as new materials and material trade headquarters. The output value of emerging industries accounts for 59.2%, and that of high-tech industries accounts for 50.5% of the total output value of industrial enterprises above a designated size. These examples align well with the theoretical analysis that efficiency-dimension factors drive advanced county industrial structure. The above cases all demonstrate that under conditions where efficiency-dimension factors are sufficient, industrial development tends to rely more on market mechanisms, which matches the low degree of government intervention represented by the absence of fiscal expenditure, thereby promoting advanced county industrial structure.

Configuration C1 not only promotes advanced county industrial structure but also improves county employment levels. When a county gradually shifts toward service-oriented and knowledge- and technology-intensive industries through the synergy of economy, finance, and innovation, new business forms and industries are constantly generated, thereby creating a large number of jobs. Taking Kunshan City as an example, in 2021, this county-level city had 2264 high-tech enterprises, which brought about 37,400 new urban jobs. In addition, 16,000 unemployed people and 6600 people with employment difficulties were re-employed. Kunshan has also established a chain-type cultivation system of “small and medium-sized tech enterprises → high-tech enterprises → gazelle enterprises → unicorn enterprises → listed enterprises,” which has created a strong employment-driving capacity. In Yiwu City, the number of new urban jobs in 2021 reached 96,000, and the registered unemployment rate was only 1.37%. This is mainly because the city fully unleashed the employment-driven effect of entrepreneurship by developing a full-chain talent mechanism of “attracting, cultivating, retaining, and employing.” Anji County relied on the transformation of its green industrial system. In 2021, the value added of high-tech, strategic emerging, and equipment manufacturing industries increased by 15.8%, 35.6%, and 28.3%, respectively, absorbing a large number of local workers. These examples all reflect the synergistic relationship between industrial upgrading and employment growth. Furthermore, the peripheral condition of configuration C1 is the absence of fiscal expenditure, which may somewhat weaken livelihood protection. In 2021, Kunshan promoted equalization of public services by building an “urban-rural community” mechanism, and the urban-rural resident income ratio dropped to 1.83:1. However, for many efficiency-priority counties, the lack of public service supply driven by long-term market forces may lead to a widening income gap and the marginalization of low-skilled labor. This is a risk that such counties need to monitor when promoting industrial transformation and upgrading.

4.3.2. Interpretation of Configuration C2 Results

Factor-agglomeration, agricultural-resource-substituting configuration (C2). This configuration has the presence of economic level, financial level, and innovation level as core conditions, and the absence of agricultural resources as a peripheral condition. Together, they constitute a pathway for industrial structure upgrading that compensates for the deficiency of natural agricultural resources through acquired factor agglomeration. Typical cases of configuration C2 include Xianju County (2021–2022), Yueqing City (2020–2022), Pan'an County (2020–2022), Dongyang City (2020–2022), Yongjia County (2022), Pinghu City (2022), and Yuping Dong Autonomous County (2020).

When a county has a low level of agricultural resources, it lacks basic agricultural conditions such as arable land and specialty agricultural products to rely on. It is difficult for such a county to follow a development path that depends on agricultural resources, as resource-rich areas do. This forces such counties to shift their development focus toward efficiency-dimension factor agglomeration. As in configuration C2, a higher economic level can support the development of technical talent. A higher financial level can alleviate the financing constraints faced during industrial transformation and upgrading. A higher innovation level can help upgrade traditional processes. Together, these three factors can effectively substitute for agricultural resources in driving industrial transformation and upgrading. Take Dongyang City as an example. From 2020 to 2022, this county-level city attracted more than 1500 film and television enterprises by relying on the Hengdian film and television cultural industry cluster. In 2020, the annual revenue of the film and television cultural industry reached 15.7 billion yuan, forming a modern service system centered on film and cultural tourism. Another example is Yueqing City. During 2020–2022, its electrical industry was rated as one of the top 25 national advanced manufacturing clusters. In 2020, the number of employees in the electrical industry exceeded 250,000, and there were 116 enterprises with an output value exceeding 100 million yuan. In 2021, the total industrial output value of the electrical industry was 97.945 billion yuan, a year-on-year increase of 13.3%, and it reached a new level of 250 billion yuan in 2022. Although Pan'an County is located in a mountainous area and its agricultural resources are not outstanding, its regional GDP exceeded 13.3 billion yuan in 2021, and its total fiscal revenue exceeded 2 billion yuan for the first time. It successfully cultivated national-level “little giant” enterprises such as Chunguang Technology. Wuyi County, following the strategy of “strengthening the county through industry,” achieved a total industrial output value of 88.207 billion yuan in 2021, and its ranking among the top 100 counties rose from 229 in 2017 to 172 in 2020. The above cases fully demonstrate that even without abundant agricultural resources, as long as a county forms synergistic advantages in economic level, financial level, and innovation level—substituting efficiency-dimension factor agglomeration for the lack of innate agricultural resources—it can effectively promote the transformation of its industrial structure toward a more advanced direction.

