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Green technology diversification, technology vertical spillovers, and energy intensity in Chinese cities

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ABSTRACT

Drawing from patent data spanning 2011-2016 in 249 Chinese prefecture-level cities and urban scale multi-region input-output (MRIO) table data, this paper empirically demonstrates that as green technological diversification levels escalate, the energy intensity of Chinese prefecture-level cities exhibits an initial increase followed by a decline. Green technological diversification indirectly influences urban energy intensity through vertical spillovers of green technology across the upstream and downstream sectors within the supply chain. Medium-sized cities, service industry-oriented cities, and those in the early stages of industrialization need to prioritize development of multiple green technologies to surpass the diversification turning point. The finding suggests a strategic transition for Chinese cities from a single green technology agglomeration model to a cluster model of collaborative development of multiple green technologies.

Introduction

The global community currently faces a severe energy crisis, particularly after 2021, due to the post-pandemic economic recovery and climate-induced reductions in renewable energy production, such as wind, hydro, and solar energy. This has resulted in immense pressure on the global energy market (International Energy Agency, 2022). Scholars increasingly argue that technology effects and innovation serve as effective means to alleviate both energy and environmental pressures (Du, Li, & Yan, 2019; Töbelmann & Wendler, 2020; Zhu, Wang, Yang, & Zhu, 2020). Technological advancements, particularly in green technology, play a vital role in enhancing energy efficiency (Chen, Han, & Liu, 2016; Feng, Zhang, & Liu, 2020; Li & Lin, 2018). Green technology encompasses emerging technological systems related to energy conservation, environmental protection, clean production, clean energy, ecological protection and restoration, urban and rural green infrastructure, and ecological agriculture (Jiao, Chen, & Bai, 2020). Previous studies indicate that green and non-green technologies possess distinct knowledge bases (Ardito, Messeni Petruzzelli, & Albino, 2016; Barbieri, Marzucchi, & Rizzo, 2020; Corrocher & Ozman, 2020; Del Río, Penascola, & Romero-Jordan, 2016). Green technologies often involve combinations of technological components that have not been previously attempted (Barbieri et al., 2020; Petruzzelli, Dangelico, Rotolo, & Albino, 2011). In comparison to non-green technologies, green technologies are anticipated to be more effective in reducing urban energy consumption, decreasing pollution, improving ecology, promoting ecological civilization construction, and achieving harmony between humans and nature (Destek & Aslan, 2020; Hosseini-Fashami, Motevali, Nabavi-Pelesaraei, Hashemi, & Chau, 2019; Morris, Reilly, & Chen, 2019). In 2010, the World Intellectual Property Organization (WIPO) launched the *Green List of the International Patent Classification*, a tool designed to facilitate the retrieval of environmentally friendly technology-related patent information. This classification system aligns with the United Nations Framework Convention on Climate Change and divides green patents into seven subcategories: alternative energy production, transportation, energy conservation, waste management, agriculture and forestry, administrative regulation and design, and nuclear energy.

With the development of evolutionary economic geography, scholars have gradually begun to explore technological upgrading paths from the perspectives of technological diversification and specialization. Technological upgrading paths remain controversial, with varying degrees of promotion based on the research data, time period, region, scale, and methodology used by researchers (Boschma, Balland, & Kogler, 2015; Garcia-Vega, 2006; Huang & Chen, 2010). Therefore, the measurement of technological diversity and its impact possess high research value.

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Specialization in a single technological field may entail the risk of "technological lock-in," wherein excessive specialization can hinder the emergence and evolution of innovations in other industries (Santoalha, 2019). There is consensus in the literature that environmental innovations require diverse sources of knowledge or technology (Barbieri et al., 2020; Horbach, Oltra, & Belin, 2013; Li, Heimeriks, & Alkemade, 2021; Moreno & Ocampo-Corrales, 2022). Green technology, in particular, necessitates embedding across multiple domains, with many breakthrough innovations in the environment arising from the collision of knowledge from different fields (Frenken & Boschma, 2007; Dong, Sun, Balland, & Zhang, 2022; Zeppini & van den Bergh, 2011).

Hence, investigating green technological diversification is of utmost importance for environmental technological innovation. It is essential for sustainable development to help regions break out of their technological trajectory and create new, diverse, and complex green technologies (Dong, Sun, Balland, & Zhang, 2022). Theoretically, transitioning from a single green technology agglomeration model to a cluster model involving multiple green technologies is an inevitable choice in the process of regional sustainable development. In practice, what impact will green technological diversification have on the environment? Given the increasingly severe energy crisis, this paper aims to examine the role of green technological diversification in environmental sustainability from an energy perspective, using energy intensity as a research proxy. Energy intensity, the ratio of total annual energy consumption to real GDP, indicates that the lower the value, the higher the energy efficiency, which is more beneficial for sustainable development.

There is currently no domestic or international literature analyzing the environmental impact of green technological diversification from an empirical perspective, nor any research concerning the relationship between green technological diversification and energy. The mechanism by which green technological diversification affects energy intensity, as well as whether different impacts exist in different periods, remains to be further explored. China is the largest developing country. According to data from the National Bureau of Statistics of China, China's total energy consumption has maintained rapid growth, while aggregate energy intensity and sectoral energy intensity have declined in most years. However, when compared internationally, China's energy intensity level still lags behind the international average, as well as developed countries such as the United States, European Union, and Japan (Shi, Chu, & Zhao, 2021; Wang, Zhao, Wei, & Zhang, 2021). Meanwhile, China's green patent applications have been increasing year by year (Pan, Wei, Han, & Shahbaz, 2021). Therefore, a case study and discussion of relevant conclusions will contribute to addressing the global energy crisis and achieving sustainable development goals. Consequently, this paper will take China's prefecture-level cities as research objects and examine the impact and mechanism of green technological diversification on energy intensity.

The organization of the article is as follows: Section 2 reviews the relevant literature, and Section 3 proposes a theoretical mechanism framework and research hypotheses. Research design, empirical models, and data sources are introduced in Section 3. Section 4 discusses empirical research, using regression methods to study the impact of green technological diversification and other factors on energy intensity, as well as mechanism analysis, robustness tests, endogeneity tests, and heterogeneity analysis. Lastly, Section 5 summarizes and puts forth corresponding policy suggestions and further research prospects.

Literature review

Studies on green technological diversification

Cheng, Yang, and Wen (2021) argue that technological diversity, encompassing technology spillovers and domestic innovation, negatively impacts energy intensity. Dong, Sun, Balland and Zhang (2022) assert that environmental constraints can foster the development of advanced green technologies in cities, attracting green innovations from various technological domains, as evidenced by empirical data from Chinese patents. However, there is neither a concrete indicator of green technological diversification in China nor any research examining its effects on energy challenges. The majority of recent research on green technological diversification originates from Europe. Corrocher and Ozman (2020) employed the entropy index method to quantify the green technology diversity index in the European ICT industry, exploring its relationship with business performance. Santoalha and Boschma (2021) utilized the Relative Technological Advantage (RTA) index to assess green technological diversification, examining how national and regional environmental policies influenced the ability of 95 regions across seven European nations to diversify into novel green technologies between 2000 and 2012, while technological diversification, the upper level concept of green technological diversification, is primarily concerned with how it affects company performance (e.g., Chen & Chang, 2012; Garcia-Vega, 2006; Huang & Chen, 2010; Leten, Belderbos, & Van Looy, 2007; Quintana-García & Benavides-Velasco, 2008).

Studies on the relationships between technological advancement and energy intensity

Numerous studies discuss the relationship between technological progress and energy intensity, with many considering technological progress to be key in understanding China's energy intensity changes (e.g., Ma and Stern, 2008; Li et al., 2013; Lin and Du, 2013; Crompton & Wu, 2005; Miao, Fang, Sun, Luo, & Yu, 2018; Wei et al., 2006; Zhang et al., 2019). Various methods have been used to empirically demonstrate that technological progress is a critical driving factor. Some studies, however, have explained its direct linear facilitation in this manner: For instance, Wang, Li, Zhang, Zhou, and Wang (2020) adopted a two-stage PDA model to assess technology's promoting role in reducing energy intensity, while Feng et al. (2020) and others utilized the DEA-Malmquist productivity index method to characterize technological progress and argued that it could not only directly affect energy intensity but also alleviate China's high energy intensity predicament through industrial structure optimization and energy consumption structure transformation and upgrading.

