Supporting Information for

Energy-poverty-inequality SDGs: A large-scale household analysis and forecasting in China

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Supporting Information Text

ECONOMIC SIGNIFICANCE CALCULATIONS. We use back-of-the-envelope calculations to derive the economic implications of the regression results. We analyze the impact of clean cooking fuels on household income and inequality through RIF regression analysis and assess the economic implications of the coefficients(1).

Economic implications of clean cooking fuels on income and inequality. In Table S2, the coefficient for clean cooking fuels in column (1) is 0.094, and the average non-logarithmic household income is 51173.1 CNY. With the logarithmic transformation of income in the regression model, when the proportion of clean cooking fuels increases by 10%, the average expected increase in household income is 0.094*(1+51173.1)*0.1 ≈ 481 CNY, approximately US$74.9 (1 USD=6.42 CNY during the sample period), accounting for 0.9% of the average household income (51173.1 CNY). As there are 494,157,423 households in China, the national increase in wealth from clean cooking fuels is expected to be 74.9*494157423≈US$37 billion. In column (3), the coefficient for clean cooking fuels is -0.038. Therefore, when the proportion of clean cooking fuels increases by 10%, the Gini coefficient is expected to decrease by 0.038*0.1=0.0038≈0.004, a drop from the current Gini coefficient of 0.516 to 0.512, a decrease of 0.8%.

Economic implications of health benefits. In Table S12, the coefficient for clean cooking fuels in column (1) is 0.06. That is, if the proportion of clean cooking fuels increases by 10%, the average self-reported health is estimated to decrease by 0.06*0.1=0.6%. The coefficient for clean cooking fuels in column (2) is -0.066. That is, if the proportion of clean cooking fuels increases by 10%, the average number of medical visits per month is estimated to decrease by 0.066*0.1=0.66%. During the sample period, the total number of medical visits of all households per year was 8.31 billion, and the average cost per medical visit was 274.1 CNY (US$42.69, 1 USD=6.42 CNY during the sample period)(2). Therefore, when the proportion of clean cooking fuels increases by 10%, the amount of medical cost savings due to fewer visits is about 8.31*0.66%*42.69= US$2.34 billion per year. The coefficient for clean cooking fuels in column (3) is -0.021. That is, if the proportion of clean cooking fuels increases by 10%, the average chronic disease number is estimated to decrease by 0.021*0.1=0.21%. The coefficient for clean cooking fuels in column (4) is -0.005. That is, if the proportion of clean cooking fuels increases by 10%, the average lung disease probability is estimated to decrease by 0.005*0.1=0.05%.

Economic implications of the urban-rural heterogeneity analysis. In Table S15, the coefficient for clean cooking fuels in column (1) is 0.085. The average non-logarithmic rural household income is 38242.63 CNY. With the logarithmic transformation of income in the regression model, when the proportion of clean cooking fuels increases by 10%, the average income of rural households is estimated to increase by 0.085*(1+38242.63)*0.1 ≈ 325.1 CNY, approximately US$50.6 (1 USD=6.42 CNY during the sample period), accounting for 0.9% of the average income of rural households (38242.63 CNY). In column (4), the regression coefficient for clean cooking fuels is -0.040. Therefore, when the proportion of clean cooking fuels increases by 10%, the Gini coefficient is expected to decrease by 0.040*0.1=0.004, from the current urban Gini coefficient of 0.487 to 0.483, representing a decrease of 0.8%.

Economic implications of the education heterogeneity analysis. In Table S16, the coefficient for clean cooking fuels in column (2) is 0.077, and the average household income of the non-completion of compulsory education group, without taking logarithms, is 36552.18 CNY. With the logarithmic transformation of income in the regression model, when the proportion of clean cooking fuels increases by 10%, the estimated average increase in household income for the non-completion of compulsory education group is 0.077*(1+36552.18)*0.1≈281.5 CNY, approximately US$43.8 (1 USD=6.42 CNY during the sample period). This increase accounts for 0.8% of the average household income (36552.18 CNY) for the non-completion of the compulsory education group. In column (3), we analyzed the impact of clean cooking fuels on the Gini coefficient for the completion of compulsory education groups. The coefficient for clean cooking fuels is -0.037. Therefore, when the percentage of clean cooking fuels increases by 10%, the Gini coefficient is expected to decrease by 0.037*0.1=0.0037≈0.004, resulting in a decrease in the current Gini coefficient (0.478) for the completion of compulsory education group to 0.474, representing a decrease of 0.8%.

Economic implications of the market segmentation heterogeneity analysis. In Table S17, the coefficient for clean cooking fuels in column (2) is 0.081, and the average household income of the low segmentation group, without taking logarithms, is 55138.3 CNY. With the logarithmic transformation of income in the regression model, when the proportion of clean cooking fuels increases by 10%, the estimated average increase in household income for the low segmentation group is 0.081*(1+55138.3)*0.1≈446.63 CNY, approximately US$69.6 (1 USD=6.42 CNY during the sample period). This increase accounts for 0.8% of the average household income (55138.3 CNY) for the low segmentation group. In column (4), we show the impact of clean cooking fuels on the Gini coefficient for the low segmentation group. The coefficient for clean cooking fuels is -0.036. Therefore, when the percentage of clean cooking fuels increases by 10%, the Gini coefficient is expected to decrease by 0.036*0.1=0.0036≈0.004, resulting in a decrease in the current Gini coefficient (0.520) for the completion of compulsory education group to 0.516, a decrease of 0.8%.

Economic implications of the employment opportunities heterogeneity analysis. In Table S18, the coefficient for clean cooking fuels in column (2) is 0.114, and the average household income of the low unemployment rate group, without taking logarithms, is 66257.35 CNY. With the logarithmic transformation of income in the regression model, when the proportion of clean cooking fuels increases by 10%, the estimated average increase in household income for the low unemployment rate group is 0.114*(1+66257.35)*0.1≈755.35 CNY, approximately US$117.7 (1 USD=6.42 CNY during the sample period), which accounts for 1.1% of the average household income (66257.35 CNY) for the low unemployment rate group.

