Revisiting the nexus between financial agglomeration and energy efficiency: A spatial spillover approach

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**ABSTRACT**

Financial agglomeration (FA) may play an essential role in enhancing energy efficiency (EE) and, thus, is important from both theoretical and empirical viewpoints. However, few studies have investigated the causal nonlinear relationship between FA and EE. Hence, we first extend the novel ray slacks-based measure with global technology to evaluate the urban EE in China during 2003–2018. Next, we reexamine the nonlinear causality of FA on EE and then explore the underlying impact mechanism. The empirical results show that China’s urban EE is generally relatively low with distinct patterns of regional differences. Moreover, we find that the causal relationship between FA and EE follows an inverted U-shaped function rather than a linear one. FA promotes the improvement of EE only up to a certain threshold point, after which it reverses into an inhibitory effect. A further analysis based on the two-regime spatial Durbin panel model suggests that FA can indeed improve the EE of surrounding cities through positive externalities when the degree of FA in focal cities is not substantially greater than that in surrounding cities. However, when financial resources absorbed in certain focal cities become increasingly higher than that in most surrounding cities, the positive spillover effect would gradually disappear and even reverse into an undesirable siphon, thereby inhibiting the improvement of overall EE. These findings provide new insights for understanding the role of FA in sustainable development.

**KEYWORDS**

Financial agglomeration; energy efficiency; ray slacks-based measure; spatial spillover effect; siphon effect

1. Introduction

As the biggest developing country in the world, China has experienced rapid economic development over the past 40 years. However, the rapid growth of China’s economy has been accompanied by an expansion in energy consumption, resource depletion and environmental pollution (Huang, Mo, and Chen 2021; 2018). According to the official statistics data from *BP World Energy Yearbook*\textsuperscript{1}, China’s total energy consumption has been higher than that of the United States (US) since 1978, especially in the last decade. As a result, the level and growth rate of fossil energy consumption (e.g., oil and coal) in China have far exceeded that of the US (See Figure 1a,b,c). The former stepped into a new stage of high-speed growth, while the latter has gradually entered into the period of carbon peak (See Figure 1d). To actively cope with global climate change, China has committed to peak CO\textsubscript{2} emissions before 2030 and achieve carbon

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\textsuperscript{1}Figure 1 (a), (b), (c), and (d) reported the oil, natural gas, coal energy consumption, and carbon emissions of China and the US from 1978 to 2018. All the data sources from the BP Statistical Review of World Energy. Available at: https://www.bp.com/en/global/corporate/energy-economics.html.

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neutrality before 2060 at the 75th United Nations General Assembly. However, when viewed from the historical experience, the time left for China to achieve carbon peak and carbon neutrality is far shorter than those allowed for most developed countries, thus it is imperative to enhance energy efficiency for China to deal with unprecedented pressures for achieving carbon abatement in the future (Li et al. 2021; Liu et al. 2021; Xu et al. 2022).

As China’s financialization level continued to progress in the past few decades, many large financial clusters have sprung up, such as Beijing’s Financial Street, Shanghai’s Lujiazui, and Shenzhen’s Financial Center, which have drawn broad attention from policymakers to financial agglomeration. In academic, FA is defined as financial institutions geographically concentrated in a specific region and closely linked to other industries (Kindleberger, 1973; Porter 1998; Tao et al. 2017). The classical economic theory of growth poles and financial geography believes that FA does not only spur economic development in the focal region but also affects the nearby areas through spatial externalities (Krugman 1991; Wang et al. 2019). However, there is no consensus on how FA impacts EE. For instance, others argue that FA improves regional EE (see Tian et al. 2021; Xie et al. 2021) while others hold the opposite view that FA inhibits overall energy-environment performance (see Han, Xie, and Fang 2018; Li and Ma 2021; Shahbaz et al. 2016; Usman et al. 2021; Wang and Gong 2020). The existing theoretical and empirical findings on the impact of FA on energy-environment performance are in conflict, and mostly suffer from endogeneity concerns, hence,

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Figure 1. Comparison of energy consumption and carbon emissions between China and the USA from 1978 to 2018.

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See the Chinese President Xi Jinping delivers an important speech at the general debate of the 75th UN General Assembly. Available at: [http://www.gov.cn/xinwen/2020-09/22/content_5546168.htm](http://www.gov.cn/xinwen/2020-09/22/content_5546168.htm)
the need for more rigorous empirical investigations. Besides, most studies merely construct simple linear econometric models to capture the monotonic relationship between FA and EE; hence little is known about whether there is a nonlinear linkage between them. More importantly, the economic channels of spatial heterogeneity through which FA impacts EE remain unexplored. Insights into how FA affects EE can help policymakers benchmark the ability of special green-finance initiatives as an avenue for hedging climate risk.

Theoretically, a reasonable degree of FA can enhance the EE of local and surrounding areas by mediating channels of scale economies (Liu, Huang, and Cao 2007; Madsen, Islam, and Doucouliagos 2018), information sharing (Tao et al. 2017; Thrift 1994), and technology spillovers (Ji and Zhang 2019; Levine 1997). However, excessive FA seems not to be much of a good thing (Aghion, Howitt, and Mayer-Foulkes 2005; Samargandi, Fidrmuc, and Ghosh 2015). As the degree of FA continues to increase, the scale of industries within the region will expand, resulting in greater energy consumption and CO₂ emissions, thereby decreasing the regional EE (Usman et al. 2021). Also, too much concentration of financial resources in certain focal regions inevitably causes a crowding-out effect on their own green innovation activities or a strong siphon effect for surrounding regions (Arcand, Berkes, and Panizza 2015; Xie et al. 2021). Therefore, the real relationship between FA and EE may follow an inverted U-shape function rather than a monotonically increasing or decreasing linear one.

To fill the research gap and address endogeneity issues in prior studies, this paper first utilizes a nonparametric data envelopment analysis (DEA) framework to assess the spatial-temporal performance of EE. Next, we revisit the nonlinear causal relationship between FA and EE using a large-scale sample of 282 prefectural cities in China from 2003 to 2018 and various robust estimations. Finally, we use the two-regime spatial Durbin panel model to investigate how FA in focal cities impact EE in surrounding cities.

Compared with prior studies, this paper makes important contributions to the financial economics and energy economics literature in several ways. First, we propose a novel approach that combines the ray slacks-based measure (2018) and global benchmark technology (Oh 2010) to accurately evaluate China’s urban EE. As a result, we find a more distinct disparity of inter-regional EE between North China and South China; however, to the best of our knowledge, most prior studies focused on discussing the regional differences of inter-regional EE between East China, Center China, and West China (e.g., Lin and Du 2013; Zhang and Zhou 2020), few studies have so far systematically investigated this imbalanced pattern.

