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New Energy Demonstration Cities and the Mitigation of Energy Poverty in China

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Abstract

China's New Energy Demonstration Cities (NEDCs) sought to develop affordable, clean energy. This study therefore examines the NEDCs' effectiveness in mitigating e nergy poverty (EP). We focus on electricity consumption, economic development, and renewable uptake – three components of International Energy Agency's (IEA) measure of EP. Using panel data from 281 Chinese cities (2011-2021) and propensity score ma tching with difference-in-differences, the analysis found no statistically or economically significant overall effect of NEDCs on reducing EP. This is also consist ent across the three IEA sub-components. The findings suggest this ineffectiveness may stem from weak enforcement, low public participation, and inequalities in income and education.

Keywords: Difference-in-differences; China; New Energy; Development Policy; Energy Poverty

JEL codes: Q48; C23; P28; R11

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1. Introduction

Mitigating energy poverty (EP) is essential for climate-resilient development and a sustainable future (Intergovernmental Panel on Climate Change [IPCC], 2023). Not least because EP, in developing economies, inhibits access to materially and socially necessary modern energy services (International Energy Agency [IEA], 2024a). Like other developing economies, China faces ongoing challenges in an energy system characterised by multiple inequities, in which the affordable and sustainable energy are both seemingly opposing policy objectives. This tension is evident in the side of energy consumption, where a shift from coal (declined by 5% in 2023 year-on-year) to gas (rose by 8%) has occurred in the residential sector, yet renewable energy in 2022 only accounted for 15.2% of total final energy consumption, lower than the global average of 17.9% (IEA, 2024b). Despite universal access to electricity, more than 170 million people in China still lacked access to clean cooking solutions in 2023, relying on solid biomass or coal as their primary cooking fuel (IEA, 2024b). This situation is referred to as EP, i.e., not only accessing modern energy but also its contribution to basic needs (IEA 2010; IEA, 2017). Most relevant studies focus on examining the impact of socio-economic factors on EP (see, e.g., Koomson and Danquah, 2021). However, little is known about how China's energy policies perform in mitigating EP. Understanding whether new energy policies mitigate EP is vital to monitor progress in scaling up affordable, clean, and sustainable energy consumption.

In this study, we investigate the effectiveness of New Energy Demonstration Cities (NEDCs) in reducing EP. Announced in January 2014 by the National Energy Administration (NEA), eighty-one cities were designated as NEDCs with the aim to increase the share of new energy in consumption and to facilitate the sustainable development (NEA, 2014). Demonstration cities were required to develop energy plans, set specific quantitative goals in sustainable energy consumption, and report the progress to provincial energy authorities regularly. The measures and projects under NEDCs focus heavily on electrification, gas supply, and renewables, all of which are closely linked to the main components of IEA's definition and measurement of EP in developing countries. However, the effectiveness of this policy at mitigating EP remains unclear. The current study addresses this gap in the literature by examining the impact of NEDCs on EP.

To investigate the relationship between NEDCs and EP, we brought together detailed socioeconomic and energy-related information for 281 Chinese prefecture-level cities from 2010 to 2021. This unique dataset provides a new way to measure city-level EP in China, based on IEA's definition that comprises three components: (i) affordability, i.e., per capita electricity consumption in the residential sector; (ii) development, i.e., per capita commercial energy consumption; (iii) sustainability, i.e., share of modern fuels in total energy use (discussed in more detail later). Moreover, within a Difference-in-Differences (DiD) framework, the dataset not only allows for a more causal interpretation of NEDCs' impact on EP overall and its three sub-components, but also further investigation into whether the potential impact is different based on city-level characteristics. Like other pilot studies that have previously been investigated, such as the Low-Carbon City Pilot (LCCP) and the carbon emission trading (CET) policy (se e, e.g., Zhang et al., 2024), the selection of NEDCs may be non-random. Whilst the NEDC policy has an advantage over earlier pilots, as it covers a more geographically diverse and wider range of cities, we nonetheless address potential self-selection using propensity score matching with difference-in-differences (PSM-DiD), to allow for a rigorous assessment of the policy's causal impact on EP.

Our empirical results are novel in that they show – despite NEDCs' efforts to enhance energy affordability, development, and sustainability for consumers – the NEDC policy has not had any significant impact on mitigating EP. Moreover, this lack of effect not only applies to EP overall, as defined by IEA, but also each of its three sub-components. The findings are robust across a wealth of robustness and specification checks, including alternative measures of EP. The limited impact is likely due to: (i) the policy lacking transparent and credible enforcement, which may arise from limited government support and the absence of clear regulation on reward and punishment; (i i) weak publicity, particularly on the costs and benefits of new energy adoption; and (i ii) inequalities in income and education among consumers, which could inhibit access to the potential benefits of new energy investments as proposed by NEDCs.

This study contributes to the literature in three important ways. First, it provides a novel way to *empirically* measure China's city-level EP that aligns with the IEA's definition. Among relevant literature, only Wu et al. (2024) and Song et al. (2024a) have investig ated city-level EP in China. Both studies used the Multidimensional Energy Poverty

Indices (MEPIs). However, MEPIs have been widely criticised for its complexity – particularly, the use of numerous indicators, making it difficult to identify which facto rs contribute most to EP (see, e.g., Shahzad et al., 2022). Moreover, due to lack of rele vant data at the city level, many indicators are either omitted or replaced with proxies[1]. The issue of weighting in MEPIs is also contentious, especially when a large set of indicators are involved (Nussbaumer et al., 2012). By contrast, the IEA definition of EP is a widely accepted yet underutilised way to clearly and concisely measure EP overall and its core components. Moreover, the IEA's EP measure has not been used t o systematically assess city-level EP in China – a gap in the literature this paper addresses[2].

Second, this study provides empirical evidence regarding the effectiveness of NEDCs in reducing EP. To the best of our knowledge, this is the first study to investigate the impact of NEDC policy on city-level EP using causal inference techniques. Therefore, the findings complement the few studies using DiD to examine the effectiveness of China's earlier policies in mitigating EP, more specifically the impact of the Photovoltaic Poverty Alleviation Projects (PPAPs) (Li et al., 2023a) and the Low-Carbon City Pilot (LCCP) policy (Song et al., 2024a). Li et al. (2023a) claimed that PPAPs has reduced household EP by 0.0632 on an index (scale 0 to 1) in pilot cities, and Song et al. (2024a) concluded that LCCP has reduced pilot cities' EP by 0.0029 on an index (scale 0 to 1). While the impact observed was small, this could be due to the use of data with a short time horizon. Another issue could be that the authors use MEPIs, which could hide (or reveal) the potential impacts of relevant (or irrelevant) factors. They overlook the use alternative measures of EP which could have further enhanced their policy evaluation of EP mitigation. More specifically, the authors did not use IEA's measure of EP, which could provide a clearer way to track progress in a city's t ransition to the use of modern fuels. More recently, Ma et al. (2025) studied the impac t of NEDCs on household EP measured by MEPIs, which is similar to our focus, but t heir identification strategy is less rigorous and the results are not robust as discussed i

[1] For example, China's NEA does not provide detailed data on renewable energy consumption for each city. In addition, energy prices (e.g., electricity and gas prices), and the share of household energy expenditure are also unavailable at the city level.

[2] Although IEA has mainly focused on tracking and comparing EP across countries, its EP measure can be used to measure city-level EP in China and within other countries, as it not only allows for the comparison of regional disparities but also a deeper understanding of energy challenges facing cities and the whole country.

n detail below and in Wu and Burlinson (2026).[3] In contrast to these studies of relevant polices in China, here we find that the NEDC policy does not significantly impact EP and its sub-components, the findings are stable across many robustness tests and speci fication checks. These findings contribute to the broader debate on the efficacy of ind ustrial policies with multiple objectives (see, e.g., Juhász et al., 2024), particularly hig hlighting features of policy design that may increase the risk of government failure (Clay et al., 2023; Zhang et al., 2024).

Third, this study adds to the relevant literature on the NEDC policy by examining its heterogeneity effects (or lack thereof). Prior studies have shown that NEDCs interact with other policies implemented around the same time (e.g., LCCP) and resource endowments (e.g., minerals). Yet, the potential for NEDCs to impact EP through different channels has thus far been underexplored. This study fills this gap by developing a richer heterogeneity analysis at the city-level. We gather information fro m the official document which declares and ranks the multiple priorities of NEDCs. This allows us to investigate whether NEDCs interact with their policy priorities. Our findings consistently show a clear statistically insignificant impact of NEDCs on EP either directly or via interactions with other city characteristics.

The remainder of this paper is organised as follows: Section 2 reviews the relevant literature and states the relevant hypotheses. Section 3 reports the methodology and data employed in this study. Section 4 presents the results, while Section 5 concludes by discussing the policy implications.

2. Literature review and hypotheses

2.1 Definitions of and factors influencing EP

Definitions of EP vary across countries, development stages, and research perspectives. Originating in the UK, the definition initially focused on the inability to maintain household warmth and the deprivation of fuel rights (Bradshaw and Hutton, 1983). Boardman (1991) defined fuel poverty from the perspective of expenditure needs; if h ousehold heating expenditure, based on required energy needs, exceeds 10% of

[3] For example, due to the limitations of the household data, Ma et al.'s (2025) dataset includes only 28 NEDCs, wh ile there are 81 NEDCs nationwide and 293 prefecture-level cities in total. This raises the concern about sample representativeness and the internal *and* external validity of their study. This is a primary reason behind investigatin g EP using city-level data, rather than household level data.

household disposable income, they are in fuel poverty. This definition highlights the combined influence of household income, energy price, and energy efficiency on achieving adequate thermal comfort. The UK government adopted this definition in it s 2001 Fuel Poverty Strategy.

