FROM CLEAN ENERGY TO CLEAN AIR: ASSESSING THE HEALTH OUTCOMES OF NORTHERN CHINA'S CLEAN ENERGY INITIATIVES

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(Received 27th Jul 2025; accepted 21st Oct 2025)

Abstract. In many developing countries with low clean energy coverage, environmental pollution significantly impacts residents' health. Using data from the China Health and Retirement Longitudinal Study (CHARLS), this study employs a difference-in-differences approach to evaluate the effects of the "Clean Heating Plan for Winter in Northern China (2017–2021)" on respiratory and mental health outcomes. The findings indicate a substantial reduction in the prevalence of chronic lung diseases and depression, with women benefiting more markedly, likely due to their greater exposure to indoor air pollution from household activities. To ensure robustness, various tests were conducted, including adjustments to clustering methods, sample exclusion, and alternative measures for physical and mental health variables. Additionally, mechanism analysis suggests that improved air quality (as reflected in decreased $PM_{2.5}$ concentration and AQI levels) is a critical factor in health improvement. These findings provide empirical support for policies promoting energy transitions to enhance public well-being and underscore the essential role of clean energy initiatives in advancing public health.
Keywords: *clean heating, energy transition, respiratory diseases, mental health*

Introduction

The heavy reliance on traditional energy sources, particularly firewood, coal, and fossil fuels such as gasoline or diesel, has led to the release of significant quantities of particulate matter (PM) and ground-level ozone. These pollutants are major contributors to severe air pollution, which is widely recognized as a critical factor in global health problems and mortality (Apte et al., 2015; Dedoussi and Barrett, 2014). Coal alone contributes around 85% of global carbon dioxide emissions and is a primary source of PM2.5 pollution, accounting for up to 40% of such emissions (Jacobson and Delucchi, 2011; Smith et al., 2009). The health effects of this pollution are profound. Prolonged exposure to fine particulate matter (PM2.5) and nitrogen dioxide (NO2) has been linked to various illnesses, including acute lower respiratory infections (Burnett et al., 2014; Wang et al., 2023). Over time, these pollutants induce inflammation and oxidative stress, impairing lung function, accelerating airway damage, and exacerbating chronic conditions (Burney and Amaral, 2019; Xu et al., 2024).

Studies reveal that every 5 μg/m³ increase in PM2.5 is associated with a 31% higher risk of developing chronic obstructive pulmonary disease (COPD), with a hazard ratio of 1.31 (95% CI: 1.22–1.42) (Liu et al., 2021; Wang et al., 2023). Beyond physical health impacts, air pollution also adversely affects mental well-being. For instance, studies found a significant correlation between elevated levels of PM10, NO2, and O3 and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

increased depressive symptoms among the elderly population in South Korea (Lim et al., 2012). The economic ramifications of air pollution are substantial, particularly in developing countries. In Mumbai of India, a 50 μg/m³ rise in PM10 concentration associated with an estimated economic loss of $113.08 million, primarily due to increased out-of-pocket healthcare costs among low-income households (Patankar and Trivedi, 2011).

China stands out as a major consumer of traditional energy sources. According to the International Energy Agency (IEA), in 2022 China consumed approximately 5.4 billion tons of coal, accounting for over 50% of global coal consumption. Additionally, China's fossil fuel consumption ranks among the highest worldwide, comprising about 26% of global energy use. These figures underscore China's heavy reliance on traditional energy sources that degrade air quality. For example, Fan et al. (2020) demonstrate through a regression discontinuity design that coal heating during winter in northern China significantly increases air pollution levels—resulting in a 36% rise in the Air Quality Index (AQI) and a 14% increase in winter mortality rates. Further subnational study by Chu et al. (2023) also corroborate this relationship: in Shanxi Province—China's largest coal producer—the correlation coefficient between coal consumption and average PM2.5 concentrations from 2010 to 2020 was as high as 0.88. Similarly, in Beijing, the correlation reached 0.81, indicating a consistent trend.

In rural China, reliance on traditional fuels for daily life poses an additional threat to air quality. For instance, households in Yunnan, Guangdong Province that use biomass fuels for cooking exhibit significantly higher indoor concentrations of sulfur dioxide and PM10 compared to urban households (Song et al., 2014). Air pollution—encompassing both gases and particulate matter—has been consistently linked to respiratory diseases (Guan et al., 2016; He et al., 2020). Furthermore, research suggests that its effects extend to mental health. For example, Wei et al. (2022) find a strong connection between environmental air pollution exposure and increased depression rates in China.

Nationwide surveys indicate that winter heating constitutes nearly 50% of household energy consumption in China (National Bureau of Statistics of China, 2020). In urban areas, homes typically rely on electricity or natural gas, however, rural regions, especially those lacking centralized heating infrastructure, often depend on traditional fuels like coal and wood for winter heating. Approximately 60% of rural households utilize these high-emission fuels, with residential heating and industrial furnaces significantly contributing to $PM_{2.5}$ and hazardous gas emissions (World Energy Outlook, 2019). Moreover, inadequate ventilation during solid fuel combustion often results in smoke backflow that worsens indoor air quality and elevates the risk of respiratory and cardiovascular diseases (Shen et al., 2019). Despite the introduction of improved combustion devices in some areas, their effectiveness has been limited in substantially reducing pollution levels. As a result, the widespread use of loose coal for heating in northern China during the winter has become a focal point and a major challenge for air pollution control efforts(Xiao et al., 2015).

In response to these challenges, the Chinese government has prioritized air pollution control through various policies aimed at promoting energy transition and improving air quality. Among these initiatives is the Clean Heating Plan for Northern China (2017–2021), designed to encourage transition from coal-based heating to cleaner alternatives, such as natural gas and electricity. The plan set ambitious targets for clean heating adoption, aiming for a 50% clean heating rate by 2019 and 70% by 2021 across northern

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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China. In key cities identified as "2 + 26"[1], the plan aimed for 90% clean heating by 2019 and 100% by 2021. Existing research has primarily focused on the policy's impact on mortality rates; for example, (Meng et al., 2023) reported a 32% reduction in premature deaths due to residential emissions while using the Global Exposure Mortality Model (GEMM), found that approximately 82% of avoided deaths occurred in rural regions.

Despite these valuable insights into the policy's effects on air pollution and economic costs, significant gaps remain regarding its impact on specific respiratory diseases and mental health outcomes. This study aims to provide a comprehensive assessment of the long-term public health effects of the Clean Heating Plan and to offer empirical evidence that can inform the design of more health-oriented energy and environmental policies in China.

