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Digital transition and the clean renewable energy adoption in rural family: evidence from Broadband China

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Introduction: The increasing digital transformation and the global need for sustainable energy solutions have sparked considerable interest in the examination of digital technologies' impact on the adoption of clean renewable energy. However, limited research focuses on energy consumption in rural households, especially in developing countries such as China.

Methods: This study leverages the quasi-natural experiment provided by the Broadband China Policy (BCP) and utilizes data from the China Labor-force Dynamics Survey (CLDS) spanning 2012 to 2016. Our investigation aims to understand the effect of the digital transition on the adoption of clean renewable energy within rural families. We employ staggered Difference-in-Difference (DID) and Doubly Robust Staggered DID estimators to assess this impact, allowing us to explore regional heterogeneity.

Results: Our findings reveal that implementing the BCP significantly influences clean renewable energy adoption, although this effect varies across different regions. Specifically, in the middle region, the BCP results in a notable 5.8% increase in clean renewable energy adoption compared to non-pilot cities. However, in the east and west regions, the BCP is associated with a decrease of 12.6% and 13.5%, respectively, in clean renewable energy adoption. Dynamic effect analysis further indicates that the east region had already experienced high clean renewable energy adoption prior to the BCP's implementation, while the BCP positively influences clean renewable energy intentions in the west region.

Discussion: Our analysis identifies three significant channels through which the BCP affects clean renewable energy adoption: population size, economic size, and income level. Larger populations and greater economic size enhance the BCP's impact on clean renewable energy adoption. These findings provide empirical evidence for developing countries that seek to harness digital development for technological advancement, industrial upgrading, and carbon emission reduction.

KEYWORDS

digital transition, clean renewable energy, rural family, Broadband China, Difference-in-Difference

1 Introduction

In recent years, the world's attention on environmental issues and climate change has grown significantly, leading to proactive efforts in exploring strategies to combat pollution and reduce greenhouse gas emissions. The excessive use of fossil fuels and inefficient energy structures have been identified as significant contributors to these pressing environmental challenges (Zhang and Bai, 2017; Lv et al., 2021; Li and Zhao, 2023). Reinforcing the situation's urgency, the International Energy Agency (IEA) recently released a report highlighting the concerning trends. In 2021, global coal power generation witnessed a worrisome increase of 9%, while carbon emissions from energy combustion and industrial processes grew by 6%. Particularly alarming is the staggering amount of 15.3 billion tons of CO_2 emissions resulting from coal consumption, accounting for over 40% of the total incremental emissions. Disturbingly, the IEA projects a further 0.7% rise in global coal consumption in 2022. Given these critical developments, nations worldwide are prioritizing socioeconomic sustainability by promoting and advancing clean, renewable energy sources.

The significance of sustainable energy in mitigating pollution and improving environmental conditions has sparked significant scholarly interest in comprehending the factors influencing individuals' adoption of such energy sources. Existing literature explores multiple avenues of inquiry, encompassing various dimensions. One prominent line of research delves into demographic factors such as age, education, income, and social status (Zografakis et al., 2010; Willis et al., 2011; Eshchanov et al., 2021; Irfan et al., 2021). Furthermore, scholars have explored subjective attitudes and psychological elements, including the acceptance of sustainable energy, trust, and risk perception (Zografakis et al., 2010; Upton and Snyder, 2015; Irfan et al., 2021). In addition, scholars have closely examined macro variables, such as economic development (Eren et al., 2019; Razmi and Janbaz, 2020; Wang et al., 2021), economic incentives, and energy policies (Asante et al., 2020); the development of the clean renewable energy industry (Molnarova et al., 2012; Ge et al., 2022); and environmental pollution (Zhang et al., 2021). These issues underscore the need to devise strategies for measuring and addressing the challenges associated with innovation and the adoption of clean renewable energy.

Digital technology has emerged as a potential solution to the aforementioned challenges, as noted by numerous scholars. The advent of digital technologies has transformed the way both businesses and individuals operate, ushering in a digital transition (El Hilali et al., 2020). Key elements of this transition include 5G, artificial intelligence, the Internet of Things (IoT), and information and communication technology (ICT). These evolving digital technologies have the potential to reshape the energy consumption patterns of corporations (Ren et al., 2021). However, there has been relatively limited research focusing on the energy consumption of residents.

ICT, with broadband as one of its foundational components, has already delivered significant economic benefits (Bertschek et al., 2015). Moreover, broadband is one of the most immediate and tangible aspects of the digital transition that directly affects the lives of residents. In China, for instance, urban dwellers predominantly use natural gas as a domestic fuel, whereas fossil fuels remain the primary source of energy in rural areas. Against this backdrop, it becomes particularly intriguing to investigate the causal effects of broadband connectivity on the adoption of clean renewable energy among rural residents.

We propose three potential pathways through which digital transition may promote household clean renewable energy adoption (CREA). Firstly, governance participation and pollution control play a crucial role. Improved internet accessibility resulting from the Broadband China Policy (BCP) enables the dissemination of information and knowledge (Chen et al., 2022b). It also provides a platform for rural residents to voice their opinions on environmentally friendly policies, encouraging the government to invest in and develop clean renewable energy infrastructure. This, in turn, can facilitate a shift in the energy consumption structure of households towards cleaner sources. Secondly, the availability of job opportunities and increased salary income can influence clean energy adoption in rural households. Internet access opens up new avenues for rural residents to access job opportunities and entrepreneurial platforms (Cheng et al., 2021). Higher-income levels, resulting from these opportunities, can positively impact the adoption of clean energy technologies by making them more affordable and accessible to households (Commander et al., 2011). Lastly, the process of industrial upgrading stimulated by the BCP can significantly affect clean energy adoption. As industries undergo technological advancements and upgrades, local economies are likely to experience growth. This economic growth can provide the local government with resources and the ability to invest in clean technology infrastructure (do Valle Costa et al., 2008; Yu et al., 2015). Moreover, increased income levels resulting from industrial upgrading can enable households to afford and adopt clean renewable energy solutions.

China's BCP, initiated in 2013, 2014, and 2015, presents a unique opportunity to investigate the role of broadband in promoting the adoption of clean renewable energy among rural families. This policy exhibits three distinctive features that facilitate our empirical analysis. Firstly, the BCP pilot cities are directly designated by the China central government, and while local governments can seek qualification as BCP cities, they lack the authority to decide their inclusion in the BCP list. As a result, the BCP represents an exogenous event for both local governments and residents, providing a natural experimental setting. Secondly, China's household registration system (Hukou) and the escalating real estate prices impose significant restrictions on migration between rural areas and cities. This limited mobility between regions further emphasizes the localized impact of the BCP on rural residents. Finally, the investment in broadband infrastructure, prompted by the BCP pilot cities, is temporary. After the establishment of essential infrastructure such as station towers, the primary investment in BCP tends to reduce.

We conducted a comprehensive study by hand-collecting county-level data for the "Broadband China" pilot cities in 2013, 2014, and 2015, and merged this dataset with the individual-level data from the China Labor-force Dynamics Survey (CLDS). Employing a staggered Difference-in-Difference with two-way fixed effects (TWFE DID) and dynamic staggered DID methodology proposed by Callaway and Sant'Anna (2021), our research reveals compelling insights into the impact of the BCP on CREA, while also identifying regional variations in this effect. In the middle region, the implementation of the BCP results in a noteworthy 5.8% increase in CREA compared to non-pilot cities. However, contrasting trends are observed in the east and west regions, where the BCP is associated with a decrease of 12.6% and 13.5% in CREA. Further analysis using dynamic effects demonstrates that the east region had already witnessed a high level of CREA prior to the BCP's implementation, while the BCP positively influences clean renewable energy intentions in the west region. Moreover, we investigate the role of natural gas, a clean energy source in China, and find that the BCP contributes to a 1.38% increase in natural gas usage specifically in the east region.

The identification strategy of TWFE-DID relies on the parallel assumption, which states that, in the absence of any intervention, trends in CREA should not be related to the intensity of the treatment represented by the BCP. Our findings provide evidence supporting this assumption. We employed two main approaches to confirm this premise. Firstly, we utilized an event study strategy to compare the outcome trends of the treatment group and the control group before the treatment group received the BCP. This analysis revealed no significant pre-treatment differences between the two groups.

Secondly, we thoroughly examined the potential influences of specific local characteristics, such as the level of sunshine duration and local government efforts to decrease pollution, as well as the impact of other contemporaneous historical events like green finance initiatives, the digital country program, and the innovation cities project. We found that the BCP's implementation was independent of these factors, further affirming the parallel assumption. During the study period of BCPs, the Chinese government intensified its efforts to combat environmental pollution, leading to the rapid expansion of CREA, such as the adoption of natural gas in families and solar power in manufacturers since the late 2010s. To control for this confounding factor, we collected province-by-year information on CREA. Despite the influence of pollution control policies and the expansion of renewable energy adoption during the study period, our estimation coefficients on the BCPs remained stable, indicating that the BCPs had a distinct and independent effect on CREA. Additionally, we accounted for local pollution levels in the district and the level of green finance in each city, further ensuring the robustness of our analysis.

Our study highlights the significant consequences of the digital transition on CREA among rural families, shedding new light on the role of digital transformation in promoting environmental protection and sustainable economic growth in China. While existing research has explored the macro effects of digital transition on renewable energy consumption in China, little attention has been paid to the individual level, particularly in rural areas where fossil fuel adoption is predominant. In this paper, we bridge this gap by merging individual-level and macro-level data to examine the effects of digital transition on CREA in rural areas. Our analysis primarily focuses on rural families affected by the digital transition during the late 1990s and the 21st century. This period was characterized by significant industrialization and urbanization reforms, which enabled the rural labor force to seek employment opportunities outside their hometowns. Additionally, the reform and opening up policies provided opportunities for rural residents with basic education to find work abroad, leading to higher income and improved access to better infrastructure compared to living in rural areas. Many of them took up jobs as manufacturing workers or in the flourishing Township and Village enterprises. As a result of these economic opportunities, a considerable portion of rural families now reside in cities or overseas, while still sending income back to their families living in rural areas. This interaction has facilitated the exchange of ideas and concepts, including the promotion of environmentally friendly energy consumption practices. Building on these observations, our empirical findings suggest a potential link between the increase in CREA, driven by the digital transition and the rapid expansion of internet infrastructure in China, and the country's overall economic growth during the reform era.

Our study mainly contributes to two strands of literature. The first examines the channels of digital transition and energy consumption, especially the energy consumption in a rural family. Surveys show that digital technology increased labor productivity, promoted the reorganization of the supply chain, and reduced energy consumption (Hertin and Berkhout, 2001). With the availability of digital technology adoption data, economists conduct a lot of empirical research on digital transition and energy consumption; internet technology adoption is one of the main driving forces behind economic growth, and it also promotes energy product efficiency (Atkinson and McKay, 2007). The rapid spread of internet technology changes the energy use intensity and renewable energy cost; therefore, it reduces carbon emissions and energy resource consumption (Moyer and Hughes, 2012); specifically, ICT significantly improves the electricity adoption efficiency in European manufacturing companies (Ishida, 2015). These studies focus on the macroeconomic effects of digital technology on renewable energy adoption, mainly based on the macro-level data. In contrast, our results demonstrate that increasing local digital technology adoption significantly promotes renewable energy adoption in rural families. Moreover, the development of the local economy is an important channel through which BCPs improve renewable energy adoption in a rural family. Additionally, digital technology adoption will increase electricity usage, and according to the rebound effect, the digital transition may increase energy consumption. In developed countries, electricity is important in the causal effect path between digital technology adoption and economic growth. Empirical evidence based on OECD panel data shows that internet technology adoption not only promotes the development of the economy but also increases the quantity of electricity consumption both in the short and long term (Salahuddin and Alam, 2016). In developing countries, the digital transition significantly positively increases both electricity consumption and energy consumption. Even in China, the biggest developing country, digital transition increases the total energy consumption at the province level (Ren et al., 2021). Unlike the existing literature, our paper examines the individual-level renewable energy adoption in a rural area of the biggest developing country. We also investigate the intermediate effects of other factors, such as electricity adoption in families, social connection to the neighborhoods, economic foundation, and industrial structure in the local area. Furthermore, we compare the effect of BCPs on family renewable energy adoption in cities, the developed area, and the county, the developing area. Our empirical results show that electricity consumption has a significantly positive intermediate effect on the causal path between BCP and renewable energy adoption, and the BCPs have shown more significant effects in the rural family rather than in the citizen family.

The second literature investigates the economic impact of digital transition policy, especially internet communication technology. Economists have studied this topic from a lot of perspectives including GDP (Jorgenson, 2001), economic growth rate (Czernich et al., 2011), innovation performance (Paunov and Rollo, 2016), green technology innovation and adoption (Tang et al., 2021), and financial market (Cheng et al., 2021). However, the digital transition policy impact on rural individual-level outcomes remains understudied, and our study contributes to the economic consequence of digital transition policy in two ways. First and foremost, we uncover the mechanisms by which economic growth and infrastructure improvements due to digital technology adoption affect residential energy preferences; therefore, we extend the economic impact of digital transition from the macro level to the individual level and explored the potential mechanism between macro factors and individual behavior.

Therefore, our study makes notable contributions to the existing literature by exploring the microlevel effects of digital transition on CREA within rural families, particularly in the context of China's BCP. Unlike previous research that mainly focused on macroeconomic effects, our investigation specifically targets rural areas, where fossil fuel adoption remains prevalent. Leveraging the unique exogenous nature of the BCP, a centrally designed policy, we offer compelling evidence on the causal impact of broadband connectivity on renewable energy adoption. Additionally, our paper goes beyond direct effects and examines intermediate factors, including electricity adoption, social connections, local economic foundation, and industrial structure, to unravel the mechanisms underlying the relationship between the BCP and CREA. Notably, we identify regional variations, highlighting diverse outcomes in China's east, west, and middle regions. Our comprehensive empirical analysis, combining individual-level and macro-level data with advanced econometric techniques, sheds new light on the role of digital technology in promoting sustainable energy adoption, and its potential contribution to China's environmental protection and sustainable economic growth goals.

The remainder of this paper is organized as follows. *Section 2* is the literature review. *Section 3* briefly reviews the institutional background of Broadband China. *Section 4* presents a mechanism analysis of digital transition and renewable energy adoption in rural China. *Section 5* introduces datasets and econometric setups. *Section 6* represents the empirical results of how digital transition affects renewable energy adoption in Chinese rural families. *Section 7* provides the conclusions and policy implications.

2 Literature review

The synergies between digital transition and renewable energy adoption have become central to discussions surrounding sustainable development, particularly in rural areas. This comprehensive review of recent literature aims to unearth the depth and breadth of research conducted on these topics, analyzing the impact of digitalization on renewable energy adoption among rural families.

2.1 Digital transition

The transformational influence of digital technologies is perceptible in both urban and rural environments, particularly concerning economic growth, family income, and energy consumption structures. Draca et al. (2009) scrutinized the role of digital technology in promoting productivity, deducing that access to precise and extensive information is integral to productivity growth. Koutroumpis (2009), using data from OECD countries between 2002 and 2007, explored the relationship between broadband adoption and GDP growth, confirming that broadband utilization significantly bolsters GDP growth. Furthermore, broadband adoption has a substantial positive impact on employment, annual payroll, and the establishment of businesses (Kandilov and Renkow, 2010; Mack and Faggian, 2013; Mack and Rey, 2014; Castellacci and Vinas-Bardolet, 2019), although internet growth seems unrelated to wage growth (Forman et al., 2012).

Whitacre et al. (2014) leveraged county-level data in the US from 2001 to 2010 to determine a causal link between fixed residential broadband availability/adoption and rural economic development. Their findings show that counties with higher levels of broadband adoption experienced faster growth in median household income and reduced growth in unemployment, while counties with lower levels of broadband adoption endured slower growth in employment and number of firms. Wang et al. (2022) employed macro-level data in China to investigate the causal relationship between digital transition and electricity consumption. Their findings suggest that digital transition fosters the progression of the energy consumption structure.

2.2 Renewable energy adoption

The transition towards renewable energy is shaped by a multitude of factors spanning socioeconomic and environmental aspects (Mensah, 2019). Significant research has underscored the pivotal role that energy efficiency plays in the context of environmental pollution, underlining the detrimental impact of economic activities on our ecosystems (Khan et al., 2021). Areas characterized by relative energy poverty stand to benefit significantly from the adoption of renewable energy, which has the potential to alleviate energy scarcity while also reducing income inequality, thereby fostering sustainable development (Nguyen and Nasir, 2021; Zhao et al., 2022).

However, despite the lower cost profile of renewable energy compared to traditional fossil fuels (Masterson, 2021), non-renewable sources remain the dominant form of energy in developing regions (Noor et al., 2023). This dominance is expected to wane as a country's level of development progresses, leading to increased adoption of renewable energy (Guney, 2019). Moreover, the literature illustrates an inverse relationship between GDP growth and the adoption of non-renewable energy (Chen et al., 2022a). A study that delved into public acceptance of renewable energy underscored the importance of government engagement in the decision-making process and stressed the need for awareness about the direct benefits of renewable energy for the environment and the people (Guney and Kantar, 2020).