Economic implications of detailed income outcomes. The point estimate for clean cooking fuels in Fig. 2A for the income at the 10th percentile is 0.2977, and the income at the 10th percentile for households, without taking the logarithm, is 4000 CNY. With the logarithmic transformation in the regression model for income, when the percentage of clean cooking fuels increases by 10%, the estimated average increase in income for households at the 10th percentile is 0.2977*(1+4000)*0.1=119.1 CNY, approximately US$18.6. This increase accounts for 3% of the income at the 10th percentile for households (4000 CNY).

The regression coefficient for clean cooking fuels in Fig. 2B for upward mobility is 0.03, and the current proportion of upward mobility for household income is 0.57. Therefore, the probability of upward mobility in household income is expected to increase by 0.03 when households switch to clean cooking fuels, accounting for 5% of the current proportion of upward mobility (0.57). The coefficient for clean cooking fuels in relation to downward mobility is -0.02, and the current proportion of downward mobility for household income is 0.153. Therefore, the probability of downward mobility in household income is expected to decrease by 0.153 when households switch to clean cooking fuels, accounting for 13% of the current proportion of downward mobility (0.153).

In Fig. 2C, the point estimate for clean cooking fuels for wage is 0.243, and the average household wage income, without taking the logarithm, is 35334.34 CNY. With the logarithmic transformation in the regression model for wage, when the percentage of clean cooking fuels increases by 10%, the estimated average increase in household wage income is 0.243*(1+35334.34)*0.1≈848.6 CNY, approximately US$132.2 (1 USD=6.42 CNY during the sample period). This increase accounts for 2.4% of the average household wage income (35334.34 CNY). The point estimate for clean cooking fuels for farm income is -0.329, and the average household farm income, without taking the logarithm, is 3664.652 CNY. With the logarithmic transformation in the regression model for farm income, when the percentage of clean cooking fuels increases by 10%, the estimated average decrease in household farm income is

0.329*(1+3664.652)*0.1=120.6 CNY, approximately US$18.79. This decrease accounts for 3.3% of the average household farm income (3664.652 CNY).

The point estimate for wage in Fig. 2D is -0.029. Therefore, when the percentage of clean cooking fuels increases by 10%, the Gini coefficient for household wage income is expected to decrease by $0.029*0.1=0.0029 \approx 0.003$, resulting in a decrease in the current Gini coefficient (0.0624) for wage income to 0.0621, representing a decrease of 0.5% compared to the current Gini coefficient (0.0624) for wage income.

Economic implications of cost-benefit analysis. Using the Benefits of Action to Reduce Household Air Pollution (BAR-HAP) tool developed by the World Health Organization(3), we simulated the costs and benefits under different pathways for the clean cooking fuels transition. For the transition from biomass to electricity through the technology ban pathway, when the project duration is 10 years and the social discount rate is 3.5%, the simulation showed that annual health benefits would be US$41.4 billion, time savings benefits US$4 billion, climate benefits US$445 million, environmental benefits US$197 million, administrative costs US$200 million, stove subsidy costs US$332 million, fuel subsidy costs US$0, household stove costs US$114million, stove maintenance costs US$189million, learning costs US$197million. Other costs of the ban would be US$5billion, and the fuel costs would be reduced by US$5billion. The definition and calculation method of each benefit and cost term can be found in the WHO technical document(4).

Thus, the benefits per year are 41.4+4+0.445+0.197=US$46 billion and the costs per year are 0.2+0.332+0+0.114+0.189+0.197+5-5=US$1billion. It is important to note that the economic meaning in the cost-benefit analysis here is the sum of the household and public components, i.e., it includes household costs, household benefits, public costs and public benefits. Therefore, the benefit values derived in this section are the total benefits of the clean energy transition for a given transition pathway, and are not directly comparable to the values of the other sections of this paper concerning economic implications (which are only at the household level and do not take into account the transition pathway).

Supplemental figures and tables

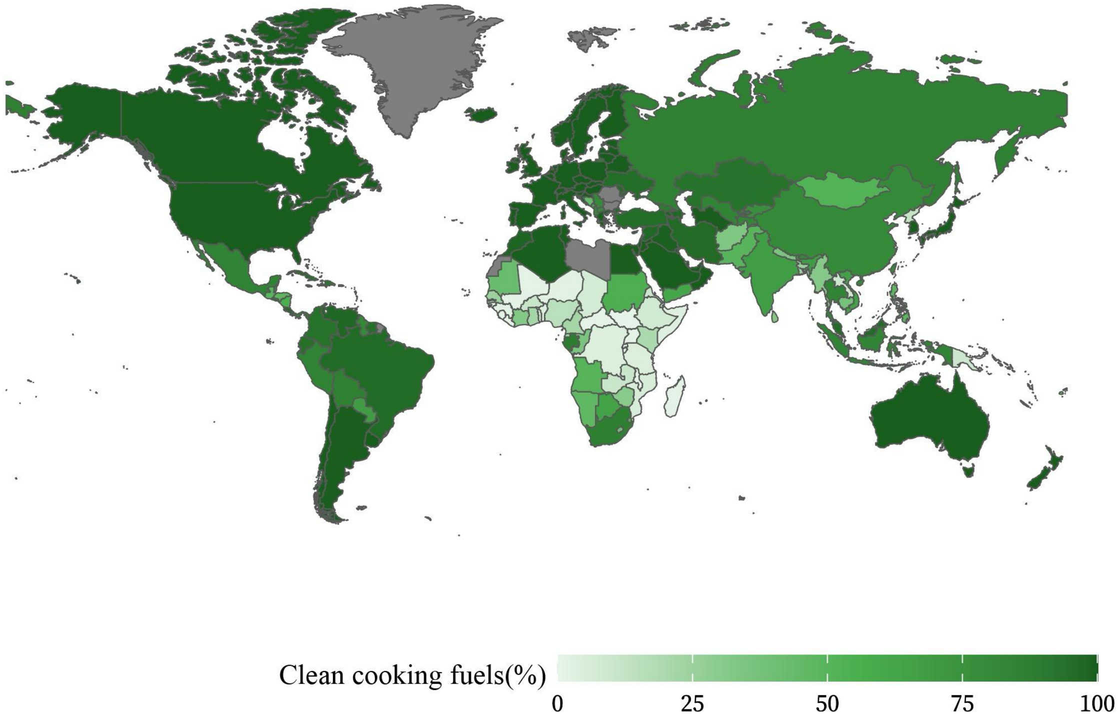

Fig. S1. Proportion of clean cooking fuels adoption in the world by country (2020).
Data source: World Development Indicators database of the World Bank.

