Heliyon 9 (2023) e21250

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Clean energy transitions and health

Meng Li [a], Yong Geng [b,*], Shaojie Zhou [c], Joseph Sarkis [d]

[a] School of Environmental Science and Engineering, Shanghai Jiao Tong University, Shanghai, China
[b] School of International and Public Affairs, Shanghai Jiao Tong University, Shanghai, China
[c] School of Public Policy and Management, Tsinghua University, Beijing, China
[d] Business School, Worcester Polytechnic Institute, Worcester, United States

ABSTRACT

Clean energy can lead to significant health benefits. Making it accessible throughout the world can address many ills. We delve deeply into one example—the transition toward clean residential heating and its relationship to health benefits—in China. We find that the health benefits can outweigh costs from energy expenses in northern provinces. Low-income households enjoy larger health benefits but also experience a higher expense increase, suggesting that extra subsidies or stimuli are needed to help them benefit from clean energy. Our findings suggest that clean energy transitions should be promoted in developing economies due to improved social health, lessened medical costs, and significant environmental improvements.

1. Introduction

Clean heating services result in both health and socio-economic benefits. Solid fuel combustion generates many harmful air pollutants and toxins. These effluents damage indoor and outdoor air quality [1–4]. Exposure to air pollutants undeniably result in public health concerns led by premature mortality [5–7]. Global estimates show that in 2019 indoor and outdoor air pollution led to over 5.4 million premature deaths [8]. In 2018, this pollution resulted in $2.9 trillion additional burdens to healthcare systems [9]. These human and economic costs can be mitigated through effective clean energy transitions that lead to improved indoor and outdoor air quality [10–13]. The health benefits are broad and direct [14–17], led by reduced morbidity and premature mortality [3,18,19].

Despite substantial health benefits [20,21], clean energy is more costly and less accessible especially in developing countries. Three billion people still rely on dirty energies such as coal, charcoal, firewood, and crop residues instead of clean energy sources [22–24]. In 2020, clean energies account for 94.7 % of the total energy consumption in the residential sector in the USA and 86.8 % in Germany, but only 57.5 % in China, 35.7 % in India, and 32.1 % in South Africa. Low-income households in developing countries are the most vulnerable to household-related air pollution and disease burdens [8], yet they are the least able to afford clean energy [25]. Despite China's unprecedented economic growth over the past four decades, only one fifth of Chinese households have phased out the use of solid fuels for their heating [26]. According to a 2015 residential survey, only 30 % of Chinese households in northern provinces enjoyed district heating, by which heat is produced in a centralized way and distributed to households via pipelines. Only 2.8 % and 4.2 % of the Chinese households were able to get heating services from gas and electricity, respectively (Fig. S2), while one-quarter (22.5 %) Chinese households used biomass such as straw and corncob and 37.1 % of Chinese households used dispersed coal to heat their homes.

Substantial health benefits and limited accessibility of clean energy has not gone unnoticed. The global community has prioritized universal access to clean energy under the United Nations' Sustainable Development Goals (SDGs), such as SDG 3 "*Good Health and*

* Corresponding author. School of International and Public Affairs, Shanghai Jiao Tong University, Shanghai, China.
E-mail address: ygeng@sjtu.edu.cn (Y. Geng).

https://doi.org/10.1016/j.heliyon.2023.e21250
Received 24 July 2023; Received in revised form 13 October 2023; Accepted 18 October 2023
Available online 31 October 2023
2405-8440/

Well-being" and SDG 7 "*Affordable and Clean Energy*" [27]. However, several issues remain to be addressed. Is clean energy transition cost-effective? That is—to what extent does clean heating improve human health, reduce medical costs, and increase energy costs? To help answer these critical questions policymakers and other stakeholders need the ability to measure different fuel type costs and benefits. Previous studies have mainly relied on estimations and simulations from engineering models or smaller samples. Much of these estimates have been ineffective due to the lack of reliable energy and medical expense data.

In this study, we use bottom-up residential survey data from 47,469 households in nine Chinese provinces, including the quantity and spending on different fuels and detailed monthly household income and expenditure bills from 2015 (Fig. S3). Using a *differences-in-differences* method (DID) [28], this balanced panel dataset allows us to investigate a causal relationship between heat energy types and their health impact during the winter season from different types of heating energy. We estimate the benefits and costs of clean energy transition using a *marginal treatment effect* (MTE) analysis, which allows us to assess the policy implications across heterogeneous households. We find that the direct health benefits—using reduced medical expenses as a proxy—can offset the additional energy costs in northern Chinese provinces.

2. Materials and methods

2.1. Data

This study uses bottom-up Chinese residential survey data from 47,469 households across nine Chinese provinces, with 569,628 observations. After cleaning the dataset and keeping only panel dataset that has observations for all 12 months, we keep 39,374 households and 472,488 observations for our analysis. This survey required all the investigated households to report their detailed socio-economic characteristics, income, expenditure bills, energy consumption, and heating energy choices in 2015. To date, this is the only resident survey that provides monthly data, which can help us measure the winter heating impacts. This panel dataset is unique as it is both fine-scaled and large-scaled. The processing of data used in this study is shown in Fig. 1. The detailed summary statistics of the mainly concerned variables are presented in Table S1.

2.2. Categorization of heating fuels

The Household Air Pollution and Health guidelines released by WHO in 2014 provide detailed information on the fuels and technologies that can be considered "clean" for health [24]. Previous studies on household fuels use have also classified energy types into clean energy and polluting energy [25]. As Fig. 2 shows, this study categorizes households into 6 + 1 groups by their heating methods (including an "other fuels" term). These six groups include no heating group, the district supply group, the biomass combustion group, the coal combustion group, the gaseous fuels group, and the electricity consumption group. As households using other fuels are very limited, we do not include these samples in our analysis. This type of categorization is applied in our baseline analysis to examine different health outcomes related to heating energy choices. We also classify these energy types into clean energies or polluting energies in the MTE analysis to estimate the impact of the clean energy transition strategy.

