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Assessing the Carbon Mitigation Impact of Energy Choices in China:
A Focus on Renewable Energy and Thermal Efficiency Improvement

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Abstract:
This study estimates the carbon mitigation effects of various energy choices, focusing on renewable energy (RE) adoption and thermal efficiency improvement. We compiled a comprehensive panel data covering 2,641 counties from 2003 to 2017 and employed a dynamic panel model for the analysis. Our results suggest that the adoption of wind power and thermal efficiency improvement, with the latter indicated by the adoption of large thermal power plants, significantly reduces carbon emissions. Notably, increasing wind power capacity exhibits a more substantial marginal reduction effect than increasing large thermal capacity. Moreover, the mitigation impact of RE is more substantial in regions with diverse renewable power types and higher renewable capacity. These results provide robust evidence regarding thermal efficiency improvement's role in carbon mitigation and underscore the growing environmental benefits of RE as its share in installed capacity increases. Our findings emphasize the necessity of policies that incentivize the utilization of various RE types and target regional environmental efficiency gaps, which are crucial for achieving enhanced carbon mitigation during the energy transition.

Keywords: Renewable energy; Thermal efficiency improvement; Carbon mitigation; Dynamic panel analysis; System GMM

1． Introduction

Climate mitigation strategies such as reducing coal capacity, sustainably using thermal energy, increasing the use of renewable energy (RE), and improving energy efficiency are considered effective methods for reducing greenhouse gas emissions. In response to these efforts, global energy intensity and carbon intensity decreased by 2% and 0.3% per year over 2010–2019, respectively (IPCC 2022). Nevertheless, disparities in regional greenhouse gas emission trends and developmental stages present challenges. Developing countries, in particular, face hurdles in adopting low-emission technologies due to financial, technology, and capacity limitations (IPCC 2022). Additionally, factors such as portfolio diversification, policy heterogeneity, and perceptions of risk and return play significant roles in shaping strategic decisions between conventional and RE technologies (Wütenhagen and Menichetti 2012).

As the world's largest emitter of greenhouse gases, China faces significant challenges due to its rapidly increasing energy demand and emissions. Currently, fossil fuels remain the dominant source in China's primary energy consumption, with coalfired electricity alone accounting for over 60% of the nation's power supply in 2020 (IEA Data Service 2022). The country has set ambitious goals to transform its energy profile by increasing the share of renewable electricity consumption to 33% by 2025, up from 27.3% in 2019. This shift is expected to significantly reduce carbon emissions.

During the initial phase of the energy transition, especially in regions abundant with coal, a strategic approach might involve replacing inefficient small thermal power plants with more efficient ones. This strategy could offer greater immediate benefits compared with the early adoption of RE sources. Transitioning to RE can be costly initially and may pose risks to energy supply stability. In some cases, this situation has paradoxically led to the concurrent expansion of thermal power for energy security. Thus, improving the efficiency of thermal power plants is a crucial aspect of the energy transition. Without such improvement, expanding thermal power could significantly boost carbon emissions instead of delivering environmental benefits. Wang et al. (2019) emphasized the importance of adopting carbon reduction technologies, managing power plant capacity, and optimizing the operational schedules of thermal power plants to control emissions. Accurately quantifying the environmental impact of various energy choices, including the adoption of RE and thermal efficiency improvement, can provide important information for regional energy investment decisions, which are highly dependent on the costs and benefits of transitioning to new energy sources.

This study aims to investigate the impacts of different energy choices on carbon emissions by addressing two main questions: Is RE more effective at reducing carbon emissions than efficient thermal power plants, and how do the effects vary across adoption types and regions? To answer these questions, we collect detailed and comprehensive information on wind, solar, and large thermal power plants to construct adoption and installed capacity measures at the county level. The adoption of large thermal plants serves as an indicator of thermal efficiency improvement. We use a balanced county-level panel dataset of 2,641 counties from 2003 to 2017 to compare the carbon mitigation effects of wind, solar, and large thermal power across energy adoption types and regions. To uncover the relationship between energy choices and carbon emissions, we conduct a dynamic panel analysis. This strategy allows us to integrate the county and year fixed effects to control for time-invariant county characteristics and time trends.

This study contributes to existing literature in several ways. First, we conduct a comparative analysis of the effects of various energy choices on carbon emissions, with a focus on RE adoption and thermal efficiency improvement. This bridges a knowledge gap, as most previous studies have concentrated on a single energy choice (Alvarez-Herranz et al. 2017; Hasnisah et al. 2019; Li et al. 2021; Lin and Zhu 2019; Wang et al. 2023; Zhang et al. 2021). It is worth noting that thermal plants in developed countries exhibit relatively high generation efficiency attributed to larger production scales, the adoption of clean coal technologies, and stringent fossil fuel regulations (Eguchi et al. 2021; Li et al. 2019). Comparing different energy choices offers valuable insights to regions dealing with the dual concerns of energy efficiency and climate change. Second, we provide empirical findings on the mitigation effects of renewables by power type and adoption type. We estimate the heterogeneous mitigation effects of wind, solar, and various combinations of renewables, whereas most studies have primarily focused on the environmental benefits of RE consumption in general (Alvarez-Herranz et al. 2017; Azam et al. 2021; Hasnisah et al. 2019; Li et al. 2021; Murshed et al. 2022; Wang et al. 2023). This deepens our understanding of their heterogeneous potential, emphasizing the need for region-specific energy strategies. Finally, the empirical literature investigating the carbon mitigation effects of RE is primarily assessed at the regional (Ahmad et al. 2021; Lin and Zhu 2019; Zhang et al. 2023), national (Azam et al. 2021; Murshed et al. 2022; Novan 2015), and global levels (Alvarez-Herranz et al. 2017; Dong et al. 2017, 2018; Hasnisah et al. 2019; Kazemzadeh et al. 2022; Li et al. 2021; Wang et al. 2022, 2023). However, many county-specific natural, historical, and political factors can affect carbon emissions and energy choices, which are not fully considered in previous studies. Our analysis contributes to the literature by identifying the causal effects, controlling for those potentially omitted characteristics.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and discusses the potential mechanisms. Section 3 describes the data, analytical framework, and estimation strategy. Sections 4 and 5 present the empirical findings and discussion, respectively. Section 6 concludes.

２． Literature Review

The relationship between economic growth, energy efficiency, and carbon emissions has garnered significant attention in the environmental literature. Generally, economic growth and increased energy intensity are positively associated with carbon emissions (Li et al. 2021; Milin et al. 2022). Industrial modernization and structural optimization are key to enhancing energy efficiency and reducing emissions (Li et al. 2022b; Rehman et al. 2023). In China's transport sector, for instance, gains in energy efficiency have led to significant emission reductions (Li et al. 2022a). Additionally, policies aimed at reducing coal use and reforming energy consumption have been shown to boost efficiency (Liu and Jin 2020; Su et al. 2023).

