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Artificial Intelligence Development and Urban Solar Energy Consumption: Panel Evidence from China, 2015–2021

Salisu A. Mohammed [1]; Isiaka O. Ibrahim [2]; Obinna O. Okafor [3]; Airat A. Aroyewun [4] and Benjamin O. Anyaehie [5]

[1]Department of Economics, Yobe State University, Damaturu, Nigeria. [2]Department of Engineering/ Industrial Management, Faculty of Engineering, University of Houston Clear Lake, USA. [3]Department of Electrical Engineering, Faculty of Engineering, Chukwuemeka Odumegwu Ojukwu University (COOU), Anambra, Nigeria. [4]Department of Computer Science, Faculty of Faculty of computing and Information technology, Lagos State University, Lagos, Nigeria. [5]Department of Civil Engineering, School of Engineering and Engineering Technology, Federal University of Technology Owerri, Nigeria.

Corresponding author: salisumohammedahmed10@gmail.com

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Abstract

Solar power is among the fastest-growing sources of final energy use in Chinese cities, and artificial intelligence (AI) is widely expected to support its integration into urban energy systems. This study tests whether city-level AI development is associated with higher solar power consumption. It uses a balanced panel of 283 prefecture-level cities for 2015–2021 (1,981 city-year observations), combining an entropy-weighted AI development index with city-level final solar power consumption measured in 10,000 tons of standard coal. Fixed-effects regressions with city-clustered standard errors are estimated with city and year effects and, as the preferred specification, with city and province-by-year effects. In the preferred model, a 10% rise in the AI index is associated with a 0.60% rise in solar power consumption (coefficient 0.062, $p = 0.078$), an estimate that is not significant level and is not stable across alternative AI measures, samples and clustering choices. With city and year effects only, the association is negative (−0.490), while a placebo test using next year's AI development is also negative, cautioning against a causal interpretation. The association is concentrated in eastern cities (0.154, $p < 0.01$), although the difference from western cities is only marginally significant, and it is not weaker where the provincial AI divide is larger. Overall, the evidence supports at most a modest, region-dependent association between AI development and solar power consumption.

Keywords: Artificial Intelligence, Solar Power Consumption, Fixed Effects, Regional AI Divide, Panel Data.

Introduction

Cities are home to about half of the world's population, but account for about 70% of carbon emissions from the energy sector and nearly 2/3 of global energy demand (International Energy Agency [IEA], 2016). The United Nations climate reporting also notes that more than two-thirds of global energy is used in cities (United Nations Framework Convention on Climate Change [UNFCCC], 2020). The increased use of clean energy in cities is thus a key

part of climate and energy policy. Solar energy has grown rapidly in China: cumulative installed photovoltaic (PV) capacity reached 43.18 GW by the end of 2015, while the 15.13 GW figure refers to capacity newly installed during 2015. Cumulative installed capacity subsequently reached approximately 306 GW by the end of 2021 (Lyu et al., 2022).

Artificial intelligence (AI) – computational systems that learn from data for predictive and assisted or automated decision-making – is hoped to enable cities to apply variable renewable energy. Weather conditions influence solar output, and weather forecasts are a prerequisite for integrating solar power into a grid; one recent review notes that AI approaches, in particular, are playing a major role in forecasting solar output (Barhmi et al., 2024). Smart-city studies also feature energy management as a significant application field for AI (Bibri & Huang, 2025; Nwaigbo et al., 2025; Szpilko et al., 2023), while a systematic review and meta-analysis of smart-building studies highlights that energy savings are considerable for AI control (Ekanayaka Gunasinghalge et al., 2025).

Econometric evidence at the city level is predominantly from China. For the period of 2008-2021, Zhang et al. (2026) analysed 281 prefecture-level cities and found that AI improves energy use efficiency in cities, especially in northeast and central cities. Gao et al. (2025) identified that AI enhances the success of the urban energy transition in 278 cities and more so in central and eastern cities. Li et al. (2024) found that the development of AI contributes to the improvement of urban energy efficiency, and that the effects of such development are stronger in eastern cities, based on data for 282 cities. Liu et al. (2025) analysed 282 cities and said there had been improvements in green total factor efficiency in energy use. Data for 271 cities is used by Du et al. (2025) to investigate the green energy efficiency in cities, finding lower positive impacts in megacities. These studies capture efficiency or overall energy impacts, and there is less evidence of the relationship between AI development and adoption of any particular clean energy source, such as solar. It is also emphasized in the literature that AI does not necessarily have a positive impact as the requirements for data and computing power of AI systems grow. The question then is whether there is a positive relationship between the adoption of AI and the use of solar energy, which is an empirical issue.

Statement of the Problem

This study is motivated by two gaps. First, existing studies examine the relationship between AI and energy efficiency, total energy consumption, or the overall energy transition in cities (Du et al., 2025; Gao et al., 2025; Li et al., 2024; Liu et al., 2025; Zhang et al., 2026). The studies reviewed for this paper do not directly examine the association between a city-level AI development index and city-level solar power consumption. This leaves a specific empirical question about whether broader local AI development is associated with the use of solar energy, rather than with energy efficiency or aggregate energy outcomes. Second, regional differences in the effects of AI are also found on a large scale (Gao et al., 2025; Li et al., 2024; Zhang et al., 2026), but a regional-level inequality of AI development, which can be measured by Gini-based indicators (Sun et al., 2023), has not

been tested as a condition for AI-related clean-energy outcomes. Without this evidence, planners cannot determine whether the association between AI development and solar energy use differs across regional contexts.

Research Questions

1. RQ1. Is higher AI development in a city associated with higher solar power consumption?
2. RQ2. Does this association differ across eastern, central and western cities?
3. RQ3. Is the association between AI development and solar power consumption weaker in provinces with a larger regional AI divide?