Configuration C2 can simultaneously promote county employment growth while advancing industrial structure upgrading. This may be because industrial structure upgrading itself generates employment creation effects, or because the various dimension factors directly affect the labor market. Regarding the employment effect of industry: when county industries gradually transform into service-oriented and knowledge- and technology-intensive industries under the joint action of economy, finance, and innovation, the development of new industries and new business forms creates a large number of jobs. Take Dongyang City as an example. In 2021, the Hengdian Film and Television Culture Industry Cluster had more than 1500 themed hotels and homestays, which created more employment opportunities for local residents and increased their income. For instance, the annual rental income of local farmers reached 438 million yuan. Similarly, Xianju County built a medical device town and a “Fairy Oxygen Bar” town. In 2020, the output

value of the medical device industry reached 260 million yuan. The oxygen bar town radiated to seven surrounding villages, driving 25,000 job placements for villagers, and the per capita net income reached 43,000 yuan, further narrowing the urban-rural gap. Regarding the direct effect of configuration C2 on employment: a high economic and financial level often implies an active local consumer market and a favorable corporate financing environment, which helps local enterprises expand their workforce. A higher innovation level means increased demand for knowledge-intensive jobs, enhancing the capacity to absorb high-quality labor. Take Yongjia County as an example. From 2020 to 2022, the county vigorously promoted the pump and valve industry. The total output value of this industry increased from 29.2 billion yuan in 2019 to 37.4 billion yuan in 2021, an average annual growth rate of 9.3%. The high-quality development of manufacturing created a large number of stable local jobs. In 2021, the county's online retail sales reached 20.09 billion yuan, and the entire industrial chain drove 8000 people to increase their employment and income. Furthermore, the peripheral condition of configuration C2 is the absence of agricultural resources, meaning the local area lacks resource-based agriculture. This may expose low-skilled workers to certain structural unemployment risks during industrial transformation and upgrading. Therefore, in the process of promoting factor agglomeration, it is necessary to simultaneously strengthen vocational skills training for low-skilled labor to enhance employment inclusiveness.

4.3.3. Interpretation of Configuration C3 Results

Efficiency-equity synergistic, agricultural-resource-dependent configuration (C3). This configuration combines elements from both the efficiency and equity dimensions. It has the presence of economic level, innovation level, human capital, and agricultural resources as core conditions, and the absence of fiscal expenditure as a peripheral condition. Typical cases of configuration C3 include Siyang County (2021), Liuyang City (2022), Jiaozhou City (2020–2022), Zhuji City (2020–2022), Jiangyin City (2022), Xixia County (2021–2022), Anxi County (2020), Huidong County (2020), Changting County (2021), and Mengzi City (2021–2022).

When a county simultaneously has a high economic level, strong innovation vitality, and abundant human capital and agricultural resources, the elements form an interdependent relationship that jointly promotes an advanced county industrial structure. This is because a higher economic level provides sufficient financial support for technology R&D, a higher innovation level pushes traditional industries toward high-value-added links, and higher human capital ensures that enough high-quality labor is available to match the innovation process. Abundant agricultural resources further foster the development of local specialty industries. Together, these four factors constitute an industrial transformation and upgrading model that balances economic growth with people's livelihood and well-being. Take Zhuji City as an example. From 2020 to 2022, this county-level city continuously optimized its industrial structure by relying on traditional advantageous industries such as socks and pearls. In addition, Zhuji accelerated the construction of a new "10,000 mu, 100 billion yuan" intelligent vision industrial platform and laid out frontier industries including new materials, aerospace, and life and health. Consequently, in 2022, the added value of Zhuji's secondary industry reached 809.28 billion yuan, and that of its tertiary industry reached 792.02 billion yuan. Another example is Jiaozhou City. In 2022, its regional GDP exceeded 150 billion yuan for the first time, and its three-industry proportion was adjusted to 4.3:48.0:47.7, with the secondary and tertiary industries almost on par. This may be attributed to the city's emphasis on the coordinated development of human capital and industrial structure upgrading. In Jiangyin City, the 2022 three-industry proportion was 0.8:52.0:47.2. This industrial structure emerged because the city, building on its foundation as a "manufacturing town," accelerated the construction of a "345"

