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Does digitalization improve firm-level energy efficiency? Evidence from a quasi-natural experiment in China

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Previous research has primarily focused on the influence of digitalization on regional energy efficiency, overlooking the variations in its impact on primary and secondary energy at the firm level. This study leverages a unique and extensive dataset sourced from tax records of Chinese firms to investigate the effects of digitalization on firm energy efficiency, utilizing a quasi-natural experiment revolving around the "Broadband China" policy (BCP). Employing propensity score matching (PSM-DID) to estimate the difference-in-difference model, our analysis reveals that BCP implementation leads to a 10.5% and 11.3% enhancement in coal and oil firm energy efficiency, respectively, while resulting in a 17.2% decrease in electricity firm energy efficiency. Further analysis indicates that BCP influences firm energy efficiency by fostering industrial upgrading and industrial intelligence. Moreover, government intervention magnifies the impact of BCP on firm energy efficiency. Lastly, the paper conducts various heterogeneity analyses and robustness checks. The proposed policies to enhance energy efficiency among Chinese firms are practical and could be applicable to firms in other emerging economies, particularly those experiencing rapid digital advancements.

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Introduction

Since the beginning of the industrial revolution, global economic progress has heavily relied on the integration of energy-related elements (Barbera et al. 2022; Devlin and Yang, 2022; Lin and Zhu, 2021; Shao and Xue, 2022; Wen and Jia, 2022). The substantial growth in energy consumption has closely mirrored the rapid pace of economic development, intensifying the severity of climate-related challenges (Adom et al. 2018; Li et al. 2021; Liu et al. 2021; Mišík and Oravcová, 2022; Shah et al. 2022; Yazar et al. 2022; Zhou and Xu, 2022; Zhu and Lin, 2022). As the nation with the greatest total energy consumption and carbon emissions in the world, China faces a pressing need to improve energy efficiency as a crucial measure to combat the climate crisis. Fortunately, with the rise of the "Fourth Industrial Revolution" led by informatization and digitalization, many traditional industries are facing disruptive changes (Hu et al. 2022; Shahbaz et al. 2022; Zhang and Chen, 2022). To explore this energy transformation driven by digitalization, researchers have focused on how digitalization influences energy efficiency. From one perspective, digitalization has significantly improved the input-output efficiency of diverse factors, including energy, as evidenced by the emergence of intelligent coal mines (Bałaga et al. 2021). The studies by Husaini and Lean (2022) and Qin et al. (2022) further affirm that digitalization has increased national energy efficiency and sustainability on the basis of panel data from five ASEAN countries. These researchers posit that digitalization creates new opportunities for increasing energy efficiency. Conversely, opposing views suggest that digitalization has also increased energy consumption, such as the electricity demands of data computing centers. Scholars who hold these views argue that digitalization either has no significant effect on energy efficiency or even reduces it (Mayers et al. 2015; Noussan et al. 2017; Qin et al. 2022). Despite these varied findings, digitalization is an inevitable trend in future global development, and its impact on energy efficiency cannot be ignored. Therefore, it is crucial to investigate the underlying reasons behind these differing perspectives.

Notably, China is experiencing a serious energy shortage. Despite its abundant coal resources (Chen et al. 2022), China relies on imports to meet over 70% of its oil demand (Chen et al. 2023), while electricity (Guo et al. 2023) is also scarce to varying degrees across different regions. This energy shortage heightens concerns over energy security, making it essential to examine energy efficiency separately for different types of energy sources (Li et al. 2023).

Some studies have focused on the influence of digitalization on overall energy efficiency, suggesting that digitalization generally has a positive impact (Bałaga et al. 2021; Husaini and Lean, 2022). However, a smaller body of research that focuses on specific energy categories has revealed unfavorable or negligible effects of digitalization on energy efficiency. For example, analyses of the service and transportation sectors have indicated that digitalization significantly reduces the energy efficiency of electricity (Dehghan Shabani and Shahnazi, 2019; Mayers et al. 2015; Noussan et al. 2017).

We propose that these divergent findings stem from differences in energy types. On the one hand, digitalization enhances resource integration, reduces losses of coal and oil during production and transportation, and improves the efficiency of primary energy (Bałaga et al. 2021; Husaini and Lean, 2022). On the other hand, the proliferation of data computing centers and communication devices associated with digitalization may worsen the inefficient use of secondary energy (Xue et al. 2022).

A review of current research revealed that no studies have assessed the effects of digitalization on the energy efficiency of various energy types while simultaneously conducting a comparative analysis. Therefore, substantiating evidence on how digitalization influences the energy efficiency of different energy sources is needed.

To address these gaps, this study employs the "Broadband China" policy (BCP) as a quasi-natural experiment and utilizes the China National Tax Survey Data (CNTSD), a comprehensive and unique dataset of firm tax records, to examine the impact of digitalization on firm energy efficiency using the PSM-DID method. Additionally, this study develops mediating and moderating effect models to investigate the mechanisms through which digitalization influences firm energy efficiency, as well as the externalities of government interventions. Moreover, the analysis provides an in-depth assessment of digitalization's effects on firm energy efficiency across different regions and industries using variable-coefficient panel models. Finally, robustness tests are performed to ensure the credibility and reliability of the analytical findings.

This study makes significant contributions to both theory and practice, enhancing our understanding of the relationship between digitalization and energy efficiency while providing valuable insights for policymakers and business leaders.

First, at the theoretical level, this study fills an important gap in the literature by evaluating the impact of digitalization on energy efficiency at the micro level of the firm. Previous research has focused primarily on improving the efficiency of individual energy sources, often overlooking the complex and interconnected effects of digitalization on overall energy efficiency within firms (Lin and Huang, 2023; Niu et al. 2022). In contrast, this study proposes a more comprehensive analytical framework that includes multiple energy sources, such as coal, oil, and electricity, and reveals the differentiated impacts of digitalization on various energy types. The findings challenge traditional assumptions about energy savings, highlighting that the effects of digital transformation depend on a firm's energy consumption structure. Consequently, this research introduces new perspectives for energy management practices. Our analysis indicates that digitalization may have unintended consequences, particularly when energy structures are not adequately considered; thus, new theoretical challenges arise, paving the way for future research directions.

Second, this study explores the mechanisms through which digitalization affects firm energy efficiency and the externalities of government intervention. We find that digitalization impacts energy usage not only directly through improved production efficiency but also indirectly through changes in industrial upgrading and intelligence. Moreover, government intervention in digitalization may create subsidies or introduce market uncertainties, offering critical insights for policymakers when designing and implementing digitalization policies. Our findings also reveal significant variations in how different industries and firm characteristics respond to digitalization, suggesting that policy design and business strategies should include the consideration of industry and firm heterogeneity to achieve optimal outcomes.

Third, the findings of this study have important implications for policy and practice. The results provide a solid theoretical foundation for governments and firms in terms of optimizing energy use during the digitalization process. Specifically, for firms with complex energy consumption structures, the findings prompt managers to comprehensively assess changes in the efficiency of different energy types when implementing digitalization strategies, cautioning against a singular focus on digitalization that may lead to an overall decline in energy efficiency. Furthermore, the mechanism analysis of this study offers practical insights for future policy design, suggesting that policymakers consider potential externalities and account for industry differences when promoting digitalization to achieve more efficient and sustainable energy use goals.

Compared with existing research, this study not only offers fresh empirical evidence but also makes significant contributions to the theoretical framework and policy applications (Jia et al. 2024; Niu et al. 2022). These contributions expand the body of literature on the relationship between digitalization and energy efficiency and provide valuable guidance for future research and practice in related fields.

In summary, our study bridges a critical research gap by simultaneously assessing the effect of digitalization on the energy efficiency of various energy types and conducting a comparative analysis. We find that digitalization improves the efficiency of primary energy sources, such as coal and oil, by enhancing resource coordination and reducing losses during production and transportation. Conversely, digitalization worsens the inefficient use of secondary energy sources such as electricity, specifically because of the proliferation of data computing centers and communication devices. These findings challenge conventional assumptions about energy efficiency improvements through digitalization, revealing that the impact of digitalization varies significantly depending on the type of energy involved.

The rest of this paper is structured as follows: Section "Literature review" provides a review of the literature, while Section "Methods and data" describes the methods employed and the dataset used. Section "Results" presents an overview of the findings, followed by a discussion of the heterogeneity analysis in Section "Further analysis". Further analysis is presented in Section "Heterogeneity analysis", culminating in the conclusions and policy implications in Section "Conclusions and Policy Implications".

Literature review

Literature review on energy efficiency. In this section, the methods used to calculate energy efficiency are described, and a brief categorization of the influencing factors is provided.

Energy efficiency is a critical component of production efficiency (Wang and Wang, 2022) and has gradually attracted increased scholarly attention since the latter half of the last century. The earliest metric for assessing energy efficiency in industrial production was economic output per unit of energy input (Berndt and Wood, 1975; Cai et al. 2022; Khoshroo et al. 2021; Zheng, 2021), a measure that has continued to be relevant in recent years. In this approach, a higher value indicates greater energy efficiency. In contrast, some researchers have adopted stochastic frontier analysis (SFA) and data envelopment analysis (DEA) methods (Dong et al. 2022a; Du et al. 2022; Kang et al. 2022).

The DEA method involves assessing energy efficiency on the basis of multiple inputs and outputs without requiring prior assumptions about the functional form of the production function. However, this advantage makes it susceptible to stochastic errors (Moon and Min, 2020; Xiao et al. 2023). Conversely, the SFA method allows greater flexibility in defining model variables to suit specific study contexts, incorporates stochastic errors, and accounts for unobserved individual-specific heterogeneity through tailored specifications (Li et al. 2024; Sun et al. 2019; Zhang et al. 2024). Nonetheless, both DEA and SFA require strict assumptions about the production function and the error term distribution or are highly sensitive to data noise (Kumbhakar et al. 2014). This can lead to unstable estimation results when it is difficult to construct an accurate mathematical model.

Nonparametric methods, in contrast, do not depend on assumptions about the production function, so they are more versatile and broadly applicable. Moreover, in scenarios with significant data noise or small sample sizes, nonparametric methods yield more robust estimates, avoiding issues that arise from inappropriate assumptions in efficiency measurement.

Given the intrinsic link between energy concerns and societal progress, numerous scholars have conducted extensive research on the determinants of energy efficiency. At the macro level, studies have investigated the relationships between energy efficiency and factors such as industrial composition, foreign investment, and GDP growth (Fisher-Vanden et al. 2006; Liu et al. 2022; Pan et al. 2019; Ramanathan, 2006). At the micro level, researchers have focused on firm-specific influences, such as R&D investments, carbon emissions, and the interaction between firm innovation and energy efficiency (He et al. 2021; Hong et al. 2022; Wen et al. 2022). As energy issues become increasingly prominent, research on energy efficiency is emerging as a critical academic priority.

Literature review on the relationship between digitalization and energy efficiency. Most previous research has focused predominantly on the economic implications of digitalization, with comparatively fewer studies addressing its impact on energy and the environment. Moreover, a consensus regarding these effects has yet to emerge.

Some scholars have argued that digitalization significantly enhances energy efficiency. For example, Lange et al. (2020) examined the relationship between digitalization and energy consumption using an analytical model. Their findings demonstrated a substantial improvement in overall energy efficiency attributed to digitalization. Amasawa et al. (2018) conducted a 3-month social experiment to investigate how e-book reading might reduce the global warming potential (GWP) in a digitalized context. They concluded that digitalization can increase industrial energy efficiency. Similarly, Husaini and Lean (2022) employed the cross-sectional augmented autoregressive distributed lag (CS-ARDL) approach, analyzed panel data from five ASEAN countries (1990–2018), and provided evidence that digitalization positively correlates with national energy efficiency and sustainability. In addition, many other researchers have produced findings that demonstrate the beneficial impact of digitalization on energy efficiency (Rawte, 2017; van den Buuse and Kolk, 2019).

Conversely, other scholars have argued that the impact of digitalization on energy efficiency is negative or uncertain. Mayers et al. (2015) explored the carbon footprint and energy efficiency of the gaming industry and revealed that downloading games via digital networks could lead to higher carbon emissions and energy consumption than disc-based games. Noussan et al. (2017) used scenario analysis to examine the effects of digitalization on Europe's prospective passenger transport sector. Their findings showed that integrating digital technology produced mixed outcomes for energy consumption and emissions, resulting in uncertain impacts on energy efficiency. Other studies have reached similar negative or inconclusive results (Dehghan Shabani and Shahnazi, 2019; Hsu et al. 2014; Strobel, 2016).