Research Objectives

The main objective is to estimate the association between AI development and urban solar power consumption in Chinese cities. The specific objectives are:

1. To measure the association between AI development and city-level solar power consumption (RQ1).
2. To compare the association across eastern, central and western cities (RQ2).
3. To evaluate whether the association between AI development and solar power consumption varies with the provincial AI divide (RQ3), and to assess the robustness of the estimates using alternative measures and samples.

Hypotheses

The hypotheses are derived from the theories discussed in Section 2.3 and are evaluated using the empirical models presented in Section 3.5.

H_1. Higher AI development is associated with higher solar power consumption ($\beta_1 > 0$). Motivated by Systems Optimization Theory.

H2. The association between AI development and solar power consumption differs across regions, with a stronger positive association expected in eastern cities than in western cities ($\delta East > 0$). The central-region interaction is also estimated to assess regional heterogeneity, but no directional hypothesis is specified for the central region.

H_3. The association is weaker where the provincial regional AI divide is larger ($\delta_3 < 0$). Motivated by Diffusion of Innovation Theory.

Scope of the Study

In this study, a total of 283 prefecture-level cities from 26 provinces and autonomous regions of China are included in the 2015–2021 Period. The four province-level municipalities (Beijing, Tianjin, Shanghai and Chongqing) and Tibet are not covered because the AI development dataset does not include them. The result is the use of solar energy, not energy efficiency (and energy intensity or carbon emissions are not modeled). The Findings are relevant only to the sampled cities and Period.

Literature Review

Introduction

The main concepts are clarified, theories that underpin the empirical model are presented, and a review of empirical studies that lead to the hypotheses is conducted in this section.

Conceptual Clarification

AI development is the extent to which a city develops an AI base. This study uses a composite index based on the entropy method (Section 3.6) to measure it, combining AI enterprise density, AI patent density and industrial robot density. The index thus reflects the supply of AI in the city, not AI use in the city's energy system.

Solar power consumption is the total amount of solar power consumed in the city in 10,000 tons of standard coal equivalent (tce). It measures the amount of solar energy a city consumes, not energy use efficiency.

The regional AI divide is the inequality in AI development among the cities in a province in a year, calculated by a Gini coefficient based on the city AI development index (Zou & Meng, 2026). A higher value means more concentrated AI development within the province.

Theoretical Review

Systems perspective and AI-based energy coordination: According to general systems theory, the behaviour of an urban energy system can be explained as a function of their interdependence and feedback (Von Bertalanffy, 1968). In this study, this view offers a general systems justification for deciding about the possibility of association between an urban growth in AI capability and the use of solar energy. Though AI forecasting and control may be useful for variable solar power to be coordinated with energy demand, AI enterprises, patents and industrial robots is the city-level AI index used here, which does not directly measure AI-based dispatch or energy management. Thus, the expected positive relationship in H1 is not an observed mechanism, but rather a theoretical one that needs to be tested.

Socio-Technical Systems Theory: The success or failure of technical systems depends on their social, organizational, and institutional fit (Bostrom & Heinen, 1977). Different levels of AI development can produce different social outcomes, depending on the city's infrastructure, human capital and institutions. This theory motivates the regional interaction terms in H_2.

Diffusion of Innovation Theory: Rogers' diffusion theory is a process theory that describes the spread of an innovation in a social system over time, in which adoption of the innovation is determined by factors including relative advantage, compatibility, complexity, and observability. Citing a current edition of Rogers' work should be done in addition to citing the original formulation. The theory has relevance to this study as a province with very high levels of AI development activity may not see very even or widespread diffusion of AI capability in cities. This unequal distribution is captured in the provincial AI-divide indicator and H3 suggests that the higher the provincial AI-divide, the weaker the AI–solar

association. The theory thus leads to the a priori expectation of a negative AI-by-divide interaction, despite the fact that this index is not directly related to diffusion or adoption in the energy sector.

Empirical Review

AI and Building and Solar Systems Energy. Overall, AI applications, particularly reinforcement learning and hybrid solutions, have shown significant energy savings across various building types, as demonstrated in a systematic review and meta-analysis (Ekanayaka Gunasinghalge et al., 2025). AI techniques, especially neural networks, were identified as a key component in short-term (minutes to a day) solar forecasting, aiding in grid integration and resource management (Barhmi et al., 2024). These studies develop technical mechanisms but don't test a city-level association.

Smart city research with AI. Energy management is one of the key application domains of AI in smart cities, as noted in literature reviews, whose benefits include efficiency but also raise issues regarding data privacy and governance (Bibri & Huang, 2025; Nwaigbo et al., 2025; Szpilko et al., 2023).

City-level econometric evidence. A comprehensive study by Zhang et al. (2026) examined 281 prefecture-level cities (2008–2021) using a two-way fixed-effects model to discover that AI optimises energy use mainly by improving green Total Factor Energy Efficiency, which is more evident in northeast and central cities, in cities that are not resource-based, and in cities that are undergoing low-carbon pilot projects, but is not fully valid in eastern and western cities. Based on 278 cities (2010-2019), Gao et al. (2025) showed how AI enhances the performance of the urban energy transition through green technology innovation, human–machine compatibility and energy efficiency, and evidenced that the effect is stronger in central and eastern cities. Li et al. (2024) applied the super-efficiency SBM efficiency measure to 282 cities (2006-2019) and concluded that AI improves energy efficiency through green technology innovations and the digital economy, with larger impacts in the eastern region. According to Liu et al. (2025), AI boosts green total factor efficiency in energy use across 282 cities (2006-2021) and has a greater impact in large cities. With data from 271 cities (2010-2022), Du et al. (2025) concluded that AI boosts urban green energy efficiency, with a weaker impact in megacities and in northeast cities. Wan & Li (2025) conducted a related quasi-experimental study and found that AI pilot zones lowered urban carbon emissions by incorporating green technology and enforcing greater environmental regulations.

