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Study on the Coupling Relationship between Urban Innovation Efficiency and High Quality Economic Development Based on Information Fusion Technology

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Abstract

This study introduces the proper classification rate based on both traditional rough set theory and fuzzy set theory to develop the VPRS evaluation model, which is based on information fusion technology. The affiliation function is built, the real-valued characteristics are fuzzified, and the resulting fuzzy affiliation degrees are then used to evaluate the categorization. Finally, the coupling degree and coupling coordination degree under the VPRS model were used to investigate the coupling connection between cities of different sizes and cities with diverse leading industries. When compared to the coupling degree, medium-sized cities have a coupling degree that is 55.58% greater, and non-resource-based cities have a coupling degree that is 5.57 percentage points higher. In terms of coupling coordination degree, large cities have a 28.49% improvement, while non-resource based cities have a coupling degree that is 8.28 percentage points greater than resource based cities. Information fusion technology may therefore be used to study the link between urban innovation effectiveness and high-quality economic development, which can therefore help to increase urban innovation capacity and economic growth.

Keywords: *Classical rough set, Fuzzy affiliation, VPRS model, Coupling degree, Coordination degree.*

Introduction

We are growing more worried about the output efficiency of innovation inputs while expanding the number of innovation factor inputs as China's economic development enters a new normal (Park & Page, 2017) (Wolf-Powers et al., 2017) The main factor propelling China's economy toward high-quality development is innovation, and increasing cities' ability for innovation is helpful for spurring opportunities and regional economic growth as well as improving the quality of urban economic development (Liu & Dong, 2021) (Lao, Gu, Yu, & Xiao, 2021) (Peter, 2021).

The primary factor of growth, innovation, is the constant thread throughout social advancement and country development (J. Wang & Dong, 2022). Under the direction of innovation-driven strategy, governments at all levels adhere to the law of science and technology development, and new technologies and products of science and technology accelerate the transformation of new models of economic development. This results in full play of innovation's supporting role in enhancing overall strength and promoting social development, as well as the transformation of

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regional development momentum to innovation-driven (Cao, Wan, Zhang, Zhang, & Zhou, 2020) (Shao & Abualhamayl, 2021) (Drucker, Kayanan, & Renski, 2019).

Urban innovation capacity and high-quality economic development are mutually beneficial and essential, and a study reported in the literature (Pang R Z, 2019) revealed that neither the importance of science and technology innovation nor the efficiency of the innovation outcomes for economic development are particularly high in China. The literature (Gao & Yuan, 2022) illustrates the influence of innovation interventions, as represented by national innovation city pilots, on urban innovation performance and innovation convergence within the context of causal reasoning taking policy spillover effects into account. Furthermore, due to scale competition and the spatial knowledge spillover of fiscal science and technology expenditures, NICP has a favorable influence on speeding innovation convergence across cities, and low-level innovation clubs have a higher late-stage advantage in innovation convergence. According to the literature (L. Wang, Chen, & Li, 2022), the growth of the digital economy can successfully encourage low-carbon sustainable urban development. The conclusions are supported by a number of robustness tests, and innovation factor flow is a crucial transmission channel for the digital economy to have an impact on low-carbon sustainable urban development.

Additionally, research (J. Li & Li, 2022) demonstrated that digital inclusive finance has a favorable impact on urban innovation and that it may foster urban innovation by enhancing the distribution of financial resources, consumption, and industrial upgrading. The literature (L. Li & Zhang, 2020) conducted on patent data from 2000-2015 in Shanghai, examined the spatial distribution of urban innovation activities and its evolution pattern at the micro-scale, and examined the influencing factors of the external environment, and concluded the key role of urban innovation in maintaining the economic resilience of cities. Using data from 30 Chinese provincial administrative regions from 2006 to 2019 to examine the relationship between green technology innovation and low-carbon economic transition from the perspective of local government competition, the literature (Xu Y, 2022) came to the conclusion that green technology innovation significantly aids in the transition to a low-carbon economy. According to the literature (Wang H Y, 2019), geographic location has a considerable impact on the success of urban science and technology innovation-driven economic quality development in China, with the eastern area greatly outperforming the central and western regions.

This research analyzes and presents evidence from three different angles in order to investigate the link between urban innovation effectiveness and high-quality economic development. The algorithmic model, which is the first section, describes the VPRS assessment model based on information fusion technology. Using classical rough set and fuzzy set theories, the interference of perceived errors and noisy data is overcome by introducing the correct classification rate, and the affiliation function is constructed to fuzzify the real-valued attributes and transform them into the corresponding fuzzy affiliation function, thus realizing the evaluation classification. The assessment indices for both high quality economic development and urban innovation efficiency are mined using the VPRS evaluation methodology in the second section. The evaluation indicators and super-efficient SBM algorithm are used to measure and analyze the innovation efficiency of cities, and the entropy value method and evaluation indicators are also used to measure and analyze the high-quality economic development of cities. The third section examines how effectively innovation and high-quality economic development are coupled. First, the degree of this coupling as well as the degree of coordination between different scales and leading industries are examined and demonstrated. Next, the relationship between urban innovation and high-quality economic development is derived.

Model for VPRS assessment based on information fusion

For the efficiency of urban innovation, it mainly refers to the innovation to break the old production equilibrium and to reunite the production systems with each other to form new economic development dynamics and drive social progress. the current definition of innovation is mainly elaborated in two dimensions: Broad innovation refers to changes in production processes and institutional innovation, whereas narrow innovation relates to advances in science and technology.

