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Climate change and efficiency losses in combined heat and power plants: Evidence from China

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ABSTRACT

Combined heat and power (CHP) plants are increasingly promoted as a key technology for the energy transition because they repurpose waste heat and improve efficiency. Yet CHP plants may be disproportionately vulnerable to climate change. Using operational data from 390 Chinese thermal power units (2019–2022), we estimate the effect of temperature on plant efficiency and separate supply-side from demand-side mechanisms. We find that an additional day above 30°C reduces monthly efficiency by 0.266 percentage points (pp) for CHP units, compared to only 0.018pp for conventional units. Roughly 70% of CHP efficiency losses stem from declining heating demand. Climate-scenario projections suggest that, in the 2050s, the average efficiency of China's thermal-power units could decline by 0.86–1.20pp, with annual revenue losses of US$6.4–8.9 billion and additional CO_2 emissions of 33–45 million tonnes. These findings highlight a paradox: while CHP plants are often promoted as efficient solutions for decarbonization, they are highly exposed to climate risks. Integrating climate considerations into CHP investment and retirement strategies is therefore critical for global energy policy.

1. Introduction

Improving efficiency in electricity and heat production is central to reducing emissions and meeting global climate goals (Oberschelp et al., 2019; Wu et al., 2023). Combined heat and power (CHP) plants are often viewed as a leading solution because they exploit economies of scope between electricity generation and useful heat production. Unlike conventional thermal power units, which release a large share of low-grade heat into the ambient environment, CHP units recover this heat and deliver it for residential district heating or industrial processes. By jointly producing electricity and useful heat from the same fuel input, CHP systems can achieve 25–30% higher total useful-energy efficiency than separate electricity and heat production (Broesicke et al., 2021; Brown and Herrera, 2021; Connolly et al., 2014; Harmsen and Crijns-Graus, 2021; Li et al., 2016). As illustrated in Fig. 1, CHP can also reduce fuel consumption and carbon emissions relative to separate thermal power generation and boiler-based heat supply (IEA, 2008). These economic and environmental advantages have supported rapid CHP deployment worldwide, with CHP's share of global thermal capacity increasing from 14% to 26% between 2005 and 2019, and from 281 GW to 600 GW in China alone between 2015 and 2022 (Cogen World Coalition, 2022; IEA, 2008, 2023; Leading Industry Research, 2023) (see Section 1 of the S.I. for development of CHP units).

However, the same heat-power coupling that makes CHP plants efficient also limits their technical flexibility. CHP units operate within a constrained feasible operating region because electricity and heat outputs cannot be adjusted independently without efficiency losses or operational penalties (Mitridati and Pinson, 2016). This creates a fundamental tradeoff. Economies of scope make CHP plants economically and environmentally attractive when useful heat demand is high, but their efficiency advantage depends on the ability to recover and deliver heat. When heat demand falls, CHP units lose part of the useful-energy output that justifies their high efficiency. This feature makes CHP plants particularly vulnerable to climate change. Higher ambient temperatures reduce thermal efficiency in all power plants through supply-side mechanisms such as reduced cooling efficiency and thermodynamic losses, but CHP units face an additional demand-side risk: warmer conditions reduce heating demand, undermining the

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heat-recovery mechanism that makes them efficient (Abdolmohammadi and Kazemi, 2013; Bartos and Chester, 2015; Henry and Pratson, 2016; Henry and Pratson, 2019; L. Liu et al., 2017; Quijano et al., 2016; Van Vliet et al., 2016; Van Vliet et al., 2012; Zou et al., 2019).

Prior studies document that higher temperatures reduce the efficiency of thermal power units by 4–19%, mainly through supply-side mechanisms such as reduced cooling water availability and lower transmission efficiency (e.g., Bartos and Chester, 2015; Henry and Pratson, 2016; Henry and Pratson, 2019; Van Vliet et al., 2016; Van Vliet et al., 2012). A second strand of research highlights demand-side effects: warmer winters reduce heating needs, while hotter summers increase cooling demand, with region- and income-specific impacts (Li et al., 2019; Miller et al., 2008; Rosenthal et al., 1995).

However, existing work does not explicitly examine CHP plants, which combine both supply and demand channels. This omission matters because CHP efficiency relies heavily on heat demand, making them more exposed to climate change than conventional plants. Our study addresses this gap by (i) quantifying CHP vulnerability using real operational data, (ii) disentangling supply and demand effects, and (iii) projecting efficiency, revenue, and emissions impacts under future climate scenarios.

We fill this gap by using a unique dataset of 390 Chinese thermal power units to estimate temperature effects on efficiency, decompose supply and demand mechanisms, and project economic and emissions consequences under various greenhouse gas (GHG) emissions scenarios.

We find that combined heat and power (CHP) units are far more sensitive to rising temperatures than conventional thermal units: a single day with average temperature above 30°C reduces CHP efficiency by 0.266 percentage points, more than ten times the loss observed in non-CHP units. This vulnerability is driven largely by heating demand, as roughly 70% of the efficiency decline in CHP plants can be attributed to reduced heating needs during warmer periods—highlighting a demand-side channel that has been largely overlooked in prior studies. Looking ahead, our projections suggest that climate change will substantially undermine the operational performance of China's thermal-power fleet, reducing average efficiency by 0.86–1.20 percentage points in the 2050s and causing annual revenue losses of US$6.4–8.9 billion and additional CO_2 emissions of 33–45 million tonnes.

In doing so, this paper makes the following contributions to the broad literature that examines the impact of climate change on power stations' efficiency.

First, by focusing specifically on combined heat and power (CHP) plants, we show that climate change has a substantially larger impact on power station efficiency than previously recognized, highlighting an overlooked vulnerability in a technology often promoted for decarbonization (Cogen World Coalition, 2022; IEA, 2008, 2023). Second, we advance the literature by separating efficiency losses into supply-side and demand-side mechanisms, demonstrating that reduced heating demand accounts for roughly 70% of the efficiency decline in CHP units. Finally, unlike studies based on simulated performance, our analysis draws on real-world operational data from 390 Chinese thermal units, enabling robust estimates and detailed heterogeneity analyses, and we extend these findings with forward-looking projections of efficiency, revenue, and emissions impacts under alternative climate scenarios.

2. Methods

2.1. Empirical approach

In examining the influence of temperature on the efficiency of power plants, the econometric approach we used is widely employed in the broad climate econometrics research literature (e.g., Hsiang, 2016; Linnerud et al., 2011; Meng and Sanders, 2019; Zhang et al., 2021). By grounding the analysis in granular and high-frequency data, this approach yields more precise estimates. We estimate the following econometric model to examine the relationship between temperature and power plants' efficiency:

$$EFFI_{it} = \beta_0 + \sum_{j=1}^{4} \theta_1^j TEMP_{it}^j + \boldsymbol{\gamma} \boldsymbol{Weather}_{it}^T + Unit_i \times year_t + Unit_i \times heatingmonth_t + \delta_t + \varepsilon_{it} \tag{1}$$

The dependent variable is $EFFI_{it}$, which represents energy efficiency (i.e., the percentage of fuel transformed into electricity and useful heat) of power plant unit i at year-month t. Changes in $EFFI_{it}$ are reported in percentage points (pp).