A closer examination reveals that these conflicting viewpoints may stem from digitalization's differentiated impacts on primary and secondary energy sources. Xue et al. (2022) suggested that digitalization has increased the share of renewable energy in total consumption, potentially affecting overall energy efficiency. The comprehensive impact of digitalization on energy efficiency depends on the direction and magnitude of its effects on primary and secondary energy sources. Specifically, if the negative impact of digitalization on secondary energy efficiency outweighs its positive influence on primary energy efficiency, overall energy efficiency may decline.

In summary, a definitive consensus on the relationship between digitalization and energy efficiency has not been reached in previous studies. This study argues that the primary reason for this divergence lies in the failure to distinguish between different types of energy. Given the varied effects of digitalization on electricity consumption versus coal and oil consumption, its impact across diverse energy efficiency categories urgently needs to be comprehensively assessed.

Research hypothesis. This paper proposes that digitalization influences firm-level energy efficiency across different energy categories through two primary pathways: industrial upgrading and industrial intelligence. These pathways illustrate how digital advancements transform both industry structures and production processes, shaping how firms consume and manage energy.

Industrial upgrading plays a pivotal role in enhancing energy efficiency by driving a shift from energy-intensive activities to those with lower energy demands. This transition typically involves movement from the manufacturing sector (secondary sector) to the service sector (tertiary sector), which generally consumes less primary energy, such as coal and oil, while generating higher economic output per unit of energy consumed (Dong et al. 2021; Usman and Balsalobre-Lorente, 2022). Digitalization facilitates this shift through the automation of processes and the optimization of resource utilization, thereby increasing overall productivity (Anthopoulos and Kazantzi, 2022; Vu and Hartley, 2022). Consequently, firms become less dependent on primary energy sources, resulting in increased economic returns per unit of coal and oil used (Sun et al. 2021).

However, this transition raises an important question: Does the reduced reliance on primary energy inevitably lead to improved overall energy efficiency? Industrial upgrading also drives higher demand for secondary energy sources, particularly electricity, owing to the increasing need for digital infrastructure. Unlike primary energy, converting electricity into economic output does not always yield proportional gains. This raises concerns about whether the growing electricity demand, which is spurred by the adoption of advanced digital systems such as data centers and automated machinery, might offset the energy savings achieved from reduced coal and oil usage. Could this create a scenario in which the anticipated improvements in energy efficiency are diminished or even negated by less efficient electricity use? On this basis, we propose Hypothesis 1.

Hypothesis 1: Digitalization improves firm-level energy efficiency for coal and oil but reduces energy efficiency for electricity due to industrial upgrading.

Digitalization has also spurred the advancement of industrial intelligence, which integrates smart technologies into production processes. This enables firms to optimize operations, minimize waste, and utilize energy more precisely. Industrial intelligence encompasses the deployment of advanced machinery and automated systems that streamline workflows and reduce energy waste. For example, smart manufacturing technologies can replace outdated, inefficient machinery that heavily relies on coal and oil, thereby further reducing primary energy consumption and increasing economic output per unit of energy used (Huang et al. 2022).

However, increased electricity usage is often needed for the adoption of these smart machines. Operating these energy-intensive technologies can substantially increase firms' electricity consumption. While the use of primary energy decreases, the higher demand for electricity might offset the gains, particularly if the economic output generated by these intelligent systems fails to fully compensate for the additional electricity costs. This highlights a potential drawback of digitalization: although it improves energy efficiency in certain areas, it may introduce inefficiencies in others. On this basis, we propose Hypothesis 2.

Hypothesis 2: Digitalization improves firm-level energy efficiency for coal and oil use but reduces efficiency for electricity use due to the rise of industrial intelligence.

Furthermore, we examine the critical role of government intervention in influencing the impact of digitalization on firm-level energy efficiency, particularly across different energy types. The effects of digitalization on energy efficiency can either be enhanced or undermined depending on how government policies and regulations are designed and implemented.

Government intervention may intensify the negative effects of digitalization on electricity-based energy efficiency. Policies that introduce uncertainty, such as fluctuating electricity prices or supply constraints, could escalate the operational costs of digital infrastructure (Dvořák et al. 2018). Stable and affordable electricity is needed for digital processes, especially those that are reliant on IT and big data. When electricity costs are unpredictable, firms may struggle to meet the energy demands of advanced digital technologies, so energy efficiency may be reduced, and operational challenges may arise. This unpredictability could also discourage firms from fully adopting digital technologies, as financial risk may outweigh efficiency benefits. Consequently, even with digital advancements, firms might experience reduced energy efficiency if the costs and stability of electricity remain significant concerns.

Conversely, government intervention can also amplify the positive effects of digitalization, especially in the context of coal and oil usage. Supportive government policies, such as subsidies for energy-efficient technologies or tax incentives, can directly lower the financial barriers firms face when investing in digitalization (Zhang et al. 2017). By reducing implementation costs, digitalization becomes not only more appealing but also more accessible to a wider range of firms.

In a policy environment that actively supports energy efficiency, firms are incentivized to adopt digital technologies that specifically target the optimization of primary energy sources such as coal and oil. For example, a firm might upgrade to more efficient machinery or implement smart energy management systems, motivated by the financial advantages provided by such policies. These investments could lead to significant improvements in energy efficiency and thus reduce waste, enhance process precision, and maximize economic output per unit of energy consumed.

As more firms take advantage of these supportive policies, the cumulative effect could drive industry-wide advancements in energy efficiency. This widespread adoption of digital technologies would not only reduce coal and oil consumption but also establish new benchmarks for energy productivity, making the entire sector more efficient and sustainable. Thus, this reasoning supports the idea that strategic government intervention aligned with energy efficiency objectives can significantly enhance the positive impacts of digitalization on the efficient use of coal and oil, yielding broad economic and environmental benefits. On this basis, we propose Hypothesis 3.

Hypothesis 3: Government intervention worsens the negative effect of digitalization on firm-level energy efficiency from electricity but enhances the positive effect on energy efficiency from coal and oil.

Methods and data

"Broadband China" policy. The advancement of digitalization relies heavily on the development of network infrastructure across society. In China, the launch of the "Broadband China" policy (BCP) in August 2013 marked a milestone in the nation's digital transformation. This policy designated broadband as a strategically important public infrastructure, signaling China's entry into a new phase of rapidly advancing broadband deployment nationwide.

Following the issuance of the BCP by the State Council, the National Development and Reform Commission and the Ministry of Industry and Information Technology introduced three batches of pilot cities for this policy. The policy was implemented in three phases: the first batch of 41 cities, selected and evaluated by experts, began implementation in 2014. This was followed by the second batch of 38 cities in 2015 and the third batch of 37 cities in 2016. The implementation of the policy focused primarily on the following: (1) Expanding access network coverage through broadband infrastructure construction. (2) Promoting industrial optimization by enabling more diverse network applications. (3) Strengthening the network industry chain through the industrialization of major broadband products.

Since its introduction, the BCP has garnered widespread attention and active public engagement, significantly boosting China's level of information technology. It has also had a notable positive impact on fostering digitalization and driving societal progress in the digital age.

Econometric model

Baseline model. To evaluate the influence of digitalization on firm energy efficiency, the foundational PSM-DID baseline model in this paper is established as follows:

$$y_{i,r,n,t} = \beta_0 + \beta_1 \times BCP_{r,t} + \varphi_i + \lambda_t + \gamma_r + \eta_n + \varepsilon_{i,r,n,t} \tag{1}$$

$$BCP_{r,t} = \begin{cases} 0, BCP\ is\ not\ implemented. \\ 1, BCP\ is\ implemented\ in\ city\ r\ at\ year\ t. \end{cases} \tag{2}$$

where $y_{i,r,n,t}$ represents the energy efficiency of firm i in industry n located in city r at year t. $BCP_{r,t}$ indicates the implementation of the "Broadband China" policy, with the estimated coefficient β_1 representing the average treatment effect of BCP on firm energy efficiency. λ_t represents time fixed effects, γ_r represents city fixed effects, η_n represents industry fixed effects, φ_i represents firm fixed effects, and $\varepsilon_{i,r,n,t}$ represents the error term.

Event study model. To estimate the PSM-DID model, there need to be no significant differences in the trends of the dependent variable between the treatment and control groups prior to the implementation of the policy. This condition is referred to as the parallel trend assumption (Li et al. 2022; Lin and Huang, 2022; Zhong and Peng, 2022). The event study model is utilized in this paper to evaluate whether this assumption holds.

$$y_{i,r,n,t} = \beta_0 + \sum_{k=-3}^{2} \beta_k \times du_r \times D_t^k + \varphi_i + \lambda_t + \gamma_r + \eta_n + \varepsilon_{i,r,n,t}, k \neq -1 \tag{3}$$

$$D_t^k = \begin{cases} 0, when\ t \neq 2014 + k \\ 1, when\ t = 2014 + k \end{cases} \tag{4}$$

where du_r denotes the dummy of the treatment group, and the value is 1 when city r belongs to the treatment group. D_t^k denotes the dummy variable of the year before or after the implementation of the BCP, and the specific measurement is shown in Eq. (4). If the coefficients β_k fail to be significant at the 10% level before the implementation of BCP ($k < 0$), this suggests that there is no significant disparity in firm energy efficiency between the treatment and control groups, thus confirming the satisfaction of the parallel trend assumption.

Mediation effect model. To examine whether BCP influences firm energy efficiency by enhancing industrial upgrading and industrial intelligence, the following mediation effect model is formulated in this paper:

$$y_{i,r,n,t} = \beta_0 + \beta_1 \times BCP_{r,t} + \varphi_i + \lambda_t + \gamma_r + \eta_n + \varepsilon_{i,r,n,t} \tag{5}$$

$$M_{r,t} = \beta_0 + \beta_1 \times BCP_{r,t} + \varphi_i + \lambda_t + \gamma_r + \varepsilon_{r,t} \tag{6}$$

$$y_{i,r,n,t} = \beta_0 + \beta_1 \times BCP_{r,t} + \beta_2 \times M_{r,t} + \varphi_i + \lambda_t + \gamma_r + \eta_n + \varepsilon_{i,r,n,t} \tag{7}$$

where $M_{r,t}$ represents the mediating variable, which encompasses industrial upgrading and industrial intelligence. Industrial upgrading is quantified by the ratio of added value from the tertiary industry to added value from the secondary industry. Industrial intelligence is measured by the logarithmic values of urban industrial robot stock. On the basis of the study of Acemoglu and Restrepo (2020), the urban industrial robot stock is calculated in this paper using the city's industrial employment structure, the number of laborers, and the number of industrial robots at the industry level:

$$int_{r,t} = \sum\nolimits_n \frac{Emp_{n,r,t}}{\sum_n Emp_{n,r,t}} \times \frac{Robots_{n,t}}{Labour_{r,t}} \tag{8}$$

where $Robots_{n,t}$ denotes the number of industrial robots of industry n at year t. $Labour_{r,t}$ denotes the labor force number of city r at year t. $Emp_{n,r,t}$ denotes the labor force number of city r of industry n at year t. If the coefficients of $BCP_{r,t}$ in Eq. (6) and $M_{r,t}$ in Eq. (7) are statistically significant, this suggests that digitalization influences firm energy efficiency by impacting industrialization.

Variable-coefficient panel model. To further explore the effects of digitalization on firm energy efficiency across various regions, industries, and firm types, the following variable-coefficient panel model is developed in this paper:

$$y_{i,r,n,t} = \beta + \beta_0 \times BCP_{r,t} + \sum_{m}^{d-1} \beta_m \times BCP_{r,t} \times D_{i,r,n,t}^m + \varphi_i + \lambda_t + \gamma_r + \eta_n + \varepsilon_{i,r,n,t} \tag{9}$$

where $D_{i,r,n,t}^m$ denotes the region categorical dummy, industry categorical dummy or categorical dummy of types of firms and where d denotes the total number of categories. Owing to the problem of collinearity, $d-1$ dummy variable interaction terms are added to the model rather than d. For example, this paper divides China into eastern, central ($D_{i,r,n,t}^1 = 1$ if city i belongs to the central region, others = 0) and western regions ($D_{i,r,n,t}^2 = 1$ if city i belongs to the western region, others = 0). The coefficient β_0 reflects the impact of digitalization on firm energy efficiency in the eastern region, $\beta_1 + \beta_0$ and $\beta_2 + \beta_0$ reflects the impact of digitalization on firm energy efficiency in the eastern and western regions.