High-quality economic development, on the other hand, refers to the total production of all goods produced in a region over a given time period; the value represents the stage of economic development currently in place as well as how quickly or slowly the economy is expanding. Unlike the connotation of economic growth, economic development involves many aspects of society, not only the total amount of change, but also the quality of improvement. In order to understand the relationship between "quantity" and "quality," the theory of high quality economic development places an emphasis on the diversity of "development" and switches from studying "quantity" to analyzing "quality." In order to attain a high degree of unity between "quantity" and "quality," the theory of high quality economic growth stresses the diversity of "development" and switches from studying "quantity" to analyzing "quality." Figure 1 depicts the connection mechanism between urban innovation effectiveness and high-quality economic development.

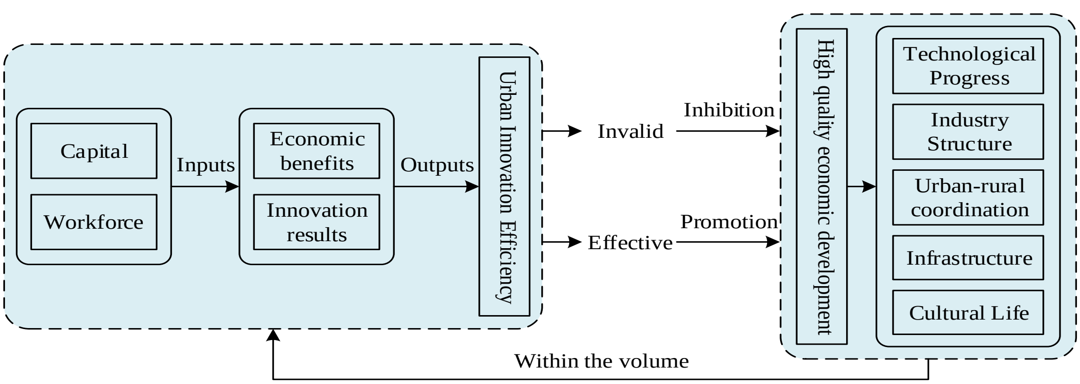

Figure 1. Innovation efficiency and economic development

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This work develops a VPRS evaluation model based on information fusion technology and VPRS theory to better quantify the coupling relationship among urban innovation efficiency and high quality economic growth. It then analyzes the link by mining evaluation indicators.

VPRS information fusion technology

In order to cope with ambiguous and partial information, Polish researchers developed the classical rough set theory. This mathematical analytical tool has been extensively applied in a variety of domains, including knowledge acquisition, attribute approximation, and pattern recognition. One of the most crucial study facets of rough set theory is attribute approximation, which preserves the categorization capacity of information systems.

The theory works well with discrete and clear attribute values, which must first be discretized for continuous attribute values, which will result in varying degrees of information loss. It is founded on a distinct equivalence relation, and in order to form an equivalence class, the attribute values of various objects must precisely equate with one another. Additionally, people's understanding or notions are typically hazy in actual implementations (Yuan et al., 2021).

The fuzzy rough set model, however, is sensitive to noise in the data, but the VPRS offered by some researchers incorporates the idea of proper classification rate, which can successfully address the misclassification issue brought on by human error or noisy data.

Based on the analysis presented above, this paper integrates variable precision rough sets with fuzzy rough sets, fuzzifies real-valued attributes by building an affiliation function, converts them into corresponding fuzzy affiliations, and classifies objects with fuzzy similarity relations to create an index reduction method based on VPRS information fusion technology.

This method improves the model's ability to cope with noisy data.

Allow the information system $S=(U,C,V,F),U=\{x_1,x_2,...,x_n\}(i=1,2,...,n)$ to consist of a finite collection of non-empty items, $c_j \in C$, V_{c_j} the value domain of attribute c_j , $C=\{c_1,c_2,...,c_m\}(j=1,2,...,m)$ a non-empty, finite collection of attributes, V an attribute value, the i th object under the j th conditional attribute with an attribute value of $v_{ij}(i=1,2,...,n;\ j=1,2,...,m)$. The value of the property for each $x_i \in U, c_j \in C, f(x_i,c_j) \in V_{c_j}$ is represented by an information function called $f: U \times C \to V$.

When an attribute of an object $x_i \in U(i=1,2,...,n)$ is fuzzified and given the value

$v_{sj}, \forall x_N, x_i \in U, \forall c_j \in C$, the fuzzy similarity relation R is as follows:

$$x_s R x_i = \{(x_s, x_i) \in U \times U \frac{1}{m}\sum_{j=1}^{m} | v_{sj} - v_{ij} | \le \alpha\} \tag{1}$$

where the resemblance between object x_s x_i and object is what is meant by $1-\alpha$.