2.3. Differences-in-differences method

Based on a typical Differences-in-Differences setting for causal inference [28], we measure the health impacts of different winter heating energies with the following log-linear specification (1):

$$lnMed_{it} = \beta_0 + \sum_{j=1}^{5} \beta_{1j}\, Heating_{ijt} + \beta_2 Winter_{it} + \sum_{j=1}^{5} \beta_{3j}\, Heating_{ijt} \times Winter_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

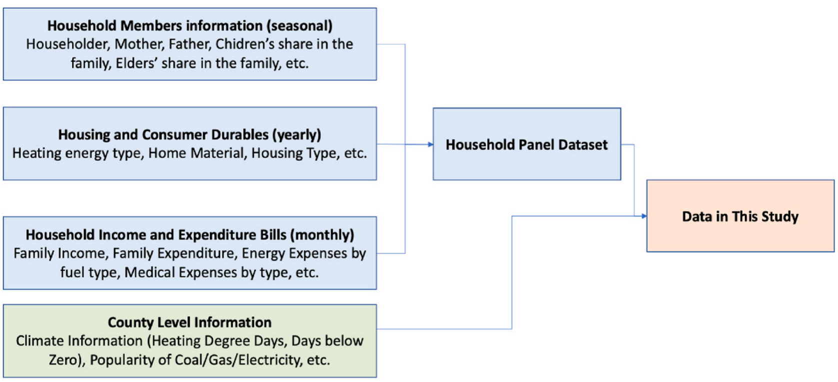

Fig. 1. | Data processing.

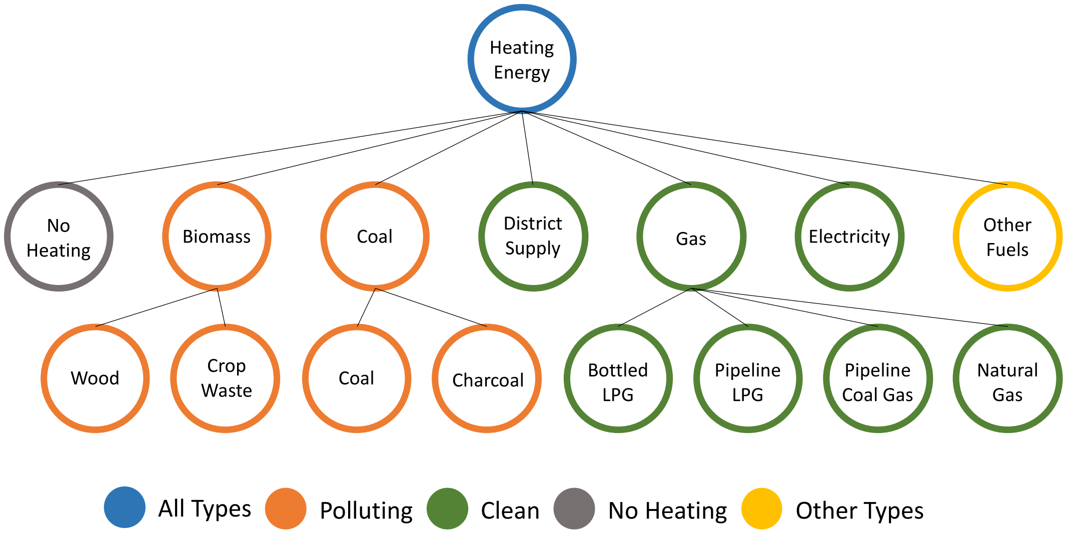

Fig. 2. | Categorization of heating fuels.

The dependent variable is the logarithm of the medical expense by household *i* in month *t*, which can reflect the changes in medical expenses. The treatment variable is $Heating_{ijt}$, in which *j* denotes different heating groups (j = 0 for no heating as the control group; j = 1 for district heating; j = 2 for biomass; j = 3 for coal; j = 4 for natural gas; and j = 5 for electricity consumption).

The parameter β_{1j} measures the differences in medical expenses associated with the heating energy choice, which is not related to winter heating. The treatment time variable is $Winter_{it}$, which is a dummy variable taking a value of 1 if it is November, December, January, February, or March. This value is set as 0 for other months. The parameter β_2 measures the universal medical expense changes induced by winter. We add the interactions between the dummy variables $Heating_{ijt}$ and $Winter_{it}$ to identify the changes in medical expenses due to different heating energy choices during the winter months. The DID estimators β_{3j} (j = 1, …, 5) denote the increase in medical expenses induced by district heating, biomass, coal combustion, natural gas, and electricity, respectively. We include household fixed effects γ_i to control for baseline differences across households that do not vary across time and month fixed effects δ_t to control for seasonal patterns and other time fluctuations. To address the sharp shock of the Chinese Lunar Year month, the data from February are not included in the baseline regressions. Normally the Chinese people do not go to the hospitals or avoid taking medicines in order to receive good omens for the new year.