Our findings reveal three key insights: First, pilot cities have seen a significant decrease in the use of non-clean energy sources such as coal and crop residue alongside an increase in clean energy sources like natural gas and electricity. This shift has led to notable reductions in air pollution levels and corresponding decreases in chronic lung diseases and depression among middle-aged and elderly populations—particularly impacting mental health positively. Second, heterogeneity analysis indicates that women benefit more substantially from the clean heating policy than men. Finally, our study provides a comprehensive assessment of the long-term health benefits associated with transitioning to clean energy, offering valuable insights for policymakers seeking to optimize energy policies while enhancing public health outcomes. By addressing these critical issues, our research not only fills a gap in the literature but also lays a foundation for developing more effective health-oriented energy policies.

Materials and methods

Clean heating plan

In northern China, severe winter air pollution is largely attributed to the extensive use of coal for residential heating and industrial furnaces, especially in rural areas. Coal combustion remains a key obstacle to improving regional air quality. By the end of 2016, the total heating area reached about 206 billion square meters—141 billion in urban areas and 65 billion in rural areas. Among them, natural gas and electric heating covered roughly 22 and 4 billion square meters (11% and 2%), clean coal–based district heating about 35 billion square meters (17%), and geothermal, biomass, solar, and waste heat sources about 8 billion square meters (4%). Overall, clean heating accounted for approximately 34% of the total heating area in northern China. To address the challenge of clean heating, the Chinese government launched the "Northern China Winter Clean Heating Plan (2017-2021)" in 2017. The plan set a goal of achieving a 50% clean heating coverage rate in northern China by 2019. Specifically, pilot cities and towns were expected to exceed 90% coverage, while rural areas aimed for 40%. By 2021, the objective was to raise the clean heating rate in northern regions to 70%, with all cities adopting clean heating and rural areas reaching over 60%. The government implemented financial subsidies and incentive policies to facilitate this transition, allocating 17.4 billion RMB annually to pilot cities, and encouraging residents to shift from traditional coal heating to cleaner alternatives such as natural gas and electricity. Furthermore,

1 It includes Beijing and Tianjin along with 26 other cities in Hebei, Shanxi, Shandong, and Henan provinces.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

substantial investments were made in constructing and expanding natural gas pipelines and power grids, especially in rural and remote areas, to enhance the infrastructure necessary for clean heating (*Fig. 1*).

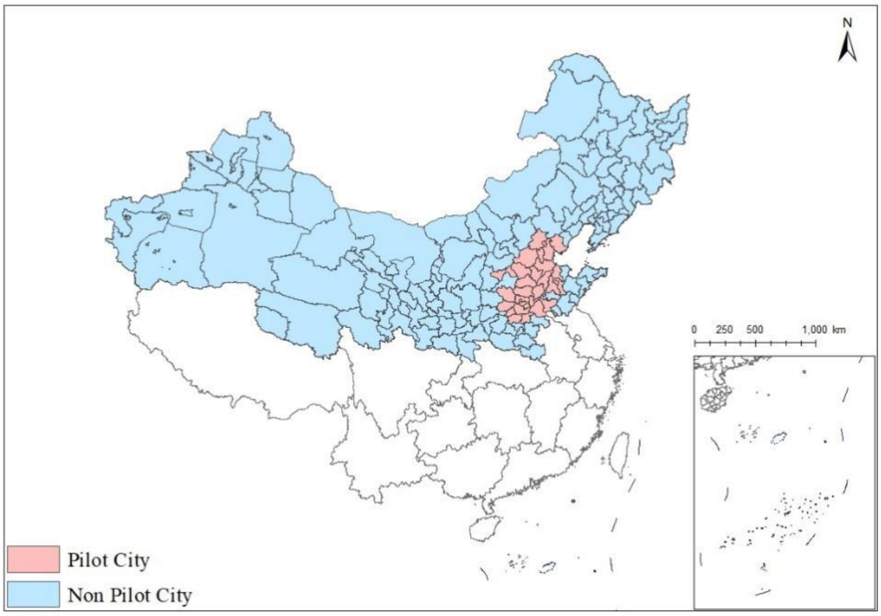

Figure 1. *Distribution map of "2 + 26" clean heating policy pilot cities*

Data and identification strategy

Individual data

This study utilizes individual data from the China Health and Retirement Longitudinal Study (CHARLS), conducted by Peking University, which targets Chinese individuals aged 45 and above. CHARLS is a nationally representative random sample survey of the middle-aged and elderly, primarily conducted during summer. The sample comprises over 10,000 households from 150 county-level units across 28 provinces. Our research mainly draws on 2011, 2013, 2015, 2018 and 2020 survey data. After these exclusions, the dataset comprises 10,683 individuals in the experimental group and 21,798 individuals in the control group.

The treatment group consists of respondents residing in the "2 + 26" pilot cities designated under the Northern China Winter Clean Heating Plan, where the clean heating policy was implemented beginning in 2017. The control group includes respondents from other northern regions that were not part of the pilot program. To ensure analytical validity and robustness, we restricted our sample to rural households without centralized heating in northern China, as these households make independent heating decisions directly influenced by policy changes. Urban households with centralized municipal heating systems, as well as households located south of the Qin ling–Huai he line, the climatic and policy boundary separating northern and southern China—were excluded. In southern regions, heating infrastructure is largely absent, and households seldom require heating due to the milder winter climate. This restriction ensures that the analysis captures the behavioral and health effects of household-level heating choices and policy interventions.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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Building on several energy-related studies, such as those conducted by Shi et al. (2023) and Fan et al. (2020), where similar control variables were employed, a consistent approach was adopted in our analysis to ensure comparability. Specifically, key personal characteristics were included as control variables, such as age, gender, years of education (used as a proxy for education level), marital status, and smoking status. In addition, household size and income were controlled, while per capita GDP and the proportion of secondary industry in GDP were included at the city level. Atmospheric height and wind speed were incorporated to account for weather-related factors. The primary dependent variables of interest in this study are respiratory diseases (including chronic lung disease) and psychological conditions (such as depression). Respondents were asked whether they had been diagnosed with any of these conditions, with responses coded as 1 for "yes" and 0 for "no" to facilitate statistical analysis. We assessed depressive symptoms using the 10-item Center for Epidemiologic Studies Depression Scale (CES-D-10) (Björgvinsson et al., 2013). This scale includes ten questions designed to capture the respondent's emotional state, physical symptoms, and optimistic mood during the past week. Respondents rated their psychological state using a 4-point Likert scale, with values ranging from 0 to 3. Of the ten items, eight were negative statements, scored from 0 (rarely) to 3 (most of the time). The remaining two items were positive statements, with scores reversed, from 3 (rarely) to 0 (most of the time). The total score could range from 0 to 30. A score of ≥ 10 indicates clinically relevant depressive symptoms, scores of ≥10 are coded as 1, while scores below 10 are coded as 0 (Andresen et al., 1994). These health outcomes constitute the central focus of the study.