The main explanatory variable in this study is temperature. A straightforward way to include temperature in the regression model is by using continuous variables (linear or higher-order polynomials). However, such approaches impose a particular functional form on the relationship between temperature and efficiency. To enable more flexibility, we adopt a widely used approach in climate econometrics models where temperature is included as a series of temperature intervals $\left(TEMP_{it}^j\right)$ (Hsiang, 2016). This method allows us to estimate a non-parametric relationship between temperature and efficiency.

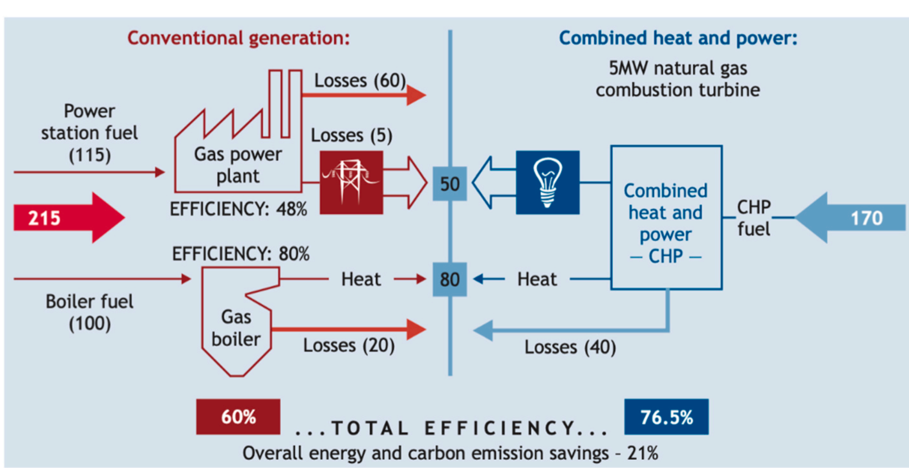

Fig. 1. The carbon reduction effect of CHP units.
Notes: In the example provided by IEA (2008), a 5 MW natural-gas combustion-turbine CHP unit supplies 50 units of electricity and 80 units of useful heat using 170 units of fuel. By contrast, producing the same outputs separately with a gas power plant and a gas boiler requires 215 units of fuel. For the specific units and operating assumptions illustrated, CHP achieves a total efficiency of 76.5%, compared with 60% for separate generation, corresponding to approximately 21% lower fuel use and associated carbon emissions. *Source: Adapted from* IEA (2008).

Specifically, daily mean temperature is divided into five mutually exclusive intervals: less than 0°C, 0°C to 10°C (the reference or excluded category), 10°C to 20°C, 20°C to 30°C, and above 30°C. The intervals are included as count variables where they represent the number of days in each year-month combination (t) that belongs to their corresponding temperature range. Thus, these variables capture the within-month distribution of daily temperature exposure rather than monthly average temperature. The interval above 30°C captures extreme upper-tail heat exposure in the context of our sample: days with a daily mean temperature above 30°C account for only 3.5% of all unit-day observations (see Section 3.5 of the S.I. for details on the temperature interval distribution).

In turn, their coefficients (θ_1^j) are interpreted as the overall marginal impact of an additional day in the specific temperature interval, relative to the excluded category, on power units' efficiency. To improve statistical efficiency and precision of estimates, we also include a host of control variables that are correlated with temperature and/or are likely to affect the outcome variable.

First, we control for a set of weather variables, denoted as $\boldsymbol{Weather_{it}}$, which is a vector of weather controls comprising average daily wind speed, average daily precipitation, and their quadratic terms: $\boldsymbol{Weather_{it}} = \left[windspeed_{it},\ windspeed_{it}^2,\ precipitation_{it},\ precipitation_{it}^2\right]$. $windspeed_{it}$ is measured in meters per second (m/s), and $precipitation_{it}$ is measured in millimeters (mm).

Second, we exploit the granularity of our dataset to include three sets of fixed effects to control for a range of time-varying and time-invariant factors. $(Unit_i \times year_t)$ denotes the thermal power unit-by-year fixed effects to control for factors that are constant for a specific power unit within a year (e.g., size, ownership, location, age, local economic conditions, and energy policies). $(Unit_i \times heatingmonth_t)$ denotes the interaction between thermal power unit and heating months, and controls for potential spatial-temporal differences in efficiency due to China's winter heating policy. δ_t denotes the month-by-year fixed effects to control for seasonal differences in efficiency caused either by nationwide government policies or broad economic and societal trends.

Lastly, ε_{it} is an idiosyncratic error term clustered at the power unit level.

A central contribution of this study is that we disaggregate the overall impact of temperature on power units' efficiency into supply and demand mechanisms. This analysis is especially critical for CHP units as a key reason for their improved efficiency is that otherwise "wasted heat" is transformed into useful energy for residential and industrial heating. By the same measure, compared to non-CHP units, they are vulnerable to additional efficiency losses during periods of high temperature.

To separately identify the supply and demand channels, we employ a mediating effect model (Rucker et al., 2011). This method has been widely used for mechanism analysis across the social sciences, public health, and energy-system research (e.g., Akan, 2023; Liu et al., 2017; Ye et al., 2024; Zhai et al., 2024). Specifically, we estimate a variant of Equation (1):

$$EFFI_{it} = \beta_0 + \sum_{j=1}^{4}\theta_2^j TEMP_{it}^j + \beta_1 HPratio_{it} + \boldsymbol{\gamma} \boldsymbol{Weather}_{it}^T + Unit_i \times year_t + Unit_i \times heatingmonth_t + \delta_t + \varepsilon_{it} \tag{2}$$

The main difference between Equations (1) and (2) is the inclusion of the ratio of heating demand to electricity supply $(HPratio_{it})$ as a mechanism variable. Intuitively, heating demand is positively correlated with CHP units' efficiency since more waste heat is then converted into useful energy. As such, this variable directly accounts for the portion of efficiency changes caused by variations in heating demand.

After controlling for the heat-demand mechanism, the coefficients for temperature intervals in Equation (2) are now interpreted as the supply-led efficiency loss. On the other hand, the difference in temperature coefficients between Equations (1) and (2) $\left(\theta_1^j - \theta_2^j\right)$ represents the demand-induced efficiency loss (see Section 2 of the S.I. for the mathematical basis for distinguishing supply-side from demand-side mechanisms and an explanation of the mediating effect model).

The interpretation of these mechanisms may depend on the operational mode of the CHP system. The mechanism analysis in this study focuses on electricity-led operation, under which temperature-induced changes in useful-heat utilization constitute an important demand-related channel affecting total useful-energy efficiency. This focus is supported by an auxiliary analysis showing that, among the CHP units in our sample, fuel consumption responds much more strongly to electricity supply than to useful heat supply. The results, reported in Section 2.4 of the S.I., are consistent with predominantly electricity-led operation in our study setting. In heat-led systems, by contrast, changes in heating requirements may also alter useful heat supply, cogenerated electricity output, fuel input, and the operating point of the CHP unit. We further discuss the application of our framework to heat-led CHP systems and provide corresponding empirical specifications in Section 2.5 of the S.I.

