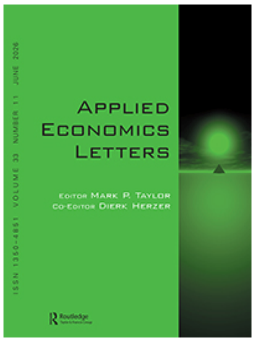


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# Temperature exposure and energy factor misallocation: the environmental regulation threshold in Chinese cities

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# Temperature exposure and energy factor misallocation: the environmental regulation threshold in Chinese cities

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**ABSTRACT**

Amid accelerating climate change, energy systems face rising stress, yet direct evidence on the link between temperature exposure and energy factor misallocation remains limited. Using panel data for 281 Chinese prefecture-level cities from 2011 to 2023, we employ an elastic-net approach to estimate output elasticities and construct a climate-zone-adaptive index of energy factor misallocation, assessing how temperature exposure affects it and whether environmental regulation sets a moderating threshold. Baseline results reveal a U-shaped relationship: very cold and very hot temperatures increase misallocation, while moderate ranges reduce it. Energy factor misallocation is mainly driven by heat in the Tropical and Subtropical Zones, by extreme cold in the Warm Temperate Zone, and by both in the Mid Temperate Zone. A single regulation threshold is identified; only above this level does environmental regulation significantly mitigate the effects of temperature exposure on misallocation. These findings clarify how temperature exposure, as a salient component of climate-related risk, reshapes energy factor misallocation and inform climate-adaptive energy governance and targeted regulatory design.

**KEYWORDS**

Temperature exposure; energy factor misallocation; environmental regulation; threshold effects; climate-zone heterogeneity

**JEL CLASSIFICATION**

Q54; Q58; Q43; D24

## I. Introduction

Global warming is reshaping economies and energy systems (Balcilar et al. 2025; Zambrano-Monserrate, Hernández Soto, and Subramaniam 2025). In 2024, the global mean near-surface temperature was about 1.48°C above the pre-industrial baseline, and around one-fifth of the world's population experienced monthly temperatures above the historical 95th percentile (Copernicus Climate Change Service 2025). Such warming shifts electricity supply and demand through hydropower variability and rising cooling loads, raising mismatch risk and making efficient energy-factor allocation more critical (Beucler et al. 2024).

Temperature exposure affects governance (Sovacool 2021), economic activity (Hou 2025), ecosystems (Pecl et al. 2017), public health (Ebi et al. 2021), and energy systems (Sarwar, Aziz, and Tiwari 2024). Energy factor misallocation arises from market distortions (Choi 2020), policy design (Tombe and Winter 2015), technological capacity (Shen and Wang 2024), and spatial conditions (Zhang et al. 2025). Temperature exposure affects misallocation through physical variability (Sarwar, Aziz, and Tiwari 2024), policy responses (Tombe and Winter 2015), and transition dynamics that improve long-run efficiency but can widen short-run mismatches when upgrading lags (Zeng, Zhou, and Liu 2022). Energy factor misallocation can lower system efficiency, raise operating costs, and widen regional disparities (He et al. 2024; Zhang et al. 2025); in this study, it is defined as a quantity and spatial mismatch between energy supply and actual demand.

Despite progress, key gaps remain: the direct temperature-misallocation link is not systematically quantified; misallocation measures often ignore climate-zone differences; and the moderating role of environmental regulation is rarely tested. This study contributes by (i) quantifying the structural impact of temperature exposure on energy factor misallocation, (ii) developing a climate-zone-adaptive misallocation index using the elastic-net method, which improves the

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robustness of elasticity estimates by addressing correlations among variables and capturing climate-zone heterogeneity, and (iii) identifying a regulatory threshold above which stronger environmental regulation mitigates temperature-induced misallocation.

## II. Materials and methods

We compile a balanced panel of 281 Chinese prefecture-level cities for 2011-2023. Climate data are from the China Meteorological Data Service Center; economic and energy statistics are from the China City Statistical Yearbook and related yearbooks; and environmental regulation information is extracted from local government work reports. Missing values are linearly interpolated, and results are robust to alternative imputation.

Energy factor misallocation (EM) follows the misallocation accounting framework of Hsieh and Klenow (2009). The required output elasticities are estimated in this study using an elastic-net procedure, implemented separately by climate zone to capture structural heterogeneity; the resulting zone-specific elasticities are combined with city-level energy input and output to compute EM.

