Household Heating Fuel Choice and Behaviours: Evidence from Rural China

Wenmei Tu

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Department of Economics

McGill University, Montreal

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Abstract

The Clean Heating Policy, aimed at encouraging households in Northern China to transition from coal to electricity or gas, marks a pivotal effort in combating air pollution. However, the effectiveness of household fuel substitution policies in fuel choices and heating behaviors has seldom been thoroughly assessed. This paper utilizes data from three rounds of a detailed panel dataset collected during the Coal to Electricity program in rural areas of Beijing to explore the dynamics of heating fuel choice and behavior among rural households. By using a difference-in-differences (DID) approach, my analysis reveals a significant yet partial transition from coal to electricity among affected households and a spontaneous transition in areas not directly targeted by the policy. This observation prompts a deeper exploration into the determinants influencing households' fuel choices and behaviors in the absence of coal ban policy. Employing the correlated random effects generalized ordered probit model to account for unobserved individual heterogeneity, I identify key variables such as fuel prices, household income, education, marital status, and house area that markedly influence these choices. Notable differences are observed in the determinants affecting fuel choices and usage patterns, particularly in the roles of coal prices and income. These findings indicate that choosing fuel types and determining usage levels might be governed by separate household decision-making processes. The study highlights the necessity to integrate both the energy ladder and fuel stacking theories into the models of household fuel consumption to effectively capture the nuanced dynamics of energy transition in rural China.

1 Introduction

Currently, approximately 2.1 billion people in developing countries rely heavily on biomass and coal for their daily cooking and heating needs, contributing significantly to both household indoor and regional air pollution. This dependence poses a substantial health risk, associated with approximately 3.2 million deaths in 2020 alone, and exacerbates the challenges of climate change (WHO (2024); Cheng et al. (2017)). Consequently, the United Nations Sustainable Development Goals (SDGs) have recognized the access to affordable, reliable, sustainable, and modern energy services as pivotal for catalyzing economic growth and enhancing quality of life. Improved access to modern energy services directly supports advancements in health, education, gender equality, while mitigating environmental degradation and global warming (UN (2016)). Evidently, residential fuel switching and fuel substitution stand out as essential strategies to achieve these broad development goals, particularly due to their significant role in reducing solid fuel combustion.

There have been numerous efforts to promote cleaner fuels through inter-fuel substitution globally. Governments and organizations worldwide have launched initiatives to replace polluting fuels with cleaner alternatives such as natural gas, liquefied petroleum gas (LPG), and electricity. These initiatives often involve financial incentives, infrastructural improvements, and educational campaigns to facilitate the transition. For instance, programs in low and middle income countries have successfully reduced the dependency on kerosene and charcoal by promoting solar energy and improved cooking stoves, contributing to enhanced public health and environmental preservation (Rehfuess et al. (2014)).

In China, reliance on solid fuels such as biomass and coal remains widespread, especially in rural areas, significantly exacerbating local air pollution and contributing to global climate change (Pachauri and Jiang (2008); Chen et al. (2024)). This dependence on traditional energy sources has led to a concerning situation where, as of 2013, an astonishing 99.6% of the Chinese population was exposed to air pollution levels that exceeded WHO guidelines. Moreover, only a mere 1% of the urban population lived in cities that met EU air quality standards, as reported by MEP (2013) and Zheng and Kahn (2013). These conditions underscore the ongoing challenges in air quality management, with particulate matters such as PM10 and PM2.5 posing major public health risks. In response to this critical issue, the Chinese government has enforced stringent policies aimed at reducing air pollution, with coal control as a central strategy. Initiated with the Air Pollution Prevention and Control Action Plan of 2013, extensive household fuel substitution programs have been deployed, particularly focusing on coal-reliant rural areas[1]. The Clean Heating Program, launched during the heating seasons in residential sectors, is pivotal in diminishing air pollution levels. In 2015, it was estimated that rural China utilized approximately 200 million tons of scattered coal for heating (NRDC (2017)). The policy's main strategies include transitioning from coal to gas or electricity, supported by financial subsidies for households to adopt cleaner heating technologies and fuels, thereby fostering a significant reduction in pollution and enhancing public health.

Xu et al. (2024) have estimated that the clean heating policy led to a significant increase in natural gas and electricity use, achieving substantial emission reductions-1.83 million metric tons of carbon dioxide equivalent in the aggregate in 2018. Song et al. (2023) further demonstrated that from 2015 to 2021, such policies reduced PM2.5 by 41.3 % Beijing and surrounding areas, significantly more than in other northern cities, and decreased China's annual PM2.5 by $1.9\,\mu\mathrm{g/m}^3$, preventing roughly 23,556 premature deaths in 2021. Despite these benefits, Li (2018) observed a significant natural gas shortage in winter 2017, which inflated prices and heating costs, making them unaffordable for many residents despite subsidies. Wu et al. (2020) noted that the coal-to-electricity shift, while cleaning the air, did not ensure adequate warmth due to decreased energy delivery.

Research extensively examines the health and environmental effects of these policies, but there has been limited focus on quantifying their impact on household fuel use and heating behaviors, which directly affects residents' welfare. This study aims to fill that gap by examining the effects of clean heating policies on household fuel choices and consumption at the micro level, utilizing data from the Beijing Household Energy Transition Project to analyze fuel substitution

[1] A comprehensive description of the series of policies regarding household fuel substitution is detailed by Wu et al. (2020).

impacts and assess changes in heating behaviors through a detailed questionnaire on heating devices usage.

The clean heating policy evaluation in this study revealed a significant reduction in polluting fuel use with electricity becoming the primary heating source, leading to an increase in total heating hours due to more clean/electric heating despite a reduction in polluting fuel use. The policy successfully maintained overall heating hours and showed more pronounced benefits in groups treated earlier, suggesting that early adoption boosts efficacy. However, coal use was not completely eliminated, even with the coal ban, and a similar shift from coal to electricity was observed in non-treated households, albeit to a lesser degree. This indicates other factors may influence fuel choices, underscoring the need for further investigation into why some households transition to cleaner fuels while others do not.

Despite extensive research on household energy choices in China, most studies use cross-sectional data, which may not effectively capture the dynamic and complex nature of these decisions and fail to control for unobserved individual heterogeneity. And there is also an emphasis on cooking energy, often neglecting heating energy, which a major component of northern households' energy use. Additionally, the phenomenon of fuel-stacking, where households adopt cleaner fuels as partial substitutes without fully abandoning traditional energy sources, has not been thoroughly examined during transitions to cleaner energy. Evidence on the determinants of fuel stacking is quite limited. Furthermore, previous empirical studies on fuel consumption often use simplistic models focusing on limited socioeconomic factors. However, household decisions in rural areas are complex due to market failures for biomass, commercial fuels, and labor. These failures mean that consumption decisions are intertwined with production decisions, including fuel production, food supply, and labor allocation, suggesting that consumption and production decisions are interconnected. Thus, I adopt a comprehensive model that integrates a broader range of socioeconomic factors affecting both consumption and production to better understand household responses to market failures. Furthermore, I emphasize the difference between the determinants of fuel choices and fuel usage, which could reveal distinct aspects of household decision-making processes.

This study bridges existing research gaps by using longitudinal data from rural Beijing to focus on heating energy and explore the dynamics of energy transition. I classify energy types into polluting, mixed, and clean fuels to provide evidence for fuel stacking behaviors and separately analyze the determinants of fuel choices and usage. Employing a random effects generalized ordered probit model with Mundlak correction helps us control for unobserved heterogeneity, thereby reducing the bias of the results. The study aims to understand why the use of polluting fuels persists in rural households, the factors driving their transition towards clean fuels, whether households ascend a fuel quality ladder with increasing income, and if the determinants of fuel choices differ from those of fuel usage. These insights are crucial for crafting effective policies to promote a fuel transition.

The analysis of heating fuel choices and behaviors highlights their interconnected yet distinct nature. Notably, while coal prices significantly affect fuel choices—driving a shift towards cleaner options as prices rise—they do not impact total heating hours, indicating that price hikes alone may not reduce pollution. Conversely, while income influences energy consumption levels, it has less impact on the type of fuels chosen. Higher income typically leads to increased electricity use for heating, aligning with the energy ladder theory, which suggests that as household income rises, families transition to higher-ranked energy sources while phasing out less advanced alternatives; however, it does not eliminate the use of polluting fuels, supporting the fuel stacking theory where households maintain a diverse energy mix. This suggests that fully transitioning to clean energy involves more than economic incentives; it also requires changes in social norms and behaviors, enhanced energy education, and better integration of rural households into broader energy policy frameworks. These findings underscore the need to combine energy ladder and fuel stacking theories to create comprehensive policies that effectively promote energy transitions.

The paper is structured as follows: Section 2 presents a detailed literature review; Section 3 describes the data used; Section 4 evaluates the clean heating policy in terms of fuel choices and heating behaviors; Section 5 examines the determinants of two processes in heating fuel consumption: the selection of fuels and the amount of heating for each fuel or device; Section 6 provides a discussion; and Section 7 offers the conclusion.

2 Literature Review

In this section, I begin by thoroughly reviewing evaluations of household energy interventions globally, with a specific focus on China, identifying key limitations and gaps in existing research. I then present the two predominant theories of fuel choices—the energy ladder and fuel stacking—and provide a summary of empirical evidence concerning various factors that influence household fuel decisions. Additionally, I investigate the existing research on household fuel choices in China, pinpointing methodological shortcomings and emphasizing the contributions of this study to the field.

2.1 Evaluation of Household Energy Interventions

Extensive fuel intervention programs have been launched worldwide to reduce air pollution and enhance public health. Numerous studies have explored the impacts of these initiatives globally, including specific analyses focused on China. A primary strategy in these interventions is the implementation of fuel bans, which have been demonstrated to significantly decrease air pollution and its associated health risks. For instance, the coal ban in Dublin led to marked reductions in air pollution levels, correlating with lowered incidences of respiratory and cardiovascular diseases (Dockery et al. (2013); Clancy et al. (2002)). Similarly, bans on residential wood-burning were shown to decrease cardiovascular hospitalizations and mortality rates due to reduced particulate matter exposure (Yap and Garcia (2015); Johnston et al. (2013)).

Another strategy for energy switching programs involves substituting clean energy by providing improved appliances or stoves. Budya and Arofat (2011) examined Indonesia's nationwide initiative to transition from kerosene to LPG, observing significant reductions in household air pollution. Pachauri et al. (2018) highlighted the necessity of effective subsidy mechanisms to facilitate such transitions, especially in economically disadvantaged communities where cost barriers could restrict access to cleaner fuels. Scott and Scarrott (2011) analyzed air quality interventions in New Zealand, noting marked improvements in PM10 concentrations resulting from stringent regulations and heater replacements.

China has dedicated significant efforts to mitigate its severe air pollution over recent decades. A major focus of these initiatives is the transition from residential coal to cleaner fuels, recognizing the heavy dependence on coal in the residential sector. As China's coal replacement policies evolve, scholarly attention on residential coal substitution within the country is increasing. Many studies focus on evaluating the economic, health, and environmental impacts via cost-benefit analysis. For instance, Zhang et al. (2019) developed an integrated model to evaluate the health impacts and economic costs of cleaner heating within the Beijing-Tianjin-Hebei (BTH) region, concluding that the overall public health improvements from enhanced air quality yield net social benefits, including spillover effects. Similarly, Xiaolin et al. (2019) applied cooperative game theory to devise cost-effective strategies that maximize environmental benefits in the BTH region, suggesting substantial potential savings if investments and support are optimally distributed.

Another focus of these evaluations is the effect of such programs on air pollution reduction and the resultant health benefits. Tian et al. (2018) highlighted the efficacy of high-quality coal replacements in reducing emissions from coal stoves. Studies such as those by Niu et al. (2024), Song et al. (2023), and Yu et al. (2021) noted modest reductions in outdoor PM2.5 levels in areas where the coal ban with heat pump subsidy was implemented, in contrast to neighboring regions without such measures. Meng et al. (2019) reported a significant 36% decrease in personal PM2.5 exposure following changes in household fuel use. However, Wen et al. (2023) observed only slight reductions in chronic lung diseases, with no significant changes in physician-diagnosed cardiovascular diseases following the coal ban policy.

Despite the proliferation of studies at the macro level, there is a notable gap in micro-level research on the impacts of residential coal replacement programs in China, especially on the fuel consumption and well-being. A few studies like those by Barrington-Leigh et al. (2019) and Wu et al. (2020) have begun to fill this void. Barrington-Leigh et al. (2019) assessed the effects of a program that subsidized electric heating devices and banned coal, analyzing its impact on household energy use, expenditure, and indoor environmental quality. Wu et al. (2020) found that the coal-to-electricity policy effectively reduced pollution but resulted in decreased energy delivery, adversely affecting winter warmth. Conversely, the high-quality coal replacement policy maintained energy delivery but failed to enhance indoor air quality.

This paper addresses this gap by evaluating the impact of coal replacement policies on household heating fuel choices and behaviors at the micro-level. It investigates how households distribute their heating needs among various fuels and devices in the context of coal replacement policies, and assesses the evidence for both the ”energy ladder” and ”fuel stacking” theories in understanding the effects of these interventions.

2.2 Determinants of Household Fuel Choices

After reviewing the evaluation of household energy interventions, I now explore another critical aspect of the literature concerning the determinants of household fuel choices. The energy ladder and fuel stacking theories prominently guide discussions on how households make fuel decisions. Empirical studies have extensively identified various determinants influencing these decisions. Additionally, I delve into the research on fuel choice dynamics within China, highlighting its limitations and underscoring the contributions of this study in addressing these gaps.

2.2.1 Energy Ladder Theory

The energy ladder theory illustrates a hierarchical relationship between a household’s economic status and the types of fuel they use for cooking and heating. As household income increases, families progressively transition to higher-ranked fuels while phasing out alternatives(Hosier and Dowd (1987); Heltberg (2005)), where the ranking of fuels is determined by cleanliness, ease of use, cooking or heating speed, and efficiency(Hiemstra-Van der Horst and Hovorka (2008)). Initially, families rely on biomass, then transition to fuels like kerosene and coal, and ultimately adopt cleaner energy sources such as LPG and electricity(See Figure 1). This transition is driven not only by the pursuit of fuel efficiency and reduced pollution exposure but also by a desire to reflect improved socio-economic status (Masera et al. (2000)).

While this correlation between income and fuel choice has been observed at both the country and individual levels (Farsi et al. (2007); Davis (1998); Gupta and Köhlin (2006)), the model’s

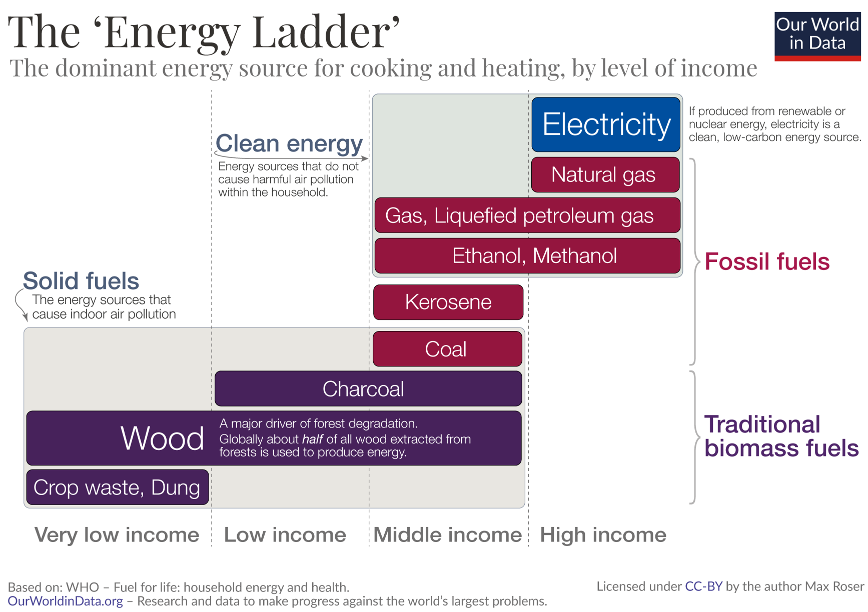


Figure 1: Energy Ladder

simplicity is often challenged by empirical evidence. Research across various developing countries indicates that fuel wood remains a vital energy source for households at all income levels despite the availability of modern fuels(Hiemstra-Van der Horst and Hovorka (2008);Hosier and Kipondya (1993); Bhagavan and Giriappa (1995); Brouwer and Falcão (2004)). Furthermore, the use of higher-ranked fuels such as electricity and LPG by low-income households (Campbell (2003)) demonstrates that energy choices are influenced by a variety of factors beyond income. This indicates a more complex interplay of factors influencing energy usage than what is depicted by the energy ladder, necessitating a broader understanding of the impact of various socio-economic variables on energy consumption behaviors.

2.2.2 Fuel Stacking Theory

Numerous studies found that the energy transition is not a simple linear progression but involves households simultaneously using multiple fuels, a concept known as fuel stacking (Leach (1992); Campbell (2003); Arnold et al. (2006); Karekezi and Majoro (2002)). This model posits that households adopt new fuels as partial substitutes without abandoning traditional energy sources. Often, fuel switching process is not unidirectional; households may revert to using traditional fuels even after adopting modern energy sources due to factors like price fluctuations (Masera et al. (2000); Arnold et al. (2006); Maconachie et al. (2009); Wickramasinghe (2011)). Masera et al. (2000) proposed the multiple fuel model, which suggests households do not entirely switch from one fuel to another but maintain a diverse portfolio of energy options for common needs such as cooking. Studies support the prevalence of fuel stacking across both urban and rural households in developing countries(Heltberg (2005); Hiemstra-Van der Horst and Hovorka (2008); Mekonnen and Köhlin (2009); Mirza and Kemp (2011)), serving as a strategy to ensure energy security (Davis (1998)), cope with fluctuating fuel prices or incomes (Hosier and Kipondya, 1993), manage unreliable fuel supplies (Masera et al. (2000); Hosier and Kipondya (1993)), and adhere to cultural traditions (Masera et al. (2000)).