2.2. Projected impacts of temperature changes on power plants' operations

We can further utilize our regression findings to project how climate change will affect operations of power plants in China. The following projections are made on a *ceteris paribus* basis, holding all other aspects of the energy system fixed except for temperature. Specifically, we hold dispatch patterns, fuel use, electricity and heat prices, installed capacity, and the generation mix fixed at their observed or baseline levels. This projection exercise is therefore designed to quantify the direct operational exposure of thermal power units to climate-induced temperature changes, based on the estimated temperature-efficiency relationship. It should not be interpreted as a market-equilibrium forecast. In particular, the projections do not account for potential adjustments in electricity or heat prices, changes in generation dispatch, substitution toward non-thermal generation, investment responses, or policy adaptation that may occur as the energy system responds to climate change.

We begin this exercise by first obtaining daily average temperature projections averaged across six global climate models (CanESM5, FGOALS-g3, GFDL-CM4, IPSL-CM6A-LR, MPI-ESM1-2-HR and MRI-ESM2-0) of the CMIP6 (The Coupled Model Intercomparison Project Phase 6) (see Section 3.6 of the S.I. for details).

Temperature is projected according to two emissions scenarios – Shared Socioeconomic Pathway SSP2-4.5, and SSP5-8.5 (see Section 3.6 of the S.I. for detailed description of SSP scenarios). The former is typically used to represent middle-of-the-road decrease in greenhouse gas emissions whereas the latter is used for illustrating a more pessimistic business-as-usual future. As the climate models compute projections in grids, we assign temperature from the nearest grid to each power unit by using their coordinates. For each power unit, we then compute their average daily temperature from 2020 to 2059 for the two emission scenarios. In this manner, each thermal power unit has 960 months of projected temperature intervals (4 decades*10 years*12 months*two emissions scenarios). After that, we compute the average monthly temperature interval on a decadal basis for each thermal power unit in different scenarios. Finally, we compute the change in temperature intervals by subtracting the baseline temperature-bin counts from the projected temperature-bin counts (defined as the average from 2001 to 2010 as the reference period). In all, this temperature projection exercise yields the change in temperature interval *j* for each power unit *i* in year-month combination from 2020 to 2059 $\left(\Delta TEMP_{it}^j\right)$.

The first outcome we examine is projected change in efficiency, which we compute using the following equation:

$$\Delta EFFI_{it} = \sum_{j=1}^{4} \theta_1^j \times \Delta TEMP_{it}^j + \sum_{k=1}^{K} \sum_{j=1}^{4} \theta_{1,k}^j \times \Delta TEMP_{it}^j \times Characteristics_{it}^k \tag{3}$$

The coefficients for temperature interval j $\left(\theta_1^j\right)$ are obtained from Column (2) (for non-CHP units) and (3) (for CHP units) of Table 1 as they represent the baseline impacts of temperature change on thermal power units' efficiency. However, results in Fig. 4 reveal highly heterogeneous relationships between temperature and efficiency over several dimensions (scale, age, and location). To arrive at a more tailored projection for each thermal power unit, we assign additional temperature coefficients based on the scale, age, and location of power units $\left(Characteristics_{it}^k\right)$.

Second, we can convert "change in thermal units' efficiency" into "change in energy production" to examine how energy production is affected for a constant level of fuel consumption (where we use 2021 usage level) ($Fuel_{i0}$):

$$\Delta EnergyProduction_{it}(GJ) = Fuel_{i0}(GJ) \times \Delta EFFI_{it} \tag{4}$$

Third, as economic viability is a key consideration behind investments in energy infrastructure, we consider how "change in energy production" will affect projected revenue of power plants in China using the following equation:

$$\begin{aligned} \Delta Revenue_{it}(US\$) &= \Delta ElectricityRevenue_{it} + \Delta HeatingRevenue_{it} \\ &= Fuel_{i0} \times \Delta EFFI_{it\_supply} \times \frac{1}{3.6} \times Electricityprice_0 + Fuel_{i0} \\ &\quad \times \Delta EFFI_{it\_demand} \times Heatingprice_0 \end{aligned} \tag{5}$$

To compute changes to revenue, we need to first disaggregate changes to energy production into electricity and heat production. To do so, we rely on results from Table 1, Column (3) and (4) where we decompose temperature-induced efficiency changes into demand (i.e., heat) and supply (i.e., electricity) channels. As electricity and heat are priced differently in China, we obtain average 2021-level unit prices for electricity and heating from across China (Beijing National Development and Reform Commission, 2019; National Energy Administration, 2019). In Equation (5), the value 3.6 is the unit conversion factor between gigajoules and megawatt-hours, as 1 MWh = 3.6 GJ. Since $Fuel_{i0} \times \Delta EFFI_{it\_supply}$ gives the change in electricity output in GJ, we divide this term by 3.6 to convert it into MWh before multiplying it by the electricity price, which is measured in US$/MWh. Heating output is kept in GJ because the heating price is converted to US$/GJ.

Finally, we calculate the additional carbon emissions resulting from efficiency losses. The efficiency losses in the demand mechanism stem from a reduction in heating demand, eliminating the need for additional fuel combustion to compensate; whereas efficiency losses in the supply mechanism lead to a decrease in electricity supply, necessitating the burning of more fuel to make up for the shortfall. We use the following equation to calculate the carbon emissions due to efficiency losses:

$$\begin{aligned} \Delta CarbonEmission_{it}(tCO_2) &= \Delta ElectricityLoss_{it} \times CoalperElec \\ &\quad \times CarbonperCoal = Fuel_{i0} \\ &\quad \times \left(-\Delta EFFI_{it\_supply}\right) \times \frac{1}{3.6} \times \times CoalperElec \\ &\quad \times CarbonperCoal \end{aligned} \tag{6}$$

Where we multiply the reduction in electricity supply due to efficiency losses by the coal consumption for electricity generation and the carbon emissions per unit of coal. Given that our dataset provides the electricity generation, coal consumption, and carbon emissions for each thermal power unit, we can directly calculate the average coal consumption for electricity generation and the average carbon emissions per unit of coal.

2.3. Dataset

The dataset used in this study is constructed using two sources.

First, we partner with one of China's top five power generation companies to obtain monthly-level operational information for thermal power units located across the country from January 2019 to November 2022. Our study primarily focuses on large-scale power plants, rather than the small-scale CHP systems that have gained popularity in recent years. There are 390 thermal power units in our dataset, with CHP units accounting for 190 units. The available information includes location, fuel, monthly electricity production, monthly heating demand, monthly fuel usage, installed capacity, and year of commissioning (see Section 3 of the S.I. for details on dataset).

Power units' efficiency ($EFFI_{it}$) is constructed as follows:

$$EFFI_{it} = \frac{ES_{it}(\mathrm{MWh}) \times 3.6(\mathrm{GJ/MWh}) + HS_{it}(\mathrm{GJ})}{Fuel_{it}(\mathrm{GJ})} \tag{7}$$

ES_{it} is the total electricity supplied by thermal power unit i at year-month t. As CHP units also supply heat, heating demand is included as part of the useful energy produced by the power unit (HS_{it}). For non-CHP units, since heat is discarded into the ambient environment, HS_{it} reduces to zero for them. Lastly, we convert each fuel type used into their energy content to arrive at $Fuel_{it}$ – the total amount of fuel used in each month measured in gigajoules.

Equation (7) measures total useful-energy efficiency by including both electricity and useful heat in the numerator after expressing them in common energy units. It therefore does not require an assumption as to whether electricity or heat is the primary output of CHP operation. The same definition is applicable to electricity-led, heat-led, and jointly dispatched CHP systems.