Air pollution and other city-level data

Pollution data comes from the National Urban Air Quality Real-time Release Platform. In addition to air pollution data, we collected other city-level characteristics as controls in the main regressions. The data were mainly from the various years of Chinese City Statistical Yearbook, and the adopted variables included the logarithm of GDP per capita and the logarithm of secondary GDP.

Summary statistics

This study draws on longitudinal survey data collected from multiple provinces between 2011 and 2020, covering over 10,000 households. The data includes survey results from the years 2011, 2013, 2015, 2018 and 2020. We focus on individuals aged 45 and above, investigating their risk of developing respiratory diseases, such as chronic lung conditions, as well as mental health issues like depression. Descriptive statistics for the key outcomes and control variables are provided in *Table 1* (*Figs. 2* and *3*).

Dynamic analysis

The parallel trends assumption is a critical step in Difference-in-Differences (DID) analysis, as it verifies whether the treatment and control groups exhibited similar trends before the policy intervention. This assumption is essential for ensuring the validity of the DID estimation results. By plotting parallel trend graphs, we can visually assess whether the outcome variables for both groups followed similar paths before and after the policy implementation. If the trend lines for both groups are approximately parallel before the policy intervention, the parallel trend assumption is considered valid, thereby strengthening the credibility of the DID model results (Angrist and Pischke, 2008;

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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Rambachan and Roth, 2023). The graphs presented here illustrate the parallel trends for chronic lung diseases and depression, with data spanning five time points: 2011, 2013, 2015, 2018 and 2020, with 2017 marking the post-policy intervention period. The 2013 point has been omitted from the graphs, while the policy effects and their confidence intervals at other time points are displayed. By examining these trend lines, we can evaluate whether the parallel trends assumption holds before the policy implementation, thus validating the reliability of the DID estimates (*Fig. 4*).

Table 1. *Summary statistics*

Variables	N	Mean	SD	Min	Max
Main variables					
Clean heating	32,481	0.140	0.347	0	1
Chronic lung diseases	32,481	0.104	0.305	0	1
Depression	32,481	9.468	6.597	0	30
Main controls					
Years of schooling	32,481	7.694	4.387	0	19
Marital status (married = 1)	32,481	0.831	0.375	0	1
Household size	32,481	3.937	1.566	2	17
Gender (Female = 1)	32,481	0.517	0.500	0	1
Age	32,481	59.74	9.566	45	98
Smoke (yes = 1)	32,481	0.273	0.445	0	1
Ln (Household income) (yuan)	32,481	10.17	0.724	8.517	14.60
Ln (Secondary GDP)	32481	3.78	0.246	2.559	4.26
Ln (GDP per capita)	32,481	10.69	0.447	9.664	11.77
Air cleaner (yes = 1)	32481	0.148	0.355	0	1
Weather controls					
Wind speed (10 ms^{-1})	32,481	2.750	0.560	1.481	4.056
Boundary layer height	32,481	498.6	63.65	330.0	714.7
Air circulation index	32,481	1,397	431.1	489.1	2,707
Energy structure					
Coal	31939	0.460	0.500	0	1
LPG	31939	0.182	0.385	0	1
Electricity	31939	0.112	0.312	0	1
Natural Gas	31939	0.215	0.452	0	1
Solar	31939	0.030	0.170	0	1
Marsh Gas	31939	0.010	0.115	0	1
Air quality index					
AQI (ug/m^3)	177	93.75	25.77	43.77	172.17
$PM_{2.5}$ (ug/m^3)	213	53.36	20.17	9.556	121.5
PM_{10} (ug/m^3)	152	105.7	51.47	27.75	292.8
SO_2 (ug/m^3)	152	30.60	28.27	2.727	132.7
CO (ug/m^3)	152	1.106	0.539	0.480	4.035

APPLIED ECOLOGY AND ENVIRONMENTAL RESEARCH 23(6):11597-11618.
http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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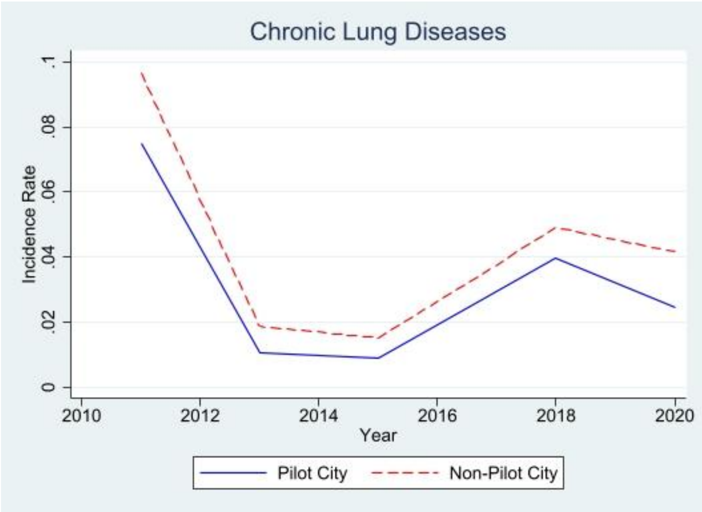