In general, it is believed that there is not a direct linear relationship between these two variables: Cheng et al. (2021) investigated the influence of innovation efficiency on industrial energy intensity, utilizing 2011–2018 Chinese industrial enterprise statistical data from a technological output perspective. The authors adopted an improved DEA-SBM method to calculate technological innovation efficiency, which included the number of effective invention patents. They posited that enhancing productivity and reducing industrial energy consumption could be achieved by optimizing technological innovation capabilities during the technological innovation stage. However, they also discovered that during economic transition, the transformation and production of new products in the process of technology commercialization could increase industrial energy consumption, negatively impacting industrial energy intensity. Moreover, Luan, Huang, Zou, and Huang (2020) found that the impact of technological progress and ownership structure on industrial energy intensity is nonlinear by using a dynamic panel threshold model. Liao and Wang (2019) used a shift production function including output, capital, labor, and energy to estimate the contribution rate of technological progress in China's transportation sector. They concluded that technological progress saved energy consumption at the micro-level while simultaneously stimulating energy consumption growth at the macro-level.

In the context of green technology, both linear and nonlinear relationships have been found. Chen et al. (2016) studied the relationship between green innovation and energy intensity using data from 29 provinces in mainland China from 1999 to 2010, represented by the green patent stock. They discovered a unidirectional negative causal relationship between green innovation and energy intensity in the short term, highlighting the importance of stimulating new green investments to promote the spread of green technologies. Wurlod and Noailly (2018) analyzed the effect of green innovation, as characterized by the green patent stock of 14 industrial sectors in 17 OECD countries from 1975 to 2005, on energy intensity and found that green innovation led to a decline in energy intensity in most industries. In terms of non-linearity, Zhang, Wei, and Lv (2015) used total-factor energy efficiency calculations under environmental constraints to determine energy-saving technological progress indicators, proposing that China's energy-saving technological progress and energy consumption exhibited a significant inverted U-shaped curve relationship. This implies that as energy-saving technological progress improves, energy consumption first increases then decreases, with the dominant force shifting from the "rebound effect" to the "energy-saving effect." The existence of the rebound effect has been widely recognized in the academic community (Ai, Wu, & Li, 2020; Lin & Liu, 2012; Wen et al., 2018; Yang & Li, 2017). The energy-saving effect of technological advancement in promoting energy efficiency depends on the magnitude of the rebound effect, which ultimately determines whether technological energy-saving policies can be effectively implemented and serve as energy-saving strategic policies (Ai et al., 2020).

Studies on technology spillovers as a mediating mechanism

Although no direct literature has explored how green technological diversification reduces energy intensity by enhancing green innovation efficiency, relevant studies Chen, Long, & Lin (2022a), Jiao et al. (2020), and Pan et al. (2021) can be referenced which all argue that, in comparison to the green technology stock itself, technology spillovers are the primary contributors to improving green innovation efficiency and influencing environmental performance. In terms of the relationship between technology spillovers and energy intensity, no literature has discussed the technology spillovers brought about by green technological diversification. Existing literature mainly focuses on the technology spillovers resulting from foreign direct investment and foreign trade, affecting energy intensity (Huang, Du, & Tao, 2017; Hübler & Keller, 2010). Moreover, Pan et al. (2021) conducted an empirical study on the impact of inter-regional green technology spillovers on energy intensity. As an intermediary mechanism, the spillover effect is primarily observed in enterprise and enterprise innovation studies. For example, Garcia-Vega (2006), Li and Zhao (2020) all believe that knowledge spillover is an essential way for technological diversification to affect enterprise innovation. These findings further inspire the current research, indicating that absorbing technology spillover is also an essential approach for regional green technological diversification to impact green technology innovation and subsequently improve energy efficiency.

Numerous studies have employed input-output tables to calculate technology spillover intensity. For instance, the measurement method for inter-industry horizontal technology spillovers primarily uses input-output tables to construct industry technology similarity matrices and obtain cosine values as weights to measure the spillover effects of inter-industry R&D (Jiao, Yang, & Bai, 2018; Los, 2000). Regarding vertical spillovers in supply chains between upstream and downstream industries, the intermediate input ratio of input-output tables is often employed as industry calculation weights. For example, Costantini, Crespi, Marin, and Paglialunga (2017) used input-output tables of 27 European Union countries to calculate the vertical spillovers of green technology, while Jiao et al. (2020) calculated the indirect impact of inter-industry technology vertical spillovers on overall carbon emission intensity in China through the national input-output table and found that the transmission of green technology throughout the supply chain has a significant impact on the reduction of carbon emissions.

It is important to note that the use of input-output tables to study spillover effects is based on product chains, while some foreign literature studies spillovers based on technology chains, such as patent citation data (e.g., Isaksson, Simeth, & Seifert, 2016; Stephan, Bening, Schmidt, Schwarz, & Hoffmann, 2019). However, as patent applications in China do not require mandatory patent citations, domestic patent citation data often comes from examiners rather than inventors, leading to biased analysis results. Therefore, this paper argues that using input-output tables to calculate technology spillovers in China is more suitable.

Gaps in the literature

First of all, there is research linking technological advancement to energy intensity, but there remains a gap in studies where technical advancement is explored from the perspective of technological diversification. The majority of literature on green innovation and energy employs green patent stock measurements, such as those proposed by Chen et al. (2016), Habiba, Xinbang, and Anwar (2022), Li, Dong, and Dong (2022) and Lv, Liu, Dong, and Su (2023), or green total-factor productivity methods by Miao et al. (2018) and Cheng et al. (2021). Nevertheless, several scholars argue that traditional metrics, such as patent quantity, are insufficient in reflecting the true accumulation of knowledge within technological domains (Xie & Zeng, 2019). Secondly, the impact of green technological diversification on vertical spillovers has yet to be investigated. Thirdly, current research has examined the influence of green technology spillovers on carbon emissions (Chen et al., 2022a; Jiao et al., 2020), its effects on energy intensity remain unexplored.

Theoretical conceptual framework and research hypothesis

From an evolutionary standpoint, growth is self-sustaining as the probability of innovation increases with the availability of a wider range of recombinable elements. This process is referred to as "recombinant growth" or "recombinant innovation" (Weitzman, 1998). This endogenous growth principle applies equally to enterprises and cities: the greater the variety of products within a firm or city, the higher the likelihood of generating new product varieties through the recombination of existing practices (Frenken & Boschma, 2007). Similarly, according to recombinant innovation theory, green technological diversification can increase the probability of generating new green products and technologies by recombining traditional practices. During this process, individuals with diverse backgrounds engage in knowledge exchange, allowing knowledge - the key driving force behind innovation - to flow between different sectors (Stephan, Schmidt, Bening, & Hoffmann, 2017). This reduces exploratory costs and uncertainty (Castaldi, Frenken, & Los, 2015) while preventing negative lock-in effects to specific technologies (Frenken & Boschma, 2007). The cross-fertilization of different green technology domains minimizes fixed effects on low-profit technologies within industries (Garcia-Vega, 2006). In summary, knowledge diversity across various sectors within the technological value chain amplifies spillover effects, implying that the development of green technological diversification results in an increased flow of subsequent knowledge between different sectors. This strengthens the vertical spillover of green technology across industries (see Fig. 1).

The cross-sectoral knowledge spillover induced by green technological diversification can expand the utilization of existing green technologies, further enhancing their efficiency. Concurrently, research and development (R&D) activities in green technologies, particularly in the energy sector, entail high costs and uncertainty (Costa-Campi, Garcia-Quevedo, & Trujillo-Baute, 2015). This vertical spillover across industries reduces the R&D costs of green technological innovation, generating a virtuous cycle that improves the efficiency of green industrial innovation and lowers energy intensity. Moreover, technological spillovers can foster industrial agglomeration (Ellison, Glaeser, & Kerr, 2010; Koo, 2005). The development and agglomeration of green industries can promote industrial upgrading, thereby reducing energy intensity. In summary, this paper proposes