modern industrial system, using emerging industries such as new energy and biomedicine as strategic pillars. The above cases all demonstrate that when the efficiency-dimension factors (economic level and innovation level) match the equity-dimension factors (human capital and agricultural resources), even with relatively limited fiscal expenditure, a county can rely on its own resource endowment and talent pool to pursue an industrial upgrading path that achieves both efficiency and equity.

Configuration C3 achieves synergy between industry and employment while promoting an advanced county industrial structure. This is because when a county relies on the synergy of efficiency and equity dimensions to optimize its industrial structure, both the upgrading of existing industries and the development of emerging industries create a large number of jobs for local residents. Take Zhuji City as an example. In 2022, through digital transformation projects such as the Dahao Technology Digital Factory, this county-level city facilitated the transfer of labor from traditional manufacturing to modern services. As a result, new urban employment remained at a high level. Consider Jiaozhou City. In 2022, the city consistently worked to stabilize and expand employment, striving to absorb labor through continuous expansion of its economic aggregate. Its annual GDP grew by approximately 5%. In Liuyang City, during the process of developing the “three main, four specialty, two new” industrial structure, the city directly promoted local employment by improving its industrial system. Furthermore, a higher level of human capital often implies that the local labor force has higher overall quality, enabling it to better match job demands after industrial upgrading, thereby reducing the risk of structural unemployment. A higher economic level and abundant agricultural resources can provide more diverse employment options for local residents, such as flexible employment through specialty agriculture and rural tourism. Take Xixia County as an example. Relying on the four 100 km industrial corridors of “mushroom, fruit, medicine, and tourism,” the county promotes the integration of multiple business formats such as “agriculture + health and wellness,” with leading enterprises like Wanxi Pharmaceutical and Zhongjing Food at the core. This industry-driven employment approach has generated an annual comprehensive output value of characteristic industries exceeding 26 billion yuan, contributing more than 80% of farmers’ per capita net income. However, the peripheral condition of configuration C3 is the absence of fiscal expenditure, which restricts employment inclusiveness to some extent. Therefore, when relying on the synergy of efficiency and equity factors to promote industrial transformation and upgrading, such counties still need to pay due attention to protecting people’s livelihoods through fiscal expenditure.

4.3.4. Interpretation of Configuration C4 Results

Government-assisted, talent–innovation dual-driven configuration (C4). This configuration presents a relatively special combination of elements. It has the presence of financial level, innovation level, and human capital, together with the absence of agricultural resources, as core conditions, and the presence of fiscal expenditure as a peripheral condition. Typical cases of configuration C4 include Wan’an County (2020–2022), Haiyan County (2020–2022), Jinggangshan City (2020–2022), Xiajiang County (2022), Wuqiang County (2022), Yongxin County (2020), Dexing City (2021–2022), Linxia City (2020), and Nancheng County (2020).

Configuration C4 shows that in counties where agricultural resources are not abundant, the synergy among finance, innovation, and human capital is strengthened mainly by increasing fiscal input, thereby promoting industrial transformation and upgrading. This is because counties with relatively scarce agricultural resources find it difficult to rely on basic conditions such as arable land and specialty agricultural products for industrial development; they must compensate for this deficiency through factor agglomeration. Similar to the roles played by finance, innovation, and human capital in configurations