The mechanism variable, heat-to-power ratio, is constructed similarly:

$$HPratio_{it} = \frac{HS_{it}(\mathrm{GJ})}{ES_{it}(\mathrm{MWh}) \times 3.6(\mathrm{GJ/MWh})} \tag{8}$$

Table 1
Impact of temperature on efficiency and fuel consumption of thermal power units.

	All units	Non-CHP units	CHP units		
Dependent variable	$EFFI_{it}$	$EFFI_{it}$	$EFFI_{it}$	$EFFI_{it}$	ln $Fuel_{it}$
	(1)	(2)	(3)	(4)	(5)
$\leq 0^\circ$C	0.121***	−0.000	0.207***	−0.003	0.005**
	(0.015)	(0.006)	(0.024)	(0.012)	(0.002)
10°C to 20°C	−0.101***	−0.001	−0.198***	−0.061***	−0.002
	(0.017)	(0.004)	(0.028)	(0.009)	(0.003)
20°C to 30°C	−0.113***	−0.012**	−0.201***	−0.068***	0.004
	(0.018)	(0.006)	(0.032)	(0.012)	(0.004)
> 30°C	−0.147***	−0.018*	−0.266***	−0.078***	0.016***
	(0.024)	(0.010)	(0.042)	(0.016)	(0.006)
$HPratio_{it}$				0.518***	
				(0.011)	
Weather variables	✓	✓	✓	✓	✓
Unit-by-year FE	✓	✓	✓	✓	✓
Unit-by-heating month FE	✓	✓	✓	✓	✓
Year-by-month FE	✓	✓	✓	✓	✓
Observations	14,827	7271	7556	7556	7556
R-squared	0.884	0.870	0.871	0.961	0.494

Notes: The reference temperature group is 0-10°C. Weather controls include precipitation and wind speed, together with their quadratic terms. Standard errors clustered at the thermal-unit level are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

$HPratio_{it}$ in Equation (8) measures the proportion of heat energy demanded to electricity supplied. For CHP units, a large heat-to-power ratio indicates that efficiency is high as more residual heat is converted into heating needs. On the other hand, $HPratio_{it}$ is, by definition, zero for non-CHP units since these thermal units do not supply direct heat.

To mitigate the effects of outliers, we clean the dataset by removing 2599 observations with zero electricity supply, and winsorizing all energy-related variables ($EFFI_{it}$,$HPratio_{it}$) at the 1st and 99th percentiles. In all, the final sample contains monthly data from 390 thermal power units spanning from January 2019 to November 2022, totaling 14,827 observations.

The second source of information is weather data obtained from the Global Surface Summary of the Day, which is provided by the National Oceanic and Atmospheric Administration. The weather variables include air temperature, precipitation, and wind speed. We follow conventional practices in the literature by assigning weather information from the nearest station to each thermal power unit (Meng and Sanders, 2019; Zhang et al., 2021). See Section 3.4 of the S.I. for descriptive statistics.

3. Results

3.1. Efficiency trends

Panels (a) and (b) of Fig. 2 illustrate the average efficiency of CHP units over time and by geographical location. From the boxplots in panel (a), we note that average efficiency of CHP units in both the Northern and Southern parts of the country is similar, at approximately 46%. However, thermal units in the former exhibit a much broader range of efficiency, reaching up to 75% at the higher end, compared to 60% for the South. Panel (b) reveals the source of the discrepancy between CHP units in these two regions. We identify a U-shaped pattern in the efficiency of Northern region CHP units throughout the year. Specifically, efficiency peaks during the winter months from November to March (around 56%) before gradually declining to its lowest during the summer (around 38%). Conversely, the efficiency of Southern region CHP units remains stable year-round at about 46%. A likely explanation for the broader efficiency variance in Northern CHP units is their role in supplying residential heating. Thus, efficiency significantly increases during colder months due to higher demand compared to warmer periods. In contrast, the Southern region of China experiences milder winters, and its CHP units are designed solely to provide heat to industrial customers, whose demand does not fluctuate with ambient temperatures (National Development and Reform Commission, 2016).

For comparison, panels (c) and (d) of Fig. 2 present analogous graphs for non-CHP units. Their average efficiency is considerably lower, at around 40%, for both the North and South. When analyzed monthly, a slight U-shaped pattern emerges in the Northern region. However, the variation is less pronounced, with average efficiency during the winter at about 40% compared to 38% in the summer. Similar to their CHP counterparts, non-CHP units in the South demonstrate stable efficiency throughout the year. The overall consistency of non-CHP units nationwide likely reflects their exclusive role in electricity provision. Although existing research has documented the impact of climate change on the operational efficiency of non-CHP units, our preliminary analysis suggests that this effect might be more pronounced in CHP units due to the added influence of fluctuations in heating demand.

3.2. Baseline results

Table 1 shows the results of estimating Equation (1).

First, findings from using all 390 thermal power units show that, relative to the reference temperature interval of 0-10°C, efficiency increases by 0.121 percentage points (pp) when temperature is below freezing (Table 1, Column (1)). However, power plants' efficiency gradually decreases from 10°C onward, and we further detect clear nonlinear impacts of temperature. On days when average temperature is between 10 and 20°C, efficiency decreases by 0.101pp. The negative impact of temperature is further exacerbated on warm days, as efficiency loss increases to 0.147pp for every additional day when the average temperature is above 30°C. In all, this first set of results not only confirms existing findings in the literature that temperature is negatively

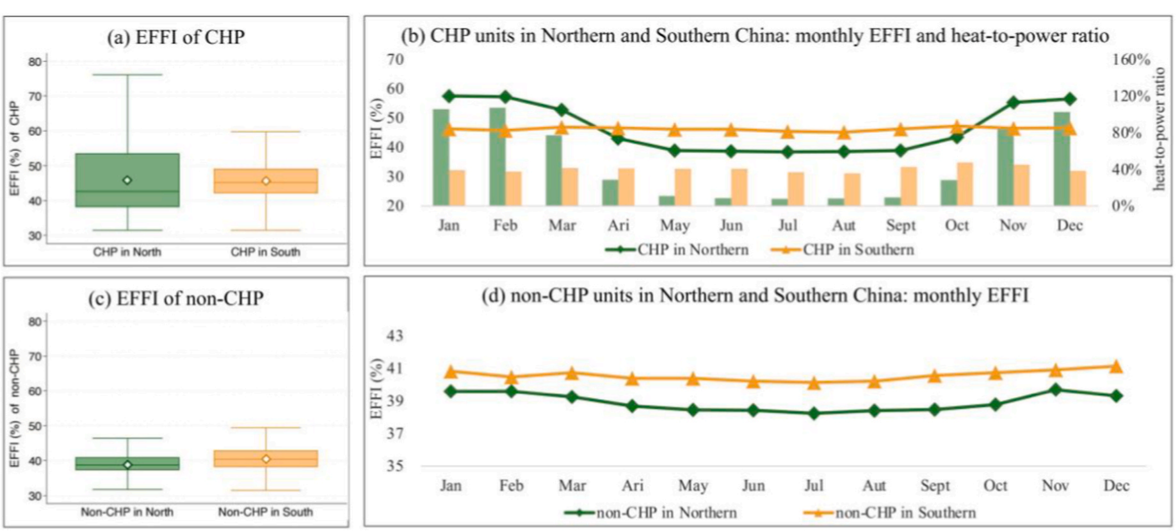

Fig. 2. Efficiency (EFFI) of CHP units and non-CHP units by region.