2.2.3 Determinants of Fuel Use

I present empirical evidence on the principal determinants of household fuel decisions. For a comprehensive review of the factors influencing fuel use, readers are encouraged to refer to the detailed studies by Muller and Yan (2018) and Van der Kroon et al. (2013).

Income The energy ladder theory has emphasized income as a important determinant of fuel choices, however, empirical studies offer mixed results. The relationship between income and fuel choice is complex and varies by context, as shown in studies like Ouédraogo (2010) in Burkina Faso and Gupta and Köhlin (2006) in urban India, where higher incomes or expenditures led to the adoption of gases like natural gas and LPG. Notably, the income effect on fuel choice is not always linear or positive; for instance, Démurger and Fournier (2011) found that Chinese rural households substitute coal for firewood as wealth increases, challenging the simple linear model of the energy ladder. This complexity is further highlighted by the varied income elasticities across fuel types and contexts, suggesting that while some fuels behave as necessities, others are luxury goods, depending on the economic and social setting (Muller and Yan (2018); Akpalu et al. (2011); Hughes-Cromwick (1985)).

Fuel Prices Extensive empirical research illustrates the significant role of fuel prices on household fuel choices, noting considerable variability in price sensitivity across fuels and regions. Numerous studies, such as those by Farsi et al. (2007) in India and Jingchao and Kotani (2012) in Beijing, demonstrate that increases in the prices of fuels like LPG significantly reduce their consumption and likelihood of selection by households. Similarly, research by Gupta and Köhlin (2006) and Akpalu et al. (2011) indicates that the relationship between firewood consumption and its price is predominantly negative. However, the effects vary; while some studies find strong negative price elasticities, others, like those on coal, show no significant price impact, emphasizing the complexity of fuel price effects across different contexts. Additionally, cross-price effects, which suggest potential substitutability or complementarity between fuels, have yielded mixed results in the literature. For example, Heltberg (2005) and Pitt (1985) observed substitution effects between various fuels, whereas others like Gupta and Köhlin (2006) report negative cross-price elasticities, challenging simple interpretations of fuel substitutability. This indicates that fuel choices are influenced by a complex interplay of price dynamics and other socioeconomic factors, necessitating nuanced economic models to accurately capture these relationships.

Age Empirical evidence on the impact of household head age on fuel choice presents mixed findings. Older household heads tend to favor traditional fuels; studies like Baiyegunhi and Hassan (2014) in Nigeria and Edwards and Langpap (2012) in Guatemala report a positive association between age and the use of wood or fuel wood. Similarly, Démurger and Fournier (2011) find a significant preference for firewood in older rural Chinese households, while Gebreegziabher and Kooten (2013) note older Ethiopian heads prefer charcoal. Conversely, some research suggests older individuals prefer modern fuels; Farsi et al. (2007) and Gupta and Köhlin (2006) observed a preference for LNG over wood in older Indian household heads, and Özcan et al. (2013) report a shift from wood to cleaner fuels like natural gas and electricity in older Turkish household heads. These divergent findings could reflect a life cycle effect, where older individuals, potentially with fewer liquidity constraints, can afford cleaner fuels, and at older ages, it may become too difficult to gather firewood or haul coal. However, several studies like those by Abebaw (2007) and Israel

(2002) argue that age has no significant impact on fuel use, adding complexity to the understanding of age dynamics in fuel choice behavior.

Gender Gender also influences household fuel choices, with mixed evidence on its impact. Studies like Farsi et al. (2007), Rao and Reddy (2007), and Rahut et al. (2020) suggest that female-headed households often prefer modern fuels over traditional ones, likely due to women's central role in cooking and their direct exposure to harmful pollutants from traditional fuels. Conversely, some research finds no significant gender effect; **?**, and Ouédraogo (2010) report an insignificant gender coefficient in varying contexts. In Nepal, Link et al. (2012) observed that households with a higher proportion of female members tended to use more fuel wood, attributing this to women's roles in fuel wood gathering. However, contrasting findings from Heltberg (2005) in Guatemala and Israel (2002) in urban Bolivia suggest that the proportion of females does not influence fuel wood use significantly, with Israel noting that women earning a larger share of family income correlates with less firewood use, possibly reflecting the higher opportunity costs of women's time. Gupta and Köhlin (2006) also find that the employment status of women in India does not impact fuel choice. These disparate findings indicate that gender's role in fuel choice may be shaped by a blend of preferences, time costs, and intra-household dynamics.

Education Education plays a pivotal role in influencing household fuel choices, often leading to a shift from traditional to modern fuels due to increased awareness of health impacts and the efficiencies offered by alternative energy sources. Studies such as Abebaw (2007) and Démurger and Fournier (2011) show a negative correlation between education level and firewood consumption, partly due to higher opportunity costs associated with fuel collection time. Further, research from Nigeria and India by Baiyegunhi and Hassan (2014) and Gupta and Köhlin (2006) supports that increased educational attainment encourages a transition towards kerosene and LPG. Similarly, in Ethiopia and Kenya, Gebreegziabher and Kooten (2013) and Lay et al. (2013)) found that higher education levels correlate with a preference for electricity over wood. These findings highlight education's role not only in enhancing income but also in promoting energy literacy, which can drive changes in fuel consumption patterns.

Household Size Household size influences energy consumption patterns, often reflecting both economic scale effects and income constraints. Studies like Abebaw (2007) and Jingchao and Kotani (2012) highlight a negative correlation between household size and per capita energy use, suggesting economies of scale. However, this association might also mask an underlying income effect, as larger households, which are often poorer, might not afford modern fuels, thus relying on cheaper alternatives like firewood. On the contrary, some research, such as by Baiyegunhi and Hassan (2014) and Gupta and Köhlin (2006), indicates that larger households are more inclined towards clean fuels, possibly due to greater aggregate resources. The relationship between household size and fuel choice remains mixed, with some studies noting no significant impact on fuel switching (Hosier and Dowd (1987); Guta (2014)), while others observe a preference for traditional fuels in larger families due to their need for larger fuel quantities and the lower unit costs of traditional energy sources (Rao and Reddy (2007)). These contrasting findings suggest that the effects of household composition on fuel usage are complex and warrant further investigation to uncover the underlying dynamics.

Availability and Accessibility The availability and accessibility of fuels is another determinant of household energy choices. Traditional fuels' availability often relates to geographical factors like proximity to fuel wood sources and community perceptions of fuel wood availability (Hosier and Dowd (1987); Hosier and Dowd (1987)). Conversely, the accessibility of modern fuels involves factors such as community access to electricity and modern renewable energy technologies (Heltberg (2005); Gupta and Köhlin (2006); Lay et al. (2013)). Studies consistently find that limited access to traditional fuel sources often pushes households toward modern alternatives due to the high opportunity costs associated with fuel collection. For instance, households with better access to electricity and other modern energy sources are more likely to transition away from traditional fuels like wood and kerosene (Lay et al. (2013); Heltberg (2005)). This shift is also affected by infrastructure reliability, as frequent power outages can hinder the adoption of electricity (Kemmler (2007)).

Production Characteristics The conrrelation between agricultural production characteristics and household fuel choice is particularly pronounced in rural areas, where the decisions surrounding consumption and production are deeply interconnected. Authors like Chen et al. (2006), Démurger and Fournier (2011), and Pandey and Chaubal (2011) demonstrate varying impacts of farmland size and livestock on fuel choices across different regions in China and India, with some findings indicating that larger farm sizes and the presence of livestock increase the use of biomass fuels due to the availability of agricultural by-products for burning. Conversely, some studies note a decrease in firewood consumption with an increase in livestock, suggesting a complex relationship between farm assets and fuel usage that transcends simple income effects. Additionally, the labor availability within households, often associated with larger family sizes, can reduce the opportunity costs related to fuel wood collection and management, influencing a continued preference for traditional fuels (Chen et al. (2006); Baland et al. (2017)). This correlation suggests that agricultural activities and labor resources within households play crucial roles in shaping fuel consumption patterns, yet these dynamics are often overlooked in energy source studies.

Other Factors Lifestyle factors impact fuel choices, particularly when traditional cooking habits demand prolonged use of a fuel, influencing the type of energy used. Baiyegunhi and Hassan (2014) note that Nigerian households hesitate to transition from fuel wood to natural gas or electricity due to prolonged cooking times. Similarly, Ouédraogo (2010) finds that frequent traditional cooking increases firewood use in Ouagadougou. The choice of fuel is also intertwined with the type of cooking and heating appliances available, which can limit or promote the use of certain fuels. For instance, the presence of modern appliances is often necessary for adopting cleaner fuels (Hughes-Cromwick (1985); Manning and Taylor (2014)). However, high appliance costs can impede this transition, a factor not yet empirically explored in depth regarding its direct financial impact on fuel choice (Edwards and Langpap (2012); Louw et al. (2008)). Additionally, household structure and regional factors can influence fuel preferences, with married heads of households and specific ethnic or regional groups showing distinct fuel usage patterns (Paudel et al. (2018); Liao et al. (2019)).

2.2.4 Literature Review on Fuel Choices in China

The existing literature on household energy choices in China has predominantly relied on either aggregated statistics or localized surveys, with a limited number of studies utilizing nationwide data. Studies like those by Cai and Jiang (2008) utilized aggregate statistics to validate the energy ladder hypothesis, showing a distinct contrast between urban and rural energy consumption patterns, with urban households favoring cleaner and more efficient fuels compared to the traditional biomass and coal used in rural settings. This hypothesis was similarly explored by Peng et al. (2010), who analyzed fuel switching at the household level within rural Hubei and noted significant geographic variations in energy source availability and preferences, highlighting a gradual shift from biomass to commercial energy sources like coal.

Further contributions to this field include Jingchao and Kotani (2012), who, through survey data from rural Beijing, identified that price factors for coal and LPG did not support substitution effects between these fuels. At a national level, Jiang and O'Neill (2004) expanded the scope of analysis by incorporating a nationally representative rural household survey combined with aggregate statistics to explore broader patterns of residential energy use across rural China.

More recent studies have applied more sophisticated econometric models to dissect the nuances of energy choice determinants. For instance, utilizing panel data from the China Health and Nutrition Survey (CHNS), Muller and Yan (2018) employed random effects multinomial logit models to confirm that fuel choices are significantly influenced by a complex interplay of socioeconomic and market factors. Similarly, Zhang and Hassen (2017) employed generalized ordered models with random effects to scrutinize urban households' cooking energy preferences, finding that policies enhancing income could lessen coal's competitive edge over liquefied natural gas. Zhang et al. (2020) employ the Seemingly Unrelated Regression (SUR) model to analyze urban household data in China, identifying building type, income, and fuel prices as key determinants of energy choice behavior.

Additionally, Zhu et al. (2022) integrate the least absolute shrinkage and selection operator (LASSO) algorithm with a multinomial Logit model to analyze the determinants of energy choice for household cooking in China, utilizing data from the Chinese Family Panel Studies (CFPS), finding household expenditure, off-farm employment, health levels, the presence of children, the education level of the household head, living conditions, and energy accessibility significantly influence the transition towards cleaner cooking fuels. Wu and Zheng (2022) further studied the energy ladder using data from the Chinese Residential Energy Consumption Survey (CRECS), revealing an inverted U-shaped relationship between income and fuel diversity and noting that the ”Coal-to-Electricity” policy might hinder natural income-driven transitions towards cleaner energy.

Despite the depth of research on household energy choices in China, the majority of studies suffer from methodological limitations, particularly the use of cross-sectional data which may not fully account for unobserved individual heterogeneity, thus possibly confounding the true effects of explanatory variables. Additionally, there is a pronounced focus on cooking energy within the existing literature, often overlooking heating energy, which constitutes a 32% of building energy use in Chinese households(International Energy Agency (2015)). Moreover, few studies have explored the distinction between the determinants of fuel choices and fuel usage, which may represent two separate decision-making processes. Wu and Zheng (2022) briefly touch on this concept but do not provide detailed insights into how these decision processes differ.

Based on the above literature review on the determinants of fuel choices, the influence of factors such as age, income, and others largely depends on the context. To better understand how these determinants impact heating fuel choices under the Beijing clean heating policy, I will need to conduct an analysis within the relevant context, as the previous literature from other settings does not provide a reliable basis for prediction.

This study addresses these gaps in the literature by implementing several methodological enhancements to provide more accurate and comprehensive insights into rural heating energy decisions. Firstly, I control for unobserved heterogeneity by utilizing longitudinal data, which enables us to offer more precise estimates of the effects being studied. Secondly, I specifically focus on heating—a critical but often under-examined aspect of household energy use—to enrich the empirical evidence regarding rural energy decisions. Lastly, I differentiate between the determinants of heating fuel choices and fuel usage, examining these two decision processes separately to highlight potential variations and to better understand the underlying mechanisms influencing each.

3 Data

3.1 Clean Heating Policy

In response to the severe smog and escalating particulate matter pollution across various regions, the Chinese government has implemented significant air pollution reduction measures over recent decades. These measures include a series of policies mandating household fuel substitutions, such as replacing coal with natural gas or electricity, especially during the heating seasons. This initiative is crucial since residential space heating is one of the largest sources of wintertime air pollution (Dispersed Coal Management Research Group (2023)). The policies primarily target the ”2+26” cities[2] in the northern region, emphasizing mandatory coal-to-gas and coal-to-electricity transitions, with financial subsidies provided to households for purchasing cleaner heating solutions. These strategies aim to ensure a clean and warm winter while reducing emissions from the residential sector, thereby enhancing regional air quality.

In the context of Beijing Municipality, where the data for this study was collected, while urban residents benefit from central heating, most peri-urban and rural households have traditionally relied on traditional coal heaters and biomass kangs[3]. In alignment with national policies, the Beijing municipal government has launched a comprehensive program that not only bans coal in certain areas but also subsidizes nighttime electricity rates and the purchase and installation of electric-powered heat pumps. This program aims to replace traditional coal-burning stoves, facilitating a shift towards cleaner heating methods in line with broader environmental objectives. For further details on the policy, please refer to WHO (2021).

[2] The ”2” refers to Beijing and Tianjin municipalities. The ”26” refers to 26 cities located in Shanxi, Henan, and Hebei provinces. The Ministry of Environmental Protection has identified these ”2+26” cities as the key transmission channel cities for air pollution in the Beijing-Tianjin-Hebei region, and they are considered a top priority in the prevention and control of air pollution.

[3] A kang is an integrated traditional Chinese heating technology that serves multiple home functions including cooking, sleeping, space heating, and ventilation.

3.2 Beijing Household Energy Transition Project

To assess the impact of the Clean Heating policy on air quality and public health, the Beijing Household Energy Transition Project[4] conducted four consecutive seasons of data collection during the winters of 2018-19, 2019-20, 2020-21 , and 2021-22 (referred to as Season 1 to Season 4, respectively) in rural Beijing. The study encompassed 50 villages across four administrative districts—Fangshan, Huairou, Mentougou, and Miyun. Initially, these villages predominantly utilized coal for heating and were eligible for, but not yet participating in, the clean heating policy.

The research project implemented a staggered treatment approach, as illustrated in Figure 2 and Table 1. By the conclusion of the study, 20 villages had adopted the clean heating policy, while 30 remained as control groups. The treatment villages were equipped with subsidized heat pumps during the preceding summer, and households began paying for electricity at reduced rates starting the subsequent winter. For the study, approximately 20 households per village were randomly selected to participate, and these households were followed up in subsequent years to complete detailed surveys on health and energy use. In addition, data on indoor air quality and temperature were collected to assess the environmental impacts. If a household drops out of the study, a new household is enrolled to maintain the sample size. The majority of the households consist of two people or fewer, with an average respondent age of 60. Most participants have received only primary education, are married, and work in agriculture. 40% of the respondents are male.

During Season 3, coinciding with the peak of the COVID-19 pandemic, data collection was confined to indoor air quality, temperature, and stove use due to travel restrictions, limiting comprehensive data on other fuel types and heating devices. Consequently, for the purposes of heating analysis, I will focus on data from Seasons 1, 2, and 4 only.

[4]The project is primarily led by Prof. Jill Baumgartner and Sam Harper at McGill University, with funding from the Health Effects Institute (HEI), the Canadian Institutes of Health Research (CIHR), the Social Sciences and Humanities Research Council (SSHRC), and the Government of Canada.

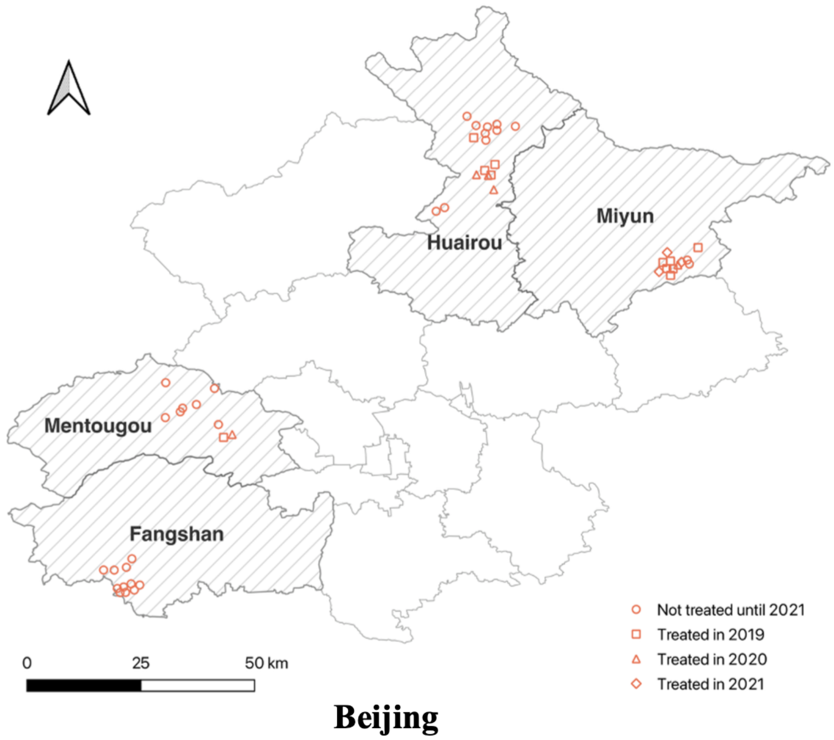


Figure 2: Treatment Map

Table 1: Treatment Schedule of clean heating policy

District	No Ban	Treated in S2	Treated in S3	Treated in S4	Total
Miyun	2	6	1	3	12
Huairou	10	4	4	0	18
Mentougou	7	0	2	0	9
Fangshan	11	0	0	0	11
Total	30	10	7	3	50

3.3 Data Description

The study collected comprehensive information on household energy choices and living conditions, including income, expenditure, demographics, health, educational status, occupation, farming activities, asset ownership, and other variables at both the household and individual levels. A strength of this dataset is its detailed recording of energy choices for all purposes, including cooking, heating, and boiling hot drinking water. Additionally, it captured detailed heating hours for various heating devices in each room of the households (see Table 2). In this study, I will utilize this information to delve into household heating energy choices.