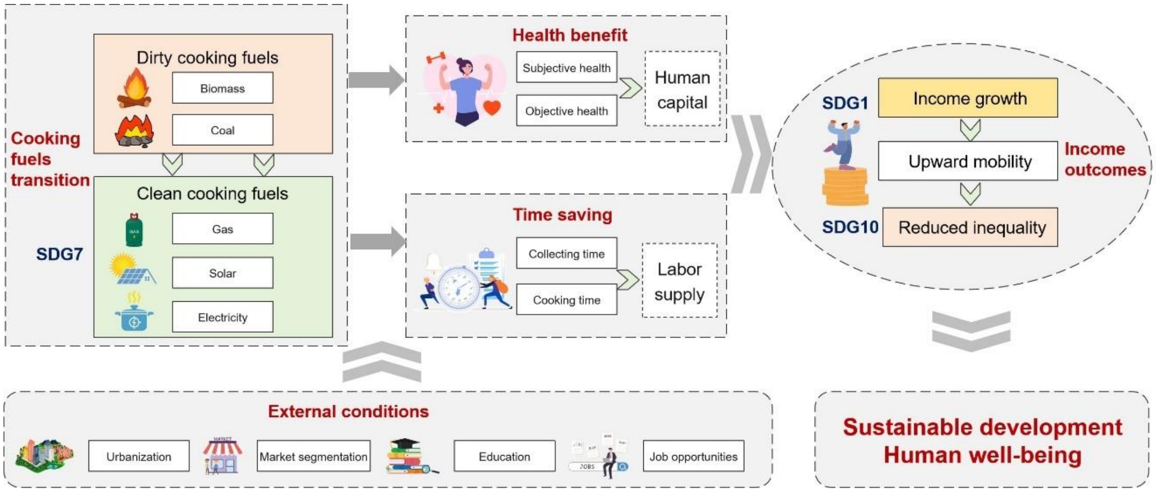

Fig. S2. Research framework.

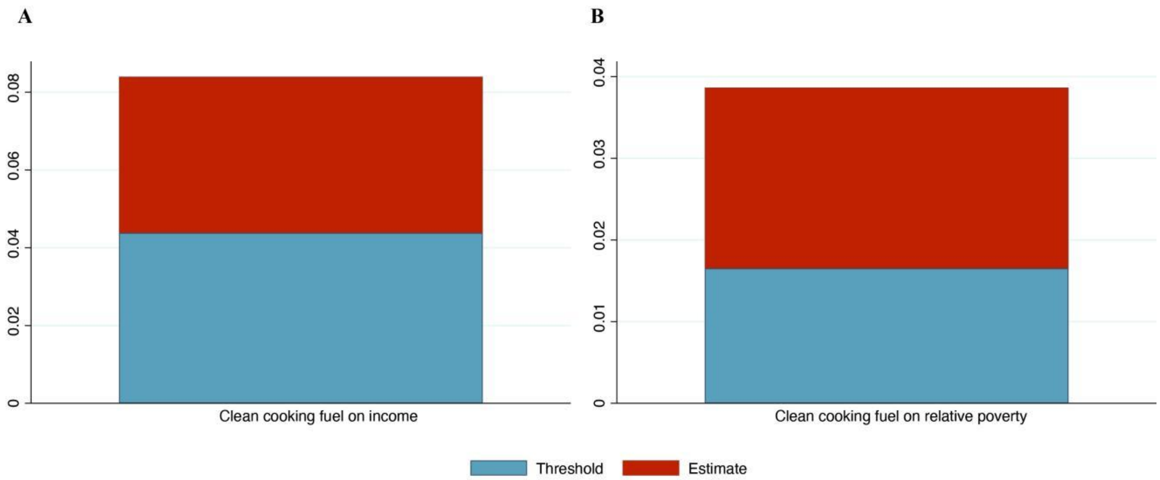

Fig. S3. Percent bias necessary to invalidate an inference from the Rubin causal model framework. For A, to invalidate the inference, 47.86% of the estimate would have to be due to bias; to invalidate the inference, 47.86% of cases (18608) would have to be replaced with cases for which there is zero effect. For B, to invalidate the inference, 57.26% of the estimate would have to be due to bias; to invalidate the inference, 57.26% of cases (22263) would have to be replaced with cases for which there is zero effect.