However, fuel poverty in developed countries such as the UK primarily considers heating and electricity expenditures, while EP in developing countries look at a broad er set of challenges in energy access, use, and source (Makate, 2024). More specificall y, IEA put forward that EP in developing countries or regions reflects the lack of access to electricity and other modern energy sources, alongside heavy reliance on traditional biomass fuels (IEA, 2002; IEA, 2010). This definition has gained widespread application in academic research (see, e.g., Sesan, 2012; Zhao et al., 2021). Composite indices have also been adopted, such as the MEPI mentioned earlier (see, e.g., Nussbaumer et al., 2012), however, IEA's Energy Development Index (EDI) is designed to track EP in a country or region using fewer components. This is particularly useful in assessing the transition and development of energy systems towards modern fuels, whereas the MEPI specifically focuses on household-level deprivations in modern energy (IEA, 2017; Apergis et al., 2022).

In China, research on EP began relatively late, but relevant definitions and theoretical frameworks have been progressively adapted. Relevant studies have mainly drawn on the mainstream (objective and subjective) indicators often used in developed countries such as the UK. [4] An early prominent systematic investigation into EP in China is by Wei et al. (2014). Similar to IEA, EP is defined by the authors as the inability to equitably access and safely use sufficient, affordable, high-quality and environmentally friendly energy. More recent literature has defined household-level EP as a relative concept similar to Boardman's fuel poverty measure (see, e.g., Lin and Wang, 2020). More specifically, if their ratio of energy expenditure to income is above twice the provincial-specific median ratio, these households are defined as EP (Xie et al., 2022). These methods provide an important foundation for applying micro-indicators of EP in

[4] Subjective and objective measures are often seen as picking up different aspects of EP. Therefore, many studies have adopted both at the household level (see, e.g., Burlinson et al., 2021; Churchill et al., 2022). While objective measures focus on the link between energy costs and household income, subjective measures rely on household perceptions of energy affordability, housing conditions, and the adequacy of energy services (Healy and Clinch, 2004; Waddams Price et al., 2012).

the context of China. [5]

The measurement of EP in China has also been explored at the provincial level. For example, Wei et al. (2014) developed a framework comprising multiple indicators of EP and has been widely used in related studies at the provincial level (see, e.g., Dong et al., 2021). Their definition brings together the accessibility and affordability of energy services, cleanliness of energy consumption, as well as energy management. While there are similarities with IEA's definition, several energy indicators, such as f uel expenditure, at the provincial level are not available at the city level. Hence, it would be inaccurate to measure city-level EP using the framework currently applied at the pr ovincial level. This is problematic given that cities are hubs of both energy consumpti on and policy implementation (Poggi and Amado, 2024).

Song et al. (2024a) and Wu et al. (2024) have assessed EP using MEPIs at the city-level in China. Specifically, Song et al. (2024a) constructed a MEPI comprising twenty-seven indicators capturing energy usage, structure, and capability, while Wu et al. (2024) selected eight indicators based on service availability, green cleanliness, and human resources. Except for MEPIs' drawbacks mentioned earlier, some of their indicators cannot directly reflect changes in urban energy structure or access of moder n energy services. For instance, Wu et al. (2024) used employment within resource and environmental sectors. While their studies contribute to understanding EP in urban areas, the use of too many indicators can obscure the role of specific EP components. Not least because certain indicators may have opposing properties which can lead to unclear interpretations, such as the share of fuel expenditure and per capita natural gas consumption – a higher value of the former increases the value of MEPI, while a higher value of the latter reduces it. Such drawbacks can make it challenging for designing clear objectives for policymaking and implementation (Nussbaumer et al., 2012).

The present study therefore further adds to the literature by providing an alternative city-level approach to measuring EP in China, focusing on the IEA's definition and its sub-components: affordability, development, and sustainability. This contributes to our understanding of the inequalities in energy access and consumption across cities in

[5] For example, the 10% indicator, LIHC indicator, energy expenditure income ratio, and availability of clean cooking fuels (see, e.g., Cheng et al., 2022).

developing countries.

2.2 Factors influencing EP

The socioeconomic and demographic factors influencing EP have been widely studied. At the macro level, economic factors are considered critical including per capita GDP, infrastructure development, financial inclusion, digital economy, and industrial structure (see, e.g., Koomson and Danquah, 2021). With respect to the maturity of an energy system, factors such as energy infrastructure investment, renewable energy adoption, and efficiency improvements are important pathways to energy equity (Zhang and Gu, 2023). Technological innovation can enhance these efforts by increasing energy sources and reducing costs, thus helping to improve energy accessibility for low-income groups (Burlinson et al., 2025).

Social and cultural factors are increasingly recognised as important determinants at the micro level. Household characteristics, such as family size, health conditions, socioeconomic attributes, and early life experiences, can influence energy access (Cheng et al., 2022). Location and migration rates also matter (Huang et al., 2022). Moreover, cultural norms, including religious practices (Churchill and Smyth, 2022), gender discrimination (Chaudhry and Shafiullah, 2021), and gambling behaviour (Farrell and Fry, 2021), may further restrict specific groups' energy consumption. Rec ent studies have also explored the role of ethnic diversity, crime rates, and race (see, e. g., Lin and Okyere, 2023).

Climate change may exacerbate EP by destabilising energy supply and demand, especially in areas prone to extreme weather events (Li et al., 2023b). The COVID-19 pandemic has also highlighted income and other inequalities, contributing to the widening EP gaps globally (Carfora et al., 2022).

Factors related to the government, such as energy subsidies, environmental regulations, and market liberalisation, are considered effective tools for alleviating EP (Li et al., 2023a). For example, the Warm Front Scheme was the UK's government's flagship programme aimed at improving domestic energy efficiency and thus reducing fuel poverty (Gilbertson et al., 2012). In the US, policy instruments have aimed to relieve energy burden, particularly through energy efficiency measures that focus on appliance upgrades such as heat pump water heaters (Kerby et al., 2024). However, upfront costs of new energy technologies could be a barrier to adoption (Davis and Metcalf, 2016). Moreover, consumers tend to place little weight on potential savings of replacing energy equipment. This can relate to psychological factors include limited capacity and motivation of consumers (Günther et al., 2025). Furthermore, plans to increase the share of renewable energy consumption may inadvertently increase household energy burdens, thereby exacerbating (or potentially creating new) energy inequalities (Henry et al., 2021). And they potentially create new inequalities. For example, while the growing adoption of solar panels and smart meters suggests a reduction in technological inequality, it may worsen the position of vulnerable groups if they get left behind in the transition to net zero (Burlinson et al., 2025).

A review by Carley and Konisky (2020) argues that low-income and less educated groups are less likely to benefit from energy transition policies (see, e.g., García-Muros et al., 2022). Due to specific mandatory measures, such as banning coal use and requiring the replacement of clean energy equipment within a specified period, these groups may face higher energy costs than before – even with subsidies, thereby increasing EP (Barrington-Leigh et al., 2019). Moreover, groups living in uninsulated buildings are more negatively affected, because they are often either transient tenants with little agency to influence landlord investments or homeowners lacking money to renovate (Xie et al., 2022).

Given the pivotal role of government intervention in reducing social inequality, some studies evaluated the effectiveness of energy policies in alleviating EP. For example, through comparative case studies, Stojilovska et al. (2022) investigated how EP intersects with policies on energy price, energy efficiency, and income in European nations. They suggested that the energy efficiency polices link most with EP. They als o highlighted that the policy (political) divide has resulted to spatial divide of EP. Hence, policy integration efforts can help to tackle EP effectively. Soto and Martinez-Cobas (2024) also provided a similar recommendation. They studied green energy pol icies on EP in Europe by using Augmented Mean Group and Fully Modified Ordinary Least Squares. They found rising renewable energy consumption brought increased E P in the context of Europe. This resulted from unequal implementation of renewable e nergy, and it made vulnerable social groups having less access to renewable energy.

While these studies provided insights on the link between energy policies and citizen's energy rights, they did not look at country-specific policy nor utilised methods such as DiD to examine policy impacts.

DiD frameworks however have been used in a few studies linking China's climate and environmental policies and EP. For example, Li et al. (2023a) examined how PPAP – a county-level project – has influenced household EP. It shows that the PPAP has incr eased income and diversified energy sources, thus reducing EP. Song et al. (2024a) in vestigated a city-level pilot policy, namely the LCCP. They found that its impact on E P mainly came from changes in energy use structure and efficiency. They also suggest ed that LCCP's effectiveness varies according to region, economic development, and r esource endowments. However, their studies do not explicitly analyse the policies' im pact channels through affordability, development, and sustainability of energy consum ption – three components of IEA's measure of EP. These components are crucial as th ey offer a development-centred perspective on how policies may affect end-users' con sumption and use of modern energy services (IEA, 2010; IEA, 2017).

Overall, while a limited number of existing studies have made valuable contributions to understanding how certain policies affect EP, the NEDCs' role in addressing EP remain underexamined. This is a gap that our study aims to address. The following section outlines the NEDC policy and reviews its potential socioeconomic impacts.

2.3 An overview of the NEDC policy

Although China has achieved universal access to electricity energy services, it has been struggling to improve civil energy-use conditions and mitigate EP (The State Council, 2012). Meanwhile, cities face a dilemma – between rising energy demand and tackling climate change – which makes the urgency to develop new energy, in an affordable and sustainable way, all the more necessary (Khan et al., 2023). Another challenge facing cities is to coordinate energy development in both urban and rural areas. In this context, the Chinese government's NEDC policy stipulated in the outline of the National New-Type Urbanisation Plan (2014-2020) that constructing NEDCs is the priority of green cities construction (The State Council, 2014). It has also been recognised as a central policy objective, which particularly aims to increase the share of new energy consumption in the whole city's energy use so that it helps to mitigate EP (NEA, 2014).[6]

[6] New energy refers to solar, wind, biomass, geothermal, and other renewable energy produced locally.

The selection of NEDCs started with a voluntary declaration to participate. Local governments of cities can decide the final goal of new energy consumption share, but it must be at least 6% stipulated by the NEA.[7] Other requirements of the candidate cities include the potential capability of new energy utilisation and submitting new energy development plans.[8] However, the government did not disclose information about which cities met these standards but did not apply, and which cities applied but were not selected.