The set of all objects that are fuzzy similar to x_i is called the fuzzy similarity class $FR(x_i)$, which can be expressed as:

$$FR(x_i) = \{x_s \in U \mid \frac{1}{m}\sum_{j=1}^{m} | v'_{sj} - v'_{ij} | \le \alpha, j = 1, 2, ..., m\} \tag{2}$$

The fuzzy affiliation between object x_s and object x_i is:

$$\mu_R(x_s, x_i) = 1 - \frac{1}{m}\sum_{j=1}^{m} | v'_{sj} - v'_{ij} | \tag{3}$$

For a fuzzy similarity relation $R \subseteq C$ on $X \subseteq U$ and U, given a threshold $0.5 < \beta \le 1$, rough set variable precision The X 's β upper approximation set and lower approximation set are as follows:

$$\begin{cases} \underline{R_\beta}(X) = \bigcup\{x \in U \mid \dfrac{| X \cap FR(x) |}{| FR(x) |} \ge \beta\} \\ \overline{R_\beta}(X) = \bigcup\{x \in U \mid \dfrac{| X \cap FR(x) |}{| FR(x) |} > 1-\beta\} \end{cases} \tag{4}$$

where $|g|$ denotes the number of elements contained in the set i.e. the base of the set. The β lower approximation set is also called the β -normative domain of X and is denoted as $POS_\beta(X)$ (C. Wang, Qian, Ding, & Fan, 2021).

Let any subset of attributes $A \subseteq C$, A determine a binary indistinguishable relation $IND(A): IND(A) = \{(x, y) \in U \times U \mid \forall c \in A, f(x, c) = f(y, c)\}$. $U / IND(B)$ constitutes 1 division of U, called a knowledge on U, where each equivalence class is called 1 knowledge grain. Allow all indicator attributes be divided into groups of $X = \{X_1, X_2, ..., X_n\}$,

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and let certain indicator attributes that have been deleted be grouped into knowledge R.

Let $X=\{X_1,X_2,...,X_n\}$ be a division on U. Knowledge R has no bearing on categorisation. X The β lower and β upper approximation sets are:

$$\begin{cases}\underline{R_\beta}(X)=\{\underline{R_\beta}(X_1),\underline{R_\beta}(X_2),...,\underline{R_\beta}(X_n)\}\\ \overline{R_\beta}(X)=\{\overline{R_\beta}(X_1),\overline{R_\beta}(X_2),...,\overline{R_\beta}(X_n)\}\end{cases} \quad (5)$$

Let $R\subseteq C$, X be the divisions generated by all attributes C, $X=\{X_1,X_2,...,X_n\}$, then the approximate classification quality is:

$$\gamma_R(X)=\sum_{i=1}^{n}|\underline{R_\beta}(X_i)|/|U| \quad (6)$$

All index characteristics have a classification quality of about 1, when compared to themselves. The estimated classification quality of the condensed set of attributes must likewise be 1, in order to guarantee the same categorization as the other attributes. Therefore, the attributes can be gradually deleted under the condition that $\gamma_R(X)=1$ is guaranteed, until any attribute is deleted from the reduced set, which will make $\gamma_R(X)\neq 1$. The calculation is halted at this point, and the reduced set that was obtained represents the smallest set of information system attributes that may be acquired.

Let the partition of all attributes into the information systems $S=(U,C,V,F)$, R, and attribute significance of attribute c_j be:

$$sig(c_j)=1-\gamma_{C-|c_j|}(X) \quad (7)$$

The weights of each indicator are obtained by normalizing the importance of the attributes.

Reduction and weighting of evaluation indexes based on VPRS model

According to the above theory, the specific steps of index simplification and weight determination using VPRS information fusion technique are as follows:

Step1: Calculate the matching fuzzy affiliation degree by fuzzifying the evaluation index data.

Step2: Combining the index data features, calculating the value of α—which means that objects with fuzzy similarity higher than or equal to $1-\alpha$ are placed into a single class—will yield the

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similarity class.

Step3: Calculate the classification quality, the lowest approximation set, and the value of β.

Step4: The computation is carried out for the remaining metrics in accordance with the attribute importance $sig_{x_i}(c_j)$.

Step5: The following equation is applied to normalize the importance of each indicator attribute from the previous step as the objective weight of each indicator.

$$P_j = \frac{sig_{x_i}(c_j)}{\sum_{i=1}^{n} sig_{x_i}(c_j)} \tag{8}$$

Figure 2 depicts the flow chart for the simplification of VPRS metrics.

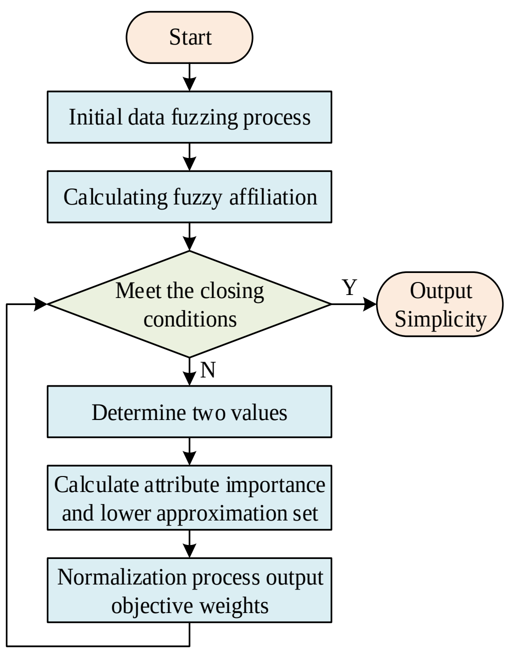

Figure 2. Streamlined flow chart of VPRS indicators

When using VPRS information fusion technology for indicator simplification, the number of indicators should not be too many. Consequently, when examining the link between urban innovation effectiveness and high-quality economic development, we should focus on selective analysis of indicators for mining, and select indicators with wide influence for analysis, so as to meet the accuracy of mining information.