Similarly, Wei and Huang (2022) conducted an exploration into the economic ramifications of renewable energy adoption by looking into adjusted national savings. They concluded that renewable energy technologies can confer significant economic advantages and act as a catalyst for sustainable development. However, the initial financial burden and technology constrain associated with adopting renewable energy may deter families under financial constraints from its adoption (Khan et al., 2023). Thus, policy interventions to reduce the initial cost of renewable energy systems could significantly bolster their adoption in rural areas.

When examining environmental factors, D'Adamo et al. (2023) conceptualized renewable energy adoption as an ecological transition, discovering a strong association between environmental consciousness and the uptake of renewable energy technologies. Interestingly, even with the adoption of renewable energy, total energy consumption continues to maintain a negative correlation with environmental protection and sustainable development (Gasimli et al., 2022). This highlights a trend among rural families with higher environmental consciousness who are more likely to adopt renewable energy technologies. Consequently, it underscores the need for persistent environmental education initiatives to bolster the adoption of renewable energy technologies.

The existing literature undeniably underscores the integral role digital technologies hold in numerous dimensions of economic development. However, it is critical to acknowledge that the digital transition profoundly influences consumer behavior at the individual level. Furthermore, considerable room remains for exploring the intricate interplay between digital technologies, industry structures, pollution levels, and family income, among other factors, particularly in the context of CREA and sustainable economic growth.

The complexity of these interactions poses intriguing questions for future research. How does digital transformation influence the energy consumption choices of individuals? In what ways do industry structures and pollution levels interact with digital technologies to impact energy consumption patterns? How does the family income level shape the influence of digital transition on CREA? Perhaps most importantly, how can these insights be leveraged to inform effective policy design?

Exploring these questions could enrich our understanding of the multifaceted relationships between digital technologies and various economic and environmental factors. This deeper understanding, in turn, could empower policymakers to more effectively employ digital technologies as a tool for promoting economic prosperity and sustainability across diverse contexts. This pursuit also aligns with the global agenda for sustainable development, particularly in light of the increasing importance of clean energy for tackling climate change and ensuring economic resilience.

3 Institutional background

3.1 The "Broadband China" Policy: a brief history

Broadband China is an ambitious initiative launched by the Chinese government to promote the development and development of high-speed broadband infrastructure across the country. Recognizing the crucial role that broadband connectivity plays in driving economic growth, social progress, and technological innovation, China has taken significant steps to bridge the digital divide and create a digitally inclusive society.

The origins of the "Broadband China" Policy can be traced back to August 2013, and the primary objective of it is to provide universal access to high-quality broadband services for all citizens, regardless of their geographic location. In this plan, the local governments play a crucial role, not only to build broadband infrastructure but also to introduce relevant policies supporting the implementation of broadband. More specifically, according to this plan, in these pilot cities, significant progress has to be made in the implementation of urban fiber-optic connectivity, extending from building to homes, as well as in the expansion of broadband access in rural areas by 2015, including villages. The penetration rate of fixed broadband in households is supposed to reach 50%; furthermore, the adoption rate of third-generation mobile communications, along with its long-term evolution technology (3G/LTE), is supposed to stand at 32.5%. Broadband access in administrative villages, whether through wired or wireless methods, is supposed to achieve a remarkable coverage of 95%. Moreover, broadband connectivity is supposed to be effectively established in educational institutions, libraries, hospitals, and other public facilities. The average broadband access speed in urban and rural households is supposed to reach approximately 20 megabits per second (Mbps) and 4 Mbps, respectively, with certain advanced cities even attaining speeds of up to 100 Mbps. To achieve these goals, during 2013–2015, the Chinese government selected 117 pilot cities to implement broadband in China in three batches. Figure 1 presents the Broadband China pilot cities in 2014, 2015, and 2016.

3.2 Digital transition in Broadband China pilot cities

Our paper uses "Broadband China" as a proxy variable for digital transition in China. The key variation used in this paper comes from the different batches of Broadband China pilot cities. The exogenous nature of broadband expansion in China about

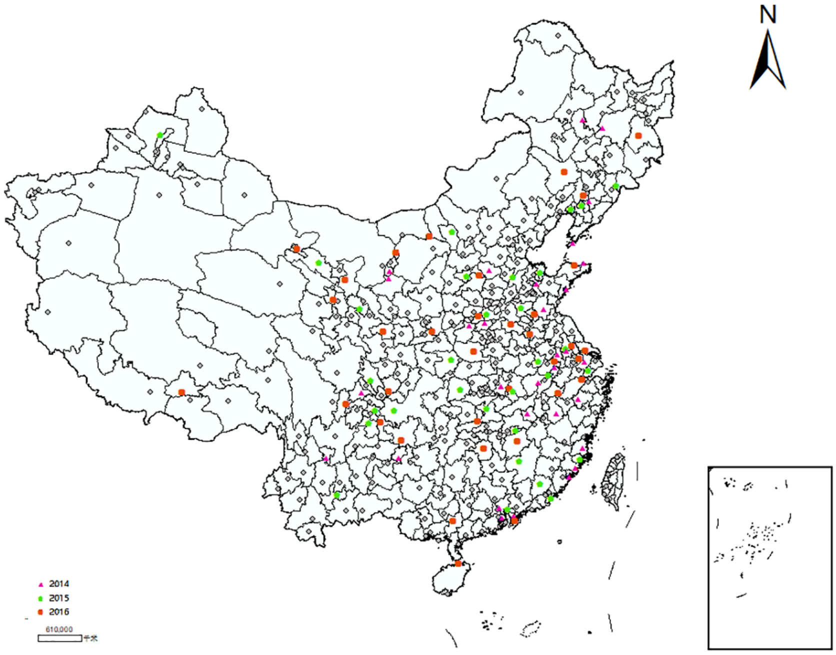

FIGURE 1
Broadband China Policy pilot cities.

household clean energy usage allows the identification strategy employed in this paper to effectively capture the causal relationship.

The broadband network serves as a crucial public infrastructure for China's economic and social development in the contemporary era. Its progress and expansion play a significant role in stimulating productive investment, fostering information consumption, facilitating the transition of development models, and constructing a prosperous society. Internationally, the broadband network is propelling a new wave of information-driven advancements, prompting numerous countries to prioritize its development as a strategic imperative. It is considered a vital measure to secure a competitive advantage in international economic, scientific, technological, and industrial arenas. Over the past years, China has witnessed a continuous expansion in broadband network coverage, augmentation of transmission and access capacities, notable strides in broadband technology innovation, and the establishment industrial ecosystem. The level of application services has improved, leading to the flourishing of emerging industries such as e-commerce, software outsourcing, cloud computing, and the IoT. Concurrently, efforts have been made to enhance network information security. However, certain challenges persist within China's broadband network landscape, including the ambiguous positioning of broadband as a public infrastructure, disparities in regional and urban–rural development, inadequate application services, limited original technological capabilities, and an imperfect development environment. These issues demand urgent attention and resolution.

To address the aforementioned challenges, BCP focuses on four key areas of intervention and improvement. Firstly, Broadband China recognizes the significance of robust infrastructure for delivering high-speed and reliable broadband services. The initiative emphasizes the expansion and enhancement of telecommunications infrastructure across the country. This includes the deployment of fiber-optic networks, the development of advanced 4G and 5G mobile networks, and the utilization of satellite communication systems. The government is investing in the construction of backbone networks, last-mile connectivity, and rural broadband infrastructure to ensure comprehensive coverage, particularly in underserved areas.

Secondly, Broadband China aims to make broadband services affordable and accessible to all citizens. To achieve this, the initiative employs various strategies, such as price regulation, subsidy programs, and encouraging healthy competition among service providers. These efforts aim to reduce the cost of internet access, ensuring that even low-income households and rural communities can afford and benefit from broadband connectivity. Additionally, the initiative encourages the development of public access points, such as community centers and libraries, to provide internet access in areas with limited infrastructure or financial constraints.

Thirdly, Broadband China is committed to bridging the digital divide and promoting digital inclusion. The initiative focuses on providing equal access to educational resources, e-government services, healthcare facilities, and e-commerce platforms. Efforts are made to support underprivileged communities, including rural areas, ethnic minorities, and people with disabilities, by implementing targeted programs and policies. Capacity-building programs are also initiated to enhance digital literacy and skills, ensuring that citizens can fully participate in the digital economy and benefit from digital services and opportunities.

Finally, BCP recognizes the transformative potential of broadband technology and its impact on economic growth and industrial development. The initiative encourages research and development in the field of ICT and promotes collaboration between academia, industry, and government. By fostering innovation, entrepreneurship, and the development of digital industries, such as e-commerce, cloud computing, artificial intelligence, and the IoT, Broadband China aims to create a thriving digital ecosystem that drives economic prosperity and technological advancement.

By focusing on these four key aspects, BCP strives to build a comprehensive and inclusive broadband network that empowers individuals, enhances social services, promotes economic growth, and positions China as a global leader in the digital age. The busy-time weighted average available download rate for network downloads for fixed broadband users in China was 9.46 Mbit/s by the first quarter of 2016, an 84.77% increase compared to the first quarter of 2015. This metric reflects the average download speed experienced by users during peak hours when network traffic is typically higher. It indicates the performance and capacity of the fixed broadband networks in delivering data to users. Figure 2 presents the busy-time weighted average available download rate for network downloads for fixed broadband users in each province in the first quarter of 2016. It indicates that the municipalities directly under the Central Government exhibit higher broadband speeds compared to the national average, even though the rate of most provinces is lower than the national average; the lowest download rate is larger than an impressive level of 7 Mbit/s.

4 Methodology

4.1 Data source

Our study incorporates two sets of data: information on renewable energy adoption in Chinese households and data on BCP pilot cities. Firstly, we collected data on renewable energy adoption in Chinese households from the CLDS. Secondly, we collected data from the Chinese Ministry of Industry and Information Technology, while macroeconomic data for prefecture-level cities were sourced from the China City Statistical Yearbook.

The CLDS serves as the primary data source for this study, with the objective of capturing the changes in social structure, labor force dynamics within communities and families, and the interplay among communities, families, and individuals. Notably, the CLDS is a nationally representative longitudinal survey that focuses on the Chinese labor force (Ma et al., 2022). The survey encompasses both urban and rural areas across 29 mainland provinces and municipalities in China. Respondents in the CLDS consist of individuals aged 15 to 64, as well as those aged 65 and above who are actively employed within their respective households.

The data for the CLDS were collected by the Center for Social Science Survey at Sun-Yat-sen University in Guangzhou, China, employing a multistage random sampling methodology. For our study, we utilized three waves of CLDS data, specifically from the years 2012, 2014, and 2016. This dataset offers comprehensive information on various cooking fuel usage, along with demographic characteristics and socioeconomic indicators. The extensive nature of the survey's data aligns well with the research topic under investigation.

To process the data, several operations were conducted. Firstly, to ensure consistency in coding strategies, the survey data from 2012 and 2014 were merged since the coding strategy in 2012 differed from the subsequent year. Following the data cleaning guidelines outlined in the CLDS manuscript, we constructed panel data by combining individual surveys, family surveys, and county surveys. Secondly, in order to maintain consistent identification, the

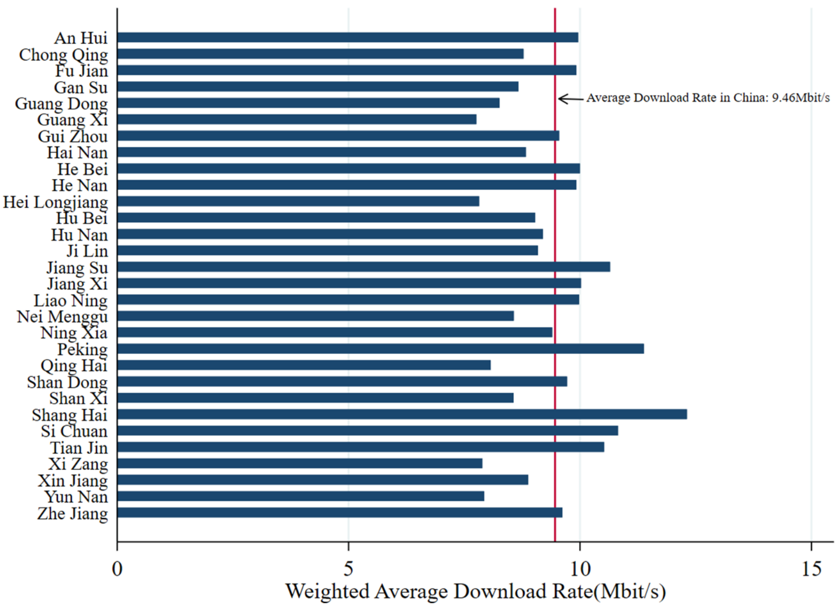

FIGURE 2
Weighted average download rate in each province.

panel data were assigned identification codes based on the coding strategy employed in the 2016 wave. Thirdly, any missing values were dropped from the dataset, and we only kept the rural residents' sample, resulting in 34,566 observations. Lastly, we obtain the macro data from the China Statistical Yearbook and combine it with CLDS based on the province code.

4.2 Variables

4.2.1 Household clean renewable energy adoption

The dependent variable in this study is household CREA. The CLDS database captures household renewable energy use for cooking through the question, "What is the main fuel used for cooking in your home?"; the available options include firewood, coal, gas (LPG), solar, biogas, electricity, and natural gas. Among these options, firewood, solar energy, and biogas are considered renewable energy sources, while the latter two are specifically categorized as clean renewable energy sources. To operationalize the explained variable, we assign a value of 1 to CREA when clean renewable energy sources are utilized, and 0 otherwise.

4.2.2 Broadband China

The explanatory variable in this paper is Broadband China pilot cities, and BCP is used as a proxy variable. In the framework of the empirical models, we defined the core explanatory variable BCP as 1 if the city was formally rated as the BCP pilot city from a given date, and 0 otherwise. Broadband China encompassed a total of 139 pilot cities, which were introduced in three separate batches. The first batch of pilot cities became operational on 1 August 2013. The second batch followed on 5 November 2014, and the third batch was implemented on 9 October 2015. Table 1 reports the details of the Broadband China pilot city.

4.2.3 Control variables

Considering that household energy adoption is significantly influenced by household member characteristics such as income, social security, working experience, and other relevant factors, it is crucial to control for these characteristics in both the treatment and control groups (Zografakis et al., 2010; Willis et al., 2011; Eshchanov et al., 2021; Irfan et al., 2021). This control is necessary to ensure comparability in terms of renewable energy adoption between the two groups. By controlling for household member characteristics, we can better isolate the impact of the treatment (BCP) on renewable energy adoption and draw more accurate conclusions from the analysis.

Moreover, it is important to note that the community environment in which residents reside significantly influences energy adoption patterns. Rapid urbanization poses a considerable threat to the environment and human health, primarily due to high levels of pollution. Industries such as iron and steel, and chemical and energy industries, known for their significant pollution output, have contributed to severe environmental pollution issues (Feroz et al., 2021). The detrimental effects of such pollution can hinder clean energy adoption and have broader implications for sustainable development. Indeed, we control the industrial structure and the pollution status of the community. According to Ren et al. (2021) and Wang et al. (2022), the energy consumption is closely related to economic development; we control the GDP and fiscal structure.

4.2.4 Descriptive statistics

The descriptive statistics presented in Table 2 provide an overview of the dataset used in this study. The table includes various variables related to CREA and its potential determinants. Starting with the dependent variable, CREA, the sample consists of 37,146 observations. The mean CREA adoption rate is 0.39649, indicating that, on average, approximately 39.65% of households in the sample have adopted clean renewable energy technologies. The standard deviation of 0.489175 suggests a considerable variation in CREA adoption levels across the sample. Moving to the explanatory variables, we find that the variable BCP, representing the availability of a specific policy intervention, has a mean value of 0.144403, indicating that the policy is present in a relatively small proportion of the sample. The standard deviation of 0.351503 suggests some heterogeneity in the implementation of the policy across regions.

Further examining the regional distribution, we observe that the middle region has a mean value of 0.291768, indicating a moderate presence of households in this region. The east region has a higher mean of 0.445835, suggesting a relatively greater concentration of households with access to clean renewable energy technologies.

TABLE 1 Broadband China pilot cities.