In January 2014, the NEA announced eighty-one NEDCs, along with their tailored new energy construction priorities and consumption goals.[9] For example, Beijing planned to achieve 7.1% new energy consumption and prioritise solar, geothermal, and biomass energy. The NEDCs were scheduled to be assessed at the end of 2015 regarding the share of new energy use and relevant organisational management. The latter refers to local policy support, construction of public service platforms, supporting facilities, as well as publicity and education.[10] For example, local governments were required to set special funds for promoting new energy technologies (NEA, 2014). The NEA proposed these aspects to guide actions of NEDCs. Actual actions implied by the NEDCs that are of relevance to mitigating EP mainly include: (i) applying new energy technologies in electricity supply, gas supply, and domestic building operations; (ii) cutting fossil fuels use for households; and (iii) enhancing the local grid to absorb renewables (NEA, 2012; NEA, 2014).

Whilst NEDCs proposed a series of measures to promote new energy consumption in their planning documentations, most are macro-level guidance rather than concrete actions. Indeed, there were gaps between their plans and the assessment requirements

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7 There are no clear economic incentives from the central government for NEDCs, yet potential benefits such as the siphon effect or greater political performance may be the motivation for cities to be a demonstration city.

8 The capability criteria include: (i) having previously completed the main pollutant (e.g., SO2) reduction tasks on schedule; (ii) assessment scores in environmental improvement and industrial energy efficiency of the past year were above the provincial average; (iii) newly built buildings complied with local energy-saving standards; (iv) the share of new energy consumption was over 3% (equivalent to 100,000 tonnes of standard coal) in 2011.

9 The NEA also approved eight New Energy Demonstration Industrial Parks in Tianjin, Qinhuangdao, Dalian, Changchun, Nanjing, Zhenjiang, Maanshan and Qingdao cities. These cities are not included in our list of our treated NEDCs, nonetheless using them as treated rather than control cities does not change the results (as discussed in Section 4.3).

10 It is noteworthy that the NEA specifies that the first three are mandatory, while the publicity and education is optional.

of NEDCs (The Energy Foundation, 2016).[11] The local governments have been given autonomy in policy implementation and adjustment, which helps make use of local resource and promote innovation in new energy technologies. Yet, some NEDCs lack continued momentum, contributing to uneven progress in the overall construction. This policy therefore is designed more like a regulation-based policy without strong econo mic incentives that emphasises administrative control of the central government. Insomuch as relevant departments have not announced the construction performance o f NEDCs since 2015, even though the NEA mentioned subsequent guidance and super vision (NEA, 2014). Moreover, the evaluation criteria of NEDCs lack clear guidance for future development.

2.4 Evaluation of NEDCs impacts

At the macro-level, existing studies suggest that the NEDC policy has facilitated the energy transition in cities in different ways. Yang et al. (2024a) measured the energy transition index from two dimensions: the energy system performance and the transition readiness. This index captures both the current energy structure and the drivers for future energy transition. The observed positive effect is argued to be driven by NEDCs' ability to improve factors enabling *future* energy development such as government guidance and technology innovation (Yang et al., 2024a). On the other hand, Hou et al. (2024) found an increase in *contemporaneous* deployment of renewable energy, however a limitation of this study is that they used emissions (CO_2, SO_2) and electricity consumption as proxies for renewable energy demand. Nonetheless, using triple DiD, their heterogeneity analysis indicated that cities responded more strongly to the policy through higher renewable energy demand. Similarly, NEDCs have also been found to be effective in promoting energy efficiency, carbon emission efficiency, and industrial restructuring (see, e.g., Cheng et al., 2023). Altogether, these studies point towards either the development of the present or future capacity of new energy in Chinese cities, yet do not show whether this actually materialised during (or even following the end of) the NEDC pilot compared to non-NEDCs.

Regarding NEDCs' impact on enterprises, existing studies have found that this policy

[11] The Energy Foundation is an independent grant making charitable organisation. It issued a research report about the Capacity Building of NEDCs (Industrial parks) in 2016, after conducting field research in some representative NEDCs. It pointed out the problems arising from NEDCs' development.

can reduce energy consumption intensity (Liu et al., 2023), improve green total factor productivity (Chen et al., 2025). Tax incentives and technological innovation were crit ical mechanisms (Song et al., 2024b). Particularly, Chen et al. (2025) suggested that NEDCs' positive effect declined over time and suggested that further research could e xamine the potential marginal decline of policy effectiveness.

At the micro-level, the only study relevant to EP using household data shows that NEDCs are associated with a reduction in an MEPI measure of EP (Ma et al., 2025). However, drawing conclusions based on this analysis is challenging due to several important limitations. This includes their choice of MEPI weights which influences the statistical significance of their analysis overall. In addition, the number of observations used in this study is severely reduced due to substantial missing data, which leads to concerns about the representativeness of sample.[12] More importantly, using the data and code provided with the study, the parallel trend test appears not to be carried out using the main EP index but, perhaps unknowingly, using one of the six subcomponents of the MEPI – i.e., *modern cooking fuels*. This latter issue proves crucial as the parallel trends assumption does not hold if their overall MEPI index is used. This could be due to the non-random selection of the data or non-random selection of NEDCs[13]. The final, most fundamental, limitation is that the authors only control for *provincial* level and time effects – and overlook individual time invariant heterogeneity at the household level (i.e., individual unit-specific effects), which implies a pooled OLS model is implemented rather than the canonical TWFEs model. In fact, it is straightforward to find that the association between EP and NEDCs is statistically insignificant when controlling for individual fixed effects and the parallel trends assumption is violated, too (Wu and Burlinson, 2026). While these results imply that NEDCs had no impact on EP, due to the other empirical limitations above, one must be careful when interpreting and drawing conclusions from these findings.

Indeed, there is some evidence suggesting the impact of other similar policies have not only been temporary but potentially detrimental. For example, Ai et al. (2025)

[12] Specifically, the authors assigned more weight to cooking in the main analysis and most robustness checks. An alternative weighting choice was considered but has not been used in their main results, likely due to weaker statistical significance (i.e., 5% instead of 1% level). Moreover, using the data and code provided with the study, it is possible to check that over half the sample was lost after including the control variables, so that it is unlikely that the missing data (and final sample of NEDCs) is random and that the final sample is representative.

[13] However, we show that the latter is not an issue using city-level data.

suggested that China’s Plan on Clean Energy Accommodation (2018-2020) has hindere d sustainable development due to declined technical efficiency. Zhang et al. (2024) fo und that the LCCP did not generate significant response due to the absence of transparent targets, economic incentives, and credible enforcement. Some studies also argue that excessive goal constraints of LCCP can damage regional economies (Pan et al., 2022). Furthermore, the benefits of such a pilot policy may be offset by factors such as income disparity, educational attainment gaps, and household characteristics (Xie et al., 2022). These factors can contribute to the heterogeneity in policy effectiveness. T herefore, this raises the question about the NEDCs’ effectiveness, especially its role in alleviating EP, which is the focus of this study.

Overall, investigating the impact of NEDCs on new energy consumption is crucial, not least because the literature to date has overlooked the extent to which NEDCs delivered on alleviating city-level EP. Existing studies suggested that NEDC policy may be a successful initiative. While these studies provide valuable insights into the outcomes of NEDCs, they do not explicitly examine how these mechanisms could impact EP an d its three sub-components, as defined by the IEA, at the city-level. What is more, the y rarely discussed the potential limitations of this policy. Since the measures and projects under NEDCs focus heavily on electrification, gas supply, and renewable energy – which are closely linked to IEA’s central components of EP (affordability, development, and sustainability), it is reasonable to expect that NEDCs may affect EP, either as a whole or through one or more of these individual components. The next section introduces the NEDC policy and the IEA’s definition of EP in more detail and discusses how the policy may affect each component.

2.5 Hypotheses of NEDCs’ impact on EP

We investigate NEDCs’ impact on EP based on IEA’s definition and its sub-compone nts, i.e., affordability, development, and sustainability of energy consumption.

Affordability refers to the ability of consumers to satisfy their basic energy needs without incurring disproportionate costs (Gafa et al, 2022). To directly reduce the energy burden on consumers, local governments in demonstration cities have implemented targeted subsidies to reduce initial investment and operational costs. For example, Beijing Municipal subsidised the installation and maintenance of “coal-to-electricity" equipment such as air source heat pumps. Moreover, smart meters were installed so that residents with heat pumps could get cheaper time-of-use tariffs (Beijing Municipal Commission of Development and Reform, 2014). Some NEDCs such as Shenzhen have introduced support for vulnerable households to use electricity, i.e., 15 kWh free electricity per month for households covered by the Minimum Living Standard Guarantee scheme and receiving the Five Guarantees[14] (Guangdong Provincial Development and Reform Commission, 2012). These measures can help enhance residents' affordability and encourage their green electricity consumption. And, according to the IEA, per capita residential electricity consumption mainly serves as an indicator of consumer's ability to pay for electricity services (IEA, 2010). Thus, this study states the following hypothesis:

Hypothesis 1a. NEDCs increase per capita residential electricity consumption.

The *development* sub-component captures improvements in economic and infrastructural factors related to greater energy use and the mitigation of EP (Murshed and Ozturk, 2023). According to IEA's EDI framework, per capita commercial energy consumption mainly serves as an indicator of overall development (IEA, 2010). Higher commercial energy consumption per capita often implies greater economic vitality, more capital stock, and better energy infrastructure. NEDCs have intended to enhance these enabling factors to facilitate EP reduction. For example, Ningbo Municipal has introduced green finance that offer low-interest loans for distributed solar PV and energy-efficient housing retrofits. Moreover, NEDCs such as Hefei and Wuhu have actively developed new energy vehicles. They provided subsidies for the construction costs of charging stations and provided free basic electricity (ICCT, 2018). These measures have advanced new energy technologies and strengthened energy infrastructure construction, which can enhance the economic basis for NEDCs to redu ce EP (Hou et al., 2024). Therefore, the following hypothesis is posed:

Hypothesis 1b. NEDCs increase per capita commercial energy consumption.

The third sub-component, *sustainability*, focuses on renewable energy access and con sumption, emphasising the integration of economic, social, and environmental benefits

[14] The childless and infirm elderly, disabled, or minors who are entitled to food, clothing, medical care, housing, and burial expenses from the state.