Figure 2. Incidence of chronic lung disease

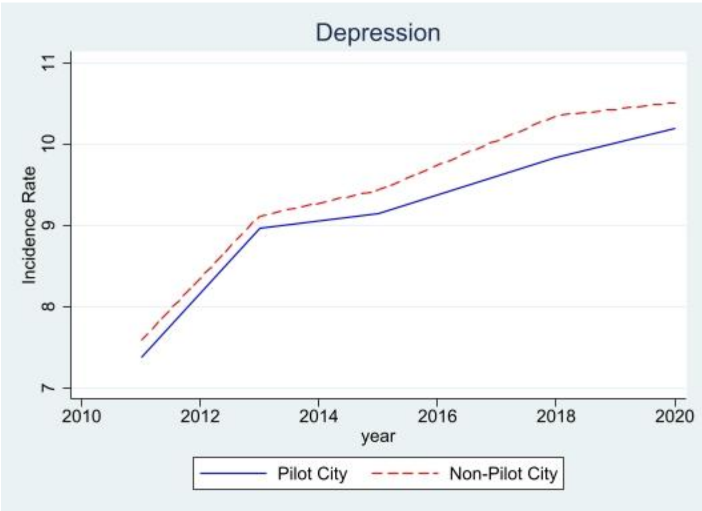

Figure 3. Mean score of the CES-D depression self-assessment scale

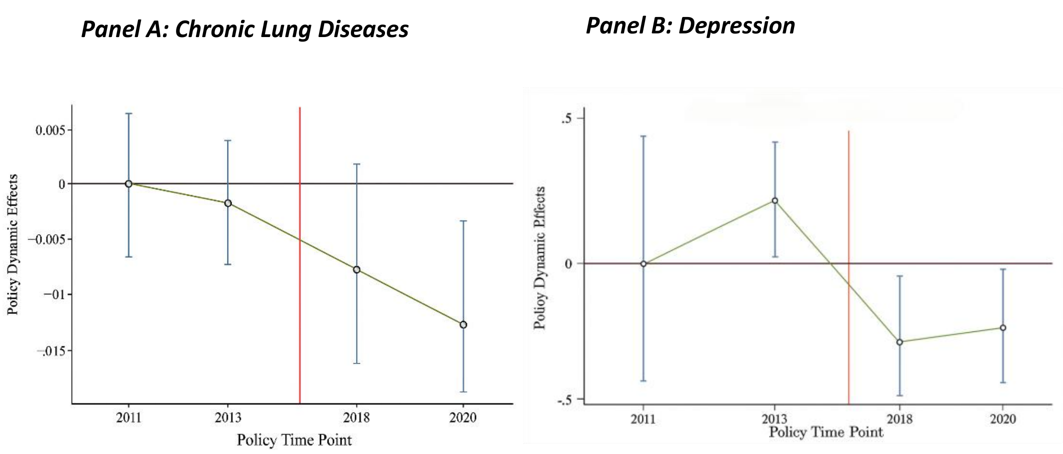

Figure 4. Parallel trend test

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DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

These two parallel trend graphs in *Figure 4* illustrate the dynamic analysis of chronic lung diseases and depression, respectively. The clean heating policy was implemented in 2017, but our data spans the years 2011, 2013, 2015, 2018 and 2020, resulting in a gap for the policy year itself. *Figure 1* shows a gradual decline in the effects of chronic lung diseases following the policy implementation, suggesting a potentially positive impact of the policy. In contrast, *Figure 2,* which represents depression, exhibits a more erratic pattern. Initially, there is an increase in effects, followed by a decline, indicating that the policy's impact on mental health may be more complex and less consistent compared to its effects on respiratory conditions.

Identification strategy

Following Barwick et al. (2019), we used the following model to examine the impact of pollution on both physical and mental health before and after the policy implementation:

$$Disease_{ijt} = \beta_0 + \beta_1 Clean\ Heating_{it} \times Policy_{jt} + \beta_2 X_{ijt} + \beta_3 M_{it} + \beta_4 N_{jt} + \beta_5 O_{jt} + \gamma_i + \sigma_p + \mu_t + \varepsilon_{ijt} \quad \text{(Eq.1)}$$

$Disease_{ijt}$ represents the respiratory disease status of individual i from city j in year t. The variable $Clean\ Heating_{it}$ is a dummy variable indicating whether the sample is from one of the "2 + 26" pilot cities, with 1 representing the pilot cities and 0 otherwise. The variable $Policy_{jt}$ indicates the start of the policy implementation in 2018 and 2020, coded as 1 for these years and 0 for others. Individual-level covariates X_{ijt} include gender, age, educational level, marital status, and smoking behavior, while household-level variables M_{it} comprise household income and household size. City-level factors N_{jt} encompass per capita GDP (log) and the proportion of secondary industry in GDP (log), and weather-related controls O_{jt} include wind speed at 10 meters and boundary layer height. Year, province, and individual fixed effects are represented by γ_i, σ_p and μ_t respectively, with ε_{ijt} capturing the error term.

Results

Baseline regressions

Table 2 presents a detailed summary of the baseline regression results, assessing the impact of clean heating on two health outcomes: chronic lung diseases and depression. The implementation of clean heating is strongly correlated with a significant reduction in the incidence of chronic lung diseases, with coefficients of -1.47 and -1.37 percentage points, both statistically significant at the 5% level. This reduction is likely attributable to the decrease in indoor air pollution following the transition to cleaner energy sources, which reduces exposure to harmful particulate matter known to aggravate respiratory conditions. Previous studies have demonstrated that indoor air pollution from traditional heating methods, such as coal combustion, significantly contributes to the development of chronic lung diseases. Thus, the shift to clean heating is likely to minimize the inhalation of these pollutants, resulting in improvements in respiratory health

Moreover, the implementation of clean heating policies is associated with a statistically significant reduction in depression rates, with an estimated coefficient of -0.3394 and -0.3293 at the 5% significance level. This result indicates that regions

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DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

adopting clean heating measures experienced a meaningful decline in the prevalence of depression, underscoring the potential mental health benefits of environmental interventions. This substantial impact may be explained by the overall improvement in living conditions that accompanies cleaner heating, as reduced air pollution has been linked to both physical and mental health improvements. Additionally, clean heating systems may alleviate stress associated with traditional heating methods, such as the physical strain of sourcing fuel and the associated financial burdens. Improved air quality may also enhance sleep quality and mood, contributing to the observed reduction in depression symptoms. These findings are consistent with a growing body of research suggesting environmental improvements (Zhang et al., 2017).

Table 2. *Baseline regressions*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Chronic lung diseases				Depression			
	OLS		Probit		OLS		Probit	
Clean heating	-0.0147** (0.0065)	-0.0137** (0.0066)	-0.1557*** (0.0300)	-0.0896*** (0.0321)	-0.3394** (0.1310)	-0.3293** (0.1334)	-0.0698*** (0.0229)	-0.0470* (0.0244)
Smoke		0.0136*** (0.0040)		-0.0040 (0.0251)		0.3113*** (0.0646)		0.1001*** (0.0191)
Education		-0.0122*** (0.0040)		0.0081 (0.0266)		0.0894 (0.0995)		-0.1331*** (0.0204)
Marriage		-0.0465 (0.0428)		-0.0946*** (0.0231)		-0.4295 (0.4738)		0.3850*** (0.0175)
Gender		-0.0004 (0.0019)		0.0197*** (0.0010)		0.0089 (0.0358)		0.0053*** (0.0008)
Age		-0.0013 (0.0011)		-0.0026 (0.0023)		0.1675*** (0.0248)		-0.0293*** (0.0018)
Ln household income		-0.0103** (0.0041)		-0.0660*** (0.0142)		0.0998 (0.1065)		-0.1591*** (0.0110)
Household size		0.0027*** (0.0009)		0.0152** (0.0074)		-0.0508** (0.0200)		0.0061 (0.0059)
Ln secondary GDP		-0.0060 (0.0161)		0.1603*** (0.0602)		-0.8485** (0.3421)		0.4632*** (0.0454)
Ln GDP per capita		-0.0007 (0.0111)		-0.1297*** (0.0258)		0.1222 (0.2148)		-0.2279*** (0.0200)
Wind speed		0.0171 (0.0227)		0.0649** (0.0295)		0.0330 (0.4903)		0.0474** (0.0233)
Boundary layer height		0.0000 (0.0001)		0.0012*** (0.0003)		0.0002 (0.0020)		0.0007*** (0.0002)
cons	0.1062*** (0.0009)	0.2318 (0.1729)	-1.2265*** (0.0315)	-1.8630*** (0.3433)	9.5585*** (0.0184)	8.5355** (3.6587)	-0.4058*** (0.0241)	1.0761*** (0.2572)
N	31891	31891	32481	32481	31891	31891	32481	32481
R^2	0.833	0.834	0.0090	0.0357	0.8679	0.8687	0.0125	0.0586