Policy Release Date	Broadband China Pilot Cities
2014 BCP Cities 2013/8/1	Beijing, TianJin, Shanghai, Changsha, Zhuzhou, Shi Jiazhuang, Dalian, Benxi, Yanbian, Haerbin, Daqing, Qingdao, Zibo Weihai, Linyi, Zhengzhou, Luoyang, Wuhan, Wuhu, Anqing, Nanjing, Suzhou, Zhenjiang, Kunshan, Jinhua Fuzhou, Xiamen, Quanzhou, Nanchang, Shangrao, Guangzhou, Shenzhen Zhongshan Chengdu, Pan Zhihua, Aba, Guiyang, Yinchuan, Wuzhong, A Laer
2015 BCP Cities 2014/11/5	Taiyuan, Hu Hehaote, Eer Duosi, Anshan, Panjin, Baishan, Dongying, Jining, Dezhou, Xinxiang, Yongcheng, Huangshi, Xiangyang, Yichang, Shiyan, Suizhou, Yueyang, Hefei, Tongling, Yangzhou, Jiaxing, Putian, Xinyu, Ganzhou, Shantou, Meizhou, Dongguan, Chongqing Jiangjin and Rongchang District, Mianyang, Neijiang, Yibin, Dazhou, Yuxi, Lanzhou, Zhangye, Guyuan, Zhongwei, Kelamayi
2016 BCP Cities 2015/10/9	Yantai, Zaozhuang, Shangqiu, Jiaozuo, Nanyang, Ezhou, Hengyang, Yiyang, Wuxi, Taizhou, Nantong, Hangzhou, Suzhou, Huangshan, Ma Anshan, Ji'an, Yulin, Haikou, Hong Kong Jiulongpo District, Chongqing Beipei District, Ya'an, Luzhou, Nanchong, Zunyi, Wenshan, Lasa, Linzhi, Weinan, Wuwei, Jiuquan, Tianshui, Xining, Yangquan, Jinzhong, Wuhai, Baotou, Tongliao, Shenyang, Mu Danjiang

TABLE 2 Descriptive statistics of variables.

Variable	Obs	Mean	SD	Min	Max
Dependent Variable					
CREA	37,146	0.39649	0.489175	0	1
Explanatory Variable					
BCP	37,146	0.144403	0.351503	0	1
Middle Region	37,146	0.291768	0.454582	0	1
East Region	37,146	0.445835	0.497064	0	1
West Region	37,146	0.262397	0.439943	0	1
Heterogeneity					
Low-Income District	37,146	0.142223	0.349283	0	1
GDP Mean Group	37,146	0.319819	0.466413	0	1
Mid GDP Mean Group	37,146	0.436009	0.495895	0	1
East GDP Mean Group	37,146	0.218785	0.413428	0	1
West GDP Mean Group	37,146	0.499596	0.500007	0	1
Mean Popu	37,146	0.46853	0.499015	0	1
Mechanism					
Pollution	37,146	0.233861	0.423291	0	1
Family Salary Income	20,629	8.906139	3.446237	−6.90776	15.76142
Industry Structure	33,438	1.032445	0.509438	0.272344	4.757226
Control Variable					
Age	37,146	48.09807	17.08312	3	114
Gender	37,146	0.482367	0.499696	0	1
Marriage	37,146	0.127335	0.333353	0	1
Health	35,860	2.388846	1.01141	1	5
Minority	37,146	0.126124	0.331994	0	1
Family Expense	36,692	10.17263	1.037794	0.336472	15.42495
Social Security	37,146	0.10063	0.300842	0	1
House Value	37,092	183565.4	5278747	0	1.00E+09
Electric Consumption	37,146	2659.899	15599.28	0	99999
Internet Usage	37,146	3.045146	1.049114	0	4
GDP	34,679	1.051193	0.507415	0.226896	3.712207
Fiscal Expense Ratio	36,762	0.203236	0.123192	0.065621	0.686978

Conversely, the west region has a lower mean of 0.262397, indicating a lower prevalence of CREA adoption compared to the other regions.

Considering heterogeneity factors, the presence of low-income districts is captured by the variable “Low Income District”, which has a mean value of 0.142223, indicating a relatively small proportion of low-income districts in the sample. The mean values of the GDP Mean Group variables provide insights into the economic conditions of different regions. Specifically, the mean values for Mid GDP Mean Group, East GDP Mean Group, and West GDP Mean Group are 0.436009, 0.218785, and 0.499596, respectively, suggesting varying levels of economic development across these regions.

In terms of the mechanisms that might influence CREA adoption, the pollution variable indicates the extent of pollution in the sample. With a mean value of 0.233861, the data suggest that pollution is present to some degree across the observed areas. The variable “Family Salary Income” represents the natural logarithm of family salary income, which has a mean value of 8.906139. This indicates that, on average, households in the sample have a relatively high salary income. Additionally, the industry structure variable has a mean value of 1.032445, suggesting a diverse industrial landscape in the observed areas.

Moving on to the control variables, we find that the mean age of individuals in the sample is 48.09807, indicating a relatively mature population. The gender variable, with a mean value of 0.482367, suggests a nearly equal distribution of men and women. The marriage variable has a mean value of 0.127335, indicating a relatively low proportion of married individuals. The mean health score, represented by the variable "Health", is 2.388846, suggesting a moderate health status in the sample. The minority variable, with a mean value of 0.126124, indicates a relatively low proportion of minority groups in the observed areas. Other control variables include family expenses, social security, house value, electric consumption, internet usage, GDP, and fiscal expense ratio. These variables exhibit varying means and standard deviations, reflecting the diversity of economic and socio-demographic factors present in the sample.

4.3 Empirical strategy

4.3.1 Benchmark regression

The impact of digital transition on the adoption of clean renewable energy in rural households encounters identification challenges due to potential confounding factors, as the city-level digital transition policy is exogenous to household behavior. This study employs a quasi-natural experiment approach by considering the BCP as the treatment group, enabling the estimation of the causal effect of digital transition on CREA through the construction of a staggered DID model. Specifically, the cities selected as part of the BCP are treated as the treatment group, while the cities not selected as part of the BCP during the sample period serve as the control group. The disparity in the change in clean renewable adoption between the two groups following the implementation of the BCP serves as an indicator of the net effect of the BCP. Therefore, we start our analysis using the following equation:

$$CREA_{it} = \alpha_0 + \alpha_1 BCP_{it} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \tag{1}$$

where the dependent variable $CREA_{it}$ refers to the clean renewable energy adoption, BCP_{it} represents a dummy variable that indicates whether city i is designated as BCP city in year t, the X refers to the control variables, μ_c refers to the province-level fixed effect, γ_t refers to year-level fixed effect, and ϵ_{it} refers to the error term. Moreover, considering the significant economic development disparity across various regions in China, we stratify the sample cities based on their provinces, dividing cities into four distinct regions. To account for time-varying factors specific to each region, such as the influence of place-based policies, we also introduce an interaction term, denoted as θ_{rt}, between region r and year t. This interaction term allows us to capture the nuanced effects of regional characteristics over time within the analysis.

4.3.2 Parallel trend assumption test

After estimating the staggered DID model, as Beck et al. (2010) recommended, we employ the event study approach to examine the validity of the parallel trend assumption. This approach not only helps assess the assumption but also captures the dynamic effects of the BCP. The model can be represented as follows:

$$CREA_{it} = \alpha_0 + \sum_{s=1}^{3} \alpha_{pres} BCP_{pres} + \alpha_{current} BCP_{current} + \sum_{s=1}^{2} \alpha_{posts} BCP_{posts} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \tag{2}$$

where BCP_{pres} presents the specific year preceding the inclusion of a pilot city in the BCP (Before BCP implementation), $BCP_{current}$ represents the city after its inclusion in the BCP (During BCP implementation), and BCP_{posts} represents the specific year following the inclusion of a pilot city in the BCP (After BCP implementation). The duration of the pre-treatment and post-treatment periods varies across the treatment group cities. The longest observed post-treatment duration in the sample is 2 years (corresponding to the initial batch of the 2014 BCP), while the longest pre-treatment duration in the sample is 4 years (corresponding to the third batch of the 2016 BCP). For the purposes of our analysis, we consider the 3-year pre-treatment period as the baseline. If the coefficients of BCP_{pres} are found to be statistically insignificant, it suggests that the parallel trend assumption holds. In turn, the coefficients of BCP_{posts} reflect the dynamic effects of the BCP on CREA in rural families.

4.3.3 Extend staggered DID estimator

The analysis follows a commonly used methodology known as the two-way fixed effects (TWFE) staggered DID regression. However, to ensure unbiased estimation of the coefficient ϵ_{it}, three conditions must be satisfied. Firstly, the treatment can only increase over time and change once. In other words, the treatment is not reversible, and once a unit enters the treatment group, it remains there. Secondly, the treatment is binary, indicating that it is a dichotomous variable with two possible values (treated and untreated). These two conditions imply that units in the treatment group can only transition from being untreated to being treated. Thirdly, there is no variation in treatment timing across the units being analyzed (De Chaisemartin and d'Haultfoeuille, 2020).

In this study, it is challenging to satisfy the aforementioned conditions. Specifically, if we use the TWFE approach, we need to impose stricter assumptions than just the parallel trend assumption to account for the dynamic effects that may be correlated with the estimation of the average treatment effect (ATT), denoted as β_{it}. For instance, if the treatment effect is constant, $TE_{it} = \delta$ for all (i,t), and the treatment effect does not systematically differ based on different weights assigned to β_{it}, then the estimator $\hat{\beta}_{it}$ is unbiased for the ATT [as shown in Corollary 2 in De Chaisemartin and d'Haultfoeuille (2020)].

However, in the analysis of the CLDS survey data, this assumption of "no correlation" is implausible due to respondents' mobility between cities. For example, a household might have lived in Beijing, the capital of China, in 2012, but moved to Guangzhou in 2013, where BCP was promoted, and in 2013, this household moved back to its hometown, Yan Bian, which is a remote city in China. During these 4 years, the household lived in both a developed city affected by BCP and non-BCP, developing area. To address this concern, we introduce the DID with multiple matching estimators proposed by De Chaisemartin and d'Haultfoeuille (2020). This estimator is a weighted average of the DID with positive treatment (DID_+) and DID with negative treatment (DID_-), specifically designed for cases with two periods and binary treatment. The DID_+ estimator is given by:

$$DID_+ = \frac{1}{N_{0,1}} \sum_{g:D_{g,1}=0,D_{g,2}=1} (Y_{g,2} - Y_{g,1}) - \frac{1}{N_{0,0}} \sum_{g:D_{g,1}=0,D_{g,2}=0} (Y_{g,2} - Y_{g,1}) \quad (3)$$

and DID_- is given by:

$$DID_- = \frac{1}{N_{1,1}} \sum_{g:D_{g,1}=1,D_{g,2}=1} (Y_{g,2} - Y_{g,1}) - \frac{1}{N_{1,0}} \sum_{g:D_{g,1}=1,D_{g,2}=0} (Y_{g,2} - Y_{g,1}) \quad (4)$$

where $N_{a,b}$ refers to the number of units for which $D_{g,1} = d_1$ and $D_{g,2} = d_2$, and the DID_+ estimator refers to the DID estimator that compares units transitioning from the control group to the treatment group between periods t_1 and t_2. Under the parallel trends assumption, this estimator is unbiased for estimating the treatment effect for units transitioning into the treatment group. On the other hand, the DID_- estimator compares units transitioning from the treatment group to the control group between periods t_1 and t_2. It is important to note that in the original definition, the control group and treatment group have the same group size. However, we extend the DID_M (Difference-in-Difference with Multiple Matching) estimator to accommodate different group sizes. This extension allows for a more flexible analysis when the treatment is binary and staggered. One advantage of using the DID_M estimator is its robustness to dynamic effects. By accounting for the different group sizes and considering staggered treatment, the DID_M estimator provides a more reliable estimate of the treatment effect while addressing concerns related to dynamic effects.

Since 2012, the first interview, there is the possibility of respondents moving between cities in the follow-up surveys. Additionally, the Broadband China pilot policy was proposed in three separate batches in 2014, 2015, and 2016. Consequently, some respondents may have been exposed to the treatment multiple times. For example, a respondent who lived in Changsha in 2014, where the first batch of Broadband China was proposed, and later moved to Taiyuan in 2015, where the second batch was proposed, would have received the treatment twice. To address this scenario, previous studies have proposed various estimators. Graham and Powell (2012) introduced an estimator that compares the outcome evolution of movers and quasi-stayers. However, this method relies on the assumption of a linear treatment effect and does not account for the period one treatment. De Chaisemartin and d'Haultfoeuille (2020) implemented a relabeling strategy to extend the DID_M estimator. However, when there are no true stayers in both the treatment and control groups, it becomes necessary to choose a bandwidth to identify the quasi-stayers. In our study, the estimator proposed by Callaway and Sant'Anna (2021) is more suitable. They define the treatment effect (TE) as:

$$TE_{c,c+1} = E[\hat{Y}_{c,c+l}(0_{c-1}, 1_{l+1}) - \hat{Y}_{c,c+l}(0_{c+l})] \quad (5)$$

where $\hat{Y}_{c,c+l}$ refers to the average outcome at period t across the treatment groups belonging to cohort c, c denotes the cohort, t denotes the periods, and $l \in 1,\ldots,t$; this estimator accounts for the multiple treatments and does not rely on the assumption of true stayers, making it well-suited for our analysis. Moreover, in terms of the average effect of having been treated for $l + 1$ period in the cohort treated at period c, the DID estimator is given by:

$$DID_{c,l} = \hat{Y}_{c,c+l} - \hat{Y}_{c,c-l} - (\hat{Y}_{n,c+l} - \hat{Y}_{n,c-l}) \quad (6)$$

This estimator extends the staggered DID estimator in several important ways. Firstly, it provides a more aggregated estimation approach. Secondly, it utilizes the not-yet-treated group as the control group instead of the never-treated group. This is particularly useful in our study, as in the case of the third batch of Broadband China, where a large proportion of individuals have already been treated by the policy; it becomes challenging to identify a never-treated group. However, this method can still estimate the causal effects of the third batch of Broadband China. Furthermore, even if there are individuals who have never been treated throughout the entire study period, the presence of a substantial not-yet-treated group can lead to more precise estimations. Another important aspect of this estimator is its reliance on a conditional parallel trend assumption. This assumption is crucial for obtaining unbiased treatment effect estimates. To address concerns regarding this assumption, Callaway and Sant'Anna (2021) propose robust placebo estimators to heterogeneous effects. These placebo tests can be used to assess the validity of the parallel trend assumption underlying their estimator. In light of these considerations, after presenting a TWFE staggered DID approach, we employ the DID_M estimator and the $DID_{c,l}$ estimator to re-estimate the causal inference of the Average Treatment Effect on the Treated (ATT). Additionally, we provide parallel assumption tests and placebo tests based on these estimators to further evaluate the validity of the parallel trends assumption.

Our estimator should be interpreted as a conservative estimate of the effect of digital transition on family financial behavior. In our study, the digital transition is represented by the external shock known as Broadband China, and we define the cities that actively promoted this transition as the treatment group. However, even if respondents did not reside in these specific cities, they may have still benefited from the digital transition through what we refer to as the overflow effect. This effect implies that the impact of the digital transition may extend beyond the treatment group and affect individuals in neighboring areas or the broader region. Furthermore, individuals outside the treatment group may also be influenced by fellow townspeople or acquaintances who reside in the cities where Broadband China was implemented. This peer effect can result in indirect exposure to the digital transition and its associated effects.

Because of these factors, our estimation may underestimate the true effect of Broadband China on the treatment group. The overflow and peer effects introduce additional channels through which the digital transition indirectly affects individuals outside the treatment group. Therefore, it is important to consider that our estimates reflect a conservative assessment of the impact of Broadband China on family financial behavior, as they may not fully capture the overall influence of the digital transition on a wider scale.

4.3.4 Heterogeneity

To mitigate the estimation bias induced by the structure of energy consumption and regional disparities, we initially incorporate natural gas utilization and coal gas adoption as the dependent variables, and the model is given by:

$$\mathbf{Y}_{it} = \alpha_0 + \alpha_1 BCP_{it} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \tag{7}$$

where Y_{it} refers to (*natural gas, coal gas*). Should the coefficient α_1 exhibit a significant positive value, this would suggest that the BCP markedly catalyzes the adoption of natural gas and/or coal gas. This interpretation would be contingent on the premise that an increased value in α_1 signifies a stronger influence of the BCP on promoting alternative energy sources.

Furthermore, we incorporate an interaction term between the *BCP* variable and dummy variables to assess regional heterogeneity. This approach enables us to estimate the nuanced variations across different geographical areas, and the model is given by:

$$CREA_{it} = \alpha_0 + \alpha_1 BCP_{it} \times Heterogeneity_{it} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \tag{8}$$

where $Heterogeneity_{it}$ represents the distinct dummy variables associated with heterogeneity, each reflecting unique attributes or characteristics of the various regions under study. The estimation of the parameter α_1 serves as an indication of the heterogeneous effects associated with BCP. This interpretation suggests a differential impact of the BCP across diverse geographical regions or contexts.