In the power sector, China launched the "Replacing small units with large ones" program in 2017 with the aim of closing small and outdated thermal plants and replacing them with efficient large thermal plants. This effort led to the retirement of over 100 gigawatts (GW)[1]1 of small thermal power plants between 2006 and 2015 (Li et al. 2019). With the promotion of large thermal installations, units larger than 600 MW accounted for 50.3% of gross installed capacity by 2013 and those larger than 1,000 MW accounted for 56.7% by 2017 (China Electricity Council 2003–2017; Li et al. 2019). Research by Eguchi et al. (2021) reinforced the benefits of this transition, indicating that larger plants achieve superior efficiency through the utilization of clean coal technologies and more effective equipment. The transition from small plants to large ones results in a significant reduction in coal consumption per unit of electricity generated, thereby enhancing overall efficiency (Li et al. 2019). Thus, the shift to larger thermal plants is a strategic move towards improved environmental performance compared to smaller thermal plants.

RE has been consistently shown to contribute to economic growth and environmental sustainability (Du and Takeuchi 2019; Halilbegović et al. 2023; Li et al. 2022b; Rehman et al. 2022). A growing body of literature highlights the positive impact of RE consumption, alongside green energy innovation and investment, in reducing carbon emissions and air pollution (Ahmad et al. 2021; Alvarez-Herranz et al. 2017; Azam et al. 2021; Dong et al. 2017, 2018; Hasnisah et al. 2019; Kazemzadeh et al. 2022; Li et al. 2021; Lin and Zhu 2019; Murshed et al. 2022; Novan 2015; Wang et al. 2022, 2023; Zhang et al. 2023). Table 1 provides a summary of relevant empirical studies on the mitigation effects of RE, along with their key findings. Most existing studies primarily examine the impacts of RE from the perspective of the consumption share due to the limited availability of micro-level data. For example, Alvarez-Herranz et al. (2017) and Wang et al. (2023) employed global panel data, and Murshed et al. (2022) used time series data in Argentina, all finding that an increased RE share reduces emissions. More recent literature has begun utilizing more detailed data to

1 As a reference, the cumulative thermal installed capacity in 2017 was about 1,105 GW.

comprehensively explore the specific impacts of different RE types. For instance, Novan (2015) quantified the heterogeneity in the marginal impacts of RE generation and capacity investments on pollution using hourly generation data from the Texas market. Using city-level data aggregated from power plants in China, Zhang et al. (2023) found significant mitigation effects of RE on air pollution.

Table 1 Summary of relevant empirical studies and key findings

Paper	Country	Energy measure	Methodology	Key findings
A. Regional/National level				
This study	China	Wind, solar, large thermal capacity	System GMM	Additional wind and large thermal capacity decrease CO_2
Novan (2015)	The US	Wind, solar capacity and power generation in Texas	Fixed-effect OLS model	Additional wind and solar capacity provide heterogeneous carbon mitigation effects
Lin and Zhu (2019)	China	RE patents	Panel threshold model	Mitigation effects on CO_2 vary across energy structures
Zhang et al. (2021)	China	RE investment	Nonparametric additive model	Limited mitigation effects on CO_2
Azam et al. (2021)	10 countries	Natural gas, nuclear and RE consumption	FMOLS	Mitigation effects of RE on CO_2 in most countries
Murshed et al. (2022)	Argentina	RE share	ARDL	Increase of RE share decreases CO_2 in both the short and long run
Zhang et al. (2023)	China	Thermal, RE power generation and share	Fixed-effect SDM model	Mitigation effects of RE on air pollution
B. Global level				
Alvarez-Herranz et al. (2017)	17 OECD countries	RE share	PLS, TSLS	Increase of RE share mitigates GHG emissions
Hasnisah et al. (2019)	13 Asia countries	RE share	FMOLS, DOLS	No significant mitigation effects on CO_2
Li et al. (2021)	147 countries	RE share	OLS, FMOLS	Increase of RE share decreases CO_2
Wang et al. (2023)	208 countries	RE share	GMM, FMOLS	Increase of RE share decreases CO_2

Note: Energy share indicates the share of RE consumption in the energy mix. Natural gas, nuclear and RE consumption are measured in Million Tons of oil equivalent in the study of Azam et al. (2021). Diverse analytical approaches are used in the literature for estimation, including the Generalized Method of Moments (GMM), Ordinary Least Squares (OLS), Fully Modified Ordinary Least Squares (FMOLS), Autoregressive Distributed Lag (ARDL), Spatial Durbin Model (SDM), Panel Least Squares (PLS), Two-Stage Least Squares (TSLS), and Dynamic Ordinary Least Squares (DOLS).

However, some findings reveal inconsistencies. Azam et al. (2021) observed a negative impact of RE on CO2 emissions in some major polluting countries but a positive effect in Russia. Drawing on empirical evidence from Asian countries, Hasnisah et al. (2019) suggested that RE consumption does not significantly contribute to carbon reduction. Zhang et al. (2021) also found limited mitigation effects and suggested that RE investment may only start to reduce emissions during the middle stages of development. Depending on the significance of RE sources, the nature of RE, and fluctuations in RE technology development and RE share, outcomes can differ from one country to another (Azam et al. 2021; Hasnisah et al. 2019). In this study, we attempt to provide a comprehensive analysis of the mitigation effects of various energy choices using county-level data aggregated from power plants, taking a multidimensional perspective into account.

3． Data and Estimation Method

3.1 Data

This study compiles a balanced county-level panel dataset from 2003 to 2017 to estimate the dynamic panel models, including 2,641 counties, across 15 years. The CO2 emissions data are sourced from Carbon Emission Accounts and Datasets (CEADs)[2], which are estimated using satellite-observed night-time light imagery. Given that county-level carbon emissions data are neither officially published nor standardized (Liang et al. 2019), we use this county-level CO2 emissions data from 2003 to 2017 to investigate power-related carbon emissions. Additionally, we use CO2 intensity as an energy-related estimate of carbon emissions. This measure, reflecting the progress of regional industrial structure and technological innovation, has been extensively used in previous studies (Liang et al. 2019; Zhao et al. 2014). CO2 intensity is calculated as the unit of CO2 emissions per unit gross domestic product (GDP)[3], CO2 intensity = CO2 emissions / GDP. Figure 1 shows the trend in county-level annual average CO2 emissions and CO2 intensity from 2003 to 2017. CO2 emissions increased until 2010 but have since remained relatively stable, likely due to the implementation of carbon mitigation policies.