Temperature exposure (Texp) is measured as city-year counts of days in nine temperature bins (<−12, [−12, −6), [−6, 0), [0, 6), [6, 12), [12, 18), [18, 24), [24, 30), ≥30°C), with [6, 12) as the reference (Chen and Yang 2019).

Environmental regulation (ER) is proxied by the frequency of environment-related keywords in government work reports using a text-recognition approach (Chen et al. 2024).

Following Cherp et al. (2021) and He et al. (2024), we control for city characteristics (industrial structure, economic scale, openness, and carbon intensity) and weather conditions (wind speed, precipitation, and sunshine duration).

We estimate the structural effect of *Texp* on *EM* using a two-way fixed-effects model.

$$EM_{it} = \alpha_0 + \sum_{m=1}^{M} \alpha_m Texp_{it}^m + \beta X_{it} + \eta_i + \nu_t + \xi_{it} \quad (1)$$

$EM_{it}$ is the misallocation index for city i in year t. $Texp_{it}$ denotes the annual count of days in temperature bin $m$; the 6–12°C bin is omitted as the reference. $X_{it}$ includes the controls. $\eta_i$ and $\nu_t$ are city and year fixed effects. Coefficients $\alpha_m$ trace departures from the moderate baseline across cold and hot ranges.

Environmental regulation as a threshold moderator. We estimate a panel threshold model:

$$\begin{aligned} EM_{it} = {} & \alpha_0 + \sum_{m=1}^{M} \alpha_m Texp_{it}^m + \chi ER_{it} + \beta X_{it} + \eta_i + \nu_t \\ & + \sum_{m=1}^{M} [\varphi_m^L (Texp_{it}^m \times ER_{it}) I(ER_{it} \le \theta) \\ & + \varphi_m^H (Texp_{it}^m \times ER_{it}) I(ER_{it} > \theta)] + \xi_{it} \end{aligned} \quad (2)$$

In the model, $ER_{it}$ represents the strength of environmental regulation, and *I()* indicates the threshold effect. The interaction term $Texp_{it} \times ER_{it}$ measures the varying impacts of temperature exposure under different levels of regulation. $\varphi_m^L$ and $\varphi_m^H$ compare temperature exposure effects below vs. above the policy threshold. Inference for $\theta$ and regime differences uses bootstrap confidence intervals.

We address endogeneity by adding a system-GMM specification with lagged EM as internal instruments (AR(2) and Hansen tests support validity). For the threshold model, we use lagged ER in the interaction terms as an additional robustness check.

## III. Results

Table 1 (Column 1) shows a U-shaped relationship between temperature exposure and energy factor misallocation: extreme cold and high heat significantly increase misallocation, whereas moderate temperature bins are associated with lower misallocation, consistent with evidence that temperature extremes strain energy systems and raise operational risk (Beucler et al. 2024; Sarwar, Aziz, and Tiwari 2024).

Results are robust to three checks: using a TFP-based dependent variable, estimating system GMM to address endogeneity, and winsorizing at the 1st and 99th percentiles; signs and significance remain stable.

Table 2 reveals pronounced climate-zone heterogeneity (Zheng, Yin, and Li 2010). In tropical cities, heat increases misallocation; in subtropical cities, mild cold reduces it, and heat increases misallocation; in warm temperate cities, sub-zero

**Table 1.** Baseline regression analysis.

| | EM | | | |
|---|---|---|---|---|
| Variables | Fixed Effects Model | Substituted Variable EM | System GMM | Winsorized Sample |
| <−12°C | 0.0028** | 0.0078*** | 0.0080** | 0.0022** |
| | (0.0012) | (0.0006) | (0.0036) | (0.0009) |
| [−12°C, -6°C) | 0.0035** | 0.0020** | 0.0117* | 0.0029*** |
| | (0.0015) | (0.0009) | (0.0070) | (0.0011) |
| [−6°C, 0°C) | 0.0018 | 0.0014 | 0.0028 | 0.0027** |
| | (0.0011) | (0.0009) | (0.0039) | (0.0012) |
| [0°C, 6 °C) | −0.0059*** | −0.0004** | −0.0129** | −0.0072*** |
| | (0.0010) | (0.0002) | (0.0059) | (0.0009) |
| [12°C, 18°C) | −0.0025** | −0.0022** | −0.0045** | −0.0027*** |
| | (0.0012) | (0.0001) | (0.0019) | (0.0008) |
| [18°C, 24°C) | −0.0031*** | −0.0002** | −0.0100* | −0.0019*** |
| | (0.0010) | (0.0001) | (0.0056) | (0.0006) |
| [24°C, 30°C) | 0.0018*** | 0.0004** | 0.0038* | 0.0027*** |
| | (0.0005) | (0.0002) | (0.0020) | (0.0009) |
| ≥30°C | 0.0116*** | 0.0009*** | 0.0228* | 0.0110*** |
| | (0.0023) | (0.0003) | (0.0120) | (0.0014) |
| City control | YES | YES | YES | YES |
| Weather control | YES | YES | YES | YES |
| N | 3653 | 3653 | 3653 | 3653 |
| $R^2$ | 0.2847 | 0.2376 | – | 0.2605 |