Data and variables. Most previous studies on the impact of digitalization on energy efficiency have focused on the national or regional levels. However, conclusions derived from aggregated macrolevel data often fail to provide a reliable foundation for addressing energy conservation and emission reduction at the microlevel, such as within enterprises. This study addresses this limitation by using the annual large-scale enterprise survey data of the China National Tax Survey Database (CNTSD) as the research sample.

CNTSD has two distinct advantages. First, the database provides three types of energy consumption indicators, including firm-level electricity consumption, coal consumption, and oil consumption. Unlike existing studies that primarily measure energy efficiency using output per unit of coal consumption, the CNTSD enables a more comprehensive assessment of how digitalization affects various types of energy efficiency. Second, compared with the widely used China Industrial Enterprise Database (CIED), the CNTSD encompasses not only industrial enterprises but also enterprise data from eight industry sectors, including the agricultural sector, mining sector, light industry sector, heavy industry sector, electricity, steam, gas, and water production sector, construction sector, service sector, and transportation sector. Because of this broader scope, the ways in which digitalization impacts firm-level energy efficiency across different sectors can be evaluated on a nuanced level.

Furthermore, the data on industrial robots by industry in China used in this paper are sourced from the International Federation of Robotics (IFR).

The CNTSD survey period spans from 2007 to 2016, with the primary dataset including information from approximately 500,000 firms annually. Since the BCP was implemented in 2014, this study focuses on firm-level data from 2011 to 2016 for evaluation. During this process, the raw data were cleaned and filtered as follows: (1) Samples with missing or abnormal values for energy consumption and business indicators were excluded. (2) Propensity score matching (PSM) was applied to match samples to the treatment group, yielding a more reliable control group. The detailed methods and matching results are provided in Appendix A.

To enhance the model's accuracy, fixed effects were chosen over random effects, enabling better control for unobserved heterogeneity. Specifically, firm, industry, year, and city fixed effects are incorporated in this study to account for unique firm characteristics, industry-specific factors, macroeconomic trends, and geographical differences. These controls effectively isolate the impact of the BCP on energy efficiency. By employing a high-dimensional fixed-effects model, the treatment effect of the BCP can be estimated simply by adding the dependent variable (Cui et al. 2021).

During the PSM process, total assets and labor were selected as covariates, with the detailed calculation methods outlined in Table 1. After PSM was applied, a total of 389,061 screened samples were identified as the final research objects. Descriptive statistics for each variable, along with the distribution of energy efficiency before and after the policy in both the treatment and control groups, are also presented in Table 1.

Results

Baseline results. Table 2 presents the regression results of the baseline model, highlighting the regression coefficients of BCP, which reflect the impact of digitalization on firm energy efficiency. The findings reveal notable variations in how digitalization influences different energy sources.

The results demonstrate that the implementation of the BCP led to a 17.2% ($p < 0.01$) reduction in firm-level energy efficiency derived from electricity. This finding highlights that the adoption of digitalization caused a significant decline in electricity efficiency among firms.

In contrast, the BCP had a positive effect on the energy efficiency derived from coal and oil, with increases of 10.5% ($p < 0.01$) and 11.3% ($p < 0.01$), respectively. These outcomes suggest that digitalization substantially enhanced efficiency in these areas.

Table 1 Descriptive statistics.

Panel A

Variables		Variable description	*N*	Mean	Min	Max	Std
Dependent variable	*Firm energy efficiency*	Output value per unit of electricity (10,000 yuan/kwh)	389,061	6.325	−6.571	14.930	2.203
		Output value per unit of coal (yuan/tons)	389,061	8.066	−8.181	14.952	3.134
		Output value per unit of oil (yuan/tons)	389,061	8.148	−6.119	14.952	2.410
	Firm energy consumption	Electricity consumption (kwh)	389,061	3.693	0.000	10.404	2.271
		Coal consumption (kg)	389,061	1.952	0.000	11.686	2.867
		Oil consumption (kg)	389,061	1.870	0.000	9.417	2.033
Independent variable	*BCP*	Dummy variables for BCP implementation	389,061	0.099	0.000	1.000	0.299
Mediating variable	*iu*	Added value of tertiary industry/added value of secondary industry	389,061	0.930	0.114	4.166	0.541
	int	Logarithmic values of urban industrial robot stock	389,061	6.777	1.562	0.297	0.913
Covariate for PSM	*Assets*	Total assets at the end of the year (10,000 yuan)	389,061	10.213	3.932	15.698	1.792
	Labor	Number of employees at the end of the year (10,000 people)	389,061	4.152	0.000	8.350	1.402

Panel B

Energy efficiency		Treatment group			Control group		
		Pre-policy	Post-policy	Change	Pre-policy	Post-policy	Change
Firm energy efficiency	Electricity	6.379	6.701	5.05%	5.959	6.891	15.64%
	Coal	8.213	8.202	−0.13%	7.898	7.864	−0.43%
	Oil	8.084	8.187	1.27%	8.144	8.377	2.86%
Firm energy consumption	Electricity	3.747	3.104	−17.16%	4.009	3.194	−20.33%
	Coal	1.913	1.602	−16.26%	2.07	2.221	7.29%
	Oil	2.042	1.618	−20.76%	1.824	1.707	−6.41%

Table 2 The average impact of digitalization on firm energy efficiency.

Variables	Firm energy efficiency			Firm energy consumption		
	Electricity	Coal	Oil	Electricity	Coal	Oil
	(1)	(2)	(3)	(4)	(5)	(6)
BCP	−0.172*** (0.018)	0.105*** (0.018)	0.113*** (0.018)	0.174*** (0.016)	−0.102*** (0.016)	−0.111*** (0.016)
C	6.342*** (0.002)	8.055*** (0.002)	8.137*** (0.002)	3.675*** (0.002)	1.962*** (0.002)	1.881*** (0.002)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	389,061	389,061	389,061	389,061	389,061	389,061
R^2	0.696	0.834	0.729	0.767	0.840	0.695
Adj-R^2	0.508	0.732	0.560	0.622	0.741	0.506
F	92.306	35.118	41.152	115.856	42.020	49.625

(1) *** signifies significance at the 1% level. (2) High-dimensional fixed effects methods are employed to concurrently control for firm characteristics, year characteristics, industry characteristics, and city characteristics. (3) Firm-level cluster robust standard errors are presented in parentheses.

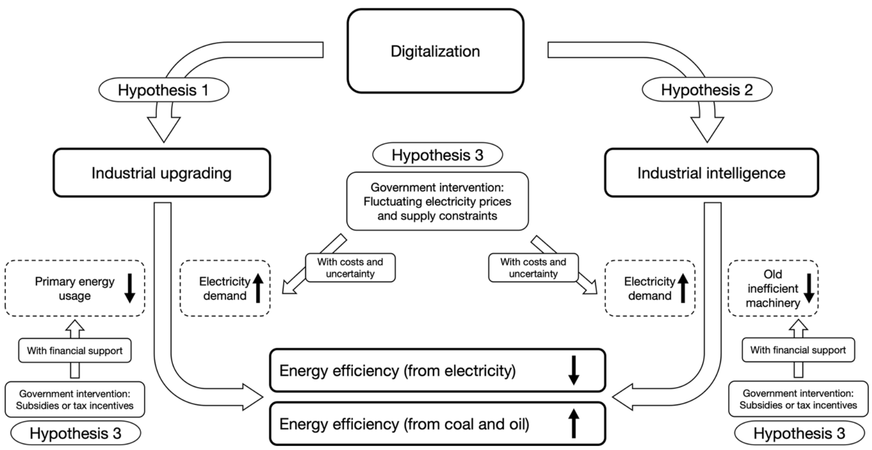

Fig. 1 Mechanism analysis.

Compared with the research findings of Hong et al. (2023), which were based on panel data from prefecture-level cities, the impact coefficients derived in this study, which focused on firms, are more significant. This discrepancy highlights that the effect of digitalization is more pronounced at the firm level, likely because of the direct and targeted implementation practices within firms.

In examining the impact of the BCP on firm energy consumption, the results reveal a 17.4% ($p < 0.01$) increase in energy consumption derived from electricity. This reflects a significant rise in electricity demand as firms adopt digitalization. Conversely, digitalization significantly reduced firm-level energy consumption derived from coal and oil by 10.2% ($p < 0.01$) and 11.1% ($p < 0.01$), respectively. These findings highlight the efficiency improvements and the reduced dependence on these traditional energy sources facilitated by the digitalization process.

The findings presented above also reveal that the increase in firm-level energy consumption derived from electricity is nearly equivalent to the decrease in energy efficiency associated with electricity. This suggests that the rapid rise in electricity consumption driven by digitalization does not yield a proportional increase in economic output. Moreover, the implementation of the BCP primarily enhances energy efficiency from coal and oil by reducing their consumption.

This finding indicates that the current stage of digital development has not yet effectively elevated the technical level of energy utilization within firms. Instead, it appears to directly influence energy consumption patterns and transitions between energy sources (Xue et al. 2022). Thus, governments should adopt a more cautious approach when evaluating the energy-saving and emission reduction effects of digitalization. Additionally, digital retrofitting should be further emphasized, with a focus on energy transitions and clean energy substitution to achieve more sustainable outcomes Figs. 1, 2.

Parallel trend test. Figure 3 shows the results of the parallel trend test. Prior to the implementation of the BCP, nearly all the regression coefficients of β_k ($k < 0$) failed to reach the 5% significance level, indicating that there were no notable differences in firm energy efficiency and energy consumption between the treatment and control groups. This outcome confirms that the parallel trend assumption is satisfied.

After the policy shock, the results depicted in the figure reveal a distinct pattern in the policy's impact on energy efficiency. Specifically, the policy's effect on energy efficiency derived from electricity is significantly negative, indicating a reduction in firms' ability to efficiently utilize electrical energy following the policy's implementation. Conversely, the policy has a positive effect on energy efficiency related to coal and oil, demonstrating an improvement in firms' ability to use these resources more efficiently.

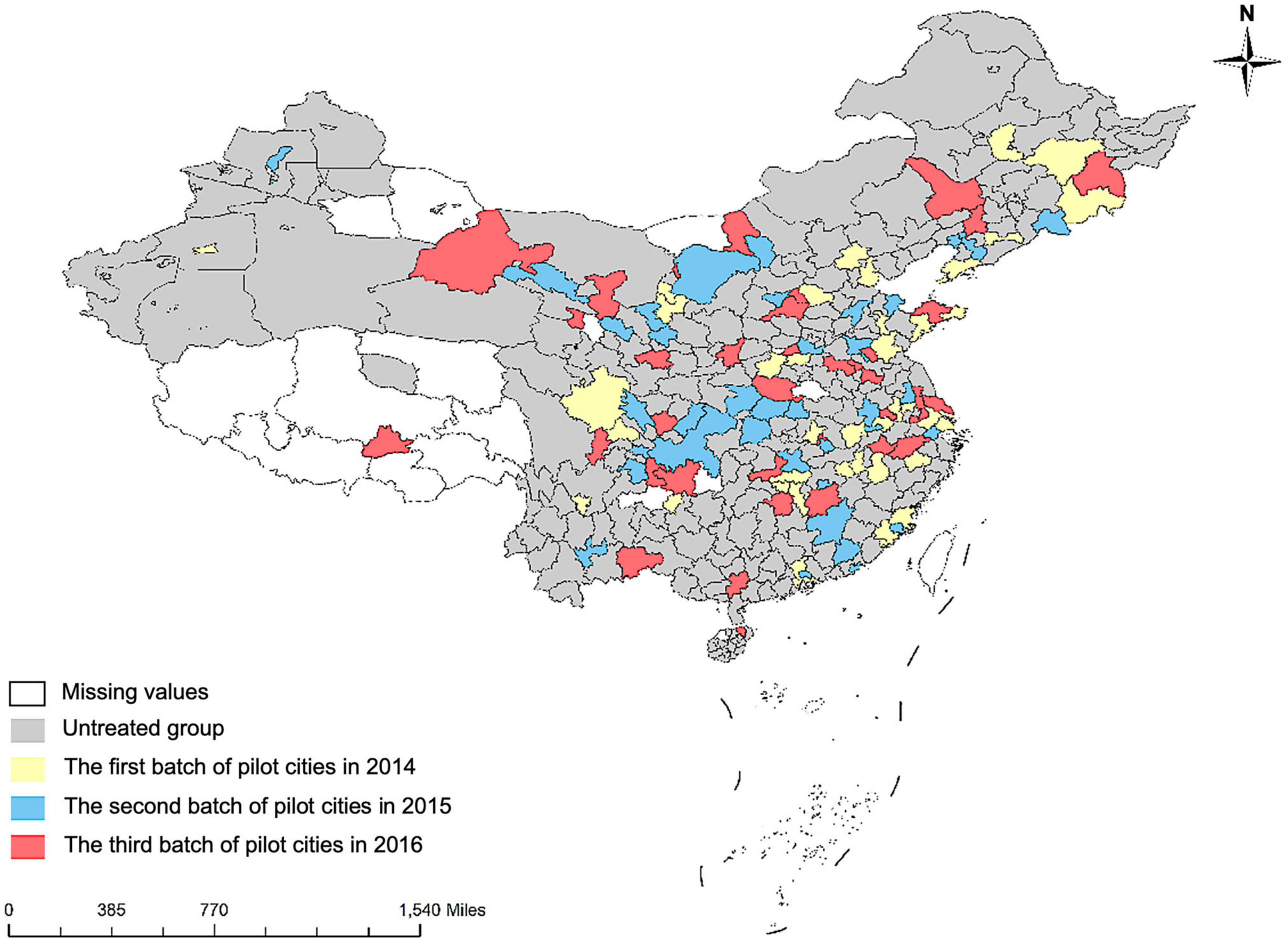

Fig. 2 Distribution of pilot cities implemented BCP.