2.4. Sensitivity analysis

Households at different income levels have different heating energy choices, meaning that they are influenced differently. We estimate each heating group's intercept and slope to capture the heterogeneous effect of winter heating on households at different income levels. Based on the baseline model, we further measure the heterogeneous health impact of winter heating energy with the following equation (2):

$$\begin{aligned} lnMed_{it} = \beta_0 + \sum\nolimits_{j=1}^{5}\beta_{1j}\, Heating_{ijt} + \beta_2 Winter_{it} + \sum\nolimits_{j=1}^{5}\beta_{3j}\, Heating_{ijt} \times Winter_{it} \\ + \beta_4 Income_{it} + \sum\nolimits_{j=1}^{5}\beta_{5j}\, Heating_{ijt} \times Winter_{it} \times Income_{it} + \gamma_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

The dependent variable is the logarithm of the medical expense by household *i* in month *t*, which can reflect the changes in medical expenses. The treatment variable is $Heating_{ijt}$, in which *j* denotes a heating energy choice (j = 0 for no heating as the control group; j = 1 for district heating; j = 2 for biomass; j = 3 for coal; j = 4 for natural gas; and j = 5 for electricity consumption). The parameter β_{1j} measures the differences in medical expenses associated with the heating energy choice, which is not related to winter heating. The treatment time variable is $Winter_{it}$, which is a dummy variable taking a value of 1 if it is November, December, January, February, or March, otherwise taking a value of 0. The parameter β_2 measures the universal medical expense changes induced by winter. We control for the centered term of the logarithm of the household income. We add the interactions between the dummy variables $Heating_{ijt}$, $Winter_{it}$, and $Income_{it}$ to identify the changes in medical expenses due to different heating energy choices during the winter months regarding different incomes. The estimator β_{3j} and β_{5j} (j = 1, …, 5) together reflect the increase in medical expenses induced by district heating, biomass, coal combustion, natural gas, or electricity consumption. We include household fixed effect γ_i to control for baseline differences across households and month fixed effects δ_t to control for seasonal patterns and other time fluctuations. To address the sharp shock of the Chinese Lunar Year month, we do not include the data from February in the baseline regressions.

2.5. Marginal treatment effect model

This study employs a marginal treatment effect model to estimate the costs and benefits of the clean energy transition. The framework is based on a Generalized Roy Model to include both observed and unobserved parts of the treatment. Define Y as the outcome variable, which is either energy or medical expense increase in the winter months relative to the non-winter months. The outcome equation of household expenses on fuels or medical issues can be expressed as equation (3):

$$Y_D = X\beta_D + V_D \tag{3}$$

where D equals 1 when clean energy is used as the primary energy source, otherwise the value of D is 0; Y_1 denotes energy expense when clean energy is used as the primary energy source, and Y_o denotes energy/medical expenses when dirty energy is used. Then the observable response, namely the outcome variable, can be expressed as equation (4):

$$Y = DY_1 + (1-D)Y_0 = Y_0 + D(Y_1 - Y_0) \tag{4}$$

The choice of major energy source D depends on the selection equation (5):

$$D = \begin{cases} 1, D^* > 0 \\ 0, otherwise \end{cases} \tag{5}$$

Each household's propensity to use clean energy depends on the net benefit from the treatment D^* as described by equation (6):

$$D^* = Z\delta - V_D \tag{6}$$

where Z is a vector of household characteristics, including all or a subset of the covariates in X, other variables not included in X but may influence the benefit and cost of treatment, as well as the instrument variable. V_D is a random error term induced by unobservable household characteristics, which represents the unwillingness to use clean energy as their heating energy choice. Clean energy is used by one household when $Z\delta \geq V_D$. Otherwise, dirty energy is used when $Z\delta < V_D$.

The marginal treatment effect is the treatment effect associated with individuals who are indifferent between treatment and no treatment, which is conditional on the covariates X and unobserved utility V_D as equation (7).

$$MTE\ (\ x, u_D\ ) = E(Y_1 - Y_0 | X = x, V_D = v_D) \tag{7}$$

Based on a transformation on the unobserved V_D by $U_D\ = F_{V|X}(V)$, in which $U_D \sim Unif[0,1]$, the marginal treatment effect can be decomposed into two parts as equation (8):

$$MTE\ (\ x, u_D\ ) = E(Y_1 - Y_0 | X = x, U_D = u_D) \tag{8}$$

where $X = x$ represents household characteristics, $U_D = u_D$ denotes the quantile distribution of the unobserved V_D. The MTE can be understood as the observable treatment effect relevant to household characteristics x, plus an unobserved part relevant to its utility quantile u_D, which is related to its propensity to be treated. Assuming the propensity score as $P(Z)\ = \Pr\ (D|Z)$, the observable outcome Y in equation (4) can be rewritten as equation (9):

$$\begin{aligned} &\mathrm{E}(Y|X = x, P(Z) = p) = \mathrm{E}(Y_0 + (Y_1 - Y_0)D | X = x, P(Z) = p) \\ &= \mathrm{E}(Y_0|X = x) + \mathrm{E}(Y_1 - Y_0 | X = x, D = 1)\ Pr(D = 1|Z = z) \\ &= \mathrm{E}(Y_0|X = x) + \int_o^p E(Y_1 - Y_0|X = x, U_D = u_D) du_D \end{aligned} \tag{9}$$

Then the MTE in equation (8) can be estimated as the partial derivative of the above expression with respect to p evaluated at $p = u_D$ as equation (10), which can be conducted through polynomial estimation or semi-parametric estimation.

$$MTE(x,p) = \frac{\partial E(Y|\ X = x, P(Z) = p\ )}{\partial p} = X(\beta_1 - \beta_0) + \frac{\partial K(p)}{\partial P} \tag{10}$$

With relevant weights calculated, the MTE can be used to estimate a variety of other treatment effects, including the average treatment effect (ATE), the average treatment effect on the treated (ATT), and the average treatment effect on the untreated (ATUT).