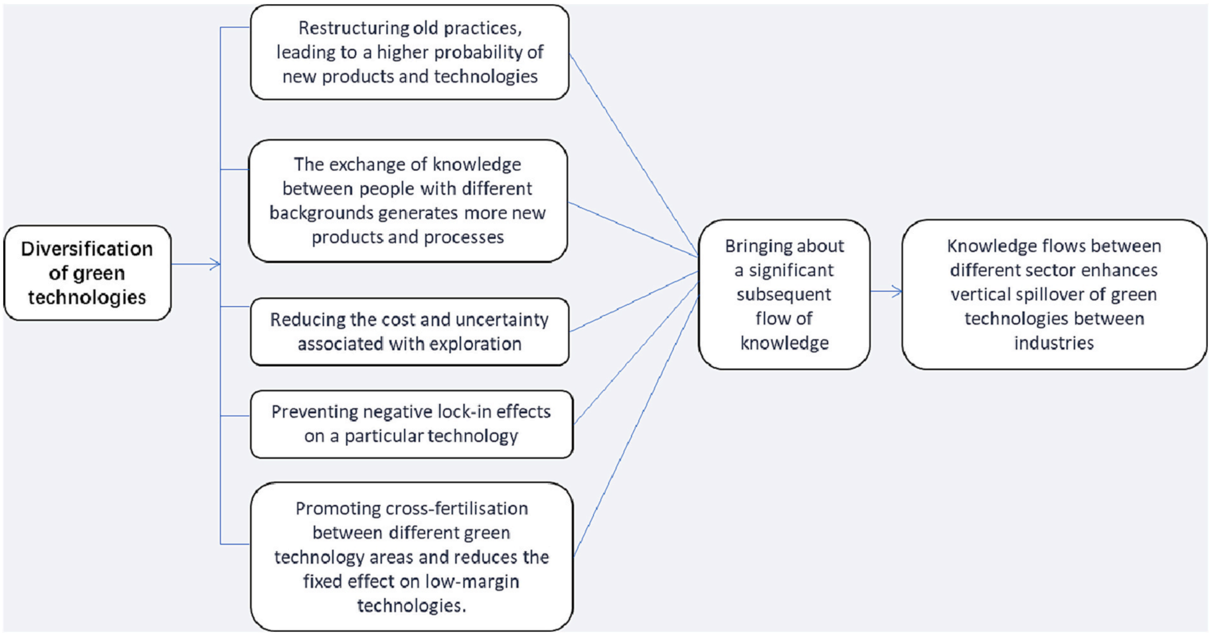

Fig. 1. Analysis of mechanisms by which green technological diversification promotes inter-industry vertical green technology spillovers.

Hypothesis 1. - Green technological diversification facilitates a decrease in energy intensity by enhancing green technology vertical spillovers.

It is crucial to acknowledge that the rebound issue may be particularly pertinent for developing countries. This is because when their final demand is not yet saturated, the production sector may significantly expand under the stimulation of more energy-efficient technologies (van den Bergh, 2011). It should be noted that the issue of rebound may be particularly important for developing countries. This is due to the fact that when their final demand is not saturated, a more energy-efficient technology may stimulate the production sector to greatly expand production (van den Bergh, 2011). In conjunction with the non-linear relationship between green technological advancements and energy intensity discussed in the literature review, according to the "Khazzoom-Brookes (K-B) hypothesis" (Saunders, 1992), during the initial stages, the energy intensity changes triggered by the cross-sectoral knowledge spillover induced by green technological diversification may be offset by increased energy consumption due to the behavioral responses of economic entities. Zhen, Jie, Bing, and Ty (2022) confirmed the K—B hypothesis in China by utilizing an elasticity analysis to reveal a significant energy rebound effect in the industrial sector of 30 Chinese provinces between 2001 and 2017. During the transition to a cluster model of concurrent green technology development, the initial stages of green technological diversification and the propagation of green technologies within the supply chain may reduce energy marginal costs, potentially leading to increased demand for energy services, more non-green industrial investment, and product output. During the economic transition

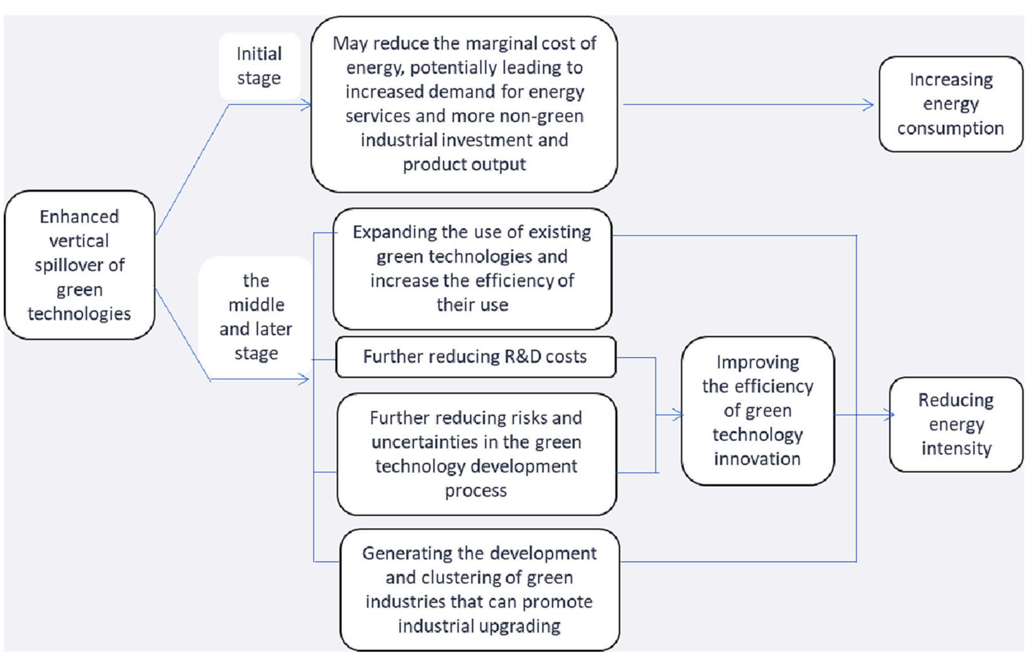

Fig. 2. Analysis of the mechanisms by which inter-industry vertical spillovers of green technologies affect energy intensity.

phase, the transformation and production of new products in the technology marketization process will increase industrial energy consumption (Cheng et al., 2021), initially resulting in increased energy demand. However, this paper posits that after a region reaches a certain level of green diversification development, enhanced technological spillovers will continuously reduce energy intensity (see Fig. 2). In summary, this paper proposes **Hypothesis 2** - The energy intensity of Chinese prefecture-level cities exhibits an inverted U-shaped relationship with green technological diversification. In the long run, as the level of green technological diversification rises, the energy intensity of Chinese prefecture-level cities will exhibit a trend of initially increasing and subsequently decreasing.

Methods and data

Econometric model

To examine the impact of green technological diversification on urban energy intensity, this study utilizes panel data from multi-region input-output (MRIO) tables of prefecture-level cities, which encompass input-output relationships across specific periods. To mitigate the endogeneity problem caused by unobserved omitted variables at the city level and control for the macroeconomic influences during the same year, the research constructs a two-way fixed-effects (year-fixed and city-fixed) multiple linear regression model as follows:

$$Energy_{it} = \alpha + \beta_1 \times ln\_entropy_{it} + \beta_2 \times (ln\_entropy_{it})^2 + \theta \times X_{it} + \lambda_i + \tau_t + \varepsilon_{it} \tag{1}$$

Where, Energy represents the energy intensity of city i in year t, X denotes a series of control variables, α is the constant term, and β1, β2, and θ are the parameters to be estimated. Detailed variable explanations are provided in Table 1.

Descriptive statistics of each indicator are shown in Table 2.

Variable description

Dependent variable

The dependent variable is energy intensity (Energy), reflecting the relationship between energy consumption and economic output in a region as well as the level of energy utilization. This study measures energy intensity using the ratio of total annual energy consumption to actual GDP. The calculation of total annual energy consumption in this research is derived from the city's total annual gas supply (including artificial and natural gas), liquefied petroleum gas supply, total electricity consumption, steam heating, and hot water heating, which are converted according to their respective standard coal reference coefficients.

Table 1
Description of variables and data.

Variable code	Explanation of variables	Method of measurement
Energy	Energy intensity	The value of energy intensity for city i in year t, i.e., the ratio of total annual energy consumption to real GDP
Population	Demographic factor	Year-end resident population of city i in year t
GDP	Wealth factor	GDP per capita of city i in year t
Tech	Technology support	Science and technology expenditure of city i in year t
FDI	Level of openness	Ratio of the amount of foreign capital used to the GDP in city i in year t
Entropy	(Technology factor) Diversification of green technologies	Diversity entropy number, see previous section for algorithm

Note: Science and technology expenditure refers to the direct financial support provided by central and local governments for scientific and technological activities, which encompasses not only research and development (R&D) but also public welfare-oriented scientific and technological activities, promoting the application of scientific and technological achievements, and related services. This constitutes government fiscal expenditure at the respective levels.

Table 2
Descriptive statistical analysis of the data.