C1, C2, and C3, these three elements mutually reinforce and depend on each other in C4. Together with the presence of fiscal expenditure as the “visible hand” of the government, they form a complete driving path for advanced county industrial structure. Take Wan’an County as an example. From 2020 to 2022, the county continuously increased its fiscal input, successfully winning recognition as a provincial circular economy transformation park in 2020 and a provincial green park in 2021. Wan’an Industrial Park focuses on the electronic information industry and has attracted nearly 200 industrial enterprises by August 2022. The county also implemented development plans for agricultural specialty industries and selenium-enriched industries, forming a modern agricultural industrial system dominated by selenium-enriched rice. Another example is Dexing City. In 2021, this county-level city intensified its cultivation of scientific and technological innovation capacity and implemented a “revealing the list and taking the lead” system for research projects. It authorized 818 patents, and its 2.28 invention patents per 10,000 people ranked first in Shangrao. As a result, the non-ferrous metals, machinery and electronics, and pharmaceutical and chemical industries accounted for 74.8% of the total industrial output value of enterprises above a designated size, forming a “1 + 2 + N” industrial development system. The above cases all demonstrate that under conditions of relatively scarce agricultural resources, finance, innovation, and human capital—supported by government fiscal expenditure—can effectively work together to promote advanced county industrial structure.

Configuration C4 has a complex impact on county employment levels while promoting advanced county industrial structure. Regression results show that both the total effect and the direct effect of configuration C4 on employment levels are significantly negative. This indicates that although this configuration promotes industrial upgrading, it simultaneously suppresses county employment growth. Considering the direct and indirect effects of C4 on employment through advanced county industrial structure, industrial upgrading itself does have a positive impact on employment growth. However, this job creation effect may be offset by a substitution effect. This can be understood from the following aspects. First, in government-assisted, talent–innovation dual-driven counties, fiscal, financial, and innovation resources are likely to be highly concentrated in technology-intensive industries such as electronics, new materials, and biomedicine. These industries generally adopt automated and intelligent equipment, which directly replaces a large number of routine middle- and low-skill jobs such as quality inspection, warehousing, and sorting. Second, as industries shift toward higher-value-added activities, firms’ skill requirements for workers often turn toward data analysis and similar competencies. However, low-skilled workers in counties often lack the necessary educational background and training experience, making it difficult for them to meet the requirements of new jobs, and they may be forced out of the labor market. Third, the presence of fiscal expenditure as a peripheral condition implies that government funds may flow more toward technological innovation and industrial park construction, while spending on livelihood security—such as employment services—is relatively insufficient. This may fail to buffer the crowding-out effect of technological upgrading on low-skilled labor. Under the joint influence of the above factors, the job creation effect of configuration C4 is offset by the substitution effect.

Take Wan’an County as an example. Although the county has successfully promoted industrial upgrading, its electronic information industry is highly automated, and its employment absorption capacity is significantly weaker than that of labor-intensive industries. Data show that in 2022, there were 109 industrial enterprises above a designated size in the county’s industrial park. Consider the local Gaoling Suji project. This project directly employs 30 villagers and receives more than 12,000 tourists annually. However, as a tourism service project, its employment absorption capacity is limited compared with

the jobs displaced by industrial upgrading. Public information indicates that employers in the electronic information industry in this county generally require an associate degree or higher for positions such as electrical engineers and automation technicians. The recruitment requirements include a background in electrical automation. However, the local working-age labor force predominantly has a junior high school education or below. Consequently, a large number of low-skilled workers struggle to enter these enterprises. This indicates a clear mismatch between job losses caused by technological upgrading and the skill requirements of emerging jobs. Another example is Dexing City. In 2021, the city authorized 818 patents and actively implemented an innovation-driven development strategy. Its total fiscal revenue reached 4.053 billion yuan, with tax revenue accounting for 79.4%. According to the Seventh National Population Census, the proportion of the population with an associate degree or higher in Dexing City is approximately 8.58%, while nationwide, the population with a university education is about 218 million, accounting for 15.47% of the total population. Therefore, although Dexing City, as a resource-based transitioning city, has cultivated 120 national-level high-tech enterprises, the professional skill requirements of high-tech positions are far higher than the average level of the local labor force.