Second, we reexamine the nexus between FA and EE by taking into account the nonlinear effect of the former on the latter. Different from previous studies that document a simple positive or negative linear correlation between FA and EE (e.g., Li and Ma 2021; Qu, Shao, and Shi 2020; Xie et al. 2021), we find strong evidence that this effect follows a solid inverted-U function. Our results survive a series of rigorous robustness and endogeneity tests.

Third, we originally uncovered a new spillover shadow phenomenon, which demonstrates that when financial resources absorbed in certain focal cities become increasingly higher than that in most surrounding cities, the positive spillover effect would gradually disappear and even reverse into a negative siphon. This novel finding reveals that too many financial resources concentrated in few focal areas can be detrimental to EE in the surrounding regions. Our study is one of the first to document that China’s spatial imbalanced financial development mode can lead to severe energy inefficiency problems in other regions. From the perspective of financial geography, our findings shed more light on the impact mechanisms behind the inverted-U causal relationship running from FA to EE. More broadly, our study speaks to the literature that suggests that excessive financial expansion may be counterproductive to the real economy (Arcand, Berkes, and Panizza 2015; Law and Singh 2014; Tobin 1984; Usman et al. 2021; Čihák et al. 2012).

The remainder of the paper is organized as follows. Section 2 reviews the related literature, followed by an introduction of the research design in Section 3. Empirical results and discussions are presented
in Section 4, followed by the further discussions in Section 5. Section 6 presents the conclusions and policy implications.

2. Literature review

With the gradual intensification of the energy shortage and impending climate risk, the issue of energy utilization efficiency has drawn more and more attention from academia and policymakers. Prior studies documented various factors that influence EE, including government intervention (Koengkan et al. 2021; Wang et al. 2021), population density (Lv, Chen, and Cheng 2020), economic development level (Hu, Li, and Zhang 2019), industrial structure and agglomeration (Tanaka and Managi 2021; Xiong, Ma, and Ji 2019), technological innovation (Destek and Manga 2021; Li and Lin 2018; Wang and Weng 2020), information development (Liu, Yao, and Wei 2019; Qu, Shao, and Shi 2020) and so on. Furthermore, as agglomeration economics plays an important role in energy economics and environmental economics, many scholars started to investigate the impact of the FA on the energy and environment performance.

In academic, the connotation of FA has been well defined as financial institutions geographically concentrated in a specific region and closely linked to other industries (Buera, Kaboski, and Shin 2011; Kindleberger 1973; Liu, Huang, and Cao 2007; Porter 1998; Kindleberger, 1973; Porter 1998; Tao et al. 2017). Many scholars hold the view that FA involves the spatial and temporal dynamic changes of coordination and allocation of financial resources based on regional conditions (Buera, Kaboski, and Shin 2011; Hall and Wójcik 2018; Ye, Sun, and Chen 2018; Yuan et al. 2019). Empirical researchers measure FA using various methods, including the location entropy of financial output value or employees in a specific region (Cheng 2016; Wang, Zhu, and Yang 2020; Ye, Sun, and Chen 2018; Yuan et al. 2019; Zheng and Lin 2018), and geographic concentration based on the number of financial institutions (Qu, Shao, and Shi 2020). Additionally, multi-level indicators through the principal component analysis (Wang, Zhu, and Yang 2020), Hirschman-Herfindahl index (HHI), and spatial EG index (Chen, Chen, and Jin 2018) are also used in measuring FA. However, there is no consensus on how FA impacts EE. For instance, others argue that FA improves regional EE (see Ji and Zhang 2019; Levine 1997; Liu, Huang, and Cao 2007; Madsen, Islam, and Doucouliagos 2018; Tao et al. 2017; Thrift 1994; Tian et al. 2021; Xie et al. 2021) while others hold the opposite view that FA inhibits overall energy-environment performance (see Han, Xie, and Fang 2018; Li and Ma 2021; Shahbaz et al. 2016; Usman et al. 2021, 2021; Wang and Gong 2020).

Recent work suggests that there is a linear linkage between FA and EE. For example, Qu, Shao, and Shi (2020) argued that FA influences EE through the scale economy effect, innovation driving effect, information spillover effect and structural adjustment effect. They documented that FA exerts a linear positive effect on EE using a panel data of 285 cities in China from 2005 to 2017, and this effect is more pronounced for eastern and central regions, megacities, and big cities. Yuan et al. (2019) also studied the influence of FA on green development in Chinese cities using financial index measures of FA and the linear spatial Durbin model. They found that FA promotes green development of both focal and surrounding cities through spatial spillover effects. Similarly, Xie et al. (2021) investigated the relationship between FA and green total factor productivity (GTFP) in Chinese cities using a linear spatial Durbin model. They also documented strong evidence that FA significantly facilitates the GTFP growth in a given city.

However, some studies reported opposite findings. For example, Wang and Gong (2020) investigated the relationship between regional financial deepening and energy consumption and found that the prosperity of the regional financial industry is often associated with intense industrial production and household consumption activities, thus significantly expanding energy consumption. Similarly, Sadorsky (2010), Shahbaz et al. (2016), Acheampong, Amponsah, and Boateng (2020), Li and Ma (2021), and Usman et al. (2021) also documented strong evidence that excessive financial expansion drives industrial activities by relaxing financing constraints, which will ultimately exert harmful effect on the energy-environment performance. In addition, Han, Xie, and Fang (2018) held the view that
urban agglomeration has a strong negative spillover effect on the corporate EE. Using firm-level data and a linear dynamic spatial Durbin model, they find that specialization agglomerations of industries have limited impact on the city itself, but they do significantly lower the EE for neighboring cities.

Concurrently, some empirical works provide evidence that too much finance may be counterproductive (Arcand, Berkes, and Panizza 2015; Destek 2019; Destek, Alsu, and Karaca 2022; Law and Singh 2014; Shahbaz et al. 2021; Shahbaz, Destek, and Polemis 2018). For example, Tobin (1984) argued that too much finance may result in the misallocation of resources from most productive areas to less productive areas. Additionally, Arcand, Berkes, and Panizza (2015) and Čihák et al. (2012) suggested that banks become less important in supporting growth as the economy continues to grow and in developed countries. Moreover, Aghion, Howitt, and Mayer-Foulkes (2005) showed that banking sector development helps economies converge to the growth rate of the world frontier but does not help them grow beyond this frontier. However, nearly all previous studies just adopt linear econometric models to capture the monotonic correlation running from FA to EE, hence, little is known about whether there is a nonlinear causality between them. Hence, the need to examine the real effects of too much finance on energy-environment performance. Besides, prior literature stressed the spatial spillover effects of FA on EE, but failed to explain how excessive FA in focal cities impact EE in neighboring cities. Therefore, this study extends and fills the gap in the literature by investigating the causal nonlinear link between FA and EE using robust estimation methods. Moreover, we push the literature further by investigating the whether the spatial interaction between focal and peripheral cities is the underlying impact mechanism behind the nonlinear causal relationship between FA and EE.