3. Results

3.1. Baseline estimates on health impacts of winter heating

This quasi-experimental study employs a DID method to evaluate causal relationships between heat energy types and their health impact. In line with previous literature [1,2], we categorize households into different groups according to their heating methods (Fig. 2), including: the bench mark group without any heating services; three clean energy groups, i.e., the district supply group, the gaseous fuels group, and the electricity consumption group; and, two dirty energy groups, i.e., the biomass group and the coal combustion group. We do not include households using other fuels, as such samples are very limited. The households with no heating are selected as the benchmark group as we assume that these households typically do not require the use of winter heating, either due to residing in a warmer area or having superior housing conditions that are capable of providing adequate insulation. The treatment period is the heating season, which usually ranges from early-November to mid/late-March of the following year. Then we employ the DID strategy to compare the differences in "differences in medical expenses between the treatment groups and the control group" in winter and non-winter months. This quasi-experimental approach sets the stage for examining the health impacts of different heating choices.

For the causality identification to be valid, the trends of the treatment groups and the control groups should be parallel before the treatment time, i.e., the "parallel trend hypothesis" [28]. To rule out potential endogeneity between medical expenses and heating preferences, the relative medical expenses—a variation from average medical expenses—are compared rather than absolute medical expenses. Fig. 3 shows plots of medical expense variations relative to their monthly averages. Fig. 3a shows monthly medical expenses are close to their averages for each heating-type group during non-winter months. The gaps between different heating types are not statistically significant during these non-winter months. However, the gaps become larger during the heating season, indicating varying impacts on health status arising from different heating choices. The coal combustion group experienced the greatest medical expense increase, while the no heating and gas-use groups experienced the least medical expense increase. Fig. 3b–g illustrate the medical expense changes for various medical sub-categories, including medicine, health products, medical devices, health care devices, outpatient expenditures, and inpatient expenditures. Fig. 3b and f shows that the gaps between different heating groups become larger during the heating season for medicine expenses and outpatient expenditures. These two sub-categories are closely related to immediate health status changes. Fig. 3c, d, and e show gaps fluctuate for health products, medical devices, and health care devices. These sub-categories are less likely to be affected by heating energy choice in the short-term.

Fig. 4 summarizes our results using a log-linear DID model. Fig. 4a plots the DID estimators, reflecting the differences in medical cost increases for different heating groups during winter months. We find that all other heating choices lead to higher overall medical costs as well as higher expenditures on medicine, outpatient expenditure, and inpatient expenditures when compared to the benchmark group. The cross-group differences are particularly conspicuous for medicine and outpatient expenditures, which is congruent with the intuition that such medical outlays are reflective of short-term health conditions. On the contrary, the impacts of winter heating on health products and nutrients, medical devices, and health care devices are not statistically significant, which means that these medical costs are less likely to be influenced by winter heating-related air pollution. By comparing various heating choices, we find that households depending on gas and electricity for winter heating—two typical energy sources regarded clean for health—are associated with a lower medical increase. The results show that the relative total medical expense increase from winter heating can be as much as 22.1 % for the coal combustion group, 18.9 % for the district heating group, 13.3 % for the biomass heating group, 10.0 % for the natural gas heating group; and 12.1 % for electricity heating group. In order to account for regional variations in climate and energy sources, differences in households heating needs, as well as the well-documented disparity in winter outdoor air pollution between northern and southern China [3] (Fig. S2), we further conduct the DID estimations using observations from northern Chinese provinces (Fig. 4b). In northern China, the impact of outdoor pollution caused by district heating supply can be considered homogeneous across all households. The results show significantly higher medical expenses for the biomass group and the coal combustion group compared to the benchmark, and significantly lower medical expenses for the electricity consumption group. Compared to coal or biomass, the application of clean energies is associated with less medical cost increases during the winter months, indicating that transition to clean energy can substantially lead to health benefits.

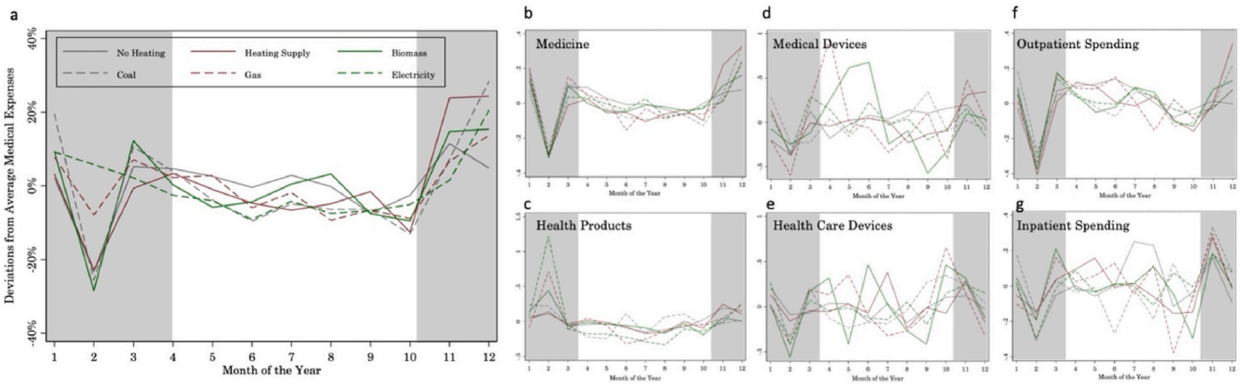

Fig. 3. | Fluctuations of medical expenses under different heating energy sources. The grey area represents the winter heating season. **a**, Medical expense fluctuations relative to monthly medical expense averages. **b**, Medicine spending fluctuations relative to monthly medicine spending averages. **c**, Health products expense fluctuations relative to monthly expense averages. **d**, Medical devices expense fluctuations relative to monthly averages. **e**, Health care devices expense fluctuations relative to monthly averages. **f**, Outpatient spending fluctuations relative to monthly averages. **g**, Inpatient spending fluctuations relative to monthly averages.