	(1)	(2)	(3)	(4)	(5)
Variables	N	max	min	mean	sd
GDP	1473	506,301	8317	54,096	50,817
Population	1473	3392	44	464.8	318.6
Tech	1473	4.035e+06	753	93,836	287,613
FDI	1473	0.0188	1.85e-06	0.00302	0.00276
Entropy	1472	3.156	0	2.431	0.444
Energy	1473	34.97	0.0363	1.746	3.189
gs	1473	60,698	0.0424	1322	4119

Independent variable

The independent variable is the green technological diversification index (Entropy). The higher the 'disordered' in the distribution of technology sub-categories within a city at the technological level, the higher the level of technological diversity (Corrocher & Ozman, 2020). Based on the green patent list published by the World Intellectual Property Organization (WIPO), green patent codes are determined, and green patents are subsequently extracted from the database of the State Intellectual Property Office of China to serve as a proxy indicator for green technology.

$$Entropy_i = \Sigma_k p_k ln(1/P_k) \tag{2}$$

Where, $Entropy_i$ represents the green technology diversity index of city i, where p_k is the proportion of patent quantity in green technology subclass k to the total patent quantity. If a city only possesses one green technology subclass, p_k equals 1, and the green technology diversity index becomes 0, indicating the lowest degree of green technology diversity in city i. If city i has all green technology sub-categories with equal patent quantities across them, the green technological diversification degree of the city i is at its highest.

Mediator variables

This study aims to compute the aggregate vertical green technology spillovers (GS) across industries within cities. The overall spillover intensity is the sum of vertical spillover intensities across all industries in a city.

To calculate the green technology spillover intensity for the kth industry in the ith city, we refer to the method employed by Jiao et al. (2018), which uses the intermediate input ratio in the input-output tables as the design weight for green technology in each industry. The proportion of intermediate inputs supplied by domestic upstream industries to downstream industries represents the weight of that industry. The spillover flow from upstream to downstream industries and the domestic inter-industry spillovers from upstream to downstream industries are obtained by multiplying the domestic green technology stock of upstream industries, which is the stock of green patents.

$$GS_{i,k} = \sum_j \left(\frac{I_{k,j,i}}{\Sigma_i \Sigma_j I_{k,j,i}} GT_{i,k} \right), \forall j \neq k \tag{3}$$

$\frac{I^{dom}_{k,j,i}}{\Sigma_i \Sigma_j I^{dom}_{k,j,i}}$ denotes the ratio of investment of the kth industry in the city i to the jth industry in the city to the intermediate investment ratio of all industries in the city. $GT_{i,k}$ denotes the green patent stock of the kth industry in the ith city.

The MRIO table used in this paper is derived from the study by Chen, Shen, and Lin (2022b), encompassing 284 prefecture-level administrative cities and 28 socio-economic sectors. Referring to Jiao et al. (2020), the green technology patent data were categorized into sectors included in the input-output table based on the International Patent Classification and National Industrial Classification Reference Relationship Table published by the State Intellectual Property Office of China in 2018. The green technology patent stock was computed using the perpetual inventory method with the subsequent formula.

$$GT_{i,k,t} = PAT_{i,k,t} + (1-\delta)GT_{i,k,t-1} \tag{4}$$

$$GT_{i,k,0} = \frac{PAT_{i,k,0}}{g+\delta} \tag{5}$$

$GT_{i,k,t}$ represents the green technology stock of industry k in city i in year t; δ represents the depreciation rate. According to Braun, Schimdt-Ehmcke, and Zloczysti (2010), the depreciation rate is set at 20 %; g represents the growth rate, with the base period for inventory calculation set to 2000 and an average growth rate of 28.08 % from 2000 to 2017; $PAT_{i,k,0}$ denotes the incremental green patent stock for that industry in that city in that year; and signifies the green patent stock in the first year. Using Eqs. (4) and (5), the corresponding green patent stocks of 28 sectors in 313 prefecture-level cities in 2010–2016 can be calculated.

The figures drawn by ArcGis (See Figs. 3–8.) illustrate the indicators of green technological diversification and green technology vertical spillover in 249 prefecture-level Chinese cities from 2011 to 2016. It is evident from the figures that those two indicators are positively correlated, offering an auxiliary test of Hypothesis 1.

Control variables

Drawing inspiration from the IPAT framework, first proposed by Ehrlich and Holdren (1971), which examined the impact of human behaviour on the environment by incorporating influencing factors such as population, wealth, and technology (York, Rosa, & Dietz, 2003), we incorporated green technological diversification index as the technology factor in the model. Other control variables in the model include: population, measured by the urban year-end permanent population; wealth, measured by GDP. Referring to the studies of Hang and Tu (2007), Ma et al. (2020) and Zeng and Ye (2019), in addition to the existing population, wealth, and technology variables, this paper intends to introduce factors such as technological input, foreign investment, energy prices, and urbanization levels which also affect energy intensity. However, due to the same energy prices for different cities in the same year and a considerable amount of missing values for the urbanization rate during the data window period, this paper finally selects technological input and foreign investment as additional control variables. Technological input can promote the generation of new technologies, thereby affecting energy consumption in the production process, so per capita government scientific expenditure is used as a measure. Existing literature shows that the use of foreign capital and foreign direct investment can generate technology transfer, thereby promoting technological upgrading and affecting energy intensity (De Vita, Li, & Luo, 2021; Wang & Chu, 2019). Due to the lack of data on foreign direct investment in some prefecture-level cities, this paper uses the actual amount of foreign capital per year as a proxy. For this study, we analyze panel data from 249 prefecture-level cities in China between 2011 and 2016. The data were primarily sourced from the China City Statistical Yearbook and the China Regional Economic Statistical Yearbook, which finally covered a total of 249 prefecture-level cities in accordance with data quality.

Data sources

The explanatory variable, green technological diversification index (ln_entropy), requires patent classification information sourced from the green patent catalog published by the World Intellectual Property Organization (WIPO) in 2010. The green patents (including invention and utility model patents) were extracted from domestic patents retrieved in the Patent Star database of the National Intellectual Property Administration based on the green patent IPC classification numbers listed on the WIPO official website. The calculation specifically uses the first three digits of the IPC code to categorize and classify cities according to the applicant's address. When calculating the intermediary variable green technology vertical spillover (ln_gs), the green technology patent stock also comes from the Patent Star database. This study obtained >2.67 million patent application data from 313 prefecture-level cities in the Patent Star database from 2001 to 2017. Among all invention patents

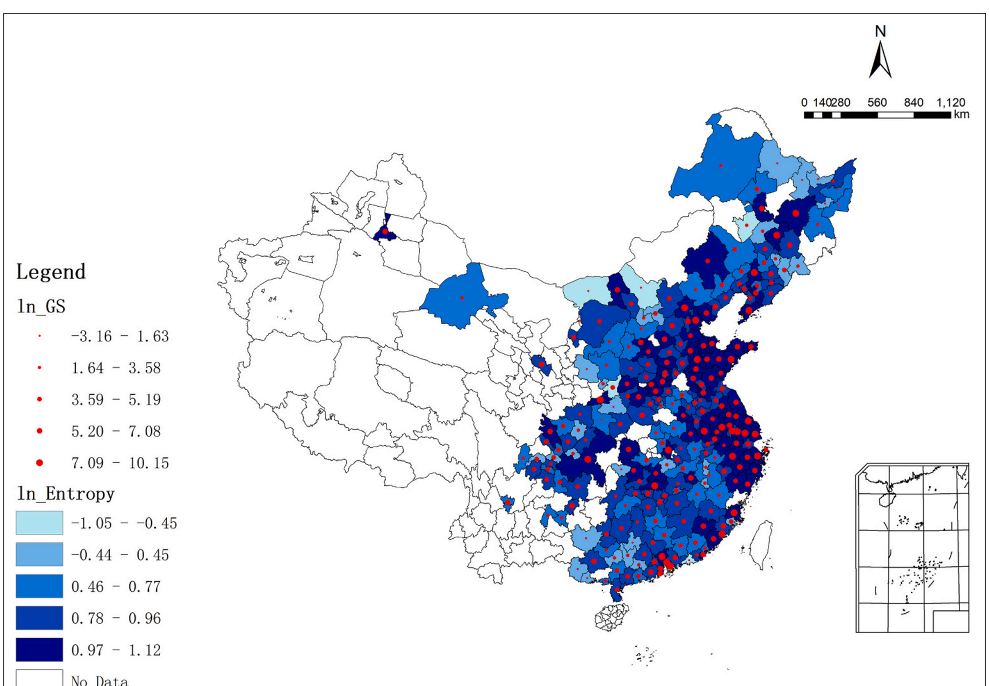

Fig. 3. Distribution of green technological diversification(ln_Entropy) and green technology vertical spillover(Ln_GS) in 249 prefecture-level Chinese cities in 2011.