Measurement of AI development. Sun et al. (2024) used the entropy-weighting method to build a provincial AI development index and measured regional inequality with the aid of Dagum Gini decomposition. This study uses the city-level data set to quantify AI development and the regional AI divide using related indicators (Section 3.6).

Synthesis and Gap

Overall, reviewed studies indicate a positive relationship between AI development and urban energy outcomes, variability in outcome measures, AI proxies and regional trends. Some studies have found more positive effects in eastern cities (Gao et al., 2025; Li et al., 2024); some studies have identified more positive effects in northeast and central cities (Zhang et al., 2026), while Du et al. (2025) have found less positive effects in megacities. These studies are energy efficiency or overall energy studies. The studies examined here do not directly examine the use of solar power at the city level or test for whether the regional AI divide conditions the association. Thus, this research explores these questions in a context where the current regional evidence is inconclusive.

Research Methodology

Introduction

This section describes the research design, data sources, sample, model specification, variable measurement and robustness strategy.

Research Design

It is a quantitative, explanatory panel design with many cities (cross-section) and seven years (time series). Panel methods absorb unobserved, time-invariant city characteristics and shocks common to all cities. Estimates are conditional associations, not causal effects because AI adoption is not randomly assigned.

Nature and Sources of Data

The study uses only secondary, aggregated, publicly releasable data from three files. Table 3.1 lists them.

Table 3.1: Data Files and Variables

Variable	Definition and unit	Source file
Solar power consumption (Solar)	City-level final energy consumption of solar power, measured in 10,000 tonnes of standard coal equivalent (tce), covering 2005–2021. The variable is transformed into its natural logarithm where applicable.	City-level final energy consumption dataset in China, Version 2, compiled by Yang et al. (2024). The dataset was published on Figshare and draws on statistical sources including the China Energy Statistical Yearbook and China Electric Power Yearbook. DOI: 10.6084/m9.figshare.25295545.v2.
AI development index (AIScore)	City-level composite index of AI development, constructed using AI enterprise numbers, AI	City-scale AI Development and Regional AI Divide Assessment Datasets for China's 283 Cities from 2003 to 2023, by Zou and

Variable	Definition and unit	Source file
	patent applications and industrial robot installation density. The index uses an entropy-weighted evaluation method and covers 283 Chinese cities from 2003–2023.	Meng (2026). Figshare repository DOI: 10.6084/m9.figshare.30690884. Related data descriptor: Scientific Data. DOI: 10.1038/s41597-026-08024-2.
Population (Pop)	City population, measured in units of 10,000 persons. The variable is expressed in natural logarithms for regression analysis.	China city-scale AI development dataset, 2003–2023, by Zou and Meng (2026), provided that the population field in the downloaded dataset is used without substituting another population series.
AI divide (AID)	Province-year measure of inequality in AI development among cities within each province, represented by a Gini coefficient calculated using the Dagum–Gini approach.	China province-scale regional AI divide dataset, 2003–2023, by Zou and Meng (2026). Figshare repository: 10.6084/m9.figshare.30690884.
Region	Categorical variable classifying each province into Eastern, Central or Western China according to the regional classification adopted in the study. The variable is used for regional comparisons or controls, as appropriate.	Authors' coding based on the stated provincial classification and the regional grouping cited in the manuscript (Li et al., 2024).

Source: Authors' compilation based on Yang et al. (2024) and Zou and Meng (2026).

A total of 327 prefecture-level units were identified in the solar file, in province blocks that don't have a province label, and each was assigned a province by block order and matched to the AI data by province and city name. Six differences in spelling (for example, Bangbu/Bengbu, Ordos/Erdos, Wulanchabu/Ulanqab and one unnamed Qinghai prefecture, Hainan) were reconciled manually. All 283 cities in the AI dataset were matched, with no missing solar values for 2015-2021; 44 units in the solar file (mainly autonomous

prefectures/leagues) are not included in the AI dataset and are excluded. The merge code and the merged panel can be obtained as a replication package.

Population and Sample Selection

Population

The population comprise prefecture-level cities in China covered by the AI development dataset and the solar power consumption file.

Sample and Period

A panel dataset at the city level is employed, which includes 283 prefecture-level cities in China during the period of 2015–2021. The analytical sample includes cities with matching variables for the data used. Therefore, the study utilizes all available city-year observations that meet the criteria rather than a smaller random sample of matched cities for the specified coverage period. This gives the panel of 1,981 city-year observations. Nevertheless, analysing all matched observations does not eliminate the possibility of measurement error, missing-data restrictions or selection issues stemming from the coverage of the original data sets. The conclusions must therefore be viewed in the context of the data presented and the extent of the data available.

Model Specification

The baseline two-way fixed-effects model (Model 1) is:

$$In(Solar_{it}) = \beta_1 In(AI_{it}) + \beta_2 In(Pop_{it}) + \mu_i + \lambda_t + \mathcal{E}_{it} \quad (1)$$

where i is the city index, t is the year index, μ_i are city fixed effects, λ_t are year fixed effects, and $\mathcal{E}_{it}$ is the error term. China's solar power has developed under national and provincial policies and depends on provincial resource and grid conditions that have changed over time. The preferred specification (Model 2) thus includes province-by-year effects λ_{pt}, instead of year effects, which means that cities are compared only with other cities in the same province and year:

$$In(Solar_{it}) = \beta_1 In(AI_{it}) + \beta_2 In(Pop_{it}) + \mu_i + \lambda_{pt} + \mathcal{E}_{it} \quad (2)$$

H1 predicts $\beta_1 > 0$. Because the AI index enters in logs, β_1 is an elasticity. The regional and divide hypotheses use interaction terms:

$$\begin{aligned} In(Solar_{it}) = {} & \beta_1 In(AI_{it}) + \delta_1[In(AI_{it}) \times East_i] + \delta_2[In(AI_{it}) \times Central_i] \\ & + \beta_2 In(Pop_{it}) + \mu_i + \lambda_{pt} \\ & + \mathcal{E}_{it} \end{aligned} \quad (3)$$

The western region is used as the reference region. The difference in the AI–solar deployment relationships in the eastern and central regions, respectively, with the western region is quantified by the corresponding coefficients, δ_1 and δ_2. Hypothesis H2 suggests that $\delta_1 > 0$, indicating a stronger positive relationship in the eastern region.