Table 2: Survey Questions on heat sources by room during winter

Heat source by room		
Room	Q. 1 How is the room heated in winter?	Q. 2 How many hours, on average, is the heat source on each day in the winter?
(1) Common room (2) Bedroom (3) Kitchen (4) Bathroom (5) Other (6) Storage	(1) Not heated (2) Hot water wall radiator (3) Heated floor (by water) (4) Kang - wood (5) Kang - coal (6) Coal stove (directly) (7) Wood stove (directly) (8) ATA heat pump (9) Thermal storage (electricity) (10) Mobile electric heater (11) Electric blanket (12) Air conditioner (13) Heated floor (by electricity) (90) Other	(1) Seldom or only on special occasions (2) < 2 hours (3) $2 - 4$ hours (4) $4 - 6$ hours (5) $6 - 8$ hours (6) $8 - 10$ hours (7) $10 - 12$ hours (8) $12 - 16$ hours (9) All day and night

3.3.1 Dependent Variables

To comprehensively analyze household heating dynamics, this study examines two pivotal categories of outcomes: heating fuel choices and heating behaviors. Heating fuel choices represent the energy sources selected by households for heating, which directly influence environmental and health outcomes due to emissions. Heating behaviors, on the other hand, encompass the frequency and intensity of fuel usage, as well as the distribution of heating needs across various fuels and heating devices. All dependent variables may be time-varying.

Heating Fuel Pattern The first set of dependent variables in this study are binary indicators representing the types of energy households choose for heating[5]. To align with the theories of fuel stacking and energy ladder, households in this study are categorized into three groups based on their energy usage: clean, mixed, and polluting. Households exclusively using electricity, natural gas, or LPG for heating fall into the ”clean energy” category. Those relying on traditional biomass fuels like firewood, charcoal, and crop residues are categorized as ”polluting fuel” users. The ”mixed fuels” category encompasses households that use a combination of both clean and polluting fuels,

[5] In this study, I concentrate on fuels and devices used regularly for daily heating, excluding those used infrequently. If a household indicates that a device is used ”seldom or only on special occasions” for heating, it is classified as not being used for routine heating purposes.

employing modern energy sources like electricity and gas for certain heating tasks while continuing to depend on traditional biomass fuels for others.

Primary Heating Fuel The primary heating fuels form the second set of dependent variables in this study, represented as binary variables. Although fuel stacking occurs, the analysis of primary heating fuel remains crucial for a comprehensive understanding of household fuel choices, as most households, at least within this study, predominantly rely on a single heating device to meet the majority of their heating needs. I utilize detailed usage data for various heating devices in each room to compute the aggregate heating hours for each device and fuel type. The primary heating device is identified as the one with the maximum aggregate heating hours across all rooms[6].Consequently, the primary heating fuel is the fuel used by the primary heating device. The vast majority of the households in the study use electricity, coal, and wood as their primary heating fuels.

Total Heating Hours across all rooms The first set of heating behaviours variables captures the total heating hours for all rooms on a typical day, organized by fuel pattern, fuel type, or specific heating device. This approach enables an exploration of how households allocate their heating hours among different types of fuels—be it clean, polluting, or more specifically, options like electricity, coal, and wood. The study also delves into the heating behaviors associated with various electric heating devices, hypothesizing that the adoption of more efficient heat pumps might reduce reliance on less efficient alternatives. However, the availability of electricity subsidies might encourage the continued use of other electric heating devices, complicating this transition. Thus, the analysis examines how heating hours are allocated among three distinct categories: subsidized heat pumps, other high-efficiency electric devices such as heated floors and air conditioners, and less efficient portable electric heaters.

Average Heating Hours per Room The second set of heating behaviours variables measures the average heating hours, defined as the total heating hours divided by the number of rooms heated

[6]In cases where two or more devices have identical heating duration, the one with the highest heating efficiency is designated as the primary device. The hierarchy of efficiency levels is as following: Heat Pump $>$ Radiator(Coal) $>$ Heated floor by electricity $>$ AC $>$ Kang(Wood) = Kang(Coal) $>$ Mobile electric heater $>$ Coal stove

daily. For this study, 'daily heating' is characterized by rooms consistently heated for a specified duration each day, excluding those heated only occasionally.

The independent variables include fuel prices, household income, age, sex, education, marital status, occupation of the respondent, household size, agricultural assets, and other factors. A summary of these variables will be presented in Table 3 in a later section.

4 Clean Heating Policy Evaluation

This section addresses the first research question of the paper: how does the clean heating policy impact the heating fuel choices and behaviors of households? I begin with a descriptive summary of the energy dynamics over the sample period, followed by an outline of the empirical strategy. Subsequently, I present the estimated treatment effects on the heating fuel choices and behaviors of households.

4.1 Descriptive Energy Dynamics

Figure 3 illustrates the current usage rates of electricity, coal, and biomass. For the treated villages, coal use decreases drastically following the implementation of the clean heating policy, although a few households continue to use coal. Meanwhile, the electricity usage rate for heating in these villages increases to nearly 100%. In the control villages, there is also an observed trend of increasing electricity use and decreasing coal use over time, even without a coal ban. This indicates that households are gradually transitioning from coal to electricity on their own. Understanding the determinants behind this spontaneous transition will be valuable for future policy design. Regarding wood usage, there is a slow decreasing trend in both the control and treated groups.

Figures 4 illustrates the heating fuel combinations for households, highlighting how they change their heating fuel mix in response to the clean heating policy. There are two main scenarios for treated households: some completely switch to electricity heating, while others do not fully switch and instead partially use biomass as a substitute for coal. Consequently, more households adopt either a completely clean or a mixed heating style. This trend is also observed among

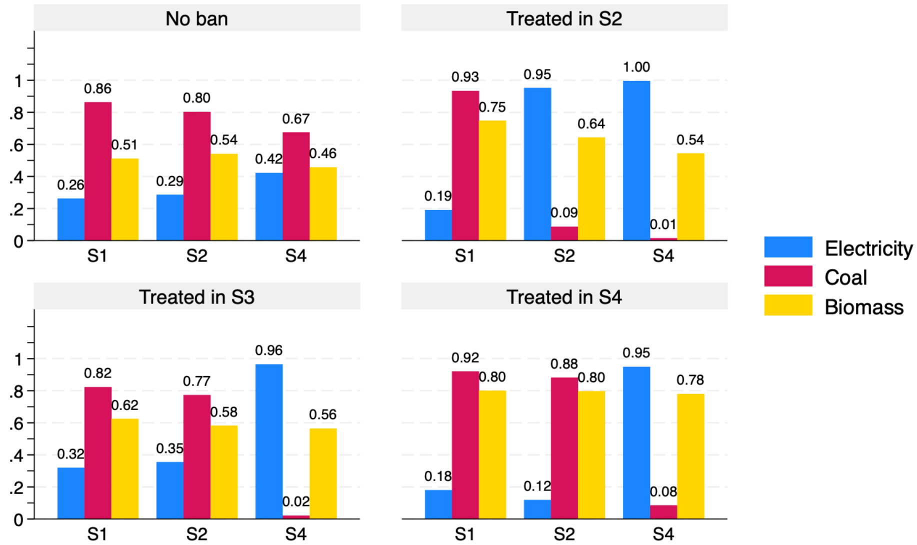


Figure 3: Current Use of Heating Fuel

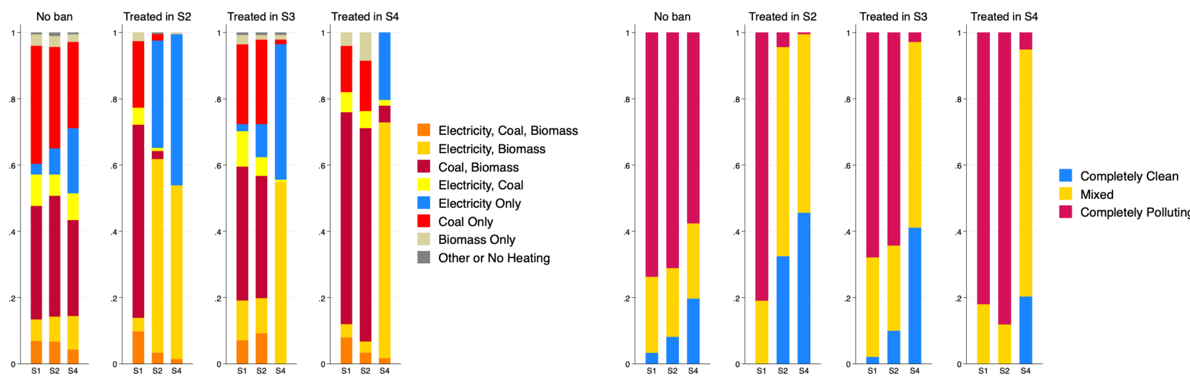


Figure 4: Heating Fuel Combination

households in the control villages. The Sankey diagrams in Figures .A.1 and .A.2 in the appendix visually illustrate the transitions households make between different fuel patterns.

Figures 5 and 6 present the heating behaviors by device and fuel, respectively. Before the coal ban, radiators fueled by coal were the main heating devices for most households. After the coal ban, the subsidized heat pump became the primary device for most treated households. Even in the control villages, an increasing number of households are adopting electric heating. Figure .A.3 in appendix illustrates the transitions in primary heating fuel.

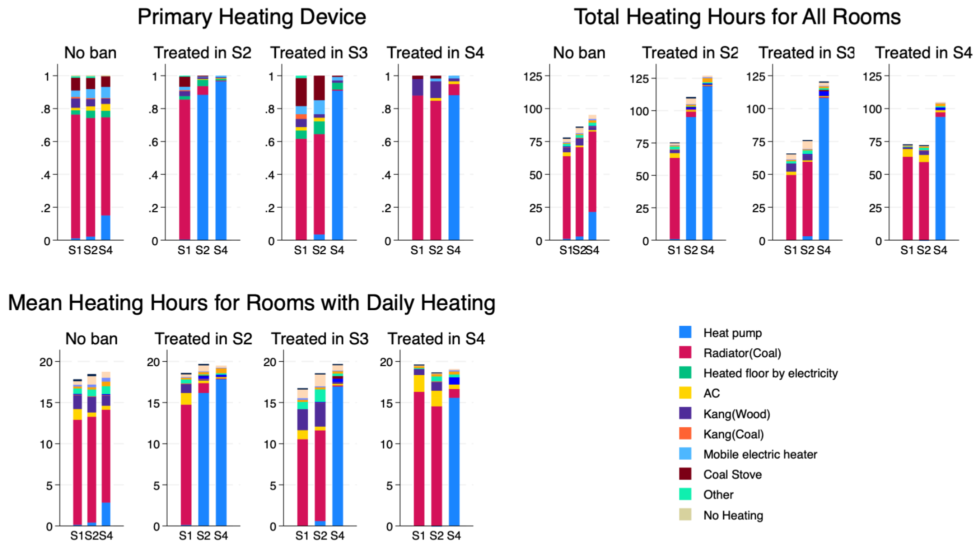


Figure 5: Heating Behaviours By Device

Figures 5 and 6 present the total daily heating hours across all rooms by heating device and fuel type, respectively, as well as the mean heating hours across rooms with daily heating in the treated group. Notably, there is a significant shift in heating hours from coal-powered devices to subsidized heat pumps for the treated households. Furthermore, there has been a marked increase in the total heating hours for the treated post-clean heating policy implementation, while the mean heating hours for rooms with daily heating have remained relatively stable. This suggests that households are choosing to heat more rooms (see Figure .A.4) rather than increasing the heating duration per room. There is a notable reduction in heating hours using polluting fuels and devices, with a corresponding increase in the use of clean energy, particularly electricity, which supports the policy's objectives.

To summarize, household heating dynamics have changed significantly following the policy implementation, as evidenced by an increased adoption of electricity and heat pumps for heating. This shift is characterized by a substantial reduction in coal usage, though coal was not completely phased out, and wood usage remained unchanged. Following the ban, there was a notable rise in total heating hours across all rooms utilizing electricity and subsidized heat pumps. However, the average heating hours per room saw only a minimal increase, indicating that households

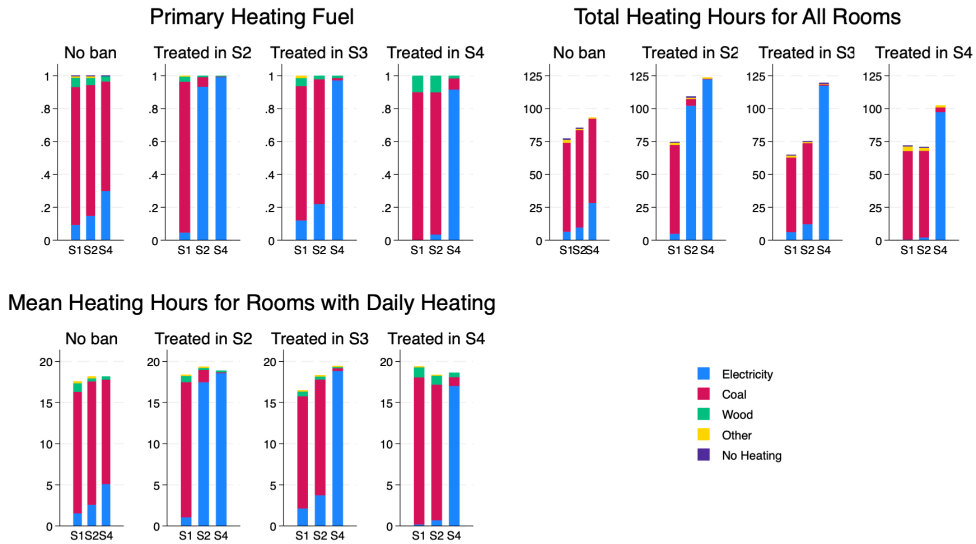


Figure 6: Heating Behaviours By Fuel Type

opted to heat more rooms rather than extend the heating duration in any single room. Additionally, a similar, albeit less pronounced, transition from coal to electricity was observed in households not directly affected by the ban, suggesting broader underlying trends in energy preferences.

4.2 Empirical Strategy

4.2.1 Two Way Fixed Effects(TWFE) Model

Based on the study design of the Beijing Household Energy Transition Project, I utilized the Difference-in-Difference (DID) method to assess the effect of the clean heating policy by comparing changes in the treatment group against the control group before and after policy implementation. I formulated the following two-way fixed effect regression equation to estimate the policy's treatment effect:

$$Y_{it} = \alpha_i + \gamma_t + \beta \times D_{it} + X_{it} + \varepsilon_{it} \tag{1}$$

where Y_{it} represents the heating outcome for household i in period t; D_{it} indicates treatment status, with 1 if unit i is treated in period t and 0 otherwise; X_{it} are control variables; γ_t is the time fixed effect for period t; α_i is the household fixed effect for household i; ε_{it} is the error term; and β measures the average treatment effect.

A critical assumption of the DID method is the parallel trend assumption, which posits that in the absence of treatment, the average outcome for both treated and untreated groups would have followed a similar trend. I test for pre-existing trend differences as a check on this assumption by estimating the following dynamic TWFE model:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{r \neq 0} 1[R_{it} = r]\beta_r \times D_{it} + X_{it} + \varepsilon_{it} \tag{2}$$

where $R_{it} = t - T_{treat,i} + 1$ denotes the time relative to treatment. A non-violation of the parallel trends is indicated by $\beta_r = 0$ for all $r < 0$.

4.2.2 Advanced DID Estimators for Staggered Treatment

Recent studies have highlighted potential issues with the two-way fixed effects model when dealing with staggered treatment adoption(Goodman-Bacon (2021); Callaway and Sant'Anna (2021); Gardner (2022); Borusyak et al. (2024); Sun and Abraham (2021); De Chaisemartin and d'Haultfoeuille (2020)). This model typically assumes homogeneity in treatment effects—implying that all units are impacted uniformly by the treatment regardless of the timing of its reception or the duration since its initiation. This can be problematic as it includes early-treated units as controls for those treated later, potentially distorting the estimated effects if the uniform effect assumption does not hold.

To address these issues, various improved Difference-in-Differences (DID) estimators have been developed that relax the homogeneity assumption, allowing for the treatment effects to vary across units and over time. A particularly notable approach among these new methodologies is proposed by Callaway and Sant'Anna (2021), which I will employ as a robustness check in my analysis. This method avoids using already-treated groups as controls and allows for the estimation of treatment effects that are specific to each group and period. These effects can then be aggregated as needed—whether as an overall effect, or segmented by treatment group, calendar time, or duration since treatment initiation. By using this method, we can address the potential biases inherent in traditional DID estimators and more accurately capture the varied impacts of the treatment across different contexts and times.