Regarding the overall effect of configuration C4 on county employment, higher financial and innovation levels often mean that financial resources tend to flow toward technology-intensive industries, which may crowd out the demand for middle- and low-skilled labor. In this context, the presence of fiscal expenditure as a peripheral condition often implies that fiscal resources are overly skewed toward scientific and technological innovation, while investment in employment-related public services and entrepreneurship support is neglected. This, to some extent, exacerbates the crowding-out effect of technology-intensive industrial upgrading on middle- and low-skilled labor. Take Dexing City as an example. In 2021, the city's total fiscal revenue was 4.053 billion yuan, with tax revenue accounting for 79.4%. This tax-led fiscal structure indicates that fiscal resources have largely flowed toward industrial development. According to relevant research reports, in 2023, the share of livelihood expenditure in national local fiscal expenditure was approximately 37.7%, while the share of productive expenditure was about 34.39%. As an industry-oriented resource-based city, Dexing likely allocates a higher proportion of its fiscal expenditure to industrial development than the national average, while its spending on employment services, skills training, and livelihood security is relatively insufficient. This, to a certain degree, intensifies the crowding-out effect of technology-intensive industrial upgrading on middle- and low-skilled labor. The above analysis shows that in the factor combination of configuration C4, the technological substitution effect accompanying advanced county industrial structure may outweigh the job creation effect, resulting in a complex impact on employment levels. Therefore, when promoting industrial transformation and upgrading, such counties should optimize their fiscal expenditure structure, appropriately tilting toward livelihood areas while ensuring industrial upgrading, so as to achieve the dual goals of industrial transformation and inclusive employment growth.

5. Discussion

5.1. Research Finding

In view of the complex nonlinear relationship between industrial structure and employment, and to address the practical need of achieving industry–employment synergy in counties while avoiding the situation where factor combinations that promote advanced county industrial structure instead suppress employment growth, this study adopts an inclusive growth perspective. Based on the efficiency and equity dimensions, we select six key factors: economic level, financial level, innovation level, human capital,

fiscal expenditure, and agricultural resources. Using these factors, we construct an analytical model to explore factor combinations that can simultaneously promote county industrial upgrading and employment growth. Applying a mixed method that combines panel-data-based dynamic QCA with regression analysis, we find that all propositions are supported. Specifically: (1) Economic level, financial level, innovation level, human capital, fiscal expenditure, and agricultural resources do not individually constitute necessary conditions for advanced county industrial structure. (2) There are four configurational pathways to achieving advanced county industrial structure: the market-driven, efficiency-first configuration (C1); the factor-agglomeration, agricultural-resource-substituting configuration (C2); the efficiency-equity synergistic, agricultural-resource-dependent configuration (C3); and the government-assisted, talent–innovation dual-driven configuration (C4). (3) Configurations C1, C2, C3, and C4 all stimulate the employment-driving effect of advanced county industrial structure. (4) Configurations C1, C2, and C3 simultaneously promote advanced county industrial structure and county employment growth, whereas configuration C4 promotes county industrial upgrading but inhibits employment growth.

5.2. Theoretical Implications

First, this study adopts a mixed method combining dynamic QCA with regression analysis, which overcomes the methodological limitation of most existing research on the industry–employment relationship—namely, the tendency to rely solely on linear thinking and test the net effects of single variables. In doing so, it enriches research on industry–employment synergy. Existing studies often employ traditional statistical methods such as regression analysis to examine the impact of industrial structure upgrading on employment. While these methods can effectively identify the net effect of a given factor, they assume that influencing factors are independent of one another and that their effects on employment are symmetric. This makes it difficult for existing research to fully explain why some counties fail to promote employment growth while achieving advanced county industrial structure. In reality, advanced county industrial structure often results from the synergy of multiple factors, and its impact on employment depends on the specific combination of those factors. This study identified four configurations—C1, C2, C3, and C4—that have differential effects on county employment levels. The findings demonstrate that there indeed exists a configurational pathway (C4) that promotes advanced county industrial structure but inhibits employment growth. This goes beyond the linear description of the industry–employment relationship found in prior research. It expands the scope of inquiry from whether a significant effect exists to what kind of significant effect is produced by different factor combinations, thereby deepening our understanding of the complex relationship between industrial structure upgrading and employment.