3. Methodology and data

3.1. Construction of econometric models

3.1.1. Benchmark panel model

As we discussed above theoretically, increasing FA will expand the scale of industries within the region, resulting in greater energy consumption and CO₂ emissions, thus decreasing the regional EE. Moreover, too much concentration of financial resources in certain focal regions inevitably causes a crowding-out effect on their own green innovation activities or a strong siphon effect for surrounding regions. Therefore, we hypothesize that the real relationship between FA and EE may follow an inverted U-shape function rather than a monotonically increasing or decreasing linear one documented by previous studies. In order to confirm our conjecture, this paper adds the squared term of FA (FA²) in the conventional panel model. We attempt to address omitted variables bias by controlling two-way fixed effects. The model specification is described as follows

\[ EE_{it} = \beta_0 + \beta_1 F_{it} + \beta_2 F_{it}^2 + Z_{it}^\prime \gamma + \alpha_i + \eta_t + \epsilon_{it} \]  \hspace{1cm} (1)

where \( EE_{it} \) is the EE of city \( i \) in year \( t \) evaluated by the RSBM approach with global benchmark technology (see section 3.2.1 in particular). \( F_{it} \) denotes the FA of city \( i \) in year \( t \), measured by the location entropy index of financial practitioners (see section 3.2.2 in particular). \( F_{it}^2 \) is the squared term of \( F_{it} \), capturing the nonlinear relationship between FA and EE. \( Z_{it} \) is a set of city-level observed time-varying control variables, including government intervention (GOVE), foreign direct investment (FDI), industrial structure (IS), the level of economic development (PGDP), information development (INFOR), innovation capability (PAT), and population density (PD) (see section 3.2.3 in particular), \( \alpha_i \) and \( \eta_t \) represent city fixed effects and year fixed effects, respectively, \( \epsilon_{it} \) is the regression error term.

Our main interest in this study is on the coefficients of \( F_{it} \) and \( F_{it}^2 \). If the estimated values of \( \beta_1 \) and \( \beta_2 \) are significantly positive and negative, respectively, this implies that FA has an inverted-U impact on EE. Furthermore, we calculate the turning point (or threshold value) corresponding to the FA by derivation as follows:
\[ FA^* = \left| \frac{\delta_i}{\delta_f} \right| \]

### 3.1.2. Two-Regime spatial Durbin panel model

Theoretically, as more and more financial resources agglomerated in some focal cities, they will have enough financial resources to improve EE by supporting technological innovation, adjusting energy structure, and promoting industrial upgrading; however, at the same time, more and more peripheral cities will face serious financial constraints. Therefore, the spatial interaction between focal and peripheral cities caused by the uneven geographical distribution of financial resources may be an important mechanism behind the inverted U-shaped relationship between FA and EE. Meanwhile, under the dual incentives of fiscal decentralization and political promotion, many macroeconomic variables across regions in China exhibit strong spillover effects (Huang, Mo, and Chen 2021; 2018). Therefore, the inverted-U impact of FA on focal EE may have beneficial or detrimental effects on surrounding EE. In the above context, in order to further explore the inverted-U impact mechanism of FA affecting EE from the perspective of spatial heterogeneity. We construct the two-regime spatial Durbin model in Appendix A following Elhorst and Freret (2009).

### 3.2. Variable selection

#### 3.2.1. Energy efficiency (EE)

A wide variety of nonparametric DEA models have been utilized to evaluate the EE (see a broad review of Sueyoshi, Yuan, and Goto (2017)). However, radial DEA models, including the Charnes-Cooper-Rhodes model (Charnes, Cooper, and Rhodes 1978), Banker-Charnes-Cooper model (Banker, Charnes, and Cooper 1984), and proportional directional distance function model (Chung, Färe, and Grosskopf 1997), assume that all inputs and outputs can be simultaneously changed without altering the proportions in which they are utilized (Tone, Toloo, and Izadikhah 2020). Given the shortfall in conventional radial DEA models, Tone (2001) incorporates the non-radial slacks into the objective function and proposes the slacks-based measure (SBM) model. However, this model fails to account for the weak disposability of undesirable outputs and desirable outputs. Following this line of research, 2018 introduced the polar theory into the SBM model and proposes the RSBM model to address this concern; notably, the classical RSBM model is constructed on the contemporaneous benchmark technology and fails to make the efficiency score of each unit across different periods comparable. To resolve this issue, the present study incorporates the global technology (Oh 2010) into the RSBM model to comparably evaluate the EE across each period. We explain how we estimated EE in Appendix B.

#### 3.2.2. Financial agglomeration (FA)

There are several approaches used to assess the degree of FA, such as the location entropy index (Wang, Zhu, and Yang 2020; Yuan et al. 2019), principal component analysis (Wang et al. 2019), spatial Gini coefficient (Ellison and Glaeser 1997), and Herfindahl index (Mitchell 2019). Notably, due to China’s vast territory and huge differences between cities (Du and Zhang 2018) we use the location entropy of employees in the financial industry to assess the degree of urban FA calculated using the following specification:

\[
FA_{it} = \left( \frac{\text{FE}_{it}/E_i}{\sum_{i=1}^{N} \text{FE}_{it}/E_i} \right) / \left( \sum_{i=1}^{N} E_i \right)
\]

(3)

Where \( N \) is the total number of cities in the study; \( FA_{it} \) denotes the degree of FA of city \( i \) in period \( t \). \( FE_{it} \) is the number of employees in the financial industry of city \( i \) in period \( t \), and \( E_{it} \) is the total number of employees of city \( i \) in period \( t \).
The histogram in Figure 2 (a) represents the average FA of 30 provincial-units in China during the study period, and the red dotted line is the reference benchmark, which represents the average of all samples. Figure 2 (b) shows the average FA of 282 prefectural cities on the Chinese map during the study period, with darker colors representing higher levels of FA. The most advanced provinces and cities in China’s FA are mainly concentrated in the economically developed Yangtze River Delta, Bohai Rim and Pearl River Delta regions. Among them, the Yangtze River Delta region with Shanghai, Nanjing, and Hangzhou as its hubs, the one in the Bohai Rim region with Beijing and Tianjin as its hubs, and the one in the Pearl River Delta region with Guangzhou and Shenzhen as its hubs. Other cities, such as Shenyang in the Northeast region, Wuhan in the Central region, Chengdu and Chongqing in the Southwest region, and Xi’an in the Northwest region, are also focal cities with relatively high levels of FA. Moreover, we find that the level of FA of many cities in the economically developed southeastern coastal provinces (i.e., Shandong, Hebei, Tianjing, Jiangsu, Zhejiang, Fujian, Shanghai, Guangdong, Hainan) is higher than the national average level. However, in the vast central, western and northeastern regions, only provincial capitals have high levels of FA, while other prefecture-level cities are generally lower than the national average level. The reason may be that focal cities in economically developed regions can exchange financial resources with peripheral cities in a benign manner, thereby achieving coordinated financial development, while those in economically backward regions absorb more financial resources from peripheral cities in one direction, and do not play a positive spillover effect.