Examination of urban efficacy in innovation and superior economic growth measurement

Analysis of urban innovation efficiency measurement

Indicator system construction

The fundamental principle of urban innovation efficiency in the context of high-quality economic development is that the investment of urban innovation resources in the process of economic and social development of cities promotes the city's own economic development, enhances the efficiency of urban economic development, and achieves the full utilization of innovation resource investment.

As a result, the urban innovation efficiency evaluation index system is established, as shown in Table 1, based on the analysis of the mechanisms of regional economic high-quality development and innovation efficiency, a thorough search of the literature related to urban innovation efficiency, and the use of the practices of relevant scholars.

Table 1. Indicators for evaluating the efficiency of urban innovation

Primary Indicators	Secondary Indicators	Tertiary Indicators
Input elements	Human input	Scientific research and technology services employees
	Capital investment	Total internal expenditure on R&D
		Intensity of investment in science and technology per unit area
		Per capita utilization of foreign investment
Output elements	Economic returns	Growth Rate of Output Value of High-tech Industries
	Innovation results	Number of patents issued for every 10,000 people
		Sales revenue of new products

Data Envelope

By assuming constant payoffs of scale, the data envelope model is used to assess the effectiveness of indicators. When every decision unit on the border surface has an efficiency value of 1, it indicates that the decision units are strongly efficient, and the main indicators affecting the efficiency of urban innovation are identified in the form of data envelopes for indicator measurement.

However, using the data envelope model, there are multiple decision units with efficiency of 1, and these decision units cannot be analyzed in more depth to further distinguish the differences between different decision units.

Based on this, the VPRS model developed in this research employs the incredibly effective SBM model to gauge the effectiveness of urban innovation, which circumvents the drawbacks of the traditional data envelope model and improves the accuracy of the measurement and analysis.

The VPRS information fusion technology-based super-efficient SBM model is stated as:

$$\min\theta = \frac{1-\left(\frac{1}{m}\right)\sum_{i=1}^{m} s_j^{-} / x_{ik}}{1+\left(\frac{1}{s}\right)\sum_{i=1}^{s} s_j^{+} / y_{rk}} \tag{9}$$

$$\begin{cases} \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^{-} \leq x_{ik} \\ \sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j - s_r^{+} \geq y_{rk} \\ \lambda \geq 0, s^{-} \geq 0, s^{+} \geq 0 \\ i = 1, 2, \ldots, q;\ j = 1, 2, \ldots, n \end{cases} \tag{10}$$

Where, θ denotes the value of urban innovation efficiency, the innovation output factor is represented by y, the innovation input factor is represented by x, and the number of input indicators is represented by m, the input slack variables are represented by s_i^{-}, and the number of output indicators are represented by k, and s_r^{+} represents the output slack variables.

When $\theta \geq 1$, the decision unit indicates validity, and when $\theta < 1$, the decision unit indicates invalidity, and parameter improvement is needed for input and output.

Analysis of urban innovation efficiency measurement

In order to assess and analyze the innovation efficiency of cities from 2010 to 2020 in accordance with the size of cities and the major industries of cities, the super-efficient SBM model under the VPRS model is utilized.

The analysis of innovation efficiency measurement according to city size is shown in Table 2. The innovation efficiency of mega-cities and mega-cities remains strong and effective, with the trend of "mega-cities > mega-cities > large cities > medium cities > small cities".

The innovation efficiency of mega-cities increases from 1.423 in 2010 to 2.365 in 2020, up by 66.19%, while that of megacities increases from 1.320 in 2010 to 1.604 in 2020, up by 21.52%. Large cities saw a rise of 100.83% from 0.722 to 1.45 in 2020. Medium-sized cities' innovation efficiency rises from 0.710 in 2010 to 1.318 in 2020, an increase of 85.63%.

Small towns' innovation efficiency rises from 0.736 in 2010 to 1.198 in 2020—a rise of 62.77%. Large cities see the quickest growth in innovation efficiency, followed by medium-sized cities, while megacities experience the slowest growth. Diffusion effects dominate small cities' total innovation factors, and the gap between them and other city sizes tends to grow.

Table 2. Analysis of urban innovation efficiency measures by city size

	Super City	Megacities	Large cities	Medium-sized cities	Small cities
2010	1.423189	1.320474	0.722235	0.710473	0.736125
2011	1.546457	1.370439	0.741922	0.818034	0.757787
2012	1.591659	1.447063	0.899989	0.893984	0.818512
2013	1.736926	0.886072	0.923087	0.949308	0.875342
2014	1.753257	1.594075	0.934373	0.988874	0.924583
2015	1.866114	1.275223	1.121638	1.099451	0.929497
2016	1.897803	1.582631	1.143702	1.128662	0.993027
2017	2.054963	1.509911	1.193524	1.162676	1.000823
2018	2.176844	1.551235	1.284828	1.218316	1.047488
2019	2.319121	1.280892	1.366122	1.286286	1.047597
2020	2.364885	1.603592	1.450312	1.318186	1.197534
Average	1.884656	1.401964	1.071067	1.052205	0.938938

The analysis of innovation efficiency measurement according to the division of leading industries of cities is shown in Table 3.