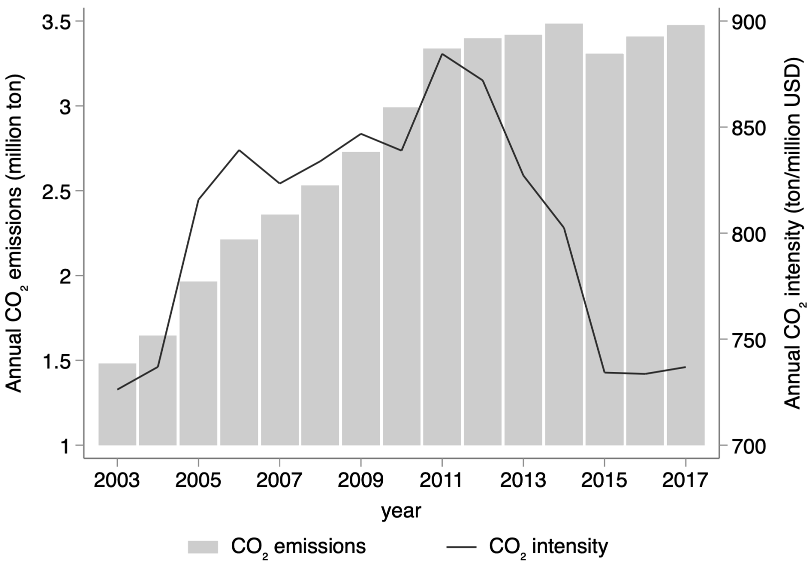

Figure 1. Trend in the county-level carbon measures

CO2 intensity followed a similar trend during 2003–2010 but significantly decreased

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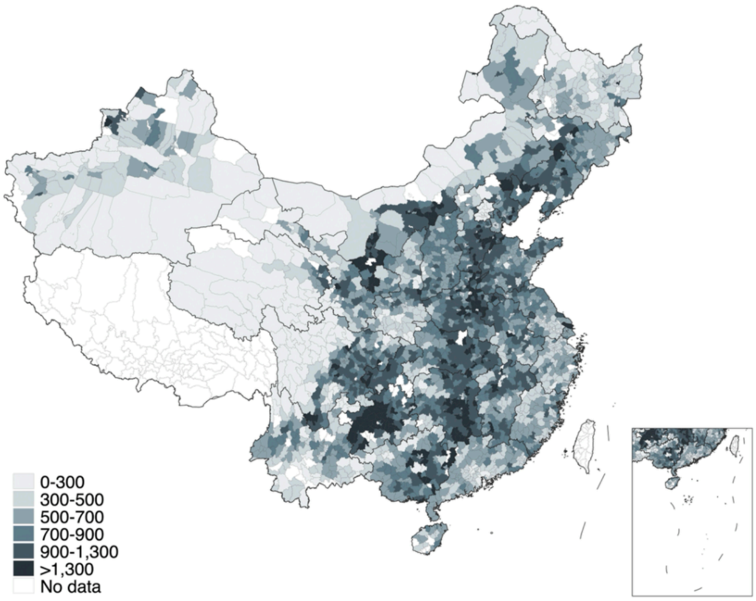
2 Carbon Emission Accounts and Datasets (2003–2017) provides information on CO2 emissions in 2,735 Chinese counties from 1997 to 2017, which is useful for the development of strategic policies tailored to local conditions.

3 We collect county-level real GDP data from Chen et al. (2022). GDP data are deflated to 2017 values using US dollars (2017=1).

thereafter, indicating that CO2 emissions grew more slowly than the GDP. By 2017, the average CO2 intensity had almost returned to the 2003 levels. Nonetheless, considerable variation in CO2 intensity exists across different regions. Figure 2 illustrates the spatial distribution of regional CO2 intensity in 2017. Counties with high CO2 intensities are concentrated in the central and west regions, characterized by lower levels of economic development. It is worth noting that more than 60% of the thermal power-sourced generation is concentrated in eastern and central China (China Electricity Council 2019). Eastern China boasts the highest thermal installed capacity and CO2 emissions but exhibits the lowest CO2 intensity. Thermal power plants in central and western China have low efficiency, while those in eastern China achieve higher intensity levels attributed to their superior energy-saving and emission reduction capabilities (Eguchi et al. 2021; Fang et al. 2022).

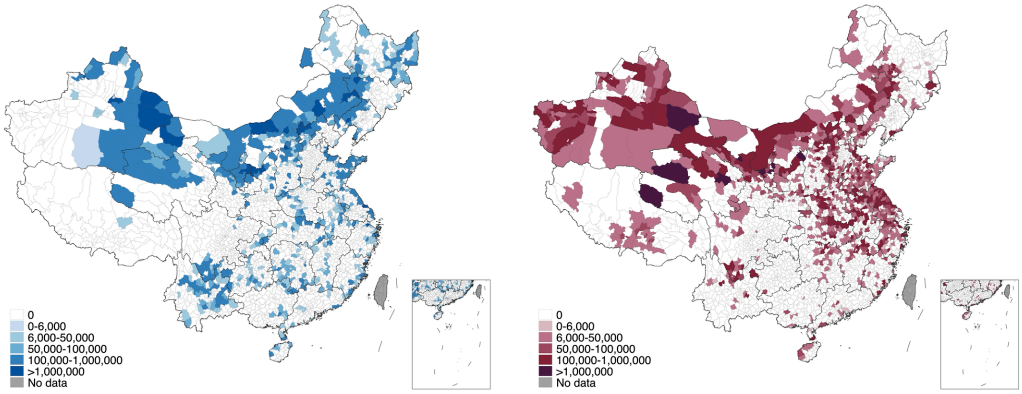


Note: This figure shows the regional CO_2 intensity (unit: tonnes/million USD) in 2017. The average CO_2 intensity in 2017 is 737.6.

Figure 2. Regional CO_2 intensity

We obtain energy data from the China Electricity Council (2003–2017) (CEC), which provides annual statistics on China's electric power industry since 1988, including details on the installed capacity and location of plants with a capacity over 6,000 kW. Given the limited operation of renewable plants before 2003, our analysis commences from that year, tracking the growth in installed capacity of renewable power plants through 2017. For large thermal power plants, we focus on those with capacities exceeding one million kW. By 2017, wind power constituted 28.3% of China's total renewable capacity at 163.2 GW, while solar capacity reached 204.3 GW by 2019, accounting for 25.9% of the total renewable capacity. The transition from thermal to renewables is marked, with wind and solar capacity increasing by 4.3% from 2000 to 2010 and surging by 15.2% from 2010 to 2019, amidst reductions in thermal capacity.

Notably, the installation of renewables exhibits significant regional disparities. Figure 3 shows the county-level spatial distribution of wind and solar power in 2017, categorized into the northeast, east, central, and west regions based on socioeconomic development levels. Predominantly, the northeast and west regions collectively accounted for 64.6% of China's wind capacity, while the east and central regions collectively accounted for 57.8% of the country's solar capacity in 2017. Despite the rapid growth of RE in China, it still represents a small proportion of the country's total energy production. In 2019, wind generation ranged from 5.4% to 14.5%, and solar generation ranged from 3.2% to 17.6% across China's provinces (China Electricity Council 2019). Regions with a larger proportion of renewable capacity are likely to see more substantial impacts on emissions reduction, even if the national average for installed capacity remains relatively low.



a Wind　　**b** Solar

Note: Figures (a) and (b) show the spatial distribution of the cumulative installed capacity (kW) of wind and solar power plants in 2017.

Figure 3. Spatial distribution of wind and solar power

This energy data, combined with other datasets, allow us to analyze the varying causal effects on CO2 emissions among different types of power. Referring to the previous literature, factors such as population density, wind speed, and sunlight duration have been considered as determinants influencing the selection of power plant locations (Su et al. 2023; Wang et al. 2024; Zhang et al. 2023). Additionally, temperature and precipitation impact both CO2 emissions and plant efficiency (Zhang et al. 2023).