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses are the standard errors.

exposure raises misallocation while moderate ranges reduce it; and in mid-temperate cities, both extremes increase misallocation, whereas mild cold lowers it.

Tables 3–4 identify a threshold at ER = 41, where stronger regulation reduces temperature-induced misallocation in moderate bins, with insignificant effects at extremes. Below the threshold,

**Table 2.** Heterogeneity by climate zone.

| | EM | | | |
|---|---|---|---|---|
| Variables | Tropical Zone | Subtropical Zone | Warm Temperate Zone | Mid Temperate Zone |
| <−12°C | – | – | 0.0114*** | 0.0072*** |
| | | | (0.0019) | (0.0019) |
| [−12°C, -6°C) | – | 0.0134 | 0.0060*** | 0.0048*** |
| | | (0.0088) | (0.0017) | (0.0017) |
| [−6°C, 0°C) | – | −0.0097*** | 0.0033*** | 0.0018* |
| | | (0.0020) | (0.0010) | (0.0011) |
| [0°C, 6 °C) | – | −0.0067*** (0.0009) | −0.0038*** | −0.0054** |
| | | | (0.0011) | (0.0021) |
| [12°C, 18°C) | −0.0091 | −0.0015 | −0.0037*** | 0.0050** |
| | (0.0087) | (0.0037) | (0.0010) | (0.0019) |
| [18°C, 24°C) | 0.0097 | 0.0018 | 0.0005 | 0.0004 |
| | (0.0065) | (0.0026) | (0.0010) | (0.0017) |
| [24°C, 30°C) | 0.0130* | 0.0034** | 0.0008 | 0.0035* |
| | (0.0071) | (0.0013) | (0.0013) | (0.0023) |
| ≥30°C | 0.0025** | 0.0036*** | 0.0013 | 0.0343** |
| | (0.0012) | (0.0011) | (0.0026) | (0.0168) |
| City control | YES | YES | YES | YES |
| Weather control | YES | YES | YES | YES |
| N | 429 | 1560 | 949 | 715 |
| $R^2$ | 0.2435 | 0.2623 | 0.2786 | 0.2510 |

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses are the standard errors.

**Table 3.** Threshold effect test results.

| Threshold Variable | Model | F-Statistic | P-Value | 10% Critical Value | 5% Critical Value | 1% Critical Value | Threshold Value |
|---|---|---|---|---|---|---|---|
| ER | Single Threshold Model | 158.51 | 0.00 | 22.84 | 30.34 | 46.14 | 41 |
| | Double Threshold Model | 5.67 | 0.75 | 43.42 | 66.27 | 115.50 | – |

Note: The F-values and critical values are calculated based on the Bootstrap method (resampling 300 times). The second threshold value in the dual-threshold model was not significantly identified and is therefore marked as '–'.

Table 4. Threshold effect of environmental regulation.

| | ER > 41 | | ER ≤ 41 | |
|---|---|---|---|---|
| Variables | EM | Texp × ER | EM | Texp × ER |
| <−12°C | 0.0012 | 0.0011 | 0.0005 | 0.0007 |
| | (0.0044) | (0.0008) | (0.0030) | (0.0009) |
| [−12°C, -6°C) | 0.0021 | 0.0007 | 0.0011 | 0.0014 |
| | (0.0047) | (0.0011) | (0.0029) | (0.0009) |
| [−6°C, 0°C) | 0.0011 | 0.0015 | 0.0010 | 0.0027 |
| | (0.0044) | (0.0010) | (0.0023) | (0.0017) |
| [0°C, 6 °C) | −0.0173** | −0.0039** | −0.0082*** | 0.0039 |
| | (0.0069) | (0.0016) | (0.0023) | (0.0027) |
| [12°C, 18°C) | −0.0041*** | −0.0075*** | −0.0018 | −0.0003*** |
| | (0.0004) | (0.0013) | (0.0011) | (0.0001) |
| [18°C, 24°C) | −0.0182** | −0.0114* | −0.0035* | −0.0004 |
| | (0.0084) | (0.0066) | (0.0020) | (0.0002) |
| [24°C, 30°C) | 0.0033 | 0.0025 | 0.0066*** | 0.0001 |
| | (0.0027) | (0.0047) | (0.0016) | (0.0001) |
| ≥30°C | 0.0056 | 0.0020 | 0.0097** | 0.0001 |
| | (0.0162) | (0.0019) | (0.0049) | (0.0001) |
| City control | YES | | YES | |
| Weather control | YES | | YES | |
| N | 1794 | | 1859 | |
| $R^2$ | 0.2741 | | 0.2586 | |
| Joint Wald test | ($\Delta\varphi_m = 0$ across bins) $\chi^2$ (8)=23.48 $p < 0.01$ | | | |