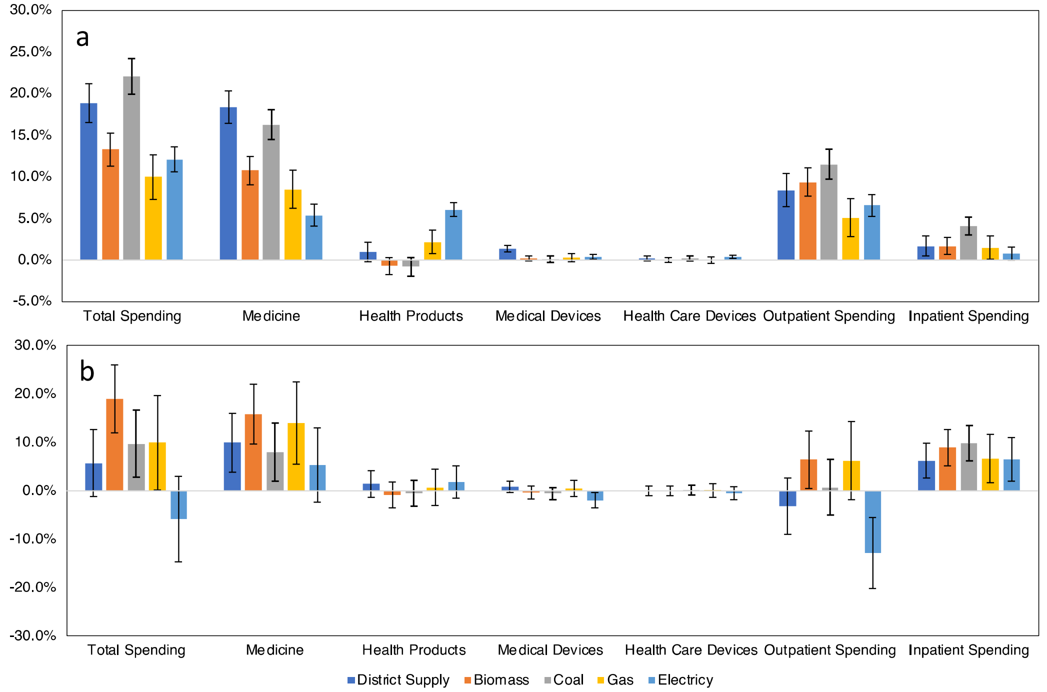

Fig. 4. | Economic impacts from different heating types in the winter months. The error bars represent the standard errors. **a**. The impact of heating energy on medical expenses estimated using the samples from all regions. **b**. The impact of heating energy on medical expenses estimated only using samples from northern Chinese provinces.

3.2. Sensitivity analysis

There are huge income disparities among households in China. Household income can result in different heating energy choices and medical expenditures. To further investigate some nuances, we introduce an alternative model, which adds an interaction term considering both winter heating choices and household income. To reflect response heterogeneity to winter heating we estimate the intercepts and slopes for various heating groups across household income levels.

Fig. 5 illustrates the results of alternative winter heating energy choices across household income levels. Specifically, Fig. 3a plots the estimated medical expense changes of households at different income levels due to winter heating. In Fig. 5a, the vertical axis

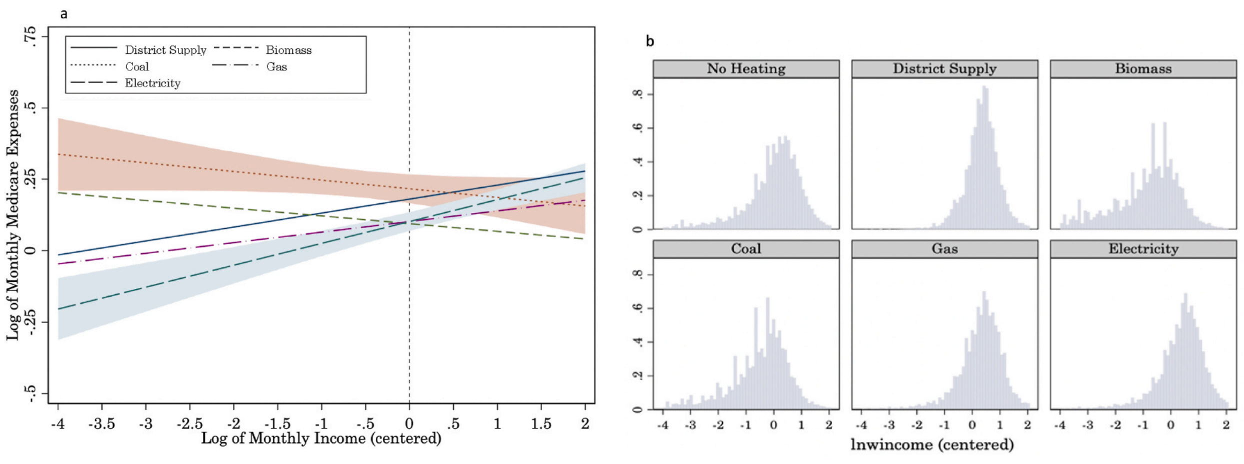

Fig. 5. | The impacts on medical expenses across household income levels from various winter heating energy alternatives. a, The heterogeneous impact of winter heating on medical expenses across income levels. The shaded area represents the 95 % confidence intervals of model estimates, in which the electricity group is shaded green and the coal group is shaded sand. b, Households distributions across different income levels for each winter heating group—including no heating, district heating, biomass, coal, gas, and electricity. 3.3 Forecasting the Clean Energy Transition.