(Wu et al, 2024). However, due to barriers such as imperfect information and cognitive biases (Gerarden et al., 2017), some consumers may hold misconceptions and avoid new energy technologies. Related to this, some NEDCs have organised public education and awareness campaigns of new energy, as well as establishing new energ y public information service platform. By associating new energy with environmental protection, these measures can foster a broader understanding of the benefits of clean energy and enhance consumers' willingness to adopt them. Additionally, NEDCs aim ed to increase renewable energy. For example, Jiaxing Municipal developed solar heating project for buildings, aiming to turn "idle rooftops" into "local power plants" (Jiaxing Municipal People's Government, 2015). Thus, we arrive at the following hypothesis:

Hypothesis 1c. NEDCs increase the share of new energy sources in total energy use.

Given that these three factors underpin the definition of EP, specified by IEA for developing countries, including China, the final hypothesis is proposed:

Hypothesis 1d. NEDCs reduce the prevalence of energy poverty.

3. Data and methodology

To test the above hypotheses, we use a balanced panel dataset covering 281 Chinese cities, from 2011 to 2021. It comes from multiple official sources, including the China Urban Statistical Yearbook, and the China Urban Construction Statistical Yearbook (2 012-2022). One of the sub-components of EP, i.e., the share of modern fuels in total energy use, is calculated using data obtained from Yang et al. (2024b). We utilise thei r dataset because no official statistics are currently available on China's city-level final energy consumption. The dataset from Yang et al. (2024b) offers the best available estimate of total energy consumption and new energy consumption. It encompasses 331 Chinese cities from 2005 to 2021, detailing final energy consumption across 30 fossil fuels, and four clean power sources. While previous studies also use top-down and downscaling methods to estimate city-level energy consumption, they fail to provide detailed consumption data of new energy such as solar and wind (see, e.g., Liu et al., 2023).

The present study focuses on prefecture-level and above cities. In order to ensure that the sample cities have the same administrative level for meaningful comparison, we re moved 19 county-level cities when constructing the treatment group (Song et al., 2024b). [15] The final sample comprises 281 prefecture-level and above cities, of which 62 are NEDCs (the treatment group) and 219 are non-NEDCs (the control group). The total number of observations is 3091, with 682 observations in the treatment group and 2409 in the control.

3.1 Measuring EP

The definition of EP utilised focuses on three components: affordability, development, and sustainability (Table 1). The three components draw on IEA's EDI, which contain s four components, i.e., per-capita commercial energy consumption, per-capita residential electricity consumption, the share of modern energy in total residential sector energy use, as well as the share of population with access to electricity. We do not include the last component as China had achieved 100% electricity access in 2015, hence there is no variation in this subcomponent between the NEDCs and non-NEDCs.

Following the IEA approach, *affordability* is measured by per capita electricity consumption in the residential sector. It refers to the extent to which households can consume and pay for electricity services. Secondly, *development* is measured as per capita commercial energy consumption, which primarily reflects the cities' economic development since higher commercial energy use is associated with stronger economic prosperity.[16] Thirdly, *sustainability* is measured by the share of modern fuels in total energy use.[17] An increasing share of modern fuels indicates structural change to more sustainable energy consumption. Overall, this indicator framework reflects the core components of EP in China.

Table 1. Framework of city-level EP index measurement.

[15] These county-level cities are also not included in the control group due to data limitations. County-level cities belong to the next level of administrative units of prefectural-level cities, which have higher administrative level and broader management authority.

[16] Commercial energy consumption is not collected by official statistics. Thus, relevant studies use the nighttime lighting data as a proxy of the commercial energy consumption since it can directly reflect the intensity of commercial activities (see, e.g., Chen et al., 2022). The technical details are not covered here but can be found in Chen et al. (2022) and Yue et al. (2020).

[17] The third indicator used by IEA is the share of modern fuels in total residential sector energy use. Due to data limitations in the residential sector, this study uses the closest proxy to this indicator (i.e., the share of modern fuels in total residential sector energy use). To test the robustness, another residential-specific measure for sustainability is applied: per capita natural gas consumption in the residential sector. This alternative measure does not make any qualitative difference to the results overall.

	Component	Indicator	Units
EP Index	Affordability	Per capita electricity consumption in the residential sector	kWh
	Development	Per capita commercial energy consumption	100 tonnes of standard coal
	Sustainability	Share of modern fuels in total energy use	%

Note: China currently uses standard coal as the unit of energy measurement; natural gas and renewable energy consumption are converted based on their heat content. Here, modern fuels refer to the combined final energy consumption from hydro, nuclear, solar, and wind power, as well as final heat and natural gas consumption. The choice of indicators is constrained by the type of data related to city-level EP that is currently available in Chinese context.

The EP index is based on the reverse standardised values of its three sub-components (see Eq. 1).

$$I'_{ij} = \frac{max\ I'_j - I_{ij}}{max\ I_j - min\ I_j},\ i = 1, 2, 3. \tag{1}$$

Where I refers to each sub-components, and I_{ij} denotes the i^{th} indicator for the j^{th} observation, and I'_{ij} is the reverse standardised value which ranges from 0 to 1. Then, the EP index is calculated as the arithmetic mean of I'_{ij} . Larger values indicate more severe EP.

As shown in Fig. 1, city-level EP in China exhibited a downward trend from 2011 to 2021.[18] Over the same period, the mean of the annual EP index has decreased from around 0.898 to 0.786.

[18] In the visualisations, darker shades indicate higher levels of energy poverty. In the robustness check section, outliers/extreme values were explored, and their impact has limited influence on the results overall.

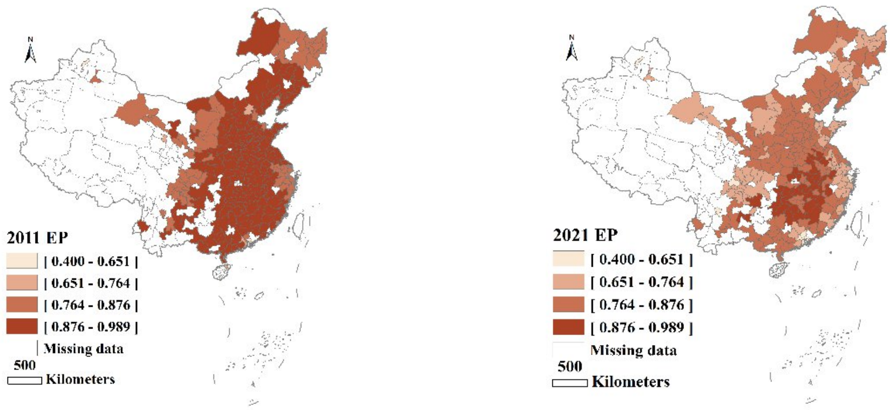


Fig. 1. Distribution of EP at city-level in China in 2011 and 2021.

3.2 Defining the NEDCs and comparison with non-NEDCs

The independent variable (*DiD*) equals 1 if a city is in the treatment group and the observation year is 2014 or later; otherwise, it is 0. The distribution of the sample cities is depicted in Fig. 2. As shown in Fig. 2, compared to the treated cities of other earlier pilot policies, such as LCCP (see Song et al., 2024a), the spatial dispersion of NEDCs appears to cover a broader set of cities.

Between 2011 and 2022, the overall sample mean of EP is around 0.847 for NEDCs (decreasing from 0.899 in 2011 to 0.788 by 2021) and around 0.845 for non-NEDCs (decreasing from 0.898 to 0.785 over the same period). The overall difference of EP b etween the groups is small, and it may indicate that the negligible effect of the NEDC policy in mitigating EP. Since some studies have claimed that NEDC policy can reduce EP (Ma et al., 2025), and a potentially zero (statistically insignificant) average treatment effects (ATE) can be heterogeneous, we cannot rely on simple statistical comparisons and therefore provide more rigorous evidence by conducting further econometric analysis.

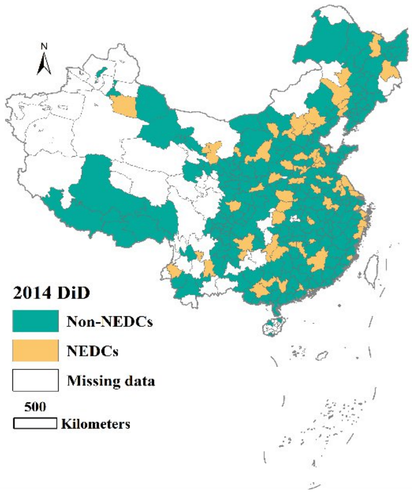


Fig. 2. Distribution of NEDCs.

Balancing tests: Comparing NEDCs to non-NEDCs

The balance of characteristics between the treatment and control group are checked using a set of city-level socio-economic and demographic covariates not only found to be associated with EP in the literature but also relevant to the uptake of development policies (see, e.g., Song et al., 2024a).

Economic development is measured by per capita GDP (logarithmic form) (*PGDP*) and its squared term to capture non-linearities. Cities with higher economic development tend to have better infrastructure and greater technological investment. This helps improve energy supply efficiency and reduce energy costs, thereby alleviating EP. However, EP may worsen during certain stages of economic development, as growth is often accompanied by issues such as unequal distribution of resources and income, especially in some developing cities.

Education level is measured by the ratio of students enrolled in higher education institutions to the total population (*HIGH_EDU*). Education reflects human capital, influencing a city's ability to train skilled workers and drive technological innovation. Higher education levels can promote the adoption of new energy sources and reduce EP. Educated individuals are often more aware of energy efficiency, thereby able to make more informed choices regarding energy consumption and conservation.

Labour market conditions are measured by the logarithm of the number of unemployed people (*UNEMPLOYMENT*). Unemployment rates directly influence household income and purchasing power, with elevated levels intensifying economic pressures that exacerbate EP.

Government R&D expenditure is represented by the proportion of science and technology expenditure in total government fiscal spending (*GOV_RD*). Investment in technology drives innovation and industrial upgrades. Greater government spending in this area accelerates the development and adoption of new energy technologies, contributing to long-term improvements in EP.

Industrial structure is measured by the ratio of the value-added output of the tertiary sector to GDP (*IND_STRUC*). A higher share of the service sector often indicates modern production and management practices. Cities with a service-oriented economy generally have higher income levels, thus reducing EP.