Table 2 presents result from both OLS and probit models, with Columns (1) through (4) showing estimates for chronic lung disease as the dependent variable, and Columns (5) through (8) for depression. Coefficients reflect the estimated impact of the clean heating initiative and other control measures on these health outcomes. Robust standard errors, clustered at the community level, are reported in parentheses below the coefficients. Individual-level controls include smoking status, age, marital status, gender, and education; household-level controls consist of log-transformed household income and household size. City-level controls include the log of per capita GDP and the share of the secondary industry. Weather-related controls encompass wind speed and boundary layer height. R^2 is pseudo R^2 if probit model is employed. Statistical significance levels are denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$

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Robustness checks

We conduct a series of robustness checks to determine whether our main results are influenced by various decisions made during the research process. These checks are crucial for ensuring the credibility and reliability of our findings by verifying their stability across different assumptions, model specifications, and potential biases.

Changing cluster levels

Different cluster levels can affect the significance of the estimation results. In this study, the error term may be correlated across various levels. For example, cities within the same province may share similar environmental policies, the government might set annual environmental policy goals, and the same month in different years may exhibit similar economic activity characteristics. To test the robustness of our results, we cluster the standard errors at both the community and provincial levels, allowing the error term to be related across different dimensions. Columns 1 and 2 in *Table 3* show clustering at the city level, while Columns 3 and 4 show clustering at the provincial level. The estimated results indicate that the coefficients remain significantly negative across different clustering levels. This suggests that the clean heating policy has effectively reduced the probability of chronic lung diseases and depression, further confirming the robustness of the benchmark regression.

Table 3. *Different clustering levels*

Variables	**(1)**	**(2)**	**(3)**	**(4)**
	Chronic lung diseases	**Depression**	**Chronic lung diseases**	**Depression**
	City level		**Provincial level**	
Clean heating	-0.0136*	-0.3287*	-0.0136*	-0.3287**
	(0.0073)	(0.1695)	(0.0060)	(0.1258)
Controls	Y	Y	Y	Y
Fixed	Y	Y	Y	Y
N	31891	31891	31891	31891
R^2	0.8341	0.8687	0.8341	0.8687

Table 3 shows results from OLS models when standard errors are clustered at different levels. In Column 1-2, the parentheses contain standard errors clustered at the city level, while in Column 3-4, the parentheses contain standard errors clustered at the province level. All models include province and year fixed effects, with some models additionally controlling weather, individual, household, and city characteristics. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

Implementation time

Given that the air pollution control policy primarily targets changes in heating and cooking energy use during the winter months (November to March), and health data is measured as an annual average, the policy's effects may exhibit a lag. To assess the long-term impact of the policy more accurately, we introduce lagged variables for policy implementation and conduct regression analysis. Considering our data is an unbalanced panel with years 2011, 2013, 2015, 2018, and 2020, we shift the policy data from the previous year to the following year. For instance, the 2011 policy variable is used as the

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DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

lagged variable for 2013, the 2013 policy variable for 2015, and so on. This approach allows us to evaluate the delayed effects of policy implementation at each time point.

As shown in *Table 4,* the regression results with lagged variables indicate that even after accounting for the lag effect, the policy implementation significantly reduces the probability of chronic lung diseases and depression. This finding further confirms the robustness of our conclusions, demonstrating that the air pollution control policy has a sustained positive impact on public health. For example, a similar study employing distributed lag non-linear models (DLNM) analyzed the lagged effects of $PM_{2.5}$ and PM_{10} on mortality rate of chronic lung diseases (Chen et al., 2013).

Table 4. *Implementation time*

Variables	(1)	(2)	(3)	(4)
	Chronic lung diseases		**Depression**	
	OLS	**Probit**	**OLS**	**Probit**
Lag Clean heating	-0.0135*	-0.0899**	-0.1572**	-0.0439*
	(0.0070)	(0.0450)	(0.0724)	(0.0354)
Controls	Y	Y	Y	Y
Fixed	Y	Y	Y	Y
N	20714	22429	20714	22429
R^2	0.8593	0.0293	0.9316	0.0534

Table 4 presents the effects of the lagged implementation of the clean heating policy on chronic lung diseases, and depression. The numbers in parentheses below the coefficients are robust standard errors, which account for clustering at the community level. Controls and fixed effects are included. R^2 is pseudo R^2 if probit model is employed. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

Residential sorting

To ensure the accuracy and robustness of our findings, we excluded samples with changes in location from 2011 to 2020 and re-estimated the model Shi et al. (2023). Specifically, we retained only respondents who indicated that their current residence at the time of the survey matched the location from the previous survey visit, as recorded in the question, "Is your current permanent residence the same as during the last visit, or is it in a different province, city, or district?" A total of 5001 samples indicated a change in location and were therefore excluded from the analysis. This exclusion is necessary because relocation may lead to exposure to different environmental conditions and local policies, introducing confounding effects and potential measurement errors in pollution and socioeconomic variables. So, this step helps minimize residential self-selection bias and ensures that the estimated effects reflect genuine policy impacts rather than changes in household location or environmental exposure (*Table 5*).