To explore the possibility of a provincial AI divide modifying the effect of AI development on solar power deployment, the following interaction model is specified:

$$In(Solar_{it}) = \beta_1 In(AI_{it}) + \delta_3\left[In(AI_{it}) \times AID_{pt}\right] + \beta_2 In(Pop_{it}) + \mu_i + \lambda_{pt} + \mathcal{E}_{it} \quad (4)$$

To test whether the provincial AI development gap moderates the relationship between AI development and the consumption of solar power in the cities, Equation 4 is computed. The AI development divide (AID) is calculated based on a province-year Gini coefficient and standardized to have a mean of zero and a standard deviation of one. The interaction term between AI development and the standardized AID measure captures whether the effect of AI development on solar power use differs when AI development inequality is higher. The interaction coefficient δ_3 should be negative if H_3 is supported, suggesting that as the provincial AI development gap widens, the positive relationship between AI development and solar power consumption diminishes.

Measurement of Variables

Dependent Variable

The solar power consumption is the final energy consumption of solar power obtained by estimation at the city level (in 10,000 tons of coal equivalent (tce)). Final energy consumption of Chinese cities at the city level is obtained from the source dataset of Yang et al. (2024) which includes solar energy. These values are estimates and derived through computational modelling and through top-down/downscaling methods and are not indicative of installed capacity but of estimated consumption. The higher the values, the more solar energy is estimated to be used. The source values are modelled and downscaled and may therefore include allocation and measurement errors. However, when interpreting the estimates, it should be noted that the population related inputs in the source estimation process and the population control in the regression might be related; the exact rule of allocation needs to be verified from the source documentation.

AI Development

In the city-scale dataset, the index "AIScore" shows AI development. The three positively oriented indicators, which are AI enterprises per capita, AI patents per capita and industrial robot density are Min-Max normalized, weighted using the entropy method and aggregated. The entropy weights are computed at the pooled city-year sample level and thus can be compared across cities and years. The index is strongly right-skewed (skewness of 7.67); the natural log is used as the main measure (skewness 0.25); the standardized level of the index is a robustness check. Since the index is built on the basis of the number of AI enterprises, patents and robots, it does not reflect AI adoption in energy management, which is discussed in Section 5.2.

Regional AI Divide, Region and Control

The regional AI divide is the Gini coefficient of the city AI index within the province and year (from the province level data matrix) after normalization to have mean equal to zero and

standard deviation equal to one. Originated from East (Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan) or Central (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan) or West (all others in the sample). The sole time varying city control that exists in the data is log population. The preferred specification also takes account of time-varying province-specific factors like solar subsidies and grid policy, and time-invariant city-specific factors are picked up by the city effects. Other omitted variable risks are discussed in Section 5.2.

Robustness Checks

1. Alternative fixed effects: city and year effects (Model 1) versus city and province-by-year effects (Model 2). All robustness checks are reported under both.
2. Lagged AI development (t − 1), and a placebo test that adds next year's AI development (t + 1), which should have no effect on current solar consumption if the association is not driven by pre-existing trends.
3. Alternative AI measures: standardized index level, log AI enterprises per capita, log AI patents per capita and standardized industrial robot density.
4. Winsorizing the AI index at the 1st and 99th percentiles, and excluding the top 1% of observations by AI development.
5. Excluding 2015–2016, when solar consumption was very low in most cities.
6. Clustering standard errors by province (26 clusters) and leave-one-province-out estimates.
7. Separate estimates for eastern, central and western cities.

Ethical Considerations and Data Governance

No human participants are involved in the study, and no personal data are collected; thus, no consent was required. Data are used in accordance with the conditions of the data providers. The merged panel, the merge code and the estimation script are available as part of a replication package to reproduce all of the tables in Section 4. Concerns about privacy, cybersecurity and the energy used by AI systems are discussed in Section 5.2.

Results

All tables and figures in this section are produced by the replication script from the merged panel. Each t-value equals the coefficient divided by its standard error, within rounding, and the script checks this relationship.

Descriptive Statistics

Table 4.1: Descriptive statistics, 283 cities, 2015–2021

Variable	N	Mean	Std. dev.	Min	Max
Solar power consumption (10,000 tce)	1,981	6.854	9.758	0.005	72.151
AI development index (AIScore)	1,981	0.0318	0.0312	0.0034	0.5682

Variable	N	Mean	Std. dev.	Min	Max
AI enterprises (number)	1,981	727.1	2360.9	2.0	45154.0
AI patents (number)	1,981	908.8	3726.4	1.0	73806.0
Industrial robot density	1,981	9.96	3.76	1.67	20.67
Population (10,000 persons)	1,981	436.5	267.8	20.3	2067.8
Provincial regional AI divide (Gini)	1,981	0.141	0.091	0.002	0.448

Source: Authors' computation from the merged city-level panel dataset (2015–2021), comprising 283 cities and 1,981 city-year observations, using the replication script.