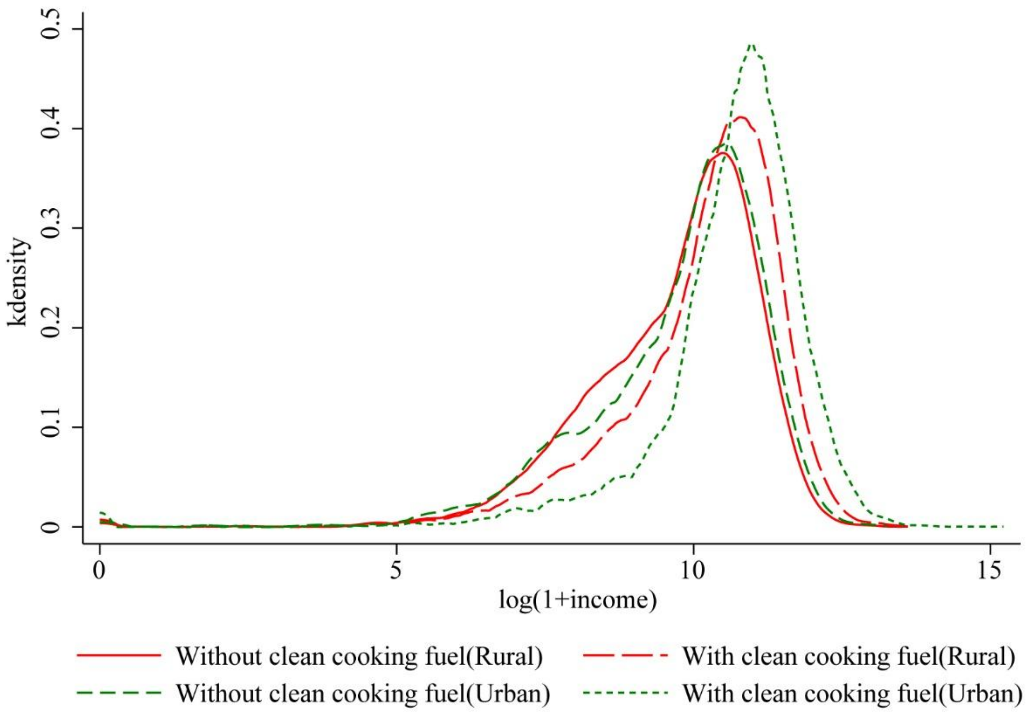

Fig. S4. Urban-rural heterogeneity in kernel density curves of clean cooking fuels and household income distribution.

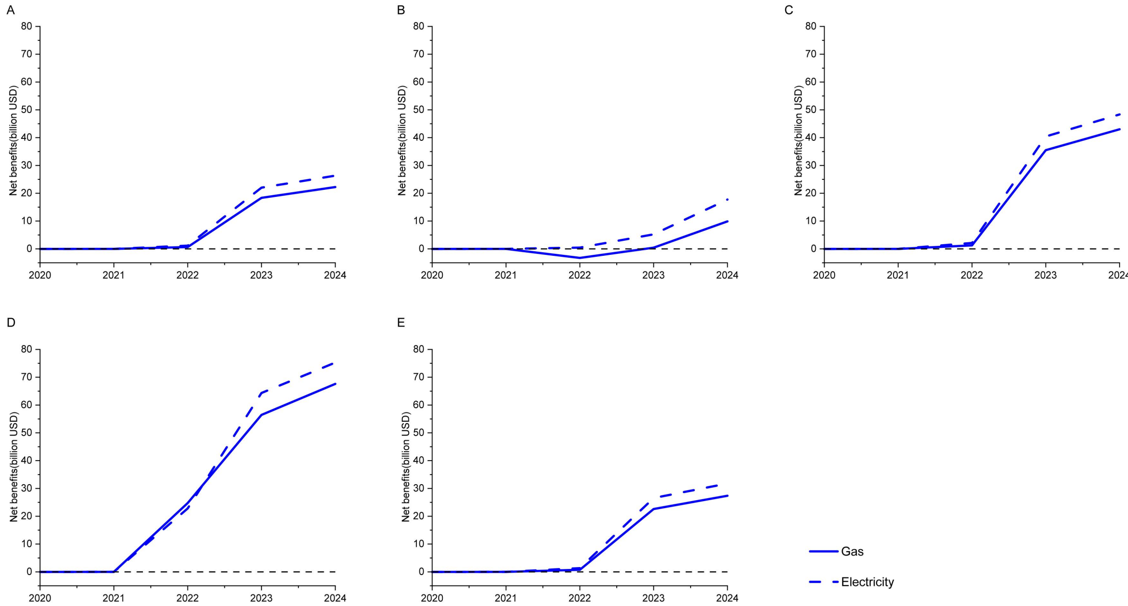

Fig. S5. Discounted net benefit curves of cooking fuels transition (from biomass to electricity/gas, 5 years, discount rate 3.5%). (*A*) Stove subsidies. (*B*) Fuel subsidies. (*C*) Stove financing. (*D*) Technology/fuel bans. (*E*) Behavior change communication.

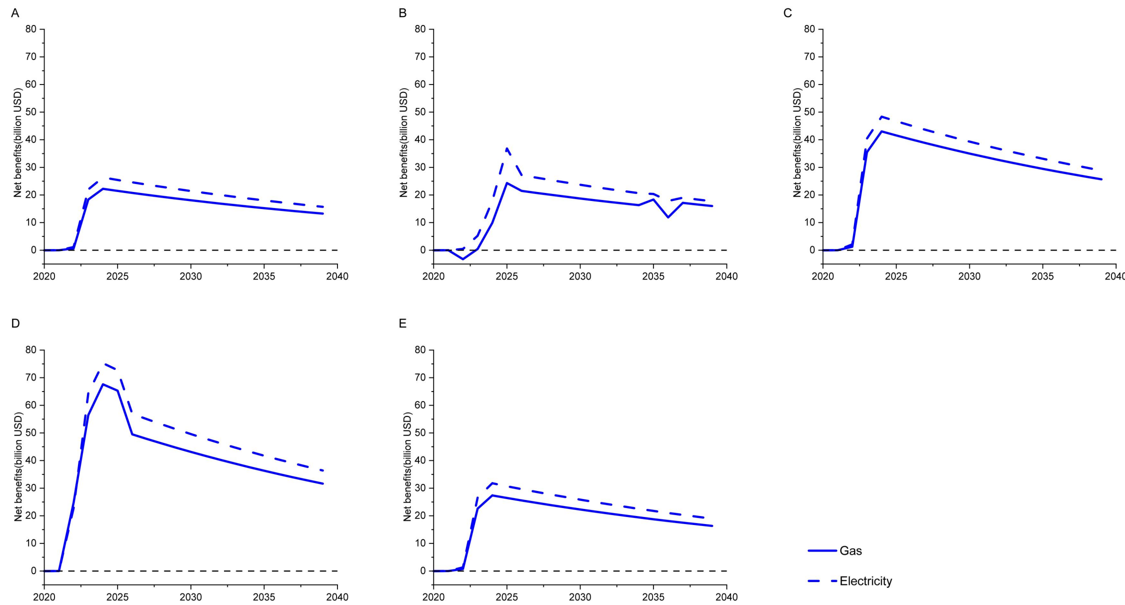

Fig. S6. Discounted net benefit curves of cooking fuels transition (from biomass to electricity/gas, 20 years, discount rate 3.5%). (*A*) Stove subsidies. (*B*) Fuel subsidies. (*C*) Stove financing. (*D*) Technology/fuel bans. (*E*) Behavior change communication.