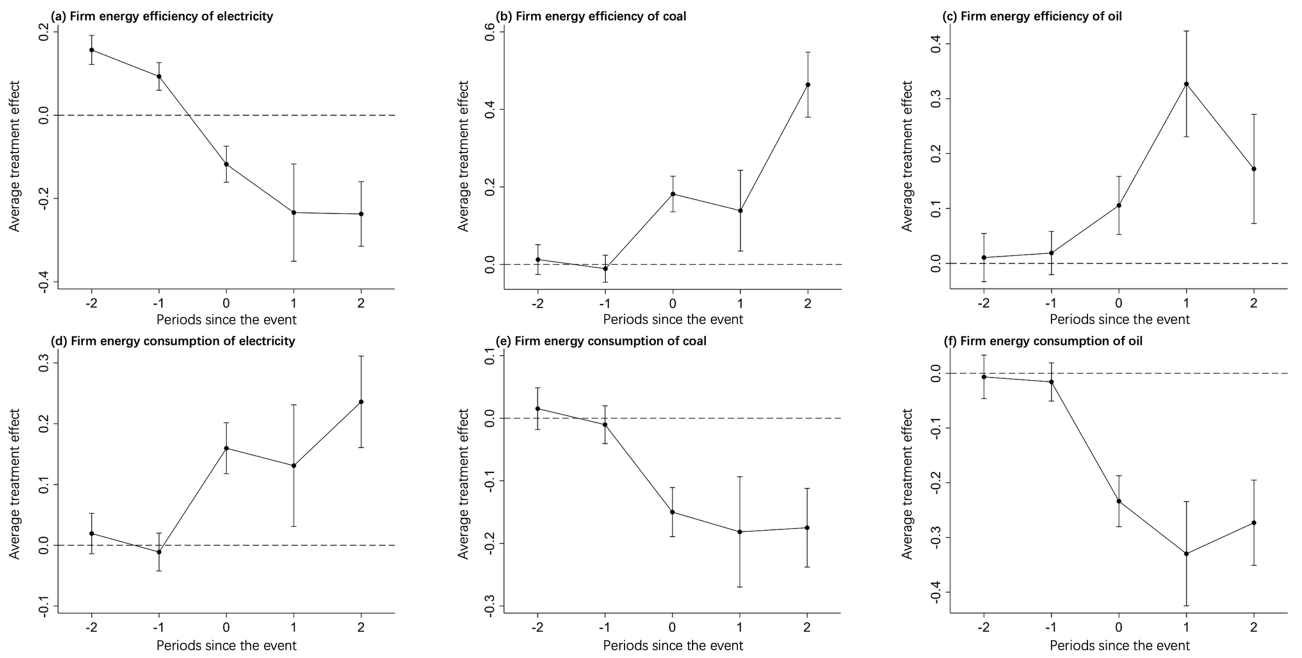

Fig. 3 Parallel trend test results. The X-axis represents the window period for BCP implementation, while the Y-axis displays the regression coefficient βk in the event study model. The year preceding BCP implementation serves as the base period. **a**–**c** present the results of the parallel trend tests using firm-level energy efficiency derived from electricity, coal, and oil. Similarly, **d**–**f** illustrate the results of the parallel trend tests with firm-level energy consumption derived from electricity, coal, and oil.

This contrasting impact highlights the differing responses of various energy sources to the policy and further corroborates that the parallel trend assumption holds for this analysis.

Robustness test

Placebo test. Since the BCP might influence firm energy efficiency in nonpilot cities, potentially leading to unreliable estimates, a Monte Carlo simulation approach is adopted in this paper. Specifically, samples from the control group are randomly selected to serve as the treated group, and the BCP parameters are re-estimated. The reliability of the analysis is then evaluated by determining whether the parameter distribution follows a normal distribution with a mean of 0 (Dong et al. 2022b; M. Li et al. 2022; Yu and Zhang, 2022).

Figure 4 illustrates the estimated coefficient distribution and the kernel density curve based on 1000 random draws. The coefficients are centered on zero and exhibit a normal distribution, which is consistent with expectations from a placebo test. This confirms that the observed changes in energy efficiency within the actual treated group are attributable to the implementation of BCP.

Re-estimation based on radius matching method of PSM. To increase the robustness of the estimation results and address potential biases arising from the PSM matching method, a radius matching approach with a radius of 0.03 is adopted in this study to better align the control group with the treated group. The results, presented in Table 3, show that the average effects of BCP on firm-level energy efficiency are −17.2% ($p < 0.01$) for electricity, 10.5% ($p < 0.01$) for coal, and 11.3% ($p < 0.01$) for oil. Additionally, the average impacts on firm-level energy consumption are 17.5% ($p < 0.01$) for electricity, −10.3% ($p < 0.01$) for coal, and −11.1% ($p < 0.01$) for oil. These results are largely consistent with the estimates in Table 2, reaffirming the reliability of the conclusions drawn in this paper.

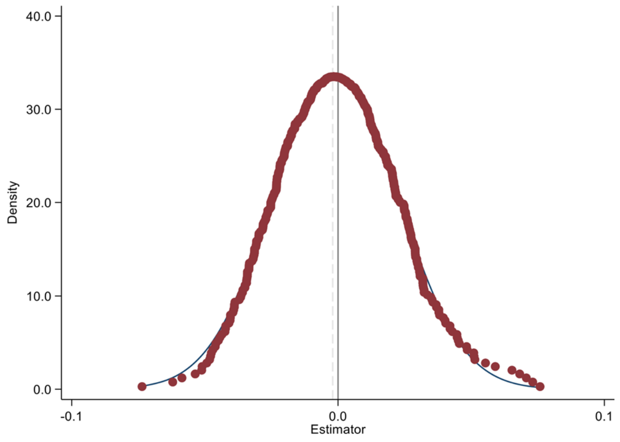

Fig. 4 Results of placebo test.

Re-estimation based on different dependent variables. To minimize the potential impact of variable selection on the estimation results, operating income per unit of energy consumption is adopted as a proxy for firm-level energy efficiency in this study. Moreover, per capita energy consumption is used to measure enterprise energy consumption. The re-estimation results, which are based on these substituted dependent variables, are shown in Table 4.

The findings indicate that the average effects of BCP on operating income per unit of electricity, coal, and oil consumption are −18.8% ($p < 0.01$), 17.4% ($p < 0.01$), and 4.9% ($p < 0.05$), respectively. Additionally, the average impacts of BCP implementation on firm energy consumption for electricity, coal, and oil were 18.8% ($p < 0.01$), −11.9% ($p < 0.01$) and −4.5% ($p < 0.05$), respectively.

These results align closely with those in Table 2, further confirming the robustness and reliability of the conclusions of this study.

Re-estimation excluding contemporaneous policy disturbances. To eliminate the potential interference of other concurrent policies on the analysis results, the policy impact of the Low-Carbon City Pilot (LCPC) initiative, which was implemented during the same period, is controlled in this paper. After this policy impact is incorporated into the model, the effects of BCP on urban carbon emission performance are presented in Table 5.

The findings in Table 5 show that BCP implementation reduced firm-level energy efficiency derived from electricity by 16.9% ($p < 0.01$) on average. Conversely, BCP significantly improved the firm-level energy efficiency derived from coal and oil, with increases of 10.4% ($p < 0.01$) and 11.1% ($p < 0.01$), respectively.

These results indicate that even when the LCPC is controlled, BCP consistently reduces the energy efficiency derived from

Table 3 Re-estimation based on radius matching methods of PSM.

Variables	Firm energy efficiency			Firm energy consumption		
	Electricity	Coal	Oil	Electricity	Coal	Oil
	(1)	(2)	(3)	(4)	(5)	(6)
BCP	−0.172*** (0.018)	0.105*** (0.018)	0.113*** (0.018)	0.175*** (0.016)	−0.103*** (0.016)	−0.111*** (0.016)
C	6.343*** (0.002)	8.057*** (0.002)	8.138*** (0.002)	3.677*** (0.002)	1.963*** (0.002)	1.882*** (0.002)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	388,650	388,650	388,650	388,650	388,650	388,650
R^2	0.696	0.834	0.728	0.767	0.840	0.695
Adj-R^2	0.508	0.732	0.560	0.622	0.741	0.506
F	93.055	35.170	40.769	116.248	42.410	49.509

(1) *** signifies significance at the 1% level. (2) High-dimensional fixed effects methods are employed to concurrently control for firm characteristics, year characteristics, industry characteristics, and city characteristics. (3) Firm-level cluster robust standard errors are presented in parentheses. (4) Re-run PSM with radius matching method ($r = 0.03$) and then regress.

Table 4 Re-estimation based on different dependent variables.

Variables	Revenue/energy consumption			Energy consumption/number of workers		
	Electricity	Coal	Oil	Electricity	Coal	Oil
	(1)	(2)	(3)	(4)	(5)	(6)
BCP	−0.188*** (0.017)	0.174*** (0.031)	0.049** (0.021)	0.188*** (0.015)	−0.119*** (0.027)	−0.045** (0.018)
C	6.383*** (0.004)	−5.804*** (0.008)	7.485*** (0.005)	−0.376*** (0.004)	−0.077*** (0.007)	−1.431*** (0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	316175	147323	213428	364589	170952	245529
R^2	0.232	0.259	0.188	0.176	0.260	0.188
Adj-R^2	0.231	0.257	0.186	0.175	0.258	0.186
F	116.191	31.995	5.393	154.516	19.854	6.474

(1) *** and ** signify significance at the 1% and 5% levels, respectively. (2) High-dimensional fixed effects methods are employed to concurrently control for firm characteristics, year characteristics, industry characteristics, and city characteristics. (3) Firm-level cluster robust standard errors are presented in parentheses. (4) The new dependent variables are in natural logarithms.

Table 5 Re-estimation excluding contemporaneous policy disturbances.

Variables	Firm energy efficiency			Firm energy consumption		
	Electricity	Coal	Oil	Electricity	Coal	Oil
	(1)	(2)	(3)	(4)	(5)	(6)
BCP	−0.169*** (0.018)	0.104*** (0.018)	0.111*** (0.018)	0.171*** (0.016)	−0.102*** (0.016)	−0.109*** (0.016)
LCPC	−0.177*** (0.015)	0.083*** (0.015)	0.210*** (0.016)	0.221*** (0.014)	−0.039*** (0.014)	−0.165*** (0.014)
C	6.419*** (0.007)	8.020*** (0.007)	8.046*** (0.007)	3.580*** (0.006)	1.979*** (0.006)	1.952*** (0.006)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	389,061	389,061	389,061	389,061	389,061	389,061
R^2	0.697	0.834	0.729	0.767	0.840	0.695
Adj-R^2	0.508	0.732	0.560	0.623	0.741	0.506
F	107.693	31.606	107.518	173.759	24.847	93.483

(1) *** signifies significance at the 1% level. (2) High-dimensional fixed effects methods are employed to concurrently control for firm characteristics, year characteristics, industry characteristics, and city characteristics. (3) Firm-level cluster robust standard errors are presented in parentheses.

electricity while enhancing the efficiency for coal and oil. This suggests that the original regression results remain robust.