Alternative measures for physical health

Table 6 represents robustness checks by using alternative physical health measures to assess the consistency of the policy intervention's effects. Specifically, we use self-reported health scores and the Activities of Daily Living (ADL) scale as dependent variables (Katz et al., 1963). The self-reported health score is rated on a 1 to 5 scale, where 1 represents very poor health and 5 represents excellent health. Given its ordinal nature, we employ an ordered probit model (oprobit) for analysis. The ADL scale

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DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

evaluates functional ability across six essential daily activities: eating, dressing, transferring from bed to chair, using the toilet, bathing, and controlling bladder/bowel functions. Each activity is scored from 1 (unable to complete) to 4 (no difficulty), with a total ADL score ranging from 6 to 24—higher scores indicate greater ease in performing daily activities. Additionally, in Columns (3) to (8), we apply ordinary least squares (OLS) regression to examine individual components of the ADL scale, providing a more detailed understanding of the policy's impact on specific functional tasks. The results indicate a significant positive effect of the "Clean heating" policy on both self-reported health (Column 1) and the total ADL score (Column 2), with coefficients of 0.0490 ($p < 0.05$) and 0.0699 ($p < 0.05$), respectively. This suggests that the policy has led to improvements in perceived health and functional ability. Notably, the policy significantly enhances residents' ability to use the toilet independently (coefficient of 0.0334, $p < 0.1$), highlighting its positive impact on specific aspects of self-sufficiency. Like findings in numerous studies Lin et al. (2017), air pollution levels can affect residents' daily functional abilities.

Table 5. *Effect on samples never change location*

Variables	(1)	(2)	(3)	(4)
	Chronic lung diseases		**Depression**	
	OLS	**Probit**	**OLS**	**Probit**
Clean heating	-0.0102*	-0.0831**	-0.3935***	-0.0440*
	(0.0068)	(0.0343)	(0.1360)	(0.0259)
Controls	Y	Y	Y	Y
Fixed	Y	Y	Y	Y
N	27285	27417	27285	27417
R^2	0.8319	0.0328	0.8664	0.0563

Table 5 presents estimate from regression models that include control variables and fixed effects, examining the impact of changes in households' primary residence pre- and post-policy on two health outcomes—chronic lung disease and depression. Robust standard errors, clustered at the community level, are reported in parentheses below the coefficients. R^2 is pseudo R^2 if probit model is employed. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

Table 6. *Impact on physical health indicators*

Variables	(1) Self-reported health	(2) ADL	(3) Using the toilet	(4) Dressing	(5) Bathing	(6) Eating	(7) Getting of bed	(8) Controlling urination
	Oprobit	**Oprobit**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
Clean heating	0.0490**	0.0699**	0.0334*	-0.0039	0.0210	-0.0086	-0.0120	0.0122
	(0.0202)	(0.0272)	(0.0180)	(0.0149)	(0.0201)	(0.0107)	(0.0134)	(0.0138)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y	Y	Y	Y
N	32427	24147	22260	22264	22231	22264	22259	22248
R^2	0.0343	0.0381	0.5337	0.5498	0.5978	0.4916	0.5412	0.4595

Table 6 replaces the dependent variables with the self-rated health index and ADL. The numbers in parentheses below the coefficients are robust standard errors, which account for clustering at the community level. All models include year fixed effects, with some models additionally controlling for weather, individual, household, and city characteristics. R^2 is pseudo R^2 if Oprobit model is employed. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

Alternative measures for mental health

To assess the specific effects of policy interventions on mental health, we replaced the primary explanatory variable for mental health with individual items from the CESD-10 scale, targeting distinct dimensions of mental well-being. For this analysis, we employed both Poisson and Tobit models. The Poisson model, particularly suitable for count data, effectively captures variations in low-frequency symptoms, such as insomnia and loneliness (Cameron and Trivedi, 1986; Mullahy, 1986). In contrast, the Tobit model is advantageous for handling censored dependent variables, thus accounting for the ceiling and floor effects present in CESD-10 scores, which yield more accurate estimates of policy impact (Tobin, 1958). The regression findings reveal that policy interventions significantly reduce insomnia, fatigue and feelings of loneliness, while enhancing positive effect, corroborating our primary results and aligning with existing literature (Lim et al., 2012; Vert et al., 2017). This provides further evidence that policy measures can play a critical role in improving mental health outcomes (*Table 7*).

Table 7. *Impact on CESD-10 mental health indicators*

Panel A: Tobit model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Variables	**Restless sleep**	**Happiness**	**Loneliness**	**Not get going**	**Fearful**	**Bothered**	**No concentration**	**Feeling down**	**No effort**	**Hope in future**
Clean heating	-0.0906*	-0.1606**	-0.1113	-0.1202	-0.0308	-0.0201	-0.0021	-0.0008	0.0200	-0.0466
	(0.0540)	(0.0778)	(0.1164)	(0.1493)	(0.1165)	(0.0701)	(0.0619)	(0.0679)	(0.0980)	(0.0655)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	29901	29781	29757	29694	29899	29700	29342	29605	29678	29158
R^2	0.0135	0.0112	0.0220	0.0211	0.0152	0.0149	0.0115	0.0145	0.0176	0.0143
Panel B: Poisson model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Variables	**Restless sleep**	**Happiness**	**Loneliness**	**Not get going**	**Fearful**	**Bothered**	**No concentration**	**Feeling down**	**No effort**	**Hope in future**
Clean heating	-0.0445**	-0.0935***	-0.0871***	-0.0908***	-0.0551*	-0.0313	-0.0085	-0.0262	-0.0037	-0.0271
	(0.0193)	(0.0200)	(0.0270)	(0.0318)	(0.0329)	(0.0211)	(0.0207)	(0.0211)	(0.0211)	(0.0178)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	29901	29781	29757	29694	29899	29700	29342	29605	29678	29158
R^2	0.0205	0.0156	0.0448	0.0534	0.0405	0.0227	0.0172	0.0212	0.0292	0.0183

Table 7 presents robustness checks for the policy’s impact on mental health outcomes. Panels A and B employ Tobit and Poisson models, respectively. Robust standard errors, adjusted for clustering at the community level, are reported in parentheses below the coefficients. All models include year fixed effects and control for weather, individual, household, and city characteristics. R^2 is pseudo R^2. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

Placebo tests

Our study primarily focuses on chronic lung disease and depression, as these conditions are more directly linked to air pollution. The China Health and Retirement Longitudinal Study (CHARLS) include self-reported diagnoses of various chronic conditions beyond respiratory and cardiovascular diseases, such as dyslipidemia, diabetes, kidney disease and gastrointestinal disorders. Existing literature on the relationship between air pollution and metabolic diseases (e.g., dyslipidemia, high blood sugar) reveals mixed findings, with no clear consensus (Clark et al., 2013). Studies on liver and kidney diseases highlight the complexity of these conditions, noting

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

that air pollution or changes in energy sources have not shown a direct, significant effect on these illnesses (Stanaway et al., 2018). Likewise, evaluations of household air pollution's impact on health have found limited effects on digestive system diseases (Lee et al., 2020). Given these findings, we extend our analysis to explore whether the policy might influence these additional chronic diseases. The results, summarized in *Table 8,* indicate that, as expected, the policy did not significantly affect the likelihood of these conditions.