We sourced population density data from WorldPop (2000-2020) and weather data from the China National Meteorological Information Centre. The latter provides daily measures of temperature, precipitation, relative humidity, and wind speed at various weather stations across China, along with precise coordinates for each station. This information enables us to extrapolate annual county-level weather data.

Table 2 summarizes the statistics of these variables. On average, the county shares of wind, solar, and large thermal adoption are 8.4%, 6.2%, and 7.2%, respectively. After 2010, there was a significant increase in RE adoption, particularly in solar power. By 2017, these shares rise to 23.7%, 32.7%, and 10.5%, respectively. When comparing average installed capacities, wind (16.5 MW) and solar (5.3 MW) are considerably lower than large thermal power (135.9 MW). Since the solar industry was established late and the installed capacity was distributed in a scattered manner, its average capacity was the smallest throughout our study period.

Table 2 Summary statistics

Variable	Mean	S.D.	Min	Max	Obs.
CO_2 emission measures (2,641 counties for 2003–2017)					
CO_2 emissions (million tonnes)	2.782	3.025	0.000	56.429	39,615
CO_2 intensity (tonnes/million USD)	803.461	531.216	0.000	11,607.128	39,615
Energy measures					
Wind (dummy)	0.084	0.277	0.000	1.000	39,615
Solar (dummy)	0.062	0.241	0.000	1.000	39,615
Large thermal (dummy)	0.072	0.259	0.000	1.000	39,615
Wind capacity (MW)	16.502	124.865	0.000	6657.500	39,615
Solar capacity (MW)	5.285	52.483	0.000	2895.800	39,615
Large thermal capacity (MW)	135.876	573.358	0.000	22770.000	39,615
Control variables					
Population density (persons/km^2)	1030.272	3045.493	0.181	45128.251	39,615
Wind speed (m/s)	2.085	0.613	0.539	6.767	39,615
Sunlight duration (hours)	2004.078	520.074	662.745	3461.756	39,615
Temperature (°C)	13.894	5.292	-4.371	26.821	39,615
Precipitation (mm)	959.297	444.136	0.000	3115.061	39,615

Note: Wind and Solar indicate counties that adopted wind and solar power plants with an installed capacity over 6,000 kW. Large thermal indicates counties that have thermal power plants with an installed capacity over one million kW.

3.2 Energy Measures

To estimate the impacts of various energy choices, we constructed six energy measures. $Wind$, $Solar$, and $Large$ thermal are dummy variables designed to assess the adoption impact of these energy sources. Both $Wind$ and $Solar$ signify counties with wind or solar power plants exceeding 6,000 kW in installed capacity. By the end of 2017, such wind and solar plants constituted over 99.9% and 79.4% of their respective total installed capacities. These variables distinguish counties with RE adoption from those without.[4] $Large\ thermal$ variable indicates counties with large-scale thermal power plants of over one million kW, which represented 56.7% of the total thermal capacity by the end of 2017. This variable differentiates counties with major thermal power plants from those without. Counties lacking large thermal facilities (i.e., the comparison group of large thermal) likely depend on smaller thermal power sources, typically coal-fired, which are prevalent in most counties. Small thermal power plants generally have higher heat rates and lower energy efficiency (Li et al. 2019), making $Large\ thermal$ an appropriate proxy for thermal efficiency improvement.

[4] A county, regardless of whether it had adopted RE, uses thermal power or hydropower as the main energy source for power generation.

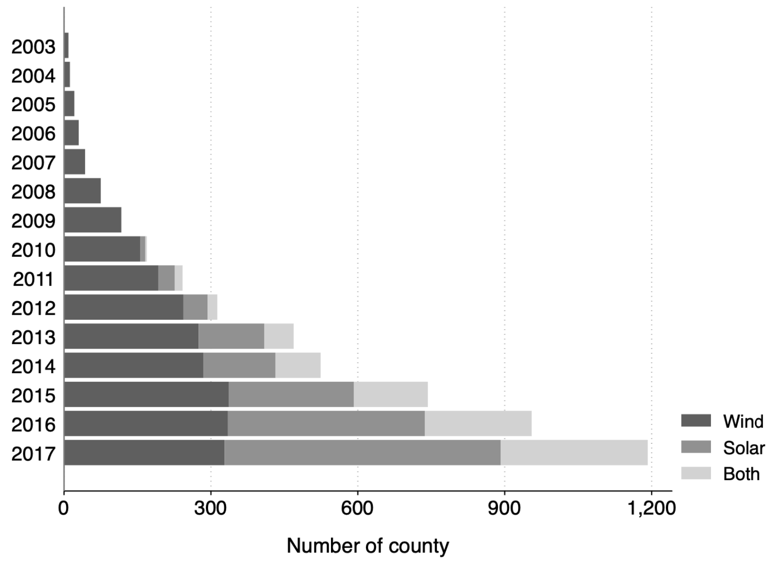


Figure 4. Staggered adoption of renewables

Additionally, we use the continuous variables $Wind\ capacity$, $Solar\ capacity$, and $Large\ thermal\ capacity$ to measure the marginal effects of the installed capacity of each power type. $Wind\ capacity$ and $Solar\ capacity$ capture the marginal effects of installed capacity for renewable power plants, while $Large\ thermal\ capacity$ captures the marginal effects of installed capacity for large thermal power plants. Figure 4 shows the county share of RE adoption by power type and year. Our sample includes a balanced panel of 2,641 counties, with approximately 45% (1,192) adopting RE by 2017. The breakdown of counties adopting wind, solar, and both types of plants by 2017 are 328, 564, and 300, respectively.

3.3 Econometric Model

This study employs a dynamic panel model to investigate the causal effects of various energy choices on carbon mitigation. Carbon emissions at the regional level are closely linked to the regional energy structure. In the short term, this structure, which is influenced by local resource endowments, energy consumption patterns, and supply, may remain unchanged. Therefore, we include the lagged values of carbon emissions measures to address the persistence in these variables. However, the inclusion of lagged dependent variables could introduce bias due to endogeneity issues. Dynamic panel models effectively control for unobservable time-invariant factors in both year and county, while also mitigating endogeneity through the incorporation of lagged or differenced terms as instrumental variables. Furthermore, our panel data comprises 2,641 counties across a span of 15 years, featuring a considerably larger number of cross-sectional units (N) than the time span (T). According to Bond (2002), when the dependent variable is persistent and close to being a random walk (i.e., the coefficient of the first lag γ is close to 1), the difference of the generalized method of moments (GMM) estimator yields a biased and inefficient estimate, particularly when T is short. Given that γ in our models are ranging between 0.955 and 1.062, as seen in the main results of Tables 3 and 4, we opt for the system GMM model proposed by Arellano and Bond (1991) to estimate the mitigation effects. The general model we use can be specified as follows:

$$Y_{it} = f(Y_{i,t-1}, E_{it}, X_{it}, \delta_i, \mu_t) \quad (1)$$

Equation (1) shows the association between carbon emission Y_{it}, its lagged term $Y_{i,t-1}$, energy strategy indicator E_{it}, weather and county controls X_{it}, regional trends δ_i, and time trends μ_t. We further expand Equation (1) to add the logarithm forms of variables to estimate the system GMM model:

$$lnY_{it} = \gamma lnY_{i,t-1} + \beta E_{it} + \theta X_{it} + \delta_i + \mu_t + \varepsilon_{\mathrm{it}} \quad (2)$$