3.2.3. Control variables
We incorporate a series of control variables that influence EE following previous studies (e.g., Li and Ma 2021; Qu, Shao, and Shi 2020; Xie et al. 2021) including (1) government intervention (GOVE), measured as the ratio of fiscal revenue to GDP; (2) foreign direct investment (FDI), measured as the ratio of FDI to GDP; (3) economic development level (PGDP), measured as the regional GDP per capita; (4) information development (INFO), measured as the sum of the per capita income of postal services and telecommunications services; (5) population density (PD), measured as the population per unit area; (6) technological innovation (PAT), measured as the number of invention patent applications per 10,000 people; (7) industrial structure (IS), measured as the ratio of the added value of the tertiary industry to the added value of the entire secondary industry.

3.3. Data description
We use a panel data of 282 prefecture-level cities in China from 2003 to 2018. We retrieve our data from the China Urban Statistical Yearbook (2003–2018) and China Energy Statistical Yearbook (2003–
2018). We supplement missing data for some cities or years using the time series model of the autoregressive moving average and eliminate cities with serious data deficiency. Moreover, to eliminate the influence of abnormal values, we winsorize continuous variables at 1% and apply natural logarithms for PGDP, INFO, PAT, and PD to normalize the data and reduce the influence of heteroscedasticity.

The descriptive statistics and multi-collinearity test results of the above variables are summarized in Table 1. We find that the largest variance inflation factor (VIF) of all independent variables is 3.68, which is well below the threshold of 10, indicating a lack of multi-collinearity between the independent variables.

4. Empirical findings

4.1. Preliminary statistical analysis of EE

We begin by discussing the EE performance using the GRSBM model. In order to intuitively investigate the spatial-temporal dynamics of EE, we first split the sample period into four intervals (i.e., 2003 to 2006, 2006 to 2010, 2011 to 2014, and 2012 to 2018) and then utilize the MATLAB software to map the corresponding average value on Figure 3 (see specific measurement results in Appendix C Supplementary materials).

The national average value of EE is 0.5347, indicating that China’s energy utilization still has vast room for nearly 47% improvement. Regarding different sub-periods, the average level of EE increased from 0.4859 to 0.5208 from the first interval to the second interval and then steadily fluctuated between 0.5664 and 0.5657 from the third interval to the fourth interval.

Next, we investigate whether there are significant differences in EE across regions in China. Many previous studies (e.g., Lin and Du 2013; Yao et al. 2015; Zhang and Zhou 2020) have documented that China’s inter-regional EE is characterized by a gradient decreasing pattern of “East-Center-West,” which demonstrates a gradual decline from the East to the Center and then the West. Recently, Huang, Mo, and Chen (2021) also found a new pattern of “South-North” in China’s regional green development. Thus, we calculated the average value of EE in these five regions (i.e., East, Central, West, South, and North China). Figure 4 illustrates the time trend of the average values of EE across the five regions from 2003 to 2018 (see specific measurement results in Appendix B).

There are distinct differences in inter-regional EE among the eastern, central, and western regions in China (namely “East-Center-West” in Figure 4(a)). Specifically, the East China region has consistently gained the highest value of EE during the study period, with an average efficiency score of 0.5836, while the Central and West China regions achieved relatively lower ones with an average efficiency score of 0.5011 and 0.5151, respectively. This conclusion is consistent with many previous studies (e.g., Yao et al. 2015; Zhang and Zhou 2020). In addition, we also find another imbalanced pattern of inter-regional EE between southern and northern regions in China (namely “South-North” in Figure 4(b)), which demonstrates that the South China region achieved a higher average efficiency score of 0.5625 versus the North China region with a lower score of 0.4791. Furthermore, regarding

| Variable | Mean    | Std. Dev | Min   | Median  | Max    | VIF |
|----------|---------|----------|-------|---------|--------|-----|
| EE       | 0.535   | 0.185    | 0.175 | 0.494   | 1.000  |     |
| FA       | 1.038   | 0.359    | 0.069 | 1.010   | 2.924  | 1.11|
| GOVE     | 0.067   | 0.028    | 0.000 | 0.062   | 0.239  | 1.56|
| FDI      | 0.284   | 0.314    | 0.000 | 0.183   | 4.540  | 1.20|
| IS       | 1.410   | 0.759    | 0.000 | 1.287   | 10.60  | 1.34|
| LnPGDP   | 10.17   | 0.832    | 4.595 | 10.23   | 13.06  | 3.23|
| LnINFO   | 8.806   | 0.604    | 5.446 | 8.841   | 11.72  | 1.35|
| LnPAT    | 3.865   | 1.991    | 0.000 | 3.689   | 10.76  | 3.68|
| LnPD     | 5.742   | 0.888    | 1.548 | 5.879   | 7.887  | 1.54|

VIF (in Table 3) represents the variance inflation factor for the linear model with EE as the dependent variable and explanatory factors as independent variables. ***, **, and * denote 1%, 5%, 10% significance levels, respectively.
the annual growth rate of EE, the differences among the eastern, central, and western regions are gradually narrowing with an average value of 0.68%, 1.67%, and 1.61%, respectively. In contrast, the gap between the southern and northern regions seems to expand after 2013, with an average value of −0.63% and −1.58%, respectively, implying a recent shift in the patterns of inter-regional EE from “East-Center-West” to “South-North.” Notably, previous related studies have widely discussed the former pattern, while less attention has been paid to the latter one.

Figure 3. Spatial-Temporal distribution of EE of 282 cities in China from 2003 to 2018.

Figure 4. EE across regions in China from 2003 to 2018.
4.2. Test of the invert U-shaped relationship between FA and EE

To intuitively visualize the relationship between FA and EE, we use the Curve Fitting Toolbox 3.6 in MATLAB software platform to draw a scatterplot presented in Figure 5. The blue dotted line in Figure 5 displays the fitting result of the linear function, and the red dotted line displays the fitting result of the quadratic function. It can be seen that when the FA is below a critical value (about 1.6), both linear and quadratic curves achieve a high goodness-of-fit. Nevertheless, when the FA is above the critical value, the quadratic function fits much better than the linear function in some cities with high FA but low EE. Although Figure 5 clearly demonstrates a clear inverted-U relationship between FA and EE, this correlation does not necessarily imply causality, and we carry more rigorous empirical analyses in the next sections.