Further analysis

Mechanisms by which digitalization affects firm energy efficiency. In Table 6, the regression outcomes regarding the mechanism of industrial upgrading are presented. In Column (1), the regression coefficient of *BCP* is 0.054 ($p < 0.01$), indicating a significant enhancement in regional industrial upgrading due to digitalization.

The regression coefficients of *iu* in Columns (2) to (4) are −0.459 ($p < 0.01$), −0.008 ($p > 0.1$), and 0.180 ($p < 0.01$), respectively. These results suggest that digitalization, by fostering industrial upgrading, leads to a reduction in firm electricity energy efficiency but an improvement in firm-level oil energy efficiency. Moreover, the regression coefficients of *iu* in Columns (5) to (7) are 0.344 ($p < 0.01$), −0.027 ($p > 0.1$), and −0.295 ($p < 0.01$), respectively. These results further illustrate that the implementation of BCP impacts enterprise energy efficiency and consumption by stimulating industrial upgrading.

The findings in Table 6 provide valuable insights into the mechanism of industrial upgrading. Additionally, this study examines whether BCP affects firm energy efficiency by promoting industrial intelligence. The regression results related to industrial intelligence mechanisms are summarized in Table 7.

In Column (1), the coefficient of *BCP* is 1.064 ($p < 0.01$), which indicates a significant enhancement in industrial intelligence as a result of the BCP policy. The coefficients of *int* in Columns (2) to (4) are −0.378 ($p < 0.01$), 0.346 ($p < 0.01$), and 0.106 ($p < 0.01$), respectively. These results suggest that BCP improves firm-level energy efficiency derived from coal and oil while reducing firm-level energy efficiency derived from electricity through the promotion of industrial intelligence.

Furthermore, the regression coefficients of *int* in Columns (5)–(7) are 0.512 ($p < 0.01$), −0.212 ($p < 0.01$), and −0.028 ($p < 0.01$), respectively. This finding indicates that BCP reduces firm-level energy consumption derived from coal and oil while increasing firm-level energy consumption derived from electricity via the enhancement of industrial intelligence.

These findings highlight the role of digitalization in shaping firm-level energy efficiency by fostering industrial intelligence.

Moderating effects of government intervention. Building on the research of Kang et al. (2022), which highlights that government

Table 6 Analysis of the mechanism of industrial upgrading.

	iu	Firm energy efficiency			Firm energy consumption		
		Electricity	Coal	Oil	Electricity	Coal	Oil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BCP	0.054***	−0.145***	0.107***	0.106***	0.152***	−0.101***	−0.099***
	(0.001)	(0.018)	(0.018)	(0.018)	(0.016)	(0.016)	(0.016)
iu		−0.459***	−0.088	0.180***	0.344***	−0.027	−0.295***
		(0.061)	(0.062)	(0.059)	(0.054)	(0.054)	(0.050)
C	0.925***	6.785***	8.189***	7.996***	3.349***	1.945***	2.138***
	(0.000)	(0.056)	(0.058)	(0.055)	(0.050)	(0.050)	(0.046)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	389,061	389,061	389,061	389,061	389,061	389,061	389,061
R^2	0.986	0.696	0.834	0.729	0.767	0.839	0.694
Adj-R^2	0.986	0.507	0.730	0.560	0.622	0.740	0.505
F	2974.897	67.536	18.040	25.762	69.715	20.834	45.309

(1) *** signifies significance at the 1% level. (2) High-dimensional fixed effects methods are employed to concurrently control for firm characteristics, year characteristics, industry characteristics, and city characteristics. (3) Firm-level cluster robust standard errors are presented in parentheses. (4) ***iu*** is defined as the ratio of added value from the tertiary industry to added value from the secondary industry within the city where the firm operates.

Table 7 Analysis of the mechanism of industrial intelligence.

	int	Firm energy efficiency			Firm energy consumption		
		Electricity	Coal	Oil	Electricity	Coal	Oil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BCP	1.064*** (0.014)	−0.041** (0.021)	0.255*** (0.021)	0.241*** (0.018)	0.056*** (0.020)	−0.239*** (0.020)	−0.226*** (0.017)
int		−0.378*** (0.010)	0.346*** (0.011)	0.106*** (0.010)	0.512*** (0.009)	−0.212*** (0.010)	−0.028*** (0.009)
C	3.971*** (0.001)	8.617*** (0.069)	5.542*** (0.075)	7.472*** (0.066)	0.533*** (0.064)	3.608*** (0.071)	1.678*** (0.060)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	389,061	389,061	389,061	389,061	389,061	389,061	389,061
R^2	0.798	0.601	0.830	0.712	0.707	0.838	0.681
Adj-R^2	0.798	0.364	0.729	0.540	0.533	0.743	0.491
F	5450.766	850.992	42.508	34.531	1780.563	41.229	34.611

(1) *** and ** signify significance at the 1% and 5% levels, respectively. (2) High-dimensional fixed effects methods are employed to concurrently control for firm characteristics, year characteristics, industry characteristics, and city characteristics. (3) Firm-level cluster robust standard errors are presented in parentheses. (4) ***int*** is measured by the logarithmic values of urban industrial robot stock.

intervention influences the energy usage of Chinese firms, this study further explores the moderating effect of government intervention levels on the relationship between digitalization and firm-level energy efficiency. The findings are summarized in Table 8.

According to the regression results in Table 8, the coefficients of $gov{\times}BCP$ are −4.490 ($p < 0.01$), 1.685 ($p < 0.01$), and 0.217 ($p > 0.1$), as shown in Columns (2), (4), and (6), respectively. These findings indicate that increased government intervention exacerbates the negative impact of digitalization on firm-level energy efficiency derived from electricity. Furthermore, government intervention enhances the positive effects of digitalization on firm-level energy efficiency derived from coal. These results highlight the need for governments to regulate firms' electricity consumption behavior during the digital transformation process and minimize inefficient electricity usage.

Heterogeneity analysis

In this study, we conduct a heterogeneity analysis by dividing the sample into subgroups on the basis of region, industry, firm size, and level of resource dependence. This approach is guided by several key considerations and directly ties into our mechanism analysis.

First, regional differences in economic development, technological infrastructure, and industrial structure lead to varying impacts of digitalization on firms' energy efficiency. Our mechanism analysis reveals that digitalization affects energy efficiency through industrial upgrading and industrial intelligence, and these effects likely vary across the Eastern, Central, and Western regions.

Second, industries exhibit distinct production processes, energy usage patterns, and levels of technological adoption, leading to distinct effects of digitalization on energy efficiency. By grouping the data by industry, we aim to identify how digitalization influences energy efficiency within each sector.

Third, firm size plays a crucial role in determining a company's capacity to access resources and enhance management efficiency during the digitalization process. Larger firms generally have more resources to leverage digitalization to improve energy efficiency, whereas SMEs may encounter greater challenges.

Table 8 Moderating effects of government intervention.

	Electricity		Coal		Oil	
	(1)	(2)	(3)	(4)	(5)	(6)
BCP	−0.162*** (0.018)	0.475*** (0.047)	0.092*** (0.018)	−0.147*** (0.042)	0.112*** (0.018)	0.081** (0.040)
gov	1.671*** (0.416)	2.108*** (0.468)	−3.185*** (0.472)	−3.349*** (0.501)	−0.752*** (0.282)	−0.774*** (0.285)
gov×BCP		−4.490*** (0.321)		1.685*** (0.273)		0.217 (0.252)
C	6.123*** (0.059)	6.063*** (0.066)	8.560*** (0.067)	8.582*** (0.071)	8.270*** (0.040)	8.272*** (0.040)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	389061	389061	389061	389061	389061	389061
R^2	0.696	0.696	0.834	0.834	0.729	0.729
Adj-R^2	0.507	0.508	0.731	0.731	0.560	0.560
F	52.420	87.059	39.362	32.744	24.463	16.531

(1) *** and ** signify significance at the 1% and 5% levels, respectively. (2) High-dimensional fixed effects methods are employed to concurrently control for firm characteristics, year characteristics, industry characteristics, and city characteristics. (3) Firm-level cluster robust standard errors are presented in parentheses. (4) ***gov*** is measured by the proportion of fiscal expenditure in GDP of the city where the firm is located.

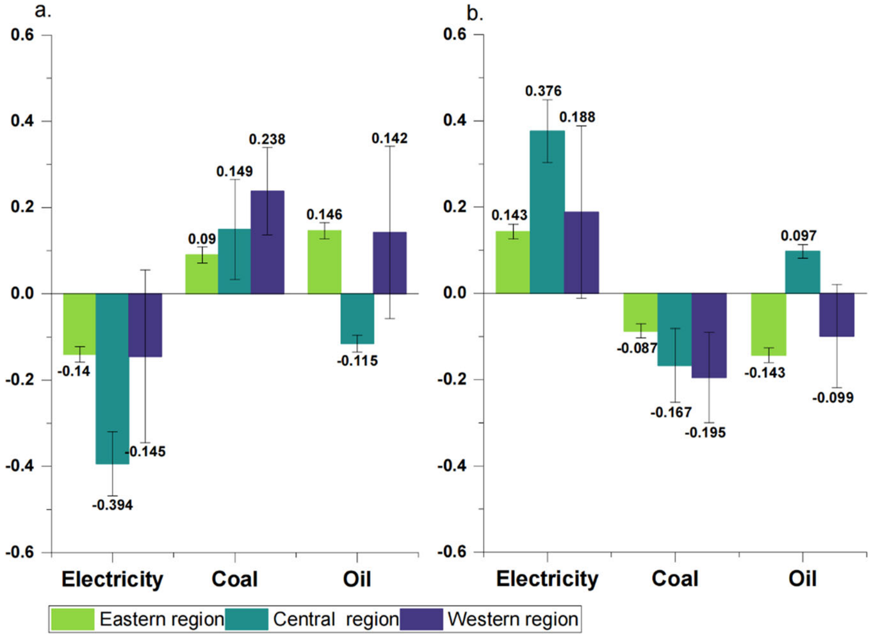

Fig. 5 Impact intensity of digitalization on firm energy efficiency in different regions (Bar graph). a denotes the impact of BCP on firm energy efficiency of electricity, coal and oil. The different colors of the bars denote Eastern region, Central region and Western region. The direction of the bar denotes whether the impact of BCP is positive or negative, and the length of the bar denotes the intensity of the impact on the firm energy efficiency in the region. The longer length means the more intense impact of BCP. **b** denotes the impact of BCP on firm energy consumption of electricity, coal and oil. The different colors of the bars denote Eastern region, Central region and Western region. The direction of the bar denotes whether the impact of BCP is positive or negative, and the length of the bar denotes the intensity of the impact on the firm energy consumption in the region. The longer length means the more intense impact of BCP. In addition, the line segment on the bar denotes the standard error of the impact. If the line segment does not intersect the x-axis, it denotes that the impact is significant.

Finally, a firm's level of resource dependence influences its sensitivity to changes in energy consumption and efficiency. Resource-dependent firms and nonresource-dependent firms are likely to respond differently to the industrial upgrading and industrial intelligence brought about by digitalization.

Through an examination of these dimensions, this study aims to uncover the subtle ways in which digitalization impacts different types of firms, providing valuable insights to inform more targeted and effective policy interventions.

Regional heterogeneity analysis. The impact of digitalization on energy efficiency and energy consumption in East China, Central China, and West China is illustrated in Fig. 5, with the bars showing the direction and magnitude of the effects of digitalization. The findings reveal that although the direction of digitalization's impact on energy efficiency and consumption is consistent across regions, there are notable differences in magnitude.