4.2.3 Advanced DID Estimators for Non-parallel Trend

In some cases, a significant pre-treatment trend is detected, suggesting that the parallel trends assumption may not hold. However, researchers may still wish to draw conclusions about the treatment effects, particularly if the violation of parallel trends is relatively small in magnitude. The conventional approach does not provide clear guidance on how to proceed in such cases (Roth et al. (2023)).

Rambachan and Roth (2023) introduce an innovative DID estimator that incorporates pre-treatment trends to assess and adjust for potential violations of the parallel trends assumption in DID analyses. Their approach formalizes two key methods: Bounds on relative magnitudes and Smoothness restrictions. The former sets limits on the extent of post-treatment trend deviations relative to pre-treatment, with parameters like $\bar{M}$ determining the allowable magnitude of these deviations. The latter imposes constraints on the rate of change in pre-treatment trends, ensuring that post-treatment deviations do not stray significantly from a linear extrapolation of earlier trends. These innovative methods enhance the robustness of DID estimators, allowing for more reliable causal inference in complex scenarios where traditional assumptions may not hold. For further details, please refer to Rambachan and Roth (2023).

4.3 Empirical Results

In this section, I analyze the impacts of the clean heating policy on two primary aspects: heating fuel choice and heating behaviors. My primary objective is to understand how this policy influences household decisions regarding which fuel portfolios to adopt. Recognizing that households frequently use multiple fuels simultaneously, it is crucial to identify not only the overall fuel patterns, but also the primary heating fuel they use. To this end, I utilize two sets of binary dependent variables: one set categorizes heating fuel patterns as clean, mixed, or polluting, and another identifies the primary heating fuel, which may be electricity, coal, or wood.

After identifying the fuel choices, I delve into the related yet different decisions about heating behaviors. This includes how much households choose to heat and how they allocate heating hours among the selected fuels. I assess the total heating hours per fuel source across all rooms on a typical day. For a detailed analysis of these behaviors, I also include in the appendix the average heating hours per room, broken down by each fuel source, for rooms that are heated daily.

Table 3 presents the descriptive statistics for the socioeconomic variables of households at baseline, clearly indicating that there are no significant differences between the treated and control groups. This provides a robust foundation for further analysis of the impacts of the clean heating policy.

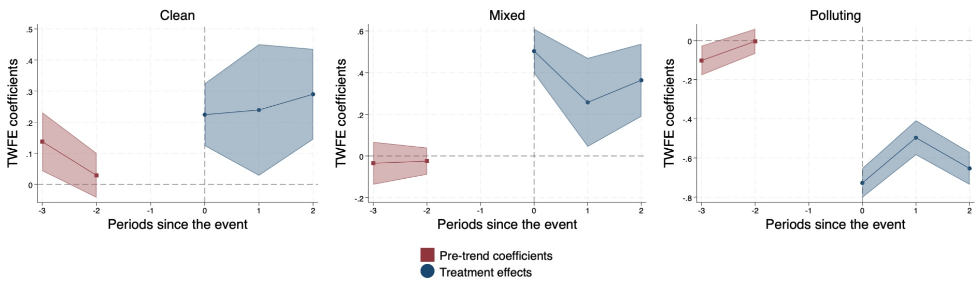
Table 3: Summary Statistics at Baseline

	Control					Ever Treated				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Covariate										
Log Price of Coal	6.27	0.22	5.86	6.91	581	6.21	0.57	-4.61	6.91	385
Log Income per Capita	9.49	0.67	8.01	11.36	581	9.46	0.72	8.01	11.81	385
Log Household Size	0.81	0.43	0.00	2.08	581	0.75	0.40	0.00	1.79	385
Age	60.34	9.36	33.75	88.95	581	60.88	9.21	37.24	85.98	385
Male	0.41	0.49	0.00	1.00	581	0.41	0.49	0.00	1.00	385
Number of Children Under 5	0.10	0.35	0.00	3.00	581	0.08	0.30	0.00	2.00	385
Education										
Primary School	0.68	0.47	0.00	1.00	581	0.73	0.44	0.00	1.00	385
Secondary or High School	0.21	0.41	0.00	1.00	581	0.14	0.35	0.00	1.00	385
Higher Education	0.08	0.27	0.00	1.00	581	0.07	0.25	0.00	1.00	385
Work in Agriculture	0.62	0.49	0.00	1.00	581	0.67	0.47	0.00	1.00	385
Married	0.90	0.30	0.00	1.00	581	0.87	0.33	0.00	1.00	385
Log Agriculture Land	-2.13	2.37	-4.61	2.71	581	-2.33	2.35	-4.61	2.30	385
Log Forest Land	-1.91	2.87	-4.61	6.21	581	-0.67	2.76	-4.61	6.21	385

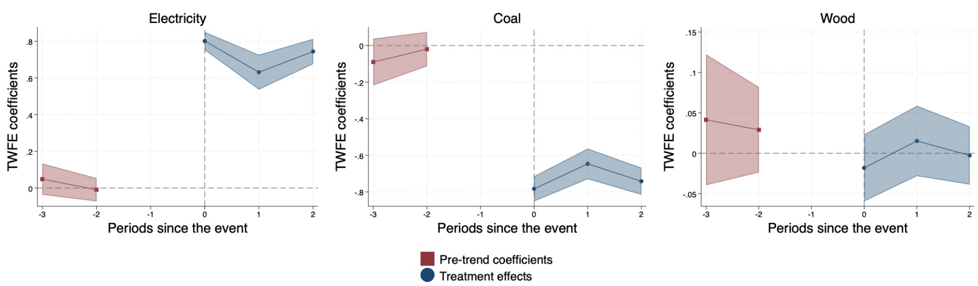
Heating Fuel Choices

Parallel Trend Figure 7 presents the results of the pre-trend testing for the binary variables representing heating fuel choices, with the -1 period omitted as the reference period. Panel

A examines heating fuel patterns, while Panel B focuses on primary heating fuel. Significant pre-treatment effects were observed for the 'Clean' and 'Polluting' heating fuel patterns three periods before the implementation of the clean heating policy, potentially suggesting violation of the parallel trends assumption essential. However, the direction of potential pre-trends is opposite to that of the post-trends, mitigating concerns about overestimating treatment effects. To further enhance the robustness of my findings, I will employ advanced DiD estimators that can accommodate non-parallel trends in later section. For all other variables, no significant pre-trends were detected.



Panel A: Heating Fuel Pattern



Panel B: Primary Heating Fuel

Figure 7: Parallel Trend for Heating Fuel Choices

Estimation Results Table 4 outlines the estimated results for binary heating fuel choices by TWFE model. Panel A details the results for heating fuel patterns, while Panel B focuses on primary heating fuels. The average treatment effect is noted at the top of each panel, with the heterogeneous effects by cohort, treated in different waves, displayed in the subsequent rows.

From Panel A, it is evident that the clean heating policy resulted in a 63% increase in the probability of households choosing entirely polluting fuel portfolios, a 40% increase in adopting a mixed fuel strategy, and a 23% increase in choosing entirely clean fuels. These results suggest that the clean heating policy significantly accelerated the transition to cleaner heating patterns. However, the policy did not completely eliminate the use of polluting fuels. Instead, a substantial proportion of households opted for a mixed fuel strategy, incorporating both clean and polluting fuels. This indicates that while the policy led to a shift toward cleaner fuels, the transition was not absolute, and many households continue to rely on a combination of both clean and traditional energy sources.

The transition from polluting to clean fuels was most marked in the group treated during season 2, and less pronounced in the group treated during season 3, possibly because this latter group had already adopted cleaner fuels before the clean heating policy (see Figure 4). The effects for transitioning fully to clean fuels were not statistically significant at the 5% level for the groups treated later in season 3 and season 4, and the impact was minimal for the group treated in season 4. This indicates that the shift to a completely clean fuel portfolio primarily occurred in the group treated early in season 2, underscoring that such a transition requires time.

The findings support the fuel stacking hypothesis, indicating that households commonly utilize multiple fuels concurrently. Despite this, most heating hours are primarily concentrated across one or two fuels or devices. As detailed in Table 5, 87% of households predominantly use their primary heating device for more than 80% of their heating duration. Furthermore, for over 99% of households, the primary and secondary heating devices combined account for 80% of total heating hours. This pattern shows that while fuel stacking is common, typically one or two main heating fuels dominate, making the analysis of primary heating fuel crucial to understanding overall household fuel choices.

In Panel B, there is a 73% increase in the probability of using electricity as the primary heating fuel following the implementation of the clean heating policy, accompanied by a nearly equal decrease in coal use, with no significant change observed for wood. This suggests that while a fully clean heating portfolio may not be widely adopted, a substantial number of households previously reliant on coal have shifted to using electricity as their primary heating fuel. This transition is consistent with the objectives of the clean heating policy, which aims to reduce the reliance on

Table 4: TWFE Model for Binary Heating Fuel Choices

Panel A: Heating fuel pattern						
	Clean		Mixed		Polluting	
ATT	0.227	***	0.403	***	-0.630	***
	(0.054)		(0.059)		(0.037)	
G2	0.288	***	0.416	***	-0.704	***
	(0.062)		(0.075)		(0.044)	
G3	0.219	*	0.274	**	-0.493	***
	(0.113)		(0.114)		(0.052)	
G4	0.073		0.583	***	-0.656	***
	(0.046)		(0.050)		(0.027)	
Panel B: Primary heating fuel						
	Electricity		Coal		Wood	
ATT	0.733	***	-0.721	***	-0.012	
	(0.030)		(0.032)		(0.016)	
G2	0.791	***	-0.791	***	0.001	
	(0.028)		(0.028)		(0.015)	
G3	0.632	***	-0.631	***	-0.001	
	(0.048)		(0.041)		(0.020)	
G4	0.735	***	-0.662	***	-0.072	
	(0.038)		(0.100)		(0.075)	

[a] *** p<.01, ** p<.05, * p<.1
[b] G# refers to group treated in season #

Heating Device Combination	Freq.	Percent	Cum.
Primary Only	222	7.49	7.49
Primary > 80%	2357	79.55	87.04
Primary+Secondary	99	3.34	90.38
Primary+Secondary > 80%	270	9.11	99.49
Primary+Secondary+Tertiary	6	0.20	99.70
Primary+Secondary+Tertiary > 80%	9	0.30	100.00
Total	2963	100.00	

Table 5: Heating Device Combination

polluting fuels and encourage the use of cleaner alternatives. Many households have adopted a mixed fuel portfolio, combining electricity and wood, as indicated by earlier panel analysis. However, the results from this panel clarify that wood is not used as a primary heating fuel but rather as a supplementary source. This is less detrimental to regional air quality and climate due to the significant reduction in the use of coal. The transition towards a completely clean heating portfolio would involve phasing out even this supplementary use of wood, a step that, while challenging, raises fewer environmental concerns.

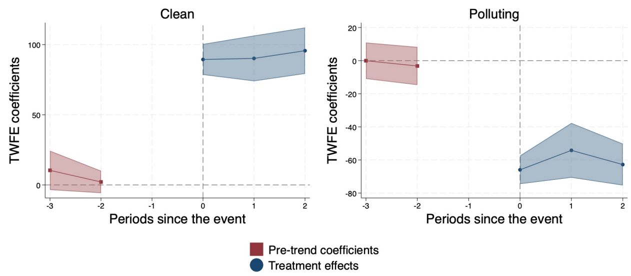
Effects were slightly less marked in households from the season 3 cohort, which already exhibited lower primary reliance on coal before the policy implementation.

Heating Behaviours Having examined the heating fuel choices of households, it is crucial to extend my analysis to heating behaviors, that is, how households allocate heating hours among the fuels or devices they have chosen. Heating behaviors—specifically, the duration of fuel use—offer additional insights into the broader impacts of clean heating policy, including efficiency, cost implications, health, environmental and welfare effects. Analyzing heating behaviors is crucial for developing more precise and effective interventions. These interventions should not only influence the choice of fuel but also enhance how these fuels are used to maximize benefits and minimize risks. By exploring heating behaviors, I bridge the gap between identifying fuel choices and understanding their broader implications, thus offering a comprehensive view of household energy consumption patterns following the clean heating policy.

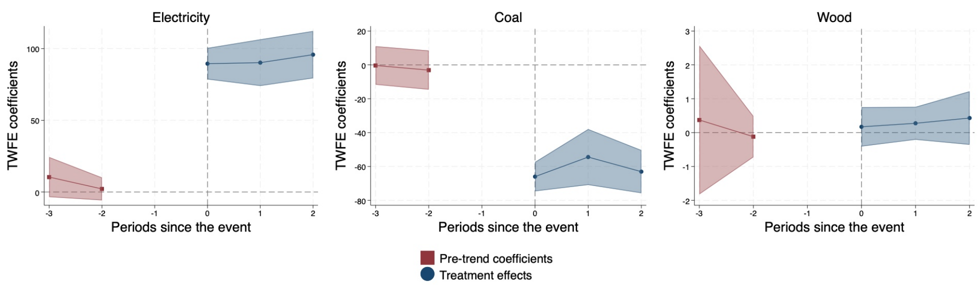
Parallel Trend Figure 8 displays pre-trends test results for total daily heating hours across all rooms, categorized by fuel type and heating device, while Figure 9 shows the average daily heating hours for rooms that are regularly heated, also broken down by fuel type and device. For most variables, there is no evidence of pre-trends. However, significant pre-treatment effects are observed for both total and mean heating hours for low-efficiency electric devices. To address this, I utilize an advanced difference-in-differences (DID) estimator later in the analysis that relaxes the parallel trends assumption, thereby enhancing the robustness of the results.

Estimation Results Table 6 details the total heating hours across all rooms on a typical day by fuel sources. Panel A presents the daily total heating hours across all rooms, categorized by clean or polluting fuels. Panel B shows the breakdown by fuel types, including electricity, coal, and wood. Panel C details the total heating hours by types of electric heating devices.

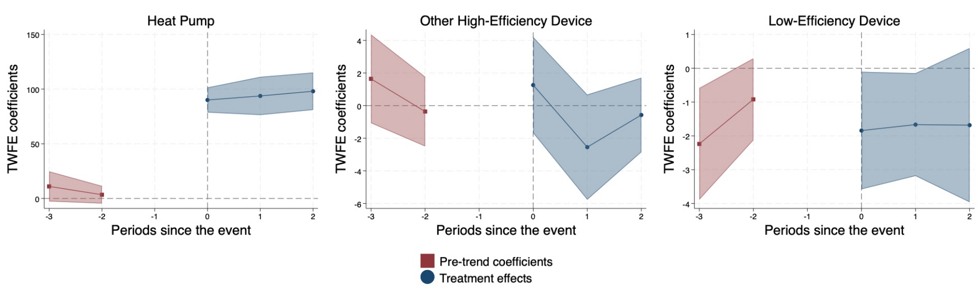
In Panel A, there is an increase of 90 hours in heating by clean energy sources and a decrease of 61 hours in polluting heating hours, resulting in a net increase of approximately 29 room hours by all fuels. The effects on clean heating hours are notably stronger for the group



Panel A: Total Heating Hours by Fuel Pattern

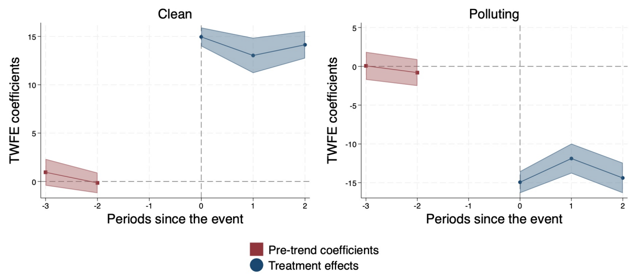


Panel B: Total Heating Hours by Fuel Type

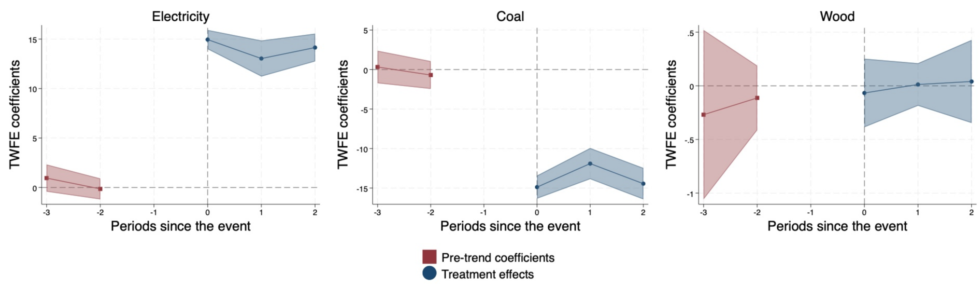


Panel C: Total Heating Hours by Heating Device

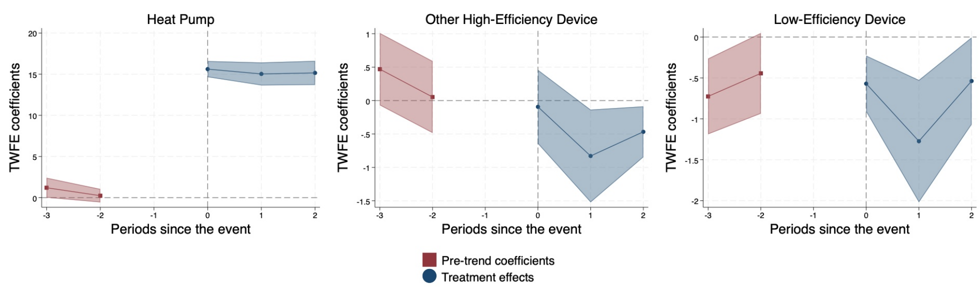
Figure 8: Parallel Trends for Heating Behaviours



Panel A: Mean Heating Hours by Fuel Pattern



Panel B: Mean Heating Hours by Fuel Type



Panel C: Mean Heating Hours by Heating Device

Figure 9: Parallel Trends for Heating Behaviours

treated earlier. Conversely, the effects on polluting heating fuels are more pronounced for the groups treated in seasons 2 and 4, and less so for the group treated in season 3. A combined analysis reveals that the group treated in season 3 experienced the most significant increase in total heating hours by all fuels, approximately 36 room hours.