Table 2 presents the estimation results of benchmark regressions. Column (1) details the estimation result of pooled ordinary least square (POLs) regression without controlling for city and year fixed effects. Columns (2) and (3) detail the estimation results of two-way fixed effects regression and instrument variable regression, respectively. The Hausman test statistic is 159.47 and highly significant at the 1% level in Column (2), indicating that the fixed effects model is more appropriate than the random effects model in describing the data generation process. Moreover, the Kleibergen-Paap rk LM statistic are 95.314 and 30.29 in Columns (3) and (6), respectively, and both are highly significant at the 1% level, indicating that the instrument passed the under-identification test. Similarly, the Cragg-Donald Wald F statistic are 139.114 and 15.506 in Columns (3) and (6), respectively, and both are above the Stock-Yogo critical value at the 10% level, indicating the instrument also passed the weak identification test.

By comparison, the coefficient of FA in Column (1) is −0.004 and not statistically significant at the 10% level. In contrast, coefficients in Columns (2) and (3) are 0.051 and 0.177 respectively, and both are highly significant at the 1% level. This indicates that the endogeneity concerns resulting from the unobserved omitted variable and simultaneity lead to biased estimation results and misguided causal inference, as indicated in Column (1). In general, FA can significantly promote the increase of urban EE in a linear econometric model setting; this conclusion is in accord with Qu, Shao, and Shi (2020)
Table 2. Estimation results of the two-regime spatial Durbin panel model.

| Dep. Var | EE  | EE  | EE  | EE  | EE  | EE  |
|----------|-----|-----|-----|-----|-----|-----|
| FA       | 0.182*** | 0.159*** | 0.161*** | 0.162*** | 0.166*** | 0.179*** |
|          | [0.8056] | [0.7897] | [0.8054] | [0.8095] | [0.8200] | [0.8274] |
| FA²      | −0.048*** | −0.045*** | −0.046*** | −0.044*** | −0.047*** | −0.052*** |
|          | [−5.792] | [−5.632] | [−5.692] | [−5.372] | [−5.566] | [−5.756] |
| ρ₁       | 0.071 | 0.105*** | 0.130*** | 0.131*** | 0.130*** | 0.122*** |
|          | [1.290] | [2.666] | [3.495] | [3.704] | [3.808] | [3.789] |
| ρ₂       | 0.163*** | 0.153* | 0.051 | −0.013 | −0.047 | −0.110 |
|          | [2.949] | [1.946] | [0.578] | [−0.123] | [−0.391] | [−0.525] |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
|          | Yes | Yes | Yes | Yes | Yes | Yes |
| City fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjust R² | 0.787 | 0.786 | 0.787 | 0.786 | 0.787 | 0.787 |
| Log-Likelihood | 4844.728 | 4843.778 | 4844.897 | 4843.390 | 4844.706 | 4845.816 |
| σ²       | 0.0068 | 0.0068 | 0.0068 | 0.0068 | 0.0068 | 0.0068 |
| Hausman test | 98.417 | 85.048 | 115.128 | 69.450 | 72.813 | 81.279 |
|          | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| Observations | 4512 | 4512 | 4512 | 4512 | 4512 | 4512 |

Notes: The parameters are estimated by the maximum likelihood estimator developed by Elhorst and Fréret (2009) when controlling the spatial fixed effects and time fixed effects; ***, **, and * denote 1%, 5%, 10% significance levels, respectively; P or Z values in bracket.

and Xie et al. (2021). However, when we add the squared term of FA into Columns (2) and (3), the causal relationship between FA and EE seems to follow a nonlinear function rather than a linear one. It is observed that the estimated coefficient on FA is 0.131 in Column (5) and highly significant at the 1% level, and that on its squared term FA² is −0.035 and significant at the 5% level. Similarly, when we used the instrumental variable regression to re-estimate the causality, the estimated coefficient on FA is 0.551 in Column (6) and highly significant at the 1% level, and that on its squared term FA² is −0.135 and significant at the 5% level.

It is worth noting that Haans, Pieters, and He (2016) argue that the coefficients on the squared term are not sufficient to infer a robust inverted U-shaped relationship. To address this concern, following the approach in Lind and Mehlum (2010), we first check whether the slope is sufficiently steep at both ends of the data range. Suppose FA_L is at the end of FA-range, and FA_H at the high end. The results of the Lind-Mehlum U test of Columns (5) and (6) show that the slopes at FA_L are 0.126 and 0.185, both significant at the 1% level, and the slopes at FA_H are −0.072 and −0.162, both significant at the 1% level. Subsequently, we find that the turning point is 1.88 and 2.04 as shown in Columns (5) and (6), respectively, which are truly located within the interval of FA-range [0.069, 2.924]. Thus, we can conclude that FA has a solid inverted U-shape impact on EE, in which FA promotes the improvement of EE only up to a point, after which it has an inhibitory effect on the increase of EE.

Further, we refer to the robust estimation results in Column (6) for analyzing the influencing mechanism among variables. The coefficient of GOVE is negative at the 10% statistical level, implying that government intervention will result in a decrease of EE. On average, every 1% increase in the government’s fiscal share will lead to a decrease of 0.199 in EE, which indicates that under the market economy mechanism, the government’s visible intervention in the market mechanism tends to aggravate the loss of EE. Foreign direct investment is found to have significantly positive effect on improving EE at the 1% level, and this finding is consistent with previous studies (Pan et al. 2022;
Table 3. Estimation results of benchmark panel model.