Specifically, in East China, the implementation of the BCP resulted in a 14.0% ($p < 0.01$) decrease in firm-level energy efficiency derived from electricity, whereas it increased firm-level energy efficiency derived from coal and oil by 9.0% ($p < 0.01$) and 14.6% ($p < 0.01$), respectively. In the central region, BCP implementation led to a 39.4% ($p < 0.05$) decrease in firm-level

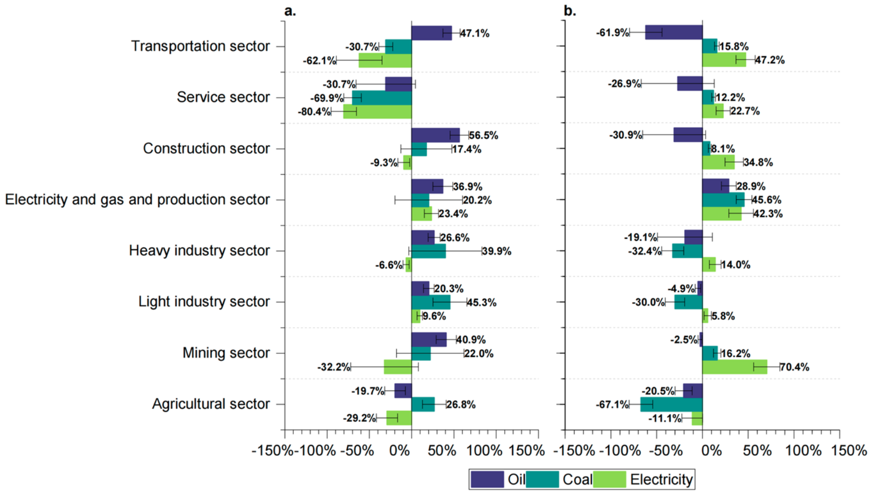

Fig. 6 The impact of digitalization on firm energy efficiency in different industry sectors. **a** denotes the impact of BCP on firm energy efficiency in different industry sectors. The different colors of the bars denote electricity, coal and oil efficiency. **b** denotes the impact of BCP on firm energy consumption in different industry sectors. The different colors of the bars denote electricity, coal and oil consumption. In addition, the direction of the bar denotes whether the impact of BCP is positive or negative. The line segment on the bar denotes the standard error of the impact. If the line segment does not intersect the x-axis, it denotes that the impact is significant.

energy efficiency derived from electricity, a 14.9% ($p < 0.1$) increase in coal efficiency, and an 11.5% ($p < 0.01$) decrease in oil efficiency. Conversely, in the western region, BCP had no significant effect on firm-level energy efficiency derived from electricity and oil but notably increased firm-level energy efficiency derived from coal by 23.8% ($p < 0.05$).

On the basis of these findings, we further investigate the influence of BCP on firm-level energy consumption. In East China, BCP implementation caused a 14.3% ($p < 0.01$) increase in electricity consumption, accompanied by significant reductions of 8.7% ($p < 0.01$) and 14.3% ($p < 0.01$) in coal and oil consumption, respectively. In the central region, BCP led to a 37.6% ($p < 0.01$) increase in firm-level energy consumption derived from electricity, a 16.7% ($p < 0.05$) decrease in coal consumption, and a 9.7% ($p < 0.01$) increase in oil consumption. In the western region, BCP implementation did not significantly affect electricity or oil consumption but notably reduced coal consumption by 19.5% ($p < 0.1$).

The implementation of the BCP has led to a notable increase in electricity consumption among firms in the eastern and central regions. However, the corresponding output does not increase significantly, resulting in a substantial decline in electricity energy efficiency. Moreover, BCP implementation significantly reduced coal consumption in the eastern, central, and western regions. For oil consumption, the BCP led to a decrease in the east region and an increase in the central region, while the output remained stable. With no significant changes in output, the BCP caused an increase in oil energy efficiency in the east and a decrease in the central region.

Notably, the improvements in firm-level energy efficiency derived from coal and oil in the Eastern region are almost entirely due to the reduced consumption of these energy sources. Conversely, the declines in electricity and oil energy efficiency are driven primarily by increased consumption of these resources. This suggests that current digitalization efforts do not effectively enhance the technological sophistication of energy use in firms, regardless of whether they are located in East China, Central China, or West China. Instead, digitalization primarily impacts direct energy consumption and shifts the use of different energy types.

Given these findings, we recommend that the government adopt a more balanced approach in evaluating the effects of digital energy savings and emission reduction across China's eastern, central, and western regions. Additionally, advancements in clean energy technologies need to be prioritized to ensure sustainable energy use and efficiency improvements.

Industry heterogeneity analysis. Figure 6 illustrates the impact of digitalization on energy efficiency and energy consumption across various industries. The bars represent both the direction and magnitude of digitalization's influence. Our findings reveal significant disparities in how digitalization affects energy efficiency across different sectors.

For example, the implementation of the BCP led to 62.1% ($p < 0.05$) and 30.7% ($p < 0.01$) decreases in firm-level energy efficiency derived from electricity and coal in the transportation sector, respectively, while simultaneously driving a 47.1% ($p < 0.01$) improvement in firm-level energy efficiency derived from oil. In the electricity, gas, and production sectors, BCP increased the firm-level energy efficiency derived from electricity and oil by 23.4% ($p < 0.01$) and 36.9% ($p < 0.01$), respectively.

Additionally, the light industry sector also experienced notable effects from BCP, with improvements of 9.6% ($p < 0.01$), 45.3% ($p < 0.05$), and 20.3% ($p < 0.01$) in firm-level energy efficiency derived from electricity, coal, and oil, respectively.

A further analysis of the impact of BCP on firm energy consumption reveals distinct effects across industries. In the transportation sector, BCP resulted in a 47.2% ($p < 0.01$) and a 15.8% ($p < 0.01$) increase in firm-level energy consumption derived from electricity and coal, while significantly reducing oil consumption by 61.9% ($p < 0.01$). In the electricity, gas, and production sector, BCP drove substantial increases in energy consumption: 42.3% ($p < 0.01$) for electricity, 45.6% ($p < 0.01$) for coal, and 28.9% ($p < 0.01$) for oil. In the mining sector, BCP significantly increased firm-level electricity consumption and coal consumption by 70.4% ($p < 0.01$) and 16.2% ($p < 0.01$). Conversely, digitalization in the agricultural sector reduced firm-level electricity, coal, and oil consumption by 11.1% ($p > 0.1$), 67.1% ($p < 0.1$), and 20.5% ($p < 0.05$), respectively.

These results demonstrate the considerable variability in BCP effects across industries. In many cases, implementing BCP leads to changes in energy consumption that are opposite in direction

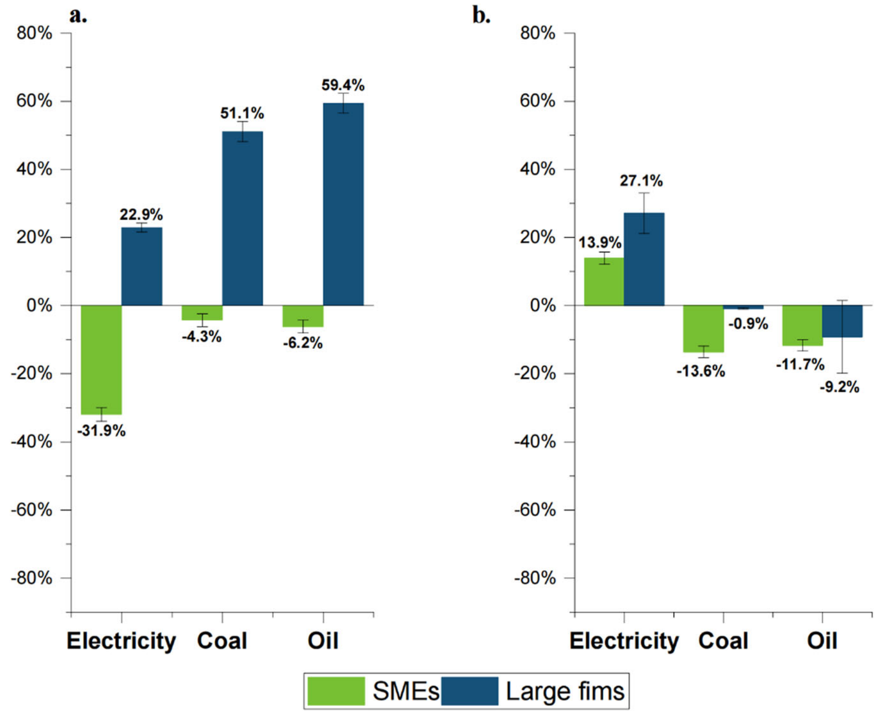

Fig. 7 Heterogeneity results of firms of different size. **a** denotes the impact of BCP on firm energy efficiency in different size. The different colors of the bars denote energy efficiency of SMEs and Large firms. **b** denotes the impact of BCP on firm energy consumption in different size. The different colors of the bars denote energy consumption of SMEs and Large firms. In addition, the direction of the bar denotes whether the impact of BCP is positive or negative. The line segment on the bar denotes the standard error of the impact. If the line segment does not intersect the x-axis, it denotes that the impact is significant.

to the corresponding changes in energy efficiency. This shows that digital development has a limited effect on enhancing technological efficiency across most industries. However, firm-level energy consumption and energy efficiency have increased simultaneously in the electricity, gas, and production sectors. This shows that BCP still contributes to output growth and technological advancement in certain sectors, particularly in the energy production industry.

These results highlight the uneven impact of digitalization on improving the technological utilization of energy across industries (Husaini and Lean, 2022). The characteristics of each industry also play a crucial role in shaping the effects of digitalization. Therefore, policy-makers should adopt a more tailored approach when evaluating the energy-saving and emission reduction effects of digitalization. Special efforts should focus on promoting digital energy transitions in highly energy-intensive industries.

Heterogeneity analysis of different firm sizes. Figure 7 illustrates the impact of digitalization on energy efficiency and energy consumption across firms of different sizes. The results reveal notable differences in how digitalization affects energy efficiency on the basis of firm size.

For example, the implementation of the BCP reduced the energy efficiency derived from electricity in small and medium enterprises (SMEs) by 31.9% ($p < 0.01$), whereas it led to a 22.9% ($p < 0.01$) increase in energy efficiency derived from electricity in large firms. Additionally, the BCP reduced the energy efficiency derived from coal and oil in SMEs by 4.3% ($p < 0.05$) and 6.2% ($p < 0.01$), respectively. In contrast, it improved the energy efficiency derived from coal and oil in large enterprises by 51.1% ($p < 0.01$) and 59.4% ($p < 0.01$), respectively.

Examining the impact of the BCP on firm-level energy consumption further highlights these differences. Among SMEs, the BCP led to a 13.9% ($p < 0.01$) increase in electricity consumption while reducing coal consumption by 13.6% ($p < 0.01$) and oil consumption by 11.7% ($p < 0.01$). For large companies, the BCP increased electricity consumption by 27.1% ($p < 0.01$) but reduced coal and oil consumption by 0.9% ($p < 0.01$) and 9.2% ($p > 0.1$), respectively.

According to the results in Fig. 7, there are significant or even contradictory outcomes for firms of different sizes. The implementation of the BCP has resulted in an increase in firm-level energy consumption derived from electricity and a decrease in firm-level coal and oil consumption across firms of all sizes. In terms of energy efficiency, the BCP has enhanced energy efficiency in large firms but reduced it in SMEs. This finding highlights that digital development is far more effective in improving energy efficiency for large firms than for SMEs.

Therefore, this paper argues that the government should pay closer attention to the changes in energy efficiency experienced by SMEs under the BCP policy while also ensuring that energy efficiency improvements continue for large firms. The energy efficiency and emission reduction effects of digitalization should be assessed more carefully, considering the distinct characteristics of firms of different sizes. Moreover, digitalization initiatives should be designed to benefit both large firms and SMEs, ensuring balanced progress in energy efficiency across the board.

Heterogeneity analysis of different resource dependencies of firms. Figure 8 reports the impact of digitalization on energy efficiency and energy consumption in firms with varying levels of resource dependence. Our findings show that the effects of digitalization on energy efficiency are generally consistent between resource-dependent and nonresource-dependent firms.