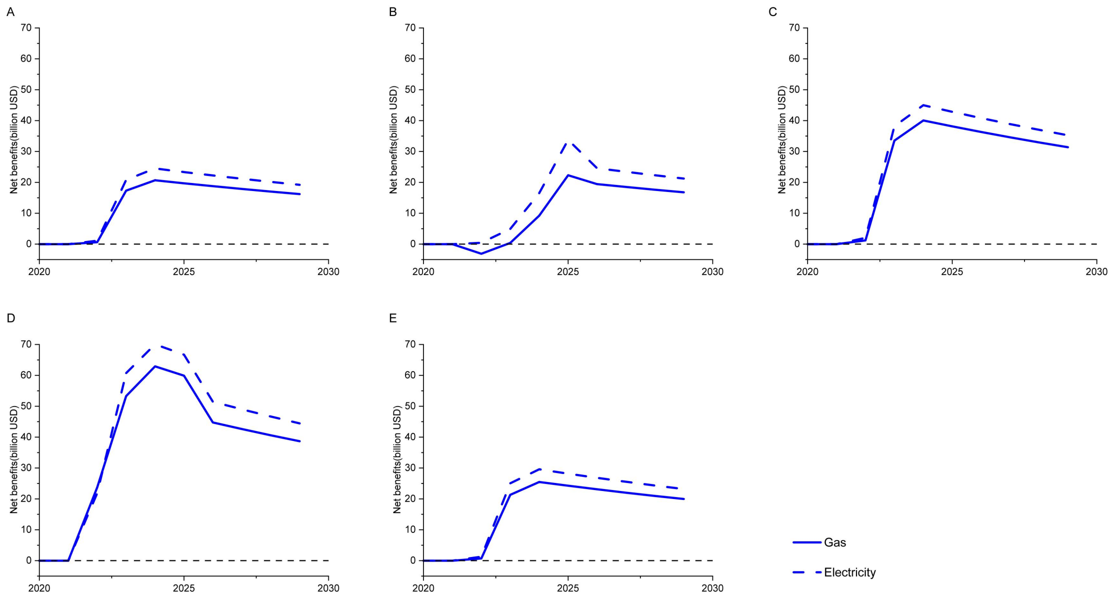

Fig. S7. Discounted net benefit curves of cooking fuels transition (from biomass to electricity/gas, 10 years, discount rate 5%). (*A*) Stove subsidies. (*B*) Fuel subsidies. (*C*) Stove financing. (*D*) Technology/fuel bans. (*E*) Behavior change communication.

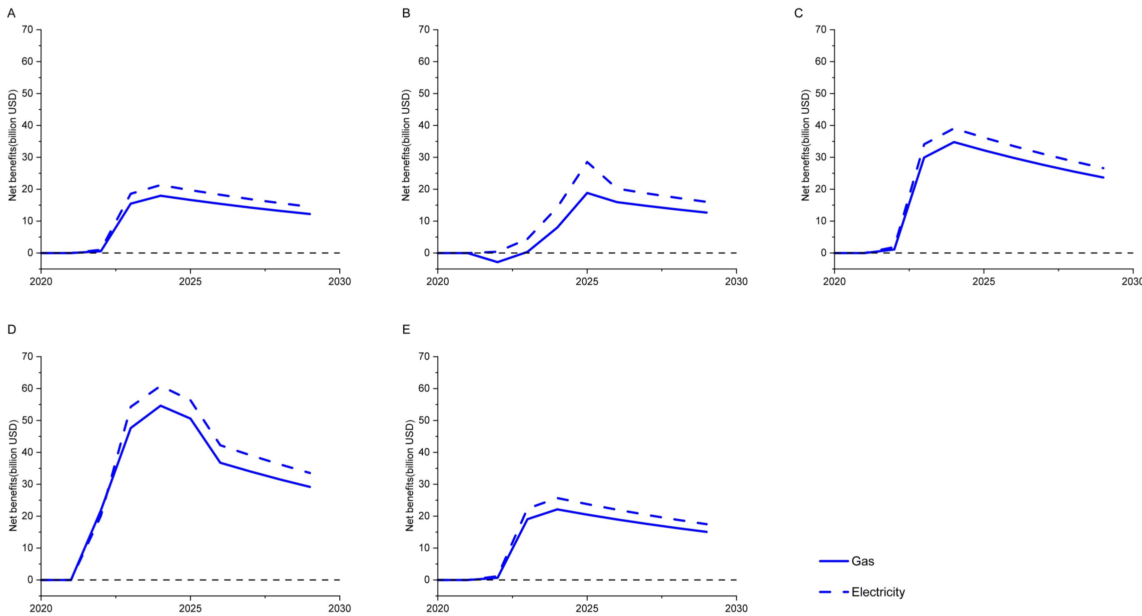

Fig. S8. Discounted net benefit curves of cooking fuels transition (from biomass to electricity/gas, 10 years, discount rate 8%). (*A*) Stove subsidies. (*B*) Fuel subsidies. (*C*) Stove financing. (*D*) Technology/fuel bans. (*E*) Behavior change communication.