| Dep. Var | (1) | (2) | (3) | (4) | (5) | (6) |
|----------|-----|-----|-----|-----|-----|-----|
|          | EE  | EE  | EE  | EE  | EE  | EE  |
| FA       | -0.004 | 0.051*** | 0.177*** | -0.070** | 0.131*** | 0.551*** |
|          | (0.008) | (0.013) | (0.035) | (0.033) | (0.038) | (0.213) |
| FA²      | 0.033 | -0.287* | -0.143 | 0.023 | -0.300* | -0.199* |
|          | (0.152) | (0.169) | (0.107) | (0.151) | (0.167) | (0.116) |
| GOVE     | 0.029*** | 0.020* | 0.025*** | 0.031*** | 0.020* | 0.023*** |
|          | (0.010) | (0.011) | (0.007) | (0.010) | (0.010) | (0.008) |
| FDI      | -0.032*** | 0.007 | 0.015*** | -0.032*** | 0.007 | 0.014*** |
|          | (0.006) | (0.009) | (0.003) | (0.006) | (0.009) | (0.004) |
| IS       | 0.010*** | 0.099*** | 0.077*** | 0.099*** | 0.088*** | 0.087*** |
|          | (0.006) | (0.024) | (0.005) | (0.007) | (0.017) | (0.008) |
| LnPGDP   | 0.063*** | 0.028*** | 0.010** | 0.064*** | 0.028*** | 0.022*** |
|          | (0.006) | (0.007) | (0.005) | (0.006) | (0.007) | (0.006) |
| LnINFO   | -0.040*** | -0.004 | -0.007*** | -0.039*** | -0.008* | -0.005* |
|          | (0.003) | (0.005) | (0.002) | (0.003) | (0.005) | (0.003) |
| LnPAT    | 0.027*** | 0.003 | 0.005 | 0.027*** | 0.006 | 0.005 |
|          | (0.004) | (0.014) | (0.013) | (0.004) | (0.009) | (0.013) |
| LnPD     | -1.022*** | -0.733*** | -0.976*** | -0.681*** |
|          | (0.073) | (0.238) | (0.078) | (0.173) |
| City fixed effects | No | Yes | Yes | No | Yes | Yes |
| Year fixed effects | No | Yes | Yes | No | Yes | Yes |
| First-stage $R^2$ | 0.399 | | | 0.374 | | |
| Second-stage $R^2$ | 0.152 | 0.230 | 0.122 | 0.152 | 0.232 | 0.215 |
| Kleibergen-Paap rk LM statistic | 95.314 | | | 30.290 | | |
| (Under-identification test) | [0.000] | | | [0.000] | | |
| Cragg-Donald Wald F statistic | 139.114 | | | 15.506 | | |
| (Weak identification test) | [16.38] | | | [7.03] | | |
| Turn point (FA') | 1.88 | | | 2.04 | | |
| (Lind-Mehlum U test) | | | | | [0.004] | [0.006] |
| Hausman test | 159.47 | | | 116.59 | | |
| | [0.000] | | | [0.000] | | |
| Observations | 4440 | 4440 | 4166 | 4440 | 4440 | 4166 |

Notes: *** and ** denote 1%, 5%, 10% significance levels, respectively; Robust standard errors in parentheses; $P$ values or Stock-Yogo critical value at the 10% level in bracket. POLS represents the pooled ordinary least square model; TW_FE represents the two-way fixed effects model; IV_GMM represents the instrumental variable generalized method of moment model.

Shahbaz et al. 2022). The reason may be that foreign-funded enterprises can bring foreign advanced technology, equipment and management experience, which is conducive to reducing unit energy consumption and unit output pollution emission intensity, thereby improving EE. The coefficient of IS is 0.014 and positive at the 1% level, indicating that the optimization of the industrial structure has a significant beneficial impact on improving EE. In general, the secondary industry will cause more energy consumption and pollutant emissions than the tertiary industry, thus the increase in the proportion of the tertiary industry has a positive structural effect on promoting EE (Chen, Chen, and Jin 2018; Wang et al. 2021). Similarly, the level of economic development is also found to have a significantly positive impact on improving EE. This finding provides empirical evidence to support the environmental Kuznets curve theory (Huang, Mo, and Chen 2021; 2018). With the continuous
improvement of the level of economic development, the dependence of economic activities on energy consumption and pollutant emission will be reduced, the industrial structure will tend to be cleaner, and the people will pay more attention to the improvement of environmental welfare. The coefficient of LnINFO is 0.022 and highly significant at the 1% level, suggesting that the development of information technology exerts a positive effect on improving EE. The reason may be that the development of digital technology provides a good infrastructure for the development of the cleaner tertiary industry, which in turn promotes the improvement of EE (Qu, Shao, and Shi 2020). However, the patent application is found to have a slight negative effect on improving EE, implying that China’s current energy-saving and emission-reduction technologies have not yet been broken through, thus failing to achieve a significant improvement in EE. Additionally, the coefficient of LnPD is not found to be significant in influencing EE. On the one hand, cities with higher population density tend to have higher energy consumption and carbon emission intensities, but on the other hand, these cities often have higher levels of economic development and greener industrial structures. Thus, the impact of population density on EE is relatively vague.

4.3. Robustness checks

We carry several robustness checks to ensure the reliability of our conclusions. First, we adopt alternative proxy variables for FA and EE. Specifically, with regard to the EE, we removed the fourth constraint condition (i.e., \( \sum_{t=1}^{T} \sum_{j=1}^{N} \lambda_j = 1 \)) from Eq. (B.4) and obtained the EE under the assumption of constant returns to scale (CRS). We present the results in Appendix Table E1. Moreover, we constructed another proxy variable for FA using the location entropy of deposit balance, which can be expressed as follows

\[
FA\text{\_Subs}_{it} = \frac{(D_{it}/E_i)}{\left( \sum_{j=1}^{N} D_{it}/\sum_{j=1}^{N} E_j \right)},
\]

(4)

where \( D_{it} \) is the total amount of the deposit balance of city \( i \) in period \( t \). The regressions in Columns (9) and (10) of Table E1 present the results. It is observed that the coefficients of FA in regression models (7)-(10) are significantly positive at 1% level, and its squared term remains at least significantly negative at 5% level. These findings confirm the inverted U-shaped causality between FA and EE is still valid.

Second, previous studies (e.g., Wang and Wang 2020; Wu, Hao, and Ren 2020) argued that China’s EE is characterized by strong persistence, such that static panel models may fail to capture this time-lag effect, thereby producing inconsistent and misleading results. To address this concern, we employed the System Generalized Method of Moments (Arellano and Bover 1995; Blundell and Bond 1998) and Differential Generalized Method of Moments (Arellano and Bond 1991) approaches to reexamine the causal relationship between FA and EE. The regression models (11) and (12) in Table E1 present the main estimation results. The results of the Hansen test in regression (11) and (12) are insignificant at 10% level, implying the validity of the instrumental variable setting in the GMM estimation. Furthermore, we find that the coefficients of FA and its squared term are still positive and negative and significant at the 1% and 5% levels, respectively.

Third, the analysis of the spatial-temporal dynamics in section 4.1 shows that the inter-regional EE in China is characterized by two patterns of regional disparities (i.e., “East-Center-West” and “South-North”). To further investigate whether the causal relationship between FA and EE has regional differences, we divided the 282 prefectural-level cities across the country into five regions: East, Center, West, South, and North to perform subsample tests following Huang, Mo, and Chen (2021) (see the specific division results of cities in Appendix B). The main estimation results are reported in Appendix Tables E2 and E3. We find that the estimated coefficients of FA and its squared term are significantly positive and negative at least at the 5% level in most regression models (except in model (18)). These
findings suggest that the inverted U-shaped causal relationship between FA and EE is stable regardless of regional differences.