Panel B analyzes specific fuel types. Heating hours from electricity align with those from clean sources, as electricity is the primary clean fuel used by the majority of households. Similarly, coal heating hours closely match polluting hours. There are no significant shifts in heating hours by wood, suggesting that the clean heating policy did not significantly affect other polluting fuels and that households did not substantially substitute coal with wood following the ban.

In Panel C, the impact on heating hours by heat pumps is slightly larger in magnitude compared to those by electricity, attributed to a reduction in the use of low-efficiency electric devices. High-efficiency electric devices other than heat pumps such as heated floors and air conditioners show no significant changes. As found in earlier results, the more pronounced effects for increases in heat pump heating hours occur in earlier treated groups. The results indicate that households have substituted lower-efficiency devices with more efficient heat pumps and have not exploited electricity subsidies to increase heating hours by other electric heating devices.

From the analysis of total room heating hours, it is evident that treated households have not only substituted coal heating with heat pump heating, but also extended their total heating hours following the clean heating policy. This raises an important question about the allocation of these additional heating hours: Are households heating more rooms or simply extending the heating duration per room? This question is crucial as it helps to understand whether the increase in heating hours is spread across more spaces or concentrated in the same number of rooms with prolonged heating periods. The answer to this will provide further insights into the behavioral changes in household heating practices post-clean heating policy and help assess the efficiency and effectiveness of the policy in real household settings.

Table 7 reports the findings regarding mean heating hours. In the Panel A and B, there is an observed increase of 14 hours in clean or electricity heating, while polluting or coal heating hours decrease by 13.6 hours. This close parity in magnitude indicates no significant change in the

Table 6: TWFE Model for Total Heating Hours

Panel A: By Fuel Pattern						
	Clean		Polluting			
ATT	89.675	***	-60.618	***		
	(5.138)		(4.830)			
G2	95.380	***	-66.499	***		
	(6.688)		(5.235)			
G3	88.544	***	-52.175	***		
	(7.992)		(7.160)			
G4	76.846	***	-58.705	***		
	(10.893)		(7.574)			
Panel B: By Fuel Type						
	Electricity		Coal		Wood	
ATT	89.772	***	-60.815	***	0.255	
	(5.131)		(4.902)		(0.277)	
G2	95.505	***	-66.912	***	0.557	
	(6.673)		(5.237)		(0.365)	
G3	88.592	***	-52.429	***	0.259	
	(7.986)		(7.209)		(0.283)	
G4	76.902	***	-57.929	***	-0.778	*
	(10.888)		(7.931)		(0.410)	
Panel C: By Electric Heating Device						
	Heat Pump		Other High -efficiency Ele-Device		Low-efficiency Ele-Device	
ATT	91.350	***	-0.329		-1.485	**
	(5.377)		(1.072)		(0.654)	
G2	96.889	***	0.548		-1.932	*
	(6.881)		(1.128)		(1.151)	
G3	91.548	***	-2.391	*	-1.225	*
	(8.674)		(1.411)		(0.663)	
G4	77.069	***	0.230		-0.396	
	(11.304)		(1.029)		(0.625)	

[a] *** p<.01, ** p<.05, * p<.1
[b] *G#* refers to group treated in season #
[c]Other high-efficiency electric heating devices includes AC, heated floor by electricity; low efficiency electric heating devices includes mobile electric heater.

average heating hours per room. Consistent with previous results, there are no notable changes in wood heating hours. This suggests that the rise in total heating hours likely results from an increase in the number of rooms heated, rather than extended heating periods per room.

Interestingly, the effects on average heating hours are milder for the group treated in season 3, which also shows the largest difference—approximately 1.5 hours—between average clean and polluting heating hours. This group also exhibits the largest increase in total heating hours, indicating they have reaped the most substantial thermal benefits, with both an increase in the number of rooms heated and longer heating duration. In contrast, the other groups primarily increased the number of rooms heated without significantly extending heating duration. This could be attributed to the fact that households in season 3 previously had shorter heating duration before the clean heating policy, whereas those in other groups might already have been heating their rooms continuously throughout the day and night.

In Panel C, which examines electric device usage, a decrease is observed in both high-efficiency and low-efficiency electric devices. The most significant reductions, around an hour per day for both device types, are seen in the group treated in season 3. This reduction highlights another thermal benefit for this group: they not only have more rooms heated and longer heating duration per room, but they also transition from lower to higher efficiency heating devices, specifically to subsidized heat pumps. Notably, the increase in heating hours attributed to subsidized heat pumps is more pronounced in groups treated earlier, emphasizing the benefits of early adoption in transitioning to more efficient energy usage.

To summarize the findings, the clean heating policy significantly reduced coal usage, establishing electricity and subsidized heat pumps as the predominant heating sources, though it did not completely eliminate coal use, and wood usage remained relatively stable. It led households away from entirely polluting fuel portfolios towards mixed fuel use, with a limited transition to fully clean fuel portfolios.

Households benefited from the clean heating policy, seeing a substitution of clean heating hours for polluting ones and an increase in total room heating hours due to both more rooms being

Table 7: TWFE Model for Mean Heating Hours

Panel A: By Fuel Pattern						
	Clean		Polluting			
ATT	14.148	***	-13.603	***		
	(0.522)		(0.711)			
G2	14.834	***	-14.832	***		
	(0.517)		(0.814)			
G3	13.037	***	-11.470	***		
	(0.879)		(1.064)			
G4	13.795	***	-14.277	***		
	(0.864)		(1.492)			
Panel B: By Fuel Type						
	Electricity		Coal		Wood	
ATT	14.158	***	-13.623	***	0.010	
	(0.519)		(0.740)		(0.131)	
G2	14.843	***	-14.939	***	0.093	
	(0.514)		(0.828)		(0.195)	
G3	13.045	***	-11.502	***	0.032	
	(0.878)		(1.095)		(0.106)	
G4	13.805	***	-13.963	***	-0.314	
	(0.861)		(1.661)		(0.208)	
Panel C: By Electric Heating Device						
	Heat Pump		Other High -efficiency Ele-Device		Low-efficiency Ele-Device	
ATT	15.250	***	-0.434	**	-0.696	***
	(0.473)		(0.204)		(0.199)	
G2	15.755	***	-0.330		-0.581	***
	(0.457)		(0.240)		(0.209)	
G3	14.826	***	-0.827	***	-1.063	***
	(0.728)		(0.303)		(0.326)	
G4	14.010	***	-0.068		-0.137	
	(0.981)		(0.209)		(0.274)	

[a] *** p<.01, ** p<.05, * p<.1
[b] *G#* refers to group treated in season #
[c]Other high-efficiency electric heating devices includes AC, heated floor by electricity; low efficiency electric heating devices includes mobile electric heater.

heated and extended heating duration per room. Additionally, there was a noticeable shift from lower to higher efficiency heating devices.

The effects of the coal ban were most pronounced in groups treated earlier and those with previously less efficient heating behaviors, highlighting a temporal sensitivity to the policy's implementation and its varied impact on different household groups.

4.4 Robustness Check

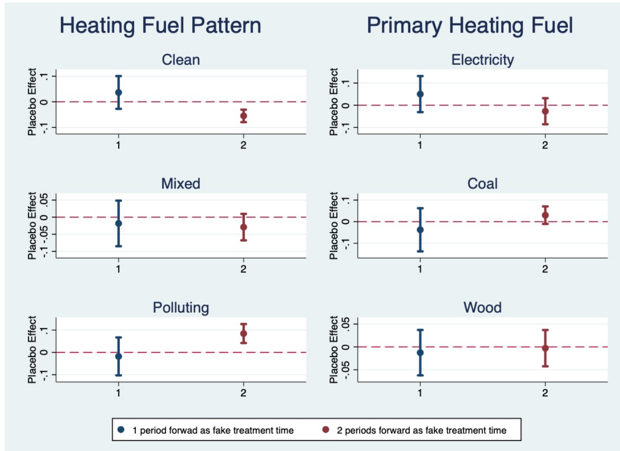
In this section, I perform multiple robustness checks on the estimators of the treatment effects of the clean heating policy. I conduct a placebo test to validate the estimated effects. Additionally, I employ advanced difference-in-differences (DID) methodologies tailored for staggered treatment adoption and potential violations of the parallel trend assumption, to ensure the robustness of my findings.

4.4.1 Placebo Tests

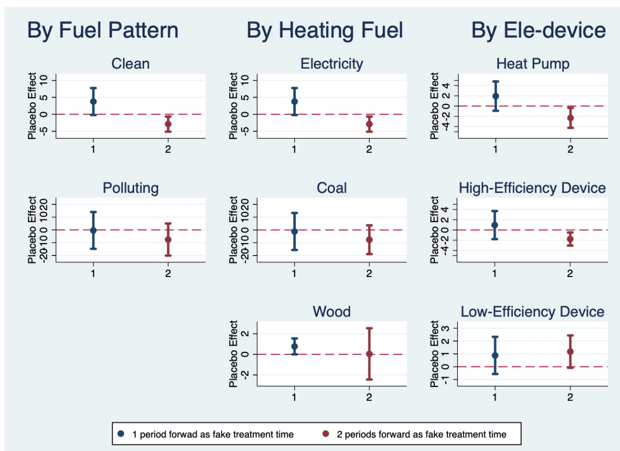
A placebo test is a widely used method in empirical research to assess the validity of causal inferences, particularly in studies that involve interventions or treatments. This test involves creating a scenario where no actual intervention is administered but the procedures of the study are otherwise followed as if it were. The goal is to establish whether the observed effects in the study can be attributed solely to the treatment or if they could be plausibly explained by other factors, such as the placebo effect, data mining biases, or external influences.

In-time Placebo Test In the context of policy evaluation, a in-time placebo test typically entails applying the analytical method to a time when the treatment is known not to have been applied. The analysis is conducted using data before the policy was implemented. By artificially advancing the treatment timing in the dataset to a period before the policy's actual implementation, the test assesses whether the effects attributed to the policy could plausibly arise in the absence of any intervention, simply due to pre-existing trends or random data fluctuations

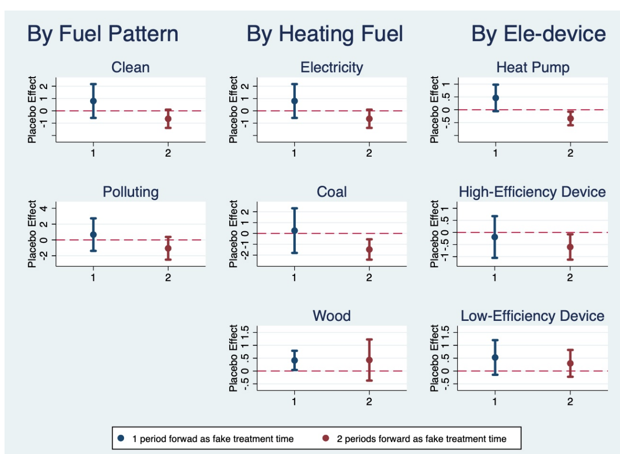
Figure 10 presents the placebo effects. Temporal placebo effects are evident when the treatment timing is artificially advanced by two periods, indicating significant pre-existing differences between the treatment and control groups prior to the implementation of the coal ban policy. This observation underscores the importance of considering these differences when interpreting the treatment effects. Notably, the placebo effects exhibit the opposite sign to the treatment effects, suggesting a potential underestimation of the actual treatment effects.



Panel A: Binary Heating Fuel Pattern



Panel B: Total Heating Hours by Fuel Sources



Panel C: Mean Heating Hours by Fuel Sources

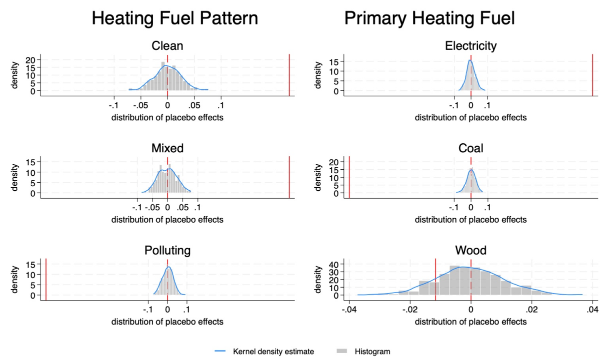
Figure 10: In-Time Placebo Test

Space Placebo Test A space placebo test is a method used in research to assess the validity of causal inferences when studying the effects of spatially-based interventions. This test works by randomly assigning the treatment to regions where no intervention is actually applied, while keeping the treatment timing unchanged. The goal is to estimate 'fake' treatment effects in these areas and compare them to the effects observed in the actual treatment region. This helps ensure that any observed effects in the treatment area are genuinely due to the intervention, rather than resulting from broader, non-local trends or coincidental spatial patterns. By conducting a space placebo test, I can control for spatial heterogeneity and potential confounding factors, which might otherwise lead to biased or erroneous conclusions about the effectiveness of a policy.

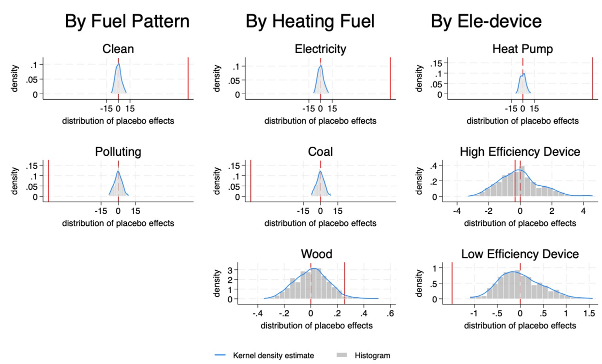
Figure 11 illustrates the results of the placebo test, depicted by the distribution of placebo effects shown as grey bars, with the estimated actual treatment effects marked by a red solid vertical line. The analysis demonstrates that for most of the estimated treatment effects, they are distinctly separate from or located at the tail of the placebo distribution, indicating that these effects are unlikely due to chance or spatial heterogeneity. For the few estimates that align more closely with the placebo distribution, the treatment effects themselves are statistically insignificant. This suggests that there is no evidence of confounding spatial placebo effects impacting the validity of the results.

Mixed Placebo Test A mixed placebo test is a combination of temporal and spatial elements to strengthen the robustness of causal inferences, particularly in studies involving interventions or policies with both time and location variables. This test involves applying the original analysis to different time periods or locations where the intervention is known not to have been implemented, thereby mixing aspects of both time-based and space-based placebo tests. By doing so, I aim to detect any confounding influences that might falsely suggest an effect due to the time or location rather than the intervention itself.

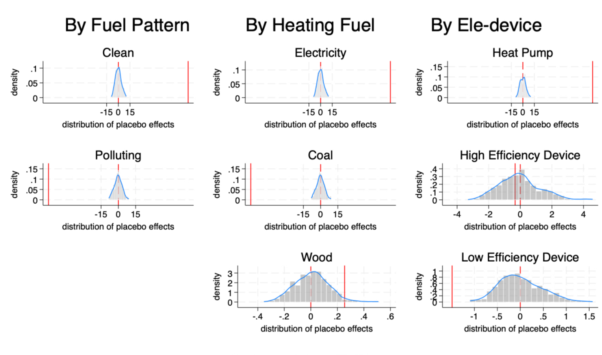
Figure 14 displays the results concerning mixed placebo effects. Analogous to the findings on spatial placebo effects, this analysis also indicates that there are no significant mixed placebo effects.



Panel A: Binary Heating Fuel Pattern

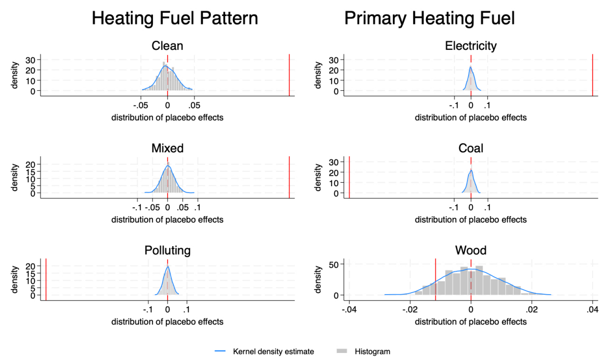


Panel B: Total Heating Hours by Fuel Sources

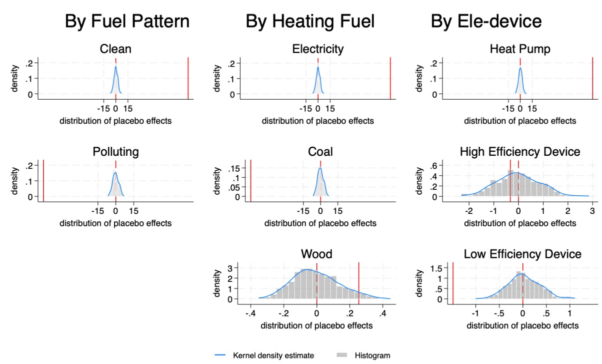


Panel C: Mean Heating Hours by Fuel Sources

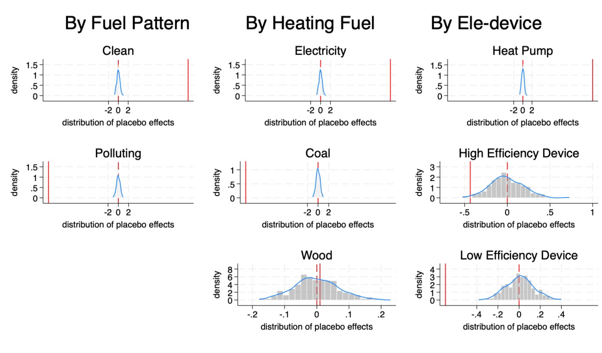
Figure 11: Space Placebo Test



Panel A: Binary Heating Fuel Pattern



Panel B: Total Heating Hours by Fuel Sources



Panel C: Mean Heating Hours by Fuel Sources

Figure 12: Mixed Placebo Test

4.4.2 Advanced DID Estimators for Staggered Treatment

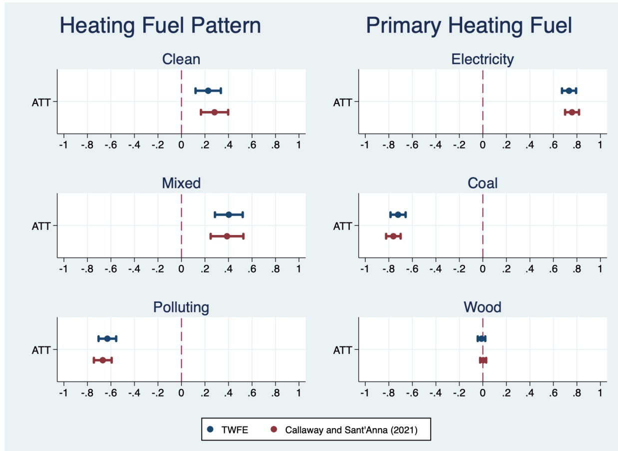
Figure 13 presents the results obtained using the Callaway and Sant'Anna (2021) method designed for the staggered treatment compared with those derived from traditional Two-Way Fixed Effects (TWFE) estimators. The alignment between the two sets of results indicates a robust consistency in the treatment effects measured, reinforcing the reliability of the findings.