For example, implementing BCP reduced firm-level energy efficiency derived from electricity by 65.7% ($p < 0.01$) in resource-

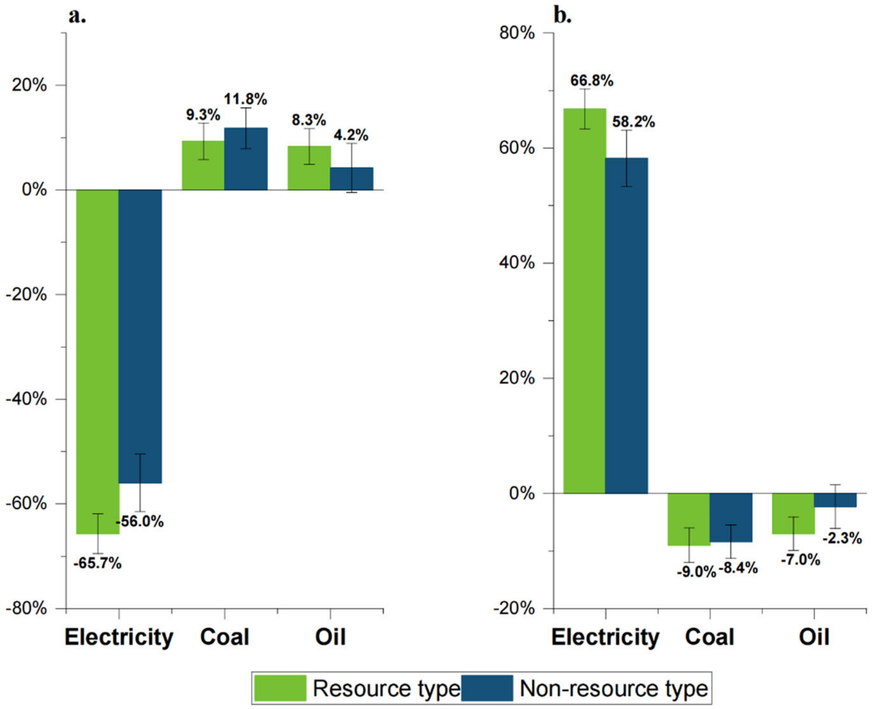

Fig. 8 Heterogeneity results of firms of different resource dependencies. a denotes the impact of BCP on firm energy efficiency of different resource dependencies. The different colors of the bars denote energy efficiency of firms in resource type and non-resource type. **b** denotes the impact of BCP on firm energy consumption of different resource dependencies. The different colors of the bars denote energy consumption of firms in resource type and non-resource type. In addition, the direction of the bar denotes whether the impact of BCP is positive or negative. The line segment on the bar denotes the standard error of the impact. If the line segment does not intersect the x-axis, it denotes that the impact is significant.

dependent firms and 56.0% ($p < 0.01$) in nonresource-dependent firms. However, it improved the firm-level energy efficiency derived from coal by 9.3% ($p < 0.01$) and 11.8% ($p < 0.01$) and increased the energy efficiency derived from oil by 8.3% ($p < 0.01$) and 4.2% ($p > 0.1$).

A further analysis of the effect of the BCP on firm-level energy consumption reveals significant increases in electricity consumption, increasing by 66.8% ($p < 0.01$) and 58.2% ($p < 0.01$) for resource-dependent and nonresource-dependent firms, respectively. Moreover, BCP reduced firm-level coal consumption by 9.0% ($p < 0.01$) and 8.4% ($p < 0.01$) and lowered oil consumption by 7.0% ($p < 0.01$) and 2.3% ($p > 0.1$), respectively.

The results presented in Fig. 8 demonstrate that BCP produces similar effects for both resource-dependent and nonresource-dependent firms. In most instances, implementing BCP results in an increase in firm-level energy consumption derived from electricity while reducing coal and oil consumption. This trend leads to changes in the opposite direction for the corresponding energy efficiency. These findings highlight that digital development has a limited impact on driving technological advancements in both resource-dependent and nonresource-dependent firms.

Conclusions and policy implications

Conclusions. While previous studies have highlighted the beneficial effects of digital transformation policies on regional energy efficiency, the influence of digitalization on firm-level energy efficiency remains largely unexplored. This paper investigates the impact of digitalization on firm energy efficiency using the PSM-DID model, leveraging a distinctive dataset of firm tax records. Additionally, this study goes beyond prior work by examining variations in the impact of digitalization on firm energy efficiency across the electricity, coal, and oil sectors.

First, the PSM-DID model results reveal that the "Broadband China Policy" improved the firm-level energy efficiency derived from coal and oil by 10.5% and 11.3%, respectively, but reduced the energy efficiency derived from electricity by 17.2%. The BCP also led to a 17.4% increase in firm-level electricity consumption, coupled with 10.2% and 11.0% reductions in firm-level coal and oil consumption, respectively. These findings suggest that the energy efficiency improvements attributed to BCP primarily stem from changes in energy consumption. Robustness checks, including parallel trend tests, placebo tests, and re-estimations using alternative variables and matching methods, validate these results.

Second, the mechanism analysis results reveal that the BCP has influenced firm-level energy efficiency through the enhancement of industrial upgrading and industrial intelligence. Furthermore, greater government intervention exacerbated the negative impact of the BCP on electricity energy efficiency while intensifying its positive effects on coal and oil energy efficiency.

Third, the heterogeneity analysis uncovers substantial differences in the impact of the BCP on firm energy efficiency on the basis of region, industry sector, firm size, and resource dependence. Regionally, the BCP had the least negative effect on electricity energy efficiency in the eastern region but most significantly improved coal and oil energy efficiency in the western region. By industry, the decline in electricity energy efficiency due to the BCP is primarily observed in the transportation and service sectors. In contrast, the effects on coal and oil energy efficiency are predominantly positive in light and heavy industries, suggesting that the service sector's transformation under BCP has reduced overall firm-level energy efficiency. With respect to firm size, the BCP has a markedly stronger positive effect on the energy efficiency of large enterprises than on that of SMEs. Finally, from the perspective of resource dependence, the BCP significantly reduces electricity energy efficiency in resource-dependent firms but has a pronounced positive effect on coal and oil energy efficiency in these firms.

Policy implications. On the basis of these findings, we propose several recommendations to assist both practitioners and policymakers in improving energy efficiency during digital transformation. Our research reveals that digitalization has led to a 17.2% decrease in firm electricity energy efficiency and a 17.4% increase in electricity consumption. To address this, firms should adopt advanced energy management systems (EMSs) that allow real-time monitoring and optimization of energy use. Policymakers can support this by offering financial incentives, such as low-interest loans or grants, specifically for the implementation of these systems. Additionally, providing training programs for facility managers would help ensure that these systems are used effectively to maximize energy savings.

This study also highlights notable energy efficiency challenges in the service and transport sectors, where digitalization has resulted in enormous efficiency declines. To address this issue, policymakers should establish sector-specific energy efficiency standards and require mandatory energy audits as part of digital transformation initiatives in these industries. Companies that meet or exceed these standards could be rewarded with tax incentives or public recognition, whereas those that do not meet these standards could face penalties. For firms in the service and transport sectors, upgrading energy-intensive digital infrastructure, such as data centers and logistics systems, should be a priority to comply with these new standards.

Moreover, this study reveals that SMEs and resource-dependent firms face particularly significant challenges due to limited resources for investing in energy-efficient technologies. To mitigate this, policymakers should introduce targeted support measures, such as energy efficiency grants or subsidies covering a significant portion of the costs for upgrading to efficient equipment. Partnering with technology providers to offer discounts on energy-efficient upgrades could further assist these firms. SMEs and resource-dependent firms should actively seek out these opportunities and consider forming alliances to share resources, enabling them to negotiate better terms for purchasing and implementing energy-efficient technologies.

Finally, we recommend the creation of a "green digitalization" certification program to encourage firms to focus on energy efficiency during their digital transformation. This certification would recognize companies that achieve substantial energy savings, offering them a competitive edge in the market. Policymakers could work with industry associations to create this program, providing benefits such as reduced regulatory burdens, priority in public contracts, or enhanced marketing opportunities. Firms should aim to earn this certification by planning their digital transformation efforts with a strong emphasis on energy efficiency, thereby improving their performance while also gaining market recognition.

Data availability
All data generated or analyzed during this study are available upon request.

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References
Acemoglu D, Restrepo P (2020) Unpacking skill bias: automation and new tasks. AEA Pap Proc 110:356–361. https://doi.org/10.1257/pandp.20201063

Adom PK, Amakye K, Abrokwa KK, Quaidoo C (2018) Estimate of transient and persistent energy efficiency in Africa: a stochastic frontier approach. Energy Convers Manag 166:556–568. https://doi.org/10.1016/j.enconman.2018.04.038

Amasawa E, Ihara T, Hanaki K (2018) Role of e-reader adoption in life cycle greenhouse gas emissions of book reading activities. Int J Life Cycle Assess 23:1874–1887. https://doi.org/10.1007/s11367-017-1417-5

Anthopoulos L, Kazantzi V (2022) Urban energy efficiency assessment models from an AI and big data perspective: tools for policy makers. Sustain Cities Soc 76:103492. https://doi.org/10.1016/j.scs.2021.103492

Bałaga D, Siegmund M, Kalita M, Williamson BJ, Walentek A, Małachowski M (2021) Selection of operational parameters for a smart spraying system to control airborne PM10 and PM2.5 dusts in underground coal mines. Process Saf Environ Prot 148:482–494. https://doi.org/10.1016/j.psep.2020.10.001

Barbera E, Mio A, Massi Pavan A, Bertucco A, Fermeglia M (2022) Fuelling power plants by natural gas: An analysis of energy efficiency, economical aspects and environmental footprint based on detailed process simulation of the whole carbon capture and storage system. Energy Convers Manag 252:115072. https://doi.org/10.1016/j.enconman.2021.115072

Berndt ER, Wood DO (1975) Technology, prices, and the derived demand for energy. Rev Econ Stat 57:259. https://doi.org/10.2307/1923910

Cai W, Li Y, Li L, Lai K, Jia S, Xie J, Zhang Y, Hu L (2022) Energy saving and high efficiency production oriented forward-and-reverse multidirectional turning: energy modeling and application. Energy 252:123981. https://doi.org/10.1016/j.energy.2022.123981

Chen S, Ding Y, Song Y, Zhang M, Nie R (2023) Study on China's energy system resilience under the scenarios of long-term shortage of imported oil. Energy 270:126831. https://doi.org/10.1016/j.energy.2023.126831

Chen Z, Tan Y, Xu J (2022) Economic and environmental impacts of the coal-to-gas policy on households: evidence from China. J Clean Prod 341:130608

Cui J, Wang C, Zhang J, Zheng Y (2021) The effectiveness of China's regional carbon market pilots in reducing firm emissions. Proc Natl Acad Sci USA 118:e2109912118. https://doi.org/10.1073/pnas.2109912118

Dehghan Shabani Z, Shahnazi R (2019) Energy consumption, carbon dioxide emissions, information and communications technology, and gross domestic product in Iranian economic sectors: a panel causality analysis. Energy 169:1064–1078. https://doi.org/10.1016/j.energy.2018.11.062

Devlin A, Yang A (2022) Regional supply chains for decarbonising steel: energy efficiency and green premium mitigation. Energy Convers Manag 254:115268. https://doi.org/10.1016/j.enconman.2022.115268

Dong F, Li Y, Gao Y, Zhu J, Qin C, Zhang X (2022a) Energy transition and carbon neutrality: exploring the non-linear impact of renewable energy development on carbon emission efficiency in developed countries. Resour Conserv Recycl 177:106002. https://doi.org/10.1016/j.resconrec.2021.106002

Dong F, Li Y, Qin C, Zhang X, Chen Y, Zhao X, Wang C (2022b) Information infrastructure and greenhouse gas emission performance in urban China: a difference-in-differences analysis. J Environ Manag 316:115252. https://doi.org/10.1016/j.jenvman.2022.115252

Dong F, Li Y, Zhang X, Zhu J, Zheng L (2021) How does industrial convergence affect the energy efficiency of manufacturing in newly industrialized countries? Fresh evidence from China. J Clean Prod 316:128316. https://doi.org/10.1016/j.jclepro.2021.128316

Du M, Feng R, Chen Z (2022) Blue sky defense in low-carbon pilot cities: a spatial spillover perspective of carbon emission efficiency. Sci Total Environ 846:157509. https://doi.org/10.1016/j.scitotenv.2022.157509

Dvořák J, Wittlingerová Z, Vochozka M, Stehel V, Maroušková A (2018) Updated energy policy of the Czech Republic may result in instability of the electricity grid in Central Europe. Clean Technol Environ Policy 20:41–52

Fisher-Vanden K, Jefferson GH, Jingkui M, Jianyi X (2006) Technology development and energy productivity in China. Energy Econ 28:690–705. https://doi.org/10.1016/j.eneco.2006.05.006

Guo D, Li Q, Liu P, Shi X, Yu J (2023) Power shortage and firm performance: evidence from a Chinese city power shortage index. Energy Econ 119:106593. https://doi.org/10.1016/j.eneco.2023.106593