5. Further analysis

The inverted-U effect of FA on EE has been confirmed before using various robust estimations. However, the following question arises: how does FA in focal cities impact EE in peripheral cities? From the perspective of financial geography, the spatial interaction between focal and peripheral cities caused by the uneven geographical distribution of financial resources may have an important impact on the overall EE. In response to this question, in-depth discussions based on the spatial econometric analysis are necessary.

5.1. Spatial correlation test and models screening

To ensure the applicability of spatial econometric models for our dataset, we first test the spatial correlation of the dependent variable from 2003 to 2018 using the global Moran index. We estimate global Moran index using the formula in Appendix D. Figure 6 reports the testing results of EE across cities in China during the study period. It is can be seen that the global Moran index of each year is positive and highly significant at the 1% level,
indicating that there is evident spatial correlation of EE across cities. Additionally, the scatter plot shows that most cities are distributed in the first and third quadrants, indicating that cities with higher or lower EE are geographically concentrated. These findings are in line with Qu, Shao, and Shi (2020), Yuan et al. (2020), Wu, Hao, and Ren (2020), and 2018.

Moreover, we reported results of each explanatory variable in Appendix Table D1. The results show that Moran’s indexes, including FA, GOVE, FDI, IS, LnPGDP, LnINFO, LnPAT, and LnPD, remain positive at 5% statistical significance level in most of the years. This implies that most explanatory variables are not entirely randomly distributed and characterized by positive geographical agglomeration. Thus, spatial econometric models employed in this study are appropriately applied.

Furthermore, following the standard practices in Elhorst (2014), we apply the likelihood ratio (LR) test and the Wald test to compare the suitability of the SAR, SDM and SEM. Appendix Table D2 reports the corresponding test results. Both the LR test and the Wald test statistics of the SDM degenerating to the SAR in the first column are significant at the 1% level; indicating that the SDM is better than the SAR to describe the data generating process. Similarly, the LR test and the Wald test in Column (2) strongly reject the null hypothesis, suggesting that the SDM will not degenerate to the SEM. Overall, these test results reveal that the SDM is more suitable to explain the spatial dependence of the data.

5.2. Two-Regime spatial Durbin panel model analysis

Before the empirical analysis, this study uses MATLAB software to visualize the spatial distribution patterns of China’s urban FA in 2006, 2010, 2014, and 2018. It is observed in Figure 7 that there are

![Figure 7](image-url) Figure 7. Spatial-Temporal distribution of financial agglomeration in local and nearby cities.
more and more financial center cities over time in China, which demonstrates that the degree of FA in these focal cities is much higher than that of surrounding cities. Moreover, there is a large overlap of cities with high-level or low-level FA in regions with high-level or low-level economic development. For example, most cities with high-level FA are located in the southeast regions, whereas the low-level ones are distributed in the northwest regions. We also find that a few large cities (e.g., Beijing, Tianjin) with high-level FA are often surrounded by more and more small and medium-sized cities with low-level FA, implying that China’s urban FA is characterized by strong imbalance. In academic, the role of financial development or deepening in promoting corporate and regional EE has been broadly discussed in the literature. Theoretically, as more and more financial resources agglomerated in some focal cities, they will have enough financial resources to improve EE by supporting technological innovation, adjusting energy structure, and promoting industrial upgrading (Li and Ma 2021; Shahbaz et al. 2022; Usman et al. 2021; Xie et al. 2021); however, at the same time, more and more peripheral cities will face serious financial constraints. For example, the industrial sector that adopts clean energy, develops green technologies and produces green products may suffer from severe financial constraints, which in turn leads to lower EE in those cities. Accordingly, we hypothesize that excessive FA in focal cities may exert a negative effect on the improvement of EE in peripheral cities, thus inhibiting the EE improvement of the entire economy.

To verify our conjecture, this paper employed a two-regime spatial Durbin panel model to identify whether the spatial interaction between focal and peripheral cities is the underlying impact mechanism behind the inverted-U causal relationship between FA and EE. Specifically, we set \( \lambda \) equal to 1, 1.3, 1.4, 1.5, 1.6, and 2 to define two regimes in model (3). According to the estimation results shown in Table 2, the inverted-U causal relationship between FA and EE remains highly consistent with previous findings when considering spatial dependence and heterogeneity. Moreover, the adjusted \( R^2 \) in regressions (23)-(28) is much greater than that in regressions (1)-(6), indicating that spatial econometric models have a more robust explanation in describing the data generation process. This finding indicates that cities with relatively low-level FA may face green financial constraints, thereby failing to play positive externalities in developing low-carbon technologies and using clean energy. This conclusion is in accord with Qu, Shao, and Shi (2020) and Yuan et al. (2019).

We uncovered two significantly different spatial spillover effects when \( \lambda = 1 \). The spatial autoregressive coefficient of the first regime is 0.071 and not statistically significant at the 10% level, whereas one of the second regimes is 0.163 and is highly significant at the 1% level. This finding indicates that cities with relatively low-level FA may face green financial constraints, thereby failing to play positive externalities in developing low-carbon technologies and using clean energy. This conclusion is in accord with Qu, Shao, and Shi (2020) and Yuan et al. (2019).

With \( \lambda \) increasing to 1.3 and 1.4 in regressions (24) and (25), the spatial autoregressive coefficient for the first regime gradually increases in value and becomes statistically significant, which indicates that the spatial spillover effects of EE in the first regime are continuously enhancing. Conversely, one of the second regimes gradually decreases in value and becomes statistically insignificant, indicating that the spatial spillover effect of EE in the second regime is continuously weakening. Furthermore, as \( \lambda \) continues to increase to 1.5, 1.6, and 2, the spatial autoregressive coefficient of the first regime remains stable at the 1% significance level, whereas the latter one continues to decrease and even becomes a negative number. This finding implies that as the degree of FA in focal cities becomes more and more significantly higher than that in surrounding cities, the spatial spillover effect that initially played a positive externality gradually fades, and even reverses to an undesirable negative effect, although it is not statistically significant. Thus, our hypothesis is initially supported. We call this phenomenon a spillover shadow.

### 5.3. Parameter sensitivity analysis

Notably, self-selection bias may occur since we only selectively performed six specific regressions with \( \lambda \) equal to 1, 1.3, 1.4, 1.5, 1.6, and 2 in Table 2. To address this concern, we conduct a parameter
sensitivity test on $\lambda$. Specifically, we set $\lambda$ to start from 1, gradually increase by 0.02 until it ends at 2, and then traverse in turn to estimate the model (A.1).