And to further control for confounding factors, this study also considered a set of othe r observable economic and environmental characteristics. Economic variables including employment in the tertiary sector (*SERV_EMP*), wages of on-the-job employees (*WAGE*), fixed asset investment (*FIXED_INV*), fiscal decentralisation (i.e., fiscal self-sufficiency of local governments) (*FISCAL_SELF*), and internet penetration rate (*INTERNET*).[19] Environmental variables including industrial SO_2 emissions (*SO2_IND*), public environmental awareness (*HAZE_AWARE*), and PM2.5 concentration (*PM2.5*).

Table 2 provides the descriptive statistics for the treated and non-treated cities before the treatment. It shows that the differences in means between NEDCs and non-NEDCs are statistically significant at conventional levels for a set of covariates. A joint significance test based on logistic regression suggests that these variables collectively can predict whether a city is a NEDC or not: Chi-square = 31.82, p = 0.004, the model is presented in Eq. 2. However, despite the statistical significance, the economic significance of these differences is clearly negligible since the standardised mean difference (Cohen's d) is small. The overall sample statistics are reported in Appendix

[19] Fiscal decentralisation is measured by the ratio of general government revenue to general government expenditure. Public environmental awareness is measured by the Baidu search index of haze. Internet penetration rate is measured by number of internet users per 100 people.

1 Table A1.

Table 2. Mean values and the difference in means for covariates by NEDC and Non-NEDC groups, before the treatment.

Variable	Pre-treatment			
	NEDCs Mean (1)	Non-NEDCs Mean (2)	Difference (3)=(1)-(2)	Cohen's d
PGDP	10.603	10.480	0.124**	0.205
PGDP_2	112.761	110.190	2.571**	0.201
HIGH_EDU	0.022	0.016	0.005***	0.236
UNEMPLOYMENT	9.977	9.728	0.248***	0.309
GOV_RD	0.018	0.014	0.004***	0.281
IND_STRUC	0.369	0.352	0.017**	0.187
SO2_IND	10.886	10.547	0.339***	0.319
SERV_EMP	49.311	51.897	-2.585**	-0.198
WAGE	14.334	14.011	0.323***	0.349
FIXED_INV	4.665	4.373	0.292**	0.192
FISCAL_SELF	0.537	0.487	0.051***	0.221
HAZE_AWARE	28.214	18.006	10.207*	0.213
PM2.5	51.619	49.105	2.514*	0.154
INTERNET	15.297	13.640	1.657**	0.182
N	186	657		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Joint significance test is based on a logistic regression using observations before 2014 (Chi-square = 31.82, $p = 0.004$).

3.3 Econometric methodology

To estimate the effect of NEDCs on EP we face the potential problem of selection bias. That is, as discussed above, NEDCs may be qualitatively different from non-NEDCs. For example, cities with severe air pollution are more likely to apply for NEDCs as they urgently need policy support for energy transition. Here we use PSM to tackle this issue. Based on a set of observable characteristics (discussed above) that influence the likelihood of being selected as NEDCs, PSM matches similar treatment (NEDCs) and control (non-NEDCs) groups, thereby reducing selection bias. For each treatment, we employ a logit model to estimate the probability that a city is treated in year 2014, i.e., the propensity score (see Eq. 2):

$$\mathrm{P}(T_{it}) = \beta_0 + \beta_1 X_{it} + \varepsilon_{it} \tag{2}$$

where X_{it} is the covariates before 2014 that may influence the probability of city i bei ng selected as a NEDC (T_{it}).

Then, we use matching algorithm to pair each NEDC to comparable non-NEDCs which have an estimated propensity score as close as possible to that of the NEDCs. Specifically, we adopt nearest-neighbour caliper matching and radius matching (Imbens, 2015). Next, we verify the consistency of the construction of NEDC group and non-NEDC group to examine the quality of the propensity score matching; the differences in the means of the above covariates are expected to be significantly reduced after matching. That is, the conditional independence assumption is satisfied (Abadie and Imbens, 2006). The balance test results showed insignificant differences in covariates between treatment and control groups post-matching (see Appendix 1 Table A2). Furthermore, the standardised deviation decreases significantly after matching (see Appendix 2 Fig. A1).

After building a suitable group of treated control cities for each NEDC, we use the following DiD framework to analyse the causal impact of the NEDC policy on EP:

$$Y_{it} = \beta_0 + \beta_1 DiD_t + \beta_2 X_{it} + a_i + \theta_t + \varepsilon_{it} \tag{3}$$

where, Y_{it} represents the *EP index* and the three sub-components for city i in year t, since this equation is estimated separately for *affordability* (Hypothesis 1a), *development* (Hypothesis 1b), *sustainability* (Hypothesis 1c), and the *EP index* (Hypothesis 1d). DiD_t is an indicator variable, equal to one for the year when a city was approved as a NEDC in 2014 onward, and zero otherwise. X_{it} represents the same covariates used in propensity score estimation, including a set of socio-economic and environmental control variables at the city-level, such as per capita GDP. a_i captures city fixed effect, which controls the time-invariant characteristics between different cities; θ_t indicates the year fixed effect, which controls the year-specific contemporaneous factors shared by all cities. β_0 is the intercept term, and ε_{it} is the idiosyncratic error term. The standard errors are clustered at the city level to account for potential intra-group serial correlation and heteroskedasticity. Eq. 3 is estimated using Two-Way-Fixed-Effects (TWFE) models.[20]

[20] We also employed DiD using pooled OLS, and standard individual fixed effects. The relevant results are

We focus on the estimation of β_1, which measures the impact of the NEDCs on EP and its three sub-components. Based on Hypothesis 1a, 1b and 1c, it is anticipated that β_1 i s greater than zero, implying that the NEDC policy has promoted affordable, clean and sustainable energy consumption respectively. Building on this, Hypothesis 1d proposes that these improvements decrease overall EP, thus β_1 is expected to be less than zero.

This procedure, the so-called PSM-DiD, allows us to move towards a more casual interpretation of the estimates of interest for the NEDC policy on EP, i.e., comparing similar cities while excluding effect of other external shocks.

4. Results

4.1 Parallel trend test

The validity of the DiD approach relies on the parallel trends assumption, which states that, in the absence of policy intervention, the outcome variable for the treatment and control groups should follow a similar trend over time. While the counterfactual cannot be observed, as standard in the literature we first conduct a graphical analysis to check whether the trends are likely to have remained on a parallel trend irrespective of the NEDC policy. Fig. 3 plots the trends of three sub-components and EP composite index for the treatment and control groups from 2011 to 2021. During the pre-intervention period (2011-2014), the trends for the three sub-components and EP were clearly parallel for both groups. This visual evidence provides support for the assumption that the treatment and control groups followed a common trend before the policy was introduced, and therefore likely to have followed this trend had the policy not been implemented. What is more, except for the affordability component, the pre-treatment trends for both treatment and control groups are also remarkably close for all other components and the EP index; hence, the differences in characteristics reported in Table 2 appear small and implies that the allocation of NEDCs are perhaps more random than the literature and policy reports suggest.

Overall, Fig.3 indicates that the NEDC policy did not affect either the EP index or its three sub-components. The individual plots in the Fig.3 similarly show that the trends in the treatment and the control groups remain parallel before and after the treatment

qualitatively identical to those presented here and are available upon request.

year. In the plot of per capita commercial energy consumption, while the non-NEDCs shows a slight downward trend and has decreased below the NEDCs in the following two years after the treatment, the difference between the two is small. The NEDC policy also has a negligible impact on the trend of the EP index. There is weak evidence to suggest the NEDC policy had a temporary effect on commercial energy consumption (i.e., development), however this was short lived.

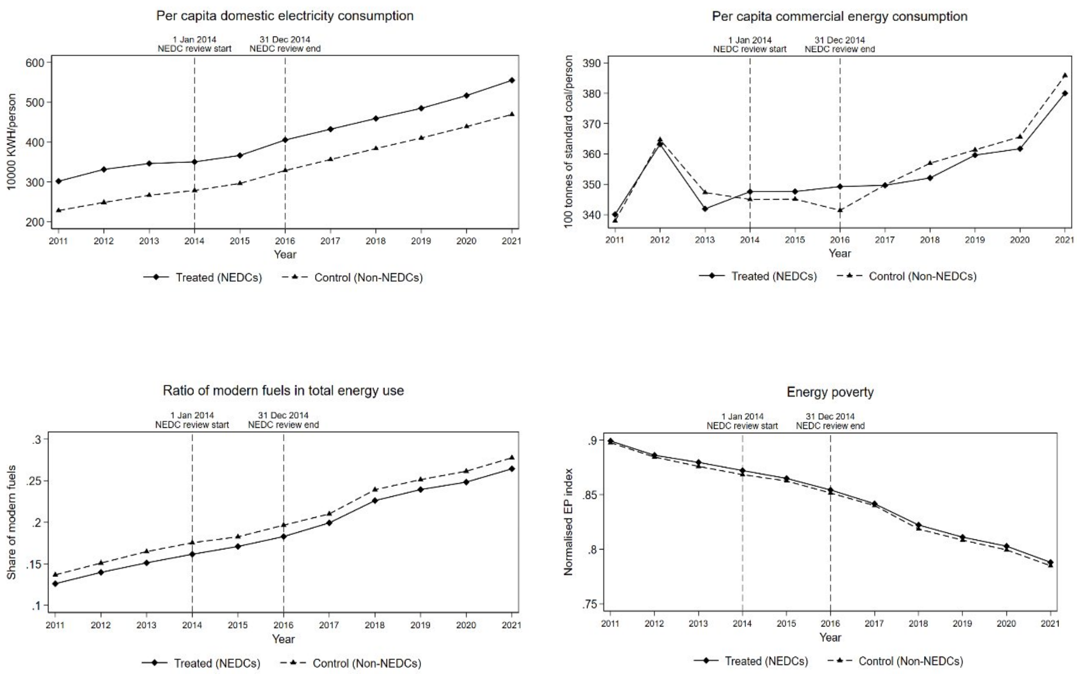


Fig. 3. Trends in the average value of sub-components and EP.[21]