4.3.5 Mechanism

The association between the promotion of renewable energy adoption and the BCP presents a conundrum. To explore the underlying mechanisms connecting CREA and BCP, we employ a strategy analogous to Chen et al. (2020) and Braguinsky et al. (2021), wherein we integrate an interaction term into the benchmark regression. The resulting formulation is as follows:

$$CREA_{it} = \alpha_0 + \alpha_1 BCP_{it} + \alpha_2 BCP_{it} \times Mechanism_{it} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \tag{9}$$

where $Mechanism_{it}$ refers to the mechanism variables.

5 Results and discussion

5.1 Benchmark regression

Table 3 elucidates the influence of the BCP initiative on CREA within rural households, as specified by Model (1). The table comprises several columns, each illustrating a different model specification. From columns (1) to (4), control variables at the individual, familial, and macroeconomic levels are sequentially incorporated. In the scenario where province fixed effects are not accounted for [columns (1) to (4)], the coefficients of BCP are significantly positive, with a statistical significance at the 1% level (0.155, 0.153, 0.147, and 0.0873, respectively). These observations indicate that the BCP significantly fosters the promotion of CREA among rural households, aligning with the results from Wang et al. (2021), which evaluated the causal impact of digital transitions on the energy consumption structure at the macroeconomic level.

In column (5), province-level fixed effects are introduced. Even with this additional layer of complexity, the coefficients of BCP retain their significantly positive status (0.0668, with statistical significance at the 5% level), albeit exhibiting a reduced magnitude compared to column (1). This pattern implies that the BCP continues to positively affect CREA in rural households, despite considering the inherent heterogeneity at the province level.

In column (6), which controls for both province-level and year-level fixed effects, the coefficient of BCP is significantly negative (−0.0764, with statistical significance at the 5% level). This outcome suggests that the influence of the BCP varies considerably across different regions within China. Notably, this finding deviates from existing well-regarded research, such as that conducted by Wang et al. (2022) and Ren et al. (2021). This discrepancy underlines the complex and dynamic nature of policy impact analysis, and may indicate unique regional factors at play in the context of this study.

From these findings, it becomes evident that the digital transition's causal effects on energy consumption, particularly as observed through individual-level data, can vary significantly. Importantly, to gain a comprehensive understanding of the policy's impacts, it is crucial to account for potential heterogeneity across both provinces and years in the estimation. This awareness of regional and temporal diversity facilitates a more nuanced interpretation of the policy's effectiveness and can better inform future policy adjustments and implementations.

Table 4 showcases the results derived from partitioning the sample into three geographic divisions: middle, east, and west, based on the respective provinces, and subsequently incorporating interactive fixed effects for region and year, as specified by model (8). The table comprises different columns, each corresponding to a unique model specification.

In column (1), the model used in column (6) of Table 3 is adjusted to introduce the interactive fixed effect of region and year. Notably, despite this adjustment, the coefficient of BCP continues to be significantly negative (−0.0804, with statistical significance at the 5% level). This result suggests that the BCP has a negative influence on CREA, a pattern that persists even when the interactive fixed effects of region and year are accounted for. This indicates that regional variations and time dynamics may not fully explain the observed negative impact of the BCP on CREA, pointing towards other potentially influential factors that warrant further investigation.

Upon examination of column (2), the interaction term *BCP* × *Middle Region* is introduced as an explanatory variable, while concurrently controlling for individual-level, family-level, and macroeconomic-level attributes. Furthermore, province fixed effects, year fixed effects, and the interactive fixed effect of region and year are accounted for. In this specific model specification, the coefficient of *BCP* × *Middle Region* is 0.0580, with statistical significance at the 1% level. This result demonstrates that the BCP exerts a significantly positive impact on CREA in the central region of China.

In contrast, columns (3) and (4) see the introduction of *BCP* × *East Region* and *BCP* × *West Region* as explanatory variables, respectively. In both scenarios, the coefficients are significantly negative, with statistical significance at the 1% level [−0.126 for

TABLE 3 The effect of BCP on CREA in rural family.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA	(5) CREA	(6) CREA
BCP	0.155***	0.153***	0.147***	0.0873***	0.0668**	−0.0764**
	[0.009]	[0.009]	[0.009]	[0.010]	[0.030]	[0.035]
Age		0.000102	5.47E-05	0.000199	0.00300***	0.00331***
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Gender		0.0312	0.0256	0.0706	0.00792**	0.00586
		[0.086]	[0.086]	[0.094]	[0.004]	[0.004]
Marriage		0.0533	0.0619	0.0757*	0.0481***	0.0455***
		[0.039]	[0.040]	[0.043]	[0.010]	[0.009]
Health		0.0230***	0.0231***	0.0225***	0.0516***	0.0507***
		[0.005]	[0.005]	[0.005]	[0.004]	[0.004]
Minority		−0.0377	−0.0353	−0.0345	2.07E-05	−0.00489
		[0.035]	[0.036]	[0.037]	[0.035]	[0.033]
Family Expense		0.00656	0.00275	−0.0387***	−0.0439***	
			[0.005]	[0.005]	[0.005]	[0.005]
Social Security		0.0139	0.0125	−0.122***	−0.0519***	
			[0.024]	[0.025]	[0.014]	[0.011]
House Value		2.53E-08	−6.26E-09	−1.13e-09***	−1.21e-09***	
			[0.000]	[0.000]	[0.000]	[0.000]
Electric Consumption		3.92E-07	4.39E-07	−2.57E-08	2.02E-07	
			[0.000]	[0.000]	[0.000]	[0.000]
Internet Usage		−0.00473	0.0015	0.0856***	0.0580***	
			[0.005]	[0.005]	[0.006]	[0.006]
GDP				0.213***	−0.0870***	−0.0927***
				[0.032]	[0.029]	[0.029]
Fiscal Expense Ratio			1.741***	1.127***	0.697***	
				[0.240]	[0.220]	[0.212]
Cons	0.374***	0.293***	0.237***	−0.337***	0.118	0.344***
	[0.002]	[0.046]	[0.067]	[0.079]	[0.076]	[0.077]
N	37,146	35,860	35,392	33,009	33,009	33,009
Province Fixed Effect	No	No	No	No	Yes	Yes
Year Fixed Effect	No	No	No	No	No	Yes
Cluster	No	No	No	No	Family	Family

Robust standard errors are in parentheses; *, **, and *** denote significances at 10%, 5%, and 1% levels, respectively.

column (3) and −0.135 for column (4)]. This indicates that the BCP contributes to a reduction in CREA in both the east and west regions of China. The results thus highlight a region-specific effect of the BCP on renewable energy adoption, underscoring the necessity of context-sensitive policy implementation and analysis.

The observed differences in the effects of BCP across regions can be attributed to various factors. In the economically developed east region, many rural young people migrate to work in coastal cities and do not reside in rural areas (Wang and Mesman, 2015). Moreover, the use of gas and natural gas as a living fuel is widespread among the elderly population (Zou et al., 2018). In the west region, the economy is less developed and rural residents often choose to work in the east region or middle region cities. Additionally, the availability of abundant natural gas resources in

TABLE 4 The region heterogenous effect of BCP on CREA in rural family.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA
BCP	−0.0804** [0.035]			
BCP		0.0580***		
Middle Region		[0.015]		
BCP			−0.126***	
East Region			[0.011]	
BCP				−0.135***
West Region				[0.016]
Age	0.00330***	0.00334***	0.00328***	0.00334***
	[0.000]	[0.000]	[0.000]	[0.000]
Gender	0.00566	0.00555	0.00548	0.00561
	[0.004]	[0.005]	[0.005]	[0.005]
Marriage	0.0451***	0.0450***	0.0448***	0.0451***
	[0.009]	[0.007]	[0.007]	[0.007]
Health	0.0501***	0.0498***	0.0498***	0.0499***
	[0.004]	[0.002]	[0.002]	[0.002]
Minority	−0.00658	−0.0139	−0.0136	−0.00595
	[0.033]	[0.010]	[0.010]	[0.010]
Family Expense	−0.0436***	−0.0440***	−0.0435***	−0.0439***
	[0.005]	[0.002]	[0.002]	[0.002]
Social Security	−0.0514***	−0.0540***	−0.0493***	−0.0545***
	[0.011]	[0.008]	[0.008]	[0.008]
House Value	−1.18e-09***	−1.19e-09***	−1.20e-09***	−1.17e-09***
	[0.000]	[0.000]	[0.000]	[0.000]
Electric Consumption	1.69E-07	1.54E-07	1.59E-07	1.73E-07
	[0.000]	[0.000]	[0.000]	[0.000]
Internet Usage	0.0584***	0.0579***	0.0580***	0.0580***
	[0.006]	[0.003]	[0.003]	[0.003]
GDP	−0.0873***	−0.0985***	−0.0868***	−0.0982***
	[0.029]	[0.006]	[0.006]	[0.006]
Fiscal Expense Ratio	0.646***	0.739***	0.718***	0.638***
	[0.210]	[0.042]	[0.041]	[0.043]
Cons	0.382***	0.364***	0.358***	0.393***
	[0.078]	[0.032]	[0.032]	[0.032]
N	33,009	33,009	33,009	33,009
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes	Yes
Cluster	Family	Family	Family	Family

Robust standard errors are in parentheses; *, **, and *** denote significances at 10%, 5%, and 1% levels, respectively.

10.3389/fevo.2023.1241410

the west region leads to a preference for natural gas as living energy resource.

In contrast, the middle region exhibits a relatively homogeneous industry and is rich in natural resources such as biogas and solar energy. Rural residents in this region have access to various energy resources, including firewood, biogas, and solar energy (Wang et al., 2016; Wang et al., 2017). Some residents even generate electricity from solar panels and sell it to the local government.

Overall, these findings highlight the regional variations in the effects of the BCP on CREA in rural areas of China, with positive effects observed in the middle region and negative effects observed in the east and west regions.

5.2 Parallel trend test

The validation of the benchmark regression and the parallel trend assumption is crucial in assessing the reliability of the results. In addition to the baseline estimates, model (2) employs the event study approach to examine the parallel trend assumption and provide insights into the dynamic effects of the BCP on CREA in rural families.

The event study model allows for a more detailed analysis of the treatment effects over time, capturing the dynamic of the BCP's impact on CREA. By examining the coefficients of the BCP variable across different periods relative to the policy implementation, we can assess whether the parallel trend assumption holds. Furthermore, the event study model provides valuable information on the dynamic effects of the BCP on CREA in rural families. It allows us to observe how the treatment effect evolves, providing insights into any lagged or cumulative effects of the policy. This helps us understand the long-term implications and sustainability of the BCP in promoting CREA. By incorporating the event study approach, the analysis goes beyond the average treatment effect captured by the baseline model. It provides a more nuanced understanding of the temporal patterns and dynamic effects of the BCP on CREA in rural families, allowing for a comprehensive assessment of the policy's impact. Figure 3 presents the estimation results for the parallel trend assumption test, providing evidence to support the validity of the parallel trend assumption in our specification. The graph illustrates that the renewable energy adoption of rural families in the BCP pilot cities is not statistically different from that in the non-pilot cities before the implementation of the BCP. This indicates that the treatment and control groups had similar trends in renewable energy adoption before the policy intervention, validating the parallel trend assumption.

Moreover, Figure 3 also displays the dynamic effects of BCP on CREA over time. It demonstrates that the policy's effect diminishes gradually as time progresses. Specifically, the estimated coefficient for the BCP variable is not statistically significant in the year preceding the policy implementation. However, in the year of implementation and the subsequent year, the coefficient becomes statistically significant, indicating a positive effect of the BCP on CREA during these periods. It is important to note that the magnitude of the coefficient decreases in the 2 years following the implementation, suggesting a diminishing effect of the policy over time.

These findings provide valuable insights into the temporal dynamics of the BCP's impact on CREA in rural families. They suggest that the policy's effect is most pronounced in the year of implementation and the immediate aftermath, highlighting the importance of early policy implementation for promoting CREA. However, the diminishing effect observed in the subsequent years highlights the need for continuous policy support and potential challenges in sustaining the initial positive impact over time.

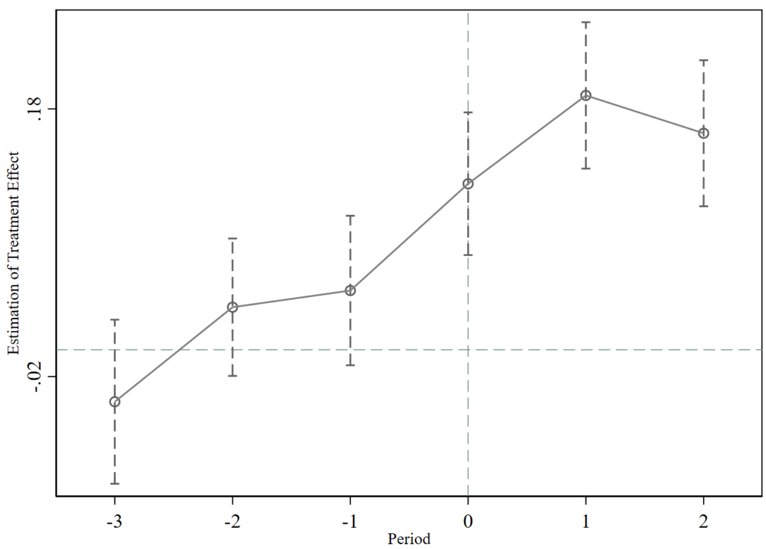

FIGURE 3
Parallel test.

5.3 Robustness test

5.3.1 Propensity score matching

While our benchmark regression aligns with the parallel trend assumption, it is important to acknowledge that the selection process for BCP may not be completely exogenous. The choice of pilot cities could be influenced by various external factors, including economic foundations, internet development, residents' living conditions, and fiscal conditions. Consequently, disparities between pilot cities and non-pilot cities may result in divergent trends concerning the adoption of clean renewable energy over time. To alleviate the potential estimation bias caused by sample selection, we apply the propensity score matching (PSM) method to re-estimate the baseline staggered DID regression model. We first take the relevant characteristics, including GDP, family total income, the ratio of fiscal expense and income, family expense, internet adoption, family electric consumption, house value, health condition, and age, as covariate variables and use the logit model to calculate the propensity score of each city in our entire sample. Figure 4 illustrates the results of the PSM test. The analysis reveals that the treatment group and control group exhibit a comprehensive distribution, implying a reasonable comparison between the two groups.

Subsequently, we utilize the weighted sample, samples with support, and the weighted average samples to re-estimate the staggered DID model. This approach allows us to account for the varying weights of the observations and focus on the samples that satisfy the common support condition. We aim to obtain more robust and reliable estimates for the staggered DID model with a PSM sample by employing these methods.

Table 5 presents the results of our analysis; we control for the control variables as in the benchmark regression, incorporating province fixed effects, year fixed effects, and region and year fixed effects. Additionally, we cluster the standard errors at the family level. The table includes several rows of interest; in the full sample row, we utilize BCP as the explanatory variable and CREA as the dependent variable, considering the entire sample. In the middle region row, we introduce the interaction term *BCP × Middle Region* as the explanatory variable, focusing specifically on the middle region. In the east region row, we employ the interaction term *BCP × East Region* as the explanatory variable, concentrating on the east region. In the west region row, we use the interaction term *BCP × West Region* as the explanatory variable, focusing on the west region. By analyzing the coefficients and statistical significance of these explanatory variables in each row, we can elevate the sample selection bias and gain insights into the impact of the BCP on CREA in different regions.

The estimation results align with the benchmark regression, showing a marginal increase in the policy effect. This suggests that any underestimation of the effect due to potential sample selection bias is minimal. Overall, the analysis reveals heterogeneous effects of the BCP across regions. Specifically, in the middle region of China, the BCP significantly increases CREA in rural families. However, in the east and west regions of China, the BCP significantly reduces CREA in rural families.

5.3.2 Robust staggered DID estimator with multiple periods

Figure 5 presents the estimation results of the re-estimated staggered DID model using a doubly robust staggered DID

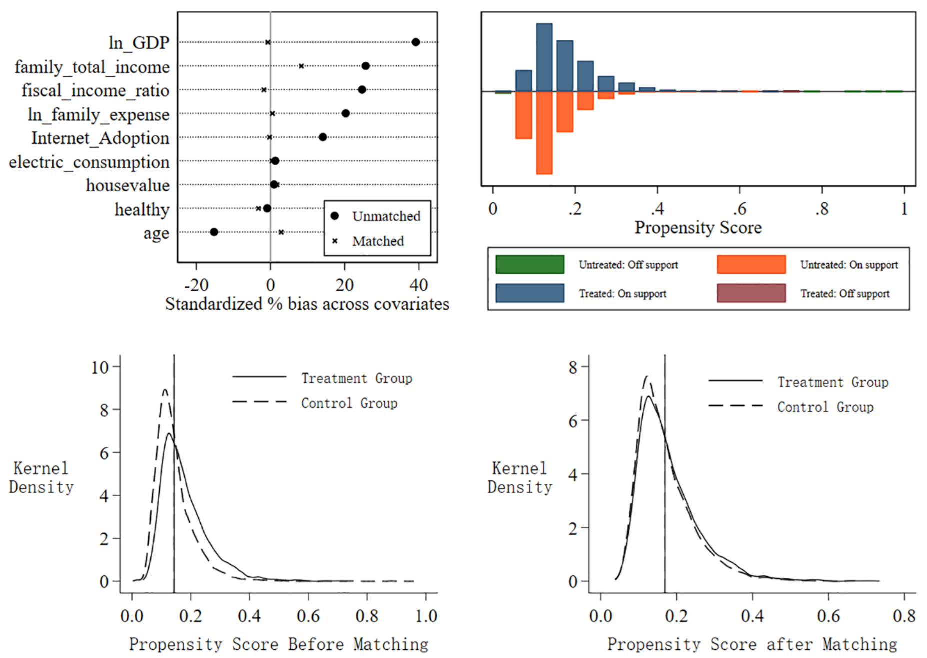

FIGURE 4
Propensity score balance test.