Those with a high reliance on resources have a poorer innovation efficiency than cities without such a reliance.

It is primarily because resource-based industries, such as the coal industry, are the foundational industries of economic growth in resource-based cities, and when compared to non-resource-based cities, the contribution of the urban innovation industry is insufficient, and the overall innovation input-output efficiency is low.

In terms of growth rate, from 2010 to 2020, the innovation efficiency of resource-based cities increased from 0.485 to 1.195, up 146.39%, and the innovation efficiency of non-resource-based cities increased from 0.824 to 1.539, up 86.77%.

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This shows that the innovation efficiency of resource-based cities and non-resource-based cities increased at different rates. The difference between resource-based and non-resource-based cities is getting smaller, resource-based cities actively change their industrial structure, and the speed at which urban innovation leads to transformation grows.

Table 3. Analysis of innovation efficiency in leading urban industries

	Resource Cities	Non-resource-based cities
2010	0.484988	0.823742
2011	0.535267	0.841135
2012	0.553338	0.863371
2013	0.771191	0.887569
2014	0.815231	1.018989
2015	0.813712	1.144423
2016	0.782466	1.189788
2017	0.852817	1.247538
2018	0.859509	1.288952
2019	1.121356	1.351955
2020	1.194568	1.539359
Average	0.798586	1.108802

Analysis of urban economic quality development measurement

Indicator system construction

The basis for building urban economic quality development indicators is the new development concept, and the specific contents of economic quality development indicators are shown in Table 4.

These metrics were developed using data from the reality of Chinese cities, an analysis of economic quality development, and research on urban economic quality development by both domestic and international academics.

Table 4 (a). Indicators of quality urban economic development

Primary Indicators	Secondary Indicators	Tertiary Indicators
Innovative developments	Innovation potential	Employees in higher education as a percentage of the population
		The percentage of the population enrolled in tertiary education
		Years of schooling per capita
Green development	Government intervention	Government Environmental Regulation Index
	Resource consumption	Total tonne of standard coal consumption
	Environmental pollution	Emissions of industrial wastewater, exhaust gas and solid soot per unit
	Environmental Protection	Built-up regions with a green canopy

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Table 4 (b). Indicators of quality urban economic development

Coordinated development	Industrial structure	Industrial Structure Rationalisation Index
		Industrial Structure Rationalization Index
	Urban and rural structure	Urbanization Rate
		The difference between rural and urban citizens' per capita
Open Development	Foreign Trade	Total imports and exports as a proportion of GDP
	Utilization of Foreign Investment	Amount of foreign direct investment
	Economic Results	Real GDP growth rate
		Real GDP per capita
Shared Development	Public Services	Public library collections per capita
		Disposable incomes and the number of beds in hospitals and other medical facilities per 10,000 persons
	Social Security	The percentage of budgetary expenditure that goes to culture and the media
		Share of health and social work employment

Methodology for measuring high-quality urban economic development

In this section, the entropy approach from the VPRS model is used to gauge the degree of high-quality development of the urban economy. Even in the presence of several assessment index systems, the entropy technique can objectively represent the changes in each component of each system while remaining flexible. The fundamental tenet is that the proportionate effect of the index information's change on the entire system determines the weight of the index. For a given set of raw data, if an index's information entropy is lower, the index will have a higher discrete degree, which means that the index will have a greater role in the overall evaluation system because it will contain and transmit more information. Inversely, if the index's discrete degree is lower, the index will have a lower weight. The following are the precise measuring procedures:

Step1: When standardizing data and standardizing evaluation indices using the extreme difference method, the following standardization calculation formula is used:

$$X_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{11}$$

where X_{ij} is the data obtained after standardization of the j rd indicator in the i nd municipality.
Step2: Determine the entropy of the j st index., i.e.:

$$e_j = -k\sum_{i=1}^{m} y_{ij} \ln y_{ij} \tag{12}$$

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Among them, $k = \dfrac{1}{\ln n}$.

Step3: Calculate the deviation value d_j of the j st index, i.e.:

$$d_j = 1 - e_j \tag{13}$$

Step4: Calculate the weight w_j occupied by the j st indicator, i.e.:

$$w_j = \frac{d_j}{\sum_{i=1}^{n} d_j} \tag{14}$$

Step5: Calculate the evaluation score of the i st city single indicator, i.e.:

$$Z_{ij} = w \times x_{ij} \tag{15}$$

Step6: Calculate the composite weight score of i municipality, i.e.:

$$Z_i = \sum_{j=1}^{n} Z_{ij} \tag{16}$$

Analysis of urban economic quality development measurement

According to the size of the city and the major industries there, the entropy approach is employed in the VPRS model to assess and analyze the high quality urban economic development from 2010 to 2020.

Table 5 displays the examination of economic quality development measurement by city size. According to the number of urban population, the cities are separated into five categories: mega-cities, megacities, major cities, medium cities, and small cities. The degree of qualitative development of mega-cities and megacities is trending upward from 2010 to 2020. Megacities' economic quality development score climbed from 0.173 in 2010 to 0.449 in 2020—a 159.54% increase—and their economic quality development level rose from 0.033 in 2010 to 0.039 in 2020—a 21.88% increase.