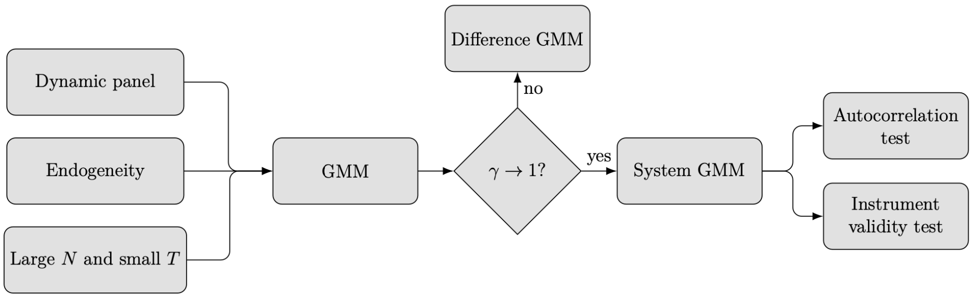
where lnY_{it} is the logarithm of the carbon emission measures in county i in year t during 2003–2017, including CO2 emissions and CO2 intensity (see the details in Subsection 3.1). $lnY_{i,t-1}$ is the lagged value of lnY_{it}. E_{it} indicates the energy measures of the energy adoption[5] or cumulative installed capacity in county i in year t. X_{it} is the set of control variables that can affect regional carbon emissions and energy location choices, including county-level population density, wind speed, and sunlight duration, as well as the two weather controls of temperature and precipitation. δ_i denotes the county fixed effects, controlling for unobservable time-invariant county characteristics. μt denotes the year fixed effects common to all counties in period t, which controls for national energy policies, environmental regulations, and trends that shape carbon emissions over time. ε_{it} denotes the error term. The main variable of interest is E_{it}, and the parameter β captures the effects of the energy measures on carbon emissions:

$$\Delta lnY_{it} = \gamma \Delta lnY_{i,t-1} + \beta \Delta E_{it} + \theta \Delta X_{it} + \Delta \mu_t + \Delta \varepsilon_{\mathrm{it}} \quad (3)$$

The dynamic panel analysis removes the county fixed effects by time differencing, and we obtain Equation (3). The estimates will be biased if we use ordinary least squares regression because $\Delta lnY_{i,t-1}$ is correlated with $\Delta \varepsilon_{it}$. We thus use the GMM estimator developed by Arellano and Bond (1991) and $lnY_{i,t-s}$ $(s \geq 2)$ as the instrument for $\Delta lnY_{i,t-1}$. Similarly, lags of Eit are used as instruments for the energy measures. Additionally, we use the first-order autocorrelation test AR(1) and second-order autocorrelation test AR(2) statistics to

[5] Energy adoption refers to whether a certain type of renewable power facility exists in county i in year t. A dummy variable is used to illustrate energy adoption, which accounts for 1 when wind/solar power facility exist in county i in year t, and 0 otherwise.

investigate whether the assumption of no serial correlation in εit can be rejected. The Hansen J test assesses the presence of overidentifying restrictions, helping determine whether the chosen instruments are correlated with the error term. In our presentation of the results, we include the p-values for both the AR(1) and AR(2) tests, as well as the Hansen statistics. Low p-values in the AR(1) test indicate that the fundamental assumption of no serial correlation is met, whereas high p-values in the AR(2) and Hansen J test suggest that potential sources of correlation have been effectively addressed in our analysis. As a result, a combination of a low AR(1) p-value and high AR(2) and Hansen J test p-values is indicative of the appropriateness of our estimation approach. Our choice of estimation strategy and the estimation procedure follow the analytical framework in Figure 5[6].



Note: γ denotes the coefficient of the first lag of carbon emissions measures.

Figure 5. The flow diagram of analytical framework

We develop three hypotheses based on the literature review in Section 2. H1: Both RE adoption and thermal efficiency improvement are linked to reductions in carbon emissions. H2: An increase in the installed capacity of RE sources is expected to result in a more significant mitigation effect. H3: Higher installed capacity leads to higher marginal benefits.

4. Results

4.1 Effects of energy adoption and installed capacity

We first examine the effects of energy adoption by power type and report the results in Table 3. The results for CO2 emissions and CO2 intensity are detailed in columns 1–3 and 4–6, respectively. In addition to the lagged dependent variables, we also treat the energy measures as endogenous in our regression models.

The results in columns 1–3 reveal a significant positive correlation between past and present CO2 emissions. $Wind, Solar,$ and $Large\ thermal$ exhibit negative and statistically significant effects on CO2 emissions. The coefficients in column 3 imply that wind and solar

[6] We used the econometric software Stata 16.1 for the analysis. The specific Stata commands employed for data visualization and model estimation included grmap, tabstat, xtset, xtabond2, among others.

power adoption reduce CO2 emissions at the county level by 1.6% and 2.3%, respectively. In comparison, $Large\ thermal$ demonstrates a more pronounced reduction effect of 2.9%. Similarly, the results in columns 4–6 indicate that lagged CO2 intensity significantly influences current CO2 intensity. Both CO2 emissions and intensity display persistence over time. The coefficients in column 6 imply that wind and large thermal power adoption leads to 1.2% and 1.4% decreases in CO2 intensity, respectively, while solar power adoption shows no statistically significant effect on CO2 intensity. Despite similar county shares (8.4% for $wind$, 6.2% for $solar$, and 7.2% for $Large\ thermal$), wind and solar power exhibit smaller mitigation effects compared to large thermal power due to their lower installed capacities.

The reduction effect observed in large thermal adoption can be attributed to the phasing out of inefficient small thermal units. Tang et al. (2019) reported a substantial decrease in installed capacity from smaller coal-fired units and a significant drop in overall coal-fired capacity from 2014 to 2017. The adoption of ultra-low emissions technology in new and refurbished units since 2014 has further improved the efficiency of coal-fired power plants. The potential rise in carbon emissions from increased large thermal power capacity is mitigated by advancements in efficiency, underscoring the carbon mitigation potential of large thermal adoption.