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses are the standard errors.

interactions are small. A joint Wald test rejects equality across regimes ($p < 0.01$). The result is robust to adjacent cut-offs (ER = 40, 42) and lagged ER (Table 5).

## IV. Discussion

This study documents a structural relationship between temperature and energy factor misallocation: extremes increase misallocation, while moderate ranges reduce it. The effect is heat-driven in the Tropical and Subtropical Zones, cold-driven in the Warm Temperate Zone, and driven by both extremes in the Mid Temperate Zone. Environmental regulation mitigates these effects only when ER exceeds 41.

Policy implications are threefold. First, cities with higher exposure to extreme temperature ranges

Table 5. Robustness check for threshold effect of environmental regulation.

| | Texp × ER | | |
|---|---|---|---|
| Variables | Cutoff = 40 | Cutoff = 42 | Texp × $ER_{t-1}$ |
| <−12°C | 0.0009 | 0.0010 | 0.0008 |
| | (0.0007) | (0.0008) | (0.0006) |
| [−12°C, -6°C) | 0.0006 | 0.0008 | 0.0007 |
| | (0.0010) | (0.0011) | (0.0010) |
| [−6°C, 0°C) | 0.0012 | 0.0014 | 0.0013 |
| | (0.0009) | (0.0010) | (0.0009) |
| [0°C, 6 °C) | −0.0038** | −0.0040** | −0.0037** |
| | (0.0015) | (0.0016) | (0.0015) |
| [12°C, 18°C) | −0.0074*** | −0.0076*** | −0.0073*** |
| | (0.0013) | (0.0013) | (0.0013) |
| [18°C, 24°C) | −0.0112* | −0.0115* | −0.0110* |
| | (0.0065) | (0.0066) | (0.0066) |
| [24°C, 30°C) | 0.0022 | 0.0023 | 0.0020 |
| | (0.0044) | (0.0047) | (0.0047) |
| ≥30°C | 0.0019 | 0.0021 | 0.0018 |
| | (0.0017) | (0.0019) | (0.0019) |
| City control | YES | YES | YES |
| Weather control | YES | YES | YES |
| N | 1963 | 1352 | 3372 |
| $R^2$ | 0.2801 | 0.2792 | 0.2755 |

Note: Columns (1)–(2) re-estimate Eq. (2) using alternative cut-offs (θ=40,42) and report the high-regime interaction coefficients (ER>θ); Column (3) replaces $ER_t$ with $ER_{t-1}$in the interaction terms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels; values in parentheses are standard errors.

should expand flexibility through short-duration storage, flexible peaking capacity, and demand response, while using time of use pricing and congestion management to smooth peaks and reduce allocation frictions in moderate ranges. Second, climate zone differences imply different priorities: cooling load management where heat dominates, heating system preparedness where cold dominates, and integrated planning where both extremes matter. Third, for jurisdictions near the environmental regulation threshold of 41, the most effective levers are targeted efficiency programmes such as building insulation and heating and cooling upgrades, smart metering with feeder level monitoring, and incentive based demand response, supported by green finance tools such as green bonds for retrofit and grid modernization, preferential loans for verified efficiency projects, and credit support for distributed renewables and storage.

Overall, our framework links temperature exposure to energy factor misallocation and provides a transferable basis for measuring misallocation and evaluating regulation under climate change. Future work could test these mechanisms across countries and sectors using higher-frequency operational data to assess persistence and welfare effects.

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## Author contributions

CRediT: **Heng Ma:** Funding acquisition; **Bingqian Zhang:** Writing – original draft; **Lawrence Loh:** Supervision; **Siliang Guo:** Writing – review & editing.

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