Notes: Panels (a) and (c) employ box plots to illustrate the efficiency distribution of different types of unit samples across various regions. The line charts in Panels (b) and (d) depict the monthly variation trends in the average efficiency of CHP unit samples and non-CHP unit samples. The bar chart in Panel (b) represents the monthly variation trend of the average heat-to-power ratio of CHP unit samples. According to National Development and Reform Commission (2017), the Northern region consists of the following 15 provinces: Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Henan, Shandong, Shaanxi, Gansu, Ningxia, Xinjiang, and Qinghai. The Southern region includes the following 16 provinces: Jiangsu, Zhejiang, Shanghai, Fujian, Guangdong, Guangxi, Hubei, Hunan, Anhui, Jiangxi, Sichuan, Yunnan, Chongqing, Guizhou, Hainan, and Tibet. Each boxplot in panels (a) and (c) is constructed using the following statistics: diamond (representing the average); central line (median); upper boundary of the box (75th percentile); lower boundary of the box (25th percentile); upper tail (furthest data within 1.5 times the interquartile range above the 75th percentile); lower tail (furthest data within 1.5 times the interquartile range below the 25th percentile).

correlated with power plants' efficiencies, but also uncovers a nonlinear relationship that could be important in projecting future climate impacts.

Second, the central thesis of this study is that operations of CHP units are more exposed to temperature since both supply and demand are affected. As such, we re-estimate Equation (1) separately on non-CHP and CHP units. The results collected in Column (2) and (3) of Table 1 confirm our hypothesis as we see that efficiency of CHP units is much more sensitive to temperature compared to their non-CHP counterparts. On days with below-freezing temperatures, CHP efficiency increases by approximately 0.207pp whereas there is no change for non-CHP units. On the other hand, high temperature also has an outsized detrimental impact on CHP units as efficiency decreases by 0.266pp for days above 30°C whereas the impact on non-CHP units is much smaller at 0.018pp.

Third, a key innovation of this study is that we can decompose efficiency loss of CHP units into supply and demand mechanisms by exploiting the variation in demand for heat. Column (4) of Table 1 shows the outcomes of estimating Equation (2) using CHP units. After controlling for demand mechanisms by using heat-to-power ratio, the coefficients for temperature bins are now interpreted as supply mechanisms. Similarly, the demand channels are measured as the difference in temperature coefficients between Column (3) and (4). For easier interpretation of the respective efficiency loss via the two mechanisms, we illustrate their corresponding coefficients in Fig. 3. We first observe that the increase in efficiency of CHP units at below freezing (0.207pp) is entirely attributed to increased heating demand. This outcome is not surprising as a key argument for the efficiency gains of CHP units is that they can meet heating needs by utilizing "waste heat". The reverse is also true when temperature increases. In the band of 20-30°C, the decline in heating demand accounts for around 66% of the total decrease in efficiency because heat demand is lower on such days than on days in the 0–10°C reference interval. By the same token, in the highest temperature bin of above 30°C, this efficiency loss incurred by fall in heating demand is around 70%. In all, we can see that the previously unconsidered demand channels are non-trivial as they account for around 70% of temperature-induced efficiency loss.

Fourth, a plausible counter-argument to our current findings is that climate change may lead to overall reduced fuel usage, and would thus offset the efficiency loss (Rode et al., 2021). We investigate this possibility by using total fuel usage as the dependent variable. The results

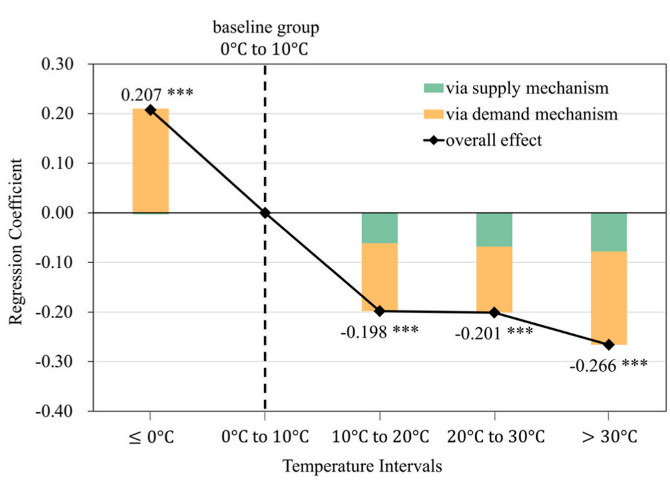

Fig. 3. Impact of temperature on efficiency of CHP units.
Notes: The black line illustrates the overall impact of temperature on the efficiency of CHP units. The reference temperature group is 0-10°C interval. ***, ** and * denote statistical significance at 1%, 5%, and 10% levels, respectively. The cyan bar chart displays the effect via supply mechanism; the orange bar chart displays the effect via demand mechanism. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

collected in Column (5) of Table 1 show that fuel usage among CHP units increases on hot days (i.e., above 30°C) by around three times compared to days below freezing. One reason for this result is because Chinese households typically rely on private air-conditioners to cope with hot days, and rely on centralized heating for cold days. In all, the results presented here suggest that CHP units not only incur efficiency losses when temperature increases, but they also use more energy on warm days. However, to gain a complete overview of the implications of climate change on efficiencies and fuel usage, Section 3.4 shows the projected impacts under various emissions scenarios.

We also conduct robustness checks by relaxing several model specifications and assumptions in Section 4.2 of the S.I., namely i) permutations of fixed-effects, ii) clustering of standard errors, iii) changing of reference temperature interval, and iv) size of temperature intervals. The results from this set of checks are consistent with our baseline findings.

3.3. Heterogeneity analyses

The results presented so far confirm that the enhanced efficiency of CHP units is a double-edged sword. While they are more efficient than conventional power units at low temperature, they also lose efficiency at a faster rate when ambient temperature increases.

In this sub-section, we undertake further analyses to uncover what other factors can moderate the relationship between temperature and efficiency for CHP units. To allow for such heterogeneous temperature responses, we augment the baseline specification by interacting the temperature-bin variables with the corresponding unit and regional characteristics:

$$EFFI_{it} = \beta_0 + \sum_{j=1}^{4} \theta_1^j TEMP_{it}^j + \sum_{k=1}^{K} \sum_{j=1}^{4} \theta_{1,k}^j TEMP_{it}^j \times Characteristics_{it}^k$$
$$+ \gamma \boldsymbol{Weather}_{it}^T + Unit_i \times year_t + Unit_i \times heatingmonth_t + \delta_t + \varepsilon_{it} \quad (9)$$

Where $Characteristics_{it}^k$ denotes the k-th unit or regional characteristic, including unit scale, unit age, and geographic location. The three dimensions capture different sources of heterogeneity in the temperature–efficiency relationship. Unit scale is associated with substantial differences in generation technology and operating conditions between small- and large-scale CHP units. Unit age captures differences in equipment vintage and potential technological depreciation. Geographic location captures differences in climatic conditions and in the primary heating roles of CHP units.