Table 3 Effects of energy adoption

	$\ln CO_2$			$\ln CO_2$ intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
L.$\ln CO_2$	1.061***	1.058***	1.062***			
	(0.030)	(0.030)	(0.033)			
L.$\ln CO_2$ intensity				0.966***	0.969***	0.969***
				(0.019)	(0.018)	(0.018)
Wind	-0.020***	-0.015***	-0.016***	-0.010*	-0.011**	-0.012**
	(0.007)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Solar	-0.026*	-0.024*	-0.023*	0.003	0.003	0.003
	(0.016)	(0.013)	(0.013)	(0.004)	(0.004)	(0.004)
Large thermal	-0.033**	-0.030**	-0.029*	-0.014**	-0.015**	-0.014**
	(0.015)	(0.014)	(0.015)	(0.007)	(0.007)	(0.007)
lnPopulation density	-0.052***	-0.048***	-0.042***	-0.014***	-0.015***	-0.014***
	(0.014)	(0.013)	(0.012)	(0.003)	(0.003)	(0.002)
Wind speed		-0.015*	-0.022*		0.002	0.001
		(0.009)	(0.012)		(0.002)	(0.002)
lnSunlight		0.008	-0.018		-0.001	-0.007
		(0.007)	(0.015)		(0.011)	(0.007)
Temperature			-0.004**			-0.001
			(0.002)			(0.001)
lnPrecipitation			0.004			-0.002
			(0.006)			(0.003)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
$AR(1)$ test	0.001	0.001	0.001	0.001	0.001	0.001
$AR(2)$ test	0.149	0.151	0.148	0.122	0.122	0.121
Hansen p-value	0.143	0.152	0.163	0.180	0.174	0.170
Observations	36,974	36,974	36,974	36,974	36,974	36,974

Note: The constant term is included but not reported. System GMM regressions with robust standard errors are in parentheses. * p <0.1, ** p <0.05, and *** p <0.01.

Table 4 presents the effects of installed capacity by power type. Specifically, the coefficients in column 3 suggest that a 1% increase in wind and large thermal capacity decreases CO2 emissions by 0.017% and 0.008%, respectively. Similarly, the results in column 6 suggest that a 1% increase in wind and large thermal capacity leads to 0.008% and 0.004% decreases in CO2 intensity, respectively, while additional solar capacity shows no significant effect on both CO2 emissions and intensity.

The estimates of installed capacity are quantitatively small compared with those of county-level energy adoption. However, the marginal reduction effects of wind capacity are more substantial than those of large thermal capacity. As reported in Table 4, a 1% increase in $Wind\ capacity$ — equivalent to a 0.165 MW[7] increase — reduces CO2 emissions by 0.017%. A 1% increase in $Large\ thermal\ capacity$ — equivalent to a 1.359 MW[8] increase — reduces CO2 emissions by 0.008%. Essentially, a 1 MW increase in the installed capacity of wind and large thermal results in CO2 emission reductions of approximately 10.303% and 0.006%, respectively. This translates to a reduction of about 0.287 and 0.0002 million tonnes of CO2 emissions.[9] We find that increasing the installed capacity of wind power by 1 MW reduces carbon emissions much more efficiently than increasing the installed capacity of large thermal power plants by the same amount.

Despite the higher efficiency of large thermal power plants compared to smaller ones, they still depend on fossil fuels, unlike wind power, which operates without fossil fuel consumption. Therefore, wind power, for the same installed capacity, offers greater carbon reduction benefits than large thermal power. Additionally, wind power installations have seen rapid growth within counties, increasing from 0.069 MW in 2003 to 54.229 MW in 2017, averaging an annual increase of 21.9%. In comparison, large thermal power grew from 38.578 MW to 225.116 MW during the same period, with an average annual growth of 9.2%. This brisk expansion of wind capacity could be a key factor in its heightened carbon mitigation impact.

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[7] This number is calculated based on the mean of Wind capacity in Table 2. A 1% increase is $0.01 * 16.502 = 0.165$ MW.

[8] This number is calculated based on the mean of Large thermal capacity in Table 2. A 1% increase is $0.01 * 135.876 = 1.359$ MW.

[9] This number is calculated based on the mean of CO2 emissions in Table 2. A 1 MW increase in the installed capacity of wind leads to a $0.103 * 2.782 = 0.287$ million tonne reduction in CO2 emissions and that of large thermal leads to a $0.00006 * 2.782 = 0.0002$ million tonne reduction in CO2 emissions.

Table 4 Effects of installed capacity

	$\ln CO_2$			$\ln CO_2$ intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
L.$\ln CO_2$	1.040***	1.042***	1.044***			
	(0.022)	(0.026)	(0.025)			
L.$\ln CO_2$ intensity				0.959***	0.954***	0.955***
				(0.021)	(0.023)	(0.024)
lnWind capacity	-0.017**	-0.015***	-0.017***	-0.008**	-0.007*	-0.008*
	(0.007)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
lnSolar capacity	-0.011	-0.013	-0.012	0.004	0.006	0.005
	(0.011)	(0.011)	(0.010)	(0.005)	(0.006)	(0.006)
lnLarge thermal capacity	-0.008*	-0.008*	-0.008*	-0.004*	-0.004*	-0.004*
	(0.004)	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)
lnPopulation density	-0.041***	-0.040***	-0.035***	-0.013***	-0.013***	-0.013***
	(0.011)	(0.012)	(0.010)	(0.003)	(0.003)	(0.002)
Wind speed		-0.011	-0.015*		0.003	0.003
		(0.007)	(0.009)		(0.002)	(0.003)
lnSunlight		0.010	-0.011		-0.009	-0.012
		(0.006)	(0.012)		(0.014)	(0.010)
Temperature			-0.003**			-0.000
			(0.001)			(0.001)
lnPrecipitation			0.002			-0.003
			(0.006)			(0.003)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
$AR(1)$ test	0.001	0.001	0.001	0.001	0.001	0.001
$AR(2)$ test	0.147	0.150	0.147	0.121	0.121	0.121
Hansen p-value	0.170	0.153	0.174	0.171	0.158	0.156
Observations	36,974	36,974	36,974	36,974	36,974	36,974

Note: The constant term is included but not reported. System GMM regressions with robust standard errors are in parentheses. The unit of installed capacity is one million kW. Controls and year dummies are included in all the regressions. * p <0.1, ** p <0.05, and *** p <0.01.

4.2 Effects across adoption types

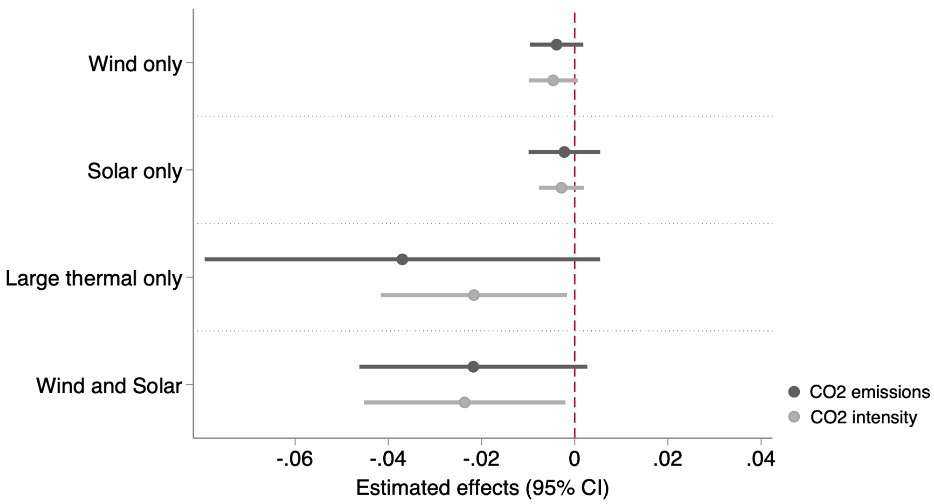
We further explore how the effects of energy choices vary across seven types of adoption, depending on the number of power generation sources utilized in a county. Counties using a single energy source are categorized as either $Wind\ only$, $Solar\ only$, or $Large\ thermal\ only$. Those employing two energy sources are categorized as $Wind\ and\ solar$, $Wind\ and\ large\ thermal$, or Solar and large thermal. Those adopting threeenergy sources are categorized as Wind, solar, and large thermal. Table 5 presents a summary of the county share and average installed capacity for each adoption type. $Wind\ only$ (5.5%), $Solar\ only$ (3.4%), and $Large\ thermal\ only$ (5.5%) counties account for the largest shares, followed by counties adopting $Wind\ and\ solar$ (1.8%). Counties usually adopt a single energy source, with those opting for multiple types favoring a combination of wind and solar.