represents the percentage changes in medical care expenditures relative to the benchmark group, and the horizontal axis represents the normalized income, which is calculated as the logarithm of the ratio between household income and average income of the population. The intercepts of various response functions and the vertical dashed line, where the normalized income equals 0, represent the average effects of various winter heating options at the average income level. These intercepts confirm our previous estimation results, which are shown in Fig. 4a. From the slopes of the curves in Fig. 5a, we can observe the heterogeneity of the impacts of winter heating choices on household medical expenses vary with household income changes. Fig. 5a shows that a 1 % change in household income is related to a further medical expense increase of 0.048 % for the district heat group, 0.037 % for the natural gas group, and 0.077 % for the electricity use group, and a decrease of −0.027 % for the biomass group, −0.030 % for the coal combustion group. The steepest relationships occur for the electricity heating households (shaded green), whose medical expenses increase with income even faster than other heating types because these families are usually wealthier than other groups. The distribution of the normalized income for each heating group is shown in Fig. 5b. Additional robustness tests are summarized in Figs. S4 and S5. These models confirm how energy adoption influences the variation of medical costs.

Despite the great efforts on clean energy transition, electricity consumption in the Chinese residential sector did not exceed coal usage until 2018 [29]. The Chinese government has released its *Clean Energy Strategy* as an effort to mitigate air pollution from burning coal and solid biomass. The strategy aims to increase the fraction of clean heating to 70 % by 2021 [30]. The "Planning of Winter Clean Heating in North China" was proposed in 2017 b y the Ministry of Ecology and Environment of China [31], followed by a particular focus on the "2 + 26" cities in the north China region (specifically in the Beijing-Tianjin-Hebei region) [32]. A key component of this clean energy strategy is to replace traditional household coal-fired stoves by wall-mounted natural gas heaters or electric stoves—these efforts have been termed *coal-to-gas* and *coal-to-electricity* transitions [10]. Previous studies of these residential energy transition processes confirmed ambient air quality improvements and health benefits using exposure-response functions [14,17,33]. Nevertheless, it is still essential to evaluate the costs and benefits using high-quality survey data to facilitate formulating policies in larger scopes.

In this study we estimated the health benefits and relative energy costs of the clean energy policy using the MTE analysis. In this section the outcome variables include the change of household medical expense (benefits) or the change of household energy expense (costs) from a shift to clean energy. In the regressions, we control household characteristics, including householder's age and age square, education level, work status, disposable income, family size, the share of children and elders in each family, room area, urban or rural residential status. County-level coal popularity, electricity popularity, and heating days are also included as instrument variables for the treatment variable (Fig. S2). To forecast the impact of the clean energy transition strategy, we drop the cases that adopt no winter heating and classify the remaining heating types into either clean energy sources or dirty energy sources based on a classification of heating fuels [24,25]. For households using dispersed coal or biomass for winter heating, the choice variable is set to 0; for households using district heating supply, natural gas, or electricity for winter heating, the choice variable is set to 1. First, we use a latent variable discrete choice model to represent the household's decision to adopt clean heating, which depends on both observed and unobserved household characteristics (see *method*). Then, we assess the heterogeneous treatment effect for households with different unobserved resistance to accept the policy treatment [34–38].

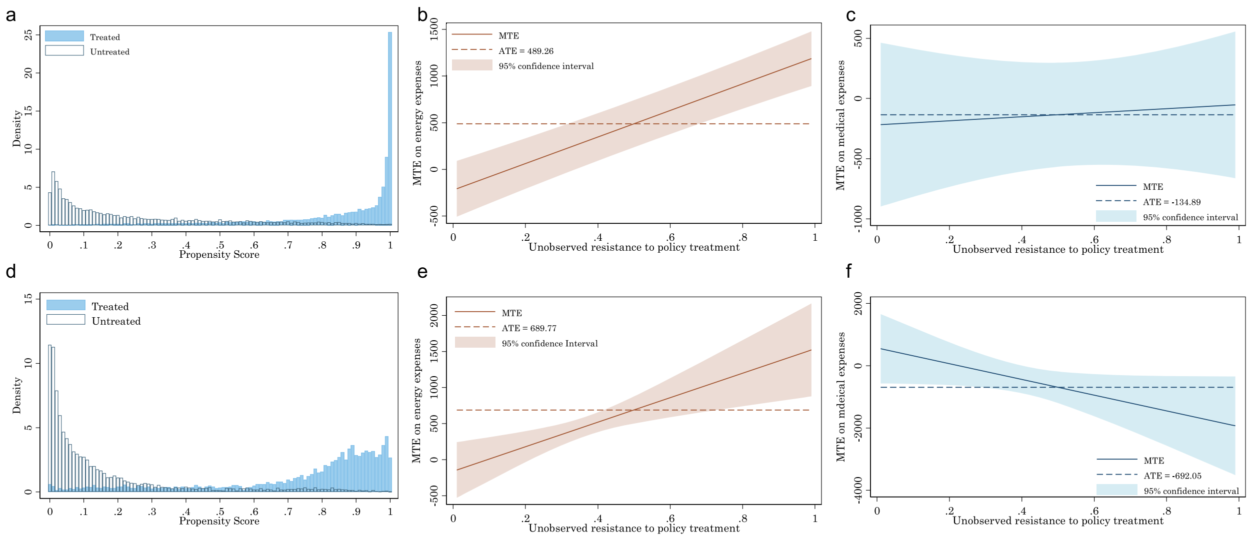

Fig. 6. | Marginal treatment effects for clean energy transition. The solid lines represent the marginal treatment effects. The dashed lines represent the average treatment effect estimated by a weighted average of the marginal treatment effects. The shaded areas represent the 95 % confidence interval, based on bootstrapped standard errors (100 replications). **a**, **d** Distribution of propensity scores for both the treated (clean energy group) and untreated (polluting energy group) households in all provinces and northern provinces, respectively. **b**, **e** The impact of clean energy transition on winter energy expenses in all provinces and northern provinces, respectively. **c**, **f** The impact of the clean energy transition on extra monthly medical expense during the winter season in all provinces and northern provinces, respectively.