Mean solar power consumption rose from 1.40 in 2015 to 12.98 in 2021 (10,000 tce), about a ninefold increase, while the mean AI development index rose from 0.022 to 0.047. Both series trend upwards, which is why year effects are necessary. Eastern cities have the highest mean solar consumption (8.74) and the highest mean AI development (0.048), compared with 6.70 and 0.023 in the west and 5.15 and 0.024 in the centre. Solar consumption is highly dispersed across cities (standard deviation 9.76), which supports the use of logs.

Correlation Analysis

Table 4.2: Pairwise correlations

Variable	ln Solar	ln AI index	ln AI ent.	ln AI pat.	Robot dens.	ln Pop	AI divide
ln Solar	1.00	0.30	0.59	0.45	0.19	0.19	0.12
ln AI index	0.30	1.00	0.67	0.70	0.83	0.21	0.27
ln AI ent.	0.59	0.67	1.00	0.81	0.36	0.01	0.28
ln AI pat.	0.45	0.70	0.81	1.00	0.36	0.16	0.26
Robot dens.	0.19	0.83	0.36	0.36	1.00	0.18	0.28
ln Pop	0.19	0.21	0.01	0.16	0.18	1.00	0.07
AI divide	0.12	0.27	0.28	0.26	0.28	0.07	1.00

Source: Authors' computation from the merged city-level panel dataset (2015–2021). Pairwise Pearson correlation coefficients were calculated using the transformed study variables.

Table 4.2 presents the pairwise correlations among the study variables. Log solar consumption is positively correlated with the AI index (0.30), AI enterprises (0.59), and AI patents (0.45). Robot density and log population both have weak positive correlations with solar consumption (0.19), while the AI divide has a correlation of 0.12. The AI index and robot density are correlated at 0.83, and AI enterprises and AI patents are correlated at 0.81. The pooled correlation between solar consumption and the AI index differs from the within-city relationship after removing city and year effects, which is −0.12. The baseline model's VIF of 1.05 indicates that multicollinearity is not a concern. However, correlations among

alternative AI indicators should be considered when specifying extended models. These results show associations, not causal relationships.

Regression Analysis

Table 4.3 reports the baseline models. The Mundlak test rejects the random-effects specification (χ^2 (2) = 17.17, p < 0.001), so fixed effects are used.

Table 4.3: Fixed-effects estimates, dependent variable ln (solar power consumption)

Variable	Coefficient	Std. error	t-value	p-value
Model 1: city and year effects, no control				
ln AI development	−0.4844	0.1444	−3.36	<0.001
Model 1b: city and year effects, with control				
ln AI development	−0.4900	0.1534	−3.19	0.002
ln Population	−0.0522	0.1228	−0.42	0.671
Model 2 (preferred): city and province-by-year effects				
ln AI development	0.0623	0.0352	1.77	0.078
ln Population	0.1217	0.0477	2.55	0.011**

Source: Authors' estimation. Standard errors clustered by city. Asterisks denote significance: one asterisk p < 0.10*, two p < 0.05**, three p < 0.01***.

Table 4.3 (continued): Model statistics

Model	Fixed effects	N	Cities	R^2 (within)	Adj. R^2 (within)	F (df)	F p-value
1	City, year	1,981	283	0.015	−0.154	11.26 (1, 282)	<0.001
1b	City, year	1,981	283	0.015	−0.154	8.27 (2, 282)	<0.001
2	City, province×year	1,981	283	0.019	−0.262	3.27 (2, 282)	0.039

Source: Authors' estimation. Adjusted R^2 uses the degrees of freedom absorbed by all fixed effects and is negative when the regressors explain little within-city variation. F-tests are cluster-robust Wald tests that all regressors are jointly zero. Asterisks denote significance: one asterisk p < 0.10*, two p < 0.05**, three p < 0.01***.

Findings. With city and year effects (Models 1 and 1b), the association between AI development and solar power consumption is negative: a 10% increase in the AI index is associated with a 4.56% fall in solar consumption (−0.490, p = 0.002). This sign is not credible as an AI effect, as the placebo test in Section 4.5 shows. In the preferred model with province-by-year effects (Model 2), the coefficient is positive but small and imprecise: 0.0623 (SE 0.0352, p = 0.078). A 10% rise in the AI index is associated with a 0.60% rise in solar power consumption, and a doubling of the index is associated with a 4.4% rise. The

estimate is not significant at the 5% level (95% confidence interval −0.007 to 0.131), so H1 receives at most weak support. Log population has a positive coefficient in Model 2 (0.122, p = 0.011), implying that larger cities consume more solar power in total but less per person.

Tests of the Regional and Divide Hypotheses

Table 4.4: Interaction models, dependent variable ln(solar power consumption)

Variable	Coefficient	Std. error	t-value	p-value
City and province×year effects (preferred)				
ln AI (West slope)	0.0316	0.0431	0.73	0.463
ln AI × East	0.1227	0.0650	1.89	0.060*
ln AI × Central	−0.0005	0.0809	−0.01	0.995
ln AI (at mean divide)	0.0329	0.0373	0.88	0.378
ln AI × AI divide	0.0258	0.0144	1.80	0.074*
City and year effects				
ln AI (West slope)	−0.9261	0.1599	−5.79	<0.001
ln AI × East	0.6015	0.1794	3.35	<0.001
ln AI × Central	1.4549	0.2162	6.73	<0.001
ln AI (at mean divide)	−0.4876	0.1514	−3.22	0.001
ln AI × AI divide	0.0111	0.0377	0.29	0.769

Source: Authors' estimation. Regional and divide interactions are estimated in separate models (3) and (4); each also includes log population. Standard errors clustered by city. Asterisks denote significance: one asterisk p < 0.10*, two p < 0.05**, three p < 0.01***.