Table 5 Statistics by adoption type

Variable	County share of adoption	Installed capacity mean (MW)
One energy source		
Wind only	0.055	8.198
Solar only	0.034	2.107
Large thermal only	0.055	98.682
Two energy sources		
Wind and solar	0.018	8.216
Wind and large thermal	0.007	14.920
Solar and large thermal	0.006	13.869
Three energy sources		
Wind, solar, and large thermal	0.004	11.672

Note: Counties that adopted only one energy source are defined as *Wind only*, *Solar only*, or *Large thermal only*; two energy sources, as *Wind and solar*, *Wind and thermal*, or *Solar and thermal*; and three energy sources, as *Wind, solar, and large thermal*.

Figure 6 plots the estimated effects of the installed capacity by adoption type on CO2 emissions and CO2 intensity, respectively. These figures do not include adoption types with a county-level share below 1%: $Wind\ and\ large\ thermal$ (0.7%), $Solar\ and\ large\ thermal$ (0.6%), and $Wind, solar, and\ large\ thermal$ (0.4%). We find that counties adopting both wind and solar exhibit a greater marginal mitigation effect in installed capacity compared with those adopting either wind or solar alone. Capacity increases in counties with Large thermal only or Wind and solar lead to reductions in both CO2 emissions and CO2 intensity. This aligns with our main findings for large thermal. Interestingly, while an increase in Wind only capacity shows no significant effect on CO2 emissions, it does contribute to a decrease in CO2 intensity.



Note: This plot shows the estimated effects of installed capacity on CO_2 emissions and CO_2 intensity by adoption type. The circle displays the point estimate, and the spike indicates the associated 95% confidence band.

Figure 6. Estimated effects by adoption type

4.3 Effects across regions

The costs and benefits of fuel switching and energy efficiency vary by region, depending on the mix of energy sources. Different regions face distinct trade-offs between emission mitigation and energy choices. To examine this heterogeneity and its alignment with these trade-offs, we estimate different regional samples.

Table 6 details the county shares of adoption and installed capacity by power type and region. Notably, the northeast boasts the highest county share (15.8%) and installed capacity (28.3 MW) for wind. By comparison, Western China exhibits high installed capacities for both wind (approximately 22.8 MW) and solar (around 8.7 MW). Eastern China has the highest county share (11.0%) and installed capacity (230.3 MW) for large thermal power, while the shares of renewables in Eastern and Central China are comparatively low. Our main findings indicate that the capacity share of renewables is a more significant factor than the county share of adoption. Therefore, regions with a higher share of wind and solar installed capacity are more likely to demonstrate notable carbon mitigation effects.

Table 6 County share of adoption and installed capacity by region

	Wind	Solar	Large thermal	
Variable	Mean	Mean	Mean	N
County share of adoption				
Northeast	0.158	0.028	0.056	4,050
East	0.085	0.083	0.110	11,010
Central	0.055	0.046	0.073	10,230
West	0.082	0.067	0.047	14,325
Installed capacity (MW)				
Northeast	28.319	0.873	81.932	4,050
East	13.305	4.488	230.329	11,010
Central	6.458	3.176	122.270	10,230
West	22.790	8.651	88.249	14,325

Note: Wind and Solar indicate counties that adopted wind and solar power plants with an installed capacity over 6,000 kW, respectively. Large thermal indicates counties that have thermal power plants with an installed capacity over one million kW.

Table 7 reports the heterogeneous effects of installed capacity across regions. The first four columns present the results for CO2 emissions, while columns 5 to 8 show those for CO2 intensity. As shown in columns 1 and 4, an increase in Wind capacity significantly reduces CO2 emissions in the northeast and west regions, while an increase in Solar capacity shows a significant reduction effect only in the west (column 4). In terms of $Large\ thermal\ capacity$, a capacity increase is positively associated with CO2 emissions in Central China (column 3). One explanation for this is that in Cen-tral China, both small and large thermal power plants exhibit lower carbon emission efficiency owing to high coal intensity, high managerial inefficiency, and poor technical operating parameters of equipment (Eguchi et al. 2021; Fang et al. 2022).

Columns 5 and 8 of Table 7 similarly demonstrate that an increase in $Wind\ capacity$ in the northeast and west has a significant reduction effect on CO2 intensity. An increase in $Large\ thermal\ capacity$ does not decrease CO2 emissions, although it has a significant reduction effect on CO2 intensity in the east (column 6). Overall, an increase in $Wind\ capacity$ yields large and statistically significant estimates of -0.121 and -0.073 in columns 1 and 5, respectively. This significant impact is attributed to the high installed capacity in the northeast. Similarly, an increase in $Solar\ capacity$ yields a statistically significant estimate of -0.011 in the west (column 4), yet the effects in other regions are not significant. In summary, our findings highlight the considerable regional heterogeneity in the effects of energy choices, with the mitigation impacts of renewables largely dependent on the regional availability of energy resources. Regarding large thermal power, there is a notable environmental efficiency gap across regions. Power units in the east exhibit larger capacities, higher energy savings, and greater emission reduction capabilities, as discussed in the works of Fang et al. (2022); Xie et al. (2018). This heterogeneity leads to diverse environmental outcomes.

Table 7 Effects of installed capacity by region

	$\ln CO_2$				$\ln CO_2$ intensity			
	Northeast (1)	East (2)	Central (3)	West (4)	Northeast (5)	East (6)	Central (7)	West (8)
L.$\ln CO_2$	0.372***	0.812***	0.507*	0.994***				
	(0.126)	(0.204)	(0.262)	(0.010)				
L.$\ln CO_2$ intensity					0.374**	0.463**	0.627***	0.985***
					(0.146)	(0.196)	(0.057)	(0.011)
lnWind capacity	-0.121**	-0.005	0.174	-0.013**	-0.073*	0.010	0.058	-0.013**
	(0.059)	(0.020)	(0.189)	(0.007)	(0.043)	(0.022)	(0.169)	(0.006)
lnSolar capacity	0.136	0.040	-0.319	-0.011**	-0.064	0.016	-0.076	-0.001
	(0.089)	(0.035)	(0.269)	(0.005)	(0.116)	(0.021)	(0.087)	(0.005)
lnLarge thermal capacity	0.036	0.018	0.094*	-0.001	0.050	-0.026**	0.011	-0.002
	(0.030)	(0.021)	(0.057)	(0.004)	(0.040)	(0.013)	(0.009)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$AR(1)$ test	0.035	0.038	0.031	0.033	0.028	0.038	0.049	0.034
$AR(2)$ test	0.401	0.107	0.371	0.861	0.369	0.131	0.424	0.921
Hansen p-value	0.130	0.156	0.543	0.173	0.138	0.225	0.189	0.178
Observations	3,780	10,276	9,548	13,370	3,780	10,276	9,548	13370

Note: The constant term is included but not reported. System GMM regressions with robust standard errors are in parentheses. The unit of installed capacity is one million kW. * p <0.1, ** p <0.05, and *** p <0.01.