Nonetheless, we conduct an event study analysis to statistically test the parallel trends assumption and examine the effects of NEDCs on EP, based on the post-matching sample. The specification is as follows:

$$Y_{it} = \beta_0 + \alpha_{pre} Pre_{it} + \alpha_{post} Post_{it} + X_{it}\delta + a_i + \theta_t + \varepsilon_{it} \quad (4)$$

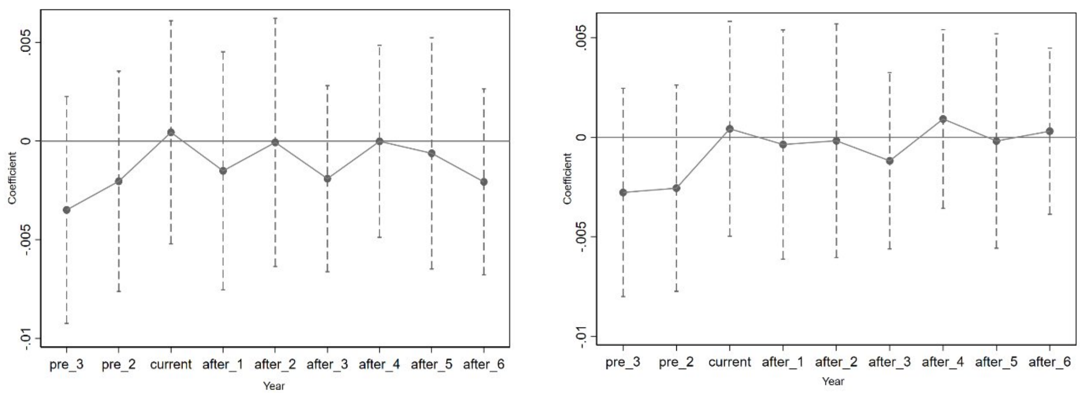
where, the indicator variable Pre_{it} denotes the years before the policy intervention, while $Post_{it}$ represents the years after the intervention. The coefficients α_{pre} and α_{post} capture the effects before and after the policy implementation, respectively. Other

[21] The trends in relevant total value of energy consumption are shown in Appendix 2 Fig. A2 for more contextual information.

symbols are the same as Eq. 3. The year before policy implementation (i.e., 2013) is set as the baseline. Using the *EP index* as an example (since the event study findings are consistent across all sub-components[22]), Fig. 4 presents the point estimates and their 95% confidence intervals for each year. The coefficients for the pre-policy periods have confidence intervals crossing zero, indicating no statistically significant differences between groups before the policy and supporting the parallel trends assumption.

In addition, this event study approach identifies the dynamic changes of average treatment effects (ATEs). If the policy indeed worked to reduce EP, it is expected that the coefficients α_{post} are significantly different from zero. However, in line with the preceding visual analysis, according to Fig. 4, the point estimates of post-treatment are statistically insignificant.

Overall, despite the figures showing a parallel trend before the NEDC policy was implemented, after the policy was implemented, the difference in the trends appear statistically insignificantly different from zero. Together with Fig. 3 and the event study (Fig. 4), this initial evidence suggests that the NEDC policy may have had limited impact on mitigating EP.



(a) Caliper nearest neighbour matching. (b) Radius matching.

Fig. 4. Event study diagrams after PSM under conditional parallel trends.

[22] For brevity, the results are not presented here and available upon request.

4.2 Baseline regression

Based on the baseline model (Eq. 3), this study tests the impact of the NEDCs on EP. Using PSM-DiD and TWFEs, the estimation results, with the *EP index* as the dependent variable, are shown in Table 3.[23] Across a broad range of specifications, the ATEs (i. e., β_1 in Eq. 3) are consistently close to zero and statistically insignificant at all conventional levels.[24]

EP and selection into NEDCs might have been influenced by socio-economic and other factors. Thus, columns (1) and (3) present the TWFE results without controls, while c olumns (2) and (4) with controls. Whether controlling for socio-economic and city characteristics or not, the ATEs for EP reduction remain statistically insignificant and close to zero.

The results are clearly in line with the visual and event study analyses. Therefore, Hypothesis 1d is not supported, meaning that the NEDC policy has not statistically significantly reduced the prevalence of EP in demonstration cities, compared to non-NEDCs.

As presented in Table A3 (Appendix 1), Hypothesis 1a, 1b, and 1c are also not suppor ted. This suggests that the NEDCs did not bring the expected increases in electricity consumption per capita (H1a), commercial energy consumption (H1b), and the share of modern fuels (H1c).

In what follows, to address potential concerns that our empirical results arise due to the use of specific econometric specifications and/or measures of interest, we conduct multiple robustness checks including sample sensitivity analysis (replacing the indepe ndent variables) and employ alternative EP measures respectively.

[23] For brevity, given the consistency across results, the regression results for Hypotheses 1a-1c are reported in Appendix 1 Table A3.

[24] The estimated results are robust when using province-clustered standard errors, which accounts for the potential correlation among cities within the same province. It is also robust after introducing year-province fixed effects an d city-trend. These results are shown in Appendix 1 Table A4.

Table 3. Baseline regression results.

	Caliper nearest neighbour matching		Radius matching	
	(1)	(2)	(3)	(4)
DiD	-0.000	0.001	0.000	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
PGDP		0.196***		0.196***
		(0.051)		(0.046)
PGDP_2		-0.008***		-0.009***
		(0.002)		(0.002)
HIGH_EDU		-0.242**		-0.187
		(0.116)		(0.120)
UNEMPLOYMENT		0.001		0.001
		(0.001)		(0.001)
GOV_RD		0.029		0.053
		(0.074)		(0.073)
IND_STRUC		0.026		0.001
		(0.023)		(0.019)
SO2_IND		0.000		-0.000
		(0.001)		(0.001)
SERV_EMP		-0.000		0.000
		(0.000)		(0.000)
WAGE		-0.004		-0.004
		(0.003)		(0.003)
FIXED_INV		0.001		0.000
		(0.001)		(0.001)
FISCAL_SELF		-0.028**		-0.027***
		(0.011)		(0.010)
HAZE_AWARE		-0.000*		-0.000**
		(0.000)		(0.000)
PM2.5		0.000***		0.000***
		(0.000)		(0.000)
INTERNET		-0.000		-0.000*
		(0.000)		(0.000)
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	2189	2189	3056	3056

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors, clustered at the city-level, are presented in parentheses. The lower sample size reflects the process of nearest neighbour and radius matching.

4.3 Alternative specifications and robustness checks

4.3.1 Sample sensitivity analysis

China's directly governed municipalities differ significantly from ordinary prefecture-level cities in terms of administrative status, policy backing, economic development and resource distribution (Hou et al., 2024). For example, the directly governed municipalities often receive higher policy priorities, have greater access to resources, and benefit from a more developed economic foundation. To evaluate any dominant effect of these cities, samples from Beijing, Tianjin, Shanghai and Chongqing are sequentially excluded (see Table 4). The results show that the policy effect coefficients are statistically insignificant across all specifications and therefore consistent with the benchmark regression results. [25]

Table 4. Robustness results excluding 4 municipalities one by one.

	(1) Ex. Beijing	(2) Ex. Beijing and Tianjin	(3) Ex. Beijing, Tianjin, and Shanghai	(4) Ex. Beijing, Tianjin, Shanghai, and Chongqing
DiD	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	3050	3040	3032	3021

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors, clustered at the city-level, are presented in parentheses. The results are based on the radius matching sample (Since the balance tests in Table A2, along with feature deviation plots in Fig A1, show that the radius matching has smaller bias across covariates after matching, we intend to refer to the results using radius matching sample. For brevity, relevant robustness checks are based on radius matching sample. The regression results based on caliper nearest neighbour matching sample are available upon request). The results are all statistically insignificant when taking sub-components and alternative EP (mentioned below) as the dependent variable with this robustness check.

4.3.2 Alternative EP outcome

Given the availability of alternative measures of city-level EP, we use the MEPI to check whether the results hold, following the framework proposed by Wu et al. (2024).

[25] As a robustness check, 5% winsorisation was applied to the sub-components and EP index. The results remain consistent and are reported in Appendix 1 Table A5 columns (1)-(2). Reintroducing eight cities with demonstration parks into the sample, as discussed earlier, does not change the results (see Appendix 1 Table A5 column (3)).

The related data is sourced from the China Urban Statistical Yearbook and the China Urban Construction Statistical Yearbook.

Columns (1)-(2) in Table 5 show the regression results using the MEPI as the dependent variable. The results indicate that after replacing EP, the effectiveness of the NEDCs is still statistically insignificant. This means that the estimated results remain robust after accounting for the influence of unofficial data sources.

As an additional check, we create an "energy poverty line" (EPL) to reflect relative EP among cities by drawing on the World Bank's concept of the Social Poverty Line (SPL)[26]. Specifically, we define the EPL as follows:

$$EPL_t = E_{min} + 0.5\ Median_t \tag{5}$$

where E_{min} is the basic energy needs, it is set to 1000 kWh[27]. $Median_t$ is the per capita electricity consumption in t year. Cities whose per capita electricity consumption is below EPL are considered energy-poor and are set to 1, otherwise it is coded as 0. Since this is a dichotomous variable, the results will be estimated using linear probability models. The results using this alternative measure are displayed in Table 5 columns (3)-(4). They also do not support Hypothesis 1d, meaning that the findings are not driven by a specific EP indicator.

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[26] According to the World Bank, the SPL is 1 dollar plus half the median level of consumption in a country with 2011 PPPs.

[27] The Energy for Growth Hub (a global think tank) proposed the Modern Energy Minimum as 1000 kWh, as an additional indicator for tracking progress against EP (Last visited on Oct. 25th, 2025).

Table 5. Robustness results using an alternative measure of EP

	MEPI		EPL	
	(1)	(2)	(3)	(4)
DiD	-0.000	0.002	-0.022	-0.017
	(0.004)	(0.003)	(0.048)	(0.047)
Controls	N	Y	N	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	3056	3056	3056	3056

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors, clustered at the city-level, are presented in parentheses.