Fig. 6 illustrates MTEs of adopting clean energy for winter heating. The distribution of propensity scores for both treated and untreated groups, namely the clean energy and dirty energy groups, is presented in Fig. 6a, d. The overlapping regions span almost the unit interval, suggesting that the common support area identified by controlled and the instrument variables are sufficient to estimate the MTE. The MTE estimates of energy expenses based on polynomial estimation are displayed in Fig. 6b, e. The y-axes denote the values of MTEs, while the x-axes represent the unobserved components of the treatment choices, i.e., u_D in the method section. A higher x-value implies greater resistance to clean energy. The results show that adopting clean energy for winter heating would increase energy costs by 489.26 and 689.77 yuan for an average Chinese household and a family in northern provinces, respectively. Notably, the incorporation of clean energy in winter heating systems can result in considerable reductions in associated winter medical costs for both the average Chinese household and a family living in northern provinces. These reductions amount to 134.89 and 692.05 yuan, respectively, when five months are assumed as winter months, as shown in Fig. 6c, f. Thus, the direct health benefits are significant enough to offset the higher energy costs in northern China. Improved health status can also yield long-term benefits, including lower gross medical expenses, prevention of premature death, and increased healthy labor supply, although these benefits may not be immediately reflected in short-term medical cost reductions. It is worth noting that upward slopes have been found in Fig. 6b, e while downward slopes have been found in Fig. 6f. This suggests that households that are disinclined to use clean heating, which usually comprise the disadvantaged population with tighter budget set or less awareness [38], would face a clean energy dilemma. While they will have to bear higher transition costs, they also benefit more from such clean energy transition. Although current poverty eradication policies tend to focus on improving the welfare of the disadvantaged households, additional subsidies are still required to "nudge" them to enjoy the benefits of clean energy transition.

4. Conclusions and discussions

Previous studies found that various household heating sources can result in different health outcomes. But few studies could test the causality due to the lack of natural experiments or randomized controlled trials. This study uses monthly updated nationwide household survey data, with information on energy consumption, medical expenses, and socio-economic variables. This panel dataset can facilitate measurement of both health and economic impacts across winter heating energy sources, especially during periods of clean energy transition contexts. The results show that medical expenses can be avoided by replacing biomass or household coal source heating with clean energy and electricity heat sources. The direct health benefits resulting from the clean energy transition are significant enough to outweigh the associated energy costs in northern provinces, where winter household heating is unavoidable and high levels of health damage can be linked to winter heating pollution [7].

Our results underline the importance of clean energy transition and provide valuable implications for policy makers. First, although higher energy costs are considered a barrier to clean energy strategy household adoption, our findings suggest that we can be more optimistic about this. Converting to clean energy is beneficial for both immediate and long-term health advantages and such benefits can be large enough to counterbalance the aggregate transition costs. In this regard, it is essential for the Chinese governments to recognize the economic advantages of subsidizing the transition to clean energy. By aiding poor households in adopting clean energy, the Chinese governments can reduce the overall expenditure in public health, which could further lead to long term public health benefits. Thus, it is urgent to facilitate such energy transition by providing more financial subsides. Second, our study points to a critical dilemma: worse-off families might enjoy the largest health benefits from the clean energy transition although they would face the highest economic burdens. Minimal financial resources, limited awareness, as well as many other unobservable characteristics may result in that they are reluctant to adopt clean energy choices. Therefore, it is necessary for the Chinese governments at different levels to provide additional subsidies to support low-income households so that they can benefit from such a clean energy transition. For instance, we recommend low-interest loans or microfinancing options to support these poor households to transit to clean energy. We also recommend the Chinese governments to initiate different public awareness capacity-building efforts so that more households can realize such significant health and long-term financial benefits. Third, our study shows that SDGs such as "*Affordable and Clean Energy*" and "*Good Health and Well-being*" can be achieved simultaneously. However, different stakeholders should work together, especially between public and private sectors. For example, the Chinese government may directly provide subsides to private energy companies so that clean heating infrastructure is available to poor households. During this process, a careful monitoring mechanism should be created so that such funds can be fully used for public goods.

Several research limitations exist in this study. Although our study uses a large-scale household survey dataset, not all Chinese provinces are included. Thus, a more complete Chinese picture cannot be presented. Consequently, it will be necessary to collect more data from other Chinese provinces—and even from other developing countries—to achieve broader insights for policy makers. Another limitation is the marginal treatment effect model used in this study. This model can only estimate the binary transition from dirty energy to clean energy. This limitation emphasizes the need to extend this econometric model so that the marginal costs and benefits between two clean heating energy choices can be accurately estimated.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Meng Li: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yong Geng:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Shaojie Zhou:** Data curation. **Joseph Sarkis:** Writing – original draft, Validation.

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.

Acknowledgements

We gratefully acknowledge funding support by the National Natural Science Foundation of China (72204159, 72088101, 71810107001).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e21250.