It is clearly observed in Figure 8 that, with the continuous increase of $\lambda$, the spatial autoregressive coefficient of the first regime increases first and then floats steadily. In contrast, one of the second regimes begins with a stable floating phase and then decreases. Moreover, the estimated coefficient sign of the $\rho_2$ starts to change from positive to negative when $\lambda$ reaches around 1.5, indicating that the positive spatial spillover effect ceased to exist. The corresponding $T$ statistics of the $\rho_1$ and $\rho_2$ also showed similar changes. Therefore, the estimation results of the parameter sensitivity test show that the spillover shadow phenomenon is robustly observed rather than occurring as a result of the subjective setting of specific $\lambda$.

Combining with the research analysis in section 5.2, we conclude that the spatial interaction between focal and peripheral cities is one of the underlying impact mechanisms behind the inverted-U causal relationship between FA and EE. Theoretically, it can indeed improve the EE of surrounding cities through positive spillover effects such as knowledge sharing and technology diffusion when the degree of FA in focal cities is not much greater than that in surrounding cities. Thus, we observed the total effect of the impact of FA on EE is positive when the degree of FA is below a certain critical value (i.e., $FA < FA^*$). However, when the degree of FA in certain focal cities becomes more and more significantly higher than that in most surrounding cities, the positive spillover effect would gradually disappear since the financial resources of the latter would have been over-absorbed by the former. There is no doubt that for most of the surrounding cities, suffering from the spillover shadow would greatly hinder the research and development of green and low-carbon technologies, the use of clean energy, and the consumption of green products, thereby exerting a negative indirect effect on the increase of their EE. Thus, we can observe that the total effect of the impact of FA on EE turns negative when the degree of FA exceeds a certain critical value (i.e., $FA > FA^*$). This may also be the fundamental reason why the FA has no significant or even negative effect on EE in western China, medium-sized and small cities (Qu, Shao, and Shi 2020).

If the current trend continues, we may see a tale of two tiers in the process of green and low-carbon development in Chinese cities. On the one hand, more and more financial resources are agglomerated in a few focal big cities, and firms located there will not be constrained by green financial restrictions and can even set aside a lot of idle funds for financial investment. On the other hand, the degree of FA in more and more surrounding small and medium-sized cities continues to decline, and firms located there will face severe green financing challenges. In order to maintain normal operations and make up
for production costs, they have to abandon the purchase and application of clean energy and the research and development of green and low-carbon technologies. Under the Matthew effect of inter-urban FA, the green development of a few focal and large cities is expected to make significant progress in the long run, whereas that of the most surrounding small and medium-sized cities will be hindered and even regress sharply. On the whole, this situation is obviously not conducive to the improvement of EE of the entire economy.

6. Conclusions and policy implications

Using a large scale of prefecture-level panel data in China from 2003 to 2018, this study first proposes a novel DEA approach to evaluate the EE by combining the ray slacks-based measure (2018) and global benchmark technology (Oh 2010) into a framework. Then, we reexamine the causal nonlinear relationship between FA and EE and explore the underlying impact mechanism behind that from the spillover perspective. The empirical results show that China’s urban EE is generally relatively low with two distinct patterns of regional differences, namely “East-Center-West” and “South-North.” Moreover, we find that the causal relationship between FA and EE follows an inverted U-shaped function, in which FA promotes the improvement of EE only up to a certain point, after which it reverses into an inhibitory effect. A further impact mechanism analysis based on the two-regime spatial Durbin panel model revealed that it could indeed improve the EE of surrounding cities through positive spillover effects when the degree of FA in focal cities is not much greater than that in surrounding cities. However, when the degree of FA in certain focal cities increases significantly higher than that in most surrounding cities, the positive spillover effect would gradually disappear and even reverse into an undesirable siphon, thus impeding overall EE’s improvement.

Based on these conclusions, this study has rich policy implications for sustainable urbanization and financial development. On the one hand, the inter-regional EE in China presents apparent regional disparities, with an emerging shift from “East-Center-West” to “South-North.” In order to coordinate the regional green development, we should take more measures to narrow the gap between North and South. First, transform the development mode of the northern region, and enhance the financial component of Beijing-Tianjin-Hebei’s coordinated development strategy. Increase the economic strength of the central cities of the Beijing-Tianjin-Hebei urban agglomeration and develop a strong radiation center for the development of the northern hinterlands. Second, make full use of the relatively strong industrial base of the north, explore and make full use of its innovative resources, and promote the high-quality development of the northern manufacturing industry.

On the other hand, there is a stable inverted U-shaped relationship between FA and EE. For the regions with FA below the threshold value, local governments should put more effort into the development of the financial industry through green financial policies such as fiscal incentives and tax breaks. Introducing green financial policies, such as tax incentives and fiscal incentives, to encourage the concentration of financial resources in the region so that FA can benefit from economies of scale. And for others that exceed the FA threshold, they should control the speed and degree of agglomeration with the help of knowledge and technology to avoid the adverse effects caused by excessive agglomeration. At the same time, the allocated resources should be appropriately transferred to the surrounding backward areas in order to promote the innovation and development of the neighboring areas, reduce the redundancy of their own financial resources and promote the development of the financial industry in these areas, so as to exert its marginal effect on EE.

This paper provides new insights for understanding the real nonlinear causality running from FA to EE, but there are still some limitations that require further research. Firstly, since our study used macro sample data of Chinese prefectural cities, further discussion can expand the research using firm level data. This could provide more detailed and robust analysis for understanding the FA-EE nexus. Secondly, although we analyzed the impact mechanism on how FA in focal cities impact EE in surrounding cities, it is still worthwhile to explore other economic channels in future research. In
addition, future work can build theoretical models to intuitively clarify the internal linkage between FA and EE.

**Abbreviations**

| Abbreviation | Description                  |
|--------------|------------------------------|
| EE           | Energy Efficiency            |
| FA           | Financial Agglomeration      |
| GOVE         | Government Intervention      |
| FDI          | Foreign Direct Investment    |
| PGDP         | Gross domestic product per capital |
| INFO         | Information Development      |
| PD           | Population Density           |
| PAT          | Patent Applications          |
| IS           | Industrial Structure         |

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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**Authorship contribution statement**

Fengrong Wang: Validation, Review, Project administration, Funding acquisition. Chenxi Zhang: Writing – original draft, Data curation, Investigation, Formal analysis. William Mbanyele: Writing – review & editing, Validation, Review, Formal analysis. Hongyun Huang: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. Tomas Balezentis: Conceptualization, Methodology, Software, Formal analysis.

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