H2 (regional heterogeneity). In the preferred specification the implied AI elasticity is 0.154 in eastern cities (p < 0.01), 0.032 in western cities (p = 0.463) and 0.031 in central cities (p = 0.650). The East–West difference is 0.123 (p = 0.060), and the joint test that both interactions are zero does not reject (p = 0.112) are insignificant. Separate regressions give the same pattern, with a positive and significant coefficient for eastern cities only (0.164, p = 0.007; central 0.029, p = 0.688; western 0.031, p = 0.476). H2 is therefore partly supported: the association is visible only in the east, but the formal test of regional differences is weak. With city and year effects only, the regional coefficients are large and opposite in sign (joint test p < 0.001), which again points to unmodelled provincial dynamics.

H3 (regional AI divide). The interaction between AI development and the provincial AI divide is 0.026 (SE 0.014, p = 0.074). The sign is positive, the opposite of the predicted negative sign, and the effect is significant only at the 10% level. H3 is therefore not supported: the data provide no evidence that a larger AI divide weakens the association, and if anything, the association is slightly stronger where AI development is more unequally distributed.

Table 4.4.1: Implied regional elasticities

Region	Implied elasticity	Estimated SE	p-value
West	0.0316	0.0431	0.463
East	0.1543	0.0780	0.048*
Central	0.0311	0.0917	0.734

Source: Authors' estimation. Implied regional elasticities are calculated as linear combinations of the estimated coefficients. based on the preferred regional interaction model in Table 4.4. Asterisks denote significance: one asterisk p < 0.10*, two p < 0.05**, three p < 0.01***.

Table 4.4.1 shows the implied elasticities in the use of solar power with respect to AI development for the western, eastern and central regions. The results show that elasticity is the highest (0.1543) in eastern region with the p-value of 0.048, which is considered positive and statistically significant at 5%. That means that for every 1% rise in AI development, the use of solar power in the eastern region increases by 0.154%. By contrast, the elasticity in the west is 0.0316 (p = 0.463), and in the centre 0.0311 (p = 0.734), both of which are not statistically significant. This reflects the correlation between the development of AI and the use of solar energy more clearly in the east.

Robustness Checks

Table 4.5: Robustness of the AI coefficient (standard error in parentheses)

Check (variable of interest)	City + year FE	City + province×year FE	N
Baseline: ln AI index	−0.490 (0.153)	0.062* (0.035)	1,981
Lagged ln AI (t − 1)	−0.222* (0.125)	0.017 (0.031)	1,698
Placebo: ln AI at t + 1 (current ln AI shown in text)	−0.511 (0.146)	−0.009 (0.030)	1,698
Standardized AI index (level)	0.007 (0.024)	0.021** (0.010)	1,981
ln AI enterprises per capita	0.417 (0.152)	0.040 (0.032)	1,981
ln AI patents per capita	−0.151 (0.054)	0.014 (0.010)	1,981
Industrial robot density (standardized)	0.267 (0.086)	−0.003 (0.016)	1,981
ln AI index, winsorized 1/99	−0.459 (0.165)	0.052 (0.041)	1,981
ln AI index, top 1% of AI excluded	−0.594 (0.170)	0.052 (0.036)	1,961
ln AI index, 2017–2021 only	−0.122 (0.098)	0.064 (0.044)	1,415
ln AI index, province-clustered SE (26 clusters)	−0.490** (0.222)	0.062 (0.049)	1,981

Source: Authors' estimation. All models include log population. Asterisks denote significance: one asterisk p < 0.10*, two p < 0.05**, three p < 0.01***. Standard errors clustered by city unless stated.

The placebo test is based on the lead of AI development, ln AI at time t+1, whereas the current-period ln AI coefficient is presented in the accompanying text. The placebo

coefficient is equal to −0.511 (SE = 0.146) under the city and year fixed-effects specifications. In the preferred specification, including city and province-by-year fixed effects, the coefficient is −0.009 (SE = 0.030), which is not statistically significant. This indicates that the negative effects identified with the city and year fixed effects are unlikely to remain with province-specific shocks that vary from year to year.

The contemporaneous AI development coefficient in the restricted sample is 0.038 ((p = 0.285)), compared with 0.0623 ((p = 0.078)) in the full-sample preferred specification. Because these estimates come from different samples, their differences should not be attributed solely to the placebo test. Overall, the placebo result is consistent with the preferred specification not detecting a significant lead association, but the evidence should be interpreted cautiously and alongside the other robustness checks.