TABLE 5 The effect of BCP on CREA using PSM-DID estimation.

Method Variable	Weighted Sample CREA	Support Sample CREA	Weighted Average Sample CREA
Full sample			
BCP	−0.0890**	−0.143***	−0.0782**
	[0.036]	[0.036]	[0.036]
_cons	0.415***	0.453***	0.387***
	[0.105]	[0.024]	[0.106]
Middle Region			
BCP × Middle Region	0.0491**	0.119***	0.0500**
	[0.021]	[0.019]	[0.020]
_cons	0.343***	0.368***	0.323***
	[0.058]	[0.002]	[0.052]
East Region			
BCP × East Region	−0.102***	−0.191***	−0.0856***
	[0.016]	[0.050]	[0.014]
_cons	0.357***	0.433***	0.339***
	[0.058]	[0.023]	[0.052]
West Region			
BCP × West Region	−0.206***	−0.203***	−0.193***
	[0.023]	[0.069]	[0.020]
_cons	0.447***	0.444***	0.416***
	[0.059]	[0.023]	[0.052]
N	12,305	32,934	15,179
Control Variable	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes
Cluster	Family	Family	Family

Robust standard errors are in parentheses; *, **, and *** denote significances at 10%, 5%, and 1% levels, respectively.

estimator specified in Equation (6). As mentioned above, this estimator addresses the potential biases arising from residents migrating across regions, being treated multiple times, and transitioning between treatment and control groups. The results align with the benchmark regression, which suggests that the findings are robust and reliable. This consistency strengthens the validity of the estimated treatment effects of the BCP on CREA.

It is worth noting that the impact of BCP on CREA demonstrates a greater magnitude within the full sample compared to the benchmark regression. Moreover, the adverse effect of BCP on CREA exhibits increased significance when considering two lagged periods. Notably, the reduction in CREA is particularly pronounced in the east region, characterized by a pre-existing high utilization of clean domestic energy before the implementation of the BCP. Subsequently, residents in this region displayed a decreased inclination toward employing clean renewable energy after the policy enactment. In the central region, BCP exerts a noteworthy driving force on CERA, albeit with a diminishing impact observed after a two-period lag. Conversely, the west region reveals a negative regression coefficient for BCP. However, BCP fosters an inclination among residents to embrace clean renewable energy.

There are four possible reasons. Firstly, the varying impacts of the BCP on CREA across different regions could be attributed to pre-existing economic disparities (Zhang and Bai, 2017). The east region, having a relatively high utilization of clean renewable energy before the policy implementation, might indicate greater availability of alternative energy sources or a stronger market for renewable energy. Consequently, residents in this region may have been less motivated to adopt clean renewable energy after the policy was

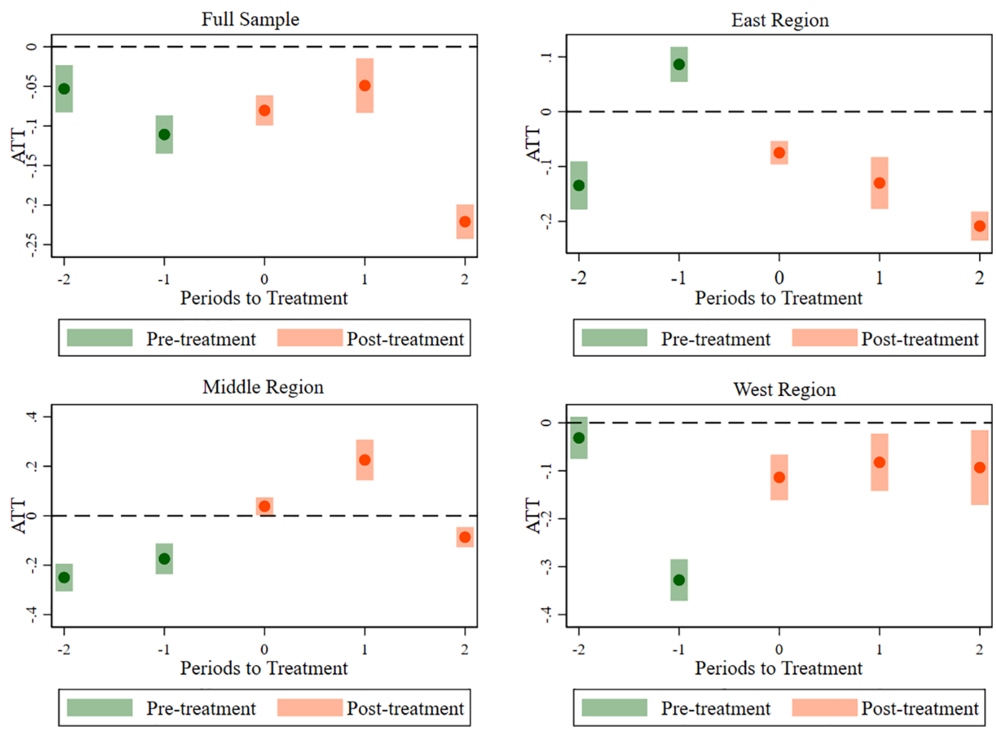

FIGURE 5
Doubly robust staggered DID estimator.

enforced. In contrast, the central and west regions may have had lower levels of clean renewable energy usage initially, leading to different responses to the BCP. Secondly, the effectiveness of the BCP in driving CREA could be influenced by variations in infrastructure and accessibility across regions. The east region, with its established clean energy infrastructure (Liu et al., 2011), may have faced fewer barriers in utilizing alternative energy sources. In contrast, the central and west regions might have encountered challenges related to infrastructure development, making it more difficult for residents to adopt clean renewable energy, particularly after the initial period.

Thirdly, economic factors such as market incentives and cost considerations play a vital role in CREA. The higher prevalence of clean renewable energy usage in the east region before BCP implies that residents may have already taken advantage of existing incentives or enjoyed relatively lower costs associated with CREA (Schulte et al., 2016; Feng et al., 2017). Consequently, the policy implementation may have had a diminishing effect on CREA in this region, as residents may have perceived fewer economic benefits compared to other regions.

Finally, regional differences in the composition of industries and economic activities can also influence the response to the BCP and CREA. For instance, if the east region had a greater concentration of industries or economic sectors that heavily relied on clean renewable energy, the impact of BCP on CREA might have been mitigated due to the existing utilization of renewable sources.

5.3.3 Clean energy in China: natural gas and coal gas

To address concerns surrounding regional heterogeneity and potential estimation bias caused by variations in energy consumption structure, a revised analysis is proposed. This re-estimation modifies the dependent variable to include the adoption of natural gas and coal gas, as suggested by Zou et al. (2018). Notably, while most existing studies focus on macro-level energy consumption, our emphasis is on the individual level, which we argue is crucial for sustainable development.

In China, natural gas is considered a clean energy source and its adoption has been actively promoted by the government in the east region over the past three decades. In contrast, gas and firewood are still the dominant sources of energy for rural families in the middle and west regions. By incorporating these variables, a staggered DID model can be utilized to study the impact of the BCP initiative on natural gas and coal gas adoption across different regions (Beck et al., 2010). This revised approach offers insights into how the policy influences the adoption of cleaner energy sources (natural gas) versus traditional energy sources (coal gas) in diverse geographical areas. Moreover, by comparing changes in natural gas and coal gas consumption, as well as CREA before and after the BCP implementation, within and across regions, it becomes possible to untangle the specific impact of the policy on each energy source. The regression results of this analysis are reported in Table 6.

After including the control variables, province fixed effects, year effects, and the interactive fixed effect of region and year, the revised analysis reveals notable findings. The BCP appears to have a significant positive impact on clean energy adoption in the middle and east regions of China, as evidenced by coefficients of 0.0138 at the 1% significance level for the middle region and 0.0109 at the 10% significance level for the east region. Conversely, in the west region, the policy seems to hinder the adoption of natural gas (with a coefficient of −0.0327 at the 1% significance level) while significantly reducing coal gas adoption (with a coefficient of −0.0563 at the 1% significance level).

A potential explanation for the observed reduction in clean energy adoption in the west region may lie in the migration of rural residents to more developed regions in China, a phenomenon suggested by both Zou et al. (2018) and Wang et al. (2016). Rural residents, especially those with internet access, might be able to find online job opportunities and subsequently leave their hometowns. This migration could result in a decreased demand for clean energy adoption in the west region, as the population engaged in energy consumption declines due to outmigration. This finding underscores the importance of considering broader socioeconomic factors and regional dynamics when analyzing the impact of policies on energy adoption. In this case, employment opportunities, internet access, and rural–urban migration patterns seem to play a role in shaping energy consumption patterns and moderating the effectiveness of the BCP in promoting clean energy adoption in the west region.

5.3.4 Placebo test

To address concerns related to sample selection bias and potential estimation bias caused by unobservable confounders, a placebo test is conducted following a non-parametric permutation method similar to the approach used by Ferrara et al. (2012). The purpose of this test is to examine whether the baseline regression results are affected by unobservable variables.

The placebo test involves the random selection of 106 cities from the entire sample, designating them as the false treatment group, while the remaining cities serve as the false control group. For each city in the false treatment group, a random year between 2007 and 2016 is assigned as the false policy implementation year. This process is repeated 500 times, resulting in 500 sets of estimated coefficients obtained from the random assignments. Figure 6 illustrates the kernel density distributions of these 500 estimated coefficients. The distribution closely approximates a normal distribution, and the average value of the coefficients is close to zero. These findings indicate that the impact of the BCP on CREA is unlikely to be driven by omitted unobservable variables. Therefore, the robustness of the baseline estimates is supported.

6 Mechanism

In this section, we analyze the mechanism underlying the impact of Broadband China Policy (BCP) on the adoption of clean renewable energy (CREA) in rural households. As previously discussed, this impact is multifaceted and encompasses various dimensions of economic activities.

One of the primary objectives of the BCP initiative is to enhance broadband adoption. Through the implementation of BCP, rural residents have gained improved affordability and faster internet speeds, enabling them to access online resources more readily. This improved internet accessibility plays a crucial role in facilitating the dissemination of information and knowledge concerning clean

TABLE 6 The effect of BCP on natural gas and gas.

	(1) Natural Gas	(2) Natural Gas	(3) Natural Gas	(4) Coal Gas	(5) Coal Gas	(6) Coal Gas
BCP × Middle Region	0.0138*			−0.0153		
	[0.008]			[0.015]		
BCP × East Region		0.0109*			−0.0330***	
		[0.006]			[0.011]	
BCP × West Region			−0.0327***			−0.0563***
			[0.009]			[0.016]
_cons	−0.0665***	−0.0647***	−0.0594***	0.351***	0.347***	0.360***
	[0.018]	[0.018]	[0.018]	[0.033]	[0.033]	[0.033]
N	33,009	33,009	33,009	33,009	33,009	33,009
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Family	Family	Family	Family	Family	Family

Robust standard errors are in parentheses; * and *** denote significances at 10% and 1% levels, respectively.

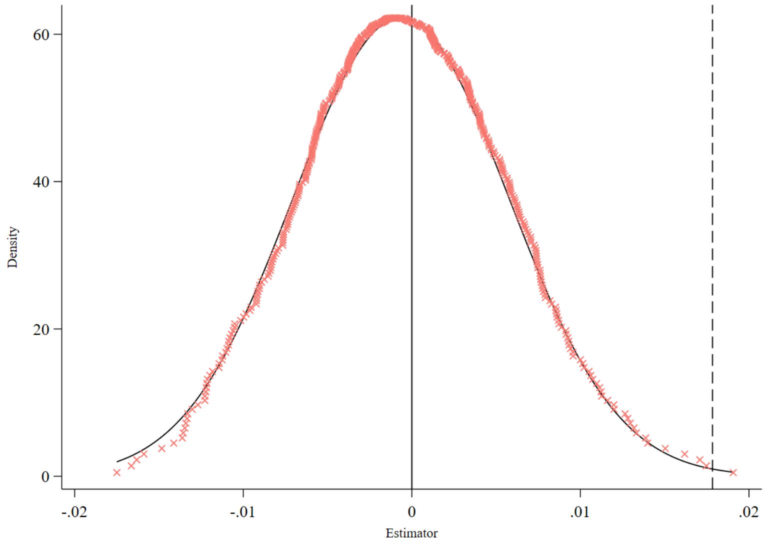

FIGURE 6
Placebo test.

energy technologies and practices. The internet serves as a valuable platform for educational resources, providing rural residents with access to relevant information (Zaharov et al., 2018; Jang and Song, 2022), case studies, and success stories related to clean renewable energy. By leveraging these resources, individuals can make informed decisions regarding the adoption of clean renewable energy (CREA). Consequently, internet accessibility serves as a vital channel connecting BCP to CREA, as it enhances awareness and understanding of the benefits and feasibility associated with CREA. Therefore, we propose three distinct avenues through which BCP can facilitate the promotion of CREA in rural families.

6.1 Governance participation and pollution

The accessibility of the internet not only empowers rural residents to voice their concerns, provide feedback, and actively participate in discussions related to pollution control and clean energy policies but also plays a crucial role in facilitating effective governance and policy reforms (Flew et al., 2019; Haggart, 2020). By harnessing the power of the internet, residents can engage in environmental issues, express their opinions, and advocate for sustainable practices, thereby exerting pressure on local governments to allocate more resources to pollution control efforts.

Moreover, the advent of new digital technologies has revolutionized environmental monitoring and management. Real-time monitoring systems, remote sensing technologies, and advanced data analysis tools have become invaluable assets in the identification and mitigation of pollution sources (Cheng et al., 2021; Chen et al., 2022b). These digital innovations enable authorities to promptly detect and address environmental hazards, leading to the implementation of more stringent regulations and the enhancement of enforcement mechanisms.

Furthermore, the internet acts as a catalyst for promoting clean renewable energy alternatives. Digital platforms provide a space for knowledge sharing, where information regarding the benefits and feasibility of clean energy technologies can be disseminated (Jang and Song, 2022). Online resources such as case studies, success stories, and educational materials are readily accessible, enabling rural residents to make informed decisions regarding clean energy adoption. The availability of such information not only raises awareness but also enhances the understanding of clean energy solutions, further driving the shift toward sustainable practices.

The digital transition also brings about increased government investment and efficiency in addressing environmental challenges. With the aid of digital tools and technologies, governments can streamline administrative processes, facilitate data-driven decision-making, and improve resource allocation. This results in more effective and targeted interventions to combat pollution and promote clean energy. Additionally, the transparency and accountability enabled by digital platforms foster trust between governments and citizens, creating a conducive environment for collaboration and the implementation of sustainable policies.

6.2 Job opportunities and salary income

The accessibility of the internet opens up avenues for rural residents to access a wider range of job opportunities, fostering economic empowerment and financial stability (Stevenson, 2008; Maurer-Fazio, 2012; Suvankulov et al., 2012; Castellacci and Vinas-Bardolet, 2019). With the advent of digital platforms and online marketplaces, individuals residing in rural areas can engage in remote work or venture into entrepreneurship, regardless of their geographic location. This expanded economic activity not only provides individuals with additional sources of income but also enhances their financial capacity to invest in various aspects of their lives, including clean energy technology.

By leveraging digital platforms, rural residents can participate in remote work arrangements (Ghislieri et al., 2022), such as freelancing, consulting, or telecommuting. This flexibility allows individuals to harness their skills and expertise, serving clients and organizations worldwide (Sako, 2021). Additionally, online marketplaces offer opportunities for rural entrepreneurs to showcase and sell their products or services to a global customer base, transcending traditional geographical limitations. This newfound economic potential provides rural residents with a pathway toward financial independence and improved livelihoods.

The increased income and financial stability resulting from these digital opportunities can indirectly impact the adoption of clean renewable energy (CREA) in rural areas. As individuals' economic circumstances improve, they gain the means to invest in clean energy technologies for their households or businesses. This could involve installing solar panels, purchasing energy-efficient appliances, or implementing sustainable farming practices. The availability of reliable and sustainable income sources enables individuals to allocate resources towards environmentally friendly solutions, gradually transitioning towards a cleaner and more sustainable energy future.