We begin by separating CHP units according to their scale. Units with a capacity above 600 MW are categorized as large-scale units, while those with a capacity of 600 MW or below are categorized as small-scale units. Panel (a) of Fig. 4 shows that large-scale CHP units generally exhibit more favorable efficiency outcomes than small-scale units. The disparity is most apparent at above-freezing temperatures, at which the difference is approximately 0.1pp.

Second, we group CHP units into "young" and "old" groups, with units less than 20 years old placed in the former and those aged 20 years or above placed in the latter. As shown in panel (b) of Fig. 4, the estimated differences between young and old units are relatively small, at approximately 0.05pp or less, and are mostly not statistically significant at the 10% level. We therefore find limited evidence that the temperature–efficiency relationship differs systematically between young and old CHP units.

Third, using the *Huai* River as a demarcation line, we categorize CHP units as being located in northern or southern China (Chen et al., 2013). Panel (c) of Fig. 4 shows substantial regional disparities across temperature intervals. At below-freezing temperatures, northern CHP units are approximately 0.12pp more efficient than their southern counterparts. However, the pattern is reversed at above-freezing temperatures, when southern CHP units are at least 0.4pp more efficient. As discussed

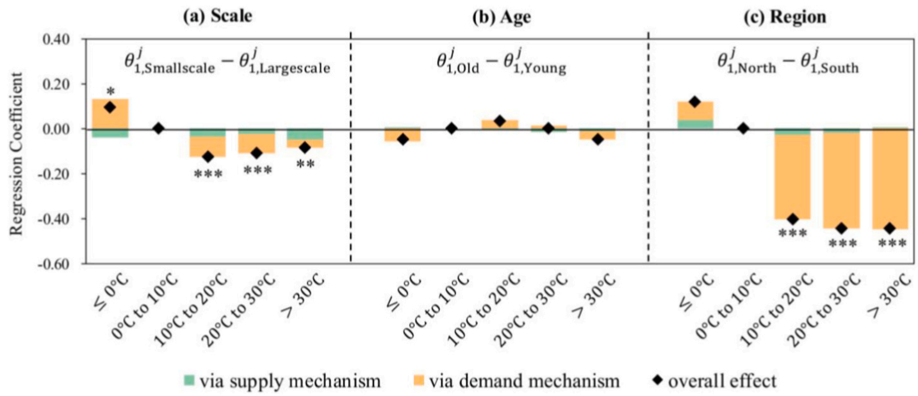

Fig. 4. Heterogeneous relationship between temperature and efficiency.
Notes: The black diamonds display the difference of impact between CHP unit samples with different characteristics. Green bars denote effects via supply mechanism, and orange bars are for demand mechanism. The reference temperature group is 0-10°C. ***, ** and * denote statistical significance at 1%, 5%, and 10% levels, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

in Section 3.1, one plausible explanation for this regional heterogeneity is the difference in the primary heating roles of CHP units. Northern CHP units are more closely linked to temperature-sensitive residential heating demand under the centralized-heating system. By contrast, southern CHP units tend to be more oriented toward industrial heat supply, which is generally less sensitive to short-term changes in ambient temperature. As a result, southern CHP units may be better able to maintain their efficiency levels on warmer days.

Overall, the results reveal more pronounced heterogeneity by unit scale and geographic location, but relatively limited heterogeneity by unit age. These patterns have practical implications for the design of climate-adaptation measures for CHP units. In particular, unit age alone may not be sufficient for identifying temperature-sensitive CHP units, whereas differences in unit technology, generating capacity, and regional heating roles should be considered when designing operational adjustments and efficiency-enhancing investments.

3.4. *Projected impacts on efficiency, revenue, and GHG emissions*

The results presented so far confirm that operational efficiencies of CHP units are adversely impacted by increasing temperature. However, to provide a clearer picture of the implications of climate change, we need to translate our findings of marginal impacts to total projected impact.

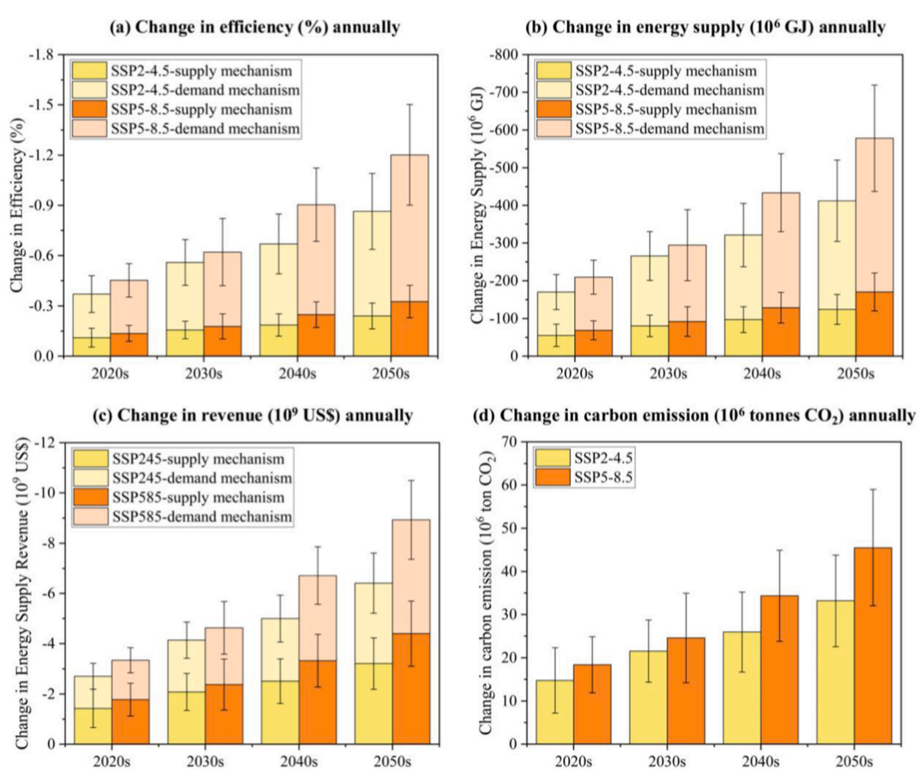

Fig. 5. Projected impacts of climate change on China's thermal power units at the national level.
Notes: Panels (a)-(d) illustrate the projected impacts of climate change on China's thermal power units at the national level in the 2020s, 2030s, 2040s, and 2050s under the SSP2-4.5 scenario and the SSP5-8.5 scenario. Panel (a) illustrates the annual changes in efficiency. Panel (b) illustrates the annual changes in energy supply. Panel (c) illustrates the annual changes in revenue. Panel (d) illustrates the annual changes in carbon emissions due to efficiency losses. The error bars represent the 95% confidence interval of the projected changes for each decade.

In this sub-section, we combine our estimates with projected temperature through 2050 to examine, under a *ceteris paribus* scenario, how climate change will affect near- and mid-term efficiency, energy supply, revenue, and carbon emissions of thermal power units in China under two greenhouse gas (GHG) emissions scenarios: SSP2-4.5 and SSP5-8.5 (see Section 4.4 of the S.I. for projected impacts on total fuel usage). To scale projected changes in energy production and revenue to the whole of China, we aggregate all power plants, and multiply the total by 7.14 since the company from which this dataset is obtained accounts for around 14.01% of all installed capacity in the country. These projections should be interpreted as direct partial-equilibrium estimates of climate exposure, rather than forecasts of the future market equilibrium. They do not incorporate price feedbacks, changes in dispatch, substitution toward renewables or other non-thermal sources, changes in electricity or heat demand, or future policy and investment responses. As such, the national revenue and emissions estimates are best viewed as benchmarks for the magnitude of direct efficiency-related risks under fixed operating conditions.