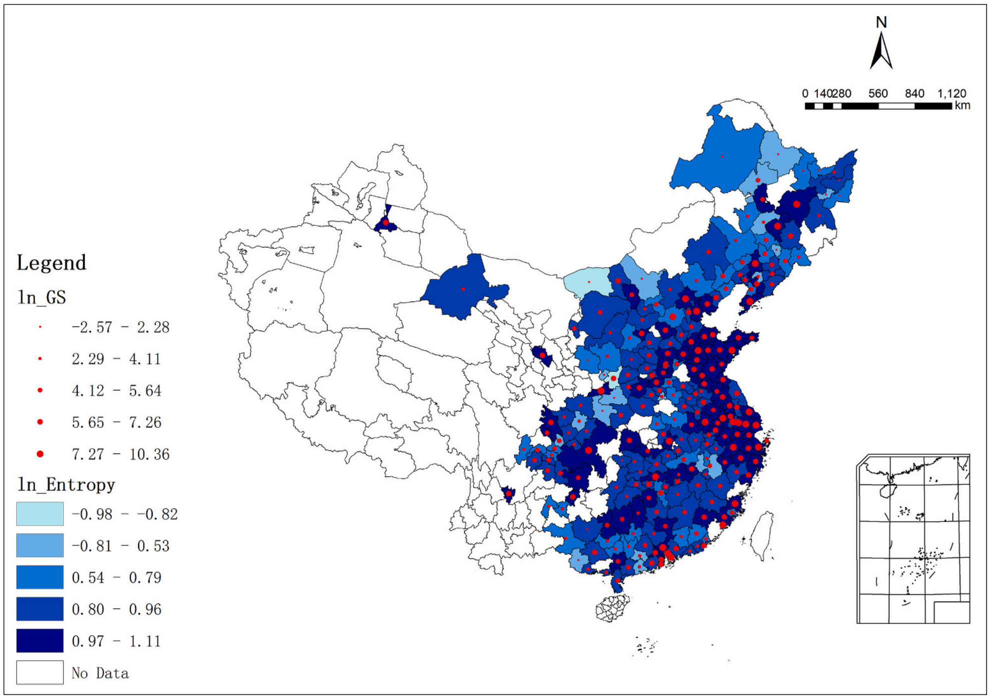

Fig. 4. Distribution of ln_Entropy and Ln_GS in 2012.

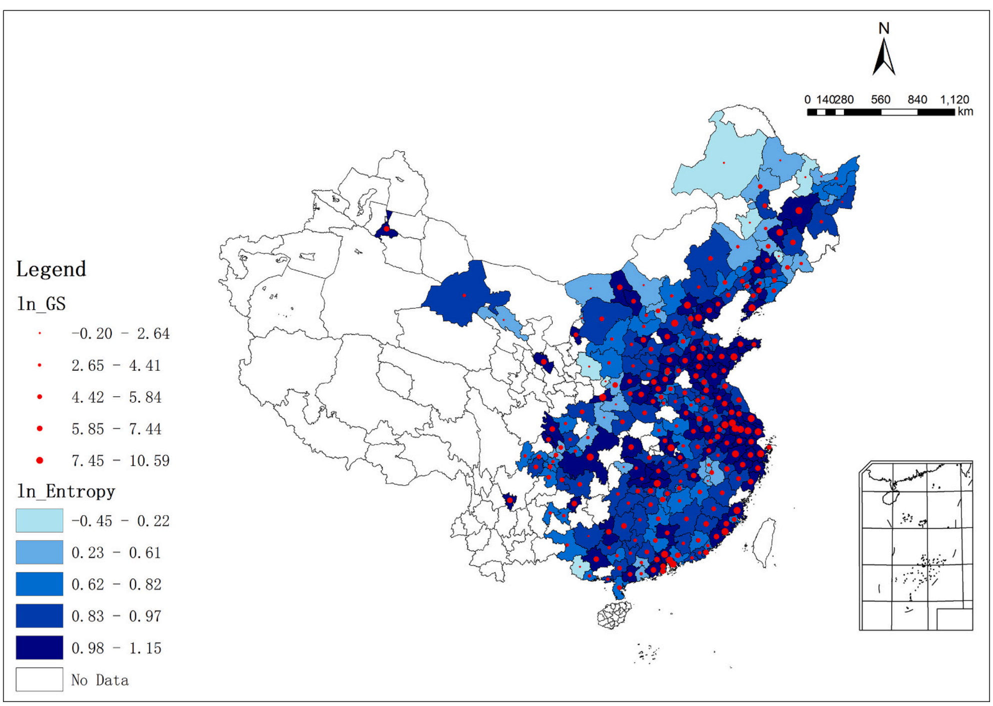

Fig. 5. Distribution of ln_Entropy and Ln_GS in 2013.

and utility model patents, >2.81 million valid green patents were retrieved, which serves as the basis for calculating green patent stock using the perpetual inventory method.

As the MRIO table of Chinese prefecture-level cities can be regarded as data from 2013, this table covers the input-output relationship for the previous and following three years. Excluding individual cities with missing historical data, this paper selects a panel data analysis of 249 prefecture-level and above cities in China from 2011 to 2016. The data of the explanatory variables and control variables in this paper mainly comes from the China Urban Statistical Yearbook and the China Statistical Yearbook from 2011 to 2016, and the missing data of individual cities are supplemented by interpolation.

Discussion

Baseline model

After progressively incorporating control variables and accounting

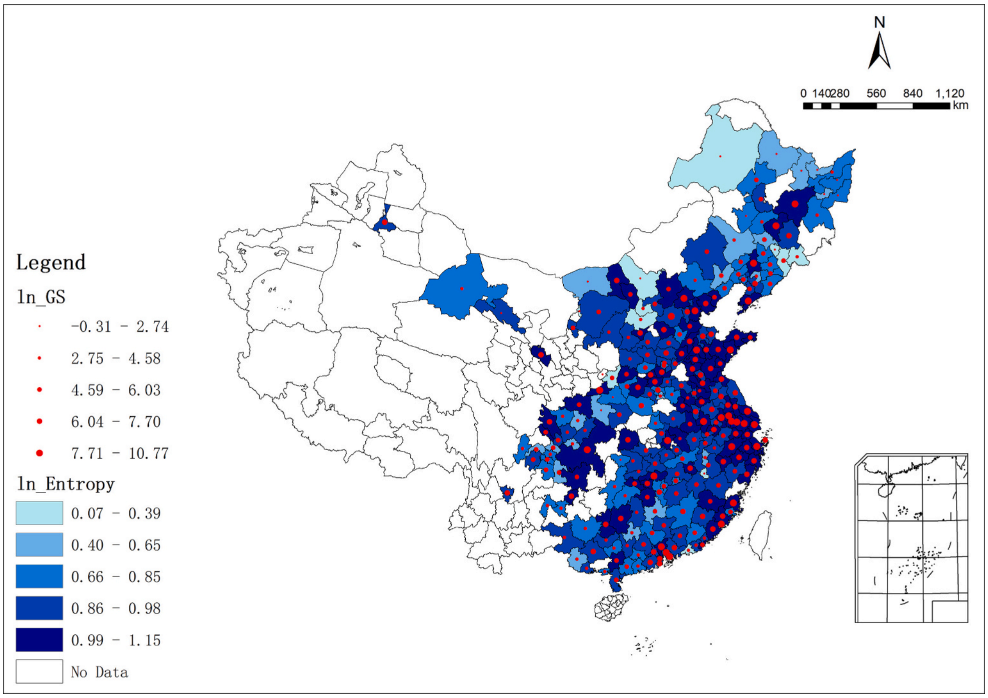

Fig. 6. Distribution of ln_Entropy and Ln_GS in 2014.