5. Discussion

This study investigates the carbon mitigation effects of RE adoption and thermal efficiency improvement from a multidimensional perspective. We first estimate the mitigation effects of energy adoption and find that both RE adoption and thermal efficiency improvements contribute to reduced carbon emissions. Consistent with previous research by Ahmad et al. (2021); Kazemzadeh et al. (2022); Wang et al. (2022, 2023), among other studies, our results affirm that RE plays a pivotal role in emission reduction. Furthermore, we present new empirical evidence suggesting that large thermal power adoption, representing thermal efficiency improvement in this context, has a significant role in carbon mitigation. Most existing literature has identified minimal environmental benefits from non-renewable power generation (Li et al. 2022b; Zhang et al. 2023), often overlooking the effects of thermal efficiency improvement. While some studies recognize the potential of efficient thermal power for carbon mitigation (Eguchi et al. 2021; Li et al. 2019), empirical evidence remains sparse. Our analysis, leveraging power plant data, uniquely identifies the impact of thermal efficiency improvement through the adoption of large thermal power.

Our results confirm the carbon mitigation benefits of RE and large-scale thermal power. However, it is possible that counties already equipped with these energy sources had naturally lower emissions. Further analysis, specifically focusing on the installed capacity by type of power, indicates that expansions in wind and large thermal capacity have effectively reduced carbon emissions. This finding is consistent with existing literature that highlights the mitigation effects of RE. On the other hand, additional solar capacity did not show a significant mitigation effect. Solar power's limited carbon mitigation effects could be due to several factors. Firstly, the impact of a power source is often proportional to its installed capacity, which must exceed a certain threshold to have a significant effect. Novan (2015) found that external benefits increase as renewable capacity grows, and Zhang et al. (2023) suggested that an increase in RE share significantly reduces air pollution, especially when the share exceeds 28.22%. The average installed capacity of solar (5.285 MW) is less than one-third of wind (16.502 MW), which is too small to yield any significant marginal benefits within our study period. Secondly, the relatively low average capacity factor[10] of renewables, exacerbated by high curtailment rates (15% for wind and 12.6% for solar in 2015), could impact solar power performance. Finally, accurately capturing the mitigation effect of small-scale distributed photovoltaic (PV) solar systems[11] is challenging. In our sample, an increase in solar capacity may have a more pronounced impact in regions with a high installed capacity of centralized grid-connected PV power systems, such as the northeast and west. Our findings highlight that wind power significantly outperforms large thermal power in carbon emission reduction per unit of installed capacity. Additionally, the lagging development and low installed capacity of solar power can diminish its benefits, echoing the findings of minimal mitigation impacts of RE in previous studies (Azam et al. 2021; Hasnisah et al. 2019; Zhang et al. 2021). We also investigate the heterogeneous mitigation effects of different energy choices across adoption types and regions. Our results present evidence that

10 The capacity factor is the ratio of the actual electric power generation of a power plant to its maximum generation potential (Li et al. 2019).

11 Distributed PV refers to smaller solar power generation facilities that are located close to consumers and connected to distribution systems, with access voltages below 35 kilovolts (World Resources Institute 2018).

diversifying RE sources leads to greater carbon mitigation than relying on a single source. Furthermore, we find that an increase in wind capacity led to reduced carbon emissions in the northeast and west regions, while an increase in solar capacity achieved this effect in the west. Contrasting with Zhang et al. (2023), who emphasized the role of a clean energy mix in reducing air pollution in various regions of China, our results indicate that higher installed capacities are associated with lower emissions, offering a complementary view on the benefits of scaling up RE installations.

Our study has several limitations. First, we did not consider the effects of hydropower in our analysis. Although data on hydropower plants is available from the CEC, accurately pinpointing their locations is challenging, as many are situated on rivers at county borders. Further, hydropower, as a base load energy source, has shown minimal change in installed capacity and generation over the past 20 years compared to RE. Consequently, its mitigation effects are likely limited within our study period. Second, county-level power generation data are unavailable after 2012. Given that power generation is intricately linked to carbon emissions, a more comprehensive dataset is essential to fully understand how energy choices impact carbon emissions. Lastly, our analysis did not account for inter-regional transmission networks and power dispatch. Wang et al. (2024) used a non-dynamic spatial econometric model to assess the carbon emission reduction effects of inter-regional transmission. Future research could be improved by including spatial analyses to capture these dynamics and examining how inter-regional transmission supports RE usage and emission reductions.

６． Conclusions

This study uses a county-level panel data spanning 15 years to examine the carbon mitigation impact of various energy choices. Our results suggest that improving thermal efficiency can be a potent tool for carbon mitigation, especially in the initial stages of RE development. The carbon mitigation potential of RE might be constrained during its early development phases due to a limited replacement effect. As coal remains the primary source of energy in China, promoting the clean and efficient use of coal-fired thermal power is vital for advancing green industry and reducing carbon emissions. This energy strategy is also relevant to other countries that are rich in coal yet struggling with underinvestment in domestic resources. Efficient and clean thermal power generation offers a cost-effective method for controlling carbon emissions (Rehman et al. 2021). Therefore, to achieve the most substantial reduction in carbon emissions, policy efforts should focus on balancing the enhancement of thermal power efficiency with the expansion of RE capacity.

Furthermore, our findings reveal that an increase in wind capacity significantly reduces carbon emissions, with the marginal mitigation benefits of wind capacity far exceeding those associated with increases in large thermal capacity. The rising utilization rates and installed capacity of wind and solar power, coupled with decreasing costs, position these renewables as increasingly cost-competitive options for future energy transitions (Lu et al. 2021). Therefore, energy policies that reduce curtailment rates and promote the adoption of solar power and other RE could significantly contribute to achieving carbon emission mitigation goals.

Additionally, our study highlights that carbon mitigation effects vary across regions. For example, implementing policies that fully utilize distributed solar panel capacity can optimize the carbon mitigation potential of solar power in Central and Eastern China. Our results suggest the need for regional investment priorities that consider the environmental impacts of different energy choices and account for regional environmental efficiency disparities. Development plans addressing regional imbalances should parallel structural adjustments and technological advancements in the power industry, fostering sustainable regional economic growth and mitigating carbon emissions.

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