He Y, Fu F, Liao N (2021) Exploring the path of carbon emissions reduction in China's industrial sector through energy efficiency enhancement induced by R&D investment. Energy 225:120208. https://doi.org/10.1016/j.energy.2021.120208

Hong J, Shi F, Zheng Y (2023) Does network infrastructure construction reduce energy intensity? Based on the "Broadband China" strategy. Technol Forecast Soc Change 190:122437. https://doi.org/10.1016/j.techfore.2023.122437

Hong Q, Cui L, Hong P (2022) The impact of carbon emissions trading on energy efficiency: evidence from quasi-experiment in China's carbon emissions trading pilot. Energy Econ 110:106025. https://doi.org/10.1016/j.eneco.2022.106025

Hsu P-H, Tian X, Xu Y (2014) Financial development and innovation: cross-country evidence. J Financ Econ 112:116–135. https://doi.org/10.1016/j.jfineco.2013.12.002

Hu B, Zhou P, Zhang LP (2022) A digital business model for accelerating distributed renewable energy expansion in rural China. Appl Energy 316:119084. https://doi.org/10.1016/j.apenergy.2022.119084

Huang G, He L-Y, Lin X (2022) Robot adoption and energy performance: evidence from Chinese industrial firms. Energy Econ 107:105837. https://doi.org/10.1016/j.eneco.2022.105837

Husaini DH, Lean HH (2022) Digitalization and energy sustainability in ASEAN. Resour Conserv Recycl 184:106377. https://doi.org/10.1016/j.resconrec.2022.106377

Jia S, Chen X, Jin J (2024) Digital disruption and energy efficiency: the impact of regional digitalization on China's industrial sector. Energy 300:131542. https://doi.org/10.1016/j.energy.2024.131542

Kang J, Yu C, Xue R, Yang D, Shan Y (2022) Can regional integration narrow city-level energy efficiency gap in China? Energy Policy 163:112820. https://doi.org/10.1016/j.enpol.2022.112820

Khoshroo A, Izadikhah M, Emrouznejad A (2021) Energy efficiency and congestion considering data envelopment analysis and bounded adjusted measure: a case of tomato production. J Clean Prod 328:129639. https://doi.org/10.1016/j.jclepro.2021.129639

Kumbhakar SC, Lien G, Hardaker JB (2014) Technical efficiency in competing panel data models: a study of Norwegian grain farming. J Product Anal 41:321–337. https://doi.org/10.1007/s11123-012-0303-1

Lange S, Pohl J, Santarius T (2020) Digitalization and energy consumption. Does ICT reduce energy demand? Ecol Econ 176:106760. https://doi.org/10.1016/j.ecolecon.2020.106760

Li B, Han Y, Wang C, Sun W (2022) Did civilized city policy improve energy efficiency of resource-based cities? Prefecture-level evidence from China. Energy Policy 167:113081. https://doi.org/10.1016/j.enpol.2022.113081

Li F, Zhang J, Li X (2023) Energy security dilemma and energy transition policy in the context of climate change: a perspective from China. Energy Policy 181:113624

Li M, Pan X, Yuan S (2022) Do the national industrial relocation demonstration zones have higher regional energy efficiency? Appl Energy 306:117914. https://doi.org/10.1016/j.apenergy.2021.117914

Li Q, Li M, Zhang L (2024) Revisiting the relationship between ESG, institutional ownership, and corporate innovation: An efficiency perspective. https://doi.org/10.1002/csr.2937

Li Y, Zhang J, Yang X, Wang W, Wu H, Ran Q, Luo R (2021) The impact of innovative city construction on ecological efficiency: a quasi-natural experiment from China. Sustain Prod Consum 28:1724–1735. https://doi.org/10.1016/j.spc.2021.09.012

Lin B, Huang C (2023) Nonlinear relationship between digitalization and energy efficiency: evidence from transnational panel data. Energy 276:127601

Lin B, Huang C (2022) Analysis of emission reduction effects of carbon trading: Market mechanism or government intervention? Sustain. Prod. Consum. S2352550922001622. https://doi.org/10.1016/j.spc.2022.06.016

Lin B, Zhu R (2021) Energy efficiency of the mining sector in China, What are the main influence factors? Resour Conserv Recycl 167:105321. https://doi.org/10.1016/j.resconrec.2020.105321

Liu J, Li X, Zhong S (2022) Does innovation efficiency promote energy consumption intensity? New evidence from China. Energy Rep. 8:426–436. https://doi.org/10.1016/j.egyr.2022.05.096

Liu Y, Wang X, Zhou S, Chen H (2021) Enhancing public building energy efficiency using the response surface method: an optimal design approach. Environ Impact Assess Rev 87:106548. https://doi.org/10.1016/j.eiar.2020.106548

Mayers K, Koomey J, Hall R, Bauer M, France C, Webb A (2015) The carbon footprint of games distribution: the carbon footprint of games distribution. J Ind Ecol 19:402–415. https://doi.org/10.1111/jiec.12181

Mišík M, Oravcová V (2022) Ex ante governance in the European Union: Energy and climate policy as a 'test run' for the post-pandemic recovery. Energy Policy 167:113076. https://doi.org/10.1016/j.enpol.2022.113076

Moon H, Min D (2020) A DEA approach for evaluating the relationship between energy efficiency and financial performance for energy-intensive firms in Korea. J Clean Prod 255:120283. https://doi.org/10.1016/j.jclepro.2020.120283

Niu Y, Lin X, Luo H, Zhang J, Lian Y (2022) Effects of digitalization on energy efficiency: evidence from Zhejiang Province in China. Front Energy Res 10. https://doi.org/10.3389/fenrg.2022.847339

Noussan M, Jarre M, Degiorgis L, Poggio A (2017) Data analysis of the energy performance of large scale solar collectors for district heating. Energy Procedia 134:61–68. https://doi.org/10.1016/j.egypro.2017.09.619

Pan X, Ai B, Li C, Pan X, Yan Y (2019) Dynamic relationship among environmental regulation, technological innovation and energy efficiency based on large scale provincial panel data in China. Technol Forecast Soc Change 144:428–435. https://doi.org/10.1016/j.techfore.2017.12.012

Qin P, Liu M, Su L, Fei Y, Tan-Soo J-S (2022) Electricity consumption in the digital era: Micro evidence from Chinese households. Resour Conserv Recycl 182:106297. https://doi.org/10.1016/j.resconrec.2022.106297

Ramanathan R (2006) A multi-factor efficiency perspective to the relationships among world GDP, energy consumption and carbon dioxide emissions. Technol Forecast Soc Change 73:483–494. https://doi.org/10.1016/j.techfore.2005.06.012

Rawte R (2017) The role of ICT in creating intelligent, energy efficient buildings. Energy Procedia 143:150–153. https://doi.org/10.1016/j.egypro.2017.12.663

Shah WUH, Hao G, Yan H, Yasmeen R, Padda IUH, Ullah A (2022) The impact of trade, financial development and government integrity on energy efficiency: an analysis from G7-Countries. Energy 255:124507. https://doi.org/10.1016/j.energy.2022.124507

Shahbaz M, Wang J, Dong K, Zhao J (2022) The impact of digital economy on energy transition across the globe: The mediating role of government governance. Renew Sustain Energy Rev 166:112620. https://doi.org/10.1016/j.rser.2022.112620

Shao M, Xue M (2022) Decomposition analysis of carbon emissions: considering China's energy efficiency. Energy Rep. 8:630–635. https://doi.org/10.1016/j.egyr.2022.05.114

Strobel T (2016) ICT intermediates and productivity spillovers—evidence from German and US manufacturing sectors. Struct Change Econ Dyn 37:147–163. https://doi.org/10.1016/j.strueco.2016.04.003

Sun H, Edziah BK, Kporsu AK, Sarkodie SA, Taghizadeh-Hesary F (2021) Energy efficiency: the role of technological innovation and knowledge spillover. Technol Forecast Soc Change 167:120659. https://doi.org/10.1016/j.techfore.2021.120659

Sun J, Du T, Sun W, Na H, He J, Qiu Z, Yuan Y, Li Y (2019) An evaluation of greenhouse gas emission efficiency in China's industry based on SFA. Sci Total Environ 690:1190–1202. https://doi.org/10.1016/j.scitotenv.2019.07.093

Usman M, Balsalobre-Lorente D (2022) Environmental concern in the era of industrialization: Can financial development, renewable energy and natural resources alleviate some load? Energy Policy 162:112780. https://doi.org/10.1016/j.enpol.2022.112780

van den Buuse D, Kolk A (2019) An exploration of smart city approaches by international ICT firms. Technol Forecast Soc Change 142:220–234. https://doi.org/10.1016/j.techfore.2018.07.029

Vu K, Hartley K (2022) Effects of digital transformation on electricity sector growth and productivity: A study of thirteen industrialized economies. Util Policy 74:101326. https://doi.org/10.1016/j.jup.2021.101326

Wang Z, Wang X (2022) Research on the impact of green finance on energy efficiency in different regions of China based on the DEA-Tobit model. Resour Policy 77:102695. https://doi.org/10.1016/j.resourpol.2022.102695

Wen J, Okolo CV, Ugwuoke IC, Kolani K (2022) Research on influencing factors of renewable energy, energy efficiency, on technological innovation. Does trade, investment and human capital development matter? Energy Policy 160:112718. https://doi.org/10.1016/j.enpol.2021.112718

Wen S, Jia Z (2022) The energy, environment and economy impact of coal resource tax, renewable investment, and total factor productivity growth. Resour Policy 77:102742. https://doi.org/10.1016/j.resourpol.2022.102742

Xiao Y, Huang H, Qian X-M, Chen L (2023) Can carbon emission trading pilot facilitate green development performance? Evidence from a quasi-natural experiment in China. J Clean Prod 400:136755. https://doi.org/10.1016/j.jclepro.2023.136755

Xue Y, Tang C, Wu H, Liu J, Hao Y (2022) The emerging driving force of energy consumption in China: Does digital economy development matter? Energy Policy 165:112997. https://doi.org/10.1016/j.enpol.2022.112997

Yazar M, York A, Larson KL (2022) Adaptation, exposure, and politics: Local extreme heat and global climate change risk perceptions in the Phoenix metropolitan region, USA. Cities 127:103763. https://doi.org/10.1016/j.cities.2022.103763

Yu Y, Zhang N (2022) Does industrial transfer policy mitigate carbon emissions? Evidence from a quasi-natural experiment in China. J Environ Manag 307:114526. https://doi.org/10.1016/j.jenvman.2022.114526

Zhang H, Zhang L, Zhang N (2024) When and under what conditions does an emission trading scheme become cost effective? Energy J 45:261–294. https://doi.org/10.5547/01956574.45.2.hzha

Zhang Y, Zhang M, Liu Y, Nie R (2017) Enterprise investment, local government intervention and coal overcapacity: the case of China. Energy Policy 101:162–169

Zhang Z, Chen H (2022) Dynamic interaction of renewable energy technological innovation, environmental regulation intensity and carbon pressure: Evidence from China. Renew Energy 192:420–430. https://doi.org/10.1016/j.renene.2022.04.136

Zheng Z (2021) Energy efficiency evaluation model based on DEA-SBM-Malmquist index. Energy Rep. 7:397–409. https://doi.org/10.1016/j.egyr.2021.10.020

Zhong Z, Peng B (2022) Can environmental regulation promote green innovation in heavily polluting enterprises? Empirical evidence from a quasi-natural experiment in China. Sustain Prod Consum 30:815–828. https://doi.org/10.1016/j.spc.2022.01.017

Zhou S, Xu Z (2022) Energy efficiency assessment of RCEP member states: a three-stage slack based measurement DEA with undesirable outputs. Energy 253:124170. https://doi.org/10.1016/j.energy.2022.124170

Zhu J, Lin B (2022) Economic growth pressure and energy efficiency improvement: Empirical evidence from Chinese cities. Appl Energy 307:118275. https://doi.org/10.1016/j.apenergy.2021.118275

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Author contributions

We declare that each of us made a significant contribution to conducting this work. HL, YW, JL and CY drafted the design and work. HL, YW and XZ improved the methods. HL, AW and SS did the data collection and drew the figures. JL and CY revised the work. All authors were involved in analyzing and interpreting the data for the paper. HL, YW, JL and CY reviewed and proofread the manuscript. All authors approved the final version.

Competing interests

The authors declare no competing interests.

Ethical approval

No human participants were involved.

Informed consent

No human participants were involved.

Additional information

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