4.4 Heterogeneity analysis

In the official policy document on NEDCs, it specifically states the proposed construction objectives for each of the NEDCs (NEA, 2014). Indeed, they have different and multiple priorities in developing new energy. For example, Beijing focused on solar, geothermal, and biomass energy, while Chengde identified wind and geothermal energy as a priority. Regarding implementation, some NEDCs prioritised clean heating of households (such as Beijing), while others focused more on the application of new energy across industries, for example, Bozhou highlighted onsite biomass energy generation and consumption in industrial parks related to medicine manufacturing and wine-making.

Moreover, NEDCs' priorities not only reveal cities' resource endowments (e.g., sunlight) but also reflect their different and multiple objectives across industries, albeit a clear overall objective in new energy consumption. Multi-energy construction can complement one another, like wind-solar or hydro-geothermal hybrids, it could help to minimise the risk of not meeting the final objective (Zhang and Gu, 2023). However, due to lack of clear trade-off rules, as well as limited financial and administrative capacity, it may be hard to reconcile or evaluate multiple objectives jointly for NEDCs with more priorities. Moreover, multiple objectives may be related to weaker administrative capacity (Juhász et al., 2024), this can bring about the heterogeneity of policy effect.

Therefore, we further investigate heterogeneity in the text ordering of policy objectives (i.e., those of "first-focus") and the number of energy development priorities outlined in the NEDC policy document. We use the order of text to rank the level of priorities of local governments (Laver et al., 2003). First, we create indicator variables equal to one for each "first-focus" type of energy, and zero otherwise. For example, solar is Beijing's "first-focus" energy while biomass is Bozhou's, as they are listed *first* in their proposed key construction areas. We include the interaction term between the DiD estimator and the "first-focus" energy variable (*DiD* ▪ *I*) in the baseline regression, with the results presented in columns (1)-(3) of Table 6. Second, we count the number of priorities proposed by each NEDC, i.e., energy construction objectives, with maximum value at four.[28] Similarly, we include the interaction term between DiD and the energy priorities count (*DiD* ▪ *domiC*), with the result reported in column (4) of Table 6. All these interaction terms are not statistically significant.

Overall, the results suggest that although the focus areas of NEDCs vary, the policy effect does not have a statistically significant difference across these specific classifications. [29]

Given the concerns of relevant studies, we also test the heterogeneity that arising from: 1) an overlapping policy – LCCP – the most relevant city-level pilot programme, with objectives closely aligned to the NEDC policy (Yang et al., 2024a); and 2) disparities in resource endowments, i.e., whether a NEDC is resource-based or not (Cheng et al., 2023). The results also show that the NEDCs did not reduce EP in the treatment group regardless of any potential interactive effects with LCCP or resource endowments (see Appendix 1 Table A7 and A8).

[28] In this study, only four NEDCs set a single priority of developing new energy: Shaoyang, Yuncheng, Fuxin and Nanning. The rest of the fifty-eight NEDCs all have at least two priorities.

[29] We also construct indicator variables for each energy type (*solar*, *wind*, *biomass*, *geothermal* and *hydro*), which equal to one if the NEDCs listed that energy type not only if it is "first-focus". The results are reported in Appendix 1 Table A6, which also show no statistically significant effect. Moreover, for further heterogeneity tests, we have split the sample into quartiles of initial EP and initial educational attainment or income levels, the results still show no effect. For brevity, the results are not presented here and available upon request.

Table 6. Heterogeneity regression results using policy objectives interaction terms.

Variable	(1)	(2)	(3)	(4)
DiD ▪ I(solar)	-0.001			
	(0.005)			
DiD ▪ I(biomass)		-0.000		
		(0.006)		
DiD ▪ I(other)			0.001	
			(0.005)	
DiD ▪ domiC				0.001
				(0.001)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	3056	3056	3056	3056

Note: * $p < 0.1$, ** $p < 0.05$, ***$p < 0.01$. Standard errors, clustered at the city-level, are presented in parentheses. The Freq. of *I(solar)* is 264 while that of *I(biomass)* is 187. *I(other)* refer to the "first-focus" of wind, geothermal and hydro power – the three has the least sample (231 in total). The results for sub-components also support the findings.

5. Conclusion

Against the backdrop of climate change and decarbonisation pressures, it is critical to promote a shift in energy consumption from traditional to new energy. During this process, EP remains a challenge, especially in populous developing countries like China. Establishing NEDCs was one important focus of China's effort to mitigate EP. The responding measures taken by NEDCs are centred on increasing electricity consu mption, modern fuels, as well as the economic and infrastructural factors related to gr eater energy use – the three core components used by the IEA to capture EP.

This study investigates whether China's NEDC policy is effective in promoting broader and more sustained adoption of new energy. Our results differ from the current studies on the effectiveness of NEDCs that touts a generally positive but small impact (see, e.g., Liu et al., 2023; Hou et al., 2024). Our findings, instead, consistently reveal that NEDCs have no significant impact on EP, neither as a whole nor through one or more of the sub-components. Moreover, such non-impacts do not interact with other city characteristics such as policy priorities, overlapping policies, and resource endowment s.

There are several potential reasons. First, the NEDC policy lacks credible enforcement across some NEDCs. Differences exist in the implementation and priorities of NEDC construction by local governments, and their corresponding performance is not highly assessable. On the one hand, the NEDCs are selected on a voluntary basis, they have g reat autonomy in developing new energy. Most NEDCs have set multiple priorities w hich corresponds to multiple objectives. This makes it harder to evaluate their perform ance and increase the risk of "government failure" (Juhász et al., 2024). On the other hand, the upper governments appear to lack timely oversight and feedback regarding NEDCs' development. Indeed, due to the absence of rigorous evaluations of whether NEDCs deliver on their objectives, the NEDCs may relax enforcement of relevant me asures. The problem is compounded by the fact that the central government has not set clear reward and punishment regulation, so even if the NEDCs fail to achieve their energy goals, there will not be clear punishment. Moreover, most NEDCs did not disclose their specific energy implementation plans and energy consumption outcomes by the required time (end of 2015). This reflects not only insufficient information disclosure among NEDCs but also challenges in tracking policy progress. Such phenomenon is also recognised by Zhang et al. (2024) regarding the non-impact of LCCP on carbon emissions.

Second, although some NEDCs have adopted a series of measures on the energy consumption side, their long-term effects reflected on the consumption side are potent ially limited due to insufficient public participation (Zhang et al., 2019). This may be due to a lack of incentive for consumers to engage in new energy use, which is correlated with energy consumption behaviour (Shen and Sun, 2023). In the assessme nt outline of NEDCs, promoting new energy knowledge and raising awareness are only considered as optional action. Thus, some NEDCs may have paid little attention to this aspect. Moreover, there is always a gap between plans and actual actions. For example, Dunhuang City did not plan any publicity or education initiatives and did not implement related measures, while Weiwu City had planned such measures but failed to execute them (The Energy Foundation, 2016). Such lack of intended incentives in designing policies has been argues, more generally, as the source of the absence of potential policy impacts (Clay et al., 2023).

Third, the potential benefits of NEDCs may be offset by factors such as income disparity and educational attainment gaps, as mentioned in the literature review (Zhang et al., 2024). These factors can contribute to EP heterogeneity. However, while such household-level heterogeneities are difficult to capture at the city level, we control for these using relevant covariates.

Given the above, it is crucial to consider more credible enforcement in future energy a nd environmental policies. While local governments should retain flexibility to tailor implementation plans, it is important to ensure clear assessment criteria, a robust regulatory framework, as well as transparent incentive mechanisms. Higher-level authorities should regularly monitor relevant progress and outcomes. Moreover, policymakers should take fully into account the potential implications for energy cons umers who are unfamiliar with new energy and lack the necessary incentives to adopt. Indeed, many countries could learn from such indifference in enforcement, publicity and education of a potentially ambitious energy and environmental policy, otherwise the effectiveness of future policy design and global development and sustainability goals might be undermined.

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Appendix 1: Tables

Table A1. Descriptive statistics, estimation samples, 2011-2021.

Variable	Definition	Mean	St.D.	Min.	Max.
PGDP	GDP per capita	10.759	0.570	8.773	13.056
PGDP_2	Squared term of GDP per capita	116.078	12.298	76.964	170.451
HIGH_EDU	Education level	0.020	0.026	0.000016	0.207
UNEMPLOYMENT	Number of unemployed persons	9.811	0.858	6.653	19.675
GOV_RD	Science and technology expenditure of government	0.017	0.018	0.000568	0.207
IND_STRUC	Tertiary sector share	0.425	0.102	0.101	0.839
SO2_IND	Industrial SO2 emission	9.737	1.313	0.693	13.183
SERV_EMP	Employment in tertiary sector	54.340	13.606	15.390	94.820
WAGE	Wages of on-the-job employees	14.493	0.997	11.789	18.777
FIXED_INV	Fixed asset investment	4.841	2.176	0	17.168
FISCAL_SELF	Fiscal self-sufficiency	0.457	0.221	0.057	1.541
HAZE_AWARE	Public environmental awareness	44.600	66.140	0	1118.208
PM2.5	Average PM2.5	41.411	15.169	11.637	108.955
INTERNET	Internet penetration rate	24.226	14.272	0.380	125.868

Note: N=3091.

Table A2. PSM balance test results.