Visual Summary of the Panel

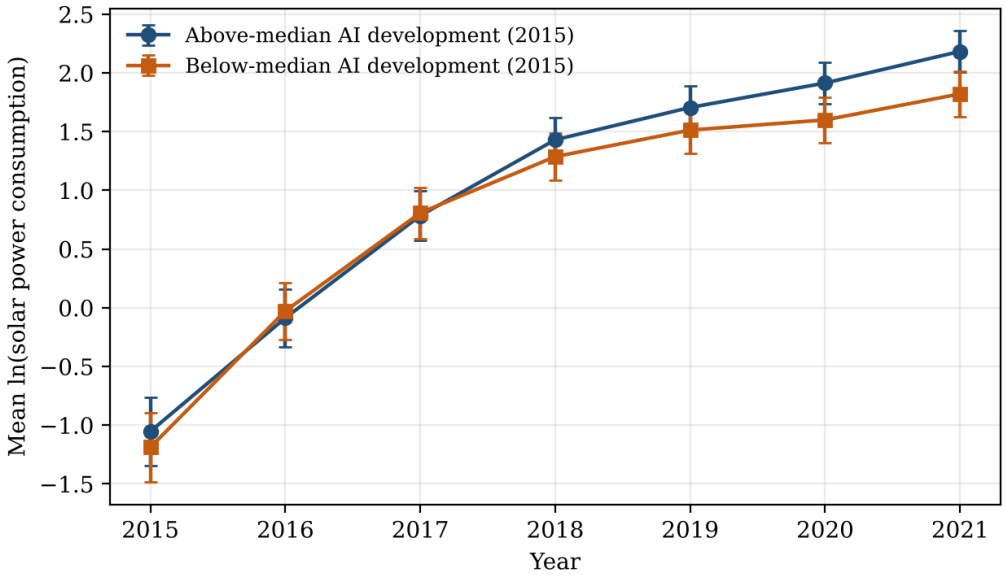
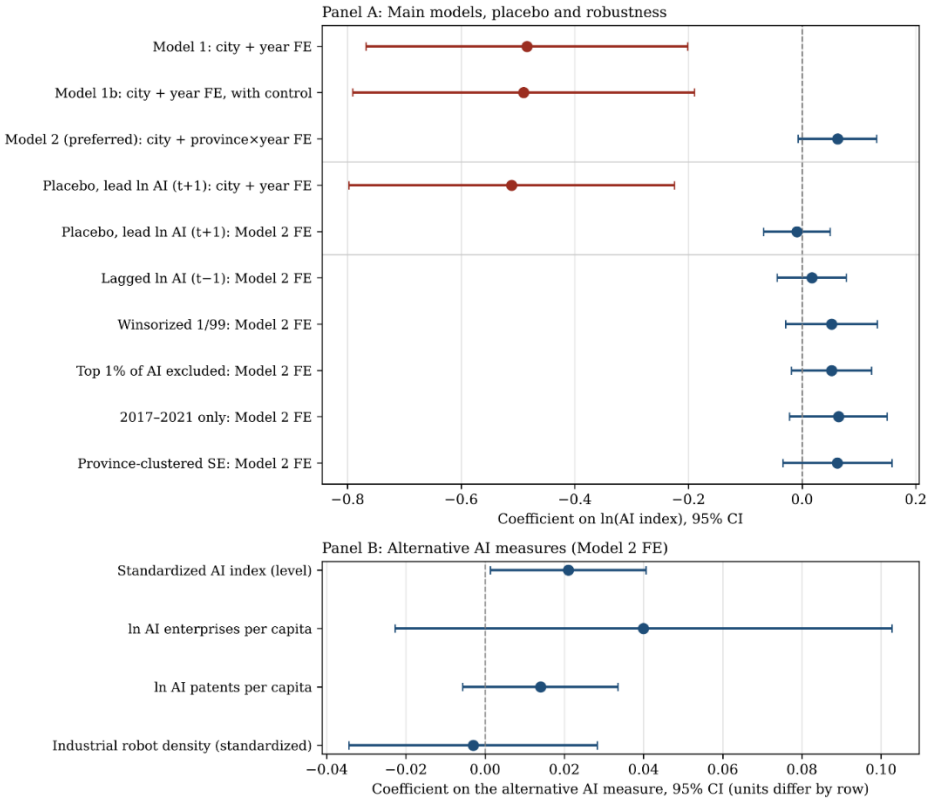


Figure 4.1: Mean ln (solar power consumption) by year, cities grouped by AI development in 2015

Source: Authors' computation from the merged panel. Cities are split at the 2015 median of the AI development index (142 above, 141 below). Bars show 95% confidence intervals of the group mean. The comparison is descriptive and unadjusted.

Figure 4.1 shows that solar power consumption grew rapidly in both groups. In 2015 the mean log consumption was almost identical (−1.05 for higher-AI cities and −1.19 for lower-AI cities). By 2021 higher-AI cities had pulled ahead modestly (2.18 versus 1.82, a gap of 0.36 log points). This pattern is consistent with the small positive coefficient in Table 4.3 but is not evidence of an effect, because the groups also differ in region and province, which the regressions take into account.



Source: Authors' estimation (Tables 4.3 and 4.5). The coefficient on ln (AI index) with 95% confidence intervals are presented in Panel A for Models 1, 1b and 2, placebo test of the lead of ln AI and robustness checks. Units differ by row; the estimates in Model 2 effects for alternative measures of AI are not comparable in size, as shown in Panel B. Model 2 effects are city and province×year effects. The dashed line represents 0. Unless indicated, standard errors are grouped by city.

The summary of the major sensitivity result is in Figure 4.2. Only the placebo has a clearly negative interval, and it is due to the city and year effects, and not due to an AI effect. For Model 2, the coefficient for the placebo is −0.009, and the interval contains zero. All Model 2 estimates for the AI index are positive with intervals that include zero. The interval for the standardized AI index is the only one that does not contain zero (0.021, $p < 0.05$). The estimate of enterprise, patent and robot-density is small and not accurate.

Discussion of Findings

The main finding is that at best there is a weak and imprecise link between the intensity of AI development (captured in an index of AI enterprises, AI patents, and AI robots) and the use of solar power in Chinese cities. In the preferred specification, the elasticity is 0.062, corresponding to a 4.4% increase in solar energy use for a doubling of the AI index; the estimate is not significant at the 5% level. This aligns with the positive trends noted in Chinese city-based studies for urban energy outcomes (Gao et al., 2025; Li et al., 2024;

Zhang et al., 2026), but is considerably less pronounced than the clear trends in efficiency and overall energy outcomes reported in those studies. The discrepancy could be due to the outcome - the use of one energy source - which is very dependent on provincial policy and resources; the AI measure - local AI capability and not the use of AI in energy systems; or the design - the province-by-year effects may remove much of the variation that previous studies use.

Systems Optimization Theory & H1. The positive sign is what the theory predicts, and it indicates that, if the feedback is indeed of an artificial intelligence type, more solar output can be utilized. However, the estimate's size and accuracy do not support a definite conclusion, and the configuration of the AI measures does not indicate that it is driven by any one dimension of AI capability. There is consequently a weak level of evidence for H1.