Table 8. *Placebo tests*

Variables	(1) Kidney disease	(2) Liver disease	(3) Dyslipidemia	(4) Arthritis	(5) Stroke	(6) Stomach disease
Clean heating	-0.0056	0.0007	-0.0064	-0.0236	0.0064	-0.0162
	(0.0064)	(0.0053)	(0.0209)	(0.0088)	(0.0042)	(0.0097)
Controls	Y	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y	Y
N	32032	32073	31728	31297	32154	31322
R^2	0.6570	0.6040	0.6849	0.7714	0.5647	0.7593

All columns are estimated with OLS model. The dependent variables include 6 diseases such as kidney and liver disease, with controls for individual, family, city, and weather variables, and both individual and year fixed effects applied. The numbers in parentheses below the coefficients are robust standard errors, which account for clustering at the city level. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

Mechanism

While the previous section highlighted the primary findings that suggest a potential impact of policies on chronic lung disease and depression, the underlying mechanisms through which these effects occur remain unclear. In this section, we explore whether changes in air pollution levels and energy usage types might be key mechanisms driving these outcomes. For instance, a shift from coal to cleaner energy sources could directly reduce air pollution, particularly by lowering concentrations of fine particulate matter ($PM_{2.5}$), which is closely linked to the incidence of chronic lung diseases (He et al., 2020). On the other hand, the adoption of cleaner energy might lead to increased household energy expenditures, especially in low-income households, potentially creating financial stress that could indirectly affect mental health. To test these mechanisms, we utilized city-level air quality data and household energy expenditure information, drawing on the analytical framework of Shi et al. (2023). We employed fixed-effects models to control potential temporal and regional heterogeneity, allowing for a more nuanced understanding of the complex health impacts of clean energy policies.

Outdoor and indoor air pollution

Several studies, including those by Fan et al. (2020) and Peabody et al. (2005), have demonstrated that China's coal-based winter heating system produces significant harmful emissions, leading to a substantial deterioration in air quality. Conversely, substituting coal with natural gas for heating has been shown to significantly enhance air quality and overall social welfare. This indicates that shifts in energy usage, particularly the transition from coal to cleaner energy sources, can markedly reduce pollution levels. In this analysis, key indicators such as $PM_{2.5}$, PM_{10}, SO_2, CO, and the Air Quality Index (AQI) are employed to assess air pollution (Jo et al., 2021). The results presented in *Table 9* reveal that the clean heating policy exerts a significant negative impact on all these

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

pollutants, thereby supporting the hypothesis that the policy reduces pollution by promoting the adoption of cleaner energy sources. These findings underscore the effectiveness of policy interventions aimed at mitigating environmental damage through strategic adjustments in energy structure.

While direct measurements of indoor air pollutants were not available, we used household ownership of air purifiers as a proxy indicator to assess indoor environmental quality. Following the policy implementation, the share of households owning air purifiers declined significantly, suggesting that improvements in outdoor air quality also translated into better indoor air conditions. The results are illustrated in *Table 9,* which captures the change in air purifier usage before and after the policy.

Table 9. *Outdoor and indoor air pollution*

Variables	**(1)** **$PM_{2.5}$**	**(2)** **PM_{10}**	**(3)** **SO_2**	**(4)** **CO**	**(5)** **AQI**	**(6)** **Air cleaner**
Clean heating	-0.1099^{**} (0.0929)	-0.0824^{**} (0.0747)	-0.3674^{***} (0.0839)	-0.1187^{**} (0.0932)	-0.1416^{*} (0.0740)	-0.0627^{**} (0.0125)
Controls	Y	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y	Y
N	213	152	152	152	177	32481
R^2	0.3335	0.5559	0.5187	0.1915	0.3321	0.2040

All columns are estimated with OLS model. Columns (1)– (5) report city-level estimates of outdoor air pollution indicators ($PM_{2.5}$, PM_{10}, SO_2, CO and AQI). Column (6) presents household-level results for indoor air quality, proxied by air-purifier ownership. The explanatory variable clean heating represents the interaction term between the clean energy policy and the treatment group over time. Robust standard errors are clustered at the city level for Columns (1)– (5) and at the household level for Column (6). Control variables include population, the proportion of GDP from secondary industry, wind speed, air circulation speed. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

Energy usage structure

The questionnaire specifically asked households to indicate the type of energy they use for heating and cooking, with options including coal, liquefied petroleum gas (LPG), solar energy, natural gas and electricity. Respondents could select only one option for each use, and we coded the use of a particular energy type as 1, and non-use as 0. This created five binary variables representing the energy preferences of households in different contexts. *Table 10* reveals a clear transition from coal-based to electricity-based heating in response to the clean heating policy, aligning directly with its primary goal of reducing coal dependency and promoting cleaner energy use in households. The significant reduction in coal use for heating (-0.1455) and cooking (-0.0415), combined with increased electricity use for the same purposes (0.0338 for heating and 0.0402 for cooking), underscores the policy's success in shifting energy consumption patterns toward cleaner alternatives.

Heterogeneity analysis

We conducted a detailed heterogeneity analysis to evaluate the differential impact of the clean heating policy on the likelihood of respiratory diseases across male and female respondents. Given that women typically assume the primary responsibility for household

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

tasks such as cooking and cleaning, they are more likely to experience prolonged exposure to indoor air pollution (Qiu et al., 2019). Based on this, we hypothesized that female respondents would benefit more significantly from the policy, as it would reduce their risk of developing respiratory diseases. The regression results presented in columns 6 of *Table 11* support this hypothesis. Specifically, the findings show that the clean heating policy leads to a significant reduction in the probability of chronic lung disease among women, by approximately 0.3384 units (statistically significant at the 5% level), whereas the effect for men is not statistically significant (coefficient = -0.2764). This suggests that women, owing to their greater exposure risk associated with domestic roles, derive a larger health benefit from the policy. Like the findings by Kioumourtzoglou et al. (2017), *Table 12* reports a significant effect of the policy on depression indicators among women, with a substantial reduction of 0.3014 units.