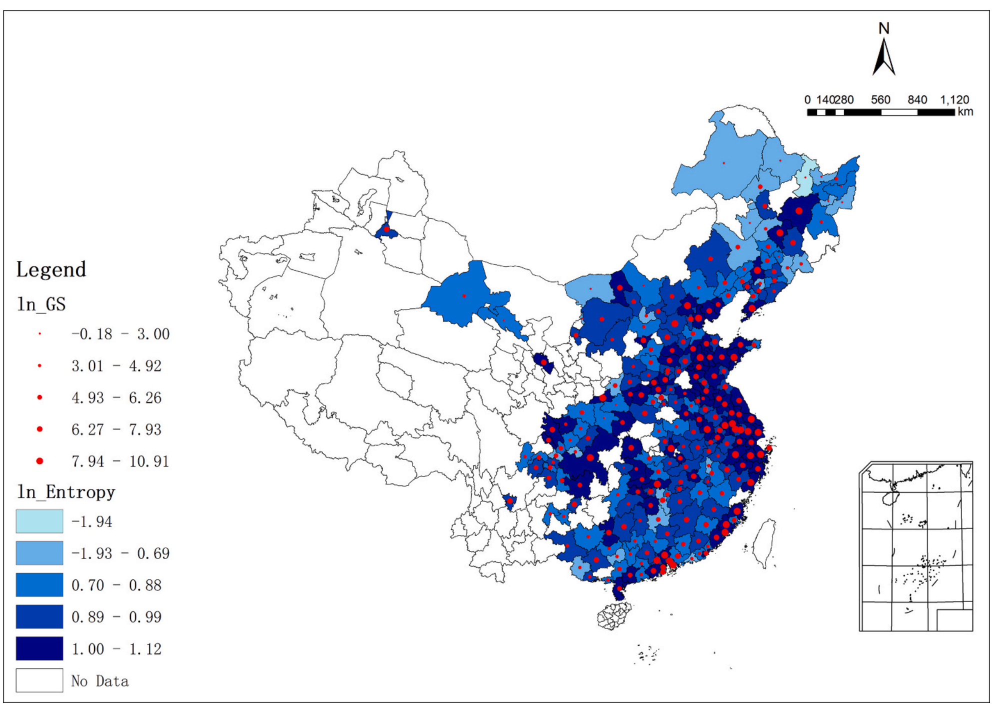

Fig. 7. Distribution of ln_Entropy and Ln_GS in 2015.

for time and city fixed effects, Table 3 displays the baseline regression results for the relationship between green technological diversification and energy intensity. The influence coefficient of green technological diversification (ln_entropy) on energy intensity is significantly negative. We included a quadratic term for green technology diversification ((ln_entropy) ^{2}) in the model, and the coefficient on the quadratic term is also significantly negative, with both passing the 99 % confidence level. If the estimated parameter of the quadratic term is significantly <0, then it can be considered to have an inverted "U" shape effect on the explanatory variable. As shown in Table 3, the regression coefficient of (ln_entropy) 2 is −0.165 and its *t*-test statistic is <0.01. Therefore, we can assume that green technology diversification has an inverted "U" shaped relationship on energy intensity.

To make the findings more robust, we additionally tested this relationship using the Utest tool of Stata. The results are shown in Fig. 9. As can be seen, the calculated extreme point value is −0.3837, falling

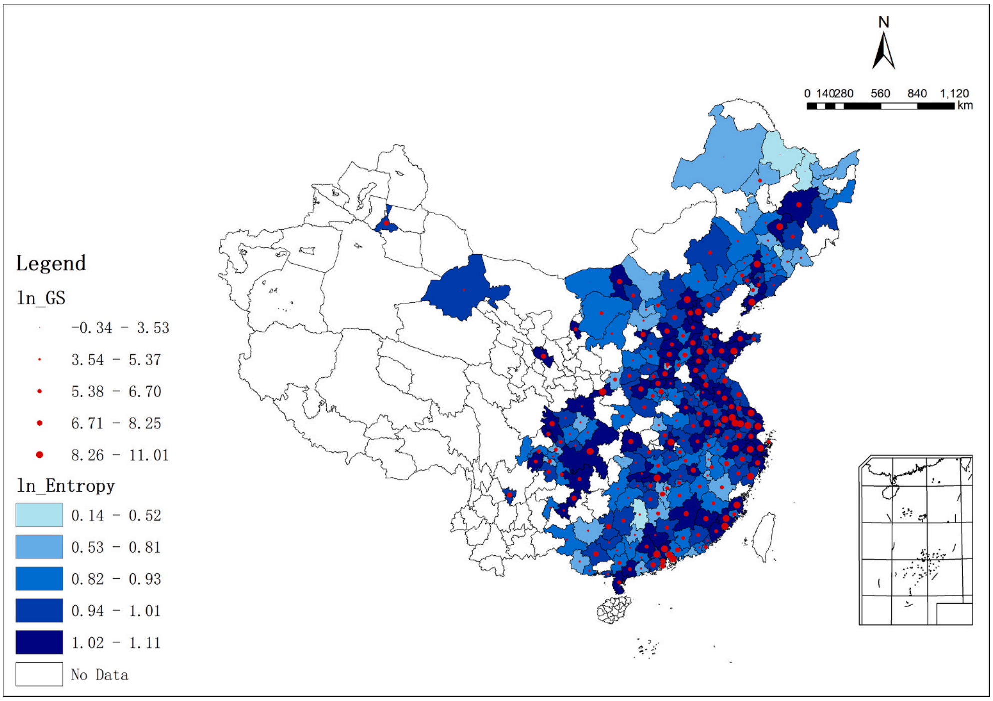

Fig. 8. Distribution of ln_Entropy and Ln_GS in 2016.

Table 3
Baseline regression.

	(1)	(2)	(3)	(4)	(5)
Variables	Energy	Energy	Energy	Energy	Energy
ln_entropy	−0.215***	−0.218***	−0.194***	−0.198***	−0.202***
	(−4.76)	(−4.83)	(−4.51)	(−4.60)	(−4.65)
$(ln\_entropy)^2$	−0.169***	−0.167***	−0.164***	−0.161***	−0.165***
	(−3.31)	(−3.29)	(−3.31)	(−3.27)	(−3.34)
ln_gdp		0.237*	0.355**	0.182	0.232
		(1.89)	(2.51)	(1.08)	(1.37)
ln_pop			1.591**	1.386**	1.422**
			(2.56)	(2.21)	(2.27)
ln_tech				0.081**	0.085**
				(2.20)	(2.27)
ln_fdi					−0.020
					(−1.20)
Constant	2.070***	−0.452	−11.205***	−8.983**	−9.550**
	(28.15)	(−0.34)	(−2.88)	(−2.19)	(−2.34)
Observations	1471	1471	1471	1471	1471
Adjusted R-squared	0.974	0.974	0.974	0.974	0.974
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

within the range of the entropy index (ln_entropy, ranging from −1.941127 to 1.149179). The fact that extreme point value is within the range and the *p*-value is 0.00134 shows that the original hypothesis of no U-shaped relationship can be rejected at the 5 % statistical level. In addition, the slope ranges from 0.6 to −0.59, showing a negative sign in the interval, thus we can assume that there is an inverted U-shaped relationship, further supporting hypothesis 2 that green technological diversification initially contributes to the increase of energy intensity, but after the turning point, it promotes the reduction of energy intensity.

Regarding control variables, per capita GDP and population scale both increase the effect of energy intensity. Meanwhile, scientific investment (ln_tech) is positively correlated with energy intensity, a finding consistent with Zhang et al. (2015). Their study revealed a significant positive correlation between R&D expenditure and energy consumption, which contradicts economic intuition. This phenomenon may be attributed to the pursuit of economic development at the expense of environmental protection, with institutional arrangements prioritizing economic growth. Consequently, scientific and technological expenditures tend to be directed toward enhancing capital and labor efficiency, overlooking investments in environmental protection technologies and reducing energy intensity. The use of foreign investment (ln_fdi) in regression results shows a non-significant constraint on energy intensity. Generally, the effect of fdi could be either a "pollution halo" or a "pollution haven" effect. The regression results indicate that the dominant force between the two remains unclear.

```
Specification: f(x)=x^2
Extreme point: -.3837009

Test:
     H1: Inverse U shape
 vs. H0: Monotone or U shape

                 |   Lower bound      Upper bound
-----------------+--------------------------------
Interval         |   -1.941127         1.149179
Slope            |    .6004832         -.591019
t-value          |    3.008845        -3.924226
P>|t|            |     .001338         .0000459

Overall test of presence of a Inverse U shape:
     t-value =      3.01
     P>|t|   =     .00134

95% Fieller interval for extreme point: [-.78209837; -.18384746]

. sum ln_entropy

    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
  ln_entropy |      1,716    .8133537     .297767  -1.941127   1.149179
```

Fig. 9. The Utest result exported from Stata.