Second, by introducing the efficiency–equity framework from the inclusive growth perspective, this study addresses the limitation of existing industry–employment research, which relies predominantly on the economic dimension in its theoretical framework. It systematically integrates the equity dimension—a relatively neglected analytical perspective. Existing studies, often grounded in industrial structure theory, have examined the impact of industrial structure changes on employment, while largely overlooking the important influence of resource allocation equity on employment inclusiveness. This study introduces the inclusive growth perspective into research on the relationship between industrial structure and employment. It identifies configurational pathways that achieve advanced county industrial structure while balancing efficiency and equity, and further analyzes the employment effects produced by these pathways. This helps reveal the complementary characteristics of efficiency- and equity-dimension factors in jointly

promoting advanced county industrial structure and county employment growth. Moreover, it addresses the governance challenge of balancing efficiency and equity in the high-quality development of counties. The findings indicate that investing capital resources in improving people's livelihoods does not necessarily lead to employment growth; rather, the key lies in the matching of efficiency- and equity-dimension factors. This extends the application of the efficiency-equity framework from the inclusive growth perspective.

Third, this study focuses on China's county areas, addressing the limitation of most existing industry–employment research, which predominantly takes countries or urban areas as the unit of analysis. In doing so, it enriches the analytical units of industry–employment research. Most existing empirical studies are based on countries, provinces, or cities, and their conclusions are generally applicable to macro or meso regions with relatively strong industrial bases and abundant factor endowments. However, the pathways to advanced industrial structure in county areas differ from those in cities in terms of resource endowments, factor allocation, and policy environments. Yet research on industry–employment synergy specifically in county areas remains relatively scarce. Directly extending research conclusions drawn from countries, provinces, or cities to county areas—which connect urban and rural regions—inevitably fails to capture the finer details of the industry–employment relationship. Using 1128 Chinese counties as research cases, this study identifies four configurational pathways that achieve advanced county industrial structure and reveals that different configurations may produce different employment effects in counties with varying resource endowments and industrial bases. This responds to both the practical and theoretical demands of studying industry–employment coordinated development at the county level, providing an empirical basis for understanding high-quality county development in the context of Chinese-style modernization.

5.3. Practical Implications

First, for counties that conform to the market-driven, efficiency-first configuration (C1). These counties have a solid economic foundation, active financial markets, and strong innovation capacity, and they rely primarily on market mechanisms to drive industrial upgrading. Local governments can reduce institutional transaction costs by simplifying enterprise registration and project approval processes. They can also establish industrial guidance funds to support high-tech enterprises and specialized and sophisticated small and medium-sized enterprises (SMEs), and set up bank-enterprise matching platforms to alleviate financing difficulties faced by SMEs. At the same time, although this pathway promotes employment growth, the absence of fiscal expenditure may lead to insufficient public service supply. Therefore, vigilance is needed regarding the risk of widening income inequality driven by long-term market forces. It is recommended that local governments keep fiscal expenditure basically stable and allocate part of fiscal funds to vocational skills training, the development of public welfare jobs, and employment support for disadvantaged groups, thereby enhancing employment inclusiveness during the industrial upgrading process.

Second, for counties that conform to the factor-agglomeration, agricultural-resource-substituting configuration (C2). These counties have relatively scarce agricultural resources but compensate for this congenital deficiency through the synergistic advantages of the economy, finance, and innovation. It is recommended that local governments, under the constraint of agricultural resource scarcity, focus on making up for the shortfall through acquired factor agglomeration. Specific actions include: Drawing on the existing industrial base, mapping the industrial chain, and carrying out targeted investment promotion for missing links; Co-building industrial cooperation zones with developed regions to leverage external innovation resources; Establishing special funds for talent introduction, providing housing subsidies for urgently needed talents and facilitating their

children's school enrollment. At the same time, local governments should pay attention to potential employment structure mismatches that may arise during factor agglomeration. It is advisable to establish a county-level labor skills database, regularly publish a list of jobs in short supply, and conduct order-based training in cooperation with vocational colleges to improve the match between local labor and jobs in emerging industries.

Third, for counties that conform to the efficiency-equity synergistic, agricultural-resource-dependent configuration (C3). These counties have abundant economic level, innovation level, human capital, and agricultural resources, and the four factors are well matched, providing a basis for industrial upgrading that balances efficiency and equity. Local governments should fully leverage this synergistic advantage by relying on local specialty agricultural products and ecological resources to build a regional public brand of "one county, one product." They can expand sales through channels such as e-commerce live streaming and farm-supermarket direct sourcing, and promote deep integration of agriculture with tourism, health care, and other industries. In addition, given the constraint of limited fiscal expenditure, priority should be given to ensuring the supply of basic public services. Specifically, a cross-departmental joint meeting system for employment services can be established, integrating resources from human resources and social security, agriculture, education, and other departments to provide "one-stop" employment services for the rural labor force. Enterprises that absorb a certain proportion of local labor can be granted social security subsidies or tax rebates. Through the virtuous interaction of efficiency- and equity-dimension factors, a sustainable development pattern characterized by mutually reinforcing industrial upgrading and employment growth can be formed.