Variable		Mean		%reduct		t-test	
		Treated	Control	%bias	|bias|	t	p>|t|
PGDP	U	10.862	10.73	23.2		5.38	0.000
	M-1	10.853	10.841	2.1	91.0	0.39	0.699
	M-2	10.853	10.85	0.5	97.8	0.10	0.924
PGDP_2	U	118.31	115.44	23.2		5.40	0.000
	M-1	118.12	117.85	2.2	90.4	0.41	0.681
	M-2	118.12	118.05	0.6	97.5	0.10	0.917
HIGH_EDU	U	0.024	0.018	22.3		5.33	0.000
	M-1	0.024	0.023	3.9	82.4	0.67	0.504
	M-2	0.024	0.024	1.8	91.7	0.31	0.755
UNEMPLOYMENT	U	10.009	9.755	32.0		6.89	0.000
	M-1	9.992	9.990	0.3	98.9	0.06	0.951
	M-2	9.992	9.992	0.0	100.0	0.00	0.998
GOV_RD	U	0.021	0.016	26.2		6.86	0.000
	M-1	0.020	0.020	3.0	88.5	0.55	0.584
	M-2	0.020	0.020	2.4	90.8	0.44	0.662
IND_STRUC	U	0.437	0.421	15.3		3.60	0.000
	M-1	0.434	0.429	4.4	71.2	0.84	0.403
	M-2	0.434	0.433	1.2	92.0	0.23	0.818
SO2_IND	U	9.920	9.685	18.2		4.12	0.000
	M-1	9.923	9.982	-4.6	74.7	-0.87	0.387
	M-2	9.923	9.945	-1.7	90.6	-0.32	0.746
SERV_EMP	U	52.523	54.854	-16.6		-3.96	0.000
	M-1	52.367	52.132	1.7	89.9	0.31	0.755
	M-2	52. 367	52.214	1.1	93.4	0.20	0.839
WAGE	U	14.760	14.417	33.6		8.01	0.000
	M-1	14.728	14.703	2.4	92.8	0.44	0.663
	M-2	14.728	14.718	0.9	97.2	0.17	0.865
FIXED_INV	U	5.027	4.788	11.3		2.54	0.011
	M-1	5.043	5.123	-3.8	66.4	-0.70	0.482
	M-2	5.043	5.122	-3.8	66.6	-0.69	0.490
FISCAL_SELF	U	0.501	0.445	26.0		5.95	0.000
	M-1	0.498	0.500	1.3	94.9	0.24	0.810
	M-2	0.498	0.497	0.6	97.8	0.10	0.918
HAZE_AWARE	U	60.469	40.107	25.1		7.16	0.000
	M-1	53.613	52.648	1.2	95.3	0.28	0.776
	M-2	53. 613	53.194	0.5	97.9	0.12	0.902
PM2.5	U	43.101	40.933	14.0		3.30	0.001
	M-1	42.995	43.462	-3.0	78.5	-0.54	0.589
	M-2	42.995	43.140	-0.9	93.3	-0.17	0.866
INTERNET	U	24.747	24.079	4.8		1.08	0.281
	M-1	24.693	24.450	1.7	63.6	0.33	0.740
	M-2	24. 693	24.779	-0.6	87.2	-0.12	0.908

Note: M-1 is the result of caliper nearest neighbour matching, and M-2 is the result of radius matching. The standardised mean difference (Cohen's d) has also decreased after matching.

Table A3. Regression results of 3 sub-components.

Variable	Affordability		Development		Sustainability	
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	-0.017	-0.040	-0.009	-0.008	0.015	0.010
	(0.052)	(0.051)	(0.036)	(0.036)	(0.017)	(0.017)
Controls	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	2189	3056	2189	3056	2189	3056

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors, clustered at the city-level, are presented in parentheses. Here the sub-components before standardisation are used as dependent variables (taking logarithm). Columns (1), (3), and (5) report the results based on caliper nearest neighbour matching sample, while the columns (2), (4), and (6) are based on radius matching sample. Affordability refers to per capita electricity consumption in the residential sector; Development refers to per capita commercial energy consumption; Sustainability refers to the share of modern fuels in total energy use.

Table A4. Regression results changing model specification

	(1)	(2)	(3)
DiD	-0.001	0.000	-0.001
	(0.001)	(0.003)	(0.001)
Controls	Y	Y	Y
City FE	Y	Y	Y
Year FE	Y	Y	Y
Year Province FE	Y	N	Y
City-specific trends	N	Y	Y
N	2997	3056	2997

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors, clustered at both the city-level and provincial level, are presented in parentheses. The results are consistent when taking sub-components and alternative EP (i.e., MEPI and EP line) as the dependent variable.

Table A5. Regression results adjusting sample

Variable	EP using winsorised sub-components	Winsorised EP index	Expanding treatment group
	(1)	(2)	(3)
DiD	0.005	0.001	0.003
	(0.008)	(0.003)	(0.003)
Controls	Y	Y	Y
City FE	Y	Y	Y
Year FE	Y	Y	Y
N	3056	3056	3056

Note: * p < 0.1, ** p < 0.05, ***p < 0.01. Standard errors, clustered at both the city-level and provincial level, are presented in parentheses. Column (1) uses an EP index recalculated after applying 5% winsorisation to each sub-indicator; column (2) applies 5% winsorisation directly to the original EP index; column (3) adds cities with new energy demonstration industrial park to treatment group. The results are all statistically insignificant when taking sub-components and the alternative EP as the dependent variable, with the above robustness check methods.

Table A6. Policy heterogeneity regression results.

Variable	(1)	(2)	(3)	(4)	(5)
DiD ▪ *solar*	0.004				
	(0.003)				
DiD ▪ *wind*		0.003			
		(0.004)			
DiD ▪ *biomass*			0.001		
			(0.003)		
DiD ▪ *geothermal*				0.004	
				(0.004)	
DiD ▪ *hydro*					-0.001
					(0.005)
Controls	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	3056	3056	3056	3056	3056

Note: * p < 0.1, ** p < 0.05, ***p < 0.01. Standard errors in parentheses, clustered at the city-level. The results remain statistically insignificant across all combinations of key energy development areas, e.g., the combination of solar with biomass or any other development focuses.

Table A7. Heterogeneity regression results using other policy instrument and resource endowments interaction terms.

Variable	(1)	(2)
DiD ▪ LCCP	-0.001	
	(0.005)	
DiD ▪ RE		0.004
		(0.003)
Controls	Y	Y
City FE	Y	Y
Year FE	Y	Y
N	3056	3056

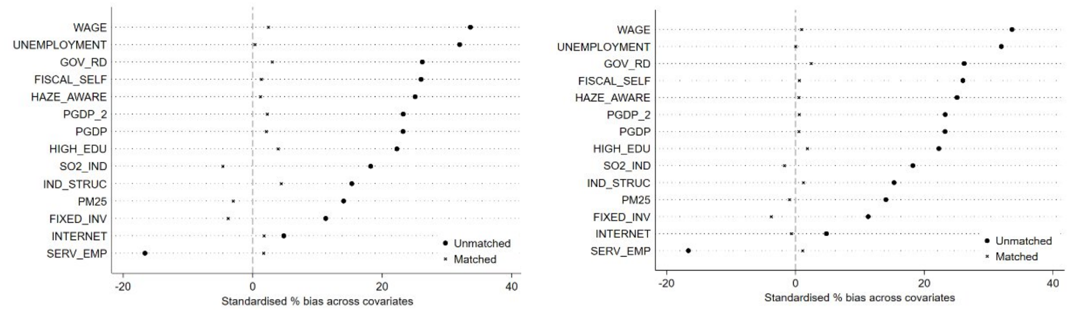
Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors, clustered at the city-level, are presented in parentheses. Table A8 reports the robustness check results using group regression and Chow tests, which also support the findings. The results are all statistically insignificant when taking sub-components as the dependent variable.

Table A8. Heterogeneity regression results by sub-groups.

	Overlapping policy		Resource endowments	
Variable	LCCP	Non-LCCP	Resource-based cities	Non-resource-based cities
DiD	0.001	0.002	-0.000	0.003
	(0.005)	(0.003)	(0.003)	(0.004)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	1012	2044	1234	1822
Chow Test	9.37		2.74	
	[0.0000]		[0.0000]	

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors, clustered at the city-level, are presented in parentheses. P-Value in [].

Appendix 2: Figures



(a) Caliper nearest neighbour matching. (b) Radius matching.

Fig. A1. Feature deviation plots before and after matching.

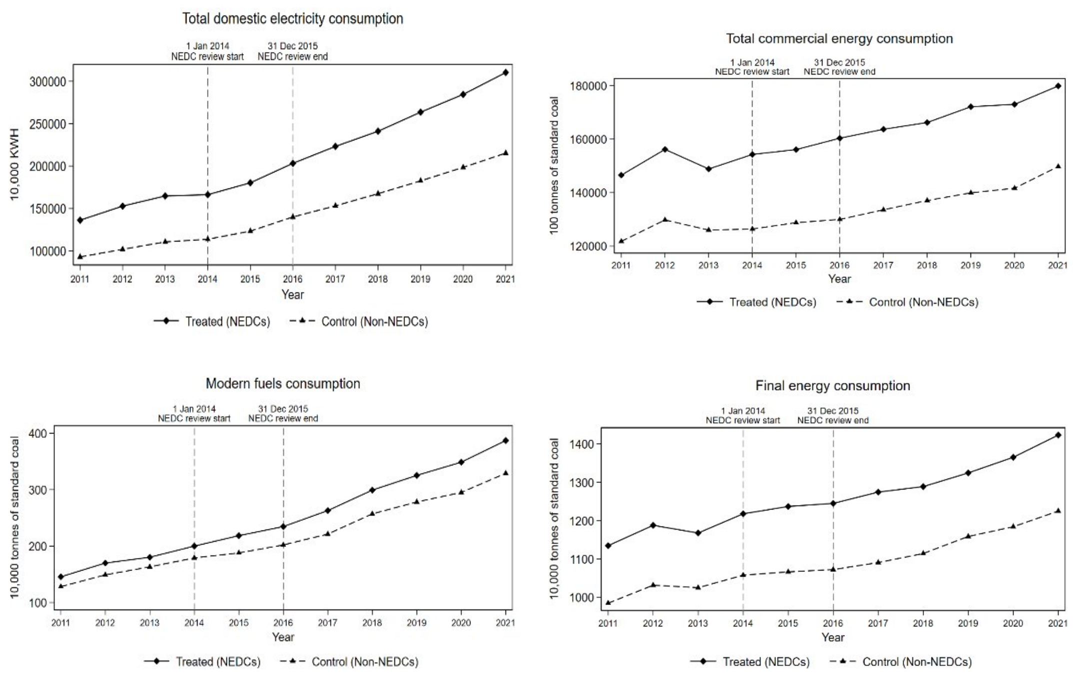


Fig. A2. Trends in the total value of energy consumption.

Note: Taking the total value of each sub-component as dependent variables, the results also show that the NEDCs has no statistically significant impact on these total value variables.