4.4.3 Advanced DID Estimators for Non-parallel Trend

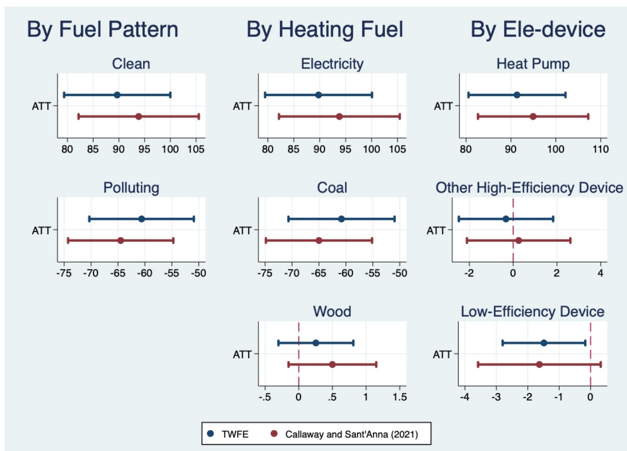
Figure 14 illustrates the application of Rambachan and Roth (2023)'s first method to the data, which imposes limits on the extent of post-treatment trend deviations relative to pre-treatment trends. Parameters such as $\bar{M}$ determine the allowable magnitude of these deviations. The analysis demonstrates that the treatment effects remain robust, even when deviations are allowed up to twice the magnitude of pre-treatment trends for most variables with initially significant effects. However, it is important to note the broader confidence intervals, which reflect increased uncertainty around these estimates under the new methodological constraints.

5 Determinants of Fuel Choices and Heating Behaviors

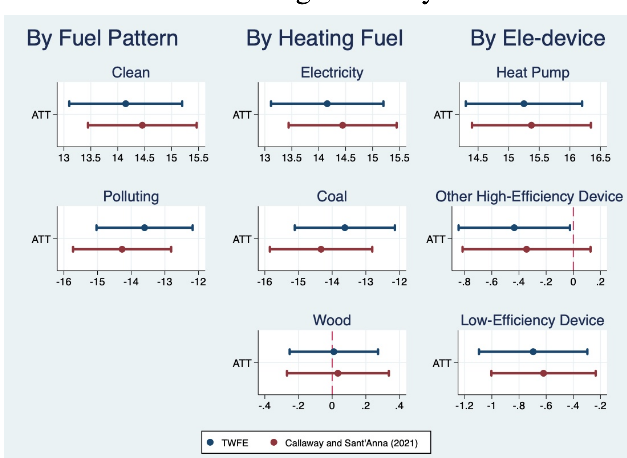
The analysis from the previous section shows that the clean heating policy has effectively facilitated the transition towards clean heating fuels, significantly reducing coal usage, however, it did not completely eradicate the use of polluting fuels, as evidenced by some households' continued coal use and the unchanged wood consumption levels. Concurrently, a spontaneous transition toward cleaner heating portfolios is observed in untreated villages, albeit without achieving a complete shift to clean fuels. These observations indicate that neither spontaneous transitions nor policy-driven bans have led households to fully embrace clean fuel portfolios, which necessitates a deeper investigation into the underlying factors that govern fuel usage decisions. Consequently, this analysis will now pivot to a detailed examination of the determinants influencing households' fuel choices and behaviors, to better understand the complexities of energy consumption dynamics.



Panel A: Binary Heating Fuel Pattern

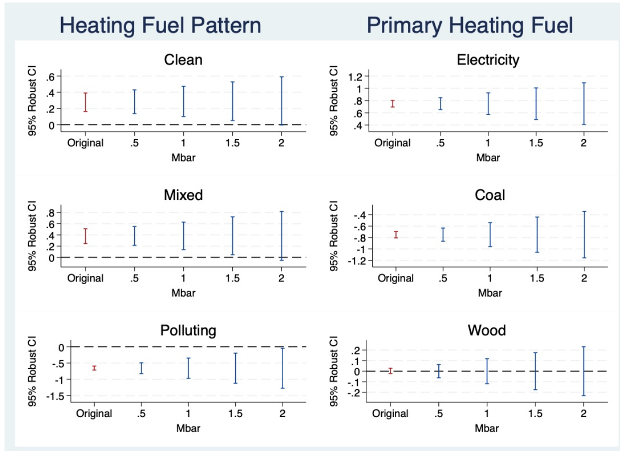


Panel B: Total Heating Hours by Fuel Sources

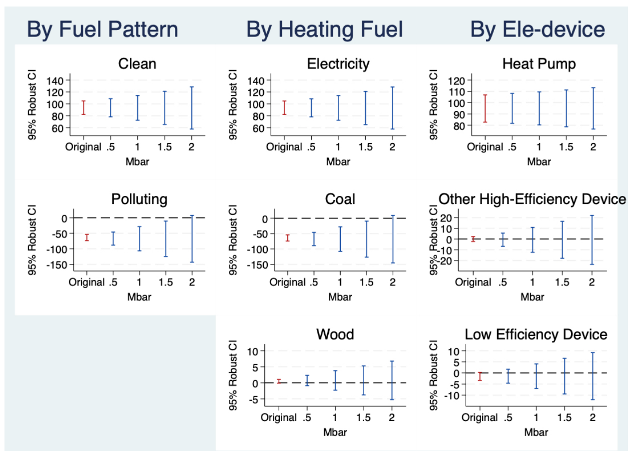


Panel C: Mean Heating Hours by Fuel Sources

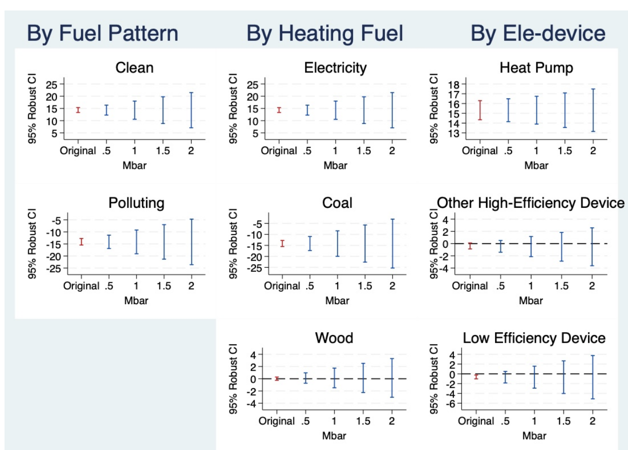
Figure 13: Comparison between TWFE and Advanced DID Estimator



Panel A: Binary Heating Fuel Pattern



Panel B: Total Heating Hours by Fuel Sources



Panel C: Mean Heating Hours by Fuel Sources

Figure 14: Advanced DID Estimators By Roth(2022)

This section is structured as follows: Initially, I introduce the theoretical model for heating fuel choices. Subsequently, I outline the Correlated Random Effects Generalized Ordered Probit (CORE-GOP) Model as the empirical strategy. Lastly, I explore the determinants influencing households' fuel choices and behaviors separately, acknowledging that these decisions may be driven by different processes. This analysis focuses exclusively on households not yet affected by the clean heating policy, to prevent confounding effects from the clean heating policy.

5.1 Theory Model

Economists have developed various fuel consumption models that conceptualize a household as a profit-maximizing producer and subsequently as a utility-maximizing consumer, based on the profits earned (Singh et al. (1986); Edwards and Langpap (2005); Gupta and Köhlin (2006)). However, such models assume the absence of market failures and may not be fully applicable to rural households in developing countries. These households often face incomplete or absent markets, not only for fuels such as firewood, crop residues, and animal dung but also for agricultural products, labor, and credit (Chen et al. (2006); Shi et al. (2009); Bowlus and Sicular (2003); Heltberg et al. (2000)). Under these conditions of market failure, the decisions regarding production and consumption cannot be distinctly separated but are instead made jointly in a non-separable fashion, reflecting the complex inter-dependencies within the household's economic activities.

Building upon the insights of Muller and Yan (2018) and recognizing the incomplete market for firewood in the sampled villages, I have developed an agricultural household fuel consumption model. This model posits that households maximize their utility over fuel use (F) , other good consumption(excluding fuels) C, and leisure (l):

$$U = U(C, F, l; Z)$$

Here, Z represents a vector of household characteristics that influence their preferences. The model assumes that the preferences for other consumption goods are sufficiently independent, allowing us to concentrate specifically on the decision-making processes related to fuel use. The fuel function integrates choices between polluting and clean fuels:

$$F = \left(F^P(F^{wood}, F^{coal}), F^C(F^{ele}); V\right)$$

where F^P and F^C denote polluting fuels (wood and coal) and clean fuels (electricity), respectively, with V encompassing variables pertinent to fuel choice.

The market for firewood is assumed to be missing: firewood consumption, F^{wood}, is tied directly to the amount gathered: $q^w(L_{wood})$, where L_{wood} is the labor time dedicated to collecting firewood.

$$F^{wood} = q^{wood}(L_{wood})$$

Households also engage in agricultural activities, producing crops Q_c based on labor L_c and fixed farm inputs A_c, influenced by land endowments ϕ

$$Q_c = Q_c(L_c, A_c; \phi)$$

This model's budget constraint reflects the integration of farm income, labor income, and other exogenous income sources:

$$p^C C + p^{coal} F^{coal} + p^{ele} F^{ele} = \left(p^H Q_c - p^{ac} A_c\right) + wL_{off} + Y_0$$

where L_{off} denotes the household labour time allocated to off-farm work; w is the wage rate; p^H is the crops price and Y_0 denotes the other exogenous income.

And the time constraint for the household balances time spent on various activities against the total available time:

$$L_{wood} + L_c + L_l + L_{off} + l = T$$

Finally, the Lagrangian of the constrained optimization problem is:

$$
\begin{aligned}
\Gamma = & U\left[C, F\left(F^P\left(F^{wood}, F^{coal}\right), F^C\left(F^{ele}\right); V\right), l; Z\right] \\
& -\lambda\left[p^C C + p^{coal} F^{coal} + p^{ele} F^{ele}\right. \\
& \left.-\left(p^H Q_c(L_c, A_c; \phi) - p^{ac} A_c\right) - w L_{off} - Y_0\right] \\
& -\eta\left(L_{wood} + L_c + L_l + L_{off} + l - T\right) \\
& -\mu\left(F^{wood} - q^{wood}(L_{wood})\right)
\end{aligned}
$$

where λ, $\eta$and μ are Lagrange multipliers. Assuming convexity in both preferences and technology sets, and focusing on interior solutions, the constrained optimization problem within the agricultural household fuel consumption model can be solved as

$$
\left.\begin{array}{l}
F^{wood} \\
F^{coal} \\
F^{ele}
\end{array}\right\} = f\left(p^C, p^{coal}, p^{ele}, Y, Z, V, \phi\right)
$$

In this formulation, the fuel demands are influenced by a comprehensive set of factors: market prices (p^C, p^{coal}, p^{ele}), household income (Y), household preferences and characteristics (Z), variables pertinent to fuel choice (V), and agricultural endowments (ϕ). These elements collectively define the household-specific shadow prices of fuel, underscoring how production-side factors shape energy consumption patterns in environments marked by market imperfections, beyond individual preferences and broader socio-economic influences.

5.2 Empirical Strategy

Having outlined the theoretical model of agricultural fuel consumption, I now transition to the empirical strategy that will enable us to estimate and test the derived hypotheses. The subsequent analysis employs a correlated random effects generalized ordered probit model, an approach specifically chosen for its robustness in handling the ordinal nature of fuel consumption categories and its ability to account for unobserved heterogeneity across observational units. This model is adept at capturing the latent variables that influence the probability of a household transitioning between different ranked fuel pattern. By integrating the theoretical constructs into this empirical framework, we can rigorously assess the factors that drive fuel consumption patterns in the agricultural households, thus providing a comprehensive understanding of the energy transition dynamics.

Correlated Random Effects Generalized Ordered Probit (CORE-GOP) Model Research on household fuel choices often employs multinomial logit (MNL) and multinomial probit (MNP) models. The MNL model is commonly chosen for its computational simplicity but requires adherence to the Independence of Irrelevant Alternatives (IIA) assumption. Failure to meet this assumption can lead to biased and inconsistent results. On the other hand, the MNP model does not require the IIA assumption, offering a more flexible estimation approach, but it overlooks the ordinal nature of fuel preferences, which is essential for capturing the preference hierarchy among different fuels.

To address these limitations and accurately reflect the hierarchical preferences for different fuel types, I will employ the random effect ordered probit model in this study. This model allows us to incorporate the ordinal ranking of fuel types based on convenience, comfort, and efficiency. In the analysis, electricity is deemed the most efficient and convenient, followed by coal, with firewood ranked as the least. This ranking aligns with the energy ladder theory, illustrating the transition of households in rural China from traditional solid fuels to cleaner and more efficient energy sources. Furthermore, to acknowledge the fact of fuel stacking, I also categorize fuel patterns, ranking completely clean portfolios as superior to mixed ones, and mixed ones as better than entirely polluting ones.

Household heating fuel choices are posited to depend on a latent variable Y_{it}^*, formulated as:

$$Y_{it}^* = x_{it}'\beta + \alpha_i + \mu_{it} \tag{3}$$

where
$$(\mu_{it}|x_{it}) \sim N(0,1) \tag{4}$$

$$(\alpha_i|x_{it}) \sim N(0,\sigma_\alpha^2) \tag{5}$$

$$corr(\alpha_i + \mu_{it}, \alpha_i + \mu_{i\tau}) = \rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\mu^2} \quad \text{for any} \quad t \neq \tau \tag{6}$$

where x_{it} represents the vector of explanatory variables of household i in period t; β is the vector of coefficients to be estimated; α_i denotes time-invariant unobserved heterogeneity, assumed to follow a normal distribution conditioned on x_{it} ; the error term μ_i is also assumed to be normally distributed. In this study, heating fuel choices are categorized into three patterns: completely polluting, mixed, and completely clean. The dependent variable is thus treated as an ordered variable with these three categories. The observed heating fuel choice Y_{it} is defined by thresholds:

$$Y_{it} = j \Leftrightarrow k_{j-1} < Y_{it}^* \leq k_j \Leftrightarrow Y_{it} = \begin{cases} 1, \text{ if } -\infty \leq Y_{it}^* \leq k_1 & \text{(Completely Polluting)} \\ 2, \text{ if } k_1 < Y_{it}^* \leq k_2 & \text{(Mixed)} \\ 3, \text{ if } k_2 < Y_{it}^* \leq \infty & \text{(Completely Clean)} \end{cases} \tag{7}$$

where $-\infty = k_0 < k_1 < k_2 < k_3 = \infty$ defining the unknown intervals for each choice, $j \in \{1,2,3\}$. The probability of choosing heating fuel pattern j is defined as

$$\begin{aligned} Pr(Y_{it} = j|x_{it}) &= Pr(k_{j-1} < Y_{it}^* \leq k_j|x_{it}) & (8)\\ &= Pr(k_{j-1} < x_{it}'\beta + \alpha_i + \mu_{it}|x_{it}) & (9)\\ &= \Phi(k_j - x_{it}'\beta - \alpha_i|x_{it}) - \Phi(k_{j-1} - x_{it}'\beta - \alpha_i|x_{it}) & (10) \end{aligned}$$

where Φ is the standard normal cumulative distribution function.

The random effects ordered probit model offers a nuanced approach to handling unobserved heterogeneity, allowing us to account for household-specific traits that standard ordered probit analysis might miss. Nonetheless, this model enforces the parallel regression assumption, implying constant effects of explanatory variables across different choices (Maddala (1983); Boes and Winkelmann (2006)). To address this limitation, I extend to a generalized ordered probit model, which allows for varying impacts of explanatory variables across outcomes by modeling the thresholds k_j as a linear functions of x_{it}(Ierza (1985)): $k_{ij} = a_j + x'_{it}\lambda_j$, where λ_j represents the influence parameter of the covariates on the thresholds; k_{ij} denotes the threshold values for household i for each heating fuel choice j; a_j is a constant term. Therefore, the probability of choosing alternative j will be

$$Pr(Y_{it} = j|x_{it}) = \Phi(a_j - x'_{it}(\beta - \lambda_j) - \alpha_i|x_{it}) - \Phi(a_{j-1} - x'_{it}(\beta - \lambda_{j-1}) - \alpha_i|x_{it}) \tag{11}$$

where the estimated coefficients $\beta_j = \beta - \lambda_j$ are specific to each fuel alternative.