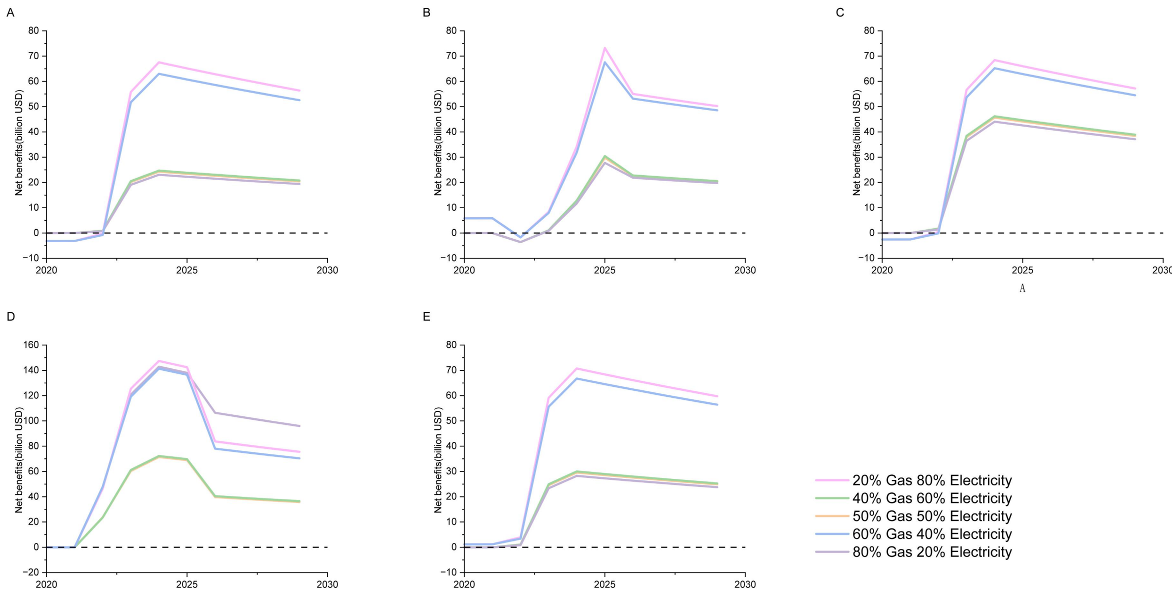

Fig. S9. Discounted net benefit curves of cooking fuels transition (from biomass to the mix of electricity and gas, 10 years, discount rate 3.5%). (*A*) Stove subsidies. (*B*) Fuel subsidies. (*C*) Stove financing. (*D*) Technology/fuel bans. (*E*) Behavior change communication

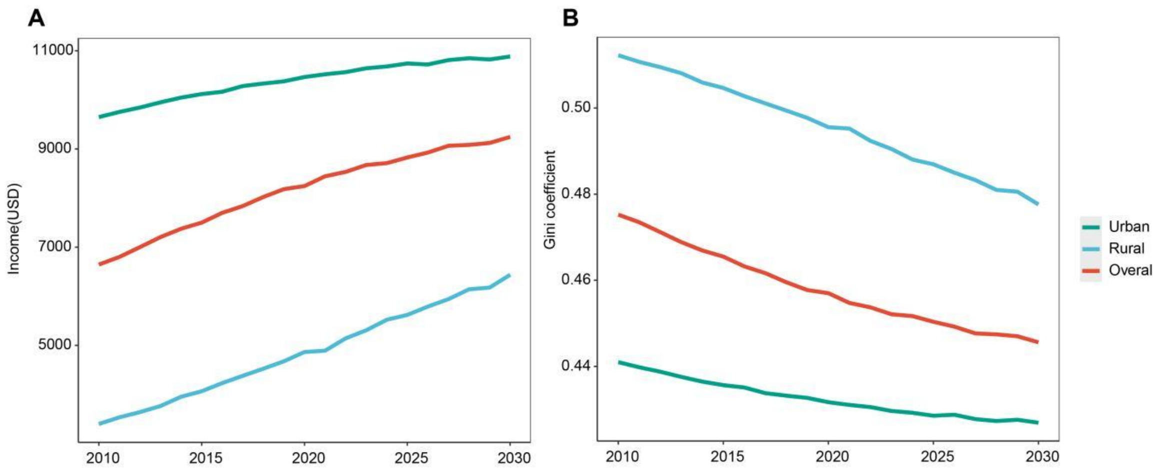

Fig. S10. Robustness of income and inequality projection. (*A*) income projection. (*B*) inequality projection.

Table S1. T-test for differences in means between clean and dirty cooking fuels groups

	Clean cooking fuels		Dirty cooking fuels		
VARIABLES	Observations	Mean	Observations	Mean	Mean Difference
Income	27,340	62,000	14,850	32,000	30,000***
Wage	28,042	42,000	15,265	22,000	20,000***
Farm income	27,805	3,021	14,970	4,864	-1,843.217***
Transfer income	27,695	11,000	15,031	2,892	8,108***
Property income	28,008	2,030	15,255	320.6	1,709.4***
Other income	27,965	1,800	15,243	970.2	829.315***
Housework time	26,332	1.953	13,682	2.356	-0.403***

Note: ***p<0.01, **p<0.05, *p<0.1. The unit of income is CNY, with an exchange rate of 1 USD=6.42 CNY during the sample period (2012-2018).

Table S2. Impact of access to clean cooking fuels on household income and inequality in China

	(1)	(2)	(3)	(4)
VARIABLES	Income	Income	Inequality	Inequality
Clean cooking fuels	0.094***	0.084***	-0.038***	-0.034***
	(0.024)	(0.022)	(0.005)	(0.005)
Control variables	No	Yes	No	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	No	Yes	No	Yes
Sample mean	51,173.100	51,173.100	0.516	0.516
Observations	40,184	38,880	40,184	38,880
R-squared	0.600	0.665	0.470	0.465

Note: Columns (1) and (3) do not include control variables and province fixed effects. The sample mean reports the average household income or Gini coefficient for the full sample. Standard errors clustering at the household level are in parentheses. The unit of income is CNY, with an exchange rate of 1 USD=6.42 CNY during the sample period (2012-2018). ***p<0.01, **p<0.05, *p<0.1.