On the contrary, the degree of excellent development of large cities, medium cities and small cities generally shows a decreasing trend, with the degree of excellent development of large cities decreasing from 0.022 in 2010 to 0.017 in 2019, a decrease of 22.73%, the degree of excellent development of medium cities decreasing from 0.022 in 2010 to 0.014 in 2020, a decrease of 36.36%, and the degree of excellent development of small cities decreasing from 0.022 in 2010 to 0.014 in 2020. The degree of excellent development in small cities decreases from 0.016 in 2010 to 0.009 in 2020, a decrease of 43.75%, indicating a widening trend of the gap between cities in terms of the degree of excellent development.

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Table 5. Data on quality economic development by city size

	Super City	Megacities	Large cities	Medium-sized cities	Small cities
2010	0.172806	0.032521	0.021973	0.021703	0.016019
2011	0.195463	0.035147	0.014087	0.014798	0.018374
2012	0.198918	0.040754	0.018502	0.01433	0.008525
2013	0.229373	0.029241	0.019276	0.013528	0.008361
2014	0.235672	0.03648	0.015321	0.013615	0.008214
2015	0.270115	0.027328	0.014064	0.014763	0.011944
2016	0.272806	0.03913	0.018789	0.014076	0.011335
2017	0.359545	0.036676	0.017399	0.013232	0.011728
2018	0.376362	0.028406	0.017929	0.013921	0.011169
2019	0.441214	0.033428	0.018167	0.013557	0.011765
2020	0.449422	0.039655	0.015312	0.014285	0.009291
Average	0.291063	0.034433	0.017347	0.01471	0.01152

The analysis of economic quality development measurement according to the division of leading industries of cities is shown in Table 6. The quality of economic development in resource-based and non-resource-based cities has remained consistent between 2010 and 2020, the difference in quality is not significant, and the quality of economic development in resource-based cities has slightly declined. Resource-based cities need to further improve their high-quality economic development in order to close the quality gap in economic development between their city and non-resource-based cities, as evidenced by the continued existence of this gap.

Table 6. Development measurement analysis

	Resource Cities	Non-resource-based cities
2010	0.016312	0.026217
2011	0.015721	0.027228
2012	0.015576	0.027919
2013	0.015029	0.029311
2014	0.012733	0.029531
2015	0.01143	0.029639
2016	0.010582	0.029686
2017	0.010393	0.030283
2018	0.009766	0.030451
2019	0.008829	0.031896
2020	0.008589	0.031978
Average	0.012269	0.029467

Combining study of high-quality economic growth and urban innovation efficiency

Coupling analysis measurement method based on VPRS model

Through coupling and coordination, the developed VPRS model is used to assess the degree to

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which the components of efficient urban innovation and high-quality economic growth are coupled and coordinated, and the degree of connection and coordination is used to determine if the urban economic development subsystems of high quality and efficient innovation coexist.

The relationship between effective urban innovation and high-quality economic growth is expressed as:

$$C_n = \{U_1, U_2, ..., U_n\} / \Pi\{U_i + U_j\}^{1/n} \tag{17}$$

Where the value range for C is [0, 1], the greater the value indicates the higher the coupling degree.

The coupling degree expression in the VPRS model only reflects whether the systems are coordinated with each other, and cannot judge the absolute level of the system itself. In order to make up for the shortcomings of the coupling index, we introduce the coupling coordination index, which not only looks at the degree of close connection between subsystems and the coordination of development, but also looks at whether the trend of common development is good, which can reflect the level of system development more accurately and can reflect the current situation more comprehensively and objectively. The expressions are as follows:

$$\begin{cases} D = \sqrt{C \times T} \\ T = (\alpha U_1 + \beta U_2 + ... + \gamma U_n) \end{cases} \tag{18}$$

Where D is the degree of coordination, and the range of values is [0, 1], the greater the value, the higher the degree of coordination, T is the subsystem's overall coordination index, which reflects the effect of the overall level of coordination between the subsystems, and α, β, γ is the weight of the subsystem.

Coupling degree analysis

The coupling calculation under the VPRS model is used to examine the relationship between the effectiveness of urban innovation and high-quality economic growth. from 2010-2020 from two perspectives of city size and leading urban industries, respectively.

Coupling degree analysis of different city sizes

According to their sizes, cities are classified as mega-cities, megacities, large cities, medium-sized cities, and small cities. The degree to which high-quality economic development and innovation efficiency are coupled for each type of city is then analyzed, and the findings are displayed in Figure 3. Megacities' ability to innovate effectively and high-quality economic growth will continue to be strongly correlated from 2010 through 2020, and the coupling degree between mega-cities, mega-cities, large cities and medium cities is on the rise.

The coupling degree between megacities, mega-cities, large cities, and medium cities is on the rise.

Megacities' coupling degree rises by 16.48%, from 0.522 to 0.608; that of large cities increases from 0.376 to 0.469, up by 24.73%; that of medium cities increases from 0.412 to 0.641, up by 55.58%; and that of small cities increases from 0.402 to 0.484, up by 20.39%.

Large cities and medium-sized cities have a higher rise, and the gap between them and mega-cities and mega-cities tends to narrow, while the gap between the two coupling degrees of small cities and cities of other sizes tends to expand.