Panels (a)-(d) in Fig. 5 show changes in efficiency, annual energy supply, annual revenue, and annual carbon emissions owing to efficiency losses of Chinese thermal power units due to climate change in the 2020s, 2030s, 2040s, and 2050s under SSP2-4.5 and SSP5-8.5 scenarios. From the 2020s to the 2050s, efficiency reduction in thermal units increases from 0.37 to 0.45pp to 0.86-1.20pp, reflecting accelerated increase in global temperature. Similarly, the reduction in annual energy production also amplifies over time from 170 to 210 million GJ (in the 2020s) to 412-578 million GJ (in the 2050s). Importantly, annual revenue of all power plants in China is projected to decline by US$2.7-3.3 billion (in the 2020s) (or around 0.9% to 1.2% of total revenue), and US$6.4-8.9 billion (in the 2050s) (or around 2.2% to 3.0% of total revenue). Due to climate-induced efficiency losses, carbon emissions are projected to increase from 15 to 18 million tonnes of CO_2 in the 2020s

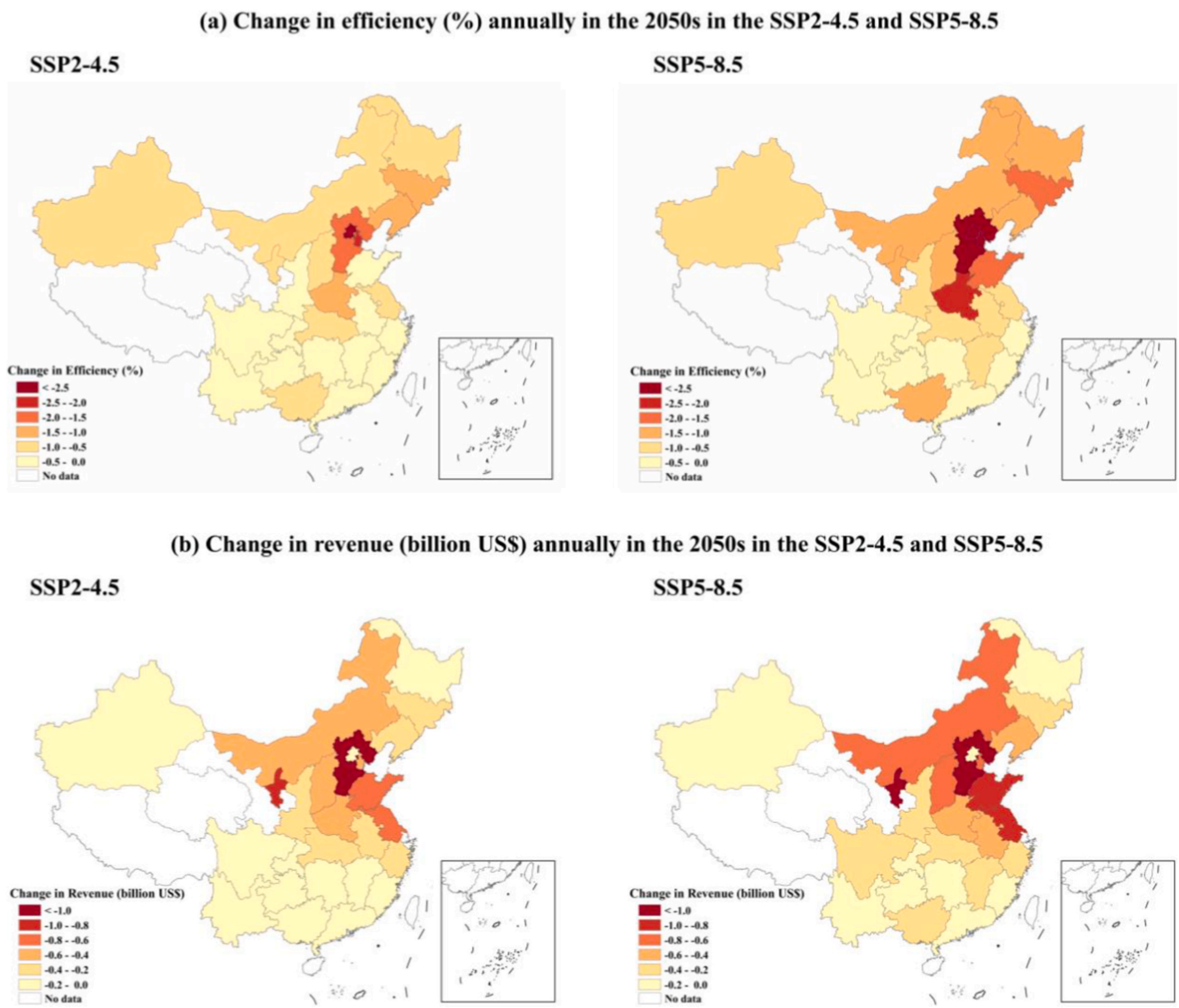

Fig. 6. Projected impacts of climate change on China's thermal-power units at the provincial level.
Notes: Panel (a) illustrates the impact of climate change on the efficiency of thermal power units in China at the province level in the 2050s under the SSP2-4.5 scenario and the SSP5-8.5 scenario. Panel (b) illustrates the impact of climate change on the revenue of thermal power units in China at the province level in the 2050s under the SSP2-4.5 scenario and the SSP5-8.5 scenario. All provincial boundaries are drawn from the Ministry of Civil Affairs of the People's Republic of China (http://xzqh.mca.gov.cn/map; map content approval number: GS(2023)2767).

(or around 0.13%-0.16% of China's total carbon emissions in 2022) to 33-45 million tonnes of CO_2 in the 2050s (or around 0.29%-0.40% of China's total carbon emissions in 2022).

As climate change is projected to affect China in varied ways across locations, we can also examine if there are any heterogeneous impacts across different parts of the country. Panel (a) in Fig. 6 shows that the provinces from Northern region, e.g., Beijing, Tianjin, Hebei, Henan, and Jilin, incur the greatest decrease in thermal units' efficiency where efficiency decreases by over 1.5pp under the SSP5-8.5 scenario. By contrast, the average decrease in efficiency for thermal power units is only 0.5pp in Southern provinces. Not surprisingly, the reduction in revenue for thermal power units is also higher in Northern regions. However, these are led by power plants located in the provinces of Hebei, Ningxia, Jiangsu, Shandong, and Inner Mongolia as they have a higher proportion of small-scale thermal power units.

Finally, we compare the efficiency losses across unit types; detailed results are provided in Section 4.3 of the S.I. By the 2050s under SSP5-8.5, the mean efficiency loss for units in the Northern region reaches 1.57pp, 2.56-fold that observed in the Southern region. Under the same scenario and time horizon, CHP units suffer an average efficiency reduction of 2.08pp, 6.74 times the decline projected for non-CHP units. These impacts are also substantial in the context of power stations' efficiency. Due to the mature technology, large leaps in efficiency are rare, and changes of 0.5 to 2 percentage points are considered substantial (IEA, 2012; MIT, 2007). Similarly, a report issued by the International Energy Agency showed that a single percentage point improvement can avoid millions of tonnes in CO_2 emissions over the plant's life (IEA, 2014).