Fourth, for counties that conform to the government-assisted, talent-innovation dual-driven configuration (C4). Such counties lack agricultural resources and rely mainly on fiscal input to drive industrial upgrading through the synergy of finance, innovation, and human capital. However, regression analysis shows that this pathway promotes industrial upgrading but suppresses employment growth. Therefore, while promoting industrial upgrading, local governments should simultaneously implement an employment-first strategy and mitigate the crowding-out effect on low-skilled labor by optimizing the fiscal expenditure structure. Specific efforts can be made in the following areas: (1) Establish special funds for job-transfer training, allocating part of fiscal resources to re-employment training for displaced workers, with a focus on positions vulnerable to automation, such as electronic assembly and mechanical operation. (2) Provide wage subsidies to enterprises that actively absorb local low-skilled labor, based on the actual number of workers employed. (3) Develop public welfare jobs such as ecological rangers, rural cleaners, and community grid workers, and give priority to workers unemployed due to technological upgrading. (4) Establish business incubation bases, offering free space, small secured loans, and entrepreneurship guidance to returning migrant workers who wish to start their own businesses. Those who create jobs can receive a one-time start-up subsidy. Through the above combination of policies, employment support for low-skilled labor can be achieved while ensuring industrial upgrading, thereby reaching a dynamic balance between industrial transformation and upgrading and inclusive employment growth.

Although the findings of this study are empirically based on Chinese counties, their theoretical and practical implications still possess a certain degree of cross-context transferability. The tension between industrial upgrading and employment growth is a common challenge for developing economies worldwide. Existing research shows that while participation in global value chains generally promotes structural transformation and labor productivity growth in developing countries, digitalization and skill-biased technological progress within these chains often come at the expense of manufacturing employment shares [64]. This aligns with our finding that the substitution effect outweighs the

creation effect, as revealed by configuration C4. Moreover, our between-group consistency analysis finds that configurations C2 and C3 exhibit stronger resilience to shocks due to their factor diversity. This echoes existing international research showing that industrial diversity is a key factor in enhancing regional economic resilience [65]. Furthermore, as automation and digitalization accelerate the reshaping of the global industrial landscape, many developing countries face the dilemma of deindustrialization before completing industrialization. Automation not only suppresses job creation and deepens income inequality but also exacerbates the dual economic structure [66]. The government-guided pathway identified in this study—which may inhibit employment—and the policy tools designed to buffer this negative effect thus have a certain degree of cross-context transferability. Of course, when extending the conclusions of this study to other countries and regions, the specific characteristics of China's counties in terms of administrative systems, policy environments, and stages of economic development should be fully considered. Future research could use cross-national panel data to further test whether the configurational pathways identified here have broader applicability.

5.4. Limitations

Although this study has produced some findings, it still has the following limitations.

- (1) Measurement of antecedent conditions. All six antecedent conditions are measured by single indicators, making it difficult to capture the multidimensional connotations of each variable. Specifically, fiscal expenditure is measured as the ratio of general public budget expenditure to GDP, which fails to distinguish between livelihood expenditures (e.g., education, healthcare) and productive expenditures (e.g., infrastructure construction). This may oversimplify the complex relationship between factors and outcomes when interpreting results. Human capital is measured as the ratio of the number of primary and secondary school students to the registered population, which mainly reflects the coverage of basic education but cannot capture differences in vocational skills or work experience. Agricultural resources are proxied by the value added of the primary industry, which reflects agricultural economic output rather than the stock of natural resources themselves. These measurement choices are primarily constrained by the availability of public statistical data at the county level. Although existing studies support these measures, readers should remain aware of these measurement limitations when interpreting the role of each antecedent condition. Future research could construct more comprehensive indicators using field surveys or big data.
- (2) Selection of antecedent conditions. The antecedents were selected based on inclusive growth theory, focusing on six factors representing the efficiency and equity dimensions. However, as noted in the theoretical framework, variable selection is theory-driven and clearly focused. The coordinated development of county industry and employment may also be influenced by other factors—such as digital infrastructure, business environment, and cultural service supply—which were not included in this study. Thus, the explanatory boundary of the theoretical model may be limited. Future research could incorporate additional efficiency- or equity-dimension factors.
- (3) Time span of the sample. The study covers the period from 2020 to 2024, which includes the COVID-19 pandemic shock. Although robustness tests excluding the most severe pandemic years show relatively stable configurational results, the influence of pandemic-related policies cannot be completely ruled out. Moreover, because some counties do not disclose relevant data, only 1128 Chinese counties were included in the analysis, which may limit the generalizability of the findings to other counties. Future research could extend the time span and supplement the county sample to