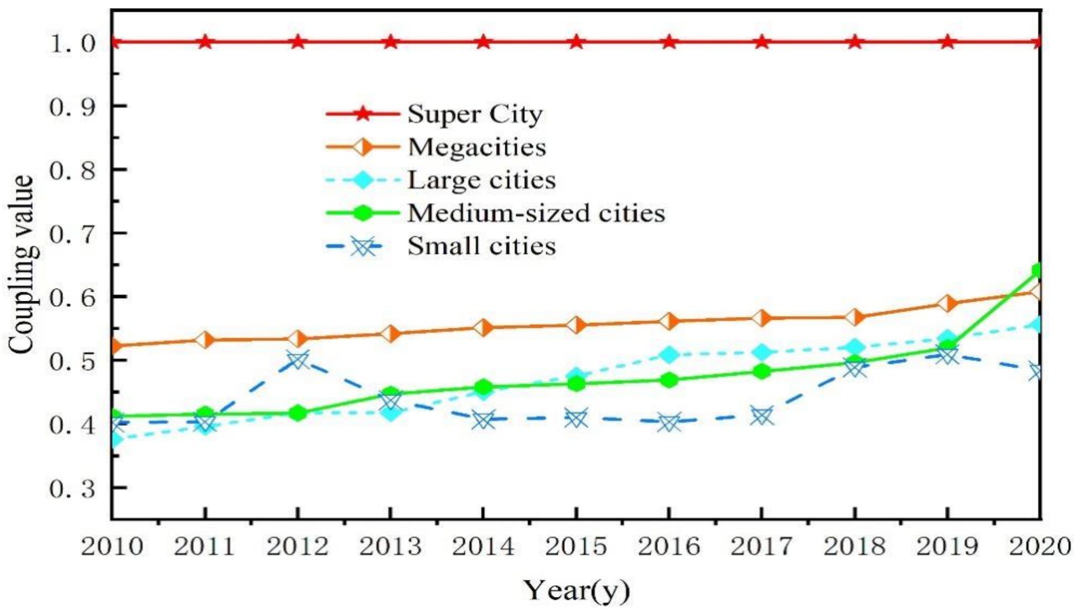

Figure 3. Coupling analysis for different city sizes

Coupling degree analysis of leading industries in different cities

Cities are separated into resource-based and non-resource-based cities based on their various main sectors. The degree to which efficacy in innovation and superior economic growth are coupled for each kind of city is then evaluated, and the findings are displayed in Figure 4.

According to the leading industries of cities, the degree of coupling between high quality economic development and innovation efficiency in non-resource-based cities is greater than the degree of coupling between the two.

Resource-based cities' coupling degree rises from 0.364 in 2010 to 0.509 in 2020, a 39.84% increase. Cities without access to natural resources will have a coupling degree that has increased by 45.41% from 0.425 in 2010 to 0.618 in 2020.

The two-coupling degree of non-resource-based cities is growing at a faster pace than resource-based cities, suggesting that the gap between both types of cities' levels of innovation effectiveness and high-quality economic development has grown.

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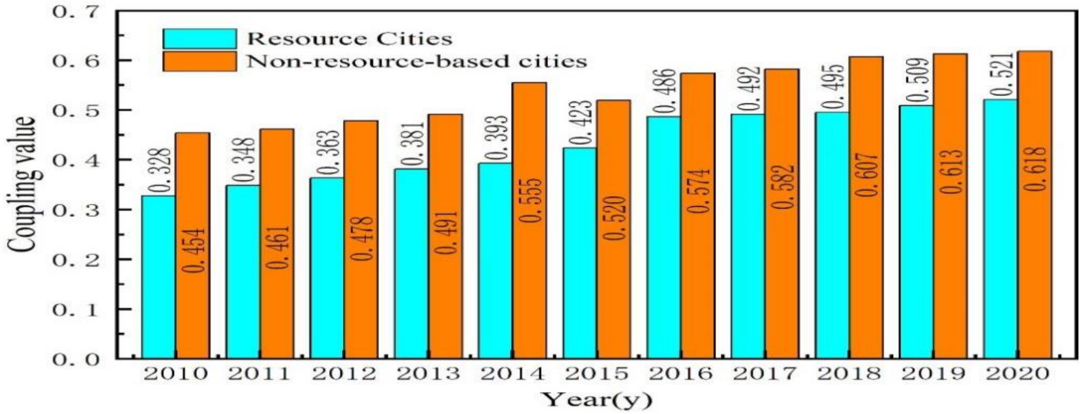

Figure 4 Coupling analysis of the leading industries in different cities

Coupling coordination degree analysis

The degree to which urban innovation effectiveness and superior economic development are coupled can only indicate whether the two are coordinated with each other, but cannot judge the development level between the two. To further assess the state of coordinated development between the two systems, it is important to quantify the degree of coupling coordination between efficacy in innovation and superior economic growth using a coupling coordination model. According to the coupling coordination degree, urban innovation effectiveness and high-quality economic growth are assessed from 2010 to 2020.

Analysis of the coordination of connectivity between various city sizes

According to the different sizes of cities, mega-cities, megacities, big cities, medium-sized cities, and small cities are some of the many types of cities. For each kind of city, the degree to which efficacy in innovation and superior economic growth are coupled is evaluated., and the results of the analysis are shown in Figure 5.

According to the degree of coupling coordination, the tendency is "megacity > megacity > huge city > medium city > small city." 11 years later, the megacity's high level of innovative efficiency and high-quality economic development is still present, and the coupling degree between mega-city, megacity, large city and medium city is increasing. The coupling degree between megacities, mega-cities, large cities, and medium cities is on the rise.