Table S3. 2SLS estimation using the instrumental variable method

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Income	Inequality	Inequality	Income	Inequality	Inequality
Clean cooking fuels	2.305***	-0.079***	-0.828***	2.150***	-0.076***	-0.808***
	(0.702)	(0.017)	(0.272)	(0.668)	(0.016)	(0.263)
First-stage results						
IV	-0.050***	-0.050***	-0.050***	-0.052***	-0.052***	-0.052***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
First-stage SW F-statistics	29.897	29.897	29.897	31.635	31.635	31.635
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Additional control	No	No	No	Yes	Yes	Yes
Observations	38,880	38,880	38,880	38,880	38,880	38,880
R-squared	-0.388	-2.237	-0.355	-0.320	-2.090	-0.336

Note: Since the instrumental variable method is not applicable for RIF regression, we employ two-stage least squares (2SLS) estimation and utilize the Kakwani index (in columns (2) and (5)) and relative poverty (in columns (3) and (6)) to measure income inequality, addressing the issue of limited variability of the Gini coefficient in regression. In columns (4)-(6), we introduce an additional control variable, namely household agricultural livelihood, to address concerns regarding the channel effects of instrumental variables that may influence household income and inequality across different agricultural types. Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S4. Oster (2019) Bounds analysis

Treatment variable	Baseline effect	Controlled effect	$\|\delta\|$ for $\beta = 0$ given R^2_{MAX}
Panel A: income			
Clean cooking fuels	0.094***	0.084***	1.869
	(0.024)	(0.022)	
R^2	0.025	0.113	0.146
Panel B: Relative poverty			
Clean cooking fuels	-0.035***	-0.039***	16.945
	(0.008)	(0.008)	
R^2	0.008	0.018	0.023

Note: Only year and household fixed effects are controlled for the baseline effect, and control variables and province fixed effects are added to the controlled effect. R^2_{MAX} is set to 1.3 times the R^2 value of the controlled effect and passes the test when $|\delta|$ is greater than 1. In panel A, we analyzed the stability of coefficients when the dependent variable is income. In panel B, we analyzed the stability of coefficients when the dependent variable is inequality. In Panel B, because the RIF regression for the Gini coefficient is not available to the Oster (2019) test, we choose the relative poverty (household income below the median) indicator to measure inequality. Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S5. Robustness tests for changing clean cooking fuels measurements

VARIABLES	(1) Income	(2) Gini	(3) Income	(4) Gini
Clean cooking fuels	0.069***	-0.005***		
	(0.023)	(0.002)		
Energy transition				
Second stage			-0.011	0.000
			(0.040)	(0.003)
Third stage			0.082***	-0.005***
			(0.024)	(0.002)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
R-squared	0.665	0.506	0.665	0.507
Observations	38,880	38,880	38,880	38,880

Note: In columns (1) and (2), we redefine clean cooking fuels to include coal as a clean fuel, and traditional biomass, such as fuelwood and animal manure that needs to be collected, is considered as a dirty fuel. In columns (3) and (4), we delineate three stages of the energy transition, with traditional biomass such as fuelwood and animal manure that has to be collected in the first stage, coal in the second stage, and clean energy such as electricity, natural gas, liquefied gas, and biogas in the third stage. Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S6. Heterogeneity analysis of cooking fuel types on income

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Income	Income	Income	Income	Income	Income
Biomass	-0.069***					
	(0.023)					
Coal		-0.063*				-0.014
		(0.038)				(0.040)
Gas			0.074***			0.105***
			(0.021)			(0.027)
Solar & Biogas				-0.016		0.036
				(0.094)		(0.096)
Electricity					0.010	0.061**
					(0.020)	(0.026)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,880	38,880	38,880	38,880	38,880	38,880
R-squared	0.665	0.665	0.665	0.665	0.665	0.665

Note: Biomass is omitted in column (6) to address multicollinearity. Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S7. Heterogeneity analysis of cooking fuel types on inequality

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Gini	Gini	Gini	Gini	Gini	Gini
Biomass	0.005***					
	(0.002)					
Coal		0.003				0.000
		(0.003)				(0.003)
Gas			-0.004***			-0.006***
			(0.001)			(0.002)
Solar & Biogas				-0.000		-0.004
				(0.006)		(0.006)
Electricity					-0.002	-0.005***
					(0.001)	(0.002)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,880	38,880	38,880	38,880	38,880	38,880
R-squared	0.506	0.506	0.506	0.506	0.506	0.507

Note: Biomass is omitted in column (6) to address multicollinearity. Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S8. Robustness of electrification

VARIABLES	(1) Income	(2) Gini
Clean cooking fuels	0.084***	-0.034***
	(0.022)	(0.005)
Electrification	0.014	-0.039
	(0.137)	(0.034)
Control variables	Yes	Yes
Household fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Province fixed effect	Yes	Yes
Observations	38,876	38,876
R-squared	0.665	0.465

Note: Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S9. Robustness tests for changing income inequality measurements and correcting sampling bias

	(1)	(2)	(3)	(4)	(5)
VARIABLES	iqr(90 10)	Std	Relative poverty	Income	Gini
Clean cooking fuels	-0.325***	-0.077***	-0.039***	-0.005***	0.087***
	(0.079)	(0.029)	(0.008)	(0.002)	(0.027)
Control variables	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	38,880	38,880	38,880	24,883	24,883
R-squared	0.475	0.421	0.432	0.494	0.653

Note: In columns (1) - (3), we use the 90-10 quantile distance, standard deviation, and relative poverty as the measure of income inequality. In columns (4) and (5), we use the resampling method to correct the possible oversampling problem in some areas of CFPS data. Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S10. Robustness tests for reweighting estimation of Probit and Logit model

VARIABLES	(1) Income	(2) Gini	(3) Income	(4) Gini
Clean cooking fuels	0.087***	-0.026***	0.081***	-0.074***
	(0.023)	(0.002)	(0.022)	(0.002)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Reweighting method	Probit	Probit	Logit	Logit
Observations	38,880	38,880	38,880	38,880
R-squared	0.742	0.660	0.791	0.833

Note: For the reweighting adjustment of the group treatment effect for clean cooking fuels, we used the probit model in columns (1) and (2) and the logistic (logit) model in columns (3) and (4). Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S11. Robustness tests for adjusting clustering levels for standard errors

VARIABLES	(1) Income	(2) Gini	(3) Income	(4) Gini
Clean cooking fuels	0.084***	-0.005***	0.084***	-0.005***
	(0.027)	(0.002)	(0.030)	(0.001)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Observations	38,847	38,847	38,880	38,880
R-squared	0.665	0.507	0.665	0.507

Note: Standard errors are reported in parentheses. Standard errors are clustered at the county level in columns (1) and (2) and clustered at the province level in columns (3) and (4). ***p<0.01, **p<0.05, *p<0.1.