While the generalized random effects ordered probit(RE-GOP) model relaxes the parallel regression assumption, it traditionally assumes that the unobserved heterogeneity α_i is independent of the explanatory variables x_{it}. This assumption can be restrictive as it neglects potential correlations between the unobserved heterogeneity and the regressors, which may introduce bias into the coefficient estimates. To address this, I incorporate the Mundlak approach, following the methodologies of Boes and Winkelmann (2010), Mentzakis and Moro (2009) , Chamberlain (1982), and Mundlak (1978), which involves integrating the averages of time-varying regressors within households into the model. This transformation posits that the unobserved effects are linearly related to the explanatory variables:

$$\alpha_i = \bar{x}_i\gamma + \epsilon_i \tag{12}$$

where $\bar{x}_i$ represents the average of x_{it} over time, γ is the parameter, and ϵ_i is an orthogonal error term with $\epsilon_i|\bar{x}_i \sim N(0, \sigma^2_\epsilon)$. Incorporating the Mundlak approach transforms the equation (5.2) as follows:

$$Pr(Y_{it} = j|x_{it}, \bar{x}, \epsilon_i; \gamma, \beta_j) = \Phi(a_j - x'_{it}(\beta - \lambda_j) - \bar{x}_i\gamma - \epsilon_i|x_{it}) \tag{13}$$

$$- \Phi(a_{j-1} - x'_{it}(\beta - \lambda_{j-1}) - \bar{x}_i\gamma - \epsilon_i|x_{it}) \tag{14}$$

Equation (5.2) describes the correlated random-effects generalized ordered probit(CORE-GOP) model.

Therefore, the CORE-GOP model not only controls for unobserved heterogeneity but also allows for heterogeneous effects of explanatory variables across different choices. Additionally, it accounts for potential correlations between unobserved heterogeneity and the regressors. Unobserved factors such as an individual's family background or socio-economic upbringing may be correlated with observable explanatory variables like education and income. By incorporating these correlations—for instance, acknowledging that individuals from more affluent or educated families are likely to have higher education and income levels—the CORE-GOP model provides more accurate results than the standard ordered probit model. This is particularly important when such correlations exist, as accounting for them helps to avoid biased estimates and results in a more reliable analysis. The CORE-GOP model can be estimated via maximum likelihood as detailed in Boes and Winkelmann (2010).

Previous studies, such as Wu and Zheng (2022), propose that household fuel consumption decisions unfold in a two-stage process: initially deciding which fuels to use, followed by determining the quantity of fuel to consume. These stages are potentially influenced by distinct factors. To further explore this hypothesis, I investigate the determinants of heating behaviors—specifically, how households allocate their heating hours among chosen fuels. For this purpose, I employ fixed effects models, using log-transformed total heating hours across all rooms by fuel source as the dependent variable. Like the analysis of fuel choices, this segment of the study focuses exclusively on households not yet treated by the policy.

5.3 Results

5.3.1 Determinants of Fuel Choices

Table 8: CORE-GOP Model: Determinants of Household Heating Fuel Pattern

Variables	Clean		Mixed		Polluting	
Log Price of Coal	0.087	***	-0.055		-0.033	
	(0.029)		(0.034)		(0.021)	
Log Income per Capita	0.003		0.004		-0.007	
	(0.007)		(0.010)		(0.017)	
Age	0.000		0.001		-0.001	
	(0.000)		(0.001)		(0.001)	
Male	-0.018	**	-0.027	**	0.045	**
	(0.008)		(0.012)		(0.021)	
Married	-0.024	*	-0.037	*	0.061	*
	(0.013)		(0.020)		(0.033)	
Secondary or Higher Education	0.017	**	0.026	**	-0.044	**
	(0.009)		(0.013)		(0.022)	
Log Household Size	0.012		0.103	***	-0.115	***
	(0.018)		(0.029)		(0.041)	
Number of Children Under 5	-0.001		-0.001		0.002	
	(0.017)		(0.026)		(0.043)	
Log Household Size	0.064	***	0.095	***	-0.159	***
	(0.011)		(0.016)		(0.027)	
Agricultural Assets						
Log Agriculture Land	0.003	*	0.005	*	-0.009	*
	(0.002)		(0.003)		(0.005)	
Log Forest Land	0.000		-0.012	***	0.012	***
	(0.003)		(0.004)		(0.005)	
Region						
Fangshan	0.136	***	0.104	***	-0.240	***
	(0.027)		(0.032)		(0.040)	
Huairou	0.087	***	0.130	***	-0.217	***
	(0.016)		(0.022)		(0.037)	
Mentougou	0.159	***	0.105	***	-0.265	***
	(0.023)		(0.030)		(0.041)	
Time						
Wave 2	0.066	***	-0.052	***	-0.014	
	(0.014)		(0.020)		(0.018)	
Wave 4	0.095	***	-0.000		-0.095	***
	(0.016)		(0.022)		(0.020)	
Number of observations	2332		2332		2332	

[a] *** p<.01, ** p<.05, * p<.1

Table 8 reports the marginal effects of CORE-GOP model on fuel choices. It is evident that coal price, gender, education, marital status, agricultural assets, house area, household size, region, and season dummies significantly influence household heating fuel choices in rural China.

Fuel prices play a role in shaping heating energy patterns in rural China, influencing household decisions to transition towards cleaner energy sources. The findings indicate that an increase in coal prices encourages the adoption of clean heating patterns. Specifically, a one-unit increase in the log of coal prices enhances the likelihood of households opting for completely clean fuels by 8.8%. This highlights the potential of fuel price control as an effective policy tool to promote a transition to clean heating among rural households.

The impact of fuel prices is well illustrated in the Fangshan district during season 4, a period marked by a near doubling of coal prices. This significant price increase led to a 23% rise in the adoption of clean heating portfolios among households, indicating a direct correlation between fuel pricing strategies and the shift towards cleaner heating options. This observation underscores the importance of strategic fuel pricing in driving significant and sustainable changes in heating energy patterns, particularly in regions that are traditionally dependent on polluting fuels.

The marginal effects of income per capita on heating choices are found to be insignificant, contradicting the energy ladder hypothesis, which suggests that households should transition to cleaner fuels as their income increases. This finding supports the fuel stacking theory, indicating that households continue to use traditional solid fuels alongside more advanced fuels, rather than completely transitioning away. This observation implies that the persistence of polluting fuels is not merely a result of financial constraints or the affordability of clean energy. Consequently, providing subsidies for electricity or other clean energies may have limited effectiveness in encouraging households to fully transition to clean energy solutions.

Gender significantly influences household fuel choices. The analysis reveals that men are 4.5% more likely than women to opt for completely polluting heating fuels and are less likely—by 1.8% and 2.7%—to select clean or mixed fuels, respectively. This trend aligns with findings from other studies suggesting that women are more inclined to choose cleaner fuels. This preference may be due to women typically handling labor-intensive tasks like collecting biomass fuels and managing traditional heating sources, such as kangs or stoves, including the continual addition of fuel. This gender difference highlights the importance of incorporating social and behavioral factors into the development of energy policies and interventions to promote cleaner heating solutions.

Additionally, marital status plays a significant role in heating fuel decisions. Married couples are 6.1% more likely than single individuals (including divorced, separated, widowed, and never married) to choose completely polluting heating fuels. This trend could be attributed to married couples having more household labor available to gather solid fuels, such as firewood, which requires considerable effort and time.

According to existing literature, education is an important policy tool to raise households' awareness about the benefits of clean energy sources and the risks associated with dirty fuel sources. As anticipated, higher educational levels within a household tend to increase the likelihood of opting for cleaner energy sources. The findings support this perspective, albeit with a modest effect. Households with secondary education or higher are 1.7% more likely to choose clean fuels and 2.6% more likely to opt for mixed fuels compared to those with no or only primary education, and are 4.3% less likely to choose entirely polluting fuels.

Regarding household size, existing studies provide mixed evidence on its impact on fuel choice and fuel switching behaviors. The analysis reveals that larger household sizes negatively influence the use of completely polluting fuels and positively affect the adoption of mixed fuels, while their impact on clean fuel use is positive but not statistically significant. Larger households typically face greater heating demands, which drives a preference for more efficient heating methods compared to smaller households.

House size significantly impacts household heating fuel choices. A larger house size is associated with a preference for clean or mixed heating fuels. A one-unit increase in house size (log) reduces the likelihood of selecting clean fuels by 4% and mixed fuels by 9.5%, while the probability of opting for polluting fuels decreases by 11.5%. House size often correlates closely with household wealth, with wealthier households more likely to select higher-ranked fuels as suggested by the energy ladder theory. Additionally, a larger house size typically necessitates greater heating needs, prompting households to choose more efficient heating methods to meet these demands more effectively than smaller households.

Agricultural assets significantly influence household heating pattern choices, aligning with the agricultural household consumption model where fuel choices are affected by production-side factors due to incomplete markets in rural areas. However, the effects of agricultural land and forest land on fuel choices are divergent, likely due to the interplay of two opposing influences. On one hand, households with more agricultural and forest land have easier access to freely available but polluting fuels such as crop residues and firewood, encouraging the use of these fuels. This is particularly evident with forest land, which positively correlates with the choice of polluting fuels. On the other hand, crop residues are scarcely used in rural Beijing, with less than 1% of households reporting their use as fuel in this study, suggesting that agricultural land may influence fuel choices predominantly through an income effect. Households with larger expanses of agricultural and forest land are generally wealthier and can afford cleaner and more convenient energy sources. The contrasting impacts of these assets highlight the complex dynamics influencing rural household energy decisions.

The marginal effects of the seasonal dummies illustrate a clear trend of households increasingly transitioning from polluting to clean heating fuels over time. Regional differences also significantly influence heating fuel choices, which can be attributed to geographic and climatic variations across different areas.

Contrary to much existing literature, this study finds that age does not significantly impact household heating fuel patterns. A potential explanation for this discrepancy lies in the method of data collection concerning age. While most studies collect age data specifically for the household head, the dataset captures this information from a randomly selected household member who responded to the survey. Although it is reasonable to assume that the household head often dictates heating decisions and is likely the survey respondent, this methodology may introduce substantial measurement bias if other household members, who might not represent the head's perspective, provide the data.

The results confirm the agricultural household fuel consumption model's predictions that a variety of factors influence household fuel choices. These include market prices, household characteristics such as gender, marital status, education, household size, and area, as well as variables tied to production decisions, notably agricultural assets. These elements collectively establish the household-specific shadow price of fuel. Notably, my findings deviate from the energy ladder theory by demonstrating that income does not significantly predict fuel choices, highlighting the fuel stacking behavior in rural settings.

5.3.2 Determinants of Heating Behaviors

Table 9: FE Model: Determinants of Household Heating Behaviours

Variables	Electricity		Coal		Wood		All Fuels	
Log Price of Coal	0.232		-0.273		-0.100		0.062	
	(0.218)		(0.273)		(0.067)		(0.052)	
Log Income per Capita	0.259	**	-0.020		-0.022		0.084	**
	(0.105)		(0.106)		(0.067)		(0.038)	
Age	0.002		-0.011		0.022	***	-0.006	*
	(0.010)		(0.014)		(0.006)		(0.003)	
Male	-0.310	*	0.321	*	-0.002		0.046	
	(0.171)		(0.191)		(0.095)		(0.041)	
Married	-0.387	*	0.179		0.449	***	0.017	
	(0.211)		(0.279)		(0.165)		(0.085)	
Secondary or Higher Education	0.481	**	-0.202		-0.311	**	0.075	
	(0.191)		(0.179)		(0.120)		(0.055)	
Log Household Size	0.058		1.070	***	0.355	**	0.453	***
	(0.257)		(0.256)		(0.162)		(0.066)	
Number of Children Under 5	-0.082		0.126		-0.415	***	-0.007	
	(0.255)		(0.219)		(0.144)		(0.048)	
Log Household Area	1.266	***	0.097		-0.324	*	0.557	***
	(0.235)		(0.275)		(0.172)		(0.058)	
Agricultural Assets								
Log Agriculture Land	0.017		-0.027		0.024		-0.008	
	(0.034)		(0.032)		(0.026)		(0.012)	
Log Forest Land	-0.011		0.050	*	-0.003		0.015	*
	(0.024)		(0.027)		(0.021)		(0.008)	
Fixed Effects								
Village	Yes		Yes		Yes		Yes	
Time	Yes		Yes		Yes		Yes	
Number of observations	2346		2346		2345		2345	

[a] *** p<.01, ** p<.05, * p<.1
[b] Dependent variable are log-transformed total heating hours across all rooms by fuel sources

Having explored the determinants of heating fuel choices, I shift my focus to the determinants of heating behaviors. While fuel choices pertain to the selection of energy sources, heating behaviors examine how extensively and in what manner these fuels are utilized. This transition in focus enables us to investigate the factors that influence the actual usage of fuels, providing insights into household heating practices and their broader energy consumption patterns.

Table 9 outlines the determinants influencing heating behaviors. Key factors include income, age, gender, marital status, education, household size, the number of children under five, household area, and forest land. These determinants largely align with those influencing fuel choices, although there are variations in their effects between choosing fuels and determining heating behaviors, which implies differences between these two decision-making processes.

Interestingly, while coal prices influence fuel choices, they do not significantly impact heating hours. This distinction underscores the separate decision-making processes for choosing and utilizing fuels. Although price fluctuations may encourage a transition to cleaner fuels, they do not necessarily impact the volume of heating. On the other hand, although income does not significantly affect fuel choice, it markedly influences heating hours. With every unit increase in log income per capita, households increase their electricity heating hours by 26% and their total heating hours by 8.4%. These findings align with both the energy ladder and the fuel stacking hypothesis regarding heating hours allocations, suggesting that as income rises, households tend to increase their use of clean fuels without completely phasing out polluting fuels.

In my previous analyses, age did not emerge as a significant determinant of fuel choices. However, it significantly influences wood usage, with each additional year in age increasing wood heating hours by 2.22%. This finding aligns with existing literature, suggesting that older individuals tend to use more polluting fuels.

Gender differences are also notable in heating behaviors. Males use 31% less electricity and 32% more coal for heating than females, which corroborates both my earlier findings on fuel choices and broader research indicating that females prefer cleaner fuels.

Similarly, marital status impacts heating behaviors. Married couples use 39% less electricity and 45% more wood for heating compared to singles, echoing trends observed in fuel choice preferences.

Educational attainment significantly affects heating behaviors as well. Households with a secondary education or higher use 48% more electricity and 31% less wood, consistent with their tendency to choose cleaner fuels, as noted in the fuel choice analysis.

Interestingly, household size influences heating behaviors differently than fuel choices. Although larger households tend to opt for cleaner fuel portfolios, the findings indicate they use significantly more coal and wood for heating as household size increases. For example, a doubling in household size correlates with a doubling in coal heating hours and a 35.5% increase in wood heating hours. This suggests that while electricity might be adopted as a supplementary heating method in larger households, the predominant fuels used remain polluting.

The presence of young children also significantly impacts heating behaviors. Households with an additional child under five use 41.5% fewer wood heating hours. This could be due to reduced time for fuel collection due to care giving responsibilities and concerns over the health and safety risks posed by traditional wood stoves to young children.

House area also affects heating hours, with a 100% increases in area leading to a 126% increase in electricity heating hours and a 32.4% decrease in wood heating hours. This change suggests a shift towards more efficient heating methods as house size increases, which aligns with the broader patterns observed in fuel choice dynamics.

Lastly, agricultural assets show a minor influence on heating behaviors. Unlike expectations, ownership of forest land does not lead to an increase in wood heating hours but slightly raises coal heating hours and total heating hours. This suggests that the availability of agricultural and forest lands as resources for fuel does not straightforwardly translate into increased use due to potential logistical constraints, such as the distance of land from the household or other uses for the land. Thus, the impact of these assets is likely mediated through income effects rather than direct fuel access.

Heating hours are significantly influenced by a variety of factors such as income, age, marital status, education, household size, area, and the presence of children under five, with each factor exerting a relatively substantial impact. Notably, the determinants of how heating hours are allocated differ from those influencing fuel choices for some factors. For instance, income and agricultural assets demonstrate different effects on these two decision-making processes, highlighting distinct dynamics in heating behavior compared to fuel selection.

6 Discussion

The findings contribute to provide more evidence on household fuel choices, particularly in the context of rural Beijing. Contrary to the singular progression predicted by the energy ladder theory—where households move from less to more efficient fuels as income increases—the results reveal a more complex behavior consistent with fuel stacking. Households in this study continue to utilize multiple heating fuels and retain older heating devices alongside newer technologies like heat pumps. However, since the models primarily focus on comparison within the household across time, it is possible that the inconsistency with the energy ladder is because in a short survey period, the household income do not change a lot to make a progression to upper ladder. If you have data for a enough long time with large variation in income, we could possibly observe the evidence for energy ladder. However, the models focus primarily on intra-household comparisons over time. The apparent inconsistency with the energy ladder theory may be due to the short duration of the survey period during which household incomes may not change significantly enough to observe a transition up the energy ladder. If data were available over a longer period with greater variation in income, we might observe clearer evidence supporting the energy ladder theory.

Furthermore, the analysis confirms an inverted U-shaped relationship between income and the diversity of fuel types used, as also identified by Wu and Zheng (2022). This pattern, illustrated in Figure 15, suggests that households initially increase the variety of fuels they use as their income grows but later consolidate to more efficient fuels once a certain income threshold is reached. Interestingly, I observe a concurrent increase in the use of electricity for heating with rising income, aligning with the broader principles of the energy ladder that suggest a shift towards more efficient energy sources at higher income levels. These observations underline the importance of integrating the energy ladder and fuel stacking theories to provide a more comprehensive framework for understanding household fuel choices.