Mechanism examination

Referring to Persico, Postlewaite, and Silverman (2004) for the test steps of mediation effect, we identify whether green technological diversification impacts energy intensity through vertical technology spillovers. The specific steps are as follows: First, test whether the explanatory variable (ln_entropy) affects the independent variable using Eq. (1); Second, test whether the explanatory variable (ln_entropy) affects the mediator variable (ln_gs) using Eq. (6); Third, incorporate both the explanatory variable (ln_entropy) and the mediator variable (ln_gs) into the model simultaneously and use Eq. (7) to test their influence on the independent variable. Under the condition that the coefficient values of the explanatory variables are significant in the first and second steps, if the coefficient value of the mediator variable is significant in the third step and the influence of the explanatory variable on the independent variable decreases (comparing the coefficient values and significance of the explanatory variables in the third and first steps), this implies that the explanatory variable's partial impact on the independent variable might be absorbed by the mediator variable. In other words, the explanatory variable may affect the independent variable through the mediator variable.

$$ln\_gs_{it} = \alpha + \beta_3 \times ln\_entropy_{it} + \beta_4 \times \left(ln\_entropy_{it}\right)^2 + \theta X_{it} + \lambda_i + \tau_t + \varepsilon_{it} \tag{6}$$

$$Energy_{it} = \alpha + \beta_1^{'} \times ln\_entropy_{it} + \beta_2^{'} \times \left(ln\_entropy_{it}\right)^2 + \beta_5 \times ln\_gs_{it} + \theta X_{it} + \lambda_i + \tau_t + \varepsilon_{it} \tag{7}$$

In Table 4, columns (1) and (2) present the estimation results for Model 6, while columns (3) and (4) display the results for Model 7. Regardless of the inclusion of control variables, the coefficient of ln_entropy in Model 6 is positively significant, indicating that green technological diversification can significantly enhance green technology vertical spillovers. The coefficient of ln_gs is negatively significant,

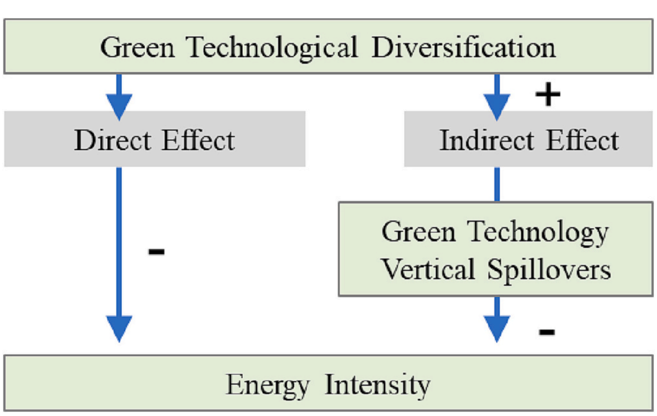

Fig. 10. The relationship among independent, mechanism and dependent variables (Source: Own creation).

Table 4
Mechanism tests.

	(1)	(2)	(3)	(4)
Variables	GS	GS	Energy	Energy
ln_entropy	0.172**	0.151**	−0.198***	−0.178***
	(2.18)	(1.96)	(−4.60)	(−4.14)
$(ln\_entropy)^2$		0.070		−0.154***
		(1.27)		(−3.16)
ln_gs			−0.114**	−0.157***
			(−2.31)	(−2.93)
Constant	5.275***	3.844***	2.666***	−9.589**
	(75.65)	(3.56)	(8.85)	(−2.35)
Observations	1471	1471	1471	1471
Adjusted R-squared	0.981	0.981	0.974	0.974
Control	NO	YES	NO	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

suggesting that vertical technology spillovers have a negative impact on energy intensity. Simultaneously, the absolute values of the coefficients of ln_entropy in columns (3) and (4) of Table 4 are 0.198 and 0.178, respectively, smaller than the corresponding absolute values of 0.215 and 0.202 in columns (1) and (6) of Table 3. This confirms the intermediary mechanism and validates Hypothesis 1 proposed in this paper, as illustrated in the impact diagram (Fig. 10).

Robustness tests

Next, this paper conducts robustness tests through changing time windows, replacing explained variables, and reconstructing entropy values to further strengthen the reliability of the research conclusions.

1. Firstly, the time frame is changed from 2011 to 2016 to 2011–2015, and the results remain consistent with the previous findings (see Table 5).

2. Secondly, the indicator of dependent variable (energy intensity) is replaced. The total energy consumption in this paper is mainly calculated by the total annual gas supply of cities (including artificial and natural gas), the total liquefied petroleum gas supply, the total electricity consumption of the whole society, the total steam heating supply, and the total hot water heating supply, according to their respective standard coal conversion coefficients. For the robustness test, the natural gas usage intensity indicator replaces the energy intensity and maintains consistent results with the previous findings (see Table 6).

3. Lastly, the independent variable used in this paper - the green technological diversification entropy index - contains some zero values. After taking the logarithm, some samples are missing, but these cities still have an impact on the results. As a result, the entropy index is reconstructed by adding 0.1 to the original basis, incorporating the missing samples back into the regression. The results remain consistent with the previous findings (see Table 7).

Endogeneity issues

Green technological diversification, as an indicator measured by the entropy index, inevitably introduces measurement errors. Simultaneously, energy intensity often influences a city's industrial choices, which in turn affects the city's green technological diversification, thus creating a reverse causality relationship between the two. These issues introduce new endogeneity problems; therefore, we employ a two-stage least squares regression to address endogeneity concerns. Firstly, we use the relief degree of land surface (rdls) as the instrumental variable for the endogenous variable "green technological diversification," which is a comprehensive representation of regional altitude and surface roughness (You et al., 2018). Based on the measurements of You, Feng, and Yang (2018) and Yang, Jiang, Chao, Li, and Liu (2021), we calculated the reciprocal of the relief degree of land surfaces in Chinese cities. Since the rdls is cross-sectional data, and the endogenous variable is panel data, we followed Angrist's method (Angrist & Krueger, 1991) and employed the interaction term of rdls and year dummies as the final instrumental variable. This approach overcomes the data dimension limitation of cross-sectional instrumental variables while also reflecting the impact of instrumental variables on endogenous variables across different years. The choice of rdls as an instrumental variable is primarily due to two reasons. First, rdls reflects the degree of urban terrain undulation; the higher the city's rdls, the more convenient the interaction between industries, increasing the likelihood of diversified green technology production in the same area, thus leading to a higher degree of green technological diversification. Second, a city's rdls is a natural geographical feature, unrelated to its energy use intensity and unaffected by it, satisfying the exogeneity requirement. Therefore, it is theoretically sound to choose the rdls of city i as an instrumental variable for green technological diversification, and we need to further examine its validity through empirical results.

Table 8 reports the results of the instrumental variable two-stage least squares regression. Column (1) presents the first-stage regression results, indicating that rdls has a significant positive impact on green technological diversification, consistent with our expectations. Column (2) displays the second-stage regression results, revealing that after addressing endogeneity issues, green technological diversification still has a significant negative effect on energy intensity, and the coefficient is even larger. This finding suggests that prior reverse causality and

Table 5
Robustness test 1 (changing time window).

	(1)	(2)	(3)
Variables	Energy	GS	Energy
ln_entropy	−0.139***	0.202**	−0.118***
	(−3.51)	(2.44)	(−3.02)
$(ln\_entropy)^2$	−0.143***	0.086	−0.134***
	(−2.97)	(1.31)	(−2.81)
ln_gs			−0.107**
			(−2.31)
Constant	−21.616***	0.697	−21.699***
	(−3.78)	(0.27)	(−3.82)
Observations	1231	1231	1231
Adjusted R-squared	0.980	0.982	0.980
City FE	YES	YES	YES
Year FE	YES	YES	YES
Control		YES	NO

Robust t-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6
Robustness test 2 (replacing dependent variable indicator).

	(1)	(2)	(3)
Variables	Energy	GS	Energy
ln_entropy	−9.450***	0.151**	−7.786***
	(−3.81)	(1.96)	(−3.20)
$(ln\_entropy)^2$	−9.066***	0.070	−8.292***
	(−3.04)	(1.27)	(−2.81)
ln_gs			−11.074***
			(−3.10)
Constant	−544.417**	3.844***	−547.195**
	(−2.50)	(3.56)	(−2.50)
Observations	1471	1471	1471
Adjusted R-squared	0.938	0.981	0.939
City FE	YES	YES	YES
Year FE	YES	YES	YES
Control	YES	YES	YES

Robust t-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7
Robustness test 3 (reconstructing entropy index).

	(1)	(2)	(3)
Variables	Energy	GS	Energy
ln_entropy2	−0.226***	0.171**	−0.199***
	(−4.67)	(1.98)	(−4.14)
$(ln\_entropy)^2$	−0.154***	0.062	−0.145***
	(−3.23)	(1.10)	(−3.04)
ln_gs			−0.157***
			(−2.93)
Constant	−9.516**	3.819***	−9.560**
	(−2.33)	(3.53)	(−2.34)
Observations	1471	1471	1471
Adjusted R-squared	0.974	0.981	0.974
City FE	YES	YES	YES
Year FE	YES	YES	YES
Control		YES	NO

Robust t-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8
Tests for endogenous issues.