Megacities' coupling degree climbed from 0.543 to 0.567, up 4.42%; large cities' from 0.372 to 0.478, up 28.49%; and medium cities' from 0.377 to 0.429, up 13.79%; and that of small cities increased from 0.302 to 0.348, up by 15.23%. Due to the rapid growth of both innovation efficiency and economic quality in large cities as well as the incremental scale efficiency, the coupling and coordination degree of both develops more tightly in these cities. This is likely why the coupling and coordination degree of both develops more tightly in these cities.

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The slow growth of innovation efficiency and scale efficiency of economic development in megacities and mega-cities inhibits the coupling and coordination between them. The innovation efficiency and economic development of medium-sized cities and small cities have not yet reached the scale efficiency, so they need to further promote the innovation efficiency and economic development quality of cities. In megacities and mega-cities, the coupling and coordination between economic growth scale efficiency and innovation efficiency is inhibited. Medium-sized and small cities need to do more to advance the innovation efficiency and economic development quality of their cities because they have not yet attained scale efficiency in these areas.

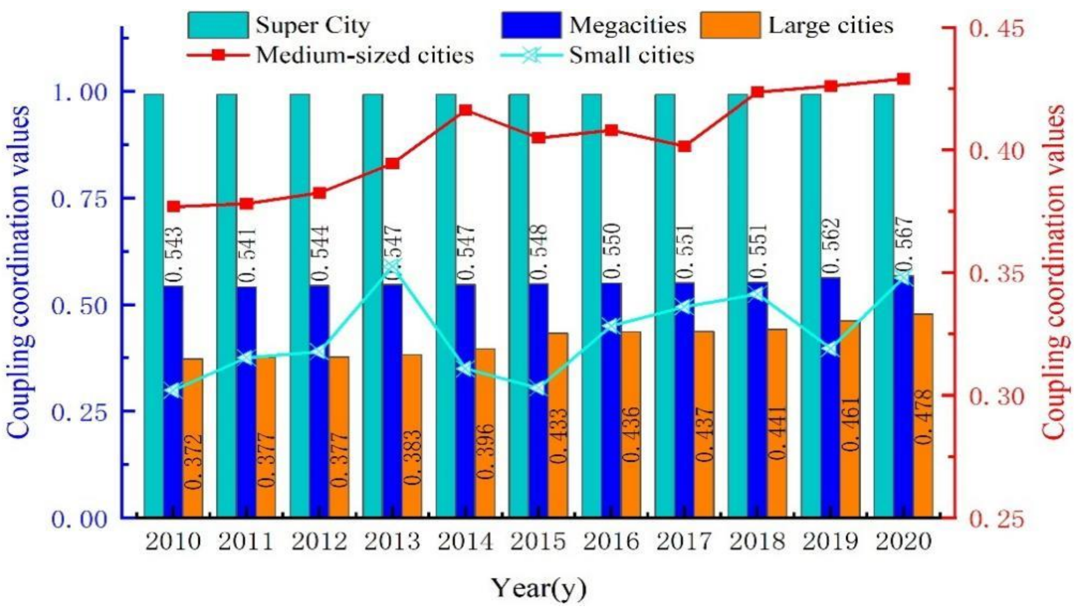

Figure 5. The degree to which various city sizes are coupled and coordinated

Analysis of the coordination and coupling of major businesses in various cities

Cities are separated into resource-based and non-resource-based cities based on their various main sectors. The degree to which efficacy in innovation and superior economic growth are coupled for each kind of city is then evaluated, and the findings are displayed in Table 7.

Leading sectors in cities claim that greater economic development and innovation effectiveness in non-resource-based cities are more closely correlated than their respective levels of coordination, because in non-resource-based communities, the effectiveness of innovation and better economic growth more strongly support one another. The two's coupling degree in resource-based cities increases from 0.351 in 2010 to 0.379 in 2020, an increase of 7.98%, while it increases from 0.412 in 2010 to 0.479 in 2020, an increase of 16.26%.

The two's coupling degree in non-resource-based cities grows at a faster rate than it does in resource-based cities.

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Table 7. The degree of coupling and coordination of leading industries

	Resource Cities	Non-resource-based cities
2010	0.351092	0.411502
2011	0.321504	0.413197
2012	0.321123	0.417556
2013	0.354853	0.421278
2014	0.362659	0.421403
2015	0.353227	0.426362
2016	0.344322	0.432886
2017	0.351218	0.437416
2018	0.337642	0.455126
2019	0.362547	0.459118
2020	0.379043	0.479254
Average	0.349021	0.4341

Conclusion

To look at the link between effective urban innovation and high-quality economic growth, using the VPRS model and SBM model, this study examines the degree of coupling and coupling coordination of cities' innovation effectiveness and high-quality economic growth based on information fusion technology. According to the overall coupling degree and coupling coordination degree, the trend among major cities and industries is "mega-city > mega-city > large city > medium city > small city." Those with multiple leading industries have higher coupling degrees than cities with a focus on natural resources. This leads to the following recommendations for the effectiveness of urban innovation and superior economic growth.

(1) Improving the ability to transform innovation results and perfecting the innovation system.

(2) Optimize the natural environment, promote common prosperity, and achieve high-quality economic development.

(3) Coordinating innovative input-output mechanisms to improve the quality of urban economic development.

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