Moreover, the economic empowerment facilitated by internet accessibility can have wider community benefits. As rural residents engage in remote work or establish online businesses, they contribute to local economic development and job creation. This virtuous cycle stimulates economic growth within rural communities, fostering a supportive ecosystem for the adoption of clean energy. Local businesses, service providers, and community organizations may also respond to the growing demand for clean energy solutions, further promoting the uptake of CREA.

However, with the development of the internet and the increase in income, online platforms provide multiple products and delivery services with coupons (Duan et al., 2022). This convenience and attractive pricing often lure residents to order take-out meals instead of cooking at home (Jiang et al., 2021). Furthermore, residents may choose to purchase more advanced electrical equipment due to their increased purchasing power. While these trends may seem beneficial, they have the potential to reduce the utilization of renewable energy sources. To address this issue, it is crucial to examine the impact of these factors on the energy consumption patterns of residents. Firstly, the widespread adoption of online platforms for food delivery can lead to a higher demand for transportation and logistics services. The increased frequency of delivery vehicles on the roads can result in greater fuel consumption and emissions, indirectly contributing to environmental pollution. This aspect needs to be considered when evaluating the overall energy efficiency of the online food delivery system.

Secondly, the availability of coupons and discounts on online platforms can influence consumer behavior (Duan et al., 2022). By offering reduced prices for take-out meals, online platforms encourage residents to order food instead of cooking at home. This shift in behavior can lead to increased energy consumption, as households relying on take-out meals are likely to use more electricity for lighting, refrigeration, and other related purposes. Consequently, the energy demand may rise, potentially placing additional strain on non-renewable energy sources.

Furthermore, the affordability of advanced electrical equipment, made possible by increased income, can also impact energy consumption patterns. While these appliances may provide convenience and improved functionality, they often require substantial amounts of energy to operate. If the trend of purchasing such energy-intensive equipment continues, it could contribute to higher overall energy demand, possibly relying more heavily on non-renewable energy sources.

6.3 Industrial upgrading

The adoption of the internet and digital technologies, including IoT devices, smart systems, and data analytics, plays a pivotal role in optimizing energy usage, monitoring emissions, and integrating renewable energy sources across industrial and household sectors (Ishida, 2015; Lahouel et al., 2021; Chen et al., 2022b). This process of digital transition catalyzes industrial upgrading, leading to the adoption of cleaner production processes and promoting the adoption of clean renewable energy solutions in daily life.

By leveraging IoT devices and smart systems, industries and households can enhance their energy efficiency and reduce their environmental impact (Wang et al., 2021; Chen et al., 2022b). Smart grids enable real-time monitoring and control of energy consumption, allowing for more efficient allocation and utilization of resources. Industrial processes can be optimized through data analytics, identifying areas for improvement, and implementing energy-saving measures. This optimization not only reduces energy waste but also minimizes emissions and environmental pollutants. Furthermore, the integration of renewable energy sources is facilitated by digital technologies. IoT devices and data analytics enable the seamless integration of renewable energy systems, such as solar panels and wind turbines, into existing infrastructure. These technologies provide real-time monitoring and management of renewable energy generation, ensuring efficient utilization and grid integration. The intelligent control systems allow for dynamic load balancing, storage management, and demand response mechanisms, optimizing the overall energy mix and promoting the use of clean energy sources.

The impact of BCP is significant in this context as it accelerates the digital transition and promotes the widespread adoption of these technologies. Improved internet accessibility through BCP facilitates the dissemination of digital innovations, enabling industries and households to embrace energy-efficient practices and renewable energy solutions. By enhancing energy efficiency and reducing environmental impacts within industries and households, BCP contributes to the wider availability and adoption of clean energy sources.

In summary, the adoption of the internet and digital technologies empowers industries and households to optimize energy usage, monitor emissions, and integrate renewable energy sources. This digital transition, supported by initiatives like Broadband China, drives industrial upgrading and promotes the adoption of cleaner production processes and clean renewable energy solutions. Ultimately, it improves energy efficiency, reduces environmental impact, and paves the way for a more sustainable and clean energy future.

6.4 Mechanism analysis

To test the mechanisms discussed above, we have introduced the interactive terms of BCP with pollution, industry structure, and family salary income in our baseline regression, as specified in model (9). The results of these regressions are presented in Table 7.

In column (1), the interaction term between BCP and pollution, represented as *BCP* × *Pollution*, is introduced. The coefficient corresponding to this interaction term is quantified as 0.0238, demonstrating statistical significance at the 10% level, and is decidedly positive. This empirical evidence suggests that the local district's pollution levels modulate the relationship between BCP and CREA.

The positive coefficient affiliated with the *BCP* × *Pollution* interaction term is concordant with the hypothesis that BCP avails residents with expanded avenues for expressing their perspectives and concerns about pollution. Through the medium of online platforms, residents are empowered to articulate their sentiments and advocate for an enhanced environmental living standard.

The positive coefficient also denotes that as pollution escalates, the positive influence of BCP on CREA becomes increasingly discernible. This finding infers that the digital transition, embodied by online platforms, equips residents with the tools necessary to champion and strive for betterment in their living conditions, specifically regarding the reduction of pollution.

In column (2), we incorporate the interaction term between BCP and Industry Structure, denoted as *BCP* × *Industry Structure*. Relative to the baseline model, there are significant alterations in the coefficients and subsequent interpretations. Primarily, the coefficient associated with BCP becomes statistically significant and positive (0.043 at a 1% significance level), thereby signifying that BCP profoundly fosters CREA among rural families when industry structure is factored in. This indicates that the utilization of online platforms, including BCP, exerts a positive influence on the economic welfare of rural families, considering the distinct characteristics of the industry structure.

Contrastingly, the coefficient for the interaction term *BCP* × *Industry Structure* is statistically significant yet negative (−0.117 at a 1% significance level). This observation intimates that the relationship between BCP and CREA is shaped by the proportion of tertiary industry in the region. As the proportion of this industry, characterized by a dominance of service-oriented sectors such as hospitality and restaurants, swells, the effect of BCP on CREA appears to decline or even reverse, becoming negative.

This discovery is supported by the analysis delineated earlier, although it diverges from macro-level analyses, as cited in previous studies. When the tertiary industry dominates the local industrial structure, residents may prefer dining in restaurants as opposed to home cooking, thereby reducing both traditional and clean renewable energy usage. Simultaneously, this shift may incite an increase in electricity consumption due to the availability of more accessible and affordable electrical devices. Such a transition in consumption habits can potentially negate the positive effect of BCP on CREA.

TABLE 7 Mechanism analysis.

	(1) CREA	(2) CREA	(3) CREA
BCP	−0.0822***	0.0453***	0.444***
	[0.008]	[0.016]	[0.168]
BCP × Pollution	0.0238* [0.014]		
BCP × Industry Structure		−0.117*** [0.012]	
BCP × Family Salary Income			−0.0508*** [0.016]
_cons	0.344***	0.300***	0.177**
	[0.031]	[0.033]	[0.085]
N	33009	30398	19259
Control Variable	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes
Cluster	Family	Family	Family
Adjust R^2	0.2893	0.2982	0.2606

Robust standard errors are in parentheses; *, **, and *** denote significances at 10%, 5%, and 1% levels, respectively.

In column (4), we incorporate the interaction term between BCP and family salary income, denoted as *BCP* × *Family Salary Income*. The coefficients corresponding to BCP and the interaction term yield significant insights into the tripartite relationship among digital transition, familial income, and consumption structure.

In a manner analogous to the preceding model, the coefficient associated with BCP is significantly positive (0.444 at a 1% level) in column (4). This implies that BCP has a beneficial influence on CREA in rural families when we account for family income. The digital transition facilitates economic activity, contributes to the economic wellbeing of households, and fosters CREA among rural families. Contrarily, the coefficient for the *BCP* × *Family Salary Income* term is significantly negative (−0.0508 at a 1% level). This indicates that as family salary income escalates, the relationship between BCP and CREA is negatively impacted.

Elevated income levels induce changes in consumption habits, such as a predilection for meal delivery services or restaurant dining, over home cooking. Specifically, the rise in family income may enable households to afford more convenient food options, instigating a departure from traditional home cooking. This shift in consumption behavior may precipitate a reduction in traditional energy costs but an uptick in electricity consumption due to the utilization of more contemporary, energy-demanding devices. Thus, the negative coefficient for the *BCP* × *Family Salary Income* interaction term underscores the importance of considering income's role in understanding BCP's impact on consumption patterns and energy usage. Heightened family income levels may attenuate the positive influence of BCP on CREA due to consumption behavior changes engendered by increased affordability and convenience.

These findings highlight the importance of various factors and the diverse effects of BCP on CREA. They imply that policymakers and stakeholders should be cognizant of the differing impacts of digital transition on various industries, household financial circumstances, and consumption behavior. This understanding is pivotal for nurturing sustainable economic growth and promoting energy efficiency in rural locales.

7 Heterogeneity and alternative interpretation

7.1 Heterogeneity

According to the analysis presented earlier, it is evident that the impact of BCP on CREA is influenced by multiple economic factors. Additionally, the considerable gap in economic development across different regions in China introduces significant heterogeneity in the causal inference between BCP and CREA. In this section, we delve further into this heterogeneity to gain a deeper understanding of the nuanced dynamic at play.

7.1.1 Heterogeneity of real estate district

Real estate holds significant importance for Chinese families, serving as both a living space and an investment asset (Ren et al., 2012). However, the high prices of real estate and the traditional cultural significance of owning a home create substantial financial burdens for families (Deng et al., 2012). Many Chinese families find themselves stretching their financial resources to meet the expenses associated with purchasing a house, often having to exhaust their savings and rely on various sources of funding.

It is worth noting that the heterogeneity in the types of housing available in China further contributes to the financial diversity across families. The CLDS survey includes a question that provides an opportunity to identify this heterogeneity by asking respondents about the type of district they reside in. The responses include non-reformed old districts, districts for workers in mining enterprises, districts for government officials and state-owned enterprise employees, social welfare housing communities, general commercial housing districts, upscale commercial housing communities, districts for rural-to-urban migrants, and shantytowns.

The majority of families residing in districts other than commercial housing districts and districts for government officials and employees of state-owned enterprises often face financial challenges, particularly those in rural areas. These families struggle with mandatory expenses such as food, education, and housing rent. Moreover, owing to the lack of comprehensive social security coverage, residents are often required to make upfront payments for medical treatment, and some may even find themselves unable to afford hospital bills. Consequently, the financial strain they face makes it difficult for them to afford the costs associated with adopting clean renewable energy sources. Moreover, the financial constraints experienced by families living in poverty or facing economic hardships underscore the challenges they encounter in adopting clean renewable energy technologies. Access to affordable and clean energy sources is crucial for sustainable development and environmental conservation. However, the financial limitations faced by these families restrict their ability to invest in renewable energy solutions, which often require upfront costs and infrastructure investments.

To examine the impact of low-income districts on the relationship between BCP and CREA, we introduce a dummy variable called "Low Income District", which takes a value of 1 if residents live in a low-income district, and 0 otherwise. Additionally, we incorporate the interaction term between BCP and Low-Income District, denoted as *BCP* × *Low Income District*, into the baseline model. To capture the heterogeneity across different regions, we divide the sample into the middle region, east region, and west region.

The results presented in Table 8 demonstrate that all of the coefficients of the interaction term, *BCP* × *Low Income District*, are statistically significant and negative. This indicates that rural families residing in low-income districts across China are likely to experience a reduction in CREA. These findings highlight the adverse impact of living in low-income districts on the relationship between BCP and CREA, regardless of the geographical region. The negative coefficients suggest that the combination of BCP usage and residing in a low-income district has an amplifying effect on the reduction of CREA. This outcome is noteworthy as it indicates that the potential benefits of BCP adoption in promoting CREA are diminished in low-income districts. The financial constraints and challenges faced by families in these districts hinder their ability to invest in clean and renewable energy

TABLE 8 Heterogeneity of Real Estate District.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA
	Full Sample	Middle Region	East Region	West Region
BCP × Low Income District	-0.223***	-0.182**	-0.177***	-0.504***
	[0.056]	[0.084]	[0.066]	[0.105]
_cons	0.324***	0.350**	0.419***	0.142
	[0.077]	[0.169]	[0.107]	[0.137]
N	33009	9782	15668	7559
Control Variable	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	No	No	No
Adjust R^2	0.2917	0.2908	0.2307	0.3071

Robust standard errors are in parentheses; ** and *** denote significances at 5% and 1% levels, respectively.

technologies, ultimately impacting their CREA levels. Furthermore, the results indicate that the heterogeneity across different regions does not significantly alter the causal inference of BCP on CREA in low-income districts. Regardless of whether the sample consists of the middle region, east region, or west region, the coefficients of the interaction term remain consistently negative and statistically significant. This suggests that the detrimental impact of low-income districts on the relationship between BCP and CREA extends throughout China.

The findings underscore the need for targeted interventions and policy measures to address the challenges faced by rural families living in low-income districts. Such measures should aim to alleviate financial constraints, improve access to affordable clean energy solutions, and promote sustainable development in these areas. By implementing policies that specifically target low-income districts, policymakers can help bridge the gap and ensure that the benefits of BCP and clean renewable energy are accessible to all, irrespective of their income levels or geographical location. In conclusion, the inclusion of a dummy variable for low-income districts and the corresponding interaction term in the analysis reveals that rural families living in low-income districts experience a reduction in CREA across China. This highlights the importance of addressing the financial constraints and challenges faced by these families in adopting clean and renewable energy technologies. The consistent findings across different regions emphasize the need for targeted policies to promote sustainable energy practices and mitigate the adverse effects of low-income districts on CREA.

7.1.2 Heterogeneity of population size

Population size plays a significant role in determining the level of public infrastructure, public services, and economic foundation in Chinese cities. Larger population centers tend to have more extensive public facilities and services to cater to the needs of a larger number of residents. Moreover, the larger population base offers attractive investment opportunities and a target market for both the government and enterprises. As a result, these areas are more likely to attract investments in green technology research and development, clean technology applications, and clean renewable energy infrastructure.

The heterogeneity arising from population size has several implications. Firstly, cities with larger populations often have a higher demand for energy and resources. This increased demand necessitates the development of robust and sustainable energy systems to meet the needs of the population. Consequently, policymakers and stakeholders are more inclined to invest in clean and renewable energy infrastructure in these areas to ensure a reliable and environmentally friendly energy supply.

Secondly, the availability of a large population provides a more significant market for clean technology products and services. With a large group, companies and entrepreneurs are motivated to develop and commercialize clean technologies to cater to the needs and preferences of a diverse consumer base. This, in turn, drives innovation and fosters the growth of the clean technology sector in these populous areas.

Furthermore, the concentration of the population in larger cities facilitates knowledge exchange, collaboration, and the sharing of best practices. These cities often serve as hubs for research and development, attracting skilled professionals and experts in the field of clean renewable energy. The presence of a knowledgeable workforce and a vibrant intellectual environment accelerates technological advancements and the adoption of clean renewable energy solutions.

However, it is crucial to consider the potential drawbacks and challenges associated with large population centers. Rapid urbanization and population growth can strain existing infrastructure and resources, leading to increased energy consumption and environmental pressures. Managing the energy demands of a large population requires careful planning efficient resource allocation, and sustainable urban development strategies.

To investigate the impact of population size on the relationship between BCP and CREA, we introduce a dummy variable called

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"Mean Popu". This variable takes a value of 1 if the population of the city is larger than the mean population across China, and 0 otherwise. Additionally, we divide the sample into the middle region, east region, and west region to capture the regional heterogeneity. Incorporating the interaction term between BCP and Mean Popu, denoted as *BCP × Mean Popu*, into the baseline model, we present the results in Table 9. The coefficients of *BCP × Mean Popu* are found to be statistically significant and positive. This indicates that in cities with larger populations, the presence of BCP significantly promotes CREA.

Comparing these results to the baseline model, it becomes evident that population size introduces significant heterogeneity across China. Larger cities not only attract migration but also attract technological advancements and investment. The concentration of population in these cities creates an environment that fosters the adoption and utilization of BCP, leading to a positive impact on CREA. On the other hand, smaller cities may face challenges associated with a declining population and limited investment opportunities. These factors may hinder the adoption of BCP and limit the potential benefits for CREA in these areas.

The findings highlight the importance of considering population size and its impact on the effectiveness of BCP in promoting CREA. Policy interventions and strategies should take into account the varying dynamics across cities of different sizes. It is crucial to support smaller cities in overcoming barriers and creating an enabling environment for the adoption of BCP and clean renewable energy technologies. Furthermore, the regional heterogeneity observed in the results emphasizes the need for tailored approaches in different regions. Middle, east, and west regions may have unique characteristics and specific challenges that require region-specific policies and initiatives to enhance CREA. By understanding and addressing the specific needs of each region, policymakers can foster sustainable economic growth, encourage investment in clean energy technologies, and promote energy efficiency.