References

[1] Q. Zhang, K. He, H. Huo, Cleaning China's air, Nature 484 (2012) 161–162.
[2] J. Liu, D.L. Mauzerall, C. Qi, Z. Qiang, T. Zhu, Air pollutant emissions from Chinese households: a major and underappreciated ambient pollution source, Proc. Natl. Acad. Sci. USA 113 (2016) 7756–7761.
[3] B. Zhao, et al., Change in household fuels dominates the decrease in PM2.5 exposure and premature mortality in China in 2005–2015, Proc. Natl. Acad. Sci. USA 115 (2018).
[4] G. Shen, M. Ru, W. Du, X. Zhu, S. Tao, Impacts of air pollutants from rural Chinese households under the rapid residential energy transition, Nat. Commun. 10 (2019) 1–8.
[5] J. Lelieveld, J.S. Evans, M. Fnais, D. Giannadaki, A. Pozzer, The contribution of outdoor air pollution sources to premature mortality on a global scale, Nature 525 (2015) 367–371.
[6] S. Archer-Nicholls, et al., The regional impacts of cooking and heating emissions on ambient air quality and disease burden in China, Environ. Sci. Technol. 50 (2016) 9416.
[7] A. Ebenstein, M. Fan, M. Greenstone, G. He, M. Zhou, New evidence on the impact of sustained exposure to air pollution on life expectancy from Chinas Huai River Policy, Proc. Natl. Acad. Sci. USA 114 (2017) 10384–10389.
[8] IEA, World Energy Outlook 2020, 2020.
[9] CREA, Quantifying the Economic Costs of Air Pollution from Fossil Fuels, 2018.
[10] S. Wang, et al., Natural gas shortages during the "coal-to-gas" transition in China have caused a large redistribution of air pollution in winter 2017, Proc. Natl. Acad. Sci. USA 117 (2020) 31018–31025.
[11] C. Barrington-Leigh, J. Baumgartner, E. Carter, B.E. Robinson, S. Tao, Y. Zhang, An evaluation of air quality, home heating and well-being under Beijing's programme to eliminate household coal use, Nat. Energy 4 (2019) 416–423.
[12] A.J. Cohen, et al., Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015, Lancet 389 (2017) 1907–1918.
[13] K. Aunan, Q. Ma, M.T. Lund, S. Wang, Population-weighted exposure to $PM_{2.5}$ pollution in China: an integrated approach, Environ. Int. 120 (2018) 111–120.
[14] Q. Zhang, et al., Drivers of improved $PM_{2.5}$ air quality in China from 2013 to 2017, Proc. Natl. Acad. Sci. USA 116 (2019) 24463–24469.
[15] X. Zhang, Y. Jin, H. Dai, Y. Xie, S. Zhang, Health and economic benefits of cleaner residential heating in the Beijing–Tianjin–Hebei region in China, Energy Pol. 127 (2019) 165–178.
[16] W. Meng, et al., Energy and air pollution benefits of household fuel policies in northern China, Proc. Natl. Acad. Sci. USA 116 (2019) 16773–16780.
[17] B. Zhao, et al., Health benefits and costs of clean heating renovation: an integrated assessment in a major Chinese city, Environ. Sci. Technol. 55 (2021) 10046–10055.
[18] WHO, Evaluation of the Costs and Benefits of Household Energy and Health Interventions at Global and Regional Levels: Summary, 2006.
[19] H.E. Staff Mestl, K. Aunan, H.M. Seip, Potential health benefit of reducing household solid fuel use in Shanxi province, China, Sci. Total Environ. 372 (2006) 120–132.
[20] WHO, Burden of Disease from Household Air Pollution for 2016, 2018.
[21] WHO, Exposure to Household Air Pollution for 2016, 2018.
[22] WHO, Household Air Pollution and Health, 2014.
[23] Cameron, et al., Policy trade-offs between climate mitigation and clean cook-stove access in South Asia, Nat. Energy 1 (2016), 15010.
[24] IEA, World Energy Balance Highlights 2021, 2021.
[25] S. Pachauri, M. Poblete-Cazenave, A. Aktas, M. Gidden, Access to clean cooking services in energy and emission scenarios after COVID-19, Nat. Energy 6 (2021) 1067–1076.
[26] E. Carter, et al., Household transitions to clean energy in a multiprovincial cohort study in China, Nat. Sustain. 3 (2020) 42–50.
[27] United Nations, Transforming Our World: the 2030 Agenda for Sustainable Development, 2021.
[28] D. Card, A.B. Krueger, Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania, Am. Econ. Rev. 84 (1994) 772–793.
[29] National Bureau of Statistics of China, N. B, National Statistical Yearbook 2019, 2019.
[30] National Development and Reform Commission of China, Work Plan for Clean Heating in Winter in Northern China 2017–2021, 2017.
[31] Ministry Of Environmental Protection of China, Planning of Winter Clean Heating in North China, 2017.
[32] Ministry Of Environmental Protection of China, Work Plan for Air Pollution Control in Beijing-Tianjin-Hebei and its Surrounding Areas in 2017, 2017.
[33] S. Tao, et al., Quantifying the rural residential energy transition in China from 1992 to 2012 through a representative national survey, Nat. Energy 3 (2018) 567–573.
[34] J.J. Heckman, E.J. Vytlacil, Local instrumental variables and latent variable models for identifying and bounding treatment effects, Proc. Natl. Acad. Sci. USA 96 (1999) 4730–4734.
[35] J.J. Heckman, E.J. Vytlacil, Structural equations, treatment effects, and econometric policy evaluation, Econometrica 73 (2005) 669–738.

[36] J.J. Heckman, E.J. Vytlacil, Chap. Econometric Evaluation of Social Programs, Part I: Causal Models, Structural Models and Econometric Policy Evaluation, 2017.

[37] T. Cornelissen, C. Dustmann, A. Raute, U. Schönberg, Who benefits from universal child care? Estimating marginal returns to early child care attendance, J. Polit. Econ. 126 (2018) 2356–2409.

[38] M. Li, T. Jin, S. Liu, S. Zhou, The cost of clean energy transition in rural China: evidence based on marginal treatment effects, Energy Econ. 97 (2021), 105167.