Table S12. Impact of access to clean cooking fuels on health

	(1)	(2)	(3)	(4)
VARIABLES	Self-reported health	Medical visits	Chronic diseases number	Lung disease
Clean cooking fuels	0.060***	-0.066*	-0.021***	-0.005*
	(0.010)	(0.039)	(0.007)	(0.003)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Community fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Sample mean	3.028	0.518	1.888	0.129
Observations	78,049	50,892	74,718	78,049
R-squared	0.438	NA	NA	0.472

Note: Standard errors clustering at the household level are in parentheses. Column (2) and column (4) are estimated using Poisson pseudo-likelihood regression. ***p<0.01, **p<0.05, *p<0.1.

Table S13. Robustness of the impact of access to clean cooking fuels on health

	(1)	(2)	(3)	(4)
VARIABLES	Number of body aches	Frailty index	Cognition	Depression
Clean cooking fuels	-0.048***	-0.274*	0.071*	-0.272***
	(0.018)	(0.145)	(0.039)	(0.069)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Community fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Observations	68,284	47,800	59,104	74,892
R-squared	NA	0.619	0.590	0.508

Note: Standard errors clustering at the household level are in parentheses. Column (1) is estimated using Poisson pseudo-likelihood regression. ***p<0.01, **p<0.05, *p<0.1.

Table S14. Impact of access to clean cooking fuels on housework time

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Housework time				
	All	Low income	High income	Male	Female
Clean cooking fuels	-0.124**	-0.141*	-0.150	-0.161**	-0.117
	(0.057)	(0.080)	(0.116)	(0.080)	(0.078)
Control variables	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	37,819	18,610	19,181	17,590	20,229
R-squared	0.468	0.514	0.487	0.684	0.627

Note: Standard errors clustering at the household level are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table S15. Urban-rural heterogeneity in the impact of access to clean cooking fuels on income and inequality

VARIABLES	(1)	(2)	(3)	(4)
	Income		Gini	
	Rural	Urban	Rural	Urban
Clean cooking fuels	0.085***	0.059	-0.013*	-0.040***
	(0.027)	(0.038)	(0.007)	(0.008)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Sample mean	38,242.630	64,928.880	0.512	0.487
Observations	19,547	18,038	19,547	18,038
R-squared	0.622	0.708	0.509	0.443

Note: Standard errors clustering at the household level are in parentheses. The unit of income is CNY, with an exchange rate of 1 USD=6.42 CNY during the sample period (2012-2018). ***p<0.01, **p<0.05, *p<0.1.

Table S16. Education heterogeneity in the impact of access to clean cooking fuels on income and inequality

VARIABLES	(1)	(2)	(3)	(4)
	Income		Gini	
	Completion of compulsory education	Non-completion of compulsory education	Completion of compulsory education	Non-completion of compulsory education
Clean cooking fuels	0.053	0.077***	-0.037***	-0.011*
	(0.034)	(0.028)	(0.008)	(0.007)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Sample mean	64,607.280	36,552.180	0.478	0.521
Observations	18,513	17,797	18,513	17,797
R-squared	0.694	0.673	0.446	0.531

Note: Standard errors clustering at the household level are in parentheses. The unit of income is CNY, with an exchange rate of 1 USD=6.42 CNY during the sample period (2012-2018). ***p<0.01, **p<0.05, *p<0.1.

Table S17. Heterogeneity analysis of energy market segmentation

	(1)	(2)	(3)	(4)
VARIABLES	Income		Gini	
	high segmentation	low segmentation	high segmentation	low segmentation
Clean cooking fuels	0.056	0.081***	-0.017*	-0.036***
	(0.035)	(0.027)	(0.010)	(0.006)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Sample mean	43,806.440	55,138.300	0.488	0.520
Observations	12,857	24,967	12,857	24,967
R-squared	0.658	0.678	0.513	0.457

Note: Standard errors clustering at the household level are in parentheses. The unit of income is CNY, with an exchange rate of 1 USD=6.42 CNY during the sample period (2012-2018). ***p<0.01, **p<0.05, *p<0.1.

Table S18. Heterogeneity analysis of the unemployment rate

	(1)	(2)	(3)	(4)
VARIABLES	Income		Gini	
	high unemployment rate	low unemployment rate	high unemployment rate	low unemployment rate
Clean cooking fuels	-0.019	0.114*	-0.027**	-0.034**
	(0.049)	(0.066)	(0.011)	(0.015)
Control variables	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Sample mean	63,923.970	66,257.350	0.495	0.476
Observations	9,742	6,869	9,742	6,869
R-squared	0.739	0.688	0.471	0.517

Note: Standard errors clustering at the household level are in parentheses. The unit of income is CNY, with an exchange rate of 1 USD=6.42 CNY during the sample period (2012-2018). Since the unemployment rate applies only to urban areas, we used a subsample of cities for our analysis. ***p<0.01, **p<0.05, *p<0.1.

Table S19. Cost and benefit analysis

Fuel	Policy	Total costs (USD,per year)	Total benefits (USD,per year)	NPV (USD, full program duration)
Gas	Stove subsidies	735,108,763	561,751,177	141,552,092,655
Gas	Fuel subsidies	4,180,972,621	15,025,468,314	113,049,962,448
Gas	Stove financing	1,413,257,666	28,710,582,758	274,011,787,171
Gas	Technology/fuel bans	8,531,986,732	48,607,416,715	402,283,320,146
Gas	Behavior change communication	940,515,389	18,304,087,336	174,308,322,285
Electricity	Stove subsidies	-526,008,320	16,240,475,162	168,387,492,313
Electricity	Fuel subsidies	1,693,757,497	17,441,714,490	163,593,641,621
Electricity	Stove financing	-971,908,215	29,813,329,568	309,154,788,696
Electricity	Technology/fuel bans	1,047,713,745	46,017,755,135	451,512,637,031
Electricity	Behavior change communication	-590,587,348	19,633,688,763	203,110,356,951

Note: The program duration is 10 years, the discount rate is 3.5%.

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