In conclusion, the inclusion of the dummy variable "Mean Popu" and the corresponding interaction term *BCP ×Mean Popu* provides insights into the relationship between population size and the impact of BCP on CREA. The positive and statistically significant coefficients suggest that in cities with larger populations, BCP has a significant positive effect on CREA. This underscores the importance of considering population size and its associated heterogeneity when designing policies and interventions to promote sustainable energy practices and enhance CREA in different regions of China.

7.1.3 Economic size

The gaps in economic development across regions pose another important consideration in understanding the impact of BCP on CREA. In China, the east region holds a pivotal role in the country's economy, fiscal income, foreign communication, and technology innovation. On the other hand, the middle region and the west region are still in the process of development. To explore the potential heterogeneity resulting from economic size, we calculate the mean total GDP to be 3,617.536 billion. Furthermore, the mean GDP in the east region is 5,424.964 billion, that in the middle region is 2355.583 billion, and that in the west region is 1900.047 billion. These figures indicate substantial disparities in economic size across the regions.

Given these disparities, it is reasonable to expect that the impact of BCP on CREA may vary significantly across regions. The larger economic size of the east region, coupled with its advanced technological capabilities and greater investment opportunities, may create a more conducive environment for the adoption and utilization of BCP. The positive impact of BCP on CREA in the east region is likely to be more pronounced compared to the middle and west regions. However, as discussed above, the residents living in the east region will change their consumption structure due to the developed economic and digital transition; as a result, the BCP

TABLE 9 Heterogeneity of population size.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA
	Full Sample	Middle Region	East Region	West Region
BCP × Mean Popu	0.0719**	0.141***	0.0354***	0.105***
	[0.031]	[0.016]	[0.012]	[0.023]
_cons	0.121	0.154***	0.247***	−0.169***
	[0.075]	[0.060]	[0.045]	[0.064]
N	33,009	9,782	15,668	7,559
Control Variable	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	No	No	No
Adjust R^2	0.2582	0.2655	0.1938	0.2597

Robust standard errors are in parentheses; ** and *** denote significances at 5% and 1% levels, respectively.

shows a lower impact on CREA in rural families residing in the east region.

Conversely, the middle and west regions, characterized by lower economic sizes and relatively less developed infrastructure, may face challenges in realizing the full potential of BCP for promoting CREA. The limited resources and investment in these regions could hinder the adoption and utilization of BCP, leading to a relatively weaker impact on CREA. To comprehensively understand the heterogeneity resulting from economic development gaps, it is crucial to conduct further analysis and regression models that explicitly account for regional economic factors. This would enable a more nuanced examination of the relationship between BCP and CREA, considering the varying economic sizes across regions and their impact on the adoption and effectiveness of BCP.

To further investigate the heterogeneity related to economic size, we introduce a dummy variable called "GDP Mean Group". This variable takes a value of 1 if the GDP of a region is larger than the mean GDP across all regions, and 0 otherwise. Additionally, we introduce the dummy variables "Mid GDP Mean Group", "East GDP Mean Group", and "West GDP Mean Group" based on the means of GDP in the middle, east, and west regions, respectively. Table 10 presents the results of the regression analysis. We find that GDP plays a significant role in determining the impact of BCP on CREA across China. The coefficients of the interaction term between the BCP and GDP Mean Group are statistically significant and positive in the full sample. Comparing these results to the baseline model, it becomes evident that economic development amplifies the impact of BCP on CREA. Regions with higher levels of economic development tend to experience a stronger positive effect of BCP on CREA.

Furthermore, when we examine the results for specific regions, we observe some interesting findings. In the middle and west regions, the coefficients of the interaction term are statistically significant and positive, indicating that the impact of BCP on CREA is amplified in these regions. This aligns with our previous analysis, highlighting the challenges faced by less-developed regions and their potential to benefit from BCP adoption. Surprisingly, in the east region, the coefficient of the interaction term is not statistically significant. This suggests that the relationship between BCP and CREA may be influenced by other factors in the east region, such as advanced technological infrastructure and higher levels of investment. These factors may overshadow the specific impact of BCP on CREA in the east region.

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7.2 Alternative interpretation

7.2.1 Social study

In order to examine the potential influence of social study on the impact of BCP on CREA, we introduce the interaction term *BCP × Social Study* into the analysis. The frequency of social study

TABLE 10 Heterogeneity of economic size.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA
	Full Sample	Middle Region	East Region	West Region
BCP × GDP Mean Group	0.0540*** [0.009]			
BCP × Mid GDP Mean Group		0.0739*** [0.017]		
BCP × East GDP Mean Group			0.00823 [0.012]	
BCP × West GDP Mean Group				0.0343*** [0.010]
_cons	0.114***	0.102*	0.244***	0.251***
	[0.031]	[0.060]	[0.045]	[0.045]
N	33,009	9,782	15,668	15,668
Control Variable	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	No	No	No
Adjust R^2	0.2575	0.2608	0.1934	0.194

Robust standard errors are in parentheses; * and *** denote significances at 10% and 1% levels, respectively.

activities, as reported by the respondents in the CLDS survey, serves as a proxy for their engagement in acquiring knowledge, training, and technical support related to clean renewable energy technologies. Additionally, we consider the role of natural gas, another important source of energy in China, to test whether social study has a greater impact on promoting CREA compared to BCP. This allows us to assess whether social study activities have a specific influence on the adoption of clean renewable energy technologies, independent of the overall impact of BCP and other energy sources.

In columns (1) and (2) of Table 11, we observe that the coefficients of the interaction terms between BCP and Social Study are statistically insignificant and positive. This implies that the frequency of social study activities, as reported by the respondents, does not appear to have a significant influence on the relationship between BCP and CREA. These results suggest that while social study activities may provide channels for rural residents to access clean renewable energy knowledge and training, it does not significantly enhance the impact of BCP on the adoption of clean renewable energy technologies in rural areas. Other factors or mechanisms might be more influential in driving the adoption of CREA.

It is important to interpret these findings cautiously and consider the potential limitations of the analysis. Other factors not captured in the model or variations in the sample characteristics could also contribute to the insignificant relationship between BCP, social study, and CREA. Further research and analysis may be required to explore additional factors or alternative explanations for the observed results.

Overall, the analysis suggests that social study activities alone may not be a significant determinant of the impact of BCP on CREA. Policymakers and stakeholders should consider other strategies and interventions to promote CREA in rural areas, taking into account the specific context and characteristics of the target population.

7.2.2 Energy conservation and emission reduction pilot city

To address concerns regarding potential confounding factors, we examine the impact of other policies related to clean energy adoption, such as the Energy Conservation and Emission Reduction Pilot City (ECERP) program. The ECERP program aims to enhance energy conservation and emission reduction efforts in selected cities, integrating various fiscal policies to achieve China's targets

TABLE 11 Alternative interpretation.

	(1) CREA	(2) Natural Gas	(3) CREA	(4) CREA	(5) CREA	(6) CREA
	Full Sample		Exclude the ECERP pilot City			
BCP × Social Study	0.000685	0.0129				
	[0.007]	[0.008]				
BCP			-0.0487***			
			[0.009]			
BCP × Middle Region				0.0598***		
				[0.016]		
BCP × East Region					-0.0764***	
					[0.013]	
BCP × West Region						-0.116***
						[0.017]
_cons	0.368***	-0.0654	0.325***	0.305***	0.311***	0.336***
	[0.079]	[0.050]	[0.036]	[0.036]	[0.036]	[0.036]
N	33009	33009	29061	29061	29061	29061
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Family	Family	Family	Family	Family	Family
Adjust R^2	0.2901	0.3342	0.2763	0.2759	0.2764	0.2767

Robust standard errors are in parentheses; *** denotes significance at 1% level.

in these areas. The program was initiated in 2011, with additional cities being promoted in 2013 and 2014, totaling 28 cities. To eliminate the potential influence of ECERP on our baseline estimation, we exclude the ECERP cities from the total sample and re-estimate the baseline model. Columns (3) to (6) in the analysis report the results. By excluding the ECERP cities, we can isolate the specific impact of the BCP on CREA, independent of any potential effects resulting from the ECERP program. This allows us to examine the true relationship between BCP and CREA, without the confounding influence of this particular policy intervention. The coefficients of BCP and the interaction terms are statistically significant. Compared to the baseline model, the coefficient is smaller, which suggests that the ECERP has affected the adoption of renewable energy in rural family, and it also supports the idea that the BCP has a significant impact on CREA, and it shows heterogeneity across regions.

The results of the analysis in columns (3) to (6) indicate that the coefficients of BCP and the interaction terms remain statistically significant, even after excluding the ECERP cities from the sample. However, it is observed that the magnitude of the coefficients is smaller compared to the baseline model. This finding suggests that the presence of the ECERP program has affected the adoption of renewable energy in rural families. The program may have influenced the overall energy conservation and emission reduction efforts in the ECERP cities, which could have indirectly affected the adoption of clean renewable energy technologies in these areas. Nonetheless, the significance of the coefficients of BCP and the interaction terms, even in the absence of the ECERP cities, supports the idea that BCP has a significant impact on CREA. It further reinforces the notion that BCP plays a vital role in promoting the adoption of clean renewable energy technologies in rural areas.

Additionally, the presence of heterogeneity across regions is observed, indicating that the impact of BCP on CREA varies across different parts of China. This regional variation suggests that factors such as economic development, policy environment, and infrastructure may influence the effectiveness of BCP in promoting CREA.

Overall, by excluding the ECERP cities and observing the significance of the coefficients in the remaining sample, we can conclude that the BCP has a significant impact on CREA, even after accounting for the potential influence of the ECERP program. The presence of heterogeneity across regions underscores the need for tailored policies and strategies to effectively promote CREA in rural areas across different parts of China.

8 Conclusion

The ongoing digital transition and the urgent need to address global warming have brought attention to the energy consumption patterns in rural families. However, there is currently a lack of theoretical frameworks and empirical research focusing on this specific context. Furthermore, the impact of digital transition on the adoption of clean renewable energy in rural families remains understudied. This paper aims to fill these research gaps by utilizing Broadband China Policy (BCP) as a quasi-natural experiment and analyzing data from the CLDS spanning the years 2012 to 2016. To assess the impact of digital transition on CREA in rural families, the study employs a staggered DID approach and the Doubly Robust Staggered DID estimator. The use of a traditional staggered DID estimator allows for a rigorous examination of the causal relationship between digital transition and CREA, by analyzing the CLDS datasets, which provide valuable insights into the energy consumption patterns of rural families, and the study aims to shed light on the potential effects of digital transition on CREA in this specific context. By applying a robust statistical method, the study seeks to provide reliable and accurate estimates of the impact of digital transition on CREA; moreover, it also provides the chance to analyze its dynamic effects. This rigorous analysis contributes to the existing literature on energy consumption patterns and the role of digital technology in promoting sustainable energy practices.

Our findings demonstrate that the digital transition has a significant impact on the adoption of clean renewable energy in rural families, with notable heterogeneity across regions. Specifically, the implementation of the BCP resulted in a significant increase in CREA in the middle region, with a 5.8% increase compared to non-pilot cities. However, in the east and west regions, the BCP led to a reduction in CREA, with a 12.6% decrease in the east region and a 13.5% decrease in the west region. Furthermore, our dynamic effect analysis reveals interesting patterns in the causal relationship between the BCP and CREA. In the east region, we observe that CREA was already high before the implementation of the BCP, suggesting that other factors may have played a significant role in driving adoption in this region. In contrast, in the west region, the BCP had a positive impact on the intention to adopt clean renewable energy after its implementation, indicating the potential for the BCP to facilitate adoption in this region.

Additionally, considering natural gas as a clean energy source in China, we find that the BCP led to a 1.38% increase in natural gas usage in the east region. This suggests that the BCP may have influenced the choice of clean energy sources, with a shift towards natural gas in this particular region. Furthermore, our analysis reveals that the impact of the BCP on CREA operates through three channels: population size, economic size, and income level. Cities with larger populations and greater economic size experience a more significant impact of the BCP on CREA in rural families. However, low-income families tend to prefer using fossil energy rather than clean renewable energy following the implementation of the BCP.

These findings provide empirical evidence for countries, particularly developing nations, that aim to leverage digital development for technological progress and industrial upgrading to reduce carbon emissions, increase CREA, and improve the welfare of residents. By understanding the heterogeneity of the effects and the underlying channels through which digital transition impacts CREA, policymakers can design targeted interventions and policies to promote sustainable energy practices and enhance overall societal wellbeing.

9 Further research direction

Building upon the findings of this study, future research should aim to further delineate the nuanced relationships between BCP and consumer behavior. The digital transition's varied impact on different industries and diverse household income levels, as well as consumption behaviors, warrants further exploration. Specifically, a deeper understanding of how digital tools like BCP can be optimized to stimulate CREA in different socioeconomic and industrial contexts is imperative.

Furthermore, it would be beneficial to expand the scope of this research to a broader geographical context. This study predominantly focused on rural families; however, the impacts of BCP and digital transitions might differ in urban settings due to contrasting living conditions, industry structures, and income levels. Cross-regional comparisons would provide comprehensive insights into the generalizability of the current findings.

In addition, the role of government policy in influencing and possibly amplifying the positive effects of BCP on CREA should not be overlooked. Policymakers should consider incentives to encourage the use of online platforms to promote energy efficiency and sustainable practices among citizens. Therefore, future research could examine how different policy interventions affect the relationship between BCP and CREA.

Lastly, it would be intriguing to examine the long-term impacts of changes in consumer behavior on energy consumption patterns. As income levels rise and consumption habits shift, what are the long-term implications for traditional and renewable energy usage? Unraveling the potential impacts of these dynamics could provide valuable insights into sustainable economic growth strategies and the promotion of energy efficiency in both rural and urban areas.

Data availability statement

The datasets presented in this study are a result of the combination of three separate datasets, namely: China Labor-force Dynamics Survey (CLDS), Data from Chinese Ministry of Industry and Information Technology, and China City Statistical Yearbook. These datasets have been integrated and summarized in the Supplementary Material.

Author contributions

JY: original writing and revision. JL: data collection. XL: data collection and polishing the paper. YL: supervision and polishing the paper. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2023.1241410/full#supplementary-material

References

Asante, D., He, Z., Adjei, N. O., and Asante, B. (2020). Exploring the barriers to renewable energy adoption utilising multimoora-edas method. *Energy Policy* 142, 111479. doi: 10.1016/j.enpol.2020.111479

Atkinson, R. D., and McKay, A. S. (2007). Digital prosperity: understanding the economic benefits of the information technology revolution. *SSRN* 1004516. doi: 10.2139/ssrn.1004516

Beck, T., Levine, R., and Levkov, A. (2010). Big bad banks? the winners and losers from bank deregulation in the United States. *J. Finance* 65, 1637–1667. doi: 10.1111/j.1540-6261.2010.01589.x

Bertschek, I., Briglauer, W., Huschelrath, K., Kauf, B., and Niebel, T. (2015). The economic impacts of broadband internet: A survey. *Rev. Netw Economics* 14, 201–227. doi: 10.1515/rne-2016-0032

Braguinsky, S., Ohyama, A., Okazaki, T., and Syverson, C. (2021). Product innovation, product diversification, and firm growth: Evidence from Japan's early industrialization. *Am. Economic Rev.* 111, 3795–3826. doi: 10.1257/aer.20201656

Callaway, B., and Sant'Anna, P. H. (2021). Difference-in-Differences with multiple time periods. *J. Econometrics* 225, 200–230. doi: 10.1016/j.jeconom.2020.12.001

Castellacci, F., and Vinas-Bardolet, C. (2019). Internet use and job satisfaction. *Comput. Hum. Behav.* 90, 141–152. doi: 10.1016/j.chb.2018.09.001

Chen, Y., Fan, Z., Gu, X., and Zhou, L.-A. (2020). Arrival of young talent: The send-down movement and rural education in China. *Am. Economic Rev.* 110, 3393–3430. doi: 10.1257/aer.20191414

Chen, Y., Shao, S., Fan, M., Tian, Z., and Yang, L. (2022b). One man's loss is another's gain: does clean energy development reduce co2 emissions in China? evidence based on the spatial durbin model. *Energy Economics* 107, 105852. doi: 10.1016/j.eneco.2022.105852

Chen, J., Su, F., Jain, V., Salman, A., Tabash, M. I., Haddad, A. M., et al. (2022a). Does renewable energy matter to achieve sustainable development goals? the impact of renewable energy strategies on sustainable economic growth. *Front. Energy Res.* 10, 829252. doi: 10.3389/fenrg.2022.829252

Cheng, C.-Y., Chien, M.-S., and Lee, C.-C. (2021). Ict diffusion, financial development, and economic growth: An international cross-country analysis. *Economic Model.* 94, 662–671. doi: 10.1016/j.econmod.2020.02.008