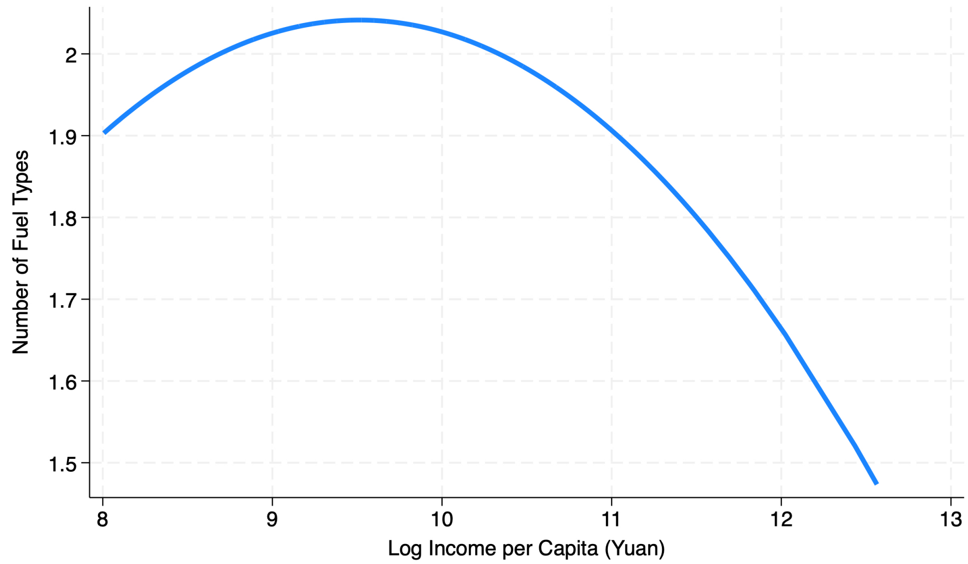


Figure 15: Relationship between Income and Number of Fuel Types

However, despite the apparent diversity in fuel use, the data indicate that most households rely predominantly on one primary fuel type that satisfies the majority of their heating needs. This finding highlights the critical role of dominant fuels in shaping overall household heating strategies and suggests that the primary fuel choice is a pivotal factor in understanding household energy dynamics. Thus, identifying primary fuel sources is also crucial in depicting household energy needs. This dual perspective on household fuel use—recognizing both the diversity of fuels employed and the dominance of primary fuels—provides a more detailed understanding of the complexities involved in transitioning to cleaner energy sources.

The findings from this study demonstrate that the clean heating policy effectively encouraged the transition from coal to electricity, with a notable increase in the use of electricity and subsidized heat pumps, alongside a significant reduction in coal use. Additionally, the intervention led households to increase their heating hours by warming more rooms and extending heating durations, contributing to warmer winters in treated regions. More pronounced effects were observed in regions that adopted the policy earlier or had more polluting initial heating setups. However, the transition to completely clean heating was not fully realized, as coal use was not entirely phased out and the usage of other polluting fuels, like wood, remained unchanged. Concurrently, a spontaneous but incomplete shift towards cleaner heating was observed in areas not directly affected by the policy.

Further investigation into the determinants of fuel choices and behaviors reveals multiple factors that could enhance the effectiveness of future policies. For instance, controlling fuel prices may serve as an effective tool to facilitate the transition to cleaner fuels. Household income also emerged as a crucial factor, suggesting that ensuring the affordability of new technologies through subsidies for purchase and installation is essential for sustaining thermal benefits without imposing additional financial burdens on households.

Moreover, the analysis indicates that other demographic factors such as gender, education, and age significantly impact heating fuel choices and behaviors. These insights are valuable for designing effective policy. For instance, as households adopt heat pumps, targeted guidance on their use could be specifically directed towards women and younger adults, who are more likely to adopt cleaner heating solutions. Emphasizing the health and environmental advantages of using heat pumps might also enhance compliance and satisfaction with the policy. Such tailored approaches in policy implementation could maximize the benefits of clean heating interventions, promoting broader and more effective adoption of cleaner heating solutions.

This study acknowledges several limitations that suggest avenues for future research. Firstly, the data collection was confined to rural regions in Beijing, which may limit the generalizability of the findings to other regions. I examined the households' self-reported heating fuel choices and behaviors rather than the actual use, which could introduce bias. However, the study attempted to mitigate this by installing temperature sensors on heating devices such as kangs and heat pumps to capture actual usage. The analysis of these direct measurements yielded results consistent with the self-reported data, reinforcing the reliability of the findings.

Methodologically, there are pre-existing differences between the outcomes of the treatment and control groups, which potentially violate the parallel trends assumption. Although the data includes detailed records of quantity and expenditure for each type of fuel used for all purposes, I lack specific data on the quantity of fuel or expenditure solely for heating. I used heating hours as a proxy for fuel consumption, which, while informative, is not a perfect measure. Additionally, my approach to separately estimate the determinants of fuel choices and fuel consumption aimed to clarify whether these decisions are driven by different processes. However, this method does not account for the potential interconnections between these two decisions.

For future research, a more comprehensive model that integrates the dual aspects of fuel choice and usage would be beneficial. Such a model could explore the two-stage decision-making process in greater detail. Both qualitative analyses and the development of sophisticated econometric models will be demanded for this topic. Additionally, I didn't explore the interactions between various factors that influence fuel choices and the intervention, there might exist heterogeneous effects of policies across different demographics, which could yield insights that enhance the effectiveness and targeting of similar interventions.

7 Conclusion

This paper explores the micro-level effects of a mandatory residential coal-to-electricity transition in rural Beijing, shedding light on the dynamics of household heating behaviors under the clean heating policy. This policy aims to reduce reliance on polluting fuels and foster a transition towards cleaner energy alternatives, which has been implemented in the context of China's broader environmental goals. Utilizing three rounds of panel data captured through a quasi-experimental design, this study evaluates the causal impacts of this policy on household heating fuel choices and behaviors. I delve into how households adjust their fuel selection and allocate heating hours across different fuels and devices in response to the policy intervention.

The analysis, leveraging a difference-in-differences methodology, indicates that the clean heating policy has effectively decreased coal use and facilitated a significant shift towards electricity and subsidized heat pumps. However, it did not entirely eliminate the use of coal, and other polluting fuels such as firewood remained in use. The policy also resulted in increased total heating hours and a shift towards more efficient heating devices. Interestingly, the policy encouraged a mixed-fuel usage pattern, incorporating both clean and polluting fuels, which reflects the nuances of both the energy ladder and fuel stacking theories. This suggests that while households have progressed up the energy ladder by adopting cleaner fuels like electricity, they have not fully transitioned away from traditional fuels such as wood, supporting the idea of fuel stacking where multiple fuel types continue to meet diverse household needs.

This partial transition and the continued reliance on mixed fuel portfolios highlight the complexity of achieving a full shift to clean energy in rural settings, influenced by economic, cultural, and logistical factors. Furthermore, spontaneous transitions towards cleaner fuels were observed in regions not directly targeted by the policy, indicating broader shifts in energy preferences and practices.

To address these dynamics further, the latter part of the paper investigates the determinants influencing households' fuel choices and heating behaviors in regions unaffected by the policy. Employing a correlated random effects model, I uncover that factors such as fuel prices, household income, and agricultural assets play significant roles in these decisions, emphasizing that the choice of fuels and the volume of energy consumed are influenced by distinct factors. For example, while fuel prices affect the type of fuels chosen—promoting cleaner options as prices of polluting fuels rise—they do not significantly influence the total heating hours. Conversely, income predominantly affects energy consumption volumes without altering fuel type preferences, underscoring the limitations of price mechanisms alone in driving complete transitions to cleaner energy.

This study highlights the importance of integrating both energy ladder and fuel stacking theories to fully understand and address the complexities of household energy transitions. It suggests that policies aimed at encouraging clean heating should consider the diverse economic and socio-demographic factors affecting household energy decisions.

Appendix A: Supplemental Figures

The figures from .A.1 to .A.3 display Sankey diagrams illustrating the transitions in fuel types among households. Figure .A.4 depicts the number of rooms heated by these households.

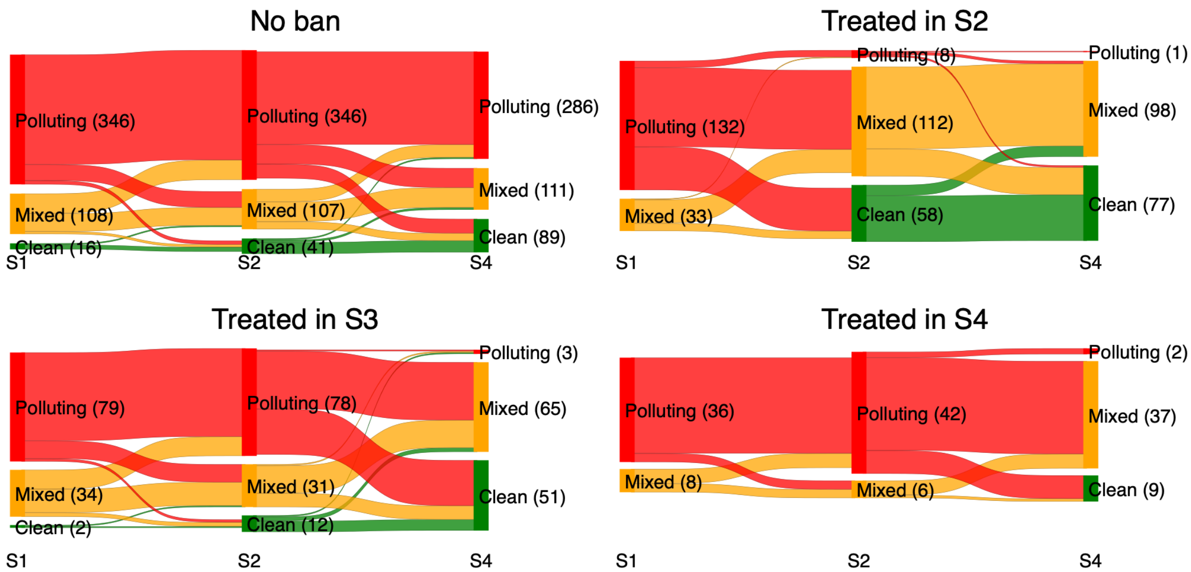


Figure .A.1: Heating Fuel Pattern Transition

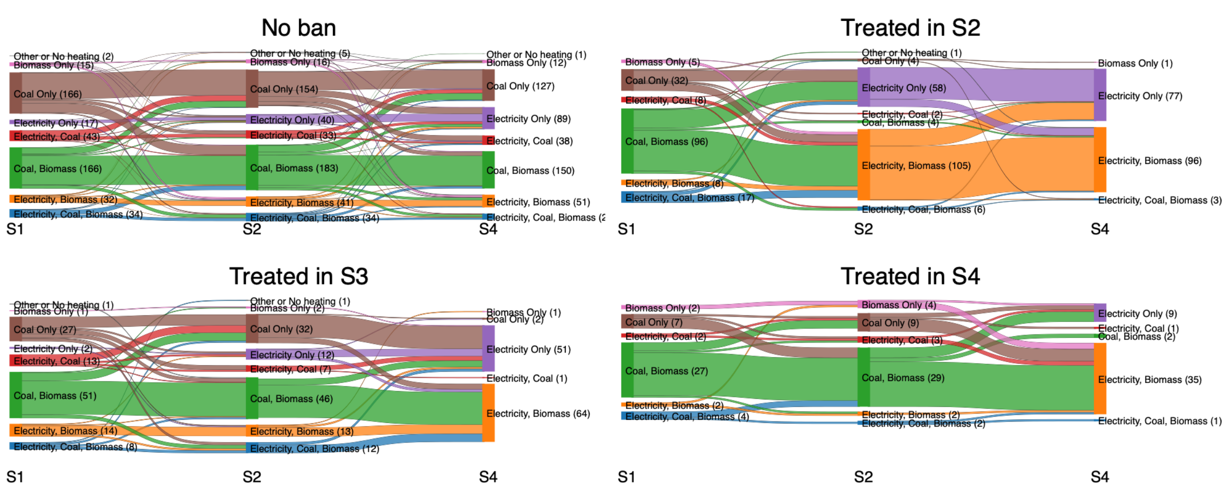


Figure .A.2: Heating Fuel Combination Transition

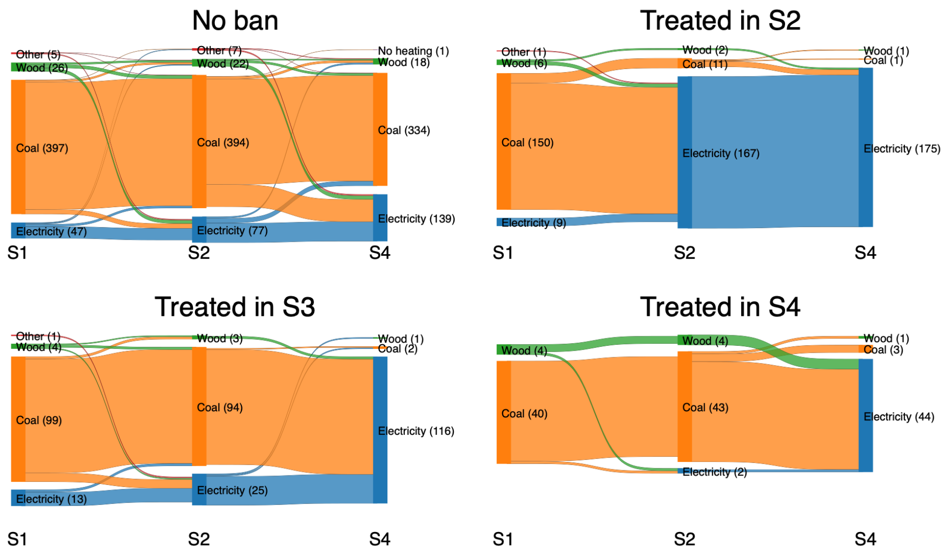


Figure .A.3: Primary Heating Fuel Transition

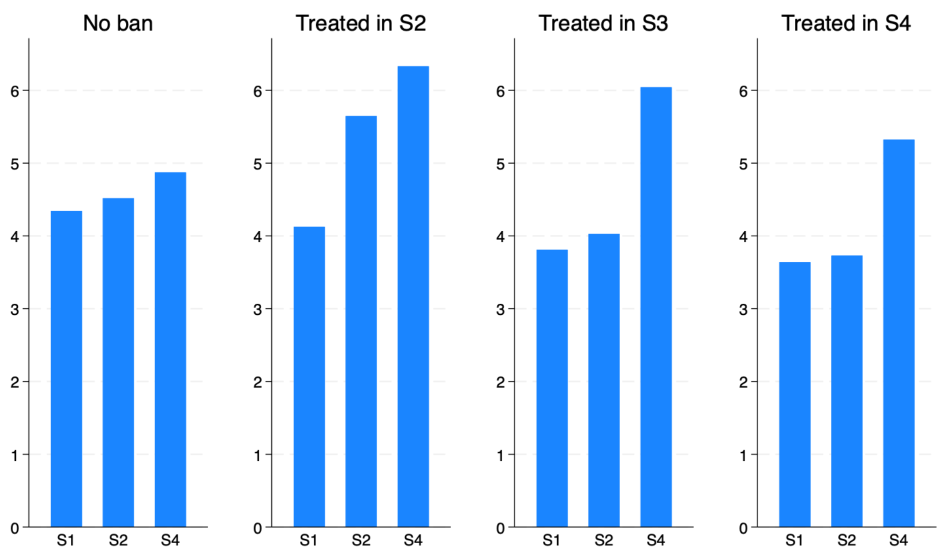


Figure .A.4: Number of Rooms with Daily Heating

Appendix B: Treatment Effects on Average Heating Hours per Room

B1 Determinants of Fuel Choices

One may argue that the true decision-making process is unknown to econometricians, and thus, the ranking of fuels may not be clear. As an alternative, a multinomial logit model can be used instead of ordered regression models. The standard multinomial logit model using the pooled sample assumes that households' choices are independent both within a choice (i.e., for multiple observations over time of the same choice) and across all alternative choices made by the household over time, ignoring individual heterogeneity. The random effects specification relaxes the assumption that multiple observations within a choice are independent. In this model, the choice probabilities for repeated choices made by a household share the same time-invariant unobserved heterogeneity. The household-specific effects act as a random variable, producing a correlation among the residuals for the same household within choices, but leaving the residuals independent across households.

Table .B.1 displays the results from the multinomial logit model, which fails to capture the effects of many variables compared to the CO-REMNP model.

Table .B.1: Unordered Multi-nominal Model: Determinants of Household Heating Fuel Pattern

Variables	Clean		Mixed		Polluting	
Log Price of Coal	0.097	**	-0.044	*	-0.053	*
	(0.032)		(0.019)		(0.026)	
Log Income per Capita	0.009		0.010		-0.019	
	(0.008)		(0.012)		(0.015)	
Age	0.000		0.001		-0.001	
	(0.001)		(0.001)		(0.002)	
Male	-0.004		-0.044	*	0.048	
	(0.014)		(0.019)		(0.025)	
Married	-0.051	*	0.008		0.044	
	(0.023)		(0.031)		(0.031)	
Secondary or Higher Education	0.024		0.023		-0.047	
	(0.017)		(0.026)		(0.027)	
Log Household Size	-0.025		0.045		-0.020	
	(0.017)		(0.026)		(0.029)	
Number of Children Under 5	0.010		0.007		-0.017	
	(0.021)		(0.025)		(0.032)	
Log Household Area	0.055	**	0.092	**	-0.147	**
	(0.020)		(0.023)		(0.029)	
Agricultural Assets						
Log Agriculture Land	0.002		0.004		-0.006	
	(0.003)		(0.004)		(0.005)	
Log Forest Land	0.000		-0.001		0.001	
	(0.002)		(0.002)		(0.003)	
Region						
Fangshan	0.118	**	0.066	*	-0.183	**
	(0.032)		(0.033)		(0.039)	
Huairou	0.086	**	0.129	**	-0.215	**
	(0.030)		(0.038)		(0.048)	
Mentougou	0.162	**	0.126	**	-0.288	**
	(0.053)		(0.034)		(0.057)	
Time						
Wave 2	0.065	**	-0.041	*	-0.025	
	(0.013)		(0.017)		(0.018)	
Wave 4	0.095	**	-0.008		-0.087	**
	(0.017)		(0.021)		(0.027)	
Number of observations	2332		2332		2332	

[a] *** p<.01, ** p<.05, * p<.1

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