Table 10. *Energy usage structure*

Panel A: Heating Variables	**(1) Coal**	**(2) LPG**	**(3) Electric**	**(4) Natural gas**	**(5) Solar**
	Non-clean energy		**Clean energy**		
Clean heating	-0.1455***	-0.0050	0.0338**	0.0007	0.0119
	(0.0261)	(0.0044)	(0.0145)	(0.0027)	(0.0136)
Controls	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y
N	31939	31939	31939	31939	31939
R^2	0.4468	0.2550	0.3770	0.2527	0.4148
Panel B: Cooking Variables	**(1) Coal**	**(2) LPG**	**(3) Electric**	**(4) Natural gas**	**(5) Marsh gas**
	Non-clean energy		**Clean energy**		
Clean heating	-0.0415**	-0.0012	0.0402*	-0.0029	0.0054
	(0.0168)	(0.0175)	(0.0206)	(0.0021)	(0.0168)
Controls	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y
N	31939	31939	31939	31939	31939
R^2	0.6159	0.4732	0.5355	0.5312	0.6685

Panels A and B present the effects of policy implementation on heating and cooking energy types. There are five different energy types, with types 1 to 2 classified as traditionally non-clean energy sources, and types 3 to 5 categorized as clean energy sources. The numbers in parentheses below the coefficients are robust standard errors, which account for clustering at the community level. All models include control variables, year fixed effects, individual fixed effects and province fixed effects. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

Table 11. *Heterogeneous impacts on chronic lung diseases*

Variables	**(1) Male**	**(2) Female**	**(3) Age > 55**	**(4) Age ≤ 55**	**(5) High education**	**(6) Low education**	**(7) High income**	**(8) Low income**
Clean heating	-0.2764	-0.3384**	-0.0157*	-0.0165*	-0.0181**	-0.0095	-0.3287*	-0.3916**
	(0.0341)	(0.0066)	(0.0081)	(0.0088)	(0.0088)	(0.0079)	(0.1806)	(0.1828)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y	Y	Y	Y
N	14100	17784	19080	11270	15415	16477	1161	30524
R^2	0.8591	0.8684	0.8498	0.8639	0.8400	0.8300	0.8511	0.8362

Each column in the table represents a subsample estimated with OLS model. All regressions control for individual, household, city, and weather effects. The numbers in parentheses below the coefficients are robust standard errors, which account for clustering at the city level. Fixed effects are applied at the individual and year levels. $^{***}p < 0.01$. $^{**}p < 0.05$. $^{*}p < 0.1$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

Table 12. *Heterogeneous impacts in depression*

Variables	(1) Male	(2) Female	(3) Age > 55	(4) Age ≤ 55	(5) High education	(6) Low education	(7) High income	(8) Low income
Clean heating	-0.2013	-0.3014**	-0.2542*	-0.4413**	-0.3353*	-0.3329**	-0.2017	-0.4321**
	(0.1186)	(0.1294)	(0.1453)	(0.2115)	(0.1848)	(0.1558)	(0.1492)	(0.1729)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed	Y	Y	Y	Y	Y	Y	Y	Y
N	14100	17784	19080	11270	15415	16477	1161	30524
R^2	0.8612	0.8697	0.8936	0.8620	0.8423	0.8806	0.9122	0.8692

Each column in the table represents a subsample estimated with OLS model. All regressions control for individual, household, city, and weather effects. The numbers in parentheses below the coefficients are robust standard errors, which account for clustering at the city level. Fixed effects are applied at the individual and year levels. ***p < 0.01. **p < 0.05. *p < 0.1

We further divided the sample into a middle-aged group (45-55 years) and an older group (55 years and above) to examine the age-related heterogeneity in policy effects. The results reveal that after policy implementation, the reduction in the incidence of chronic lung disease (coefficient = -0.0165) and depression (coefficient = -0.4413) are more pronounced in the middle-aged group than in the older group (with coefficients of -0.0157 and -0.0254, respectively). Zou et al. (2022) indicate that middle-aged individuals generally possess stronger pulmonary function and immune system resilience, enabling more effective respiratory health improvements in response to reduced air pollution. Additionally, findings from Adams (2017) suggest that middle-aged adults benefit from more efficient neurological regulation, which enhances mental health recovery following health interventions. These findings imply that middle-aged individuals are better equipped to cope with health risks associated with air pollution reduction, supporting our study results.

Similarly, given the reported median income of 26,300 RMB, we categorize households below this threshold as low- to middle-income. These households tend to experience a more pronounced impact from policy interventions. Financial constraints in these households' limit access to healthcare and preventive services, making them particularly susceptible to health issues associated with pollution (Yusuf et al., 2020; Zhang and Churchill, 2020). Clean heating policies help mitigate these risks by reducing pollutant exposure, partially offsetting the gap in healthcare resources for these populations. Furthermore, we observe that individuals with higher educational attainment are more inclined to adopt clean energy programs. This trend may reflect a greater willingness to engage with new heating technologies and the financial capacity to invest in necessary household infrastructure upgrades. Together, these insights underscore the heterogeneity of policy effects, showing that economic and educational factors play a critical role in shaping health benefits from environmental interventions (Tan et al., 2023; Yamamoto et al., 2019).

Discussion

This study evaluates the impact of clean heating policies on individual health outcomes. The results indicate a significant decrease in the incidence of chronic lung disease and depression among middle-aged and older adults in regions where these policies have been implemented. The transition toward cleaner energy sources and reduced reliance on polluting fuels has improved air quality, thereby lowering rates of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1159711618

respiratory illness and depression. These effects are particularly pronounced among women, middle-aged individuals, those with higher education levels, and low-income groups. For instance, women who are more frequently engaged in cooking and other household tasks, benefit substantially from the reduction in indoor air pollution, while individuals with higher education levels are more likely to adopt cleaner and eco-friendly heating technologies.

Although the CHARLS dataset enables the examination of the health effects of outdoor air pollution on a nationally representative sample, it also presents certain limitations, particularly in the precise measurement of indoor air pollutants (e.g., $PM_{2.5}$ levels) and exposure duration. Such trade-offs are common in large-scale surveys, where extensive coverage often comes at the expense of environmental detail. It is reasonable to infer that individuals exposed to higher concentrations or longer durations of indoor pollution are more vulnerable to adverse health outcomes. Therefore, incorporating more direct and continuous measures of indoor air quality, beyond household fuel use alone, would likely produce more accurate estimates of health impacts.

Conclusion

Overall, this study provides strong evidence that China's clean heating policies have delivered measurable health benefits, particularly in reducing respiratory and mental health burdens among vulnerable populations. The results underscore the broader social and environmental value of transitioning toward clean energy in residential heating.

However, given the limited evidence on indoor air pollution and health outcomes in China, there remains a critical need for nationally representative studies that incorporate detailed indoor air quality measurements. Future research should prioritize the integration of household-level monitoring and behavioral data to better inform public health and energy policy decisions. Such efforts will contribute to more effective policy design and implementation, ensuring that the ongoing clean energy transition maximizes its health and environmental co-benefits.

Acknowledgments. Li Zhou acknowledges funding from the National Social Science Foundation of China (Grant No. 23VRC053), while Xi Tian receives financial support from the National Natural Science Foundation of China (Grant No. 72473068).

Conflict of interests. 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.

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