Commander, S., Harrison, R., and Menezes-Filho, N. (2011). Ict and productivity in developing countries: New firm-level evidence from Brazil and India. *Rev. Economics Stat* 93, 528–541. doi: 10.1162/REST_a_00080

Czernich, N., Falck, O., Kretschmer, T., and Woessmann, L. (2011). Broadband infrastructure and economic growth. *Economic J.* 121, 505–532. doi: 10.1111/j.1468-0297.2011.02420.x

D'Adamo, I., Mammetti, M., Ottaviani, D., and Ozturk, I. (2023). Photovoltaic systems and sustainable communities: New social models for ecological transition. the impact of incentive policies in profitability analyses. *Renewable Energy* 202, 1291–1304. doi: 10.1016/j.renene.2022.11.127

De Chaisemartin, C., and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *Am. Economic Rev.* 110, 2964–2996. doi: 10.1257/aer.20181169

Deng, Y., Gyourko, J., and Wu, J. (2012). Land and house price measurement in China. *Natl. Bur. Econ. Res.* w18403. doi: 10.3386/w18403

do Valle Costa, C., La Rovere, E., and Assmann, D. (2008). Technological innovation policies to promote renewable energies: Lessons from the european experience for the Brazilian case. *Renewable Sustain. Energy Rev.* 12, 65–90. doi: 10.1016/j.rser.2006.05.006

Draca, M., Sadun, R., and Van Reenen, J. (2009). Productivity and ICTs: A Review of the Evidence. In *The Oxford Handbook of Information and Communication Technologies*. (Oxford and New York: Oxford University Press), 100–147. doi: 10.1093/oxfordhb/9780199548798.003.0005

Duan, Y., Liu, T., and Mao, Z. (2022). How online reviews and coupons affect sales and pricing: An empirical study based on e-commerce platform. *J. Retailing Consumer Serv.* 65, 102846. doi: 10.1016/j.jretconser.2021.102846

El Hilali, W., El Manouar, A., and Idrissi, M. A. J. (2020). Reaching sustainability during a digital transformation: a pls approach. *Int. J. Innovation Sci.* 12, 52–79. doi: 10.1108/IJIS-08-2019-0083

Eren, B. M., Taspinar, N., and Gokmenoglu, K. K. (2019). The impact of financial development and economic growth on renewable energy consumption: Empirical analysis of India. *Sci. Total Environ.* 663, 189–197. doi: 10.1016/j.scitotenv.2019.01.323

Eshchanov, B., Abdurazzakova, D., Yuldashev, O., Salahodjaev, R., Ahrorov, F., Komilov, A., et al. (2021). Is there a link between cognitive abilities and renewable energy adoption: Evidence from Uzbekistan using micro data. *Renewable Sustain. Energy Rev.* 141, 110819. doi: 10.1016/j.rser.2021.110819

Feng, Y., Hong, Z., Zhang, Z., Zhang, Z., and Tan, J. (2017). Interval analysis and dematel-based reliability apportionment for energy consumption optimization with energy internet. *IEEE Access* 5, 4769–4778. doi: 10.1109/ACCESS.2017.2672758

Feroz, A. K., Zo, H., and Chiravuri, A. (2021). Digital transformation and environmental sustainability: A review and research agenda. *Sustainability* 13, 1530. doi: 10.3390/su13031530

Ferrara, E. L., Chong, A., and Duryea, S. (2012). Soap operas and fertility: Evidence from Brazil. *Am. Economic J: Appl. Economics* 4, 1–31. doi: 10.1257/app.4.4.1

Flew, T., Martin, F., and Suzor, N. (2019). Internet regulation as media policy: Rethinking the question of digital communication platform governance. *J. Digital Media Policy* 10, 33–50. doi: 10.1386/jdmp.10.1.33_1

Forman, C., Goldfarb, A., and Greenstein, S. (2012). The internet and local wages: A puzzle. *Am. Economic Rev.* 102, 556–575. doi: 10.1257/aer.102.1.556

Gasimli, O., Haq, I., Munir, S., Khalid, M. H., Gamage, S. K. N., Khan, A., et al. (2022). Globalization and sustainable development: empirical evidence from cis countries. *Sustainability* 14, 14684. doi: 10.3390/su142214684

Ge, J., Fan, L., Rao, A. M., Zhou, J., and Lu, B. (2022). Surface-substituted pRussian blue analogue cathode for sustainable potassium-ion batteries. *Nat. Sustainability* 5, 225–234. doi: 10.1038/s41893-021-00810-7

Ghislieri, C., Dolce, V., Sanseverino, D., Wodociag, S., Vonthron, A.-M., Vayre, E., et al. (2022). Might insecurity and use of ict enhance internet addiction and exhaust people? a study in two european countries during emergency remote working. *Comput. Hum. Behav.* 126, 107010. doi: 10.1016/j.chb.2021.107010

Graham, B. S., and Powell, J. L. (2012). Identification and estimation of average partial effects in "irregular" correlated random coefficient panel data models. *Econometrica* 80, 2105–2152. doi: 10.3982/ecta8220

Guney, T. (2019). Renewable energy, non-renewable energy and sustainable development. *Int. J. Sustain. Dev. World Ecol.* 26, 389–397. doi: 10.1080/13504509.2019.1595214

Guney, T., and Kantar, K. (2020). Biomass energy consumption and sustainable development. *Int. J. Sustain. Dev. World Ecol.* 27, 762–767. doi: 10.1080/13504509.2020.1753124

Haggart, B. (2020). Global platform governance and the internet-governance impossibility theorem. *J. Digital Media Policy* 11, 321–339. doi: 10.1386/jdmp_00028_1

Hertin, J., and Berkhout, F. (2001). *Ecological modernisation and EU environmental policy integration* (Brighton: University of Sussex, SPRU).

Irfan, M., Zhao, Z.-Y., Rehman, A., Ozturk, I., and Li, H. (2021). Consumers' intention-based influence factors of renewable energy adoption in Pakistan: a structural equation modeling approach. *Environ. Sci. pollut. Res.* 28, 432–445. doi: 10.1007/s11356-020-10504-w

Ishida, H. (2015). The effect of ict development on economic growth and energy consumption in Japan. *Telematics Inf.* 32, 79–88. doi: 10.1016/j.tele.2014.04.003

Jang, A., and Song, C. (2022). Internet of things platform technology used in undergraduate nursing student education: a scoping review protocol. *BMJ Open* 12, e058556. doi: 10.1136/bmjopen-2021-058556

Jiang, Y., Liu, F., and Lim, A. (2021). Digital coupon promotion and platform selection in the presence of delivery effort. *J. Retailing Consumer Serv.* 62, 102612. doi: 10.1016/j.jretconser.2021.102612

Jorgenson, D. W. (2001). Information technology and the us economy. *Am. Economic Rev.* 91, 1–32. doi: 10.1257/aer.91.1.1

Kandilov, I. T., and Renkow, M. (2010). Infrastructure investment and rural economic development: An evaluation of usda's broadband loan program. *Growth Change* 41, 165–191. doi: 10.1111/j.1468-2257.2010.00524.x

Khan, D., Nouman, M., Popp, J., Khan, M. A., Ur Rehman, F., and Olah, J. (2021). Link between technically derived energy efficiency and ecological footprint: Empirical evidence from the asean region. *Energies* 14, 3923. doi: 10.3390/en14133923

Khan, D., Nouman, M., and Ullah, A. (2023). Assessing the impact of technological innovation on technically derived energy efficiency: A multivariate co-integration analysis of the agricultural sector in south asia. *Environment Dev. Sustainability* 25, 3723–3745. doi: 10.1007/s10668-022-02194-w

Koutroumpis, P. (2009). The economic impact of broadband on growth: A simultaneous approach. *Telecommunications Policy* 33, 471–485. doi: 10.1016/j.telpol.2009.07.004

Lahouel, B. B., Taleb, L., Zaied, Y. B., and Managi, S. (2021). Does ict change the relationship between total factor productivity and co2 emissions? evidence based on a nonlinear model. *Energy Economics* 101, 105406. doi: 10.1016/j.eneco.2021.105406

Li, X., and Zhao, C. (2023). Can national forest city construction mitigate air pollution in China? evidence from a quasi-natural experiment. *Environ. Geochem Health* 45, 3003–3024. doi: 10.1007/s10653-022-01386-7

Liu, W., Lund, H., Mathiesen, B. V., and Zhang, X. (2011). Potential of renewable energy systems in China. *Appl. Energy* 88, 518–525. doi: 10.1016/j.apenergy.2010.07.014

Lv, C., Bian, B., Lee, C.-C., and He, Z. (2021). Regional gap and the trend of green finance development in China. *Energy Economics* 102, 105476. doi: 10.1016/j.eneco.2021.105476

Ma, W., Zheng, H., and Gong, B. (2022). Rural income growth, ethnic differences, and household cooking fuel choice: Evidence from China. *Energy Econ.* 107, 105851. doi: 10.1016/j.eneco.2022.105851

Mack, E., and Faggian, A. (2013). Productivity and broadband: The human factor. *Int. Regional Sci. Rev.* 36, 392–423. doi: 10.1177/0160017612471191

Mack, E. A., and Rey, S. J. (2014). An econometric approach for evaluating the linkages between broadband and knowledge intensive firms. *Telecommunications Policy* 38, 105–118. doi: 10.1016/j.telpol.2013.06.003

Masterson, V. (2021). "Renewables were the world's cheapest source of energy in 2020, new report shows," in *World Economic Forum*, vol. 5.

Maurer-Fazio, M. (2012). Ethnic discrimination in China's internet job board labor market. *IZA J. Migration* 1, 1–24. doi: 10.1186/2193-9039-1-12

Mensah, J. (2019). Sustainable development: Meaning, history, principles, pillars, and implications for human action: Literature review. *Cogent Soc. Sci.* 5, 1653531. doi: 10.1080/23311886.2019.1653531

Molnarova, K., Sklenicka, P., Stiborek, J., Svobodova, K., Salek, M., and Brabec, E. (2012). Visual preferences for wind turbines: Location, numbers and respondent characteristics. *Appl. Energy* 92, 269–278. doi: 10.1016/j.apenergy.2011.11.001

Moyer, J. D., and Hughes, B. B. (2012). Icts: do they contribute to increased carbon emissions? *Technol Forecasting Soc. Change* 79, 919–931. doi: 10.1016/j.techfore.2011.12.005

Nguyen, C. P., and Nasir, M. A. (2021). An inquiry into the nexus between energy poverty and income inequality in the light of global evidence. *Energy Economics* 99, 105289. doi: 10.1016/j.eneco.2021.105289

Noor, M., Khan, D., Khan, A., and Rasheed, N. (2023). The impact of renewable and non-renewable energy on sustainable development in South Asia. *Environ. Dev. Sustain.* 1–18. doi: 10.1007/s10668-023-03210-3

Paunov, C., and Rollo, V. (2016). Has the internet fostered inclusive innovation in the developing world? *World Dev.* 78, 587–609. doi: 10.1016/j.worlddev.2015.10.029

Razmi, A. R., and Janbaz, M. (2020). Exergoeconomic assessment with reliability consideration of a green cogeneration system based on compressed air energy storage (caes). *Energy Conversion Manage.* 204, 112320. doi: 10.1016/j.enconman.2019.112320

Ren, S., Hao, Y., Xu, L., Wu, H., and Ba, N. (2021). Digitalization and energy: How does internet development affect China's energy consumption? *Energy Economics* 98, 105220. doi: 10.1016/j.eneco.2021.105220

Ren, Y., Xiong, C., and Yuan, Y. (2012). House price bubbles in China. *China Economic Rev.* 23, 786–800. doi: 10.1016/j.chieco.2012.04.001

Sako, M. (2021). From remote work to working from anywhere. *Commun. ACM* 64, 20–22. doi: 10.1145/3451223

Salahuddin, M., and Alam, K. (2016). Information and communication technology, electricity consumption and economic growth in oecd countries: A panel data analysis. *Int. J. Electrical Power Energy Syst.* 76, 185–193. doi: 10.1016/j.ijepes.2015.11.005

Schulte, P., Welsch, H., and Rexhauser, S. (2016). Ict and the demand for energy: Evidence from oecd countries. *Environ. Resource Economics* 63, 119–146. doi: 10.1007/s10640-014-9844-2

Stevenson, B. (2008). The Internet and job search. *Natl. Bur. Econ. Res.*, No. w13886.

Suvankulov, F., Chi Keung Lau, M., and Ho Chi Chau, F. (2012). Job search on the internet and its outcome. *Internet Res.* 22, 298–317. doi: 10.1108/10662241211235662

Tang, C., Xu, Y., Hao, Y., Wu, H., and Xue, Y. (2021). What is the role of telecommunications infrastructure construction in green technology innovation? a firm-level analysis for China. *Energy Economics* 103, 105576. doi: 10.1016/j.eneco.2021.105576

Upton, G. B.Jr, and Snyder, B. F. (2015). Renewable energy potential and adoption of renewable portfolio standards. *Utilities Policy* 36, 67–70. doi: 10.1016/j.jup.2015.08.002

Wang, Q., Hu, A., and Tian, Z. (2022). Digital transformation and electricity consumption: Evidence from the Broadband China pilot policy. *Energy Economics* 115, 106346. doi: 10.1016/j.eneco.2022.106346

Wang, X., Lu, X., Yang, G., Feng, Y., Ren, G., and Han, X. (2016). Development process and probable future transformations of rural biogas in China. *Renewable Sustain. Energy Rev.* 55, 703–712. doi: 10.1016/j.rser.2015.09.097

Wang, L., and Mesman, J. (2015). Child development in the face of rural-to-urban migration in China: A meta-analytic review. *Perspect. psychol. Sci.* 10, 813–831. doi: 10.1177/1745691615600145

Wang, J., Yang, S., Jiang, C., Zhang, Y., and Lund, P. D. (2017). Status and future strategies for concentrating solar power in China. *Energy Sci. Eng.* 5, 100–109. doi: 10.1002/ese3.154

Wang, J., Zhang, S., and Zhang, Q. (2021). The relationship of renewable energy consumption to financial development and economic growth in China. *Renewable Energy* 170, 897–904. doi: 10.1016/j.renene.2021.02.038

Wei, Z., and Huang, L. (2022). Does renewable energy matter to achieve sustainable development? fresh evidence from ten asian economies. *Renewable Energy* 199, 759–767. doi: 10.1016/j.renene.2022.07.101

Whitacre, B., Gallardo, R., and Strover, S. (2014). Broadband s contribution to economic growth in rural areas: Moving towards a causal relationship. *Telecommunications Policy* 38, 1011–1023. doi: 10.1016/j.telpol.2014.05.005

Willis, K., Scarpa, R., Gilroy, R., and Hamza, N. (2011). Renewable energy adoption in an ageing population: Heterogeneity in preferences for micro-generation technology adoption. *Energy Policy* 39, 6021–6029. doi: 10.1016/j.enpol.2011.06.066

Yu, F., Han, F., and Cui, Z. (2015). Evolution of industrial symbiosis in an eco-industrial park in China. *J. Cleaner Prod* 87, 339–347. doi: 10.1016/j.jclepro.2014.10.058

Zaharov, A. A., Nissenbaum, O. V., Ponomarov, K. Y., and Shirokih, A. V. (2018). "Use of open-source internet of things platform in education projects," in *2018 Global Smart Industry Conference (GloSIC)* (Chelyabinsk, Russia: IEEE), 1–6.

Zhang, X., and Bai, X. (2017). Incentive policies from 2006 to 2016 and new energy vehicle adoption in 2010–2020 in China. *Renewable Sustain. Energy Rev.* 70, 24–43. doi: 10.1016/j.rser.2016.11.211

Zhang, S., Wang, J., Zhang, Y., Ma, J., Huang, L., Yu, S., et al. (2021). Applications of water-stable metal-organic frameworks in the removal of water pollutants: A review. *Environ. pollut.* 291, 118076. doi: 10.1016/j.envpol.2021.118076

Zhao, J., Dong, K., Dong, X., and Shahbaz, M. (2022). How renewable energy alleviate energy poverty? a global analysis. *Renewable Energy* 186, 299–311. doi: 10.1016/j.renene.2022.01.005

Zografakis, N., Sifaki, E., Pagalou, M., Nikitaki, G., Psarakis, V., and Tsagarakis, K. P. (2010). Assessment of public acceptance and willingness to pay for renewable energy sources in crete. *Renewable Sustain. Energy Rev.* 14, 1088–1095. doi: 10.1016/j.rser.2009.11.009

Zou, C., Zhao, Q., Chen, J., Li, J., Yang, Z., Sun, Q., et al. (2018). Natural gas in China: Development trend and strategic forecast. *Natural Gas Industry B* 5, 380–390. doi: 10.1016/j.ngib.2018.04.010