4. Discussion

Due to concerns over climate change, the world is rapidly transitioning toward cleaner and more efficient forms of energy and energy-delivery systems. Toward this end, CHP units are a popular strategy for energy transition as they can readily increase energy efficiency by simply repurposing otherwise "wasted heat" (Topal et al., 2022; Wang et al., 2023; Zhou et al., 2021). Due to their perceived simplicity and environmental advantages, governments worldwide are ramping up construction of CHP units in lieu of conventional power units. However, to the extent that CHP units are more efficient, they are also possibly more vulnerable to climate change for two reasons. First, thermal power plants operate less efficiently at high ambient temperatures because of reduced cooling efficiency and thermodynamic losses. Evidence from multiple regions supports this concern. Studies of the United States show that extreme heat, drought, warmer surface waters, and environmental regulations can reduce thermoelectric generating capacity and plant output (Bartos and Chester, 2015; Henry and Pratson, 2019; L. Liu et al., 2017). At the global scale, both hydropower and thermoelectric plants are found to be vulnerable to climate-induced changes in water resources (Van Vliet et al., 2016). Related evidence from France further shows that climate-induced water scarcity can alter electricity system planning by reducing hydro and nuclear production (Megy, 2025). Second, on top of supply-led reasons, efficiencies of CHP units are potentially susceptible to demand-led reasons as heating needs reduce when temperature rises.

While prior literature highlights the supply-side vulnerability of power systems to climate and water constraints, less is known about how rising temperatures affect CHP units through both supply-side efficiency losses and demand-side reductions in heat use, particularly in rapidly expanding thermal power systems such as China's. Here, we contribute to the limited literature on operations of CHP units by pairing a novel operations-derived dataset from China with rigorous econometric approaches to empirically examine the relationship between temperature and efficiency of CHP units.

We first find the efficiency of an average thermal power unit (both CHP and non-CHP) varies non-linearly across temperature intervals. Relative to a day in the 0-10°C reference interval, efficiency increases by 0.121 percentage points (pp) when temperature is below freezing, while it decreases by 0.147pp at the highest temperature interval of above 30°C. However, these average effects are masked by wide variation between CHP and non-CHP units. Compared to the latter, CHP units enjoy an efficiency dividend on cold days (i.e., below freezing) as efficiency improves by 0.207pp. This gain dissipates rapidly on hot days as CHP units incur an efficiency loss of 0.266pp on days above 30°C, more than 10 times larger than non-CHP units. Moreover, these efficiency losses are even larger when viewed from China's context as we find that warmer winters do not reduce fuel usage (Rode et al., 2021).

Importantly, we exploit the granularity of our dataset to disaggregate the impact of temperature on efficiency into supply and demand mechanisms for CHP units. We find that variation in heating demand drives the majority of the estimated efficiency changes. At below freezing, almost all of the gains are due to increases in heating needs. Conversely, drops in heating demand at higher temperatures account for approximately 70% of the estimated efficiency loss.

Finally, we combine the estimation results with projected temperature to project changes in the efficiency and revenue of both CHP and non-CHP units under two emissions scenarios (SSP2-4.5 and SSP5-8.5). We find that by the 2050s, climate warming will reduce the efficiency of China's thermal power units by 0.86pp to 1.20pp, causing thermal power companies to incur economic losses of US$6.4-8.9 billion annually.

Our findings reveal a paradox: CHP plants deliver efficiency gains under cold conditions but are disproportionately vulnerable to climate warming, in part because warmer temperatures reduce heat demand. This has four major policy implications.

First, projected climate conditions and future heat demand should be explicitly incorporated into CHP deployment and investment decisions. Evaluations based mainly on historical temperatures and heat-load profiles may overestimate the future efficiency, utilization, and economic returns of CHP projects, especially in regions expected to experience substantial warming. Planners and investors should therefore conduct location-specific assessments that combine climate projections with expected changes in heat and electricity demand, accounting for low-heat-demand operation and the risk of underutilized or stranded assets. This is particularly important because CHP units cost approximately 35% more to construct than conventional power units, and the economic rationale for this additional investment depends on realizing efficiency gains (Kalam et al., 2012). CHP may remain valuable in cold regions with stable and concentrated heat demand, whereas proposed projects in warmer regions should be carefully compared with alternatives such as renewable electricity, heat pumps, industrial waste-heat recovery, and thermal storage.

Second, adaptation and retirement policies for the existing CHP fleet should reflect unit characteristics and local heating conditions. In the short run, more accurate heat-demand forecasting and joint scheduling of heat and electricity production may help align CHP output with actual demand, thereby reducing excess heat production and inefficient low-load operation during warmer winter periods. In the medium term, thermal storage, heat-network interconnection, and integration with alternative heat sources can increase operational flexibility as heat demand declines. Our heterogeneity results show that large-scale CHP units generally exhibit more favorable efficiency outcomes than small-scale units, whereas differences between young and old units are limited and mostly statistically insignificant. Unit age alone should therefore not determine retrofit or retirement priorities. Policymakers should also consider unit scale, projected efficiency losses, operating flexibility, local heat demand, and the availability of replacement heat sources. Small-scale units with substantial efficiency losses and limited adaptation potential may warrant earlier retirement, while viable units could be retained or retrofitted to preserve reliable heating services.

Third, regional heterogeneity in efficiency outcomes indicates that a one-size-fits-all approach to CHP adaptation is unlikely to be effective.

CHP planning and operation should instead reflect regional climate conditions and the composition of heat demand. In regions dominated by temperature-sensitive residential heating, such as northern China, adaptation should focus on improving heat-demand forecasting, increasing operational flexibility, integrating thermal storage and multiple heat sources, and adjusting capacity to declining winter heat loads. By contrast, our smaller estimated effects for southern CHP units suggest that CHP may retain greater value where it serves substantial and relatively stable industrial heat demand. In such regions, CHP planning should prioritize a close and durable match between heat output and industrial demand. These differentiated strategies may also inform CHP policies in other countries with similar heating structures.

Fourth, the role of CHP in broader decarbonization pathways should be evaluated dynamically rather than treating it as either a universally desirable transition technology or an asset that should be uniformly retired. CHP may retain a transitional role where stable heat demand allows combined production to deliver meaningful efficiency and reliability benefits. However, new long-lived fossil-fuel CHP capacity should be considered cautiously where heat demand is expected to decline or where feasible low-carbon heating options are available. Besides, any phase-down of existing CHP should be coordinated with the development of replacement heat capacity and, where needed, targeted support to protect heating affordability and reliability, particularly for low-income households.

In sum, climate projections should inform where new CHP capacity is built, which existing units are adapted or retired, and how regional heating systems are planned. Aligning these decisions with long-term decarbonization strategies can help preserve CHP's efficiency benefits where heat demand remains stable while avoiding inefficient investment where those benefits are likely to decline.

CRediT authorship contribution statement

Qiyong Xiao: Formal analysis, Writing – original draft, Writing – review & editing. **Ping Qin:** Resources, Supervision. **Hao Chen:** Resources. **Jie-Sheng Tan-Soo:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2026.115546.

Data availability

Data will be made available on request.

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