test the robustness of the configurational pathways across different periods and regions.

- (4) Measurement of county employment level. This study measures county employment level as the ratio of newly created urban jobs to the registered population, which fails to capture changes in rural employment or unemployment. Therefore, this study can only provide an incomplete assessment of whether the configurational pathways truly achieve inclusive employment growth. Specifically, for configurations C1, C2, and C3-identified as promoting employment-the actual inclusiveness of county employment may be lower than our estimates, because growth in newly created urban jobs may be accompanied by hidden rural employment losses. For configuration C4, identified as inhibiting employment, the negative impact on rural employment may be even more severe than on urban employment. Conversely, if informal rural employment is more active in some counties, the negative effect of C4 could be partially buffered. Thus, when interpreting the employment effects of each configuration, readers should confine their conclusions to urban employment and be cautious about inferring rural employment inclusiveness. Future research could leverage big data to more comprehensively capture county-level employment dynamics.

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Appendix A

Anlong County	Fuhai County	Kangping County	Ningnan County	Wudalianchi City
Ansai District	Gengma Dai and Va Autonomous County	Horqin Right Front Banner	Pingle County	West Ujimqin Banner
Aohan Banner	Gongcheng Yao Autonomous County	Horqin Right Middle Banner	Pingluo County	Xishui County
Baishui County	Guazhou County	Horqin Left Rear Banner	Pingyin County	Xiangzhou County
Baicheng County	Guanyang County	Horqin Left Middle Banner	Qitai County	Xinji City
Baoqing County	Guangze County	Korla City	Qingtongxia City	New Barag Right Banner
Boli County	Hanggin Rear Banner	Ledong Li Autonomous County	Qingcheng County	New Barag Left Banner
Cangxi County	Heshui County	Lianzhou City	Quwo County	Xingtang County

Cangyuan Va Autonomous County	Hejing County	Linze County	Quanzhou County	Xingye County
Qapqal Xibe Autonomous County	Hoxud County	Lingchuan County	Raohe County	Yanchuan County
Changjiang Li Autonomous County	Hutubi County	Longling County	Renhua County	Yanchang County
Changning County	Huadian City	Luanping County	Rong County	Yangshan County
Changtu County	Huanan County	Luobei County	Ruoqiang County	Yao'an County
Chen Barag Banner	Huidong County	Malong District	Shenzhou City	Yi'an County
Chengde County	Ji'an County	Markit County	Shiping County	Yizhou District
Chongxin County	Ji County	Mei County	Shulan City	Yingshan County
Datong Hui and Tu Autonomous County	Jiyang District	Mengla County	Shuangjiang Lahu, Va, Blang and Dai Autonomous County	Yongfu County
Ding'an County	Jiange County	Mishan City	Shunping County	Yongjing County
Dongfang City	Jiangyong County	Minqin County	Sonid Left Banner	Yongsheng County
East Ujimqin Banner	Jinta County	Mingshan District	Suiyang County	Yuqing County
Dulan County	Jinghe County	Morin Dawa Daur Autonomous Banner	Suizhong County	Yumen City
Dorbod Mongol Autonomous County	Jinggu Dai and Yi Autonomous County	Nandan County	Sui County	Yun County
Ergun City	Jingyuan County	Nehe City	Tiandong County	Jalaid Banner
Oroqen Autonomous Banner	Jingning County	Neihuang County	Tongjiang City	Zhalantun City
Fengkai County	Harqin Left Wing Mongol Autonomous County	Neixiang County	Ongniud Banner	Zhenyuan County
Fenggang County	Kailu County	Nilka County	Urad Front Banner	Zhongning County
Fengqing County				

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