Socio-Technical Systems Theory H2. The association is also skewed toward the east (0.154), where infrastructure, human capital and institutional capacity are high, and in line with the previous studies that found the highest AI effects in the east (Gao et al., 2025; Li et al., 2024), as well as Liu et al. (2025) on larger cities. This is different from Zhang et al. (2026), whose results indicated the greatest impacts in northeast and central cities. Regional results are suggestive, but statistical differences among regions are small.

Contrary to expectations, the preferred specification yields a positive interaction (0.026) between the regional AI divide and AI–solar association; the estimate is marginally significant. One hypothesis is that the focus of AI development is in a handful of major cities, and that these cities (which might have higher solar deployment) have an influence on the estimated association. This is not a result of the current analysis but a conjecture based on data that do not directly test the hypothesis of whether the relationship is due to the leading cities.

Interpretation is important with the specification comparison. The AI coefficient is negative in the model with city and year fixed effects (Model 1/Model 1b), as is the lead-AI placebo coefficient. In the model of choice with city and province-by-year fixed effects (Model 2), the contemporaneous AI coefficient is positive but not precisely estimated, and the lead-AI placebo coefficient is near zero and statistically indistinguishable. The different outcomes illustrate how common year impacts alone might not be sufficient to explain province-specific changes that impact both AI development and solar consumption. The estimates are thus conditional association not causal effects.

Conclusion, Limitations and Recommendations

Conclusion

This study examines the correlation between the growth of solar power usage and the development of AI in Chinese cities between 2015 and 2021. The preferred estimate of H1 is positive (0.062) and marginally significant at the 10% level ($p = 0.078$), and is sensitive to the choice of AI measure, sample and clustering. The outcome is suggestive (not conclusive) evidence of positive association. H2 is also not supported at conventional significance levels as the joint test of regional differences is not statistically significant ($p = 0.112$) although the

estimate for the eastern region is positive and the difference between the East and the West is marginally significant. Contrary to H3, no evidence that the provincial AI divide weakens the association. The model with city and year effects only yields negative association, and the placebo result warns to not take the estimate as an effect of AI. The results only refer to solar energy use for the cities sampled and the time period of the sample; the study did not consider energy efficiency or carbon emissions.

Limitations

1. **Causality:** AI development is not an arbitrary process. While many confounders are eliminated by province-by-year and city effects, city-specific shocks that impact both AI development and solar use are not eliminated, and the placebo test does not eliminate all forms of reverse causality.
2. **Measurement of AI:** The index is not a measure of AI usage in energy management but rather a measure of AI capabilities within the region (enterprises, patents and robots). The linkage to Solar use is therefore indirect and the results cannot be interpreted as impact of AI-based energy systems.
3. **Controls:** Log Population is the only time-varying city control. Solar resource, electricity prices and local subsidies, and industry structure and GDP are not in the data, and the province-by-year effects do not reflect city-level differences.
4. **Outcome:** The dependent variable is estimated final solar electricity consumption, not solar electricity efficiency, installed solar electricity capacity or necessarily gross solar electricity generation. The city-level outcome is adopted from the final energy consumption data created by Yang et al. (2024) via computational modelling and top-down/downscaling approaches. The city estimates that result may include allocation error, and measurement error; the exact allocation rule and whether that rule is related to population should be taken into account when interpreting the estimates from the regression. The data does not differentiate between utility-scale and distributed solar power.
5. **Period and sample**: The window is 2015–2021 as the solar file ends in 2021; the AI data goes to 2023 but is not usable with this outcome. No data is available for Tibet or some autonomous prefectures, nor for municipalities.
6. **Rebound and governance:** Notably, the energy consumption of AI computing and data centres, privacy and cybersecurity concerns, and interoperability challenges are not addressed (Li et al., 2024; Szpilko et al., 2023).

Recommendations

1. Consider AI development as an augmentation, rather than a replacement for solar and grid policy. Federal and provincial energy policymakers and electricity-grid operators should not look for AI industry growth alone to increase solar energy usage since the preferred AI elasticity is small and imprecise (0.062, p = 0.078). Energy strategies need to take into account investments in grid infrastructure,

storage and forecasting, as well as AI. This recommendation aligns with the technical contribution of AI in solar forecasting as presented by Barhmi et al. (2024); however, this study does not explicitly quantify the impact of such investments.

2. Investigate solid evidence prior to the implementation of AI interventions at regional level. The regional test of difference is not significant at conventional levels (joint test p = 0.112), although the eastern-region estimate is positive. So, it would be a mistake for provincial development agencies and energy-planning authorities to use the eastern results as evidence that investments in AI would yield more solar-consumption benefits in the east. Monitoring of regional programmes should be accompanied to identify if there is measurable change in solar use correlated to difference in AI capability, infrastructure and solar resources.
3. Make comparisons for AI related energy pilots within the same province and year, and look for pre-trends before crediting changes in solar energy use to AI pilots. This is a methodological recommendation that comes out of the sensitivity of the estimates to the fixed-effects specification, and can more appropriately be thought of as a priority for future evaluations designs rather than a direct policy finding.
4. Collect and exchange information about the use of AI in energy systems. The current AI index assesses the AI capability of cities at the city level and not its use in energy management. Energy authorities and city governments should make more data on the use of AI in electricity networks and buildings available and data on city-level solar consumption sources and types available, allowing the mechanisms discussed in Section 2.3 to be tested in the future.
5. Data governance and the energy footprint of AI are relevant policy considerations and should be measured, but were not in this study. Broad AI governance frameworks should take into account the privacy, cyber security and interoperability requirements of AI computing systems, as well as their electricity use. It is important to understand that these are policy considerations in context of the present estimates, and not conclusions proved by the estimates themselves.

For future studies, it is suggested to compare the energy saving pilots related to AI, increase the panel as solar data become available, use direct measures of AI use in the energy sector, check pre-trends, and explore energy intensity and carbon results using separate models explicitly specified to do so.

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