	(1)	(2)
	First stage	Second stage
Variables	ln_entropy	Energy
rdls_2011	0.000**	
	(2.29)	
rdls_2012	0.000	
	(0.57)	
rdls_2013	0.000	
	(0.72)	
rdls_2014	0.000	
	(0.71)	
rdls_2015	0.000	
	(0.35)	
ln_entropy		−3.962*
		(−1.94)
Observations	1471	1471
Control	YES	YES
City FE	YES	YES
Year FE	YES	YES

Robust t-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

measurement errors led to an underestimation of the regression coefficient, and the actual impact of green technological diversification on energy intensity is stronger.

Heterogeneity analysis

Significant disparities exist in the energy intensity across various regions in China, and the heterogeneous impact of green technological diversification on energy intensity at different developmental stages in different regions cannot be overlooked. As the development of the western regions and the rise of central regions strategies are implemented, technological investment in inland areas is strengthening, while high-energy-consuming industries are in a stage of rapid growth. Different provinces or cities within the same province also possess diverse policy environments (Yuan, Xu, Li, & Yao, 2022). Distinct technological foundations, industrial structures, and energy demands result in considerable variations in overall research and development levels, industrial evolution trends, and resource and environmental constraints among cities. China's open frontier regions possess a more mature and comprehensive industrial system, and their highly developed manufacturing sector creates favorable preconditions for green development. The spillover effects of upstream and downstream green technologies may also be more pronounced. Research should thoroughly explore regional differences and the logic behind them, proposing tailored technology innovation strategies based on local conditions and respective levels and scale characteristics. Based on this, the paper proposes to further investigate the regional heterogeneity of the impact of green technological diversification on energy intensity.

Group by urban population

First, cities were grouped by population, as shown in Table 9 which is divided into three groups: cities with a population of <1 million (columns 1, 2, and 3), cities with a population of 1 to 5 million (columns 4, 5, and 6), and cities with a population of >5 million (columns 7, 8, and 9). It can be observed that, without considering the quadratic term, green technological diversification is significantly negatively correlated with energy intensity in small cities (relative concept) with a population of <1 million and medium-sized cities with a population of 1 to 5 million. This correlation is not significant in large cities with a population of >5 million, which mainly include developed cities such as provincial capitals and sub-provincial cities. After including the quadratic term, green technological diversification and energy intensity exhibit a significant inverted "U-shaped" relationship in medium-sized cities, with a significant mediating effect in this group.

Group by industrial structure

In this study, cities were divided into two groups based on the ratio of secondary sector output value to urban GDP, which represents the industrial structure, as shown in Table 10. Columns (1) and (2) represent

Table 10
Heterogeneity test based on the contribution of the secondary sector.

	(1)	(2)	(3)	(4)
Variables	Energy	GS	Energy	GS
ln_entropy	−0.166***	0.353***	−0.257***	0.092
	(−3.71)	(3.49)	(−3.37)	(0.97)
$(ln\_entropy)^2$	−0.070	−0.173**	−0.210***	0.124**
	(−0.81)	(−2.09)	(−2.90)	(2.08)
ln_gs				
Constant	−1.907	3.486***	−36.084***	5.738*
	(−0.63)	(3.03)	(−4.69)	(1.71)
Observations	771	771	700	700
Adjusted R-squared	0.958	0.983	0.980	0.980
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Control	NO	YES	NO	YES

Robust t-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9
Tests for heterogeneity according to urban population groupings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Energy	GS	Energy	Energy	GS	Energy	Energy	GS	Energy
ln_entropy	−0.078*	0.090	−0.079*	−0.296***	0.442***	−0.141	−16.458	−1.822	−18.362
	(−1.77)	(1.05)	(−1.83)	(−2.81)	(3.38)	(−1.07)	(−1.15)	(−0.52)	(−1.22)
$(ln\_entropy)^2$	−0.046	0.058	−0.047	−0.259*	−0.083	−0.292*	5.525	1.403	7.044
	(−0.96)	(0.91)	(−0.98)	(−1.70)	(−0.85)	(−1.81)	(0.71)	(0.76)	(0.85)
ln_gs			0.013			−0.362**			−1.259**
			(0.30)			(−2.56)			(−2.46)
Constant	−2.700	2.694*	−2.711	−16.544**	5.458***	−17.942**	−71.924**	9.095***	−69.513*
	(−0.74)	(1.75)	(−0.75)	(−2.10)	(3.47)	(−2.22)	(−2.05)	(3.99)	(−1.95)
Observations	756	756	756	643	643	643	72	72	72
Adjusted R-squared	0.933	0.972	0.932	0.966	0.985	0.967	0.996	0.996	0.996
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control		YES	NO		YES	NO		YES	NO

Robust t-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

cities with a secondary sector ratio above the median, while columns (3) and (4) represent cities with a secondary sector ratio below the median. It is evident that, when considering the linear term, green technological diversification exhibits a significant negative relationship with energy intensity in both groups of cities. Moreover, the impact coefficient of green technological diversification on energy intensity is larger in cities with a lower secondary sector ratio. After incorporating the quadratic term, a significant inverted U-shaped relationship between green technological diversification and energy intensity is observed only in cities with a lower secondary sector ratio, which significantly promotes vertical technology spillovers in the supply chain industries. This finding suggests that, in terms of environmental impact, it is crucial to adopt a multifaceted approach to the introduction and development of green technologies in cities with a lower industrial ratio, service-oriented cities, or possibly those in the early stages of urban industrial development, to surpass the diversification inflection point.

Conclusions and recommendations

Considering the heterogeneity of Chinese cities, this paper overcomes the limitations of previous studies that used the number of green patents to measure the relationship between green technology effects and energy, and delves deeper than past research conducted at the national and provincial levels. By employing prefecture-level city input-output tables for the first time, the paper investigates the impact of green technological diversification and the transmission of green technologies in the supply chain on energy intensity. The study finds that within the window period, an inverted U-shaped relationship exists between green technological diversification and energy intensity in Chinese cities. After surpassing the energy "rebound effect" threshold, green technological diversification can contribute to the reduction of energy intensity by promoting vertical green technology spillovers in the supply chain industries. This effect is more pronounced in medium-sized cities and those with a lower industrial ratio.

The policy implications of this paper are as follows: only when the level of green technological diversification is sufficiently high and surpasses a tipping point can energy intensity be reduced. Consequently, cities should continue to increase research and development (R&D) investment, enhance R&D intensity, and adopt targeted policies tailored to local conditions to foster a conducive environment for green technological innovation. Furthermore, it is essential to encourage cross-sectoral communication and actively introduce various green industries and technologies in investment promotion and industrial layout planning, thus avoiding "technological lock-in." Particularly for medium-sized cities, service-oriented cities, and regions in the developmental phase of industrialization, it is crucial to avoid potential risks of "path dependence" on existing natural resources and single industries or technologies while utilizing their inherent advantages. In tandem, efforts should be made to continue improving energy efficiency and implement a variety of complementary policies to mitigate the negative effects of energy rebound, especially market-based policy measures such as the elimination of energy subsidies, the imposition of energy taxes, and the encouragement of energy-saving transactions.

In light of China's recent economic performance, the integration of industries, acceleration of talent mobility, continuous growth of R&D investment scale, and the exponential growth of knowledge and technology stocks and types provide strong support for technological spillover across upstream and downstream industries. Consequently, the inter-industry spillover effect may expand over time. In the context of the supply chain, there should be a constant increase in investments made in the development of green public services, particularly green technology trade intermediary platforms. In conventional supply chain management, concepts such as a full life cycle and extended producer responsibility must be incorporated. Moreover, supply chain management technology should be integrated with green manufacturing theory. In order to achieve green development, it is essential for the core enterprises to optimize their emissions, while guiding upstream and downstream enterprises to continuously improve their energy and resource efficiency.

Due to data source limitations and article length constraints, this study has certain limitations. Firstly, since the input-output tables of prefecture-level cities are based on data from 2000 to 2013, the mechanism analysis and main regression analysis data timeframes are restricted, and longer-term data trends and relationships have not been analyzed. Secondly, a precise measurement of technological spillover requires more reliable data mining. Future research should explore various reliable data sources for mutual verification, conduct comprehensive analysis on dual scales of prefecture-level cities and urban agglomerations, and analyze the impact of green technology innovation in different fields on environmental performance by subdividing green technology categories.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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